Queen Mary University of London

School of Business and Management

Momentum and Contrarian Trading Strategies: Implication for Risk-sharing and Informational Efficiency of Security Markets

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Statement of originality

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Abstract

This thesis investigates the profitability of the Momentum and Contrarian strategies in international equity markets. In particular, I introduce for the first time the use of countries' indices performance to momentum and contrarian portfolio selection. I show that investors can switch back and forth from one country to the other in designing worldwide strategies. The global momentum strategy is consistently profitable between 1969 and 2014. The most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months. This strategy yields 3% per month (42.57% per year). Interestingly, countries' indices' portfolios formed based on prior 48 months; prior losers outperform prior winners by 0.83% per month (10.40% per year) during the subsequent 60 months. The reversal effect is substantially stronger for emerging countries where it yields 1.37% per month (17.70% per year). It remains profitable in the period post-globalization. In addition, I examine for the first time the role of world risks factors in explaining the global momentum and contrarian profits and find that the global momentum strategies obtain significant abnormal returns after adjusting consecutively for world Fama and French risks (0.9% per month or 11.35% per year), and world market states risks (1.31% per month or 16.76% year). Of particular interest, I find a strong relation between world macroeconomic risks factors, notably world industrial production and the momentum return. Second, I find no substantial relation between world risks factors and the contrarian profit. These results suggest that excess return can be earned in the long run by using global investment strategies based on historical prices, challenging the weak form of the Efficient Market Hypothesis. In Chapter 1, I explain the momentum and the contrarian strategies, motivate the importance of what I propose as global momentum and contrarian strategies, and present the results obtained. In chapter 2, I review the Efficient Market Hypothesis' literatures in conformity with the Standard Finance theory. Additionally, I review the Behavioural Finance literatures with a focus on the psychology of investor decision, and the stock market under-reaction and overreaction approach of explaining the momentum and contrarian profitability. In chapter 3, I explain in details the main methodologies used to examine the global momentum and contrarian strategies profitability, and motivate the dataset used. In Chapter 4, I examine the new global momentum strategy profitability internationally. In Chapter 5, I examine the new contrarian strategy profitability internationally. In Chapter 6 I examine the role of global risks factors in explaining the momentum and contrarian profits. Finally, in Chapter 7 I conclude and highlights the limitations of the thesis.

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Chapter 1: Introduction

1.1 Background

Over the last two decades, financial globalization has become a crucial trend of the world economy. The financial perspective of this process, the correlation between international equity markets and international portfolio management become especially interesting topics that capture the attention of many scholars and investment practitioners. However, Scholars and Investment practitioners have not always agreed. The main sources of their disagreement have been the Efficient Market Hypothesis. The strength of the Efficient Market Hypothesis is questionable. If the weak form of the Efficient Market Hypothesis is correct, the existence of trading strategies will be pointless (Fama, 1991). The weak form of the Efficient Market Hypothesis suggests that it is not possible to use market data to make profits from investment analysis. According to the weak form, well-known trading strategies such as momentum and contrarian are not useful, but many investors including institutional investors use momentum and contrarian trading strategies to generate profit.

For international investors, the understanding of how to achieve a portfolio reallocation across market and the factors that affect international portfolio returns are the crux of the success of global trading strategies. Chan et al. (2000) examined the momentum strategies based on individual stock market indices and found that momentum strategies could work well in international investing. In particular, they found that increasing portfolio weights in countries whose stock markets had recently performed well, and reducing weights in relatively poorly performing markets, could improve portfolio performance.

The Contrarian strategy is a strategy that buys stocks that have performed badly in the past and sells stocks that have performed well in the past, based on their past excess return (De Bondt and Thaler, 1985). In contrast, the Momentum strategy is a strategy of buying stocks that have performed well in the past and selling stocks that have performed badly in the past. Evidences from Jegadeesh and Titman (1993) and many others studies converge to the result that, these strategies are profitable over 3 to 12-month horizon. The 6-month formation/6-month holding period strategy produces returns of about 1% per month and that the profitability of these strategies is not due to their systematic risks or delays in stock price reactions from common factors.

De Bondt and Thaler (1985, 1987) provided evidences of the anomaly of price reversal in 3-year returns. They suggested that the profitability of the momentum strategies could be associated to investors' overreaction and reported that paradoxically, long-term past losers outperform long-term past winners over the subsequent three to five year periods; the losing stocks earned about 25% more than the winners' stocks did. Chan et al. (1996) complimented their findings. They suggested that stock price over or under-react to information and that winners and losers often show reversal patterns, which are consistent with the overreaction hypothesis.

Short-term return reversal in stock markets is also a well-established phenomenon; for many decades, it has been shown to be economically significant. For example, Jegadeesh (1990) studied a reversal strategy that buys losers and sells winners based on their prior-month returns, holds them for one month over 1934 to 1987, and found that the contrarian strategy generates a profit of about 2% per month.

Both contrarian and momentum strategies are considered to generate superior return compared to other strategies (Conrad and Kaul, 1998), implying a potential violation of the Efficient Markets Hypothesis and the contrarian profit is attributed to the overreaction phenomenon.

The overreaction phenomenon suggests that market has overreacted in the initial period, and that it subsequently corrects itself (Zarowin 1990), Shiller (1984) described the observed perverse behaviour of the price-dividend ratio in the short-term reversal strategies as evidence that market overreact to information, or fads. Another possible explanation for short-term reversal profits that received some attention in the literature is that price pressure occurs when the short-term demand curve of a stock is downward sloping and/ or the supply curve is upward sloping as demonstrated by Jegadeesh and Titman (1995).

There have been many attempts to explain momentum and contrarian profits internationally with increasingly complex models. These attempts failed to support the idea of a global coordinated and generalised phenomenon and were mainly interested in international, regional, and countries comparison instead. For example, Chan et al. (2000) suggested that momentum strategies implemented based on individual stock market indices were internationally profitable in the short run, that the profits could be link to the exchange rate and that significant profit come from emerging markets as emerging markets are more predictable given the low liquidity. However, no test has been carried out that considers the momentum and the reversal as global coordinated and generalized phenomenon, given that news motion may induce the return differences across countries. In addition, most studies focus on individual stocks on individual countries' indices. There is relatively little research, which focuses on understanding of the practical risks faced by investment practitioners in the implementation of global momentum strategies (Griffin et al., 2004).

1.2 Statement of the Purpose

In this thesis, I examine whether a Global Momentum and Contrarian investment strategies based on countries indices is profitable. I posit that following indices' performances, time-variation in international equity market will lead to momentum and contrarian profit. Especially, I conjecture that switching back and forth investment from one country to the other in designing worldwide momentum and contrarian strategies while focusing on a global coordinated and generalized phenomenon is likely to generate extra profit.

The key insight is that the concentration of equity in the hands of institutional investors (insurance, mutual and pension funds) activates the international equity trading, given that it offers the prospect of worldwide investment opportunities as institutional investors have the expertise and the logistic to trade globally. Haslam et al. (2013) reported the steadily increased of these funds in the advanced economies moving up from $22 trillion to $60 trillion and from a position where these funds were equivalent to GDP to where they were 1.7 times GDP. They established that in 2009 the global value of corporate equities under management within these main institutional sectors amounted to approximately $25 trillion, equivalent to two-thirds of the main economy stock market capitalizations in that year.

Additionally, the emergence of new ways of trading such as Exchange Traded Funds (ETFs) offer investors the opportunity to invest worldwide. These investment funds provide exposure to a portfolio of financial instrument, but have the added benefit of been traded just like shares on a stock exchange.

The logic is to construct a global strategy that allows contrarian investors to divest in selected well-performing countries (winners) and invest in selected poor-performing countries (losers) based on countries' past indices performances and inversely with momentum investors.

To test this inference, I construct deciles and quintiles portfolios; overlapping and non-overlapping portfolios using raw returns following countries indices performances, examine the international evidences of the long-term contrarian predictability in different market states, and provide alternative explanations of the international profitability of the contrarian strategies.

My expectation is that, the Global Momentum and Contrarian Strategies will be more profitable and less risky than the pure Momentum and contrarian strategies based on individual stocks as it focuses on indices which are often less risky than individual stocks. This leads to investors' ability to detect any underlying long-tern reversal effect worldwide in different market states, allowing them to understand the international reversal phenomenon in different market states. Switching their strategies constituents and horizon to avoid resulting losses from negative contrarian payoff will help them earn consistent return.

Consistent with my prediction on contrarian investing, I find that indices' portfolios formed based on prior 48 months, prior losers outperform prior winners by 0.83% per month (10.40% per year) during the subsequent 60 months. Interestingly, the reversal effect is substantially stronger for emerging countries where it yields 17.70% per year. It remains profitable in the period post-globalization, countering the concern to whether the integration of equity markets synchronize the prices reversal worldwide. Returns' differences consistent with portfolios formation approaches are also observed.

Examining the profitability of the momentum strategies based on past countries indices' returns; I find that the Global momentum is highly profitable. For portfolios formed based on prior 9 months, prior winners outperform prior losers and earn 3% per month (42.57% per year during the subsequent 3 months. Even more interesting, I did not find evidence of return continuation among countries indices. I also emphasise the point that investors may earn extra returns by investing internationally as the global momentum generates a return of about three times higher than the return indicated on Jegadeesh and Titman (1993 2001) and Chan et al. (2000).

From a practical investment perspective, the contrarian strategies with non-overlapping portfolios are long-term strategies and results in a low turnover. The optimum strategy generates a return of 10.40% per annum while the portfolios are rebalanced with 48 months' intervals, while the optimum momentum strategy also result in a low turnover with 42.57% return per annum. On other hand Jegadeesh and Titman (1993), and Berkowitz, Logue and Noser (1988) estimate one-way transaction costs of 23 basis points for institutional investors suggesting that transaction cost of 0.5% per trade with a 6-month/6-month strategy is conservative. This implies and estimated transaction cost of 0.6% per annum which is not negligible, suggesting a contrarian profit of 9.8% per annum, and a momentum profit of 41.97 which does not undermine the high profitability of these strategies. However, investment firms must demonstrate that they have executed at the best possible trade condition conformably with the European regulation.

Furthermore, ETFs are easy to access and simple to use. They can achieve diversification through one trade, allowing access to different investment and cover a broad range of asset classes. They often have lower cost than many other type of investments funds helping investors to keep more of their earnings. For example, a world equity ETFs with 5% turnover rate might incur transaction cost amounting to just 0.4 basis points per year (Morningstar, 2016). ETF are flexible to investors' needs, whether they want to invest in developed markets like US and UK, in emerging market like India and China or in commodity such as Oil and Gold.

Next, I examine the role of global risk factor in explaining the global contrarian profit and find no systematic relation between variation in global risks factor and the contrarian profit. The evidences reveal significant adjusted contrarian return of 1% per month (12.68% per year) after controlling for the joint effect of Fama and French risks, market state factors, and macroeconomic risks factors on the contrarian profit. These results remain robust for subsample analysis (established, emerging, developed markets and during the globalization period). However, abnormal returns remain during currency and banking crisis but could be wiped-out by a stock market crash. Further analyses following business cycle indicate that contrarian investors earn positive abnormal return during expansion periods.

Examining the role of global risks factors in explaining the global momentum profit, I find a strong systematic relation between variation in macroeconomic factors, notably industrial production and the adjusted momentum return. The evidence is that industrial production tends to contribute significantly in explaining the momentum return with a coefficient of 1.05, a t-statistic 3.46 and a P-value of 0.00 when I control for all risks factors. This reveals that changes in economy growth or in industry's output strongly affect the momentum profit. This positive relationship is quiet robust. For example, the findings survive with all holding periods. 6-month (0.10%), 9-month (0.00%) and 12-month (-0.40%).

Of particular interest, the size of the abnormal return decreases when I increase the holding period suggesting that this abnormal return not only disappears in the long run after controlling for global risks, it may induce a negative momentum payoff. This particular aspect attracts my curiosity given that I have a zero profit for horizon up to 9-month and a negative abnormal return (-0.40%) at 12-month.

The positive impact of macroeconomic risks factors on the global momentum profit is also significant when the sample size is restricted to emerging countries, developed countries, established market and globalization indicating that the findings are not limited. Examining the impact of crisis on the momentum, I refer to the possibility that stock market is an indicator of the state of the economy as suggested by Naes et al. (2011), given that the global momentum are based on stock market indices prices. I also find substantial remaining momentum after account for the crisis and non-crisis period with the exception made on banking crisis when taken solely. My findings also strongly support that industrial production contributes significantly in explaining the momentum return following business cycle expansion, and disappears with contraction in line with Chordia and Shivakumar (2002) who suggested that variation in momentum payoffs reflect time varying over the business cycle.

1.3 Research Hypotheses

This study examines the Momentum and Contrarian trading strategies for international investors based on countries stock market indexes worldwide, given international investors will move back and forth from one market to another in designing their strategies. My primary aim is to compare the results of using both Momentum and Contrarian strategies in the international equity market.

More importantly, the data include financial market crisis, global risks factors allowing to compare the impact of the financial crisis in both strategies and to gauge the extent to which a financial shock can affect their profitability. The sample also includes countries indices prices; it includes Fama and French risks factors (Fama and Fench’s three factors), Market state factors (Liquidity, Default spread, Term spread, and the MSCI World Market return), and Macroeconomic factors (Oil price, Market volatility, and Industrial production). Which are considered global risks factors, and allow examining whether worldwide momentum and contrarian profits are explained by global risks. They also help in examining which of these factors are consistently dominant in the momentum (winners-losers), and the contrarian (losers-winners) profitability over time.

This thesis intends to answer the following questions:

- Do momentum strategies work for international investors who target 47 stock market indices?
- Do contrarian strategies work for international investors who target 47 stock market indexes?
- Can the momentum and contrarian be explained by global risks factors?

1.3.1 Hypothesis 1 of 3

This hypothesis answers the first question of momentum strategies work for international investors by examining the momentum strategies performances over various construction and holding periods (3, 6, 9, and 12 month).

Ho1: Global momentum strategy applied across the world financial market should generate positives and significant returns.

1.3.2 Hypothesis 2 of 3

This hypothesis answers the first question of contrarian strategies work for international investors by examining the contrarian strategies over various construction and holding periods (36, 48, and 60 month).

Ho2: Global contrarian strategy applied across the world financial market should generate positives and significant returns.

The purpose of these analyses is to determine the optimum strategies, which generate significant returns for the global momentum and contrarian trading strategies during the 1969-2014 time-period with 47 countries indices. By doing this, I intend to discover that these strategies generate positive and significant profit over the sample period and that the optimum momentum strategies profit decrease gradually after financial shock appearance and the contrarian profit increase gradually after the shock.

Robustness Test

1. Does global momentum generate consistent and significant excess return in established market, developed market, emerging market, and during the globalization period?

2. Does global contrarian generate consistent and significant excess return in established market, developed market, emerging market, and during the globalization period?

3. Does the global portfolio issued from the momentum strategy generate consistent and significant cumulative excess return in bull and bear phase and in different period?

4. Does the global portfolio issued from the contrarian strategy generate consistent and significant cumulative excess return in bull and bear phase and in different period?

1.3.3 Hypothesis 3 of 3

The remaining hypothesis (Ho3) helps in examining whether the momentum and the contrarian return remain after adjusting for Fama and French's risks factors (Fama and Fench's three and five factors), Market state risks factors (Liquidity, Default spread, Term spread, and the MSCI World Market return), and Macroeconomic risks factors (Oil price, Market volatility, and Industrial production).

Ho3: Momentum and Contrarian profit are compensation for risks.

1.4 Importance of the Study

This thesis importance relies of the fact that it provides evidences of the profitability of the global momentum and contrarian strategies worldwide. It explains how the profit of the momentum and contrarian strategies varies in different market states the extent to which the initial effect dissipates or ceases to affect the momentum and the contrarian strategies profitability. It presents the Global Momentum and Contrarian Strategies as highly profitable strategies and examines the role of global crisis in explaining the momentum and contrarian profits; the results are consistent between subsample periods.

I therefore contribute to several stands in Finance. First, I promote new momentum and contrarian strategies by suggesting the use of countries' indices performances to momentum and contrarian portfolio selections. Investors can now move back and forth from one country to another in designing momentum or contrarian portfolios. My analysis includes a wider set of equity indices (47 countries indices), variety of parameters (3, 6, 9, and 12-month formation and holding periods for the momentum, and 36, 48, 60-month formation and holding periods for the contrarian), sub-periods' analysis, and event-time analysis by sub-period. The result is conclusive and rejects the weak-form efficiency that suggests excess returns cannot be earned in the long run by using investment strategies based on historical shared price or other historical data Fama (1970).

Second, I provide evidence of greater return reversal internationally consistent with Jordan's (2012) study that suggested that contrarian strategies are internationally profitable, but reported return based on national indices of about 5.60% per year with earning above the risk-free rate. My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47 per year) in emerging market, and Richards's (1996) study that found 6.60% per year over 3 years holding period and 5.80% per year over 4 years, but focus on individual countries' indices.

Even more interesting, studying the global momentum does not show evidence of return continuation among countries indices. However, I must point out that my evidences are different from Chan et al.'s (2000) study based on individual countries' indices, that suggest that, momentum strategies are internationally profitable on the point of view of U.S investor as they suggested that on average the momentum strategy generates 1% per month (12.68% per year). Which is significantly lower than the average momentum return in this study (42.57% per annum). I also emphasise the point that investors earn extra returns by investing internationally while considering the momentum as global coordinated and generalised phenomenon. Given that the global momentum generates a return of about three times higher than the return indicated on Jegadeesh and Titman (1993 2001).

Third, I add to the literature on the motivation behind the overreaction hypothesis by suggesting a highly profitable contrarian strategy. In line with the proposal that, if stock prices systematically overshoot, then their reversal should be predictable from past return data alone, with no use of any accounting data such as earnings. A direct implication of these results is that international investors will be able to beat the market using common investment strategies such as the global momentum and contrarian.

Chapter 2: Literature Review

2.1 Introduction

In this Chapter, I review the efficient market hypothesis literatures in conformity with the Standard Finance Theory. Additionally, I review the behavioural finance literatures with a primary focus on the psychology of investor decision and the stock market under-reaction and overreaction approach of explaining the momentum and contrarian profitability. I further assist us to know more about the relevant forms of arguments and models adopted over the years in support of the momentum and contrarian trading strategies. I explore preliminary evidences of the concept of momentum and contrarian trading strategies, its existence and profitability while examining evidences that seem to be significant and those, which have not been significant in determining and explaining the momentum phenomenon. More importantly, I review international momentum and contrarian articles in order to understand how momentum and contrarian strategies' performances differ from one country to another around the world.

I found that the momentum and contrarian strategies are well-documented strategies worldwide in individual countries the results suggest evidences of market inefficiency. Evidences also point to the fact that this profit could be result of investors under or overreaction to news. However, it is clear that the impact of macroeconomic risk factor may have a decisive effect on determining the performance of the momentum and contrarian strategies.

I argue that for international investors individual market are viewed as only one of a series of stock markets that provide investors opportunities. International investors will not just compare the equity markets against one another, they consider the fact that asset allocation also occurs across countries and indicate the success of global strategies that include multiple indices such as the global momentum and contrarian strategies.

The following literature review is organized as follow. The first section looks at the efficient market hypothesis. In this part, I provide evidence supporting the weak and semi-strong form efficiency, evidence relating to the strong form of the efficient market hypothesis that emphasis on the Degrees of efficiency, the adaptive market hypothesis and the fractal market hypothesis. The second section of reviews the behavioural finance literatures with a primary focus on the psychology of investor decision, the stock market overreaction and mean Reversion and the gradual diffusion of information approach of explaining the momentum and contrarian profitability. The last two sections look at evidences of the concept of momentum and contrarian trading strategies, their existence and profitability while examining evidences that seem to be significant and also those which have not been significant in determining and explaining the momentum and contrarian phenomenon.

2.2 The Efficient Market Hypothesis/Standard Finance Theory

2.2.1 Introduction

Fama (1970) has provided a careful description of the efficient market that has had a lasting influence on practitioners and academics in finance. Markets are said to be efficient with respect to information set if price `fully reflects' information set. The economical version of Efficient Market Hypothesis states that prices reflect all information to the point where the marginal benefits of acting on information do not exceed the marginal cost (Jensen, 1978). Fama (1991) also takes de view that security prices should fully reflect all available information. He emphasises the Grossman and Stiglitz's (1980) point that the cost of getting price to reflect information are always zero.

Earlier study by Bachelier (1900) suggested a Brownian motion that arises as a model of the fluctuations in stock prices. He suggested that the small fluctuations in price in the short term should be independent of its actual value. He also assumes implicitly that prices should be independent of their past behaviour. Considering the Central Limit Theorem he infers that increments of the process are independent and normally distributed. The Brownian motion was obtained as a diffusion limit of random walk. Since Bachelier's (1900) findings, Studies on the beviour of security prices began to appear after 1950 suggesting that change in share prices followed a random pattern (Kendall 1953). In actual fact, this question is still clearly unanswered. How could investors outperform the market with trading strategies like the momentum and contrarian strategies, if the market is believed to be efficient and the stock prices reflect all information?

The efficient market hypothesis is also associated with the idea of a "random walk", which is a term loosely used in the finance literature to characterize a price series where all subsequent price changes represent random departure from previous prices. The logic of the random walk idea is that if information is immediately reflected in stock prices, tomorrow's price changes will reflect only tomorrow's news and will be independent of the price change today. But news is by definition unpredictable and, thus, resulting prices change must be unpredictable and random. As a result, prices fully reflect all information, and uniformed investors buying a diversified portfolio at the market price will obtain a rate of return as generous as that achieved by the experts (Malkiel, 2003).

I consider as a definition of efficient market, market that do not allow investors to earner above-average returns without accepting above-average risks (Malkiel, 2003). I do not argue is that the market is always inefficient or perfectly efficient. Above all I know that markets have made mistakes in the past, this can be gauge through evidence such as the the Internet bubble.

However, I can not ignore that psychological factors could influence influence securities prices. in line with Malkield (2003), I am persuaded that Benjamin graham (1965) was correct in suggesting that while the stock market in the short run may be a voting mechanism, in the long run it might be a weighing mechanism. Given that the true value will win out in the end. And before this happened there is always a way in which investors can reliably exploit any anomalies or patterns that might exist. I am optimistic that some of the "predictable patterns" that have been documented in the literature could help create profitable investment opportunities at lest for the short term.

Critics of efficiency argue that there are several instances of recent market history where there is overwhelming evidence that market prices could not have played the dominant role. It is alleged, for example, that number of performances have been recorded for some well-known figures who were able to beat the market consistently using market timing and stock picking techniques, for example Graham. He became a master at researching stock in microscopic or molecular detail. In April 1919 he earned around 250% return on his first day of trading and was able to survive any crisis. History recorded that he gained at least 14.7% annually versus 12.2% for the market as a whole. Graham was able to build a successful long-term track record. He understood the concept of efficient market but he believed that it is probably fair to describe security market as nearly efficient (Graham, 1973).

History also shows that there are compiling evidences to show that, while people are still debating, on the concept of market efficiency, some evidences are put forward that trading techniques like momentum and contrarian trading strategies can generate extra returns.

Lofthouse (1994) suggested that if investors are eager to make money they will use every potential opportunity to make it, and prices will rise or fall in response to their sales and purchases. This means that stocks will be priced at their fundamental value. But even if stocks do not offer the same expected return, investors may want additional return for taking extra risks. Stocks will then be priced randomly as the proper price allows risks.

Lofthouse (1994) also made the assumptions that the model should work well if there is copious flow of information, investors will have to make rational decisions, and it must be possible to deal easily, frequently and cheaply. Which is generally the reflects of a typical modern market. In other words share prices should reflect all available information.

In addition, he suggested that for news to have full effect on price, stock price should adjust relatively well when new information comes along. This means that news should be autonomous from any earlier factor or item. Rational profit-maximizing investors will then drive all prices to the level which reflects available information. Therefore change in share price should be random as information arrive radomly.

The inconsistent paradox observed in the efficient market concept resided in the fact that it is worthless getting involved in a piece of research or seeking new information because the outcome will be reflected instantly in the general market prices. Conversly, if all researchers and analysts quit their profession, then share prices will become less efficient. Therefore markets will become efficient only if some participants believe that they are not efficient and base their trading decisions on something else or something other than new information.

Mackinlay (1997) studied the effect of firm event and found that company anoncement information can affect the price movement before, during and after the event period. He established the abnormal return presence and considered the normal return issue as expected return without condition of the event being realized. Mackinlay went on to conclude that there is a perfect correlation between company information and the change in the market value.

According to Cheol-ho and Scott (2004) empirical studies are divided into two different groups: the early group and the modern study group. Previous findings, indicate that directional trading strategies are profitable in foreign exchange markets and future markets, but not in stock markets. Modern studies indicate that technical trading strategies consistently generate economic profits in a range of speculative markets, at least until the early 1990s. Among 95 studies, 56 found that trading strategies were profitable. 20 results were negative and 19 studies indicated mixed results, but empirical studies were subject to various problems in their testing methods with the example of data snooping.

Fama (1970) suggested that the market is just efficient with respect to information set. He proposed degree of market efficiency, based on the definition of information set:

- Weak form efficiency: where information set is limited to information contained in the historical market prices.
- Semi-strong form efficiency: where all information publicly available and the history of the past prices are included.
- Strong form efficiency: which includes all public and private information available.

This explanation of the efficient market hypothesis was extended by Timmermann and Granger (2004) by specifying how variables in the set are used to generate forecasts. They added search technologies and forcasting models to the efficient market definition.

However, earlier study by Barberis and Thaler (2002) suggested that the efficient market hypothesis suggests that investment analysis is ineffective. This is because either share prices already reflect all relevant known information with the effect that they are already at their fair prices, or it is not possible to make profit from any mispricing. A semi-strong form efficient market is one in which security prices take account of all publicly available information. In addition to market information on past prices trading volumes, publicly available information includes macroeconomic data such as interest rates inflation rate, company data and non-economic events. The implication is that asset prices immediately move to reflect any new information or that no one can make profits by means of purchases or sales based on analysing the new information (Readhead, 2008).

2.2.2 Empirical Evidence on the Efficient Market Hypothesis

Fama (1970) defined the weak form of the efficient market as a market in which the information set is limited to historical prices. However, Earlier study by Kendall (1953) attempted to identify cycles in stock indices and could not find any. One day's level appeared to be the previous day's level plus or minus a random amount. Osbone (1959) found that share price movements conformed to the Brownian motion of physics in that successive movements appeared to be random and the standard deviation of cumulative changes was proportional to the square root of time. Robert (1959) showed that a series of cumulative random numbers looked like a series of share prices such that observers believed that they could identify price pattern.

Fama (1965) confirmed the absence of serial correlation. He also employed run tests, which sought to ascertain whether runs of successive upward or downward price movements were longer or shorter than would be expected based on random price movements. He concluded that lengths of runs were consistent with random series of price movements. Therefore, there was no observable tendency for prices to trend upwards or downwards.

There are counterviews and debates about the efficient market evidences. Shiller (1984, 1988) has suggested that there may be fads and fashions in investment. If such fashions spread slowly, share price trends could emerge as result. Fashion is not the only possible driving force. Since the late 1990s, some people have argued that demographic trends are also having a similar effect.

A study by Peters (1991), which analysed S&P 500 price change from 1928 to 1989, showed that securities markets exhibit fat tails in their returns distributions; the probabilities of very high and very low values are greater than would be predicted by normal distributions. This is consistent with markets trending in particular direction, which is inconsistent with price movements being related to previous price movements. Peters suggested that as few as three variables could accurately predict market movements. However, since these three variables frequently change, there may be no practical way of making profits from predicting market movements. In addition, fat tails in market returns distributions may have alternative explanations, such as the observed distribution being an amalgam of several different normal distributions this is because over a prolonged period a stock index would have been subject to numerous different distributions of returns.

In an investigation of intermediate horizon (3 to 12 month periods) stock price movements, Jegadeesh and Titman (1993) found that stocks exhibit a momentum in which good or bad recent performance continues. They concluded that while the performance of individual stocks is insufficiently predictable, portfolios of the best performing stocks from the recent past appear to outperform other stocks with enough reliability to provide opportunity for profit.

However, Niederhoffer and Osbone (1996) found slight evidence of serial correlation and runs using intra-day rather than weekly or daily data. Intra-day serial correlation appeared to be slightly negative.

Another approach to testing for efficiency is to ascertain whether trading rules, such as those used by chartists, have any predictive value. One trading rule that has been investigated is the filter rule. A typical filter rule might involve buying when a stock price is5% above its previous low point and selling when the stock price falls 5% from its previous high. Fama and Blume (1996) established that it was not possible to make profits by using filter rules to forecast price movements. Campbell et al (1997) found that daily stock returns contained a strong element of predictability.

Technical analysts argue that tests of simple and mechanical trading rules cannot be used to draw conclusions about the complex and subtle techniques actually employed. There is also the point that it is impossible to test the infinite variety of trading rules, and hence it is always possible that effective trading rules exist among those that have not been tested. Furthermore, technical analyst would not publicise effective technique for fear that widespread knowledge of the technique would reduce the profits available to them. Perhaps it is only the effective trading rules that become widely known, and hence subject to testing (Redhead, 2008)

Contrary to much of the other evidence, one study has suggested that some widely-known chartist techniques have predictive power. Lo et al. (2000) found that some technical analysis patterns occurred far more frequently than would be expected based on chance. The most common patterns were double top (and bottom), followed by head and shoulders (and inverted head and shoulders). Although the researchers ascertained that the charts provided information about future share prices, they did not investigate whether the information could be used to make trading profits.

Most the evidences on the performance of professional fund managers support that returns net of costs are at best average (Blake and Timmermann, 1998). The literature on the performance of UK funds has failed to find evidence that information on past investment performance can be used as good guide by retail investors in choosing funds. The general pattern is one in which investment performance does not persist and small groups of funds may show some repeat performance over a short period, particularly poorly performing funds. However, the size of this effect and the fact that it is only very short-lived means that there is no investment strategy for retail investors that could usefully be employed (for a detailed survey please see Appendix G). The results of manager's performance in the U.S. concurred with the earlier analyses of finding that there was no persistency in the performance of managed funds after 1987. There was evidence of repeat performance before this point but it would be misleading to suggest that retail investors could use this finding in the present day (Redhead 2008).

The weight of evidence is that retail investors cannot exploit information on past performance usefully. Against all this evidence is the observation that a few individuals seem to have records of accomplishment of persistently good investment performance. Such names include Warren Buffet, Anthony Bolton, George Soros, Peter Lynch, John Neff, John Templeton, and Neil Woodford. They present an unresolved anomaly from the perspective of the efficient market hypothesis.

2.2.3 Level of Efficiency and the Adaptive Markets Hypothesis

Arguably, the issue is not whether a market is, or is not, efficient. The issue is how efficient a particular market is. Market efficiency could be seen to parallel the perfectly competitive market of economy theory. They are rarely, if ever, achieved in reality. Nonetheless, they both constitute a useful benchmark against which to compare actual markets. They also serve to provide models that are useful for the interpretation and understanding of the real word.

Simon (1995) argued that investors exhibited `bounded rationality', which means that they have limited capacities to absorb and analyse information. They are not able to make the precise calculations, which would provide the optimum solutions to their investment problems. Correspondingly, market prices do not reach their fundamental levels. Instead, investors attain acceptable approximation to their optimum positions. Trial-and-error processes based on the use of behavioural heuristics when market participants have achieved such satisfactory portfolios, means that the market will approximate information efficiency that could achieve satisfying portfolios.

Lo (2004) argue that, from time to time, circumstances would change. Changes in circumstance require new portfolios and new equilibrium prices. Market participants move towards the new satisfactory portfolios using heuristics in a trial-and-error process. According to this view, behavioural heuristics are not compatible with the efficient markets hypothesis. Behavioural heuristics are an aspect of the process whereby market move from one approximation of efficiency to another. Lo called this the `adaptive markets hypothesis'. Markets could be seen as following evolutionary paths wherein they adapt to change, circumstances by behavioural iterative process that mirror the survival of the fittest process of natural selection. Successive solutions to the problem of determining optimal portfolios are tried using heuristics, and the solutions that approximate most closely to the optimum are the ones that survive. The heuristics of behavioural finance are the means of adjusting from one approximation to market efficiency to the next. Behavioural finance is complementary to, rather than a contradiction of, the efficient market hypothesis.

An implication of the adaptive market efficiency is that the degree of market efficiency is not constant. Lo (2004) presented evidence showing that market efficiency, as measured by serial correlation, fluctuates over time. It is tempting to think that a market becomes steadily more efficient over time as the market participants become more sophisticated, but that does not appear to be the case. Degree of efficiency shows period of decline as well as periods of advance. This is consistent with the view that changes in circumstances disrupt (approximate) efficiency and that markets take time to reach a new (approximate) efficiency.

Lo (2004) also explains how the new equilibrium positions can be path dependent. A new set of stock prices are path dependent if they are affected by the process, which achieve the new equilibrium. Therefore, a stock market crash could permanently deter some investors from the market. In consequence, the market will have fewer investors. The absence of those investors will also affect the risk preference of the market, and hence the equilibrium stock prices. A stock market crash does not simply cause a temporary deviation of stock prices from their 'correct' levels; it also changes the `correct' levels towards which the market eventually tends to move.

As far as the Efficient Market Hypothesis is concerned, broadly all market participants should have the same information at some point in time, there are compiling evidences to suggest that this is not always the case. The degree of efficiency shows period of decline as well as periods of advance (Lo, 2004); my intuition is that such market behaviour can lead to return predictability and perhaps helping investors to forecast time variations in stock markets.

2.2.4 Summary

From the Efficient Market literature, I recorded that there are two alternative meanings of the market efficiency. The first suggests that security prices fully reflect all relevant information Fama (1970). The second suggests that there is no opportunity for investors of making abnormal profits. Diverse evidences on the first meaning of the market efficiency support the idea that the degrees of efficiency matter, rather than the existence of the full efficiency. However, there are evidences of the second definition to provide strong support for market efficiency. Market Efficiency in the second sense supports the idea that investors are better off with index tracker funds than attempting to outperform the market using trading strategies or even opting for actively managed fund, given that change in share prices are random (Lofthouse, 1994). The question remains to whether investors or fund managers could outperform the market with trading strategies such as global momentum and contrarian when they appear to be unable to do so.

2.3 Behavioural Finance and Investment Decisions

2.3.1 Introduction

Behavioural finance is the finance field that applies the findings of psychological research on decision-making to investment decisions. Perceptible irrationalities in decision-making could be seen as rising from errors in processing of information in the stock market. De Bondt and Thaler (1985) argue that investors are subject to representativeness bias, they become too optimistic about past winners and too pessimistic about past losers. They suggested that investment decision influenced by representativeness bias could move stock prices away from the level that reflect all information.

Behavioural finance pleads that, with a consistent tendency to over-or under-reaction to new information, investors will profit from the information. Over-reaction would provide profits from selling after the news. Under-reaction would imply that investors could profit from buying subsequent to news. Lui et al. (2001) suggested that stock markets tend to underreact to information such as earnings reports. The prospect to make such profit will be inconsistent with the efficient market hypothesis.

The behavioural finance psychology aspect covers a wide range of theories and concepts. In the following building blocks, I will elaborate upon, but as there is not unifying theory; several these theories will be introduced focussing on their potential economic means.

2.3.2 Limit to Arbitrage

The law of one price suggests that identical assets should have the same price in different markets. If prices differed between markets, arbitragers would buy in the cheaper market and sell in the expensive one. This would generate a profit, and would be inclined to move the price into equality. The extra demand in the low-price market would tend to raise the price at hand, and the supplementary supply in the high-price market would be inclined to reduce the price in that market. The efficient market hypothesis implies that the price of an asset should be the same in all markets; the reason for this is what Fama (1970) labelled the "Joint hypothesis problem".

A related idea is that comparable financial assets should trade at comparable prices. If they did not, there would be an arbitrage opportunity available from buying the cheaper and consecutively selling the more expensive one. Such arbitrage would be inclined to bring the prices into fairness. Objections to this view go back to Friedman (1953). He suggested that rational trader always undo any displacements in the market. The efficient market hypothesis suggests that similar assets should trade at similar prices. The argument stands on the fact that rational investors and speculators' under-reaction involve that investors profit from buying subsequent to news and they will always perceive mispricing quickly and therefore benefit from the situation by taking position on the market that will move back the price to its fair value.

However, there are evidences to suggest that the arbitrage may not succeed. Supporters of behavioural finance argue that due to the presence of irrational investors, the stock market move away from its fundamental value, they agree that rational investors will take advantage of the opportunity of a mispricing in the market. However, the question arises to the issue on self- correction of the mispricing, as investors who suppose that growth stocks are overpriced will pay less for these stocks. If growth stocks still earn higher returns in the future, this will counter the low returns they are expected to earn. Therefore, it can be very unappealing for a rational investor to correct a mispricing due to soaring costs and risk (Barberis and Thaler, 2002).

Given that the fundamental risk is the most apparent type of risk that an arbitrageur will face by buying an apparently cheap asset, an arbitrageur faces the risk of the stock decreasing further in value due to bad news, which will lead to a further loss. To put off these circumstances, the arbitrageur can hedge the asset by selling an alternative security. Regrettably, there is not perfect or alternative substitute asset that exists and a fraction of the fundamental risk will remain un-hedged as a result. This un-hedged position is unpleasant as the arbitrageur is risk averse according to the theory; he does not need extra risk without additional return. The suggestion of risk aversion ensures that the mispricing will not fade away by a single large arbitrageur taking significant large position in the mispriced asset. Besides, the obvious problem that arise even if a perfect substitute asset exists is that, this stock might be mispriced as well which implies that the arbitrageur will back to the initial position. In the same way the mispricing of the original asset, being exploited can deteriorate in the short run; this is known as noise traders risk, and means that the arbitrageur will face the risk that the pessimistic, irrational investors get even more negative, lessening the price even more. This could create massive losses for the investor. Noise trader risk is an important issue as it can force the arbitrageur to settle the position in advance than wanted in the first place. The reasoning is that, if a stock has lost a significant part of its value, investors tend to get anxious and therefore might settle early to avoid further losses. Furthermore, in reality investment and the separation of brains and capital are often associated with professional investment managers handling other people's money (Shleifer and Vishny, 1997).

The separation of brains and capital tend to create a principal-agent problem between the money manager and the investor, particularly when managers are primarily evaluated from their performance. If a known mispricing deepens, investor might withdraw their money and replace them due to lack of understanding of investment strategy. In other word, wherever investors get anxious more funds will be lost. To prevent such a situation, the fund manager may refrain from exploiting the mispricing in the first place. Accordingly, risk might affect the incentives of the manager; consequently, only short horizons arbitrage opportunities will be exploited instead of long runs, as these opportunities appear less risky. When investors faced with fundamental or noise trader risk or systematic risk, arbitrage effect will be limited in the sense that by adding small position of many individual arbitrageurs of the mispriced asset to their portfolios they will not successfully remove the mispricing (Barberis and Thaler, 2002).

In addition, I consider additional costs, which occur when a mispricing is exploited, given that transaction costs are incurred when a trade is opened and closed; this includes bid-ask spreads, commissions and more. Even more the arbitrage strategy assumes short-sale position and as a result additional costs of the short sale constraints must be considered (legal constraints as many investment and mutual funds are forbidden to short sell by law, fee for borrowing the asset, Holding costs and opportunity costs). Finally, the costs of gathering information and this involves investors requiring resources to get update about the mispricing, which may not be considerably difficult (Barberis and Thaler, 2002).

This are overall the arguments defining the existence of limits to arbitrage. Because of price moving away from the fundamental value, arbitrageurs may be unwilling to correct the mispricing due to excess risk and additional costs related to investment. This study may conclude that irrational investors' behaviour affects the prices and consequently the behaviour of the rational investors. In this sense the efficient market hypothesis does not hold at least at the global stage the implication is that international investor could invest or divest internationally following indices performances.

2.3.3 Psychology and Investor's Perception of the Market

The second behavioural finance theory building block is the psychology of investor’s perception. This field is covering by a wide range of psychological concepts and theories. In this section, I will demonstrate how investors show irrational behaviour and why investors irrationality affect the market and that investor’s irrationality influence on the market does not happened by chance. By studying the reason for existence of irrational behaviour, through an examination of psychology and investors sentiment, I will have a greater understanding of how investor psychic can influence their preferences and thereby their behaviour on the market. In the following section, I aim to examine only terms that I find relevant for this analysis.

Barberis and Thaler (2002) went over the main important points, such as systematic misconceptions that people tend to make, for example, overconfidence, optimism and wishful thinking, belief perseverance and availability biases, which to mention a few that can attenuate biases. The decision-making process of investors in selecting an asset can be affected by the above-mentioned factors. Investment experts tend to exhibit more overconfidence than private investors do, as they are more equipped with complex models (O' Shaughnessy, 2005).

Camerer and Hogarth (1999) showed in several of their studies on this topic that incentives can only take away parts of this irrational behaviour. Although, incentives to some extent can reduce a biased output, the expansion in the information technology has worsened the investor's analytical ability. It is important to a greater extent to sort out the noise from the useful information.

Deminer et al (2015) examined the impact of industry herding on the momentum profit and found that the profitability of industry momentum strategies depends on the level of herding in an industry. They show that loser industries with high level of herding yield significantly lower subsequent returns than losers industries with low level of herding but there is not significant difference for winner industries across low and high herding levels. They suggested that the level o herding in an industry should be considered in industry momentum implementation.

2.3.4 Frame Dependence and Loss Aversion

Loss aversion and narrow framing also known as frame dependence or mental, are the two most important ideas in the experimental literature on decision-making process when risk is involved, both of which play a significant function on the behavioural finance in stock market setting. They predict that the concept of a gamble can be crucial when evaluating an outcome, as the gamble is framed in a positive (gain) or negative (loss) perspective. The positive framing will cause the investor to be risk averse and the negative framing will affect investor's norms and personal characteristics that will affect the outcome of investors' decision (Kahneman and Tversky, 1981). This implies that the effects on framing can be particularly influential. There are evidences on shifts in preferences due to the framing of the problem and this is a straight violation of the rational choice theory (Barberis and Thaler, 2002).

Kahneman and Tversky (1979) studied the loss aversion; they suggested that people are more sensitive to losses than to gains of the same size. This simply indicates that losses hurt more than gains satisfy. When investors assess a gamble individually instead of evaluating the total value of all combined gambles, the effect of a gain or loss seems to be much more strong (Thaler, 1999). To illustrate this, Kahneman and Tversky demonstrated that the graph of the value functions is steeper for losses than for gains and implies loss aversion. A distinctive case of loss aversion is when people tend to reject gambles such as "win $110 with probability 1/2 lose $100 with probability 1/2" which is not only evidence of loss aversion but of narrow framing as well (Barberis, Huang and Thaler, 2003). Narrow framing refers to the tendency to perceive gambles independently from the original wealth. Loss aversion is often used side by side with narrow framing because people perform intuitively rather than through effortful reasoning (Kahneman, 2003). This means that, investors tend to appraise their gains and losses on a short-term basis, when framing decision is narrow.

In this thesis, I started by introducing the Efficient Market Hypothesis under the assumption of full rationality of all agents and the limitation of the price determination of the Standard Finance Theory. However, the reality is that investors might have limited cognitive capacity, which prevent them from being entirely rational when managing information in decision-making process since important and significant information may be under- or over-estimated or even neglected. Investors may under- or over-react to information, which may lead to the conclusion that market participants could exhibit irrational behaviour and cause strategy such as contrarian investment strategies to be profitable. Therefore, I can now focus on a strategy such as the contrarian strategies that benefit from investors' irrationality and the fact that stocks prices deviate from their fundamental value.

2.3.5 Stock Market Overreaction and Mean Reversion

Overreaction is a market hypothesis stating that investors and traders react disproportionately to new information; overreaction means that prices rise too high and fall too low. It has often been suggested that the volatility of stock market is greater than might be expected from the efficient market hypothesis. Even though evidences of short-term serial correlation tend to show that returns significantly correlated, investigation of longer time periods have suggested that markets overreact to new information. De Bondt and Thaler (1985) have put forward an overreaction hypothesis. The overreaction hypothesis suggests that when investors react to unanticipated news, which will benefit a company’s stock, the price will initially be greater than it should be. There will be a subsequent price decline to the level justified by the new information. Conversely, the priced fall arising from adverse news will initially be exaggerated, requiring a subsequent correction.

De Bondt and Thaler proposed a directional effect and magnitude effect. The directional effect is the tendency for an initial overreaction to be followed by moderating movement in the opposite direction. The magnitude effect is the tendency for the size of the correction to be related to the extent of the initial overreaction. A relative large initial overreaction will be followed by a relatively large compensating correction. Brown and Harlow (1988) added the intensity effect, which states that the shorter the duration of the initial price changes, the extreme the subsequent response will be. Brown and Harlow found that overreaction was most marked in the case of short-term responses to negative news.

The very paper also investigated if individual decision-making and market behaviour are related. They tested whether investor overreactions affect stock prices and found sign of overreaction all over the length of the study and suggested that past winners and past losers realise excess return in January, but the loser’s portfolio experiences exceptionally large excess return compared to winners’ returns even with a portfolio formation period of up 5 years.

Later on De Bondt and Thaler (1987) re-evaluated the overreaction hypothesis considering the time-varying risk premium and the market efficiency. They found that the percentage of firms in the losers’ deciles portfolio that experience above-average earnings growth is significantly larger than equivalent in the winners’ deciles and that the earnings of winning and losing firms show reversal patterns that are consistent with overreaction. However, the study did not provide satisfactory explanation of the January effect rational and their findings are consistent with Jegadeesh and Titman (1993).

Summer (1986) simulated a series of share prices, which overreacted to new information. He went on to show that the techniques used in the early tests of serial correlation were not able to discriminate between an overreacting series and a random series and suggested that test could not identify the presence of overreaction, therefore, cannot be used to refute the proportion that markets are prone to overreaction.

Fama and French (1988) found a tendency for prices to deviate from their fair value and then revert towards them, which is consistent with the idea that price overshooting is always followed by corrections that show apparent fluctuation around their fair values.

However, it has often been suggested that the observed volatility of stock markets is greater than might be expected from the efficient market hypothesis. The stock market crash is an example of volatility that are difficult to explain in terms of new information coming into market. Share prices are seen as being the present values of expected future dividend receipts, but dividends show much less fluctuation than share prices.

Shiller (1981) tested the hypothesis that stock price volatility exceeds what is justified based on variations in dividends. The basic premise of these studies is that stock prices should be more stable than dividends since stock prices reflect expectation of dividends. By considering an analogy with tossing a coin, if a coin is tossed 100 times the expectation is that there will be 50 heads. Each time the coin is tossed 100 times the forecast would be 50 heads. The forecast does not vary; it has zero volatility.

However, on most occasions that the coin is tossed 100 times the actual number of heads will differ from 50. The observed numbers of heads will tend to form a normal distribution with a mean of 50. The observed number of heads is more volatile than the forecast number of heads. The implication of this reasoning for share prices is that they should exhibit greater stability than dividends. Share prices are based on expected dividends, which should be more stable than actual dividends. The volatility of share prices should be less than the volatility of dividends. Shiller's research found that stock prices were much more volatile than dividends.

These studies have their critics. It has been suggested that the price fluctuation arises from variation in the required rate of return by which expected dividend streams are discounted, perhaps due to changes in the risk premiums (Cochrane 1991).

Although studies of short-term serial correlation tended to find that there was no significant correlation coefficient, investigations of longer time-periods have suggested that markets overreact to new information. Tests covering periods of several years (Fama and French 1988) have found a tendency for prices to deviate from their fair values and then revert towards them (mean reversion). In other words, significant negative serial correlation has been found over multi-year time horizons. This is consistent with Shiller's (1984, 1988) view that fads appear to exist in securities markets. Episodes of apparent overshooting followed by corrections give the appearance of asset prices fluctuating around their fair value. Market prices seem to exhibit excess volatility.

Research by Brown and Cliff (2005) is consistent with the view that fads or sentiment, influence stock prices. Brown and Cliff used a measure of sentiment based on the balance between bullish and bearish investment newsletters. Their results were consistent with the view that share prices initially overreact and then mean revert with the effect that, following positive sentiment, there are relatively low returns for a period as price mean revert. Prices initially show unjustified rises, but subsequently experience falls as the unjustified rises are corrected. Conversely, periods of negative sentiment are followed by relatively high returns as the under-pricing, caused by the negative sentiment, is subsequently corrected.

Kang et al. (2002) in China put further evidences on overreaction forward. They who found that there is a significant abnormal return for some short and medium term momentum strategies and suggested that it was associated with overreaction to firm specific information in short term. In addition, they discovered that there was not a distinctive effect in medium term that was explained by the dominance of overreaction effect but they were able to demonstrate that the negative cross-serial correlation can lead to momentum profits. However, their analysis was based on data only accessible by local investors.

Pan (2010) tested whether momentum in stock returns is not due to positive autocorrelation as behavioural models suggest. He found that when autocorrelations are calculated on monthly returns the results are positive, the averages and the cumulative sums of the first six- and twelve-order autocorrelation are mostly positive and confirmed that the negative auto-covariance associated with momentum as documented are indeed consistent with the explanation of positive return autocorrelations offered by the behavioural theories.

They also suggested that it is better to measure the relation between price momentums and return autocorrelation, by looking at autocorrelation of the short-term over various lags rather than autocorrelation of long-term, as the short-horizon stock returns show positive autocorrelation, but results appear to be plain.

Moskowitz et al. (2012) examined the momentum effect on dozens of diverse futures and forward contracts that include equity indexes currencies, commodities and sovereign bonds worldwide, while using regression analysis and the exponentially weighted lagged squared. They found significant signs of “time series momentum effect” in equity index, that partially reverse over longer horizon and suggested that, this was consistent with under-reaction and delayed over-reaction relatively to the dynamics of different trading position, but did not explain why this happened.

Gokecen, and Post (2013) tested the hypothesis that stock prices underreact to news. They found that short-term return continuation is strongest after recent increases in volume and or variability, and that a conditional trading strategy of buying high-information winners and selling higher-information losers leads to significantly larger profits than an unconditional version, but the study was limited to the NYSE and the AMEX.

Conversely, Zarowin (1989) examined firm’s stock over 36 months relative to extreme earning years and found that the poorest earners do outperform the best earners. However, he was able to demonstrate that when poor earners are matched with good earners, there is not substantial evidence to suggest that the factor responsible for the overreaction phenomenon is the size and not investors overreaction to earnings; this argument rejects De Bondt and Thaler (1985) suggestion. However, this study made use of market adjusted excess return and not risk adjusted.

Smith and Huynh (2013) tested the Hong and Stein’s (1999) under-reaction model on weekly momentum returns by employing the dataset of 19.9 million news items in the U.S., Europe, Japan, and Asia Pacific. They found that under-reaction to news is the main driver of momentum effects everywhere. By jointly examining two features of news namely staleness and stone, they documented a highly profitable trading strategy that buys winner stocks with stale positive news in the past week and sells loser stocks with novel negative news over the same period.

They suggested that, the news momentum portfolio' gives economically and statistically significant returns in all markets including Japan where the normal momentum strategy does not work. However, they did not record any evidence to support Hong et al (2000) hypothesis that momentum returns are driven by the slow diffusion in of bad news in Europe and Japan but the 1-52 momentum portfolio formed using stock with negative news earns 15 bps per week compared to 7bps per week among positive news stocks in Asia. The 8bps difference was not statistically significant. These findings provide strong international supports for behavioural explanations of momentum. The persistent profitability of news momentum portfolios suggests that investors everywhere have similar bias of under-reaction to news.

2.3.6 Gradual Diffusion of Information

Hong et al. (2000) provide evidence to indicate that momentum in share prices is the result of gradual diffusion of information about a company, and that stocks with slower information diffusion provide more potential for momentum profits. They point out that over investment horizons of three to twelve months, there are opportunities to profit from trading strategies based on momentum given that winners continue to perform well and losers continue to perform poorly. They suggest that slow diffusion of information is particularly characteristic of poorly performing small companies whose shares are neglected by analysts. Company management do not enthusiastically publicise bad news, and few investors seek information about neglected small companies. In consequence, share prices adjust very gradually to new information and exhibit momentum during the adjustment process.

Douglas and Mcknight (2005) used a sample of 13 European stock markets over the period 1988-2001 to test the hypothesis that momentum was caused by slow diffusion of information. They also tested an alternative explanation of momentum, which is that it results from investor conservatism. Investor conservatism is a cognitive bias identified in behavioural finance. Conservatism causes investors to be slow to change their opinions. Therefore, even if information were provided quickly, investors would be slow to respond to it. The slow response results in a slow adjustment of stock prices to the new information. The information-induced trades that move prices to their new levels occur gradually over time, rather than immediately after the release of the information. Douglas and McKnight concluded that both hypotheses contributed to the explanation of the momentum effect.

Yan (2013) studied the momentum crashes and the asymmetry in return contributions from the winners and the loser stocks. He suggested that momentum is prone to crowded trades because it is a positive feedback trading strategy with no fundamental anchor. He argues that when informed traders under-react to fundamental information due to slow diffusion of information it gives rise to continuation at short-horizons, which creates an arbitrage opportunity and arbitrageurs exploit this by engaging in momentum trading. However, the uncertainty in the amount of capital devoted to the momentum trading makes it possible that arbitrageurs overcorrect to the initial under-reaction that generate losses, causing a fire-sale of the momentum strategy. By studying the U.S. equity market, Yan (2013), identified the loser stocks that are subject to overcrowding by momentum traders (Losers stocks sold heavily) and showed that the fire-sale effect is stronger for the loser stocks than the winners stocks through high frequency short sale transactions.

Furthermore, handy evidences come from Chan et al. (1999) who used measures of prices momentum and earnings momentum, the earnings momentum measures considered the impact of unexpected earnings (profits) announcements on the behaviour of share prices and the impact of changes in analyst' earnings forecasts. Unexpectedly good earning and upward revisions and the impact of changes in analysts' earnings forecasts tend to cause share price rises; conversely, it was found that investing on the basis of price momentum and the two forms of earnings momentum could produce profits over six-month and one-year periods which is consistent with bad earnings and downward revisions.

Moreover, no evidence of reversals or profitable contrarian strategies was found. It was suggested that the evidence was consistent with the view that information is gradually incorporated into share prices. An explanation proposed for the gradual incorporation of information was the procrastination of analysts in the adjustment of their forecast. Downward revisions of forecast may be particularly slow since analysts do not want to antagonise the companies whose shares are being evaluated.

However, there could be multiple sources of momentum and contrarian profits as documented in the literatures, the need to explore the interaction between these sources is more acute in the global equity market as individual or small set of factors alone cannot explained the global momentum profitability.

2.3.7 Summary

Overall, there are significant evidences to support that stock market in the long term overreact to new information (De Bondt and Thaler, 1985). Empirical studies also offer strong evidence of stock market under-reaction (Smith and Huynh, 2013). The weight of empirical findings indicates a resilient support for stock market overreaction and under-reaction. However, the persistent profitability of news motion suggests that investors everywhere have similar bias of under-reaction and overreaction to news. The question remains to whether these hypotheses could be tested internationally with countries indices given that most of the study are done at the firm's level.

2.4 Momentum Trading and Profitability

2.4.1 Introduction

Investment strategies based on the view that the recent direction of share price movement will continue are known as momentum strategies. There is evidence that technical trading rules based on momentum strategies might produce opportunities for profit. Several studies have divided stock into winner and loser portfolios. The winner portfolios contain those stocks that have performed well in the recent past; the loser portfolios contain those that have shown poor recent return. The studies have then investigated whether there is a significant difference in their subsequent performances (Jegadeesh and titman, 1993). By opposition to the contrarian is a strategy the momentum strategy buys past winners and sells past losers. In this I section, I examine empirical properties of the momentum strategies and assess the plausibility of the theory posed in the literature to explain the momentum profitability.

2.4.2 Empirical Evidences Relating to the Momentum Profitability

In general, this work supports the the view that the stock market has some sort of memory, the way that stocks prices behaved in the past is usefull in defining how it will behave in the future leading to short term momentum profit; for example, Jegadeesh and Titman (1993) found that, momentum strategies generate significant and positive abnormal return between 1965 and 1989 and are profitable for 3 to 12 month holding period. When considering the optimum portfolio of 6-month formation and 6-month holding period, the momentum strategy appears to be consistently profitable and can generate a profit of up to 1% as the winner portfolios keep winning and significantly outperform loser portfolios. They suggested that this result cannot be explained by systematic risk or delay in stock price reaction to common factors.

Grinblatt, Titman, and Wermers (1995) analysed the extent to which mutual funds purchase stocks based on their past returns as well as their tendency to exhibit herding behaviour. They found significant evidences suggesting that large number of mutual funds earned positive risk-adjusted abnormal returns and that 77% of mutual were momentum investors, they tend to buy past winners, but there is little evidence to suggest that these funds systematically sell past losers. They also reiterated that mutual funds that use the momentum strategy tended to perform better than others did and that there is little evidence to suggest that funds tended to buy and sell the same stocks at the same time.

Conrad and Kaul (1998) studied the momentum strategies in the US NYSE and AMEX stock market with methods similar to Lo and Mackinlay (1990), and Lehmann (1990) from 1926 to 1989. The study decomposed securities' profits into two components, the cross-sectional variation and time-varying components with different formation and holding periods. They tested 120 trading strategies and found that 50% of them generate significant profits, they suggested that, on average both momentum and contrarian strategies were equally profitable respectively at medium-term (3 to 12 months) and short-term (1week to 1 month) and long-term (3 to 5 years) but they made the exception in for 1926-1947 period. They also demonstrated that the success of the momentum and contrarian strategies can also be attributed to the variation in mean returns. These results confirm that, event of random walk the momentum and contrarian strategies can still be profitable.

Moskowitz and Grinblatt (1999) studied industries momentum while ranking their data into twenty different industries groups. They found that the momentum strategies do not generate significant profit for individual industry. However, when the strategies buy the winners and sell the losers industries they tend to be significantly profitable. They also found that, in the short term the industry momentum seems to be stronger than the stock momentum and that the momentum profit persists in the medium term but dissipate after 12 months. Furthermore, they suggested that, industries factor have undeniable impact on the momentum strategy profitability.

Jegadeesh and Titman (2001) reviewed the evidence of price earnings momentum and found that there is a substantial evidence to prove that stocks that perform well or badly over a 3 to 12-month period tend to continue to perform well or badly over the next 3 to 12 months. They suggested that the strategies that make use of this type of phenomenon are consistently profitable in the United States and most developed markets. They examined the returns of the winner and loser stocks in the month 13 to 60 and found that, the cumulative returns of momentum portfolio are negative, which is consistent with the behavioural theories. They advocate that there are substantial evidences to confirm that firm's and market characteristics can determine momentum strength but the profit size issue from these factors depend on the extent to which they are incorporated in the firm or the market activities.

Moreover, George and Huang (2004) adopted a different approach; they studied the momentum strategy with an investment strategy named "52-week high". The strategy longs the winners and sorts the losers based on their previous month's prices divided by their past 12 months' highest price. They found that this strategy could generate higher momentum return compare to the Jegadeesh and Titman (1993) and the Moskowitz and Grinblatt (1999) strategies. After controlling for the size effect, the bid-ask bounce, and exclude the January return they found that the strategy profitability is two times the profit of previous momentum trading strategies, they concluded that, the 52-week high strategy predicts investors' perception of the Losers and winners.

The literature on the momentum strategy records that there could be multiple approach of testing the momentum phenomenon. There are also substantial evidences to confirm that firm's and market characteristics can determine momentum strength. However, the weight of evidence indicates that most researches were done at the countries level, using individual firm. The perception is that, given the current stage of the globalization of the world economy investors will earn higher return by considering the momentum as a global and generalized phenomenon.

2.4.3 Momentum Strategies International Evidence

To restate, this thesis support the view that international equity market has some memory and suggests that, the way in which equities markets indices behaved in the past could be useful in defining how they will behave in the future at least in the short term. I extend the analysis of the momentum strategies to the global equity markets. The original empirical work supporting the internationalization of the momentum strategy looked at such strategies between successive and individual stock market prices changes. For example, Chan, et al. (2000) studied the profitability of the momentum strategies internationally. They formed momentum portfolios based on past stocks' returns from different markets and examined whether these strategies are useful for country selection. They examine how the profitability of international momentum sytraties is affected by exchange rate movement. Considering a

US investor who implements momentum strategy that involves buying british stocks when the value of british stocks increase (in terms of U.S dollars). They found that the value of investor portfolio depends on how the equity and currency market affect each other. For example, if British pounds tends to appreciate following a rise in the British equity market, the U.S. investor profits when he liquidates british stock portfolio and convert to U.S. dollars. Similarly, if the value of British stocks tends to increase following British pound appreciation, the U.S. investor also profits. In both case, they suggested that the momentum profits do not come from return continuation in the equity market but from the interdependence between the currency and equity market. They also emphasised the link between momentum profit and trading volume and suggested that significant portion of the profit come from emerging markets as emerging markets are more predictable given the low liquidity.

However, the study did not explore the possibility that momentum could be a global coordinated and generalized phenomenon among countries, and that the gloobal momentum could be captured through portfolios of countries' indices and in different horizons given the prevalence of new ways of trading such as Exchange Traded Funds.

The crucial evidence that led the way to this study comes from the fact that Chan et al. (2000) found that momentum strategies could work well in international investing. In particular, they suggested that increasing portfolio weights in countries whose stock market had recently performed well, and reducing weights in relatively poorly performing markets, could improve portfolio performance but the study selected winners and the losers according to their performance departure from the U.S market. While, this thesis constructs winners and losers' portfolios based on raw return from countries indicess.

Empirical studies also demonstrated that European markets and US market are positively correlated. This correlation extends to the momentum strategy; for example, Rouwenhorst (1998) repeated the Jegadeesh and Titman (1993) study on non-US stock markets. He examined 12 European countries with an international portfolio that include The United Kingdom, the Switzerland, Sweden, Spain, Norway, The Netherlands, Italy, Germany, France, Denmark, Belgium, and Austria from 1980 to 1995 and found similar pattern. He found that the momentum strategies are as well as profitable in Europe as in United States, that the past winners outperformed the past losers by about 1% per month in the medium term and that the return continuation is present in all the countries after considering the firms' sizes. However, the study did not examine whether international investors could take advantage of the momentum strategies in both market.

Schiereck et al. (1999) studied all major companies listed on the FSE from 1961 to 1991 and found that the momentum and contrarian strategies appeared to beat a passive approach that invested in the market index. They suggested that factors such as beta, risk, or firm size do not easily account for the results because several strategies require limited trading, that the implementation costs are modest which implies that the results are economically meaningful. From the behavioural finance point of view, they found that the results for Germany matched the findings for the United States even though equity markets are organized very differently and even though there are profound differences in the social, cultural, and economic environment. They pointed out the fact that general traits in human behaviour and psychology could overcome these differences and ultimately drive the speculative dynamics of asset prices in the world financial markets. However, they did not explore other market as the US and the German are all developed market and may have similar economical characteristics.

The momentum strategies were also studied in the Asian market. For example, Fung (1999) studied the contrarian strategy in the Hong Kong's Heng Sang Index (HSI) while using winners and losers' portfolios formation period of 2 years. He found that, the loser portfolio significantly outperforms the winner portfolios by almost 10% a year. Which is significantly different from the approximately 8% reported by De Bondt and Thaler (1985) in the US equity market. However, the study reported different characteristics for the Hong Kong market, which include his difference in stock market capitalisation, high liquidity, the presence of a legal system and an accounting system, his similarity to the western standard, the dominance of mutual funds. Furthermore, Hong Kong market is also characterised by the fact that in most studies, selling some of the winner portfolios may be difficult if not impossible (the up-tick rule for short-selling was abolish after 25 March 1996 in Hong Kong). However, the study did not explain how international investors could take advantage of these characteristics while moving his momentum portfolio between the Hong Kong markets and other markets to consistently profit from the global momentum strategy.

Hameed and Kusnadi (2002) investigated the profitability of the momentum investment strategy in six Asian stock markets (Thailand, Taiwan, Korea, Singapore, Malaysia and Hong). They found that the momentum investment strategies do not yield significant momentum profits. They suggested that a diversified country-neutral strategy generates small but statistically significant returns of 0.37% per month over six month holding period and between 1981 and 1994 but after controlling for size and turnover they found that the country neutral profit dissipates. They concluded that factors that contribute to momentum phenomenon in the United State are not widespread in the Asian markets and that countries specifics characteristics effect are diversifiable internationally. However, the study was limited to Asian stock market and did not include the contribution of other markets, as the momentum tends to be profitable in western countries as well as in countries with low liquidity.

Kang, Liu and Ni (2002) studied the stock-return behaviour in the Chinese stock market. They found that short-term contrarian and intermediate-term momentum generate significant profits. After further analysis, the suggested, that overreaction to firm-specifics information is the single source of short-term contrarian profits that, momentum profits are not distinct in the medium term, which is explained by the dominance of overreaction effect. They also reported that negative cross-serial correlation contributes to the momentum profits that large firms tend to lead small firms in holding periods 1 to 8 weeks, while the small firms lead large firms in the holding periods 12 to 26 weeks. They reported that with value-weighted portfolio strategies, the momentum profits become more distinct because of the unique lead-lag structure in China as the large firms lead the small firms in short horizon while the small firms lead the large firms in relatively longer horizon. However, the study used the “A” shares, which are only accessible to local investors in China and did not said if the unique lead-lag effect can be seen as a sign to predict future momentum and contrarian profit.

Hurn and Pavlov (2003) examined the momentum strategies in the Australian market, they analysed 200 stocks as the small were characterised by low liquidity issues; they established the existence of short to medium-term momentum. They found that momentum strategies yield significant profit of about 4.79% to 13% for the yearly holding period and they suggested that the result are even stronger for portfolio based within individual industries. They advocated that these figures were consistent with the momentum in stock returns reported in international markets and that the contrarian strategy does not provide significant abnormal return over the same time-period but the result was only applicable on the Australian markets, as it does not give any indication of the worldwide momentum profitability.

Mclnish et al. (2008) studied the sort-term momentum strategies in Asian pacific countries while taking into account the effects of trading activity, size/value characteristics, and asymmetric investor responses to news on stock market in Singapore, Thailand, Malaysia, Hong Kong, Korea, Taiwan, and Japan from 1990 to 2000. They provided evidences of trading strategies based on past price performance for 1, 2 and 4 weeks. They suggested that, trading strategies based on past price patterns are not effectively profitable in most pacific Basin markets and that trading strategies, that combining both winners and losers are not consistently profitable over a week, that in 5 out of seven countries, winners display price reversal patterns.

However, they found that momentum profits are profitable only in Japan and Hong Kong. For the Japanese market, the results indicate that the winner stocks earn significant returns after adjusting for three-factor risk (0.30% per week for the traded stocks and 0.20% for the low volume). Which, are statistically significant and which contradict the findings of Lee and Swaminathan (2000) in United State that suggested that past volume helps to reconcile intermediate-horizon under-reaction and long-horizon overreaction effects, but the study did not test whether by combining momentum and contrarian, international investors will be able to generate consistent profit in Asian pacific countries and therefore worldwide.

Furthermore, Naughton et al. (2008) examined the momentum and strategies in Shanghai Stock Exchange, while considering the effect of trading volume in portfolio formation. They used different formation and holding periods; they discovered that momentum strategy can be profitable in the short-term and can provide long horizon positive returns in the Shanghai stock market between 1995 and 2005. They suggested that, investors could generate superior returns by investing in strategies unrelated to market movements. The same past trading volume does not provide a strong link between momentum and value strategies, as they did not find any clear pattern in stock returns between high volume portfolio and low volume portfolios. However, they recorded that around earning announcement the momentum strategies earn high short-term returns but did not explain if this is linked to the country characteristics.

A more recent work by Griffin et al. (2004) extended Jegadeesh and Titman (1993), Chan et al. (1996) study in the U.S in a global setting in 40 markets for price momentum and 34 for earning momentum by analysing several key issues: the separated the long-side positions from the short-side positions; the interaction between price and earnings momentum, the relation between individual countries monentum strategies across markets; and momentum's sensitivity to global market condition, extreme events, and seasonolity. They provided practical perspective for price and earnings momentum investing from 1975 to February 1995 in individual countries' stock markets internationally. They found that, momentum is potentially useful even for investors who are only able to take long positions. They also suggested that, ignoring transactions cost, an investor investing 1$ in European securities in 1975 would have earned $15.06 in low past 6-month return securities, as compared to $66.01 in market indices, or $192.66 in high past return securities as price and earnings momentum profits are large and positive on a global basis. However, Griffin et al.'s (2004) portfolio construction follows Chan et al. (1996) approach and is based on the performance of individual stocks within countries indices. And do not claim to test a global strategy nor considering the momentum as a global coordinate and generalize phenomenon. They attempt to show that price and earnings momentum profits are large and positive on a global basis result in countries comparison. Still, they did not explain why these return differences occur during this period and if they are consistent over time.

Former and Marhuenda (2003) found sign of momentum and contrarian effects in the Spanish stock market. They concluded that momentum strategies could be profitable on the 12-month basis and that contrarian strategies offered profitable opportunities over 60-month periods but their analysis was restricted to the Spanish market and did not explore the global perspective.

Momentum and contrarian strategies seem to be more effective where the degree of the market sensitivity is considered, Narajo and Porter (2010) studied the sources of cross-country co-movement of momentum returns across developed and emerging markets. They found that country-neutral momentum returns are significantly correlated across countries, the correlation is time varying and that co-movement among industries cannot explain the co-movement of country-neutral momentum returns but the study did not explain how international investor could take advantage of the country-neutral momentum returns correlation effect.

Griffin et al. (2010) investigated the common perception that emerging equity markets are widely thought to be places of substantial trading profits and weak- and semi-strong-form market inefficiencies when compared to developed markets. They examined the short-term reversal, and momentum strategies, and found that short-term reversal, and momentum strategies earn similar returns in emerging and developed markets but the study did not establish when and while the momentum and contrarian strategies alter in these markets and whether there are similitude and divergence in the momentum and reversal behaviour in both market.

Avramov and Hameed (2014) studied the impact of the state of the market illiquidity on the momentum payoffs. They suggested that even if Jegadeesh and Titman (1993) found that the momentum strategy generate 1.18 percent return per month, the momentum payoff realizations could be significantly low, often due to massive negative payoffs. After examining the predictability power of previous markets states on the international momentum payoffs, they found that there are overwhelming evidences across the US, Japan and the Euro zone to show that market illiquidity predicts momentum payoffs.

Avramov et al. (2015) examined the role of liquidity for arbitrage, they examine the systematic relation between variation in market liquidity and the strength of the momentum anomaly. They found that the effect goes in the opposite direction. The evidence is that momentum profits are large (weak) when the market are highly liquid (illiquid). One standard deviation increase in aggregate maret illiquidity reduces the momentum profits by 0.87 per month, over the 1928-2011 period.

To examine the predictive role of market illiquididity in explaining temporal variation in momentum payoffs they consider a time-series regression were the predictive variable include three aggregate measure of market condition in the prior month. These include the level of market illiquidity, the state of market return, the agate market volatility, they also include they Fama-French three factors and hey found that there is an identical predictive effect of the lagged market state variable on the profitability of the momentum strategy. Earning momentum payoffs are significantly lower following periods of low market liquidity, reducing market valuation, and high market volatility. Their findings on the predictive effect of market illiquidity on momentum payoffs remains unchanged when they control for various measures of the macroeconomy. The liquidity is also robust to, and partially subsumes the recent evidence that momentum payoffs depend on inter-temporal variation in investor sentiment, as documented by Stambaugh et al. (2012).

When they extend the analysis to non-U.S. of Japan and ten countries establishing the Eurozone, they found similar evidence of significant time-variation in momentum payoffs in relation to market illiquidity. Most importantly, even though it is well known that momentum is unprofitable in Japan (Griffin, et al., (2003) and Chui et al. (2010), they found that the strategy yields substantial and significant profits following periods of low market illiquidity. They key factor on this thesis is whether the momentum anomaly is a global and general phenomenon that holds over time Avramov et al. (2015) study is conducted on individual stocks, their non-U.S. sample cover a limited period of 2001 and 2010, they also leave additional work using the aggregate liquidity state unexplored, allowing a scope for future research.

Narayan, and Phan (2016) examined the profitability of the momentum strategies in Islamic stocks. They controlled for stock characteristics, the state of the market, and the seasonal patterns and found that momentum strategies work for Islamic stocks, but are characteristic-dependent. They show that up and down phases of the market offer different degree of profitability and the risks factors do explain momentum profits.

From the above review, international investors view individual markets as only one of a series of stock markets that provide investment opportunities. The global asset allocator will not just compare the equity markets of the world against one another, but he will consider the fact that asset allocation occurs within and across countries. Global asset allocation can be carried out at the strategy level, the time horizon being considered. Thus, arises the question: does a global momentum works for international investors. I find that it does.

To answer the above question, I considered the empirical approach of implementing the momentum strategies with portfolios of countries' indexes, focussing on portfolio construction approach similar to Jegadeesh and Titman (1993). The result is that, the global momentum strategy is consistently profitable between 1969 and 2014. The most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months. This strategy yields 2.98% per month (42.24% per year) and suggests evidence of market inefficiency. However, there are several factors that should prevent us from interpretating the empirical resulst reported above as an indication that markets are inefficient. First, while the stock market may not be a mathematically perfect random walk, it is important to distinguish statistical significance from economic significance. The statistical dependencies giving rise to momentum are extremely small and are not likely to permit investors to realize excess returns. Anyone who pays transaction costs is unlikely to fashion a trading strategy on the kinds of momentum found in this studies that will beat the market.

2.4.4 Momentum Trading Strategies during Financial Crisis

Choe et al. (1999) tested whether foreign investors' activities affect stock return in Korea from November 30, 1996 to the end of 1997, period that match with the Asian crisis they used order and trade data and found that there are strong evidences of positive feedback trading and herding by foreign investors before the period of Korea's economic crisis. They recorded that, during the crisis period, herding falls and positive feedback trading by foreign investors mostly disappears. They suggested that, there were no evidence of destabilizing effect of the foreign investors on the Korea stock market over their study period as the market adjusted quickly and efficiently to large sales by foreign investors. These sales were not followed by negative abnormal returns but the study did not extend this analysis to other equity market, to show whether adjustment process and speed is consistent across markets worldwide or it is just a feature of the Korean market.

Otchere and Chan (2003) examined the overreaction phenomenon in the Hong Kong market from March 1996 to June 1998, which included the pre- and the post-Asian financial crisis and found that Hong Kong market overreacted to information prior to the Asian financial crisis period. They found that the overreaction tends to be more evident for winners than the losers. They also found evidence of the overreaction in the pre-financial crisis period but reported that abnormal return obtained by exploiting such phenomenon are economical insignificant after considering transaction cost. However, they indicated that after accounting for size effect, and the day-of-week effect, the results appear to be very significant. They advocated that the Chinese culture may have significant impact on investors' view of the market, as they tend to perceive risks differently and are less risk adverse and less likely to overreact, but this study did not show how this feature of the Chinese market could help international momentum and contrarian investors in global portfolio allocation.

Muga and Santamaria (2007) examined the characteristics of the momentum effect in the Spanish stock market, with particular emphasis on the time stability aspect. The results reveal that there was not significant momentum during the 1990's that did not prove to be time-stable, since it had begun to fade by September 1997 coinciding with the pick of the stock market crisis. The momentum has been associated with small-size/ high-turnover stocks. The relation with size appears to be consistent with slow diffusion of information, as suggested by Hong et al. (2000) but the results of these analyses were not extended to other markets worldwide.

Chen et al. (2012) studied the momentum and the contrarian trading strategies in the Chinese stock market from 1995 to 2010. They examined the performance of the trading strategies following different markets states and found that contrarian strategies are more profitable down market, especially after 2007 during the economic downturn. They suggested that market conditions are good predictors of the size of the contrarian profit. They also found that no significant profit is generated from both strategies in the medium term, they reiterated that, for practitioners and investors in general, these results provide good forecasting indicator especially during the post-crisis period.

After consideration of the microstructure effect on the one to two-month formation and holding periods they found that the contrarian strategies generate on average 0.2% per week and even greater in `up' market. However, the study indicated that these results might not apply in developed markets.

These findings provide strong supports for the existence of a momentum phenomenon during crisis periods. The question remains to whether investors could exploit the momentum effect internationally during financial crisis.

2.4.5 Summary

The review of variety of studies related to the momentum strategies shows that there are compiling evidences in support of the hint that trading techniques like the momentum can generate excess returns(Jegadeesh and Titman 1993). Examining the sources of these strategies profitability shows that, there are sufficient evidence to support that momentum profit could be a result of investor under or overreaction consistent with Jegadeesh and Titman (2001) that found evidence of return continuation up to 36 months.

Some studies also explain the overreaction effect in term of gradual diffusion of information as stocks with slower information diffusion provide more potential for momentum profits (Hong et al., 2000). This theory is also supported by the behavioural theory of investor conservatism, which caused investors to be slow in changing their opinions (Douglas and Mcknight, 2005). The international evidences of the momentum phenomenon imply that individual markets represent only one of a series of stock market that provide investment opportunity.

These findings also provide strong international supports for the existence of a global momentum phenomenon, given that there might be disparity among investors reaction to news across countries. The question remains to whether investors could exploit the momentum effect internationally given that news motion may induce the return differences across countries. In others words, does the momentum strategies work for international investors during financial crisis. I found that it does.

The results show that investors can switch back and forth from one country to the other in designing worldwide strategies, that the global momentum strategy is consistently profitable between 1969 and 2014. The most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months. This strategy yields 2.98% per month (42.24% per year) but the returns may vary considerably from one market condition to another. Largely, the result suggests more evidence of market inefficiency.

2.5 Contrarian Strategy

2.5.1 Introduction

In this section, I define a theoretical outline that supports the analysis of the contrarian strategy premium's performance in international equity market and in different market states. I introduce the contrarian strategy and define the means behind the contrarian Phenomenon. After all, the behavioural finance theory is also introduced focusing on the underlying assumptions of full rationality of agents and the psychological issues that affect the decision-making process of contrarian investors, which will help frame the main reasons for irrational behaviour of contrarian investors.

This section also explores variety of contrarian trading strategies in the literature to gain insight on the existence of the contrarian strategy premium and the psychology behind the reversal phenomenon. In a prospect a contrarian investor could be an investor that believes that the route to superior returns lies in selling what others are buying and buying what others are selling. Contrarian (Reversal) in equity market are well known phenomenon throughout the past decades. Stocks that performed poorly in the past rebound in the subsequent futures.

2.5.2 Contrarian Trading and Profitability

Since De Bondt and Thaler (1985) published their landmark paper "Does the Stock Market Overreact?" in 1985, researchers all over the world have argued but come to the consensus that contrarian investment strategies yield superior returns. Most of the controversies on the contrarian strategies topic are related to the source of profitability instead of the superior return itself and the debate includes two different explanations. One possible explanation relies on the fact that markets are efficient and the excess return from the contrarian is a reward from contrarian investors bearing extra risk. The second argument suggests that risk alone cannot explain the excess profit but point out different finance explanations (Jegadeesh and Titman, 1993).

However, Overreaction was the main proposed reason; people make repeated and predictable errors, referring to why investors who are highly knowledgeable about market go off the deep end time after time. De Bondt and Thaler's (1985) study was undertaken to investigate the possibility that both market behaviour and the psychology of individual decision making are related by more than just appearance while referring to investor's overreaction, which, is the hub of contrarian strategies.

They suggested that, the term overreaction carries an implicit comparison to some degree of reaction that is considered appropriate. They attributed the appropriate reaction to one of which has a well-established norm of probability revision problems for which Bayes' rule prescribes the correct reaction to new information of how individuals respond to new data while referring to Kahneman et al., (1982) findings.

Kahneman et al. (1982) suggested that in revising their beliefs, individuals tend to overweight recent information and underweight prior information. People seem to make predictions according to simple matching rule such as the predicted value is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impressions. This rule-of-thumb was named the representativeness heuristic, as it violates the basic statistical principal that the extremeness of predictions should be moderated given the concept of predictability.

There are evidences that the actual expectations of professional security analyst and economic forecasters display the same overreaction bias. One of the earliest observations about overreaction in markets was made by Keynes (1964); he suggested the day-to-day fluctuations in the profits of existing investments, which is obviously transitory and non-significant character, and tends to have an altogether excessive, and even an absurd, influence on the market" (Keynes, 1964).

Shiller (1981) investigated the excess volatility issue; he revised the Miller-Modigliani view of the stock prices and defined it as a constraint on the likelihood function of a price-dividend sample. He suggested that, at least over the last century, dividends simply do not vary enough to justify observed aggregate price movements. More over Kleidon (1981) found that stock price movements are strongly correlated with the following year's earnings changes he suggested a clear pattern of overreaction despite the observed trendiness of dividends, and reiterated that investors tend to attach disproportionate importance to short-run economic developments.

Arrow (1982) suggested that the work of Kahneman and Tversky materializes the accurate excessive reaction of investors to current information which is characterized in all the securities and future markets. Two specific examples of the research to which Arrow (1982) was referring are the excess volatility of security prices and the price earnings ratio anomaly.

An alternative behavioural explanation for the anomaly based on investor overreaction is what Basu called the "price-ratio" hypothesis. Companies with very low P/E are thought to be temporarily "undervalued" because investors become excessive pessimistic after a series of bad earnings reports or other bad news. Once future earnings turn out to be better than the unreasonably forecasts, the price adjusts. Inversely companies with very high P/E are thought to be "overvalued," before falling in price (Dreman, 1982). However, investor overreaction is only one way that people repeatedly swing widely away from rational behaviour.

Overall, the review of evidence on the profitability of the contrarian point to the view that contrarian profit result from the excessive reaction of investors to current information. Shiler (1981) suggested that investors tend to attach disproportionate importance to short-run economic developments. Investors could be acting implicitly in a coordinated means leading to a generalized reversal following a global news motion. However, past researchers did not examine the reversal effect internationally as global and generalized phenomenon. My intuition is that global news motion will induce the return differences across countries leading to contrarian profit.

2.5.3 Contrarian Investment and Psychological Factors

The psychological pressures that this study will be discussing next might also account for anomalies. Dreman (1998) suggested that the gentlest peer pressure could lead us to bad decision, even when the facts are straightforward and easy to distinguish. When the reality is complex and the situation is hard to read, "Social reality" the consensus of the group, no matter how unbelievable, can take a grip on the mind, and turn strong, rational, independent people into sheep.

The psychological findings on group peer behaviour provide only a part of the answer. Investors, even professionals, are victim of important logical psychological failings. These psychological pressures affect decisions under conditions of uncertainty in a very predictable manner in the market place. The bottom line is that these powerful forces lead most people to make the same mistakes repeatedly. Understanding them is the best protection against flying with the crowd, and perhaps profiting from their mistakes instead.

Dreman suggested that despite what many economist and financial theorists assume that, people are not good intuitive statisticians, particularly under difficult conditions. They do not calculate likelihood properly when making investment decisions, which, causes consistent errors. This study will help understand why such mistakes occur so frequently. Once their nature is understood, the study will then explain how the contrarian strategies are anchored upon these intuitive statistical limitations.

To review the limitations of man's information-processing capabilities, the hole that is constantly exerting great force on his decisions. Dreman suggested that people are swamped with information and react consciously to only a small part of it, he affirmed that when overwhelmed with fact, people select a small part of them and usually reach a different conclusion from what the entire data set would suggest.

Researchers have found that people react to sudden large amount of data by adopting shortcuts or rules of thumbs rather than formally calculating the actual likelihood of a given outcome. This is known to psychologists as judgmental heuristics; these shortcuts are leading and simplifying strategies that people use for managing large amounts of information. Backed by the experience of a lifetime, most of these judgement shortcuts work exceptionally well, and allow investors to cope with data that would otherwise overwhelm them. People also use selective processes in dealing with probabilities. In many decisions and judgements, investors tend to be intuitive statisticians. However, being an intuitive statistician has limitations as well as blessings; the very simplifying processes that are normally efficient time-savers lead to systematic mistakes in investment decisions. They make investors believe that the likelihood is dramatically different from what they are. The distortions produced by the subjectively calculated probabilities are large, systematic, and difficult to eliminate, even after they have been made fully aware of them (Dreman, 1998).

Earlier study by Kahneman and Tversky (1982) suggested the most common of the cognitive biases call the "representativeness". They show that it is a natural human tendency to draw analogies and see identical situations where none exists. In the market, this means labelling two market environments, as the same when the actual resemblance is superficial. When people are providing with a little information and they tend to pull out a picture they are familiars with, though it may only remotely represent the current situation.

An example was the aftermath of the 1987 crash. Dreman (1998) recorded that in five trading days the Dow fell 742 points, culminating with 508 points decline on Black Monday, October 19. This wiped out almost $1 trillion of value, and many investors taking this heuristically shortcut cowered in cash, were caught up in the false parallel between 1987 and 1929.

In recounting how often crashes occurred, Victor Niederhoffer, noted that after the panic of 1837 "Prices dropped to zero." he reiterated that the panic of 1857 was much more severe, but do not say whether in the latter panic sellers had to pay buyers to carry away their stocks or bonds. So, crash and depression were not identical.

More important, it is apparent that the economic and investment climate are entirely different. The representativeness heuristic also covers several common decision-making errors. Kahneman and Tversky defined this heuristic as a subjective judgment of the extent to which the event in question "is similar in essential properties to its parent population" or "reflects the salient features of the process by which it is generated". People often judge probabilities "by the degree to which A is representative of B, that is, by the degree to which A resembles B". A and B depend on how people estimate the probability that, A, came from B, A might be a person and B might be a group. The judgment people want to make in this case is the probability A is also part of the group. Alternatively, A might be an event and B might be a potential cause. Again, people are judging the probability that A comes from B. A, for example, would be the similarity or representativeness in people's minds of the 1987 crash to B which, in this case, would be the 1929 crash and depression.

Because the definition of representativeness is abstract and a little hard to understand, this study looks at some more concrete examples of how this heuristic works, and how it can lead to major mistakes in many situations. Given that it may give too much emphasis to the similarities between events but not to the probability that they will occur, and may reduce the importance of variables that are critical in determining the event's probability. I may explore some example in the market following Dreman’s findings.

The representativeness bias occurs repeatedly in the market place. People can see the representativeness bias resulted in a near identical investor reaction to the Gulf crisis as it did to the 1987 crash. First, people put undue weight on the surface similarities between the potential oil crisis of 1990 and those of 1973/1974 and 1980. Secondly, investors again downplayed the critical differences between the two periods, which were far more important than the casual resemblances. Again, the bias contributed to major investor errors in decision-making.

The representativeness bias is responsible at least for number of other major and oft-repeat errors. All mutual fund organizations work from the principle that investors flock to better -performing mutual funds even though financial researchers have shown that the "hot" funds in one-time period are often the poorest performers in another. The final verdict on the sizzling funds in the 1982/1983 market was disastrous. For the aggressive-growth funds of 1991 to 1997, Investors lost billions of dollars in these funds. Many, although fare riskier, could not hold a candle to the long-term records of many conservative, blue-chip mutual.

Still, people are continually enticed by such "hot" performance, even if it lasts for brief periods. Because of this susceptibility, brokers or analysts who have had one or two stocks moving up sharply, or technicians who call one turn correctly, are believed to have established credible records. Therefore, they can readily find market followers. Taking us to another important probability error that falls under the broad rubric of representativeness (Dreman, 1998)

Tversky and Kahneman suggested the law of small numbers. Examining some journals in psychology and education, they found that researchers systematically overstated the importance of findings taken from small samples. The statistically valid "law of large numbers" states that large samples will usually be highly representative of the population from which they are draw on large and representative groups. The smaller the sample used, however, the more likely the findings are chance rather than meaningful.

Another flaw parallel to the previous one also indicates man's shortcomings as an intuitive statistician. In making decisions, Investors become overly immersed in the details of a situation. They neglect the outcome of similar situations in experience. These past outcomes are called "prior probabilities", and logically should help to guide similar choices in the present. This shows up clearly in the stock market by the emphasis people put on the outlook for each exciting initial public offering or concept stock, even though the substantiating data is usually flimsy at best. Still, investors rarely examine the high probability of loss in such issues (the base rate). Instead, Dreman (1998) established that, most buyers of hot IPOs in the 1980s and 1990s focused on the individual story and forgot that over 80% of these issues had dropped in price after the 1962 and 1968 market breaks. Here again, the prior probabilities, although essential, were ignored. However, it is essential to reiterate that impact of psychological pressure apply to investors worldwide indicating the need of a global study.

2.5.4 Anchoring and Hindsight Biases

I look at two other systematic biases that are relevant to the contrarian investment scene and tend to fix investment errors in place. They are also difficult to correct, since they reinforce the others. The first is known as anchoring, another simplifying heuristic. In a complex situation, such as the marketplace, investors choose some natural starting point, such as stock's current price, as a first cut at its value, and will adjust from there. The adjustments are typically insufficient. Thus, Dreman (1998) suggests that an investor in 1977 might have thought a price of $91 was too high for cascade Communications, a leader in PC networking, and that $80 was more appropriate. However, Cascade Communications was grossly overvalued at $91 and dropped to $22 before recovering modestly.

The final bias is interesting. In looking back at past mistakes, researchers have found that, people believe that each error could have been seen much more clearly, if only they had not been wearing dark or rose-coloured glasses. The inevitability of what happened seems obvious in retrospect. "Hindsight" bias seriously impairs proper assessment of past errors and significantly limits what can be learned from experience.

I find that the implications of cognitive biases are enormous, in investment. The tendency to underestimate or ignore prior probabilities in decision-making is undoubtedly the most significant problem of intuitive prediction for investors.

2.5.5 Contrarian Strategies and Investor Overreaction Hypothesis

Investors Overreaction Hypothesis predicts that after earnings or other surprises, investments previously considered to be "best" underperformed, while those considered being "worst" significantly outperformed, as both regress towards an average valuation. The hypothesis also states that the maximum price swing is produced by negative surprise on "best" stocks and positive surprises on "worst." On the other hand, positive surprise on favoured stocks and negative surprise on out-of-favour stocks reinforcing events corroborate the market's opinion of these stocks and have a lesser impact on price movements than event-triggers.

The overreaction hypothesis holds that even without the occurrence of an event trigger, the "best" and "worst" investments regress towards the market average. Because the Investor Overreaction Hypothesis is based on psychological principles, it is likely to apply in other markets and in field outside of investments and economics where risk and uncertainty exist.

The Investor Overreaction Hypothesis makes these predictions: best stocks underperform the market, while "worst" stocks outperform. For long periods; Positive surprise boost "worst" stocks significantly more than they do "best" stocks; Negative surprise knock "best" stocks down much more than "worst" stocks; There are two distinct categories of surprise: "event triggers" (positive surprise on "worst" stocks, and negative surprises on "best"), and "reinforcing events" (negative surprise on "worst" stocks and positive surprises on "best"). Event triggers result in much larger price movements than do reinforcing events; the differences will be significant only in the extreme quintiles, with minimal impact on the 60% of stocks in the middle.

The hypothesis states that overreaction occurs before the announcement of an earnings or other surprise. A correction of the previous overreaction occurs after the surprise. "Best" stocks move lower relative to market while "worst" stock move higher, for a relatively long time following a surprise. This may fall as commandants for contrarians, but it can be remembered that, all five predictions of the investor overreaction hypothesis have been confirmed earlier to a high level of statistical probability (Dreman, 1998).

Contrarian strategies is a broad variety of different strategies that attempt to make profits by going against the usual consensus in the market. This thesis, considers the contrarian investment strategies that are designed to take long positions in loser countries' indices and when applicable short positions in winner countries' indices.

It is necessary to make a distinction between a contrarian strategy and other trading strategies. The risk on contrarian strategy is measured as the risk on a value investment strategy. The payoff on a contrarian investment strategy is therefore often referred to as a value premium. The contrarian strategy premium will be positive as long as the loser or the value indices yields a higher return than the winner indices or growing indices over a given time period.

2.5.6 Types of Contrarian Strategies

An investor who wants to make money in stock exchange using contrarian investment has two different types available (prior-returns, and valuation measure strategies). The simplest and the most common is the prior-returns strategy. This strategy assumes that, extreme stocks prices movements in the one direction is followed by extreme stocks price movements in the opposite direction. Past winners are believed to become future losers while past losers become futures winners. Following this view De Bondt and Thaler's (1985) study earned substantial academic interest in this field. They suggested that three to five years after a past performance based portfolio formation, former loser stocks outperform the winner stocks.

From the perspective of investors, I argue that the expectations of futures stock return are an extrapolation of the past stock performance without taking into account the mean reversion effect as suggested by Lakonishok et al (1994). The implication is that past stock performance will be replicated in the future which are prompt to naive investor but the contrarian will always bet against this belief and therefore will buy the losers' stocks and sells the winners'.

This approach of the contrarian investing requires stock market overreaction as investors will become exceptionally excited about previous winner stocks, and thus bid their prices up till these winner stocks become overpriced and trade above their fundamental values (Barberis and Thaler, 2002). Correspondingly, investors will also overreact to previous poor performing stock and therefore oversell the previous loser stocks until they become under-priced and trade below their fundamental values. When the overreaction is corrected, poor performing stock adjust to high return while well performing stock have a low return.

A second contrarian investment is known as the valuation measure strategy. This strategy includes analysis based on different ratios (share price or book and market value) that proxy for past performance or alternatively disclose information about market expectation. But the basic idea remains the same. Contrarian investment strategies suggest that loser stocks should be chosen on criteria such as poor past performance versus good past performance and inversely (Dreman, 1998). It is therefore expected that the two types of contrarian strategies should perform well given that the two strategies involve classifying more or less the same stocks as losers and winners. However, the aim of this study is to test the contrarian investment strategies internationally based on prior returns

2.5.7 Contrarian Investment Strategies Based on Prior Returns

De Bondt and Thaler (1985, 1987) provided evidence of the anomaly of the price reversal in the US stock market. Their study was inspired by the behavioural psychology of Kahneman and Tversky (1982) that suggested that people tend to overweight recent information and underweight past data when dealing with probability revision. With reference to the stock market, they suggested that people behaviour would imply that the market would overreact to unexpected information or news, causing stock price to be mispriced from their fundamental values and then reverts in the futures, which make stock price reversal predictable from past returns.

They reported that paradoxically, long-term past losers outperform long-term past winners over the subsequent three to five years' period. The losing stock earned about 0.694% per month more than the winners did over three years on the US stock market from 1926 to 1982, and suggested that the profitability of the contrarian strategies can be associated with investor's overreaction. They also demonstrated that risks measured, as betas could not explain why past losers after portfolio formation make higher excess returns. Chan et al. (1996) complimented these findings. They suggested that stock price over- or under-react to information and that winners and loser often show reversal patterns, which are consistent with the overreaction hypothesis.

However, Chan (1988) suggested alternative explanation of the overreaction hypothesis. He put forward the risk-based explanation of the return generated by contrarian strategy as the risk of the winner and the loser's stocks change over time. Using the same sample as De Bondt and Thaler (1985), he found a considerable change in betas from the formation to the holding period but suggested that the change in betas alone cannot explain the losers' portfolio excess return.

Later on, De Bondt and Thaler (1987) re-evaluated the overreaction hypothesis with regards to the time-varying risk premium and the market efficiency. They accounted for Chan's suggestions and estimated betas in the test period as opposed to the formation period. They found that the losers' portfolios are subject to higher beta than the winners' portfolio but they suggested that differences in betas sizes alone could not explain the losers' portfolio superior return.

Following these findings further evidence on return reversal behaviour of the stock market and the overreaction effect occurred in different countries around the world with different time series. Kulpmann (2002) suggested that the overreaction effect was present on the German market. He documented that, in conformity with the overreaction hypothesis as suggested by De Bondt and Thaler, stocks with relative great capital losses or gains experienced subsequent great reversal.

He acknowledged that the CAPM-betas as a measure of risk could not explain his results. Alternatively, he suggested that for most winner firms in Germany after the period of glory their profits were invested in less profitable projects. Consequently, the winners' performances fell during the test period and reiterated that the loser firms experience a successful reengineering after period of bad performance and become triumphant during the test period.

Other studies of the return reversal behaviour of stock prices suggested that the prior period's worst stock return performers do outperform the prior period's best return performers in the subsequent period and that, contrarian strategies can be profitable in the short term (Jegadeesh, 1990). Jegadeesh (1990) studied a reversal strategy that buys losers and sell winners based on their prior-monthly returns and holds them for one month over 1934 to 1987. They found that the contrarian strategy generated a profit of about 1.99% per month and 1.75% percent per month outside January, which appears striking and suggests to which extent security return can be predictable.

Zarowin (1990) suggested that the losers tend to be small and that small firms outperform large firms (Zarowin, 1990). Other explanations support that the contrarian returns reflect changes in equilibrium required rate of returns (Chan, 1988; Chopra et al., 1992).

Contrarian strategies are considered to generate superior return compared to other strategies (Conrad and Kaul, 1998) which is a potential violation of the efficient markets hypothesis. Several explanations for the contrarian phenomenon have been put forward. The behavioural explanations centred on whether overreaction to past performance contributes to contrarian return, but one of the rational explanations attributes the contrarian return is the tax-avoidance incentives (Wu and Li, 2011)).

While researchers are still debating, on whether stock value and growth features reflect risk or mispricing, further studies of the overreaction hypothesis suggest that the overreaction is a consequence of the size effect. Wu and Li. (2011) investigated whether long-term contrarian performance on the UK market is driven low-priced stock and found that contrarian performance at low, middle, low price levels is positive. The suggested that low-priced stock are not fully responsible for contrarian performance and that the findings were consistent with the overreaction hypothesis.

2.5.8 Contrarian Strategies Empirical Evidences

Since the contrarian returns may differ from developed to emerging countries, I examine empirical evidence of the performance of the contrarian strategies in equity market internationally, and review number of related findings consecutively in developed markets and emerging markets.

2.5.8.1 Contrarian Strategies in Developed Markets

De Bondt and Thaler (1985) first encountered the long-run reversal phenomenon in developed market in US stock market. They suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 0.694% per month over 3 years and 0.6% per month for 5 years post-ranking period. Following these findings, subsequent research gathered around the profitability of the contrarian strategy in stock market.

Chopra et al. (1992) investigated stock return overreaction on the NYSE stock returns from 1926 to 1986 with monthly and annually returns. Their method included event time-varying betas created on an estimate market compensation per unit beta risk basis, which, is relatively smaller compared to the Sharp-Lintner model adopted by Ball and Kothari (1989), they found that the losers outperform the winners by approximately 0.542% per month on annual return and 0.792% per month on monthly returns. They also demonstrated that size alone could not explain the contrarian return. They suggested that a mutual consideration of size, prior return and beta could explain the contrarian return to avoid omitted variable bias.

Clare and Thomas (1995) studied the reversal strategies in the UK market using 1000 stocks from 1955 to 1990 to examine the Overreaction Hypothesis. They found that losers outperform winners by approximately 0.142% per month. After controlling for firm size, they suggested that the overreaction hypothesis is linked to the size effect.

Galariotis et al. (2007) found evidences of contrarian profitability in the London Stock Exchange listed stocks from 1964 to 2005. Using 64 strategies for 6531 stocks and controlling for key potential explanations of the strategies' profitability, they found that, the lowest size quintile outperforms the highest size quintile by a figure ranging from 0.7% per month for the 60-month formation period to 1.84% per month. They suggested that for each of the holding periods there is a clear tendency for returns to rise as the market capitalization falls.

Li et al. (2009) studied value and growth stocks in UK stock market from July 1969 to June 2006 and found that growth portfolio has low mean return of 0.81% per month, that the value portfolio has high mean returns of 1.39% per month, and that the value premium is 0.57% per month. They suggested that superior return or value premium of value stocks in UK are a result of high return volatility between 1963 and 2006.

Dissanaike and Kim-Hwa Lim (2010) studied the reversal strategies while referring to the residual income model. They used variety of variables to form contrarian portfolio, ranging from book-to-market, cash flow-to-price, earnings-to-price and past returns, to more sophisticated measures based on the Ohlson model and residual income model. They found that, most of the portfolio formation methods based on raw and size-adjusted returns yield economically important contrarian profits. They suggested that, the raw returns portfolios fall from 1.689% per month in the test period year 1 to 0.778% per month in test period year 2 and finally to 0.049% per month in test period year 3and suggested that book-to-market based contrarian model outperform the contrarian strategies based on accounting information. However, these studies were solely based on UK market.

Moever, Wu and Li (2011) combined three approaches of the contrarian strategies: the value-growth approach, the past performances approach as suggested by De Bondt and Thaler (1985), and the capital lock-in approach as suggested by George and Hwang (2004, 2007) on the FTSE-All Share between 1974 and 2009. They show that the losers outperform the winners by 0.21% per month over a 5-year horizon. Also, suggested that value-growth provides better explanation of the reversal phenomenon than past performance. The winner and loser effect diminish when the strategies include firms' characteristics (book-to-market, cash flow-to-price and earning price) but Wu and Li (2011) did not explore whether this could apply at a global level when using countries' indices.

Some researchers have found that contrarian strategies portfolios chosen based on the price changes during one-week exhibit contrarian behaviour in the following week. A relatively good performance of one week tends to be followed by a relatively bad performance the next week, and vice versa (Lehmann 1990). Using securities listed on the New York and the American Stock Exchange from 1962, he found that the weekly mean return of the two one-week portfolio strategies were of opposite sign, and the mean return of the winner's portfolio were about one-half the magnitude of the mean return of the loser's portfolio. The sample correlation of the weekly return of the one-week portfolio strategies were large and positive (0.851) for the full-week strategy and 0.873 for the four-day strategy. A short position in the winner's portfolio had a large negative correlation with a long position in the loser's portfolio but the study did not specify if these findings could be relevant at a global level.

Lo and Mackinlay (1990) studied the contrarian strategies while using US market weekly data from 1962 to 1987 and found that the average weekly long-short profit generated by the contrarian strategy over the sample periods for all stocks is $1.69 with the average weekly long-short position of $152. In contrast, the sample of small stocks yields an expected profit of $4.53 per week, but required only $209 long and short each week. They divided the contrarian return into three aspects. In the first part, they identified the of-diagonals of auto covariance matrix also known as the cross-auto correlation among stock components. In a simple term it is the difference of autocorrelation amongst stock in a portfolio between the past and the current period. Which is also called lead-lag effect. When the lead-lag relation is positive, Lo and Mackinlay explain that, the short-term stock return reversal with a regular pattern is a consequence of the delayed reaction to common factor and not investor overreaction to news or stock prices as suggested by De Bondt and Thaler (1985). This imply that the contrarian strategies' profits result from the investor's overreaction to news and related information.

The second aspect in explaining the return reversal is related to the auto correlation of individual stock during different periods. They assume that the negative autocorrelation show positive contribution to the contrarian strategy returns and can explain the market overreaction. Lo and Mackinlay concluded that stock return's time varying are good predictors of the contrarian portfolio return.

The third aspect is the cross-sectional variation of the expected return of individual stocks. They found evidences of the volatility-clustering phenomenon that shows that large stocks return tended to lead small stocks with the lead lag effect, which, tend to have negative effect on the contrarian strategies return. Overall findings contradict the traditional behavioural finance hypothesis as suggested by De Bondt and Thaler (1985) and Lehmann (1990).

Further evidence on contrarian strategies in the U.S. stocks have arisen from consideration of returns consecutively over one month and the following month (Jegadeesh 1990). He suggested that the negative first-order serial correlation in monthly stock returns is highly significant and found that the difference between the risk-adjusted excess return on the extreme deciles portfolios is 2.49% per month over the period 1934 to 1987, 2.20% per month excluding January, and 4.37 % per month when the month of January is considered separately. It is also found that the difference between the risk-adjusted excess returns on the extreme deciles portfolios formed based on one-month lagged return is 1.99% per month over the sample period and 1.75% percent per month outside January. However, Jegadeesh and Titman (1995) suggested that the cross-sectional analysis of profit was not good indicator for investor overreaction to news. By analysing firm-specific characteristics, they found that short-term contrarian profit could be explained by investor's overreaction to firm-specific information.

Lakonishok et al. (1994) defined two categories of stocks those with bad past performances or value stocks and those with better past performance or glamour. They claimed that value stocks have been undervalued and glamour stocks have been overvalued. They then defined a contrarian strategy that buys values stock and sells glamour stocks based on whether the stocks have a high book-to-market, a high sales growth in the past and low price relative to cash flow and earnings. They found that, for a five-year holding period between 1963 and 1990 value stocks could generate an excess of 0.83 to 0.916% per month compared to the glamour stocks and that the result cannot be explained by systematic risk but, the study was conducted on US stock only and did not looks at the global implication of this results.

Doan et al. (2016) examine the coexistence of momentum and contrarian strategies in the Australian equity market from 1992 to 201. They found that contrarian strategies prevail in the intermediate and long-term. They show that short-term contrarian strategies significantly outperform the simple buy-and-hold strategy of investing in the market index. the Australian mining sector undermines the momentum performances but enhance the contrarian strategies profitability. However, their analysis was based on Australian stocks solely and the momentum and contrarian profits could not be explained by standard return-generating models.

2.5.8.2 Contrarian Strategies in Emerging Markets

Evidences of contrarian strategies were also reported in emerging market: Choe et al. (1999) tested whether foreign investor activities affect stock return in Korea from November 30, 1996 to the end of 1997, period that matches with the Asian crisis. They used order and trade data, and found that there are strong evidences of positive feedback trading and herding by foreign investors before during the period of Korea's economic crisis.

They recorded that during the crisis period, herding falls, and positive feedback trading by foreign investors mostly disappears. They suggested that there was no evidence of destabilizing effect of the foreign investors on the Korea stock market over their study period as the market adjusted quickly and efficiently to large sales by foreign investors. These sales were not followed by negative abnormal returns. They suggested that the losers earn about 0.068% per month more than the winner for institutional order before the Korean crisis. However, the study did not extend this analysis to other equity market, to show whether adjustment process and speed are consistent across markets worldwide or it is just a feature of the Korean market.

Kang et al. (2002) studied the contrarian strategy in China using stock prices from the period of January 1993 to January 2000, testing methods like Lo and Mackinlay (1990), and found that there is a significant abnormal return for some short and medium term contrarian strategies. They reported up to 0.744% return for portfolio formed based on previous 1-week returns and held for 1-week and suggested that it was associated with overreaction to firm specific information in short term. In addition, they discovered that there was not a distinctive effect in medium term, which was explained by the dominance of overreaction effect, but they were able to demonstrate that the negative cross-serial correlation can lead to contrarian profits. However, their analysis was based on data only accessible by local investors.

Otchere and Chan (2003) examined the overreaction phenomenon in the Hong Kong market from March 1996 to June 1998 that includes the pre- and the post-Asian financial crisis and found that Hong Kong market overreacted to information prior to the Asian financial crisis period. They also found that the overreaction tends to be more evident for winners than the losers. They also found evidence of the overreaction in the pre-financial crisis period but reported that abnormal return obtained by exploiting such phenomenon are economically insignificant after considering transaction cost (0.124% per month).

However, they indicated that after accounting for size effect and the day-of-week effect, the results appear to be very significant. They advocated that the Chinese culture may have significant impact on investors' view of the market as they tend to perceive risk differently and are less risk averse and less likely to overreact but this study did not show how this particular feature of the Chinese market could help international momentum and contrarian investors in global portfolio allocation.

Chen et al. (2012) studied the contrarian trading strategies in the Chinese stock market from 1995 to 2010. They examined the performance of the trading strategies following different markets states and found that contrarian strategies are profitable following down market especially during the economic downturn. They suggested that market conditions are good predictors of the size of the contrarian profit. In addition, they found that no significant profit is generated from both strategies in the medium term. They reiterated that, for practitioners and investors in general, these results provide good forecasting indicator especially during the post-crisis period. After consideration of the microstructure effect on the one-to-two-month formation and holding periods they found that the contrarian strategy generates on average approximately 0.8% per month and even greater in `up' market. However, the study indicated that these results may not apply in developed markets and did not examine the reversal as a global phenomenon.

2.5.8.3 Contrarian Strategies International Evidences

Further studies of contrarian strategy examined its profitability internationally. Jordan (2012) examined the profitability of the long-term contrarian strategy using 81 years of data from 1925 to 2005and found that the contrarian based on 36 month holding period generate approximately 0.492% return per month when analysing 8 countries and even greater 0.586 per month for 16 countries. He reported that the long-term contrarian anomaly disappears when time-varying alpha are considered. He suggested that the benefits from the trades on long-term reversal do not go against a strategy based on diversification, but the method used in the construction of the losers and winners' portfolios and the test are based on 25% lowest (losers) and the 25% top (winners) or adjust for return. However, He reported contrarian results based on monthly stocks performance of 8 and 16 countries only.

Malin and Bornholt (2013) studied the profitability of the contrarian strategies on international equity markets from January 1970 to January 2011, using recent short-term performance (monthly). They proposed the late-stage strategy that buys long-term losers with relatively good recent short-term performances and sells long-term winners with relative poor recent short-term performances. They found that, with the 60-month formation period in developed countries, past long-term losers gain an average of 1.31% per month over the 6-month holding period and that long-term winner's gain an average of only 0.86% per month over the same period. The difference between long-term losers and long-term winners is 0.46% per month with a t-statistic of 2.28. In emerging countries, the strongest pure contrarian profit using 60-month formation and 6-month holding period generate 0.68% per month with a t-statistic of 1.69.

They also found that, for the late-stage strategies in developed countries the contrarian strategy generated 0.58% per month with a t-statistic of 2.48. In emerging market, they reported a return of 1.24% per month with a t-statistic of 2.47. They suggested that, the late-stage strategy is consistently more profitable than the traditional pure contrarian strategy. They suggested that the late-state strategies it provides significant evidences of reversal in long-term returns for both the developed and the emerging markets, but the study did not look at the contrarian strategy as a global and generalize phenomenon following different market state (bear and bull) and did not test whether the short-term contrarian is also profitable.

Conversely, Zarowin (1989) examined firm's stock over 36 months relative to extreme earning years and found that the poorest earners do outperform the best earners. He was able to demonstrate that when poor earners are matched with good earners, there is not substantial evidence to suggest that the factor responsible for the overreaction phenomenon is the size and not investor's overreaction to earnings, this argument reject De Bondt and Thaler (1985) suggestion. However, the study made use of market adjusted excess return and not risk adjusted and did not examine the long-term contrarian strategy as a global phenomenon.

2.5.9 Summary

In this section, I review variety of studies related to the profitability and the sources of the contrarian strategies' profit. The findings support that they could be a result of investor overreaction over the long run as suggested by De Bondt and Thaler (1985). These theories also support the behavioural theory of investor sentiment, as investor's sentiment influence stock prices (Brown and Cliff, 2005). However, study by Barberis and Thaler (2002), Dreman (1998) showed that investor's irrational behaviour influence on the market is most likely not a coincidence. Investor can make profit by going against the crowd. Other explanations of the contrarian returns reflect the changes in equilibrium required rate of returns (Chan, 1988; Chopra et al., 1992). In addition, number of studies also found evidences of the contrarian strategies profitability in different countries and regions around the world: Choe, et al. (1999) in Korea; Otchere and Chan (2003) in the Hong Kong market; Chen, et al. (2012) in China; Li et al. (2009) in the UK.

Overall, there are significant evidences of the contrarian profitability in individual country around the world. But none of the past studies consider the contrarian strategy as a global coordinated and generalized phenomenon. The question remains to whether investors could exploit the reversal effect internationally given that news motion may induce the return differences across countries. In other words, does the contrarian strategies works for international investors that target many stock market indices?

2.6 Are Momentum and Contrarian Profits due to Compensation for Risk?

2.6.1 Introduction

In this section, I review the literature on the relationship between macroeconomic risk factors and the momentum and contrarian profitability. I focus primarily in examining the theoretical outline that supports or rejects the link between individual variable and the stock market outcome. First, I define set of risk factors in the literature that could possibly affect the stock market worldwide. I further study the variable referring to whether they are evidences in the literature in support to their relation the momentum or the contrarian strategy profitability. Finally, I identify risk factors used in the study according to their nature; I assign each variable to a specific group depending on whether they are standard risk factors, stock market related or pure macroeconomic risk factors. In this prospect, I seek a prior assessment of the strength of individual variable in explaining either the momentum or the contrarian strategies.

2.6.2 Momentum and Contrarian Risk-based Explanation

Jegadeesh and Titman (2001) present evidence that U.S. momentum returns quickly dissipate after the investment period. Which is a finding difficult to reconcile with the standards notions of priced financial risk (Griffin, 2003). The principal goal of this study to investigste on a global basis the relation between global momentum returns and macroeconomic risks. I analyse whether international evidence on the dissipation of momentum and contrarian profit is consistent with risk-based models of momentum. Large number of researchers has studied the relationship between macroeconomic factors and change in stock prices. This is not surprising given that they are likely to exert important influences in stock return. Chen, et al. (1986) employed for the first time in time series specific macroeconomic factors namely, the industrial production, change in the risk premium, twists in the yield curve and, some measures of unanticipated inflation and changes in expected inflation as proxies for the theoretically undefined state variable in the Arbitrage pricing model. Macroeconomic variables are assumed to have influenced either future cash flows or the risk-adjusted discount rate.

However, financial researchers suggest that macroeconomic factors affect investment opportunities, as they are key state variables in the time series study of asset-pricing (Campbell and Cochrane, 1999). This is in line with arguments in favour of the Efficient Market Hypothesis. Macroeconomic factors can represent priced factors in Arbitrage Pricing Theory (Ross, 1976).

A more recent by Griffin et al. (2003) investigate on a global basis the relation between momentum returns and macroeconomic risks. They examined whether international evidence on the dissipation of these profits is constent with risk-based or behavioural model of momentum using data in 40 countries, and build upon the literature studying the relation between stock returns and macroeconomic risk through use of the time-tested and widely cited approach of Chen, Roll, and Ross (1986). They explore both abroad and in the US., the performance of a forecasting model based on lagged macroeconomic instrument. They examine momentum profits on a country-specific basic in 17 markets and found that momentum profits have basically no statistically or economic significant relation to the Chen, Roll and Ross (1986) macroeconomic factors. They also document that the forecasting model proposed by Chordia and Shivakumar (2002) has very low explanatory power for momentum profits when taken internationally. However, they found positive momentum profit in both sorts of economy compatible with the idea that momentum profit is a reward for priced business cycle risk. The also documented strong international evidence of reversals of momentum profits.

While I make no attempt to present a complete survey of the relation between momentum, contrarian strategies and macroeconomic risk factors, I describe the major factors' investigation in the existing empirical literature includes many factors that I name as global risks factors and use in this thesis given their empirical endorsement. I build upon the literature studying the relation between stock returns and macroeconomic risk through of the time-tested and widely cited approach of Chen, et al. (1986). I also explore the performance of forecasting model on lagged macroeconomic variable and the Fama and French risk factor following Avramov et al. (2015).

2.6.2.1 Global risk factors

Market Volatility, some articles report a connection between equity return volatility and macroeconomic conditions. Hamilton and Susmel (1994), and Sinha (1996) estimate GARCH models of monthly U.S. equity returns in which the probability of switching from a high- to a low-volatility regime depends on broad economy conditions. They concluded that macroeconomic conditions significantly affect equity returns, in the sense that equity volatility is more likely to become and remain high during a recession.

Bekaert and Harvey (1995) suggested that volatility is one of the underlying forces affecting stock market but emphasised the fact that macroeconomic data are unfortunately spared or non-existent in some of the emerging markets, given that the data are quite difficult to obtain and even if when published data are used, they are highly suspect in several countries. They advocate that political risks are also likely to influence the cross-section of volatility, but long time-series of political risk rating are difficult to obtain.

Errunza and Hogan (1998) estimated VAR models for European stock returns for 1959-1993 period. They found that Money Supply volatility granger causes equity volatility in Germany and France, and that the volatility of Industrial Production Granger causes equity volatility in Italy and the Netherlands. However, they found no evidence that past macroeconomic variables performance can affect equity returns in the United Kingdom, Switzerland, Belgium or the United States.

Using a very different methodology, Schwert (1989) tested whether the volatility of inflation, monetary growth, or real economic variables can explain the time-variation in monthly return volatilities over 1859-1987 period. Instead of finding that greater macro volatility source less stable financial return, he suggested that, it is more likely that financial asset volatility helps to predict future macroeconomic volatility.

Interest rate, the effect of nominal interest rates on stock prices is also expected to be negative. In this argument (Chen et al. 1986). Campbell (1987) suggested that the term structure of interest rates predicts excess stock returns, as well as excess return on bills and bonds. They examined some asset pricing models with US data from 1959 to 1979 and found that when realized excess return on bill, bonds, and stocks are regressed on information variables that measure the state of the term structure of interest rate, the fitted values are far from constant. Instead, they vary with a standard deviation for the period at 25% per month on annualized basis for two-month bills, and 75% for six-month bills, and almost 17% for stock. Although the same variable predicts returns on the different asset, the fitted values for bills and stock have a rather low correlation. Fama and Schwert (1977) showed that the three-month T-bill rate is negatively related to future market returns and acts as a proxy for expectations of future economic growth.

Term and default spreads, the default spread has been known to track long-term business conditions. They are higher during recessions and lower during expansions (Fama and French, 1989). Rahman and Mustafa (1997) investigated the relationship between the Standard-&-Poor's 500 and short-term corporate bond rates in the United States. They found that short-term rates and U.S stock prices tend to approach each other in the long run. They suggested that, this might be due to the substitutability between U.S common stocks and short-term corporate bonds, in terms of average holding periods, liquidity, convertibility, and risk structures. They also reiterate that, a two-way Granger causality and reversible feedback between these markets is observed in the short run. In their analysis, short-term corporate bonds were considered very close substitutes for common stocks, in terms of average holding period, liquidity risk, and default-risk.

Campbell (1987) shows that more generally the state of the term structure of interest rates predicts stock returns. In addition, he demonstrates that, the risk premia on stock move closely together with those on 20-year treasury bonds, while risk premia on treasury bills move somewhat independently. Average returns on 20-year bonds is very low relative to average return on stocks. He used this observation to test some simple asset pricing models and find that, expected stock returns have a negative relationship with the conditional variance of stock returns, but that 2-month bill return move positively with their conditional variance. He finally suggested that uncertainty about short-term nominal interest rate, as measured by the conditional variance of 2-month bill returns, is important in both treasury bills and long-term assets. In addition, the uncertainty about stock return by contrast seems to have a negative relationship with expected stock returns and does not help to explain returns in the term structure.

Fama and French (1992) identify common risk factors in the returns on stocks and bond. They show that three stock-market factors and two bond-market factors are related to maturity and default risk. They documented that, for stocks, the slope on the two term-structure returns are around 0.8, the standard deviations is 3.03 per month and suggested that the term-structure accounts for similar variation in the return on all the stock portfolios.

Furthermore, they find that, the average p-value of the term-structure return are 0.06% indicating that they do not explain the average excess returns on stock market. However, they discover that the expected term-structure vary through time with business conditions. This supports the argument put forward by Chen, et al. (1986) suggesting that, the term premia could be considered as a priced risk factor.

Industrial Production, Chen, Roll, and Ross (1986) examine the relation between state variable and stock return and find that the yearly production series was not significant in any sub-period. They suggested that deleting it has no substantial effect on the remaining state variables, although, the coefficients have the same signs as in the overall period but they conclude that industrial production is a strong candidate for being a risk factor. Cutler et al. (1989) find that Industrial Production growth is significantly and positively correlated with real stock returns over the period 1926-1986, but not in the 1946-1985 sub-period, which substantially overlaps with Chen, Roll, and Ross's (1986) sample period.

Market Indices, Chen, et al. (1986) find that market indices are not priced by the financial market. They tested the pricing influence on the market indices using macroeconomic state variables and found that the market indices failed to have a statistically significant effect on pricing in any sub-period. They suggested that the insignificance for pricing of the stock market indices contrasts sharply with their significance in time series. Although stock market indices explain much of the inter-temporal movements in other stock portfolios, their estimated exposures or their betas do not explain cross-sectional differences in average returns after the betas of the economic state variables have been included. This suggests that the explanatory power of the market indices may have less to do with economics and more to do with the statistical observation, that large positively weighted portfolios of random variables are correlated.

Oil prices, seen as an important economic factor, Chen, et al. (1986) suggested that oil prices are not priced by the financial market they advised that, stock returns are exposed to systematic economic news that is priced by market. To confirm this assertion, they referred to oil price as series of realized monthly first differences in logarithm of the producer Price Index/Crude Petroleum series obtained from the Bureau of Labour Statistics U.S. Department of labour.

2.6.2.2 Other Risk Factors

This thesis also reviews empirical evidences on factors, which may have significant impact on the stock market outcome but are not of particular interest in this study given they may have none or less effect on the momentum and contrarian profitability. These factors include:

Market capitalization, Diacogiannis (1986) find that the probability value for market capitalization is 0.12 greater than a 0.05, which implies that they do not have significant influence on the firms in different sectors' return**.**

Consumption, Chen, et al. (1986) also examined a time series of percentage change in real consumption, which was the real per capital and includes service flows. They found that consumption is not priced by the financial market. They examined the influence of the real consumption series in an inter-temporal asset-pricing model and found that the rate of change in consumption does not seem to be significantly related to asset pricing, they also found that the estimated risk premium is insignificant and has the wrong sign.

Inflation, the relationship between inflation and stock returns is highly controversial. However, empirical studies have mainly documented a negative relationship between inflation and stock returns. They suggested that an increase in inflation has been expected to increase the nominal risk-free, which in turn will rise the discount rates used in valuating stocks (Fama and Schwert, 1977).

Studies such as Bodie (1976), Fama (1981), Geske and Roll (1983), and Pearce and Roley (1983, 1985) document a negative impact of inflation and money growth on equity values. Diacogiannis (1986) find that the probability value for inflation is 0.29 greater than a 0.05, which implies that they do not have significant influence on the firms in different sectors' return. The inflation has the highest probability value, which implies that, out of the three predictors of the sectorial returns, inflation has more level of non-influence on the Nigerian stock return. Moreover, Cutler et al. (1989) provide no support for the hypothesis that Inflation, Money supply, and long-term Interest rates reliably affect stock returns.

Chen, et al. (1986) suggested that inflation effects are included in other variables that after long-term real decrease, there is subsequently a lower real return on any form of capital. Investors who want protection against this possibility will place a relatively higher value on assets whose price increases when long-term real rates decline. Such assets will carry a negative risk premium thus, stock whose returns are correlated with long-term bond returns, abstracting from unanticipated changes in inflation or in expected inflation and holding all other characteristic equal, will be more valuable than stock that are uncorrelated or negatively correlated with long term bond returns. Chen, et al. (1986) reiterated that there is weaker evidence to support the inflation claim to the status of risk factor.

Graham (1996) investigated the relationship between stock returns and inflation for the United States during the period 1953-90. He suggested that the relationship between stock return and inflation is unstable, in the sense that it was negative before 1976 and after 1982, and positive in between those years. They suggested that this instability might result from a shift in counter-cyclical to pro-cyclical monetary policy in 1982.

Aggregate output, Cutler (1989) estimate and access the respective roles that, aggregate supply and demand disturbances have in causing business cycle in the U.S. He finds that aggregate demand disturbances have been the primary cause of business cycles in the United State since the early 1960. In the same line, Balvers et al. (1990) study the relation between inter-temporal asset pricing and macroeconomic fluctuation, in a simple equilibrium model relating output to consumption opportunities. They suggested that, as consumption opportunities vary following variations in aggregate output, investors are faced with a less smooth consumption pattern. In attempting to smooth consumption, investors adjust their required rate of return on stock because of this linkage; returns should be predictable to an extent related to the predictability of aggregate output.

Exchange rate, Geske and Roll (1983) show that exchange rates have significant influence in stock price through the terms of trade effect. The depression of domestic currency increases the volume of exports, if the demand for exported goods is elastic; this in turn causes higher cash flows for domestic companies, and thus causes stock prices to increase.

Diacogiannis (1986) also find that the probability value for exchange rate is 0.16 greater than a 0.05, which implies that they do not have significant influence on the firms in different sectors' return. Bailey and Chung (1995) studied the systematic influence of exchange rate fluctuations and political risk on stock returns in Mexico. The major finding is consistent with time varying equity market premium. Abdalla and Murinde (1996) investigated the interactions between exchange rates and stock prices in India, Korea, Pakistan, and the Philippines using Granger causality, and monthly data over the period from January 1985 to July 1994. Unidirectional causality is observed from exchange rates to stock price in all countries except the Philippines, where stock prices Granger cause stock prices.

Ajayi and Mougoue (1996) studied the dynamic relationship between stock prices and exchange rates, employing a bivariate error-correction model. They investigated both the short-run relationships between the variables in 8 stock markets; this includes Canada, France, Germany, Italy, Japan, Netherlands, the United Kingdom, and the United States. The results reveal an increase in domestic currency. They suggested that a sustained increase in the domestic stock prices in the long run will appreciate the domestic currency, since the demand for the currency will be driven up.

Unemployment rate, Boyd et al. (2001) found that on average, an announcement of rising unemployment is good news for stocks during economic expansions and bad news during economic contractions, thus stock prices usually increase on news of rising unemployment, since the economy is usually in an expansion phase. They suggested that unemployment news bundles two primitive type of information relevant for valuing stocks: information about future interest rate and future corporate earnings and dividends. They also demonstrated that a rise in unemployment could typically signals a decline in interest rates, which is good news for stocks, while a decline in future corporate earnings and dividends, is bad news for stocks. The nature of the bundle and hence the relative importance of the two effects changes over time depending on the state of the economy. For stocks as a group, and in particular for cyclical stocks, information about interest rates dominates during expansions and information about future earnings dominates during contractions.

Announcement surprise, McQueen and Roley (1993) suggested that a given announcement surprise may have different implications at different points in the business cycle. For example, an increase in employment might be a bullish sign as the economy emerges from recession, but a bearish sign near a cyclical peak. They estimated a model in which each series' effect depends on overall economic conditions, defined according to the monthly growth rate of Industrial production. They found that only two of their eight announcement series significantly affect the S&P 500 portfolio in a constant-coefficient model, but six carry significant coefficients in at least one of the economic regimes.

Boyd et al. (2001) also found that macro news has distinctly time varying effects on equity returns. They examined the impact of unemployment announcement surprises on the S&P 500 return over 1948-1995, and concluded that surprisingly high unemployment raises stock prices during economic expansion but lowers stock values during a contraction. They hypothesized that higher unemployment predicts both lower interest rates and lower corporate profits, and concluded that the relative importance of these two effects vary over the business cycle

The level of real economic activity is expected to have a positive effect on future cash flows, and thus will affect stock prices in the same direction (Fama 1990). Following this line of thought, recent works on the relationship between stock returns and macroeconomic variables have employed techniques, such as VAR and VECM, which take into account dynamic linkages. Lee (1992) for example, investigated the causal relations and dynamic interactions among asset returns, real activity and inflation in the post-war in the United States. Lee's main results indicated that; real stock returns help explaining movements in real activity. Inflation is not explained by real stock returns. Real stock returns explain little variation in inflation, but interest rates explain little variation in real activity. Lee's findings are compatible with Fama's (1990) explanation for negative stock return-inflation relationship.

Trading Volume, Campbell, Grossman, and Wang (1993) argued that because the variation in the aggregate demand of liquidity traders also generate large levels of trade, volume information can help distinguish between price movement that are due to fluctuating demands of liquidity traders and those that reflect changes in expected returns. An implication of the model is that price changes accompanied by large trading volumes tend to be reversed.

Blume, Easley and O'Hara (1994) showed that volume provides information that cannot be deduced from the price statistic. They demonstrated that traders who use information contained in the volume statistic will do better than traders who do not. They investigated the information role of trading volume its applicability for technical analysis, and showed that trading volume provides information on information quality that cannot be deduced from the price statistic.

Wang (1994) examined the link between the nature of heterogeneity among investors and the behaviour of trading volume and its relation to prices dynamics. In his model, he assumes that, uninformed investors trade against informed investors and will revise their positions when they realize their mistakes. He suggested that, when returns are high in the previous period, it could be due to private information of informed investors or simply buying pressure for non-informational reasons. If it is due to private information, the high realized return accompanied by high volume in the past will be followed by high futures returns. If it is due to non-informational reasons, the high realized return will be followed by low future returns.

Money supply, Hashemzadeh and Taylor (1998) examined the direction of causality between the money supply, stock prices, and interest rates in the U.S. They showed that the relationship between money supply and stock prices is characterized by a feedback system, where money supply induces some of the observed variation in stock price levels, and vice versa. They reiterated that, causality runs from interest rates to stock prices, but not the other way.

The mixed results in the extant literature make it difficult to determine which particular macroeconomic variable (if any) are indicators of stock returns. However, there are reliable evidences to suggest that some macro variables may have effect on future stock market performance (Chen, et al., 1986) as well as current and future economic growth (Chen, 1991) I name them Global Risk Factors. They could affect investment strategies such as momentum and contrarian trading worldwide, through investment opportunities (Campbell and Cochrane, 1999).

2.6.3 Impact of Macroeconomic Factors on Momentum Profit

Since the predictability of short-term stock market returns might be affected by macroeconomic factors, this study examines whether macroeconomic factors information could affect the momentum profits. I focus on the potential set of macroeconomic fundamental suggested as sources of the momentum profits. Given that most macroeconomic fundamentals reflect or at least partially reflect the state of the economy, they are often highly correlated. This opens up the possibility that a set of specific macroeconomic variables could explain a change in Global momentum and contrarian performance. Jegadeesh and Titman (1993) show that the simple investing strategy of buying prior winners and selling prior losers generate significant profits both statistically and economically. Their initial finding has been confirmed by subsequent studies, suggesting that data mining is an unlikely explanation. One potential explanation behind momentum anomaly is that momentum profits might be a reward for risk.

Aretz, et al. (2009) show that most of the macroeconomic factors are priced. They suggested that the performance of an asset-pricing model based on macroeconomic factors is comparable to the performance of the Fama and French model, that a downward revision in economic growth expectations often coincides with increase aggregate default risk due to more conservative consumer behaviour and decrease interest rates to revive the economy. In this situation, an analysis of related macroeconomic fundamentals will offer some insights on whether the benchmark factor captures economic growth, default risk or interest rate risk. However, they found that the momentum factor contains incremental information for asset pricing.

Scherer and Kessler (2013) analysed the performance of the momentum return across asset classes and found evidence that momentum across asset is driven by macroeconomic state variables by reacting to changes in the macroeconomic environment. They suggested that, the strategy performs well in times of economic distress and established the link between momentum and more sophisticated predictive regressions.

2.6.3.1 Empirical Evidence of the Global Risk Factors

Most empirical studies have so far failed to document evidence that macroeconomic risks can be sources of return to a momentum strategy. However, one of the explanation of the momentum anomaly is that momentum might be a reward for business cycle risk.

Business cycle, Griffin et al. (2003) study the relation between momentum and the macroeconomic factors worldwide using data from 40 countries and four principal techniques to detect evidence of business cycle risk in momentum portfolios. They find that momentum portfolio profits have only a weak co-movement among countries, whether within regions or across continents. They suggested that if momentum is driven by risk, the risk is largely country-specific. They examine the ability of the Chordia and Shivakumar (2002) forecasting model to explain momentum profits abroad and in the US. They find that, expected momentum profits are close and that the predicted momentum returns estimated and generated in a manner consistent with Chordia and Shivakumar are extremely noisy. They show that, there is actually no correlation between observed momentum profits and the model predictions suggesting that, macroeconomic variables cannot predict momentum profits internationally. Related literature on momentum and macroeconomic risk factor include.

GDP growth, Griffin et al. (2003) provide international evidence that macroeconomic risk cannot explain momentum profits. They define economic states in terms of the realized market returns and GDP growth; they identify good states with high and bad states with low ex-post market return or GDP growth. They show that average momentum profit is positive during GDP growth and even larger and positive during negative market return than during positive market returns in the United States and conclude that there is no evidence that, the profitability of momentum strategies is related to risk arising from macroeconomic states. As a result, the momentum literature has mostly followed interpretation of Jegadeesh and Titman (1993) that irrational agents drive momentum payoffs.

Liew and Vassalou (2000) test whether the profitability of business variable such as HML, SMB and the momentum variable can be linked to future Gross Domestic Product (GDP) growth, using data from ten countries, they find that business cycle variable contains significant information about future GDP growth but little evidence to suggest that momentum is related to future GDP growth.

Petkova and zhang (2005) argue that more precise measure for aggregate economic conditions are default spread, the term spread and the short-term interest rate, and macroeconomic variable that are common instrument used to model expected market risk premium. They classify the economic states of the world based on the expected market risk premium as follow: state “peak” that, stand for the lowest 18% periods of the expected risk premium. State “expansion” that, stand for the periods with the negative risk premium other that the 10% lowest. State “recession” that, stand for the periods with the positive risk premium except the 10% highest and states “trough” that, stands for the highest 10% periods of the expected market risk premium.

Avramov and Hameed (2014) study the impact of the state of the market illiquidity on the momentum payoffs, they suggested that even if Jegadeesh and Titman (1993) found the momentum strategy generate 1.18 percent return per month, the momentum payoff realizations could be significantly low, often due to massive negative payoffs. After examining the predictability power of previous market states on the international momentum payoffs, they found that there are overwhelming evidence across the US, Japan and the Eurozone to show that market illiquidity predicts momentum payoffs.

The default spread, defined as the difference between the average yield of bonds rated BAA by Moody’s and the average yield of bonds with a Moody’s rating of AAA, it is included to capture the effect of default premiums, to track the long-term business cycle conditions. This variable tends to be higher during recessions and lower during expansions.

The term spread, measured as the difference between the average yield of Treasury bonds with more than 10 years to maturity and the average yield of T-bills that mature in three months. Under the suspicion that momentum strategies might embed compensation consistent with forward term premium, Durham (2013) find that momentum returns do correlate to a degree with portfolio returns based on Gaussian arbitrage-free affine term spread models.

T-bill yield, Cooper et al. (2004) tested whether the macroeconomic multi-factor model can capture the asymmetries relation of lagged market return. They found that, the lagged market return is a proxy for changes in the macroeconomic variables notably. The lagged dividend yields of the CRSP value weighted index, the lagged yield spread between Baa-rated bonds and Aaa-rated bonds the lagged yield spread between ten-year treasury bonds and six-month treasury bills, and the lagged yield on the T-bill with three months to maturity can explain the momentum profit. They suggested that, macroeconomic factors are unable to explain momentum profits after simple methodological adjustment of microstructure concerns. However, they reiterated that the lagged 3-year market return does predict momentum profits. Specifically, the momentum strategy generates significant positive return following positive market returns, but insignificantly negative returns following negative market returns.

Market volatility, Wang and Xu (2010) investigated the time-series predictability of the momentum return with the focus on the predictive power of market volatility. They found a significant and robust link between market volatility and the momentum return. They show that the time-series predictability of momentum is rather different from the aggregate stock market predictability of the momentum return. They suggested that the momentum profits tend to be higher following periods of low market volatility. In particular, the momentum strategy generates especially low average monthly returns during down market and high volatility states.

2.6.3.2 Firms' Specific Risk Factors

I also review the literature on empirical studies that record factor which may have great or direct effect on individual company trading activities, this includes risk factors such as. **Trading volume,** Chan, et al. (2000) study the momentum with individual stock in indices in the international equity market and documented that, the price change accompanied by higher trading volume tend to be reversed in the following period. Their results also indicate evidence of momentum profits that are statistically and economically significant, especially for short holding periods.

Size, Schmidt, et al. (2015) study the link between the profitability of momentum strategies and firm size in international stocks markets, covering 23 stock markets across the globe. They find that there is not significant size effect for any of the countries covered while considering the average return on the Small-Minus-Big factors. However, they also considered the difference between the biggest and the smallest deciles based on market capitalization and find that, the size effect is well pronouncing in most of the countries. They demonstrated that, international momentum profitability declines sharply with market capitalization, and that, momentum premiums are also considerably diminished by trading costs, when considering the portfolio turnover.

Exchange rate, although the momentum profits could be increased by exploiting exchange rate information, Chan, et al. (2000) studied the profitability of the momentum strategy international they buy stocks in foreign countries when these countries' equity market acquired higher value compared to the US market. The show that the exchange rate component has a negative contribution to the momentum profits for the 12-week and 26-week holding periods, indicating a negative relationship between lagged exchange rate return and equity returns. They suggested that considering exchange rate fluctuation does not add much to momentum profits but the major source of momentum profits arises from price continuations in in individual stock indices.

Chordia and Shivakumar (2002) show that macroeconomic variable can explain a large portion of momentum profits. They study the profitability of the momentum strategy using standard macro variable and include the yield on the three-month T-bill. Fama (1981) and Fama and Schwert (1977) show that this variable is negatively related to future stock market returns and that it serves as a proxy for expectations of futures economic activity.

The dividend yield is defined as the total dividend payments accruing to the CRSP value-weighted index over the previous 12 months divided by the current level of the index. It has been shown to be associated with slow mean reversion in stock returns across several economic cycles by Campbell and Shiller (1988), and Fama and French (1988). This variable is included as a proxy for time variation in the unobservable risk premium, since a high dividend yield indicates that dividends are being discounted at a higher rate.

Fama and French (1996) show that momentum is the only anomaly unexplained by their three-factor model. That this anomaly is a spurious result of data snooping. They suggested that the weak continuation of short-term return in the 1931-1963 period preceding their asset pricing regressions is suggestive. Suggesting the need of further out-of-sample tests, for example on international data.

Time-varying exposure, Grundy and Martin (2001) report that stock selection method of a momentum strategy and time varying factor exposure will be borne in accordance with the performance of the common risk factors during the periods in which stocks were ranked to determine their winner or loser status. They suggested that because factors themselves display trivial momentum, extreme factor realizations induce noise, which obscures the study of the momentum phenomenon. This noise is penetrated in many ways. They adjusted raw returns for factor risk and found that the momentum phenomenon is remarkably stable across sub periods in their entire time series of post 1926 stock returns; and factor models can explain around 95% of the returns variability on portfolios of top and bottom ten percent of prior winners and losers, but cannot explain their mean returns. They concluded that controlling for time-varying exposures to three-factors fail to explain the profitability of the momentum strategy.

Hwang and Rubesam (2015) investigated if the momentum premium has continued to exist since it became publically well known in the USA. They generalized the model used by Pastor and Stambaugh (2001), and suggest a model that, allows for multiple structural breaks. A regime-switching model that can identify statistically significant change in the relation between momentum returns and risk factors. They find that, momentum is significantly positive only during some periods, notably from 1940s to the mid-1960s and from the mid-1970s to late 1990s, and it has disappeared since late 1990s, in a process, which was delayed by the occurrence of the high-tech and telecom stock bubble of the late 1990s. They suggested that, the bubble accounted for at least 50% of momentum profit.

2.6.4 Contrarian Investment and Macroeconomic Factors

It is now widely accepted that the contrarian investment strategies deliver superior returns. However, even if these strategies appear to be profitable, the reason for superior performance is far from clear. Under the rational pricing model, the contrarian strategies are profitable because they are fundamentally riskier in some sense. This subsection reviews empirical findings related to risk factors, which might affect the contrarian.

Fama and French three factors, Lakonishok et al. (1994) investigated the characteristics of the contrarian strategies in the U.S. They found that, even though, the excess returns to value investment strategies could in general be explained by the three-factor model of the Fama and French (1993 and 1996), there is little evidence to suggest that, value stocks are fundamentally riskier than glamour stocks.

Size, Gregory et al. (2001) examined the performance of contrarian investment strategies in the UK and found that, the contrarian excess returns persist even after controlling for size effects in stock returns. They suggested that the Fama and French's three-factor model could not explain all of the excess returns to value strategies. They advocated that, when portfolios are formed based on past sales growth and the current book-to-market value equity, there are substantial difference between value and glamour portfolios that cannot be explained by their loading on the market, their book-to-market and their size factors.

Gregory et al. (2003) show that, the risk of the contrarian strategies as measure by their volatility and Sharpe ratios do not provide evidence that value portfolios are riskier than glamour portfolios. They suggested that, while the standard deviation of any value strategy is greater than that of the HML factor, the Sharpe ratio of some value strategies is almost certainly too high to be consistent with rational risk pricing. They also examined the return on the contrarian strategies using both sales growth and a combination of sale growth and book-to market and found that these returns remain significantly positive even after controlling for SMB, HML and other factors. They advocated that, these returns are not compensation for risk. Following this reasoning, the literature relates to the relation between contrarian strategies profit and macroeconomic risk factor, involves the following variables.

GDP, HML and SMB, Gregory et al. (2003) show that both HML and SMB are positively correlated with future GDP growth. They suggested that there is no evidence of correlation between contrarian strategy returns and future GDP growth once HML and SMB are included as risk factors. They also reiterated that, in the context of the Fama-French model some value strategies return exhibit negative relationships with GDP growth. However, Liew and Vassalou (2002) argue that, the HML and SMB contain information about future growth in GDP, and contradict the preceding findings.

Volatility, De Haan and Hakes (2011) analyse the contrarian investment strategies of different types of Dutch institutional investors and find that, for pension funds, there is a negative impact of the volatility variables on the contrarian returns, suggesting that contrarian trading is stronger during periods of market stress. They argue that pension sector's stabilising role is strongest when this is needed the most.

Monetary environment, Garcia-Feijoo and Jensen (2014) published a paper in which they link monetary environment and the contrarian return. Their data consists of monthly stock returns for winners and losers from 1963 to 2010. They followed the portfolio formation approach of Fama and French base on the evaluation period starting from month-60 through month-13 or five-year performance interval with a one-year skip period. This formation approach proves to be the one where long run reversal is most persistent per Fama and French. Their holding period is only one month after the skip period of one year. They demonstrated that, losers reverse in expansionary monetary environments, whereas winners only reverse in restrictive monetary conditions.

Jordan (2012) studies the long-term reversal in international market, examining whether investors should continue to diversify across international markets and finds that the long-term contrarian anomaly disappears when time varying alphas are considered, which is even true without transaction costs. They suggested that for marginal trader, conservative transaction costs subsume the long-term profits. Their results show that benefits from trades on long term reversal do not negate a strategy based on diversification and that macroeconomic factors are important for understanding the long-term reversal and their associated risk.

2.6.5 Risk Factors Description

I then identify in the literature several possible macroeconomic factors that might proxy for systematic variables. Using these factors themselves, I implicitly assume that, variables that proxy for risk factors for the momentum and contrarian strategies exist (Chen et al., 1986). Doing this, I examine some macroeconomic variables seeing as precise measures of the global aggregate economic conditions (World Industrial production, and market volatility). I also extend the literature by examining the possible impact of a basic indicator of the world economy (oil price). This is important given that the change in oil price could have a direct impact on other significant factor, which are not accounted in the study.

I allow for market variables that serve as proxy for expectation of futures economic or market activity (liquidity, Term Spread, Default spread, and world market indices) to understand their influences on momentum and contrarian strategies returns over time. I consider how crisis could affect momentum and contrarian investors' profit and how the impact of pre-determined variables on momentum and contrarian return can change during crisis period (business cycle). I assess the impact of unobservable market risk premium that could affect the momentum and contrarian return using macroeconomic variables which are known for their ability to predict market returns (default spread, the term spread and the three-month T-bill).

I, then refer to the multifactor model notably the Fama and French's three-factors as potential source of systematic risk (Fama and French, 1993). I put considerable emphasis on explaining the detailed procedure to allow the reader to follow these steps, given that my approach differ from previous empirical specifications by focussing on risk factors that have a global sway.

Following the above specification, I separate the variables that have the potential to explain the momentum and contrarian return in different sets as indicated above. Having proposed the set of relevant variables, I now shield the purpose and the measurements of these factors following individual group.

2.6.5.1 Fama and French risks

I refer to the multifactor model that occupies centre stage these days, the three-factor model introduced by Fama and French (1993). The systematic factors in the Fama-French's model are firm size and book-to-market ratio as well as the market index these factors are empirically motivated by the observations that historical average returns on stock of small firms and on stock with high ratios of book equity to market equity are higher than predicted by the security market line of the CAPM. These observations suggest that size or the book-to-market ratio may be proxies for exposures to source of systematic risk not captured by CAPM beta and thus results in the return premiums that previous studies see associated with these factors.

To make their model operational, Fama and French proposed to measure the size factor in each period, as the differential return on small firms versus large firms. This factor is usually called SMB (for small minus big). In the same way, the other extra market factor is typically measured as the return of the firms with high book-to-market ratios minus those of firms with low ratios, or HML (Fama and French, 1993).

2.6.5.2 Market State Factors

To represent a broad category of factors that, serve as proxy for expectation of futures market activity as discussed in the extended literature, I include the following variables based either on empirical evidence or on their natural justification as macroeconomic risk factors.

Liquidity, Liquidity risk is the possibility of a loss when less liquid assets must be sold to meet the liquidity need. Foreign investment are dominant factors in the global equity market and liquidity risk are extremely high. Buying or selling large number of shares might cause a substantial supply and demand imbalance; this implies that market will collapse if everyone pulls out at the same time, given that market trading volume are often relatively thin with wider bid and ask spread. Skjeltorp and Odegaard (2011) showed that, the market liquidity was pro-cyclic, that liquidity interact with the cost of capital and relate to liquidity of trading in the secondary market. They suggested that investment decision significantly affects the term at which new capital are raised. The implication is that emerging market investments should be viewed as long-term investments rather than a source of trading profits.

Brunnermeier and Pedersen (2009) established the link between asset's market liquidity and traders' funding liquidity. They suggested that traders provide market liquidity, and their ability to do so depend on assets' market liquidity. They show that margins are destabilizing, and market liquidity and funding liquidity are mutually reinforcing, leading to liquidity spirals, which, can be gauged at a world level. This study utilises Pastor-Stambaugh level of the aggregate liquidity factors (LIQ_PS) to measure the effect of the liquidity cycle on the momentum and contrarian returns as indicated in Pastor-Stambaugh (2002) study.

As I noted, market state variables can capture greater difference in momentum and contrarian return. To verify the conditional nature of the momentum and contrarian strategies profit, I refer to a series of variables, indicators of the market state such as the Pastor-Stambaugh (2003) level of the aggregate liquidity factors (LIQ_PS), to measure the effect of the liquidity cycle on the momentum and contrarian returns. This refer to an aspect of liquidity associated with temporary price fluctuations induced by order flow. The monthly aggregate liquidity measure is a cross-sectional average of individual-stock liquidity measure. Each stock's liquidity in a given month estimated using that stock's within-month daily returns and volume represents the average effect that a given volume on day d has on the return for day d+1, when the volume is given the same sign as the return on day d.

Pastor and Stambaugh (2003) suggested that if signed volume is viewed roughly as order flow then lower liquidity is reflected in a greater tendency for order flow in each direction on day d to be followed by a price change in the opposite direction on d+1 which imply that lower liquidity corresponds to stronger volume-related return reversals.

Term Default and Spread, the literature on stock market return predictability shows that expected market risk premium is higher in bad times, and is correlated with business cycle (Fama and Schwert, 1989). This is consistent with the modern asset pricing theories that indicate the countercyclical price of risk (Zang, 2005). The momentum and contrarian return also follow similar outline given that they rely on performance of the determinants of the market to move in the short run and reverse in the long term in conformity with the expected market risk premium. To model the unobservable market risk premium, I use the United State macroeconomic variables, which are known for their ability to predict market returns such as the default spread (DEF), the term spread (TERM) and the three-month T-bill (RF).

The motivation of the Default Spread is standard from the time-series predictability literature. It is the yield spread between BAA and AAA corporate bonds. The Term Spread captures the effect of the shape of the term structure on the momentum and contrarian return. I will employ another interest rate variable, the term structure that represents the difference between the long-term government bond yield measured as the average yield of Treasury bonds with more than 10 years to maturity (LGB) and the average yield of the T-bills that matures in three months (TB). TS (t) = LGB (t) – TB (t-1); Chen, et al (1986) identified this variable as a measure of the unanticipated return on long bonds under the assumption of risk neutrality (only to isolate the pure term-structure effects). The Treasury constant maturity historical values and the 3-month Treasury bill are based upon the Federal Reserve Board's H.15 release that contains selected interest rate for U.S.

2.6.5.3 Macroeconomic Factors

Most relevant to my work, and on how economic conditions affect the momentum and contrarian returns, Griffin et al. (2003) define economic states in terms of the realized market returns and GDP growth. They identify good states with high and bad states with low ex-post market return or GDP growth. They found that, on the average momentum profits are positive during GDP growth and larger during negative market return. One possible explanation of this disparity can be the rise of finance as a macro-level phenomenon also known as financializing (Krippner, 2005). Similarly, the financializing of the world economy here will be seen as shaping patterns of accumulation in which profits accrue primarily through financial channels rather than through trade and commodity production (Arrighi, 1994).

Industrial Production, I consider the monthly industrial production output as the historical value of the world industrial production index. Pinegar and Chang (1989) suggested that, the coefficients on one–month lead growth rates in industrial production for small firms are positive and significant in times-series regressions even in the presence of the market factor, whereas returns on large firms' stocks unidirectional granger predict future growth rates in industrial production. This approach is in line with Chen et al. (1986) where the basic series is the growth rate in world industrial production index. It is the average global world international not seasonally adjusted, originated by Oxford Economics.

In addition, Chen et al. (1986) also find that, yearly production series are independent from other state variables, although, the coefficients have the same signs as in the overall period; they suggested that industrial production is a strong candidate for being a risk factor. Cutler et al. (1989) find that, Industrial Production growth is positively correlated with real stock returns. However, Bai and Green (2008) suggested that, changes in these macroeconomic variables are responsible for at least part of any country effect on national stock market indices.

Monthly growth rates are examined because the equity market is related to change in industrial activity in the long term. Since stock market prices involve the valuation of cash flows over long periods in the future, monthly stock returns may be highly related to contemporaneous monthly changes in rates of industrial production, although such changes might capture the information pertinent for pricing. This month's change in stock prices probably reflects changes in industrial production anticipated many months into the future (Chen, et al., 1986).

Oil Prices, I also expect oil price to have a significant impact on the momentum and contrarian trading strategies profitability. Chen, et al. (1986) suggested that, stock returns are exposed to systematic economic news that is priced by the market. A change in oil prices may then have indirect impact in stock prices and consequently on these strategies return. To test this hypothesis, Chen, et al. (1986) referred to oil prices as series of realized monthly first differences in logarithm of the producer price Index/Crude Petroleum series. Following the practice established by Chen, et al (1986), I refer to the oil price as a series of the world crude oil Index, FBO SPOT Brent denominate in U.S. Dollard and seasonally adjusted.

Market volatility, stock volatility may have considerable impact on the global momentum and contrarian return. Wang and Xu (2010) suggested that the aggregate market volatility significantly predicts momentum profit. They found that, momentum strategy tends to perform poorly following periods of high market volatility. De Haan and Hakes (2011) find a negative impact of market volatility on contrarian returns. This study uses the standard deviation of daily value-weighted of the MSCI global market indexes over the previous month as my measure of aggregate market volatility in conformity with Doron et al (2013). The MSCI World Index captures large and mid-cap representation across 23 developed countries with 1643 constituents. It covers approximately 85% of the free float-adjusted market capitalization in each country.

2.6.5.4 Financial Crisis

Business cycle, I turn my attention to the crisis period. Another candidate to the risk based explanation of the momentum and contrarian return is the Business Cycle Risk. Griffin, Ji, Martin (2003) established the relation between momentum and business cycle risk. They suggested that if momentum is driven by business risk, the risk is largely country-specific. It represents unanticipated change in the level of real business activity. The expected values of a business activity index are often computed both at the beginning and at end of the month, using only information available at those times. Business Cycle Risk (NBC) is calculated as the difference between the end-of-month value and the beginning-of-month value. A positive realization of Business Cycle Risk indicates that, the expected growth rate of the economy, measured in constant dollars, has increased. Under such circumstances, firms that are more positively exposed to business cycle risk for example will do well when business activity increases. As the economy recovers from a recession, they will outperform those that do not respond greatly to increased levels in business activity. This scenario may have considerable implications on the momentum and contrarian profitability given that the aggregate output of the overall economy may vary from one-time to another as the world enter a period of recession or expansion. To capture the impact of such variation this study uses the United State Leading Index of the National Bureau of Economic Research Business cycle, namely the NOBER business cycle that takes the value 1 when the economic is in recession and 0 when the economic is in expansion.

Crisis, I go further by allowing a deeper analysis of the underlying pattern between the global momentum and contrarian returns over time, and global shocks or international crisis. I address this deficiency by adopting the comprehensive historical time series data on debt and banking crises, inflation, and currency crashes as suggested by Carmen and Kenneth (2010). The range of variables encompasses the currency crises, inflation crises, stock market crises the sovereign debt crises (domestic and external), the Banking crises and the total crises computed as the aggregate value of the number of crises in each period.

Carmen and Kenneth (2010) defined the inflation crisis as an annual inflation rate of 20 percent or higher. They also consider the incidence of more extreme cases where inflation exceeds 40 percent per annum; Currency crashes as the annual depreciation versus the US dollar (or the relevant anchor currency) of 15 percent or more.

Banking crisis, are characterised by two types of event: the banks' runs that lead to the closure, merging or takeover by the public sector of one or more financial institutions. If there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institutions (or group of institutions) that marks the start of the string of similar outcomes for other financial institutions.

External debt crises, is a sovereign default, defined as the failure to meet a principal or interest payment on the due date (or within the specified grace period). The episodes also include instances where rescheduled in terms less favourable than the original obligation.

Domestic debt crisis includes definition given above for external debt. In addition, domestic debt crises have involved the freezing of bank deposits and or forcible conversions of such deposits from dollars to local currency.

2.6.6 Summary

I examined the extent to which momentum and contrarian returns can be affected by macroeconomic variables with the aim of acquiring a better understanding of the actual nature of the global momentum return predictability internationally. My examination has three key features. I examined the literature on the predictability of stock returns using a set of macro variables. The macro variables I consider constitute a set of standard macro variables, including the market volatility, oil price, liquidity risk, the MSCI world market return, term spread, default spread, industrial production, unemployment rate and many more.

By considering a set of standard macro variables, I examined whether common patterns of return predictability using macroeconomic variables emerge worldwide. I also considered the impact of these variables in both momentum and contrarian strategies and find that, there is a limited set of macroeconomic variables which could have significant impact on either momentum or contrarian strategies worldwide, namely, the market volatility, the exchange rate and the GDP growth, even though the variable is positively correlated to the HML and SMB.

I finally examine the effect of each potential macroeconomic variable (default spread, the term spread and the three-month T-bill oil price, GDP growth and the World Industrial production, liquidity, volatility, and exchange rate, crises) to proxies for exposures to source of systematic risk for the global momentum and contrarian risk factors. I found that the impact of these macroeconomic risks factors might have a decisive effect on determining the performance of the momentum and contrarian strategies.

2.7 Conclusion

I review variety of studies related to the Efficient Market Hypothesis. Eugene Fama (1970) has provided a careful description of the efficient market, that has had a lasting influence on practitioners and academics in finance, the efficient market theory states that all prices should reflect all information up to the point where the benefits of acting on the information is equivalent to the cost of collecting it. However, there are compiling evidences to show that, while people are still debating on the concept of market efficiency that trading techniques like the momentum and the contrarian strategies can generate extra return.

Examining the sources of these strategies profitability, evidences to support that momentum and contrarian profits could be a result of investor under or overreaction. Jegadeesh and Titman (1993, 2001) found evidence of return continuation in stock prices. Some studies also explain the overreaction effect in term of gradual diffusion of information as stocks with slower information diffusion provide more potential for momentum profits (Hong, Lim and Stein 2000). The international evidences of the momentum phenomenon suggest that individual market represent only one of a series of stock market that provide investment opportunity. These findings also provide strong international supports for the existence of a global momentum phenomenon, given that there might be disparity among investors reaction to news across countries.

The findings also support that contrarian profit could be a result of investor overreaction over the long run as suggested by De Bondt and Thaler (1985). These theories also support the behavioural theory of investor sentiment, as investors' sentiments influence stock prices (Brown and Cliff, 2005). Other explanations of the contrarian returns reflect the changes in equilibrium required rate of returns (Chan, 1988; Chopra et al., 1992). In addition, number of study also found evidences of the contrarian strategies profitability in different countries and regions around the world: Choe, et al. (1999) in Korea; Otchere and Chan (2003) in the Hong Kong market; Chen, et al. (2012) in China; Li et al. (2009) in the UK.

By examining the extent to which momentum and contrarian returns can be affected by macroeconomic variables I find that, there is a limited set of macroeconomic variables which could have significant impact on either momentum or contrarian strategies worldwide. I also found that the momentum and contrarian strategies are well-documented strategies worldwide in individual countries the results suggest evidences of market inefficiency. Evidences also point to the fact these profits could be result of investors under or overreaction to news. However, the impact of macroeconomic risk factor may have a decisive effect on determining the performance of the momentum and contrarian strategies.

I argue that for international investors individual market are viewed as only one of a series of stock markets that provide investors opportunities. International investors will not just compare the equity markets against one another, they consider the fact that asset allocation also occurs across countries and indicate the success of global strategies that include multiple indices such as the global momentum and contrarian strategies.

For international investors, watching the increasing development of the globalization of the equities market, it appears obvious that the correlation between international equity markets and international portfolio management become especially interesting for investment practitioners.

One natural question is whether the correlation between equity markets internationally following the globalization of the world economy offers the prospect of global momentum and contrarian profit. In more simple words: Do the global momentum and contrarian strategies work for international investors? I find that they do. Can the global momentum and contrarian profit be explained by global risks?

To answer this question, I propose an alternative way of generating extra return while focusing on a global coordinate contrarian phenomenon. I suggest strategy that allows investors to invest in selected well-performing countries (winners) and in selected poor-performing countries (losers) and inversely. Based on countries' past indices performances. I construct deciles and quintiles portfolios and re-examine the international evidences for the long-term contrarian predictability in different market states.

The results suggest that, the global momentum and contrarian strategies work for international well for international investors that target 47 countries indices. The strategies are more profitable and less risky than the pure momentum and contrarian strategy as it focusses on indices and select only the extreme losers and winners. These results also show that the global momentum strategy is consistently profitable between 1969 and 2014. The most successful momentum strategy selects stocks based on their previous performances over

9 months and then holds the portfolio for the next 3 months. This strategy yields 2.98% per month (42.24% per year) but the returns may vary considerably from one market condition to another. Studying the contrarian strategy internationally reveal an economically-important and predictive reversal effect after considering the price reversal among countries' indices as a global, coordinated and generalized phenomenon. Countries' indices' portfolios formed based on prior 48 months; prior losers outperform prior winners by 0.83% per month (10.40% per year) during the subsequent 60 months. Interestingly, the reversal effect is substantially stronger for emerging countries where it yields 1.37% per month (17.70% per year). It remains profitable in the period post-globalization.

More importantly to test whether global momentum and contrarian profit can be explained by global risk factors (oil price, market volatility, industrial productuction, MSCI world market return). I use monthly observation of the world risk factors that could jointly explain the changes on momentum and contrarian profitability. Referencing to the above literature there are limited data available on world risk factors. Because this thesis uses historical data to estimate the expected momentum and contrarian returns, I get around this problem by using the U.S. macroeconomic risks factors (liquidity, default spread and term spread) when necessary as a proxy for the world risk factors, due to the multinational nature of many U.S. companies and due to the enormous global diversity of asset holdings of U.S. companies, the U.S. equity market is a fair proxy of world asset market (Chako and Evans, 2014). The variables (Liquidility, default spread, term spread) are available. Because US treasuries are free of default risk, other bond are compared to treasuries in order to get an idea of their credit risk. Investors look at the yield of bond in terms of where it is trading compared to treasuries. This gives them more context on how risky the market view this. Instead of simply looking at a yield in isolation.

Chapter 3: Methodology and Data

3.1 Introduction

The research's aim is to examine the profitability of the momentum and contrarian strategies internationally. I consider a variety of momentum and contrarian portfolios construction approaches with different combinations of formations and holding periods. I adopt an empirical research approach given that I use a large sample data consisting of 47 countries' indices 10 macroeconomic variables. The data are made with high reliability quantifiable and measurable, the testing hypothesis of the momentum strategies are extracted from the theories following Jegadeesh and Titman (1993). I also follow a deductive research approach following a logical reasoning process of the contrarian strategies (De Bondt and Thaler, 1985). The research strategy is quantitative given my reliance on testing theory-derived hypothesis, manipulation and constructing causality relationships between macroeconomic variables and the momentum and contrarian profits. The data horizon is cross-sectional and longitudinal given the monthly frequency. This section is organised as follow: first, I define the variables, examine the data for their availability and discuss their distributional characteristics. Second, I present the methods use in examining the momentum and contrarian profitability.

3.2 Data

3.2.1 Introduction

To answer the research question: 'does the momentum strategies work for international investors?', `does the contrarian strategies work for international investors?', `can momentum be explained by risk factors?' data have been collected from two mains categories of quantitative sources: world market stock indices prices, and world risk factors. To my knowledge, regarding empirical literatures on momentum, contrarian and risks a comprehensive study of this kind has not been done before due to the internationalization of the risk factors impact on momentum and contrarian profits. Given that, I test whether global momentum and contrarian profit can be explained by global risk factors (oil price, market volatility, world industrial productuction, MSCI world market return) and I only use U.S factor when necessary for example I use U.S. macroeconomic risks factors (liquidity, default spread and term spread) when necessary as a proxy for the world risk factors, due to the multinational nature of many U.S. companies and due to the enormous global diversity of asset holdings of U.S. companies, the U.S. equity market is a fair proxy of world asset market (Chako and Evans, 2014). In addition, this thesis also assumes US investors. Because US treasuries are free of default risk, other bond are compared to treasuries in order to get an idea of their credit risk. Investors look at the yield of bond in terms of where it is trading compared to treasuries. This gives them more context on how risky the market view this. Instead of simply looking at a yield in isolation.

3.2.2 World Market Stock Indices Prices

I consider global momentum portfolios of international investors. Data are collected from DataStream. The data are composed of 47 countries equity market price indices (value weighted rebalanced quarterly but we deal with the change in the structure by including time dummies in the GMM estimation), and comprised of 23 developed markets and 24 emerging markets. The length of the sample period is from December 1969 to February 2014.The dataset will include all available countries' indexes constituent of the MSCI world index in DataStream. The developed countries are listed as follow: USA, Japan, UK, Australia, France, Germany, Italy, Canada, Hong Kong, Singapore, Spain, Switzerland, Belgium, Sweden, Austria, Ireland, Netherlands, New Zealand, Norway, Portugal, Denmark, Finland, and Israel. The emerging markets are listed as follow: Brazil, China, India, Korea, Russia, Turkey, Indonesia, South Africa, Mexico, Taiwan, Thailand, Argentina, Malaysia, Chile, Colombia, Egypt, Poland, CZECH Rep, Hungary, Pakistan, Sri Lanka, Morocco, Peru, and Jordan. This analysis is conducted based on stock indices denominated in US dollars and assumes the transactions on the stand of U.S. investors. The indices are based on the MSCI Global investable market indices and the study is conducted in differents time period with different subsample and different portfolios size (full sample: 1969-2014 47 countries, develop market: 1969-2014 23 countries, emerging countries: 1987-2014 24 countries, period post 1994: 1994-2014 47 countries).

Monthly observations from all market indexes are used. The purpose of this is to be able to compare the momentum return as medium versus long run. The analysis is conducted with sample date from 1969 to 2014. I examine different time points as the sample expands to include new countries following their historical appearances. Indexes levels will be used to compute the periodical continuous compounding returns as:

$$r_{i,t} = \ln(p_t) - \ln(p_{t-1}) \tag{1}$$

Where, $r_{i,t}$ is the monthly return on indices.

p_t, Is the indices level at time t and $p_{t-1}$is the index price at time t-1.

This study defines indices level, as the value of a section of the stock market. It is computed from the prices of selected stocks typically the weighted average. It is often used by fund managers, and investors to describe the market and compared the return on specific investment.

[Insert Table 3.1 Here]

Table 3.1 above presents the distributional characteristics, average return, standard deviation, Skewness, Kurtosis and the results from the Shapiro-Wilk test of normality for 47 countries' price indices. The Developed countries price indices returns' statistics characteristics are presented in Panel A and the Emerging countries statistic characteristics in Panel B. The sample is from December 1969 to January 2014.The first monthly return is measured in January 1970 for the firsts eighteen countries (USA, Japan, UK, Australia, France, Germany, Italy, Canada, Hong Kong, Singapore, Spain, Switzerland, Belgium, Sweden, Austria, Netherlands, Norway, and Denmark); these indices are available for the full sample period. Two developed countries indices (New Zealand and Finland) start in December 1981. Two developed countries indices (Ireland and Portugal), and eleven Emerging countries indices (Brazil, Korea, Turkey, Indonesia, Mexico, Taiwan, Thailand, Argentina, Malaysia, Chile, and Jordan) start in December 1987. One developed countries indices (Israel) and eight Emerging countries indices (China, India, South Africa, Colombia, Poland, Pakistan, Sri Lanka, and Peru) start in December 1992, and five Emerging countries indices (Russia, Egypt, CZECH Rep, Hungary, and Morocco) start in December 1994.

I can see from the Table 3.1 that, the highest mean return recorded in developed countries is 0.92% (Finland) compared to 1.33% in Emerging market (Mexico). The lowest mean return is recorded in Developed countries 0.01% (Portugal) compared to 0.21% in Emerging countries (China). The highest standard deviation in developed countries is 0.10 (Hong Kong) compared to 0.16 in Emerging market (Turkey). The lowest standard deviation in Developed countries is 0.04 (USA) compared to 0.07 in Emerging countries (Chile). This indicated that the most volatile countries are in emerging markets and the largest price change is recorded in Emerging market.

For most countries, the Skewness coefficients are negative and further away from zero which indicates that on average the data in my sample are not normally distributed the same. The Kurtosis coefficient are also different from 3 in most cases indicating fat tails.

I refer to the Shapiro-Wilk test as a test for normality as it considers Both Skewness and Kurtosis. It shows that, out of 47 countries indices only two developed countries indices prices (Japan and Italy) have passed the normality test (significant above 0.10) and one Emerging country indices India (significant above 0.05). The results also show that on average the standard deviation is relatively large (0.07) with respect to the mean (0.53%) in developed countries and even larger in Emerging countries (0.14) with a mean return of (0.61%). This indicates that the return value in the distributions of indices prices in my dataset are dispersed and non-normal between 1969 and 2014 for the Developed countries indices prices, and even more for the Emerging countries with the exception made on Japan, Italy and India.

To test whether the momentum strategy is profitable internationally, this study uses the Jegadeesh and Titman's (1993, 2001) approach and long winner stock indices and short loser stock indices over the full sample period 1969-2014 (47 counties); then I divide the data-set into different subsets for further analysis as follow.

1. The 1969-2014 sample that contains all countries indices price available from 1969 only 18 countries, I call them Established Market subset.

2. The 1994-2014 sample that contains all countries including Emerging countries with data available from 1994, 47 countries, I call this globalization period subset.

3. The developed countries sub-set, that contains all developed countries only with data available from 1969 (23 countries) I call this developed countries subset.

5. The Emerging countries sub-set, that contains all Emerging countries and start in December 1987 only 24 countries, I call them emerging counties subset.

6. The sample that includes only periods affected by banking crisis, currency crisis and stock market crash I call this crisis period subset.

7. The sample that includes only period not affected by crisis, I call this Non-crisis period

8. The sample that includes only periods affected by banking crisis only, I call this Banking crisis subset.

9. The sample that includes only periods affected by currency crisis only, I call this currency crisis subset.

10. The sample that includes only periods affected by stock market crashes, I call this stock Market crash subset.

11. The sample that includes periods of world economy contraction, I call this contraction period subset.

12. The sample that includes periods of world economy expansion, I call this contraction period subset.

This is to enhance the robustness of my results, to test if the results of these analyses are similar and consistent in different periods and different markets conditions and to check whether the results hold under different sample specifications, given that investors might have different geographic preferences for investment.

3.2.3 Variable Definition

My goal is to test whether global momentum and contrarian profit can be explained by global risk factors. I use monthly observation of the world risk factors (oil price, MSCI market volatility, world industrial production, MSCI world market return) that could jointly explain the changes on momentum and contrarian profitability. I restate that there are limited data available on world risk factors. I can only have satisfactory data on them (one or two decades at best). Because this thesis uses historical data to estimate the expected momentum and contrarian returns, I would like to have historical data going a long way back to 1969. In practice, I get around this problem by using the U.S. macroeconomic risks factors (liquidity, default spread and term spread) when necessary as a proxy for the world risk factors as stated earlier. Due to the multinational nature of many U.S. companies and due to the enormous global diversity of asset holdings of U.S. companies, the U.S. equity market is a fair proxy of world asset market (Chako and Evans, 2014). The variables are available over 45-year period from 1969 to 2014 to match with the study period. I also conduct additional analysis using the Fama and French global risk factors to proxies for global risks, the EURIBOR: OIS Spread (difference between the rate at which European banks lend to each other (EURIBOR) and the overnight' risk free' swap rate (EONIA) among the same banks for 3-month period), given that this informs investor on whether risk is rising or falling in credit market and it is a good indicator of stress in the banking system and the TED Spread or the difference between the London Interbank Offered Rate (Libor) and the 3-month Treasury Bill, given that rising TED Spread is commonly known as a bearish indicator and it is evidence that liquidity is being withdrawn from the financial market. EURIBOR: OIS Spread start in 1999, while the

TED Spread start 1990 and cover a limited period but the test is conducted for robustness. I classify world risk factors in three different groups.

3.2.3.1 Fama and French Risk Factors

The first group includes the excess return on the market, calculated as the value-weight return of the MSCI World index minus the one-month Treasury bill rate (own calculation). The Small-Minus-Big (SMB) or the average return on the three smallest portfolios minus the average return on the three biggest portfolios. The High-Minus-Low (HML) or the average return of the two value portfolios minus the average return on the growth portfolios on the US market. These are available from Wharton Research Data Services (WRDS), and known as Fama and French Risk. I then refer to the U.S. Fama and French risk factor series as proposed by Fama and French (1993) to proxy for world Fama and French risks. All these variables are available for 45 years' period from 1969 to 2014. (For detailed definition of the variable, please see Appendix E4). For robustnes I also conduct a separate analysis with the global Fama and French factor (3 and 5 factors), the global Fama and French excluding the U.S., the European and the Asia Pacific excluding Japan.

The results of the distributional statistics of the Fama and French risks factors notably the excess return on the market (ERM or MKT), Small-Minus-Big Return (SMB), High-Minus-Low Return (HML) are indicated in Table 3.2.

[Insert Table 3.2 Here]

The results in Table 3.2 Panel A show that the average value of the ERM (the average premium per unit of market) is 0.50% per month. This is low from an investment perspective (about 5% per year), but it is marginal. The average value for the SMB factors are rather low and amount to 0.20% per month. The SMB values cover a range of -16.70 to 22.30%. Therefore, the estimated spread in expected returns due to the size factor is consistent. The book-to market factor HML produces an average premium of 0.30 per month, which is low in both practical and statistical terms by comparison to Fama and French (1993). However, the HML values range from -13.10 to 13.90 in line with the suggestion that Higher Book to market ratios yield poor earning Fama and French (1995).

As for the three factors, HML, SMB and the ERM. The ERM is more volatile than SMB and HML. The ERM has the highest standard deviation (0.059). This indicated that the dispersion of the market premium around the mean is the most the volatile while. I also have considerable number of observations given the study period and compared to Fama and French (1993) sample size. It is also noticeable that on average the standard deviation is relatively low (0.029 for HML to 0.059 for the ERM) by comparison to the mean value of the variable. This indicates that, the value in the distributions in my dataset are dispersed. It also indicates some signs of non-normality of the variable between 1969 and 2014.

For all variables, the Skewness are away from zero, which indicates that on average the data in my sample are not normally distributed. On average the Kurtosis are different from 3. In the cases of the kurtosis and the Skewness are significantly high indicating further deviation from the central distribution. The Shapiro-Wilk test that seems more appropriate here as a test for normality as it considers Both Skewness and Kurtosis shows that none of the variable is normally distributed given that all the P-values are below 0.05. More importantly, both ERM and MKTRF follow similar pattern.

Table 3.2 Panel B shows the correlation coefficients between Fama and French risks factor. The MKTRF return is positively related to the HML and negatively related to SMB. Although I have some sort of correlation between MKTRF, HML and SBM these correlations are weak. Considering the above factors, I refer to the Variance Inflation Factor (Index that measures how much variance of an estimated regression coefficient is increased because of collinearity) to spot any sign of multicollinearity, which may exist among variables. The test result in Table 3.2 Panel C and Panel D indicate that the Variance Inflation Factor (VIF) values are below 3 for all the variables, this suggests that the multicollinearity among these factors are less likely or do not exist. In sum the common risks factor during the 1969 to 2014, closely replicate the properties of the benchmark of common risks factors. Suggesting that the data series are suitable for further risks based analysis. Results in the Table 3.2 Panel E below indicate sign of homoscedasticity in the residual given that the probability value issued from the Breush-Pagan (0.850) is greater than 5% with a test statistic of 0.040. However, the Q test indicates the presence of serial correlation of first order for the MKTRF and HML variables**.** The distributions of Fama and French risks factors during the 1969 to 2014 are random, and do not indicate any sign of multicollinearity and predictability. This suggests that the data series that include variables such as MKTRF, SMB, and HML will be suitable for further risks adjustment analysis. This is clearly illustrated from Appendix F1, which represents the scatterplot of the Fama and French risks variables and indicates dense dispersions in for all variables. This can be observed in Appendix F2-5 which depicts kernel distributions of entries or a nonparametric representation of the probability density function of random variable, used in this study to avoid making assumptions about the distribution of the variables MKTRF, SMB, the HML, and the expected normal distribution density of each factor across the subsample.

3.2.3.2 Market State Risk Factors

As I noted earlier, market state variables can capture greater difference in momentum and contrarian return. To verify the conditional nature of the momentum and contrarian strategies profit, I refer to a series of variables, indicators of the market state such as the Pastor-Stambaugh (2003) level of the aggregate liquidity factors (LIQ_PS), to measure the effect of the liquidity cycle on the momentum and contrarian returns. This refers to an aspect of liquidity associated with temporary price fluctuations induced by order flow. The monthly aggregate liquidity measure is a cross-sectional average of individual-stock liquidity measure. Each stock's liquidity in a given month, estimated using that stock's within-month daily returns and volume. It represents the average effect that a given volume on day d has on the return for day d+1 when the volume is given the same sign as the return on day d.

Pastor and Stambaugh (2003) suggested that, if signed volume is viewed roughly as order flow then lower liquidity is reflected in a greater tendency for order flow in a given direction on day d to be followed by a price change in the opposite direction on d+1. Which, implies that lower liquidity corresponds to stronger volume-related return reversals.

To investigate the time variation of the global momentum and contrarian premium using change in default and term premium. I refer to the default spread calculated as the difference between the average yields of bonds rated BAA by Moody's and the average yield of bonds with Moody's rating of AAA (please see Appendix E4 for detailed definition). I also refer to the Term spread calculated as the difference between the average yield of the Treasury bonds with more than 20 years to maturity and the average yield of the T-bill that mature in three months. The three-month T-bill monthly value, the BAA and AAA corporate bonds data, the long-term government bond yields and the Treasury constant maturity historical values with more than 20 years to maturity are collected from WRDS. These variables are available for 45 years' period from 1969 to 2014 (for detailed definition please see Appendix E4).

Recent literature proxies for term factor using principal component analysis thus considering the entire curve instead of arbitrary selected maturities. Note that, principal component analysis uses a single correlation matrix to identity dominant pattern of yields shifts and result only informs about the correlations themselves. For instance, the existence of a global parallel shift that explains around 50% of variation in global bond yields suggests that correlations should, on average, be positive. However, in global markets, correlations are notoriously time-varying. For example, there are consistent evidence that short term correlation between 10-year bond yields in different countries are significantly less stable than correlations between yields at different maturities within a single country. This means that, at least for short time horizons, one must be especially cautious in using the results of principal component analysis to manage a global bond position (Phoa, 2000).

I also acknowledge that principal component analysis might have the advantage that it makes any scenario analysis more meaningful by keeping local factors, which have important economic interpretations as shift, twist and butterfly moves of the yield curve (Phoa, 2000). However, this thesis follow Chan et al. (2000) and assume U.S. investors. Investors often look at the yield of bond in terms of where it is trading compared to treasuries. This gives them more context on how risky the market view this. Instead of simply looking at a yield in isolation.

I also discuss the results of the distributional statistics issued from the market state risk factors. The liquidity factor (LIQ), Default spread ((DS), the Term spread (TS) and the MSCI world index return (MKT).

[Insert Table 3.3 Here]

The results in Table 3.3 Panel A show that the average risk premiums for the liquidity factor (-0.031) is trivial the lowest compared to the term structure; the default spread factor (1.112), the market return (0.133), the term spread (0.003). Therefore, the estimated spread for the liquidity factor range from -0.461 to 0.201. Indicating that the average premium of the liquidity factor is low in statistical term. Such value may hide a reasonable level of dispersion given their spread around the means.

As for the four risks factors: LIQ, the DS, the TS and the MKT. The LIQ factor is the most volatile. It has a negative mean this is not surprising given that the smallest value is also negative (-0.4610). I also have considerable number of observations given the study period (1970 to 2013), and compare to Fama and French’s (1993) study (1963-1991 period). I note though, that the LIQ is not only highly volatile but has a Low means premium. This might prevent LIQ from explaining much of the cross-sectional variation in average returns of the global strategies, but high volatility also implies that the LIQ factors can capture substantial common variation in returns. This is in line with Fama and French's (1993) study that suggested that the low means and high volatilities is more appropriate in variables characteristics. It is also noticeable that on average the standard deviations are relatively moderated by comparison to the mean value of the variables, except in the case of the liquidity factor. This indicates that, the distributions in my dataset are reasonably dispersed around the mean value. It also indicates considerable level of density of the variable between 1969 and 2014.

For all variables, the Skewness are away from Zero, which indicates that on average the data in my sample are not normally distributed. The same, on average the Kurtosis departs from 3 and does not converge with the Skewness indicating that the variables are not obviously normally distributed by means of skewness and kurtosis values.

I also refer to the Shapiro-Wilk test that seems more appropriate as a test for normality as it considers Both Skewness and Kurtosis. The results show that none of the variables is normally distributed given that all the P-values are below 0.05.

Table 3.3 Panel B shows the correlation coefficient between the four factors series. The liquidity factor (LIQ) series is negatively related to the DS factor, but this correlation is not strong. The remaining correlation coefficient among the variable are positive. These correlations are weak and do not indicate any sign of multicollinearity. I suggest that the resulting collinearity trends are less likely able to weaken individual factor impact on the global momentum and contrarian return given that, even if correlations are not negligible the variables are far from perfectly correlated.

Considering the above factors, I do not want the standard error of individual variable to be inflated more than twice his basics size or minimum size by the effect of other factors in the set I then refer to the Variance inflation factor to spot any sign of multicollinearity, which may exist among variables. The test results in Table 3.3 Panel C indicate that all Variance Inflation Factor values are below 3 among the variables suggesting that, the multicollinearity between these factors are less likely to or do not exist. Moreover, the results in the Table 3.3 Panel D indicate sign of some sort of homoscedasticity in the regression given that the probability value from the Breush-Pagan test (0.708) is greater than 5%, and the presence of autocorrelation of first order for the DS only (please see Appendix E1 for detailed definition of the Breush-Pagan test).

In sum the distribution of market risks factors during the 1969 to 2014 are random, and do not indicate any sign of multicollinearity and predictability. This suggests that the data series that include variables such as liquidity, default spread and term spread might be suitable for further risk-based analysis. This is clearly illustrated in Appendix F8, which represents the scatterplot of the market variables and indicates denser dispersions for the liquidity and the Term Spread factors. This can be observed in Appendix F9-12 which depicts kernel distributions of entries of the variables liquidity factor (LIQ), Market return (MKT), Default spread ((DS), and the Term spread (TS), and the expected normal distribution density of each factor across the subsample. Appendix F 9 shows a leptokurtic distribution of the liquidity factor. This indicates that small changes in liquidity are less likely to happen; it means that investors can overestimate the impact of this factor at low level of significance. Appendix F10 also demonstrates that the default spread variable has a negative skew. However, the terms spread shows a uniform distribution with a high pick (Appendix11). Lastly, the distribution of the market returns skew or lurch in slightly in the right (Appendix F12), indicating a lower mean compared to the mode and the median.

3.2.3.3 Macroeconomic Factors

To examine the extent to which macroeconomic variables explain the profits of the momentum and the contrarian strategies. I refer global factors that capture the aggregate change in the world economy as macroeconomics risks factors. The available macroeconomic variables that I consider are in monthly frequencies, and I match the frequency of the estimated macroeconomic risks and the global momentum and contrarian trading payoffs, all in the effort to use macro variables series that are stationary finite and constant over time. For instance, I use world industrial production index level (Total Industrial production and Manufacturing production index value SDDS+) from the Federal Reserve database, the Oil Price as a series (Producer price index crude petroleum series) obtained from the Bureau of Labour Statistics database, and the return on the MSCI world index prices from DataStream for the study time period. For all I calculate the percent change or the growth rate. All macroeconomic data are available for 45 years' period 1969 to 2014. (For detailed definition of macroeconomic variables, please see Appendix E4).

I consider the distributional statistics and the graphical analysis of individual macroeconomic factors. To confirm the explanatory power of the macroeconomic factors in my sample, I evaluate the dispersion of the entries in the distributions through the standard deviations, minimum, maximum, mean, skewness, and kurtosis. Using the correlation coefficient and the variance inflation factor (VIF) I also examine the likelihood of a multicollinearity between factors. I extend my analysis by examining the distributions for normality through the Shapiro-Wilk test. I present the results of the descriptive statistic (minimum, maximum, mean, standard deviations, skewness and the kurtosis) as well as the result of the Shapiro-Wilk test on the economic factors. I also present the variance inflation factor and the correlation coefficient results for the time series of monthly value of the Oil price (ΔOP), Market volatility (WVOL), Industrial production (ΔIP). The corresponding results are shown in Table 3.4 below.

[Insert Table 3.4]

The results in Table 3.4 Panel A show that the oil price ranges from -0.40% return to 50%, with a mean value of 0.6%. The world market volatility ranges from -4.40% to 2.40% with a mean value of 0.2%. The level of industrial production index also ranges from 0.3% to 3.90%. These perceived spreads in economic variables indicate that most observations depart considerably from the mean in statistical term. As for the factors (ΔOP, WVOL, and ΔIP) the standard deviations of all the factors are positives and significantly low indicating that macroeconomic are slightly just volatile. Low means values in industrial production might allow the ΔIP factors to provide more information in explaining much cross-sectional variation of the global momentum and contrarian returns. The higher volatility compared to the mean might imply that these factors may capture substantial common variations in the momentum and contrarian strategies returns which is in line with Fama and French’s (1993, 1995) findings.

For all variables the Skewness are different from Zero which indicates that on average the data in my sample are not normally distributed. On the average the Kurtosis are different from 3 and does not converge with the Skewness indicating that the variables are not obviously normally distributed by means of the Skewness and Kurtosis values.

I refer to the Shapiro-Wilk test that seems more appropriate as a test for normality as it takes into account Both Skewness and Kurtosis. It shows that none of the variable is normally distributed given that all the P-values are below 0.05.

Table 3.4 Panel B shows the correlation results between the four series. Market volatility and the industrial production are negatively correlated. Oil price and industrial production are positively correlated this is not surprising given that high oil price, high production level and market uncertainty may suggest concern over global growth, but this correlation is not strong. Oil price are positively correlated with the market volatility but these correlations are far from perfect and unlikely to indicate any sign of multicollinearity or to weaken the individual impact of these variables on the global momentum and contrarian return.

Considering the above factors (ΔOP, WVOL, and ΔIP) I do not want the standard error of individual variable to be inflated more than twice its basics size or minimum size by the effect of other factors in the set I then refer to the Variance inflation factor to spot any sign of multicollinearity which may exist among variables. The test results in Table 3.4 Panel C indicate that the VIF values are below 3 for all the variables suggesting that, the multicollinearity among these factors are less likely or do not exist. In sum the macroeconomic risks factors do not indicate any sign of multicollinearity and predictability during the 1970 to 2013 period suggesting that the data series that include these factors might be suitable for further risk based analysis. The results in the Table 3.4 Panel D indicate sign of homoscedasticity in the regression given that the probability value from the Breusch-Pagan test (0.67) is greater than 5%. These results also indicate the presence of autocorrelation of first order for all macroeconomic factors. These analyses also hold when the variables are jointly examined (Table 3.5 and 3.6).

Indeed, these points are made clear in Appendix F15, which represents the scatterplot of the three macroeconomic variables suggesting that, the variables are moderately dispersed. Appendix F16-19 depicts the kernel distributions of entry and the expected normal distribution density across my subsample these graphs obviously confirm my suggestions. Appendix F16 Appendix F9 shows a leptokurtic distribution of the oil factor, which appears to show a significant high and slim pick indicating. Appendix F17 shows a skewed distribution of industrial production that lurches in the right or a slight negative skew indicating that the mean is lower than the mode and the median of the series. However, Appendix F18 also indicates that market volatility has a positive skew.

3.2.3.4 Crisis

The construction of my dataset on global crisis builds on the works of scholars such as Carmen and Kenneth's (2010) study and includes considerable amount of time series. For instance, the currency crises, stock market crash, and the Banking crises. I collected the currency crisis, banking crisis and stock market crash series from Carmen Reinhart's website available from 1969 to 2010. The business cycle series are also available online from the

National Bureau of Economic Research's website from 1969 to 2014 (for detailed definition of the variable please see Appendix E4). These variables take the value 1 when the event (crisis) occurs and 0 for non-occurrence. I also use the National Bureau of Economic Research (NBER) definitions of recessionary periods in U.S.

Exploiting the multi-decade's span of these data, I study the role of repeated crises in explaining the observed patterns in momentum and contrarian return that characterise these global strategies at the global level. I use U.S data in these analyses, because comparable data are not published at the world level. In addition, Bordo et al. (2010) showed that the shocks to the global economy, particularly those from the U.S. real GDP, have a decisive effect on Individual County's GDP growth around the world. The same, the international equity market behaviour mimics those of the U.S. The recessionary period here, includes all crises periods from the end of December 1969 to the beginning of February 2014.

3.2.4 Summary

In sum the distribution of Fama and French, market state and macroeconomic risks factors during the 1969 to 2014 do not indicate any sign of multicollinearity and predictability. This suggests that the data series that include all these variables might be suitable for further risks adjustment analysis.

3.3 Methodology

3.3.1 Introduction

This thesis relies on the momentum trading strategies to examine the historical data of 47 countries worldwide. The methodology is designed as follow: First the study examines the global stock market state over the study period and defines the starting and the ending period of the bull and bear phase, while taking into consideration the differences, which may be apparent among the 47 countries, selected in the study sample. Second, this study will build the hypothesis based on the theory and the available and tested theoretical models. Third, I collect 47 countries indexes data and conduct statistical test and analysis. The study assumes that there is not restriction for investors in trading portfolios of stocks in individual markets worldwide. The US dollar is considered as the currency of reference, and the study is conducted from the perspective of US investor.

3.3.2 Global Trading Strategy

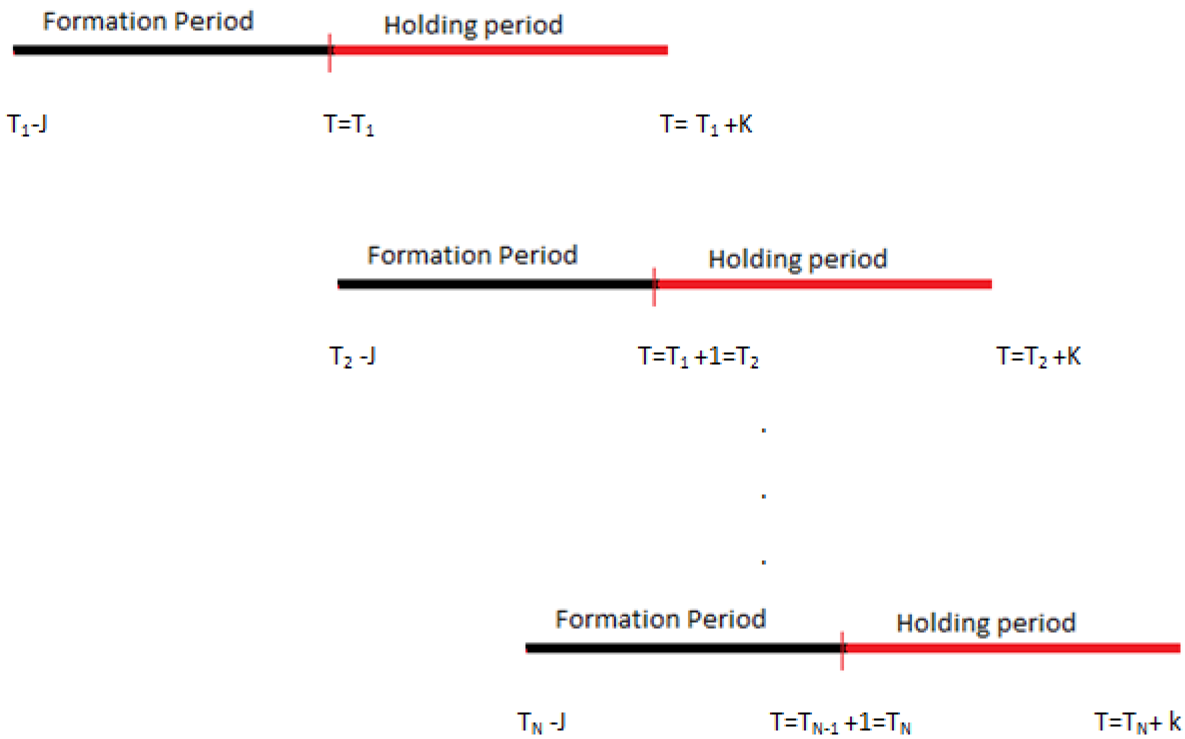
A momentum trader will divide countries' indexes by their past returns into ten deciles and rank them in ascending order, he will define the best index return or the bottom deciles as the "winner" and worst as the "Loser". Jegadeesh and Titman (1993) defined the momentum trading strategies as buying the winner and selling the Loser, and the contrarian strategy is defined as buying the Loser and selling the Winner. In this thesis, I follow the same approach. I construct the global momentum portfolio the same as Jegadeesh and Titman (1993). In addition, the contrarian portfolios like De Bondt and Thaler (1985). For each month t, I rank all 47 countries indices into deciles based on their J-month formation period. Deciles portfolios are formed by equally weighting all indices in the deciles ranking. The global momentum strategy is to take along position in the top decile portfolio (the winners) and short position in the bottom deciles portfolio (the losers). While the global contrarian takes a long position in the bottom deciles portfolios (the losers) and short position in the top deciles portfolios (the winners) (please see Appendix A and B for the momentum and contrarian flowchart, the breakdown structure, and MATLAB programming).

3.3.3 Momentum Strategy

To examine the momentum profitability, the first stage is to designate two-time period for the construction of the portfolio, which are not necessarily the same. The first-time horizon could be denoted (J) which means time of the portfolio construction and (K), which means the holding period of the portfolio. The formation or the construction period is defined as the length of time that investors observe indexes in order to compute past indexes returns and rank them into different groups of portfolios according to their past performances. The holding period is defined as the length of time that investors hold their constructed portfolio before the constituents are sold. Various formation periods (J = 3, 6, 9 and 12 month), could be considered when portfolios are constructed with various holding periods (K = 3, 6, 9 and 12 month), the choice of these horizons are conformed to empirical test (Jegadeesh and Titman 1993).

Given the combinations of the portfolio's construction period and the portfolio's holding period (J, K) where J = 3, 6, 9, and 9; K = 3, 6, 9, and 12 the sample computed returns are ranked in ascending order following countries' strength where the first 10% represent the lowest past performances and the last 10% represent the highest past performances. This approach is following Jegadeesh and Titman (1993). In other words, a portfolio, which comprises of the last lowest past performances, is regarded as the loser portfolio while the first portfolio, which constitutes of the highest past performance, is regarded as a winner portfolio. The formation period starts from the month T_1-J and ends at month T = $T_{1.}$ The end of T_1 is the starting date of the study-holding period and the study rebalances the portfolio at the end of each holding period all over the length of the sample period. The process is repeated N times. By doing this, the thesis adopts a non- overlapping portfolio approach for holding period and reports the average monthly return for the K-month holding period as equal-weighted average of the portfolio returns. For example, for the 6-month/6-month momentum strategy, at the beginning of each month all countries indices with returns from t – 6 (01/1790) to t (6/1970) = 0 are allocated to deciles based on their continuously compounded excess returns between t - 6 and t = 0. The portfolio is reformed monthly at t and hold until the end of the holding (12/1976) period and the strategy is repeated N time until the end of the sub-sample period.

3.3.3.1 Momentum Time line



Next, an equally weighted average return for each of the portfolio will be computed over the next K-month respectively for the monthly analysis where K is the holding period.

(2) $$R_{W=}\frac{1}{N}\sum_{n=1}^{N_p}\left[\sum_{t=1}^{k} r_{i,t}^{w}\right]$$

(3) $$R_{L=}\frac{1}{N_p}\sum_{n=1}^{N_p}\left[\sum_{t=1}^{k} r_{i,t}^{L}\right]$$

k, is the holding period

R_L, represents the loser portfolio average return in t month

R_W, represents the winner portfolio average return in t month

N_p, is the number of losers or the winners in the portfolios.

This analysis is performed N time for each of the momentum strategies. The study will continue by computing the sum of all of the average returns of the winner and loser portfolios consecutively as follows.

(4) $$AR_w = \frac{1}{N}\sum_{n=1}^{N} R_w$$

(5) $$AR_L = \frac{1}{N}\sum_{n=1}^{N} R_L$$

The next step is to compute the momentum strategies, which can be defined as a strategy of buying stocks that have performed well in the past and selling stock that have performed badly in the past. (Jegadeesh and Titman 1993) and the returns are computed as follows.

(6) $$Mom = AR_W - AR_L$$

3.3.3.2 Hypothesis testing: Hypotheses 1of 3

This hypothesis answers the first question: do momentum strategies work for international investors by examining the momentum strategies performances over various construction and holding periods (3, 6, 9, and 12 month).

Ho1: Global momentum strategy applied across the world financial market should generate positives and significant returns.

For the momentum strategies, the T statistics can be computed as follows.

(7) $$H_0: (AR_w - AR_L) > 0$$

(8) $$T_{M,t} = \; (AR_w - AR_L)/\sqrt{2S_{M,t}^2/N}$$

With the variance of the difference of two samples of equal size N equal to $2S_t^2/N$ where $S_{M,t}^2$ is computed as.

(9) $$S_{M,t}^2 = [\sum_{n=1}^{N}(R_w - AR_w -)^2 - \sum_{n=1}^{N}(R_L - AR_L\ -)^2/2(N-1)].$$

After all, the final step is to check if the difference between the returns of the winners' portfolios and the losers for portfolios during the N horizon changes in sign (altering point). If the cumulative average return of the winner portfolio at this point is higher than the loser portfolio's return, I conclude that I have a momentum profit but if it is lower, I may conclude that it is a contrarian profit. I further examine the momentum with a time lag between formation and holding periods. For example, to implement the 6-month/6-month strategy, at the beginning of each month all countries indices with returns from t – 6 (01/1970) to t = 0 (6/1970) are allocated to deciles based on their continuously compounded excess returns between t - 6 and t = 0. Portfolios are reformed monthly at t+1 (08/1970 and hold till the end of the holding (01/1971) period. The strategy is repeated N time until the end of the sub-sample period. To increase the power on the test, I also perform similar analysis with overlapping portfolios where momentum deciles portfolio in any month holds indices ranked in the deciles in any of the previous J months, and quintiles portfolios. The winners and the loser's portfolios are constructed using MATLAB Programming; The Script files are provided in appendix A3 to A6.

3.3.4 Contrarian Strategy

To test the contrarian strategy profitability internationally, the global contrarian strategy is designed as follow. The later analysis is repeated for the contrarian strategies (please see equation 1-5 for the winners and losers' portfolios construction). The contrarian strategies can be defined as a strategy of buying stocks that have performed badly in the past and selling stocks that have performed well in the past (Winners). (De Bondt and Thaler, 1985). I implement the contrarian strategy as follow. At the beginning of the month, the indices are ranked based on their past F-month returns (F=36, 48, or 60 months). At each month t, the strategy buys the long-term loser portfolio consisting of the 10% indices that have the lowest past F-month returns (extreme losers) and sells the long-term winner portfolio comprised of the 10% of indices that have the highest past F-month returns (extreme winners). The contrarian arbitrage portfolio (loser-winner) buys the long-term losers and sells the long-term winners.

Portfolios are held for H-month holding period where (H= 36, 48, or 60 months) in keeping with De Bondt and Thaler (1985). By doing this, the thesis adopts a non-overlapping portfolio approach for holding periods and reports the average monthly return for the H-month holding period as equal-weighted average of the portfolio returns. For example, to implement the 36-month/36-month strategy, at the beginning of each month all countries indices with returns from t – 36 (01/1970) to t (12/1972) = 0 are allocated to deciles based on their continuously compounded excess returns between t - 36 and t = 0. Portfolios are reformed monthly at t and hold till the end of the holding (01/1976) period and the strategy is repeated N time till the end of the sub-sample period.

(10) $$Con = AR_L - AR_W$$

3.3.4.1 Hypothesis Testing: Hypothesis 2 of 3

This hypothesis answers the second question: do momentum strategies work for international investors by examining the momentum strategies performances over various construction and holding periods (36, 48, and 60 month).

Ho2: Global contrarian strategy applied across the world financial market should generate positive and significant returns.

For the momentum strategies, the T statistics can be computed as follows.

(11) $$H_0: (AR_L - AR_W) > 0$$

(12) $$T_{C,t} = \ (AR_L - AR_W)/\sqrt{2S_{C,t}^2/N}$$

With the variance of the difference of two samples of equal size N equal to $2S_{C,t}^2/N$ where $S_{C,t}^2$ is computed as.

(13) $$S_{C,t}^2 = [\sum_{n=1}^{N}(R_L - AR_L)^2 - \sum_{n=1}^{N}(R_W - AR_W -)^2/2(N-1)].$$

After all, if the cumulative average return of the winner portfolio at this point is higher than the loser portfolio's return, I conclude that I have a contrarian profit but if it is lower, I may conclude that it is a contrarian profit. I further examine the contrarian strategies that skip a month between the formation and the holding periods. For example, to implement the 36-month/36-month contrarian strategy, at the beginning of each month all countries indices with returns from t - 36 to t = 0 are allocated to deciles based on their continuously compounded excess returns between t - 36 and t = 0. Portfolios are reformed monthly at t and hold until the end of the holding period and the strategy is repeated N times till the end of the sub-sample period. To increase the power on the test, I perform similar analysis on contrarian strategies with overlapping portfolios where contrarian deciles portfolios in any particular month hold indices ranked in the deciles in any of the previous F months, and quintiles portfolios.

3.3.5 Global Risk Factors, Momentum and Contrarian

I test whether investors earn significant return after adjusting for Fama and French risks, markets state risks and macroeconomic risks. To implement the risks adjustment test, I start the analysis by regressing the initial global momentum portfolios returns on the Fama and French's three-factor model, and account for time variation through a time dummy. This allows a better understanding of the ability of the Fama-French (1993) factors model to subsume the Global momentum payoff. Hence, I test the ability of the three-factor model to explain returns across momentum portfolios by regressing the global momentum returns on the three-factor model. The equation can be illustrated as follow:

$$Mom_t = \alpha_0 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + e_t \tag{14}$$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, and SMB_t(small minus big) is returns to long-short portfolios constructed using size in US market. $R_M - R_F$ market premiun on the U.S. market returm (market premium), and beta the factors loading are the slopes in the times-series regression.

I further regress global momentum portfolios' returns on the market state factors, and account for time variation through a time dummy. This allows testing the ability of market state factors to explain returns across momentum portfolios. The equation can be illustrated as follow:

$$Mom_t = \alpha_1 + \beta_1 LIQ_{t-1} + \beta_2 DS_{t-1} + \beta_3 TS_{t-1} + \beta_4 MKT_{t-1} + e_t \tag{15}$$

Where: LIQ_{t-1} is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS is the Term spread at time t-1, the $MKT_{t-1}$is the return on the MSCI world index at time t-1, and beta the factors loading are the slopes in the times-series regression. I take the first lag to avoid spurious regression by including non-stationary variables.

So far, the predictive variables have been macroeconomic in nature, but derived from financial market, which has the advantage of being forward looking with zero measurement error, see equation (9). Now I extend the analysis with the use of three pure macroeconomic factors. This results in the following regression model.

(16) $$Mom_t = \alpha_2 + \beta_2 \Delta OP_{t-1} + \beta_3 WVOL_{t-1} + \beta_4 \Delta IP_{t-1} + e_t$$

Where: ΔOP_{t-1} is the percent change in monthly oil price, $WVOL_{t-1}$ is the market volatility (standard deviation of the return on the MSCI world indices), and ΔIP_{t-1} is the (percent change) in monthly value of the US Industrial production. I take the first lag to avoid spurious regression by including non-stationary variables.

3.3.5.1 How does of Global Risk Affect the Momentum Profit

Having examined evidence for changing performance of the global momentum strategies, I adopt a risk factor model similar to Avramov et al. (2015) in order to explore deeply the dynamic relation between the momentum strategies, and macroeconomic risk factors. I use monthly observation of the world risk factors (MSCI market volatility, world industrial production, and MSCI world market return) that could jointly explain the changes on momentum and contrarian profitability. I use the U.S. macroeconomic risks factors (oil price, liquidity, default spread and term spread) when necessary as a proxy for the world risk factors as stated earlier. Due to the multinational nature of many U.S. companies and due to the enormous global diversity of asset holdings of U.S. companies, the U.S. equity market is a fair proxy of world asset market (Chako and Evans, 2014). However, Avramov et al. (2015) found that changing the state of macroeconomic factor do not affect the variation of the momentum profit in U.S. and non-U.S. countries. (Japan, and Eurozone countries). I also conduct additional analysis using non-U.S. variable such as euribo interest rate and the Fama and French global risk factors, the global Fama and French factor excluding the U.S., Asia pacific excluding Japan. The euribo interest rate start in 1999 while the global Fama Factor start in 1990 and cover a limited period but the test is conducted for robustness. The limitation is that it is not this thesis to demonstrate how local macroeconomic factors will explain the momentum at the counties level which could be done with a more complete study for the all the countries where such data are available.

(17) $$Mom_t = \alpha_3 + \beta_1 (R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 \Delta LIQ_{t-1} + \beta_5 DS_{t-1} + \beta_6 TS_{t-1} + \beta_7 MKT_{t-1} + \beta_8 \Delta OP_{t-1} + \beta_9 WVOL_{t-1} + \beta_{10} IP_{t-1} + e_t$$

Where: Mom_t is the momentum returns at time t, $R_M - R_F$ is the market premium return, HML_t (High minus low) is the return to portfolios that, is long on high book-to-market stocks and short on low book-to-market stocks in US, and SMB_t(Small minus big) is the returns to long-short portfolios constructed using size in US market. The $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, and

$MKT_{t-1}$is MSCI world indices' returns at time t-1. ΔOP_{t-1} is the percent change in monthly oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1 and ΔIP_{t-1} is the percent change in monthly value of the US Industrial production at time t-1. I estimate (17) Using the GMM method with historical data available information at the time of this study.

I go further by examining the role of crises in explaining the momentum profit. To test the link between crises and the momentum, I construct a subsample that includes only momentum during crisis period and global risks factors' observations during the crisis period and a subsample for non-crisis periods (currency crisis banking crisis and stock market crash). I conduct this analysis separately for the three different crisis factors. As in equation (17), I test the null hypothesis that the estimated intercept is equal to zero across all momentum and contrarian portfolios when the crisis effect and all macroeconomic risks factors effect are taken into account against the alternative that the estimated intercept is different from zero.

I examine the link between the performance of the global momentum and contrarian strategies and the economic development. I concentrate on the impact of business cycles on strategies performances according to the NBER business cycle definition. The sample covers 7 expansions and 7 contractions periods. While I have limited number of expansions and contractions, I aim to shed the light on the impact of business cycles on this strategies' performance.

I examine how the global momentum strategies returns vary in both expansion and contraction periods. To study the link between business cycles and the momentum strategies performance, I construct a subsample that includes only momentum during expansion periods and global risks factors observations during the expansion period and a subsample for contraction period. The selection of the period is based on NBER business cycle definition specifications. I examine how change in business cycle affects the momentum and the contrarian profit. As in equation (17), I test the null hypothesis that the estimated intercept is equal to zero across all momentum and contrarian portfolios during contraction, and expansion period when all global risks factors effects are considered against the alternative that the estimated intercept is different from zero.

One possible explanation for the momentum and contrarian profits is that investors that opt for these strategies bear extra risks. My previous results show that a significant portion of the momentum profits comes from emerging markets. This is in line with Harvey (1995) and

Bekaert et al. (1997) who showed that emerging market returns have higher autocorrelation and are more predictable. Naranjo and porter (2007) suggested that investment strategies that diversify across countries provide lower portfolio standard deviation and increased expected return. Theses returns generate form portfolios diversifications are larger when adding emerging market. Given the cultural differences, the political instability and the low liquidity of these emerging markets, there are query about the viability of the momentum strategies or the strategies being bogus. To examine the possibility that there could be disparity in risk adjustment between emerging and developed markets, I regress the strategies returns issued from the emerging market subset on risk factors discarding all developed countries effect and subsequently, the momentum strategies issued from the developed market subset, established market subset and the globalization subset. As in equation (17), I test the null hypothesis that the estimated intercept is equal to zero across all momentum portfolios against the alternative that the estimated intercept is different from zero in developed, emerging markets, in established market and during the globalisation period.

3.3.5.2 How does Crisis Affect the Momentum and Contrarian Profit?

For robustness, I add a dummy variable to my regression model to control for the impact of crisis period, the dummy variable takes the value one when the economy is in crisis mode and zero otherwise. I also conduct a separate analysis with crisis period subset (Banking crisis, currency crisis, and stock market crash) and non-crisis. I examine how crises affect the momentum and the contrarian profit using the following equation.

$$(18) \qquad Mom_t = \alpha_8 + \beta_1 D_t + \beta_2 (R_M - R_F)_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$$

Where: Mom_t is the momentum returns, D_t is the Dummy variable that is one if the economic is in crisis at time t and zero otherwise, $R_M - R_F$ is the market premium. HML_t (High minus Low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, and SMB_t(Small minus big) is returns to long-short portfolios constructed using size in US market. The $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default Spread at time t-1, TS_{t-1} is the Term spread at time t-1, and MKT_{t-1} is the MSCI world indices return at time t-1. ΔOP_{T-1} is the change in monthly oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIPY_{T-1} is the change in monthly value of the US Industrial production at time t-1. I estimate (18) using OLS and Newey West procedure consecutively with historical data available information at the time of the study, I also estimate the above regression for currency crises, debt crises cycle, and banking crises.

3.3.5.3 How do Business Cycle Affect Momentum and Contrarian Profit?

I concentrate on the impact of business cycles on strategies performances according to the NBER business cycle definition. The sample covers 7 expansions and 7 contractions periods. While I have limited number of expansions and contractions, I aim to shed the light on the impact of business cycles on these strategies performance. I examine how changes in business cycle and global risks factors affect the global momentum and contrarian strategies returns. To study the link between business cycles and the momentum and contrarian strategies performance, add a dummy variable to my regression model to control for the business cycle period. The dummy that takes the value one when the economy is in expansions mode and zero otherwise. I also conduct a separate analysis with subset of contraction, and expansion periods.

(19) $Mom_t = \alpha_9 + \beta_1 \delta_t + \beta_2 (R_M - R_F)_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_9 MKT_{t-1} + \beta_{10} \Delta OP_{t-1} + \beta_{12} WVOL_{t-1} + \beta_{13} \Delta IP_{t-1} + e_t$

Where: Mom_t are the momentum returns, $R_M - R_F$ is the market premium, HML_t (High minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size in US market, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices return at time t-1, ΔOP_{T-1} is the change in monthly oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIPY_{T-1} is the change in monthly value of the US Industrial production at time t-1. I estimate (14).

3.3.5.4 Do Risks Factors Explain the Global Momentum and Contrarian Excess Returns?

I also examine whether momentum and contrarian investors earn significant return in excess of the US risk free rate, after adjusting for macroeconomic risks factors. To examine the possibility that there could be abnormal returns generated from the momentum and contrarian strategies, I regress the excess global momentum, and contrarian portfolios returns on the macroeconomic risks factors.

(20) $Mom_t - R_{Ft} = \alpha_7 + \beta_1 (R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 LIQ_{t-1} + \beta_5 DS_{t-1} + \beta_6 TS_{t-1} + \beta_7 MKT_{t-1} + \beta_8 \Delta OP_{t-1} + \beta_9 WVOL_{t-1} + \beta_{10} \Delta IP_{t-1} + e_t$

Where: Mom_t are the momentum returns, R_{Ft} is the risk free rate at time t, $R_M - R_F$ is the market premium, HML_t (High minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size in US market, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices return at time t-1, ΔOP_{T-1} is the change in monthly oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIPY_{T-1} is the change in monthly value of the US Industrial production at time t-1.

With this approach, I measure how global macroeconomic risks factors affect the profitability of the momentum and contrarian strategies and the changes over time. As in equation (20), I test the null hypothesis that the estimated intercept is equal to zero across all momentum portfolios against the alternative that the estimated intercept is different from zero.

3.3.5.5 Hypothesis Testing: Hypothesis 3 of 3

The remaining hypothesis (Ho3) seeks to answer the question: do momentum and contrarian profits can be explained by risks factors?

Ho3: Momentum and Contrarian profit are compensation for risk.

I test the null hypothesis that the estimated intercepts (Alpha) of regressions are equal to zero across all momentum portfolios against the alternative that the estimated intercept is different from zero.

$$Ho: \alpha_3 = 0$$

$$Ho: \alpha_3 \neq 0$$

More precisely, I consider all possible combinations of predictive macroeconomic risks factors. The predictive variables include all Fama and French risks factors, all market states factors, and all macroeconomic variables included in the previous equations (14-17); starting with model (14) which drops all predictive market states and macroeconomic risks variables and ending with all-inclusive model (17). After all, If Alpha is equal to zero, I will conclude that I have a risk adjusted profit but if Alpha is different from zero I may conclude that global risks factor does not explain momentum profit.

3.3.6 Estimation Method

I start the estimation with Ordinary Least Square (OLS), follow by the Newey West estimation procedure (Avramov and Chan, 2015) with the aim to examine whether momentum and contrarian investors earn significant profit after adjusting for risks factors. Concerned with inferences that there are deviations from the assumption that the variables are jointly normal. I consider a test, which accommodates non-normality, heteroscedasticity, and temporal dependence of returns; such tests are of interest given that, without the normality assumption, finite-sample properties of asset pricing model tests are difficult to derive (Campbell, Lo, and Mackinglay, 1997). Furthermore, departures of monthly observation in the sample are clearly documented. There is also abundant evidence of temporal dependence in the sample. It is therefore desirable to consider the effects of relaxing these statistical assumptions. Considering the linear regression model, the estimation can be formulated using the development of the Generalized Method Moment (Zivot and Wang, 2006) as:

(21) $$Mom_t = z_t'\delta_0 + \epsilon_t, t = 1, \dots, n$$

Where, z_t is an $L \times 1$ vector of explanatory variables (Fama and French, market state and macroeconomic factor), δ_0 is a vector of unknown coefficients and ϵ_t is a random error term. The model (1) allows for the possibility that some or all of the elements of z_t may be correlated with the error term ϵ_t, i.e., $E[z_{tk}\epsilon_t] \neq 0$ for some *k*. If $E[z_{tk}\epsilon_i] \neq 0$ then z_{tk} is called an endogenous variable. This analysis considers the time variation as endogenous given the lend of my sample period. It is well known that if z_t contains endogenous variables then the least squares estimator of δ_0 in (1) is biased and inconsistent.

Associated with the model (1), it is assumed that there exists a $K \times 1$ vector of instrumental variablesv_t, which contain some or all the elements of z_k. Let w_t represents the vector of unique and non-constant elements of $\{Mom_{t,}z_t, v_t\}$. It is assumed that $\{w_t\}$ is a stationary and ergodic stochastic process. The instrumental variables v_t, satisfy the set of *K* orthogonality conditions.

(22) $$E[g_t(w_t, \delta_0)] = E[v_t\epsilon_t] = E\left[v_t\left(Mom_{t,} - z'_t\,\delta_0\right)\right] = 0$$

Where $g_t(w_t, \delta_0) = v_t\epsilon_t = v_t\left(Mom_{t,} - z'_t\,\delta_0\right) = 0$. Expanding (2), gives the relation

$$\Sigma_{vMom} = \Sigma_{Momz}\delta_0$$

Where, $\Sigma_{vr} = E[v_tMom_t]\ and\ \Sigma_{vz} = E[v_tz'_t]$. For identification of δ_0, it is required that the $K \times L$ matrix $E[v_tz'_t] = \Sigma_{vz}$ be of full rank *L*. This rank condition ensures that δ_0 is the unique solution to (2). Note, if $K = L$, then Σ_{vz} is invertible and δ_0 may be determined using:

$$\delta_0 = \Sigma_{vz}^{-1}\Sigma_{vMom}$$

A necessary condition for identification of δ_0 is the order condition

(23) $$K \geq L$$

Which simply states that the number of instrumental variables must be greater than or equal to the number of explanatory variables (1). If $K = L$ then $\delta_0$is said to be (apparently) just identified; if $K \geq L$ then δ_0 is said to be (apparently) over-identified; if $K < L$ then δ_0 is not identified. The world "apparently" in parentheses is used to remind the reader that the rank condition

(24) $$\text{rank}\,(\Sigma_{vz}) = \text{L}$$

Must also be satisfied for identification. In the regression model (1), the error terms are allowed to be conditionally heteroscedastic as well as serially correlated. For the case in which ϵ_t is conditionally heteroscedastic, it is assumed that $\{g_t\} = \{v_t\epsilon_t\}$ is a stationary and ergodic martingale difference sequence (MDS) satisfying

$$E[g_t g_t'] = E[v_t v'_t \epsilon_t^2] = S$$

Where S is a non-singular $K\times K$ matrix. The matrix S is the asymptotic variance-covariance matrix of the sample moment$\bar{g} = n^{-1}\sum_{t-1}^{n} g_t(w_{t,}\,\delta_0)$. This follows from the central limit theorem for ergodic stationary martingale difference sequences (Hayashi, 2006)

$$\sqrt{n}\bar{g} = \frac{1}{\sqrt{n}}\sum_{t=1}^{n} v_t\epsilon_t \to N(0,S)$$

Where avar ($\bar{g}$) = S denotes the variance-covariance matrix of the limiting distribution of $\sqrt{n}\bar{g}$.

For the case in which $\varepsilon_t$is serially correlated and possibly conditionally heteroscedastic as well, it is assumed the $\{g_t\} = \{v_t\epsilon_t\}$ is a stationary and ergodic stochastic process that satisfies

$$\sqrt{n}\bar{g} = \frac{1}{\sqrt{n}}\sum_{t=1}^{n} v_t\epsilon_t \to N(0,S)$$

$$S = \sum_{j=-\infty}^{\infty} \mathbb{r}_j = \mathbb{r}_0 + \sum_{j=1}^{\infty}(\mathbb{r}_j = \mathbb{r}'_j)$$

Where, $\mathbb{r}_j = E\left[g_t g'_{t-j}\right] = E\left[v_t v'_{t-j}\,\epsilon_t\epsilon'_{t-j}\right]$. In the above avar ($\bar{g}$) = S is also referred to as the long-run variance $\bar{g}$.

The generalized method of moments (GMM) estimator of δ in (1) is constructed by exploiting the orthogonality conditions (2), the idea is to create a set of estimating equations for δ by making sample moments match.

The population moments are defined by (2). The sample moments based on (2) for an arbitrary value δ are

$$g_n = \frac{1}{n}\sum_{t=1}^{n} g(w_t, \delta) = \frac{1}{n}\sum_{t=1}^{n} Mom_t(Mom - z_t'\delta) = \begin{pmatrix} \frac{1}{n}\sum_{t=1}^{n} v(Mom - z_t'\delta) \\ \vdots \\ \frac{1}{n}\sum_{t=1}^{n} v_{kt}(Mom - z_t'\delta) \end{pmatrix}$$

These moment conditions are a set of K linear equations in L unknowns. Equating these sample moments to the population moment $E[v_t\epsilon_t] = 0$ gives the estimating equations

(25) $$S_{vr} = S_{vz}\delta = 0$$

Where $S_{vMom} = n^{-1}\sum_{t=1}^{n} v_t Mom_t$ and $S_{vMom} = n^{-1}\sum_{t=1}^{n} v_t z_t'$ are the sample moments.

If K= L (δ_0 is just identified) and S_{vz} is invertible then the GMM estimator of δ is:

$$\hat{\delta} = S_{vz}^{-1} S_{vMom}$$

Which is also known as the indirect least squares estimator. If K > L, then there may not be a solution to the estimating equations (5). In this case, the idea is to do try to find δ that makes $S_{vr} = S_{vz}\delta$ as close to zero as possible. To do this, let $\widehat{W}$ denotes a $K{\times}K$ symmetric and positive definite weight matrix, possibly dependent on the data; such that $\widehat{W} \to W$as $n \to \infty$ with W symmetric and positive definite then the GMM estimator δ denote $\hat{\delta}\widehat{W}$ is defined as $\hat{\delta}\widehat{W} = \arg\min J\,(\hat{\delta}, \widehat{W})$

Where

(26) $$J(\hat{\delta}, \widehat{W}) = ng_n(\delta)'\,\widehat{W}g_n(\delta)$$
$$= n(Mom - S_{vz}\delta)'\widehat{W}(S_{vMom} - S_{vz}\delta)$$

Since $J\left(\hat{\delta}, \widehat{W}\right)$ is a simple quadratic form in δ, straightforward calculus may be used to determine the analytic solution for $\hat{\delta}(\widehat{W})$:

(27) $$\hat{\delta}\left(\widehat{W}\right) = \left(S_{vz}'\widehat{W}S_{vz}\right)^{-1}\left(S_{vz}'\widehat{W}S_{vz}\right)$$

3.3.7 Summary

The aims of the study are to demonstrate the global momentum and contrarian investment profitability and the reasons explaining their survival. I do this by introducing the strategies and constructing a robust test of momentum and contrarian risk adjustment using a generalized Method of Moments (GMM) framework. Within the GMM framework, given that the distribution can be both serially dependent and conditionally heteroscedastic. I need only to assume that the momentum returns are stationary (Campbell et al., 1997).

The later risk adjustment analysis on momentum is subsequently repeated step by step for the contrarian strategies risk adjustment. The following analyses draw on the above general development of the GMM. However, I also report results based on OLS and Newey West procedure (please see Appendix C1-16).

3.4 Conclusion

In this section I explain in details the main methodologies used to examine the global momentum and contrarian strategies profitability, and motivate the dataset used. I implement the global momentum and contrarian strategies the same as Jegadeesh and Titman (1993) to examine whether the global momentum and contrarian strategies work for international investors. I also adopt a risk factor model similar to Avramov et al. (2015) in order to explore deeply the dynamic relation between the momentum and contrarian strategies, and macroeconomic risks factors. However, previous researchers have attempted to explain the momentum and the contrarian profit, namely behaviourists and those who support the rational pricing and the Efficient Market Hypothesis. They suggested significant number of models. Referring to the momentum and contrarian strategy. In addition, the efficient market seems to be less challenging, the literature recorded that the three-factor asset-pricing model of Fama and French is likely to capture the reversal effect implying that the abnormal contrarian return could be a compensation for risk. Nevertheless, there is a deficiency of asset pricing model to explain the momentum and contrarian profits. Macroeconomics risks factors, the momentum and contrarian profit have been actively studied at the firm level. The global approach could be worth of further study. It is notable; however, that using multi-factors model as indicated in this thesis shows a less controversial result. The contrarian generates statistical and significant abnormal return 1% monthly (12.68% per year) after adjusting for global risk, while the momentum could be explaining by macroeconomic factors.

Chapter 4: Momentum on International Equity Indices

4.1 Introduction

In this Chapter, I examine the profitability of the global momentum profit; I implement the strategy with non-overlapping portfolios on the full sample using methodology from Jegadeesh and Titman (1993). I also examine a set of strategies that skip a month between the formation and the holding period. By doing this I avoid some of the bid-ask spread, price pressure, and lagged effects that inspire the evidences short-term price pressure or lack of liquidity in the market documented in Jegadeesh (1990). I then show how the profitability of the global momentum vary from one market state to another by examining the global momentum profit with the established markets, then during the globalization period, with developed countries, and the emerging countries. In the second section, I increase the power of the test by examining the profitability of the momentum strategies with overlapping portfolios; this includes monthly rebalancing Winners Minus Losers. In both cases, I consider the impact of return continuation by examining a second set of strategies that skip a month between the formation and the holding periods.

The overlapping portfolios demonstrate a strong consistently and significantly profitable global momentum for international investors on average over the full sample period (1969-2014). The most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months. This strategy yields 3% per month (42.57% per year) but the returns may vary considerably from one market condition to another. Evidences also indicate that the momentum strategies are highly profitable in developed country that the contribution of emerging country are less significant, although the highest momentum return could be observed in emerging country with the 9-month/3-month strategy when there is not time lag between the portfolio formation period and the holding period. The success of the global momentum strategies presented in this chapter demonstrate that trading on indices performances worldwide while considering the momentum as global coordinated a generalised phenomenon provide more evidences to challenge the Efficient Market Hypothesis.

4.2 Momentum Strategies using non-overlapping Portfolios

4.2.1 Introduction

In this section, I examined the profitability of the momentum strategies based on past returns of countries indices in international equity markets. I construct non-overlapping portfolios where the end of the formation period is the starting date of holding period and rebalance the portfolio at the end of each holding period all over the length of the sample period as indicated in section 3.3.3. I show how the profitability of the global momentum vary from one market state to another by examining the global momentum profit on the full sample 1969-2014, then with the established markets only, during the globalization period, with developed countries only, and the emerging countries only.

4.2.2 Momentum strategies for International Investors: full sample 1969-2014

I start the analysis by implementing the basic momentum strategies firstly, on the entire times series data. In period `t’ I buy the winner countries and sell the loser countries. The winners and the losers’ portfolios are constructed based on their past performances. I use four different formation periods 'J' and four for different holding periods 'K’, where J equals 3, 6, 9, and 12 months and K equal 3, 6, 9, and 12 months as indicated in Table 4.1.1. Thus, I have 16 strategies in total. The average monthly returns of the winners and the losers’ portfolio are indicated in the table below. The momentum portfolios in Table 4.1.1 panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.1 Panel B. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.1.1 Here]

Table 4.1.1 reports the results for the whole sample period, the winner, the loser, and the momentum portfolio (winner-loser) returns are reported for the 32 strategies. All the momentum strategies’ returns are positive except the 12-month/3-month and the 12-month/3-month that skip one month. The most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months. This strategy yields estimated 3% per month (42.57% per year) with a t-statistic of 4.50 and a p-value of 0.00 (Table 4.1.1 Panel A), when there is not time lag between the portfolio formation period and the holding period.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does not improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 1.46% per month (18.99% per year) with a t-statistic of 2.36 and a p-value of 0.02 (Table 4.1.1 panel B).

By doing this, I avoid some of the bid-ask spread, price pressure, and lagged effects that inspire the short-term price pressure or lack of liquidity in the market as documented in Jegadeesh (1990). Antti (2016) suggested that ETFs often exhibit similar behaviour and the difference in premiums in the short run are driven by mean-reverting shock to prices, which means that it is enormously important for investor to correctly pick which fund to trade each time. The 9-month formation period is the most profitable formation period regardless of the holding period for both set of strategies.

These results also show that the momentum strategies' returns are positive in most of the strategies, and that the returns are highly significant in most cases mainly when the strategies skip one month between the formation and the holding period. I may suggest that the momentum strategies are on average profitable internationally, that the winner portfolio outperforms the loser portfolio to generate positive average momentum profits. I then establish that the most profitable strategy is the 9-month/3-month that does not skip a month (Table 4.1.1 Panel A) and when the strategy skips a month, it remains highly and significantly profitable in all the holding period (Table 4.1.1 Panel B).

My results support Jegadeesh and Titman's (1993) findings, which suggest that the strategies that buy past winners and sell past losers, are consistently profitable and generate positive return of about 0.95% with a significant t-statistic of 3.07 in the US with the 6-month/6-month strategies. These findings also indicate a better momentum return than Chan et al. (2000) study that suggest that momentum strategies are internationally profitable on the view point of US investor as they suggested that on average the momentum strategy generates 1% per month which is significantly lower than the average momentum return in this study 2.98% per month.

However, Chan et al. (2000) weighted countries indices based on the deviation of their return in the previous period from the cross-sectional average return, and this thesis's results help restate the fact that momentum strategies returns are even higher if investors apply the initial momentum strategy as by Jegadeesh and Titman (1993) at the global level. In comparison to the Jegadeesh and Titman (1993, 2001) momentum strategies on individual stocks in US market, the momentum study on countries indices indicate that the profitability of these strategies is also function of the time horizon as the 9-month shows to generate superior return in any given horizon.

4.2.3 Momentum Strategies Return on Established Markets

In addition to the momentum strategies implemented on the on the full sample period as shown in the above analysis, I also implement the momentum strategies in a more stable sample period (1969-2014). Where all countries indices start and end in the same date to avoid any blunder, which may occur, from variation among the starting dates of countries indices and to gauge the effect of the variation in the sample size.

To implement the basic momentum strategies on the subsample1969-2014 (18 countries), at 't' I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equal 3, 6, 9, and 12 months and 'K' equal 3, 6, 9, and 12 months as indicated in Table 4.1.2 below. This gives a total of 16 strategies. The average monthly returns of the winners and the losers' portfolio are indicated in the table below. The momentum portfolios in Table 4.1.2 panel A, are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.2 Panel B. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.1.2 Here]

Table 4.1.2 reports the results for the whole sample period, the winner, the loser, and the momentum portfolio (winner-loser) returns are reported for the 32 strategies. All the momentum strategies' returns are positives. The most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months. This strategy yields 1.77% per month (23.43% per year) with a t-statistic of 3.19 and a p-value of 0.00 (Table 4.1.2 Panel A), when there is not time lag between the portfolio formation period and the holding period.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does not improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 1.04% per month (13.209 per year) with a t-statistic of 1.88 and a p-value of 0.06 (Table 4.1.2 panel B). By doing this, I avoid some of the bid-ask spread, price pressure, and lagged effects that inspire the short-term price pressure or lack of liquidity in the market as documented in

Jegadeesh (1990). The 9-month formation period remains profitable regardless of the holding period for both set of strategies.

Given that the momentum strategies return are positive in most of the case and that, the returns are highly significant in most cases mainly when the strategies skip one month between the formation and the holding period. I suggest that the momentum strategies are on average profitable internationally, that the winner portfolio outperforms the loser portfolio to generate positive average momentum profits. I then establish that the most profitable strategy is the 9-month/3-month that does not skip a month between the formation and the holding period (Table 4.1.2 Panel A). These results are complementary to the findings in Table 4.1.1 and support Jegadeesh and Titman (1993) findings, which suggest that the strategies that buy past winners and sell past losers are consistently profitable and generate positive return of about 0.95% with a significant t-statistic of 3.07. These findings also indicate a better momentum return than Chan et al. (2000) study, that suggest that, momentum strategies are internationally profitable on the view point of US investor as they suggested that the momentum strategy generate 1% per month, which is significantly lower than the result reported in this study (1.77% per month). In comparison to the Jegadeesh and Titman (1993, 2001) the momentum strategies is tested on individual stocks with the 6-month/6-month strategies, while the momentum result on this thesis are profitable regardless of the sample size and the time horizon.

4.2.4 Momentum Returns since Globalisation 1994-2014

I consider alternatively a set of momentum portfolios, which are formed on the 1994-2014 subsamples (47 countries), given that, since MSCI launched the Emerging Market Index in 1988, which consisted of just 10 countries representing less than 1% of world market capitalization. From 1994 to 2014 the MSCI Emerging Market Index consist of 23 countries representing 10% of world market capitalization. The Index is now available for a number of regions, market segments or sizes and covers approximately 85% of the free float-adjusted market capitalization each of the 23 countries. In other words, there was a significant change in 1994 in terms of volume and intensity and we can perfectly "assume" that the origins of Globalisation can be traced to 1994. In addition, this year is associated with the onset of Foreign Direct Investmet which is another strong proxy for Globalisation (see Wolrd Bank Statistical Indicators).

At 't' I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equal 3, 6, 9, and 12 months and 'K' equal 3, 6, 9, and 12 months as indicated in Table 4.1.3 below, this give a total of 16 strategies. The average monthly returns of the winners and the losers' portfolio are indicated in the Table 4.1.3. The momentum portfolios in Table 4.1.3 panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.3 Panel B. The t-statistics are reported in the parentheses and the p-value are reported next. The sample period is from January 1994 to January 2014.

[Insert Table 4.1.3 Here]

In Table 4.1.3., my attempt to examine the momentum strategies on the stock market indices with 47 counties from 1994 to 2014, which, include the global finance crisis 2007-2008 raise the alarm. It shows that the momentum strategies remain profitable on average by 9 out of 16 strategies. The optimum strategies 6-month/6-month generates positive payoffs 0.60% per month (7.44% per year) with a t-statistic of 1.39 and a p-value of 0.17 (Table 4.1.3 Panel A). The result also indicates that the 9-month/3-month portfolio of countries indices remains significant and generates negative return -1.52% per month (19.84% per year) with a t-statistic of -1,82 and a p-value of 0.08 during the globalization period.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does improve the strategy performance as the equivalent holding period returns are higher. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 1.05% per month (13.35% per year) with a t-statistic of 2.80 and a p-value of 0.01 (Table 4.1.3 Panel B) By doing this,

I avoid some of the bid-ask spread, price pressure, and lagged effects that inspire the short-term price pressure or lack of liquidity in the market as documented in Jegadeesh (1990). These results are in line with Avramov et al.'s (2014) study which suggested that momentum strategies can generate a negative return of- 0.69 percent in period of illiquidity and a significant 1.09 percent when the market is relatively liquid, but Avramov et al. (2014) are based on 5 portfolio (quintiles) while this thesis rang indices into deciles portfolios.

4.2.5 Momentum in Developed Market

To assess the contribution of the Developed countries on global momentum strategies, since the momentum profit may differ from developed to emerging countries. I implemented the momentum strategy on the developed countries subsample (23 countries) over 1969-2014. At 't' I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equal 3, 6, 9, and 12 months and 'K' equal 3, 6, 9, and 12 months as indicated in Table 4.1.4 below, this give a total of 16 strategies. The average monthly returns of the winners and the losers' portfolio are indicated in Table 4.1.4 below. The momentum portfolios in Table 4.1.4 panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.4 Panel B. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.1.4 Here]

Table 4.1.4 reports the momentum results of developed countries for the whole sample period, the winner, the loser, and the momentum portfolio (winner-loser) returns are reported for the 32 strategies. All the momentum strategies' returns are positives 16 out of 16 strategies (Table 4.1.4 Panel A) the most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months. This strategy yields 2.17% per month (29.38% per year) with a t-statistic of 4.31 and a p-value of 0.00 Table 4.1.4 Panel A, when there is not time lag between the portfolio formation period and the holding period.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does not improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 0.93% per month (11.75% per year) with a t-statistic of 1.66 and a p-value of 0.10 Table 4.1.4 panel B, when there is a month lag between the formation period and the holding period. 16 out of 16 strategies are positive (Table 4.1.4 Panel B).

These results are in line with my initial findings that the momentum strategies are consistently profitable internationally. These findings also indicate a better momentum return than Chan et al.'s (2000) study that suggest that momentum strategies are internationally profitable on the view point of US investor. They suggested that on average the momentum strategy generate 1% per month, which is significantly lower than the average momentum return in this thesis of 3% per month (42.57 per year).

The result helps reiterate the fact that momentum strategies returns are profitable in developed countries if investors apply the momentum strategy as initiate by Jegadeesh and Titman (1993) at the global level.

4.2.6 Momentum in Emerging Market

If the momentum strategies are profitable in the full sample, in different time period and consistent with the variation on the sample size with the 9-month/3-month, I will expect the momentum strategies to be also profitable in emerging market. It is understandable that there may be serious concern over the fact that emerging market might be on average illiquid and unstable and seriously segmented but this analysis is more interested in the practicality of the momentum strategies than the market condition. To test the sensitivity of the momentum strategies on the emerging market, I implement the momentum strategies on the emerging market subsample (December 1987 to January 2014) given that the first emerging market enters the sample in December 1987.

At 't' I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equal 3, 6, 9, and 12 months and 'K' equal 3, 6, 9, and 12 months as indicated in Table 4.1.5 below, this gives a total of 16 strategies. The average monthly returns of the winners and the losers' portfolio are indicated in the table below. The momentum portfolios in Table 4.1.5 panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.5 Panel B. The t-statistics are reported in the parentheses and the P-values are reported next. The sample period is from December 1987 to January 2014.

[Insert Table 4.1.5 Here]

The momentum strategies result on emerging countries are reported in Table 4.1.5. By comparison, to those of the full sample and the Developed countries, the momentum strategies in emerging countries appear to be less significant on average (2 strategies out 16 generate momentum returns that are significant). The 9-month/3-month remain the most profitable strategy 3.28% per month (47.30 per year) with a t-statistic of 1.98, and a p-value of 0.06 Table 4.1.5 Panel A.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does not improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of a considerably lower 0.64% per month (7.96% per year) with a t-statistic of 0.47 and a p-value of 0.64 Table 4.1.5 panel B, when there is a month lag between the formation period and the holding period.

The momentum strategies' returns are not positive in most of the strategies when there is not time lag between the portfolio formation period and the holding period, the returns are less significant, given that few strategies generate significant momentum return. I may suggest that the momentum strategies are on the average less reliable but highly profitable in emerging countries. The 9-month/3-month remain the most profitable strategy 3.28% per month (47.30% per year) with even greater return than the full sample period month 3% per month (42.57% per year). These results have a direct implication of the Efficient Market hypothesis given that international investors can now beat the market consistently using common investment strategy such as the global momentum.

4.2.7 Summary

In this section, I examined the profitability of the momentum strategies based on past returns of countries indices in international equity markets. My findings indicate evidences of momentum profitability. The momentum strategies have shown to be consistently and significantly profitable on average over the full sample period, and the 9-month/3-month strategy generates return as high as 3% per month (42.57% per year). A greater return come from the emerging markets 3.28% per month (47.30 per year). This strategy also performs well in established yields 1.77% per month (23.43% per year). However, the 9-month/3-month portfolio of countries indices remains significant but generates a negative return -1.52% per month (-19.84% per year) during the globalization period. The optimum strategies during this period is the 6-month/6-month, it generates a positive payoff of 0.60% per month (7.44% per year). Meanwhile, the momentum return could diminish considerably when the strategy skip a time lag between the portfolio formation period and the holding period suggesting evidence of return continuation. The exception is made on the post 1994 period when the 9-month/3-month strategy generates a negative payoff. Evidences also indicate that the momentum strategies are highly profitable in developed country that the contribution of emerging countries are great but less significant.

Even more interesting, this thesis did find evidence of return continuation among countries indices when considering the full sample. However, I must point out that, my evidences are different from Chan et al. (2000) study that suggest that momentum strategies are internationally profitable on the view point of US investors. They suggested that on average the momentum strategy generate 1% per month, which is significantly lower than the average momentum return in this study 3% per month (42.57 per year). I also emphasis the point that investors may earn extra returns by investing internationally as the global momentum generate a return of about three time higher the than the return indicate on Jegadeesh and Titman (1993, 2001).

Furthermore, from a practical investment perspective, it is important to indicate that the global momentum strategies will be profitable after accounting for transaction costs. On average, the momentum strategies with non-overlapping portfolios are rebalanced every 9 months and results in a low turnover. The optimum strategy generates a return of 42.57% return per annum. On other hand Jegadeesh and Titman (1993), and Berkowitz, Logue and Noser (1988) estimate one-way transaction costs of 23 basis points for institutional investors suggesting that transaction cost of 0.5% per trade with a 6-month/6-month strategy is conservative. This implies and estimated transaction cost of 0.6% per annum which is not negligible, suggesting a momentum profit of 41.97 which does not undermine the high profitability of these strategy.

Overall, the success of the global momentum strategies with non-overlapping portfolios presented in this chapter demonstrated that trading on indices performances worldwide might provide more evidences of market inefficiency when international investors invest in winners' countries and divest on losers' countries.

4.3 Momentum Strategies and Overlapping Portfolios

4.3.1 Introduction

In this section, I examine whether momentum strategies earn significant return after increasing the power of the test. I construct overlapping portfolios, where momentum deciles portfolio in any month holds stocks ranked in those deciles in any of the previous k ranking months as indicated in section 3.3.3. I show how the profitability of the global momentum vary from one market state to another by examining the global momentum profit in the established markets, during the globalization period, in developed countries, and emerging countries. My findings indicate evidences of momentum profitability. The momentum strategies are significantly profitable on average over the full sample period, and the 9-month/3-month strategy generates the highest returns 0.95% per month (11.20% per year), but these returns may vary considerably from one market condition to another. More importantly, the momentum strategies remain on average profitable in the period post-1994. My findings also indicate that the momentum strategies' returns are on average low with the overlapping portfolios than the non-overlapping portfolios.

4.3.2 Momentum strategies for International Investors: full sample 1969-2014

I start the analysis by implementing the basic momentum strategies first, on the entire times series data. In period 't' I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equal 3, 6, 9, and 12 months and 'K' equals 3, 6, 9, and 12 months as indicated in Table 4.1.6 below. This gives a total of 16 strategies. The average monthly returns of the winners and the losers' portfolio are indicated in the table below. The momentum portfolios in Table 4.1.6 panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.6 Panel B. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.1.6 Here]

Table 4.1.6 reports the results for the whole sample period, the winner, the loser, and the momentum portfolio (winner-loser) returns are reported for the 32 strategies. All the momentum strategies' returns are positive. The 9-month/6-month that is the most successful momentum strategy. It selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 6 months. This strategy yields 0.95% per month (12.01% per year) with a t-statistic of 5.97 and a p-value of 0.00 (Table 4.1.6 Panel A) when there is not time lag between the portfolio formation period and the holding period. However, the 9-month/3-month remain highly profitable 0.95% per month (12.01% per year) with a t-statistic of 4.16 and a p-value of 0.00 (Table 4.1.6 Panel A).

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does not improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 0.95% per month (12.01% per month) with a t-statistic of 5.97 and a p-value of 0.00 (Table 4.1.6 Panel). The 9-month/3-month yields much greater return 1.12% per month (14.30% per month) with a t-statistic of 5.05 and a p-value of 0.00 rejecting the argument that the momentum return could be due to return continuation.

By doing this, I avoid some of the bid-ask spread, price pressure, and lagged effects that inspire the short-term price pressure or lack of liquidity in the market as documented in Jegadeesh (1990). Given that the momentum strategies returns are positive in most of the strategies and that the returns are highly significant in most cases mainly when the strategies do not skip a month between the formation and the holding period. I may suggest that the momentum strategies are on average profitable internationally when using overlapping portfolios of stock indices, that the winner portfolio outperforms the loser portfolio to generate positive average momentum profits. I then establish that the most profitable strategies on average is still the 9-month/3-month (Table 4.1.6 Panel A) as to when the strategy skip a month it remains highly and significantly profitable (Table 4.1.6 Panel B).

These results support Jegadeesh and Titman (1993) findings, which suggest that the strategies that, buy past winners and sell past losers are consistently profitable and generate positive return of about 0.95% per month with a significant t-statistic of 3.07. These findings are also indicative of a positive momentum return as Chan et al. (2000) study that suggest that momentum strategies are internationally profitable on the view point of US investor as they suggested that on average the momentum strategy generate 0.25% per week.

However, Chan, et al. (2000) weight countries' indices based on the deviation of their return in the previous period from the cross-sectional average return, and this study results help reaffirm the fact that momentum strategies returns are even higher if investor apply the basic momentum strategy as initiated by Jegadeesh and Titman (1993) at the global level. In comparison to the Jegadeesh and Titman (1993) momentum strategies on individual stocks, the momentum study on countries' indices indicate that the profitability of these strategies is also a function of the time horizon as the 9-month show to generate superior return in any given horizon.

4.3.3 Momentum Returns for International Investors: Established Markets

Next, I turn to a more stable sample period; I implement the momentum strategies in the 1969-2014 subsample, where all countries' indices start and end in the same date to avoid any blunder which may occur from non-synchronized starting dates among countries' indices.

I implement the basic momentum strategies on the established market sub-set 1969-2014 period (18 countries). At 't', I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equals 3, 6, 9, and 12 months and 'K' equals 3, 6, 9, and 12 months as indicated in Table 4.1.7 below. This gives a total of 16 strategies. The average monthly returns of the winners and the losers' portfolio are indicated in the table below. The momentum portfolios in Table 4.1.7 Panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.7 Panel B. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.1.7 Here]

Table 4.1.7 reports the results for the whole sample period, the winner, the loser, and the momentum portfolio (winner-loser) returns are reported for the 32 strategies. All the momentum strategies returns are positive. The most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 6 months. This strategy yields 0.78% per month (9.77% per year) with a t-statistic of 5.94 and a p-value of 0.00 (Table 4.1.7 Panel A) when there is not time lag between the portfolio formation period and the holding period.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 0.82% per month (10.30% per year) with a t-statistic of 6.22 and a p-value of 0.00 (Table 4.1.7 panel B), when there is a month lag between the formation period and the holding period. By doing this, I avoid some of the bid-ask spread, price pressure, and lagged effects that inspire the short-term price pressure or lack of liquidity in the market as documented in Jegadeesh (1990). The

9-month formation period remains profitable regardless of the holding period for both set of strategies.

Given that the momentum strategies' returns are positive in most of the strategies and that the returns are highly significant in all cases, I may suggest that the momentum strategies are on average profitable internationally, and that the winner portfolio outperforms the loser portfolio to generate positive average momentum profits. I then establish that the most profitable strategies remain the 9-month/6-month that does not skip a month (Table 4.1.7 Panel A). The results here are complementary to the findings in Table 4.1.1 in the sense that the momentum strategies remain profitable with overlapping portfolios. These results also support Jegadeesh and Titman (1993) findings, which suggest that the strategies that buy past winners and sell past losers, are consistently profitable. Contrary to what I found in my earlier analysis with non-overlapping portfolios, the findings indicate worse momentum return than Chan et al.'s (2000) study that suggests that momentum strategies are internationally profitable on the view point of US investors. They suggested that on average the momentum strategy generates 0.25% per week, which is significantly higher than the results with overlapping portfolios in this thesis of 0.78% and 0.86%. In comparison to the Jegadeesh and Titman (1993, 2001) the momentum results in here indicate that 9-month/3-month strategies are profitable regardless of the sample size and the time horizon but the profits diminish with the overlapping portfolios approach.

4.3.4 Momentum Returns with overlapping portfolios since Globalisation

To ascertain whether the momentum strategies remain profitable with overlapping portfolio after 1994, I examine alternative sets of momentum portfolio, which are formed on the 1994-2014 subsample (47 countries). At 't' I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equals 3, 6, 9, and 12 months and 'K' equals 3, 6, 9, and 12 months as indicated in Table 4.1.8 below. This gives a total of 16 strategies. The average monthly returns of the winners and the losers' portfolio are indicated in the table below. The momentum portfolios in Table 4.1.8 Panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.8 Panel B. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.18 Here]

Table 4.1.8 shows the results of the momentum strategies implemented on the stock market indices of 47 counties for 1994 to 2014, which include the global finance crisis 2007-2008. It shows that the momentum strategies remain profitable on average (16 out of 16 strategies) without time lag and (16 out of 16 strategies) for the strategies with a month lag. The 12-month/3-month is the most profitable strategies. It generates a positive and significant payoff 1.03% per month (13.08% per year) with a t-statistic of 3.11 and a p-value of 0.00. When there is not time lag between the portfolio formation period and the holding period.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does not improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 0.93% per month (11.75% per year) with a t-statistic of 3.07 and a p-value of 0.00 (Table 4.1.8 panel B), when there is a month lag between the formation period and the holding period. By doing this, I avoid some of the bid-ask spread, price pressure, and lagged effects that inspire the short-term price pressure or lack of liquidity in the market as documented in Jegadeesh (1990). The 9-month/3-month generates a positive and significant payoff 0.88% per month (11.09% per year) with a t-statistic of 2.77 and a p-value of 0.01 and a relatively high return when there is a time lag between the formation and the holding period.

This indicates that even with the impact of the financial crisis the momentum strategies can still be profitable with the overlapping approach as the 1994-2014 period exhibit momentum with the 9-month/3-month portfolio of countries' indices generating a relative high return. This is contrary to Chordia et al. (2013) findings that show that, momentum payoffs are on average insignificant in the period starting after April 2001. It also rejects the Avramov et al. (2014) finding that suggested that momentum strategies can generate a negative return of -0.69 percent in period of illiquidity and a significant 1.09 percent when the market is relatively liquid. However, it is important to reiterate that Avramov at al. (2014) findings are based on 5 portfolios while this thesis rang indices into deciles portfolios.

4.3.5 Momentum with overlapping portfolios in Developed countries

To better understand which of the developed and the emerging market may be driving the return on the global momentum strategies, I implemented the momentum strategy with overlapping portfolio on the developed counties subsample (23 countries) over 1969-2014.

At ‘t' I buy the winner countries and sell the loser countries. The winners and the losers’ portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equals 3, 6, 9, and 12 months and 'K' equals 3, 6, 9, and 12 months as indicated in Table 4.1.9 below and this gives a total of 16 strategies. The average monthly returns of the winners and the losers’ portfolio are indicated in table 10 below. The momentum portfolios in Table 4.1.9 Panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.9 Panel B. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.1.9 Here]

Table 4.1.9 reports the momentum results of developed countries for the whole sample period, the winner, the loser, and the momentum portfolio (winner-loser) returns are reported for the 32 strategies. My findings of the momentum strategies in every strategy indicate that almost all the momentum strategies’ returns are positive 16 out of 16 strategies in Table 4.1.9 Panel A and 16 out of 16 strategies for the strategies with a month lag. The most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 6 months. This strategy yields 0.90% per month (11.35% per year) with a t-statistic of 6.85 and a p-value of 0.00 (Table 4.1.9 Panel A), when there is not time lag between the portfolio formation period and the holding period.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 0.94% per month (11.88% per year) with a t-statistic of 6.94 and a p-value of 0.00 (Table 4.1.9 Panel B), when there is a month lag between the formation period and the holding period. By doing this, I avoid some of the bid-ask spread, price pressure, and lagged effects that inspire the short-term price pressure or lack of liquidity in the market as documented in Jegadeesh (1990). The 9-month/3-month strategy remains highly profitable and the 9-month formation period is the most profitable formation period regardless of the holding period for both sets of strategies.

Given that the momentum strategies’ returns are positive in most of the strategies and that the returns are highly significant, I may suggest that the momentum strategies are on average profitable internationally for developed countries, and that the winner portfolio outperforms the loser portfolio to generate positive average momentum profits.

These findings in their most basic form imply that knowing how indices performed in the past in developed countries should be informative about how the global momentum strategies will perform in the future. However, the momentum returns here are slightly lower than those of the Chan et al.'s (2000) study that suggests that momentum strategies are internationally profitable on the view point of US investor as they suggested that on average the momentum strategy generate 0.25% per week. This result here helps reiterate the fact that momentum strategies' returns are consistently profitable in developed countries if investor apply the basic momentum strategy as initiated by Jegadeesh and Titman (1993) at the global level.

4.3.6 Momentum in Emerging Market

I reformulate the momentum strategies in the same manner in emerging counties as in developed countries. I consider a strategy that buys the winners and sell the losers' portfolio of countries indices. I implement the momentum strategies on the emerging market subsample (December 1987 to January 2014) given that the first emerging market enters the sample in December 1987.

At 't' I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 4 different formation periods 'J' and 4 for different holding periods 'K', where 'J' equals 3, 6, 9, and 12 months and 'K' equals 3, 6, 9, and 12 months as indicated in Table 4.1.10 below and this gives a total of 16 strategies. The average monthly returns of the winners and the losers' portfolio are indicated in the table below. The momentum portfolios in Table 4.1.10 Panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.1.10 Panel B. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.1.10 Here]

Table 4.1.10 reports the momentum strategies results on emerging countries. By comparison, to those of the full sample and the developed countries, the momentum strategies in emerging countries appear to be less profitable on average. 9 out of 16 strategies generate positive return without a time lag and 8 out of 16 strategies generate positive return for the momentum strategies with a month lag, none of the positive return is significant. The 9-month/3-month is profitable but not significant and it generates about 0.32% per month (3.91% per year) with a t-statistic of 0.69, and a p-value of 0.49 (Table 4.1.10 Panel A), when there is not time lag between the portfolio formation period and the holding period. The most profitable strategy is the 6-month/6-month and it yields a return of 0.39% per month (4.78% per month) with a t-statistic of 1.30 and a p-value of 0.20 (Table 4.1.10 Panel B), when there is a month lag between the formation period and the holding period.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period does improve the strategy performance as the equivalent holding period returns are lower. The winner portfolio outperforms the loser portfolio to generate positive average effective compounded momentum return of 0.60% per month (7.44% per month) with a t-statistic of 2.06 and a p-value of 0.04 (Table 4.1.10 Panel B). By doing this, I avoid some of the bid-ask spread, p rice pressure, and lagged effects that inspire the short-term price pressure or lack of liquidity in the market as documented in Jegadeesh (1990).

Given that the momentum strategies' returns are positive in most of the strategies when there is not time lag between the portfolio formation period and the holding period and that the returns are less significant. I may suggest that the momentum strategies are on average less and not consistently profitable for emerging countries with overlapping portfolio, that the winner portfolio do not always outperform the loser portfolio to generate positive average momentum profits. However, the 9-month/3-month remains profitable, but do not generate the highest return.

4.3.7 Summary

I examined the profitability of the momentum strategies with overlapping portfolios based on past returns of countries' indices in international equity markets. My findings indicate evidences of momentum profitability. The momentum strategies have shown to be consistently and significantly profitable on average over the full sample period, and the 9-month/3-month strategy shown to generate the highest returns 0.95% per month (11.20% per year) on the average, but these returns may vary considerably from one market condition to another. More importantly, the momentum strategies remain on average profitable in the period post-1994. The 12-month/3-month is the most profitable strategies. It generates a positive and significant payoff 1.03% per month (13.08% per year). These evidences also indicate that the momentum strategies' returns are on average low with the overlapping approach.

Even though the momentum strategies remain in some case profitable in emerging countries for example the most profitable strategy (6-month/6-month) yields a return of 0.39% per month (4.78% per month), it is important to reiterate that on average they are less significant. Even more interesting, this study did not find evidence of consistent return continuation among countries' indices when using overlapping portfolio. I may point out that my evidences, is different from Chan et al. (2000) study that suggests that momentum strategies are internationally profitable on the view point of US investor as they suggested that on average, the momentum strategy generates 0.25% per week, which is slightly greater than the average momentum return with overlapping portfolios in this study 0.95% per month (11.20% per year). Overall, a direct implication of these results is that international investors will be able to beat the market using common investment strategy such as the global momentum with overlapping portfolios.

4.4 Momentum Strategies in Different Market phases

The reader may note that up to now the study has examined the momentum strategies in different market conditions and different time horizon. The next step is to examine the momentum profit in different market phases. This section starts by examining the returns of the momentum in different market phases (crisis and non-crisis periods). I track the average portfolio formation returns in each of the holding period of 3-month following the formation period 9-month and provides additional insights about the riskiness of the strategy. Significant positive returns in the months beyond the holding period would indicate that the momentum portfolio systematically selects stocks that have higher than average unconditional returns either because of their risk or for other reasons such as stock market crisis or other global exposures. Significant negative returns in the months following the holding period would suggest that the indices' price changes during the holding period are at least partially temporary (Jegadeesh and Titman 1993). The returns of the 9-month/ 3-month momentum strategy are recorded in the Table 4.1.11 below.

[Insert Table 4.1.11 Here]

Table 4.1.11 presents the average monthly returns of the 9-month/3-month strategy in event time, the average return in each period is positive in the first 5 years. The first negative return occurs in period 7, the 31/03/1972 where the return is -1.89%, then at period 12 (-1.21%), the

29/12/1978. After this, the average return remains positive in each period in the next following years until period 16. Where, I record a negative return of -3.14%, the 31/12 1981. I then subsequently record: in period 25 (-6.37% return) the 30/09/1988. In period 27 (-6.03% return) on the 30/03/1990; period 32 (-13.99%) the 31/12/1993, period 35 (-6.41%) the 29/03/1996, period 41 (-1.75%) the 29/ 09/2000, period 45 (-1.66%) the 30/09/2003, period 52 (-3.88%) the 31/12/2008 and in the first half of 2011 period 55 (-0.31%) the 31/03/2011. Thereafter the study records negative returns for the next two periods. It is also interesting to note that the momentum strategy return reach a minimum of (-0.90%) at the end of 2012 months before rising to 2.46 in 2013.

The negative returns recorded over the study period are on average associated with international stock market crisis dates and indicate that the momentum strategy does not pick stocks that have high unconditional expected returns, as the selected indices are conditional to the information available at the time of the trade. The observed pattern of initially positive momentum returns and then negative returns of the strategy, or the switch between positive and negative momentum payoffs at different time point also suggests that indices' price changes after the formation period are not permanent over time.

These results clearly demonstrate how major global shocks in recent history affect the momentum performances. It also illustrates that since 1969, the global equity market has experienced a strong upward trend and therefore, much of the momentum strategy returns are positive, 46 out of 58 periods. The return turns down and the negative momentum payoffs are strongly associated with the post-stock market events. This includes secondary banking crisis of 1973-1975, the Latin American debt crisis originated in the end of the1970s to 1982, the Japanese asset price bubble 1986-2003, the black Monday 1987, the European currency crisis 1992-1993, the Asian financial crisis during 1997-98, the Russian financial crisis 1998, the burst of the technology bubble in 2000, and the 2008 financial crisis. The three consecutive negative momentum payoffs after the first half of 2011 period 55, (-0.31%) are also associated with the perceived effect of the delay recovery after the 2008 financial crisis, which may suggest that the longer the recovery period, the stronger the trim down momentum strategy returns continuation. These findings support the general association between momentum payoffs and the lagged market performances as suggested by Siganos, and Chelley-Steeley (2006).

[Insert Figure 1 Here]

Fig. 24 presents the momentum profit trend from 1969 to 2014 and provide an indication of the consistent rise of the momentum return in periods of good state and the sharp fall after the bad market state. In general, the good state tends to predict good future momentum performances while the bad state predicts worsened. One possible explanation of this pattern as indicated by the return from (1994 to 1995) is that the momentum strategy selects very risky indices and the risk change over time (Gonzalez et al. 2005). Although the results of this study strongly support that the risk of the indices selected by the 9-month/3-month does change over time, the direction of the change and the reason behind the change in momentum returns are the focus of the next section.

4.5 Momentum Returns Following Bear and Bull Markets

There is a popular agreement that the bull markets are associated with persistently rising share prices but it can be noted that there still does not exist a consensus as to the objective definition of a bull market (Gonzalez et al. 2005). This thesis utilizes a formal procedure to identify bear and bull phases in stock index series that indicate the meaningful time intervals corresponding to a bear or a bull phase. The thesis then examines the magnitude of the momentum profitability achieved following bull and bear markets using data from the MSCI World Indices, as it appears to be a good representation of the world equity markets.

To test out whether the Global momentum generates superior momentum gains following stock market state, this study examines how the performances of the optimum strategy 9-month/3-month are associated with different phases of the world equity market, because the bull and the bear markets are broad market movements and would best capture the impact of market state changes.

The bull and bear phases are defined based on the global market return (MSCI World Indices) over various time horizons. My expectation is that the global momentum should earn more return following down markets. The sample period is divided into bear and bull phase following Siganos and Chelley-Steeley (2006) approach. This paper defined bull phase as the period when the market return is positive for 9 months before the test period, and the bear state when the market return is negative for 9 months before the test and the results are shown in the Table 4.1.12 below.

[Insert Table 4.1.12 Here]

Table 4.1.12 presents the bear and bull market performances between December 1969 and January 2014, and the average momentum profits accomplished after bull and bear markets, and the 9-month market performance of the defined phases. This study noted that the longer the duration employed to define the up and down states the smaller the number of bear and bull periods. The lowest the duration used to describe the down market generate the strongest the negative market return that arise in bear phase. The optimum strategy 9-month/3-month is associated with the 9-month duration where the bull market performance (1.28% per month) is relatively higher than the equivalent bear market (-1.13% per month) in absolute value and the bear frequency (35.59%) is the lowest while the bull frequency (64.41%) is the highest compare to another horizon (3, 6, and 12). These observations suggest that the momentum strategy generates superior gains when the market rise quickly in bull and/or fall slowly in bear phase as the high market performance indicate a high and positive change in Indices prices and inversely. Therefore, a forecast of a slow recovery could be bad news for momentum investors while the inverse is not necessary a news good for global momentum investors comparatively. These results are in line with Gonzalez et al. (2005) that suggested that investors can achieve superior returns by adopting the momentum strategy after a bear phase, but this study reiterates that the return on the momentum strategy will depend upon speed of the of the rising and the falling market phases.

4.6 Conclusion

I examined the profitability of the momentum strategies with overlapping and non-overlapping portfolios, based on past returns of countries' indices in international equity markets. My findings indicate evidences of the profitability of the global momentum that select countries based on their past indices performances. The momentum strategies have shown to be significantly profitable on average over the full sample period, and the 9-month/3-month strategy has shown to generate the highest returns of 3% per month (42.57% per year). After examining the 9-month/3-month in different market states, I found that investors can achieve superior returns by adopting the momentum strategy after a bear phase, but the study also found a strong link between the rising market performances in bull market and the momentum profits. This indicates that the return on the momentum strategy will depend upon the speed of the recovery. More importantly, the momentum strategies' returns are high when the bull market performance is relatively higher than the equivalent bear market in absolute value and that the overall global momentum strategy generated significant abnormal return in long horizon. I may point out that my evidences are complementary to

Gonzalez et al. (2005) findings that suggested that momentum profit tend to stem up after bear market phases and Chen et al. (2012) that suggests that market conditions are good predictors of the size of the momentum profit. These findings are crucial, since investors can gain extra return following cycle and avoid undesirable losses. A direct implication of these results is that international investors will be able to beat the market using common investment strategy such as the global momentum strategies.

Chapter 5: Contrarian Strategies in International Equity Market

5.1 Introduction

In this Chapter, I examine the profitability of the global contrarian strategies; I implement the strategy with non-overlapping deciles portfolios on the full sample exactly like De Bondt and Thaler (1985). I show that these strategies are highly profitable and the profitability varies from one market state to another. I demonstrate this by examining the global contrarian profit with established markets, during the globalization period, with developed countries, and the emerging countries. In the second section, I increase the power of the test by examining the profitability of the contrarian strategies with overlapping portfolios; this includes monthly rebalancing the contrarian portfolio. In both cases, I consider the impact of return continuation by examining a second set of strategies that sky a month between the formation and the holding periods. In the third and the four section, I repeat these analyses with quintile portfolios to capture differences in portfolios size.

My findings indicate that contrarian strategies are highly profitable with the full sample 0.83 per month (10.40 per year). The contrarian strategies generate in emerging countries return as high as 1.38% per month (17.70% per year) with the 60-month/ 48-month strategy. The developed countries' contributions are less significant, still a consistent contrarian return of 0.93% per month (11.72% per year) could be observed in developed countries with the 60-month/48-month strategy when the strategy skips a time lag between the portfolio formation period and the holding period. My findings also show that contrarian strategies' yield on average higher return with the non-overlapping portfolio than the equivalent overlapping approaches for both deciles and quintiles portfolios and that the contrarian strategy are on the average considerably greater with deciles portfolios than quintiles portfolios.

5.2 Contrarian Strategies with Deciles Portfolios

5.2.1 Introduction

This section investigates the performances of the contrarian strategy with deciles portfolios on the international equity market, based on countries' indices past performances. Consistent with the predictions of the overreaction hypothesis, that suggested that portfolios of prior "losers" do outperform prior "winners", three to five years after portfolio formation, the losing stocks earned about 25% more than the winners and 8% annually for 5 years post-ranking period even though the latter are significantly riskier (De Bondt and Thaler, 1985). This section also discusses the empirical results of my study based on raw return for both overlapping and non-overlapping portfolios, following the pure contrarian strategies approach and concludes with a discussion of these strategies' sub-period results. Given the long research history in this field, I focus on a global coordinated contrarian phenomenon. I construct deciles portfolios and carefully re-examine the international evidences for the long-run reversal predictability in different market states and provide alternative explanations of the international profitability of the contrarian strategy. The contrarian investors will buy stocks in the losers' countries and sell stocks in the winners' countries that replicate indices performances or invest in index-trackers in these countries respectively to generate extra profit.

5.2.2 Contrarian Strategies Returns with Non-Overlapping Portfolios

5.2.2.1 Contrarian Strategies for International Investors: full sample 1969-2014

I start the analysis by implementing the basic contrarian strategies first, on the entire time series data. In period `t’ I buy the losers countries and sell the winners countries. The winners and the losers’ portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.1, this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.1 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.1 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the table, the t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.2.1 Here]

Table 4.2.1 contains the results of the contrarian strategies for the whole sample period; the winner, the loser, and the contrarian portfolio (loser-winner) returns are reported for the 18 strategies. These results show that the contrarian strategies’ returns are positive in most of the cases, 4 strategies are statistically significant. The most successful contrarian strategy selects stocks based on their previous performances over 48 months and then holds the portfolio for the next 60 months. This strategy yields 0.83% per month (10.40% per year) with a t-statistic of 3.16 and a p-value of 0.01 (Table 4.2.1 Panel A), when there is not time lag between the portfolio formation period and the holding period. The 48-month/60-month is consistently the most profitable strategy.

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period improve the 48-month/60-month strategy performance as the equivalent holding period returns are slightly greater. The loser portfolio outperforms the winner portfolio to generate positive average effective compounded contrarian return of 10.40% per year (0.83% per month) with a t-statistic of 3.63 and a p-value of 0.01 (Table 4.2.1 Panel B). This is in sequence with the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to a greater return given that Fama and French suggested 1.16%average return per month for the loser portfolio and 0.42 % per month for the winner portfolio. This implies that the loser minus winner portfolio yields 0.74% per month (9.25% per year) on the average.

I also uncover that the 48-month formation period generates significant return for both the 48- and the 60-month holding periods, with the exception made on the 36-month holding period. This indicates that the price started to reverse consistently sometimes after 36-month and continue to reverse throughout the first 60-month of the post-formation period.

Overall, the results in Table 4.2.1 validate the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They are consistent with other studies such as De Bondt and Thaler (1985) in US stock market that suggested that 3 to 5 years after a past performance based portfolio formation, Losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years (8.33 per year) and 8% annually for 5 years post-ranking period. They indicate a better contrarian return than Jordan’s (2012) study that suggested that contrarian strategies are internationally profitable; he reported about 5.60% per year with earning above the risk-free rate, and that the long-term contrarian profits is not a robust phenomenon internationally.

My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed markets and 0.68% per month (8.47 per year) in emerging markets, and Richards's (1996) study that found 6.60% per year over 3 years holding period and 5.80% per year over 4 years. In general, the tests on the contrarian strategies with overlapping portfolios, should of course, be regarded only as illustrative, since alternative techniques would yield somewhat different critical values (Richards, 1996). I must acknowledge that the short data set allows only a small number of non-overlapping tests for the longer horizons. Therefore, the lack of significance in the face of some larger profits with non-overlapping portfolio is driven by the length of the sample period (number of observation).

In addition, these findings are essential and deviate from previous studies on contrarian trading, in the sense that I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to other approaches. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan (2012) and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.2.2.2 Contrarian Strategies Return on Established Markets

The study of the full sample examines 47 countries' indices with different strating date that make sample umbalance. I also examine the contrarian strategies in a more stable sample period (1969-2014), where all countries indices start and end in the same date to avoid any blunder, which may occur, from variation among the starting dates of countries indices and to gauge the effect of the variation in the sample size.

To implement the basic contrarian strategies on the subsample1969-2014 (18 countries), at `t' I buy the loser countries and sell the winner countries. The winners and the losers' portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 different holding periods 'H', where F equals 36, 48, and 60 months and H equals 36, 48, and 60 months as indicated in Table 4.2.2; thus, I have 9 strategies in total. The contrarian portfolios in Table 4.2.2 Panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.2 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the table below, the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.2 Here]

Analyses of the contrarian strategies on the established markets reveal some very interesting aspects of the reversal effect. Table 4.2.2 shows that the contrarian strategies' returns are positive in most of the cases, 6 strategies are significant. The most successful contrarian strategy selects stocks based on their previous performances over 48 months and then holds the portfolio for the next 36 months. This strategy yields 0.84% per month (10.49% per year) with a t-statistic of 2.59 and a p-value of 0.029 when there is not time lag between the formation period and the holding period (Table 4.2.2 Panel A). The 48-month/36-month is consistently the most profitable strategy.

Testing how skipping a time lag affect the contrarian return, I find that skipping a month between the formation and the holding period (Table 4.2.2 Panel B), do not improve the 48-month/36-month strategy performance and generate 0.80% per month (11.16% per year) with a t-statistic of 2.43 and a p-value of 0.04. This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or 9.25 per year for the loser minus winner portfolio).

This thesis also reveals that the 48-month formation period generate significant return for all the holding period 36-, 48- and the 60-month holding periods, this indicate that the price started to reverse consistently sometime before or during the first 36-month and continue to reverse throughout the first 60-month of the post-formation period.

These results demonstrate that the contrarian strategies generate positive and significant return internationally and suggest that when the strategies select indices based of their 48-month past performances and hold them for 48 months, the loser portfolios tend to outperform the winner portfolios to generate high positive average contrarian returns. I then establish that the most profitable strategy is the 48-month/48-month that skip a month (Table 4.2.2 Panel B) with an effective return of 11.16% per year (0.89% per month) with a t-statistic of 3.25 and a p-value of 0.01.

Overall, my results are consistent between unbalanced sample and the established market sub-set; they validate the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They are consistent with studies such as De Bondt and Thaler

(1985) in US stock market that suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post-ranking period. They indicate a better contrarian return than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable (5.60% per year) with earning above the risk-free rate; and that the long-term contrarian profits is not a robust phenomenon internationally.

My findings also provide with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed markets and 0.68% per month (8.47 per year) in emerging markets, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years. In general, the significance tests on these contrarian strategies with overlapping portfolios, should of course, be regarded only as illustrative, since alternative techniques would yield somewhat different critical values (Richards, 1996). I must acknowledge that the short data set allows only a small number of non-overlapping tests for the longer horizons. Therefore, the lack of significance in the face of some larger profits with non-overlapping portfolio is driven by the length of the sample period (number of observation).

Additionally, these findings are essential and deviates from previous studies in the sense that I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to other approaches. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return.

These findings are also complementary given that Jordan (2012) and De Bondt and Thaler (1985) studies did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.2.2.3 Contrarian Returns since Globalisation 1994-2014

The MSCI launched in 1988 the Emerging Market Index, which consisted of just 10 countries representing less than 1% of world market capitalization. Following the MSCI reclassification in 1994 we saw a significant rise in emerging market to the strength of the globalisation. From 1994 to 2014 the MSCI Emerging Market Index consist of 23 countries representing 10% of world market capitalization. The Index is now available for several regions, market segments or sizes and covers approximately 85% of the free float-adjusted market capitalization each of the 23 countries. I consider alternative set of contrarian portfolios, which are formed on the 1994-2014 subsamples (47 countries all starting with the same date). I focus on common practice of analysing the contrarian strategies. I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 different holding periods 'H', where F equals 36, 48, and 60 months and H equals 36, 48, and 60 months as indicated in Table 4.2.3. Thus, I have 9 strategies in total. The contrarian portfolios in Table 4.2.3 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.3 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the Table 14 the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1994 to January 2014.

[Insert Table 4.2.3 Here]

Table 4.2.3 shows that contrarian strategies on the stock market indices of 47 countries for 1994 to 2014, which include the global finance crisis 2007-2008, remain profitable, all returns are positive, but none is significant. The most successful contrarian strategy selects stocks based on their previous performances over 36 months and then holds the portfolio for the next 60 months. It yields 0.64% per month (7.90 per year) with a t-statistic of 1.32 and a p-value of 0.28 (Table 4.2.3 panel A) which appears inconsistent with the overall findings. This indicates that, even though different market conditions and different time periods exhibit contrarian profit, this return varies with the study time horizon, which may arise in the period post-globalisation as the evidences suggest here.

Focussing on results using common practice of skipping a month between portfolio ranking and investment period, I find no substantial evidence to suggest that the new strategies will generate greater return in period post globalization (Table 4.2.3 Panel B). This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding month is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French (1996) suggested 1.16%

average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or 9.25% per year for the loser minus winner portfolio).

These results support Jordan’s (2012) findings that suggested that contrarian strategies are internationally profitable but the long-term contrarian profit is not a robust phenomenon. The contrarian strategies’ returns are also lower than the 8% per year as suggested by De Bondt and Thaler (1985). They are also complementary given that Jordan’s (2012) and De Bondt and Thaler’s (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.2.2.4 Contrarian Return in Developed Market

To gauge the contribution of the Developed countries on global contrarian strategies, since the contrarian profit may differ from developed to emerging countries, I implemented the contrarian strategy on the developed countries sub-sample (23 countries) over 1969-2014. At `t’ I buy the winner countries and sell the loser countries. The winners and the losers’ portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 4 for different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60, this give a total of 9 strategies. The contrarian portfolios in Table 4.2.4 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period (Table 4.2.4 Panel B). The average monthly returns of the winners and the losers’ portfolio are indicated in Table 4.2.4 below the t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.2.4 Here]

Other factors important in influencing the contrarian profitability are the markets states (Develop and emerging market). Table 4.2.4 reports the contrarian results of developed countries for the whole sample period, the winner, the loser, and the contrarian portfolio (winner-loser) returns are reported for the 18 strategies. All the contrarian strategies’ returns are positive (9 out of 9 strategies) and (9 out of 9 strategies) for the strategies with a month lag. One strategy is significant. The most successful contrarian strategy selects indices based on their previous performances over 60 months and then holds them for the next 48 months.

This strategy yields 0.93% per month (11.72% per year) with a t-statistic of 2.49 and a p-value of 0.04 (Table 4.2.4 Panel A).

Investigating whether skipping a time lag is beneficial in developed counties, I find that after skipping a month between the formation and the holding, the 60-month/48-month remain profitable although, none of the strategy is significant (Table 4.2.4 Panel B) when there is a month lag between the formation period and the holding period. This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns, given that, Fama and French (1996) suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or 9.25% per year for the loser minus winner portfolio). I then suggest that the contrarian strategies are profitable internationally and establish that the most profitable strategy is the 60-month/48-month that does not skip a month (Table 4.2.4 Panel A). The loser portfolio outperforms the winner portfolio to generate positive average effective compounded contrarian return of that yield an effective compounded return of 11.72% per year.

Overall, the results in Table 4.2.4 verify the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They are consistent with studies such as De Bondt and Thaler (1985) in US stock market, that, suggested that, 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post-ranking period. These results also indicate a better contrarian returns than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable (5.60% per year) with earning above the risk-free rate; and that the long-term contrarian profits is not a robust phenomenon internationally.

My findings also prove that, the contrarian strategies can yield greater returns than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market, and 0.68% per month (8.47% per year) in emerging market. Even more than Richards's (1996) study that found 6.60% contrarian return per year for 3 years holding period and 5.80% per year over 4 years.

However, the significance tests on the contrarian strategies with non-overlapping portfolios should be regarded only as illustrative, since alternative techniques would yield somewhat different critical values (Richards, 1996). I must acknowledge that the short data set allows only a small number of non-overlapping tests for the longer horizons. Therefore, the lack of significance in the face of some larger profits with non-overlapping portfolio is driven by the length of the sample period (number of observation).

Moreover, these findings are essential and deviate from previous studies in the sense that I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to others approaches. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan (2012), De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market indices where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler's (1985) and Fama and French's (1996) studies were conducted on US stocks only.

5.2.2.5 Contrarian in Emerging Market

Given that contrarian strategies are significantly profitable in the full sample and, on average, positive in different period, I will expect the contrarian strategies to be profitable in emerging markets. It is understandable that there may be serious concern over the fact that emerging markets might be on average illiquid and unstable and seriously segmented (Chan, et al., 2000) but this analysis is more interested in the practicality of the contrarian strategies than the market condition. To test the sensitivity of the contrarian strategies on the emerging market, I implement the contrarian strategies on the emerging markets sub-sample (December 1987 to January 2014) given that the first emerging market enters the sample in December 1987.

At `t' I buy the loser countries and sell the winner countries. The winners and the losers' portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 for different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.5 below. This gives a total of 9 strategies. The contrarian portfolios in Table 4.2.5 panel A are formed immediately after the formation period. I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.5 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the table. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1987 to January 2014.

[Insert Table 4.2.5 Here]

The emerging market state is arguably significant in influencing the international contrarian strategies. For instance, Table 4.2.5 shows that for the contrarian strategies for emerging countries, 4 strategies are positive and significant for the contrarian strategies without a month lag and 3 strategies are positive and significant for the contrarian strategies with a month lag. The most successful contrarian strategy selects stocks based on their previous performances over 60 months and then holds the portfolio for the next 48 months. This strategy yields 1.37% per month (17.69% per year) with a t-statistic of 5.15, and a p-value of 0.01 (Table 4.2.5 Panel A).

Examining whether skipping a time lag has an added benefit, I find that skipping a month between the formation and the holding period did not improve the 60-month/48-month strategy performance as the equivalent holding period returns are slightly lower. The loser portfolio outperforms the winner portfolio to generate positive average contrarian return of 1.20% per month (15.33% per year) with a t-statistic of 3.16 and a p-value of 0.05 (Table 4.2.5 Panel B). This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to a greater return given that Fama and French suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio. This implies that the loser minus winner portfolio yields 0.74% per month (9.25% per year) on average.

This indicates that, even though different market conditions and different periods exhibit contrarian profit, the highest return might be observed in emerging market with an effective compounded return of 17.70% per year as the evidences suggest with the 60-month/ 48-month. Overall, the results in Table 4.2.5 validate the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They are consistent with other studies such as De Bondt and Thaler (1985) in US stock market that suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years (8.33% per year) and 8% annually for 5 years post-ranking period. They also indicate a better contrarian return than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable and generate 5.60 % per year with earning above the risk-free rate; and that the long-term contrarian profits is not a robust phenomenon internationally.

My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47% per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years. In general, the significance tests on these contrarian strategies with non-overlapping portfolios should be regarded only as illustrative, since alternative techniques would yield somewhat different critical values (Richards, 1996). I must acknowledge that the short data set allows only a small number of non-overlapping tests for the longer horizons. Therefore, the lack of significance in the face of some larger profits with non-overlapping portfolio is driven by the length of the sample period (number of observations).

These findings are fundamental and deviate from previous studies in the sense that I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to others approaches. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan's (2012) and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index, where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler's (1985) and Fama and French's (1996) studies were conducted on US stocks only.

5.2.2.6 Summary

In this section, I examined the profitability of the contrarian strategies based on past returns of countries' indices in international equity markets. My findings indicate evidences of contrarian profitability. The contrarian strategies have shown to be profitable on average over the full sample period, and the 48-month/60-month strategy being the most profitable strategy with the whole sample period (10.40% per year). Although the contrarian return could rise considerably when the strategy skips a time lag between the portfolio formation period and the holding period, the overall result is not exceptionally significant as it appears that only 4 strategies out of 18 are significant at 5% level. Evidences also indicate that the contrarian strategies are highly profitable in emerging countries where the highest returns might be observed with an effective compounded return of 17.70% per year as the evidences suggest with the 60-month/ 48-month. developed countries' contribution are less significant and inconsistent, even though a consistent contrarian returns 11.72% per year could be observed in developed countries with the 60-month/48-month strategy when there is a time lag between the portfolio formation period and the holding period.

Even more interesting, this thesis overall did not find evidence of return continuation among countries' indices. However, I must point out that my evidences are in line with Jordan's (2012) study that, suggest that contrarian strategies are internationally profitable (5.69% per year) and that the long-term contrarian profits are not a robust phenomenon. I also emphasise the point that investors may earn extra returns over time by investing internationally as the global contrarian strategy generates a return higher than the 8% per annum as reported by De Bondt and Thaler (1985). It is important to indicate that the global contrarian strategies will be profitable after accounting for transaction costs. On average, the contrarian strategies with non-overlapping portfolios are long-term strategies and results in a low turnover. The optimum strategy generates a return of 10.40% per annum while the portfolios are rebalanced with 48 months' intervals. On other hand Jegadeesh and Titman (1993), and Berkowitz, Logue and Noser (1988) estimate one-way transaction costs of 23 basis points for institutional investors suggesting that transaction cost of 0.5% per trade with a 6-month/6-month strategy is conservative. This implies and estimated transaction cost of 0.6% per annum which is not negligible, suggesting a contrarian profit of 9.8% per annum, which does not undermine the high profitability of these strategy.

A direct implication of these results is that international investors might be able to beat the market using common investment strategy such as the global momentum with non-overlapping portfolio.

To increase the power of the test, this thesis also performs similar analysis on contrarian strategies with overlapping portfolios where, contrarian deciles portfolio in any particular month holds indices ranked in the deciles in any of the previous F months. The results are reported in the next section.

5.2.3 Contrarian Strategies with Overlapping Deciles Portfolios

In this section, I examine whether contrarian strategies earn significant return after increasing the power of the test. To increase the power of the test, I construct overlapping portfolios, where contrarian deciles portfolio in any particular month holds stocks ranked in those deciles in any of the previous H ranking months. In sequence with the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners do. I also test the contrarian strategies that sky a month between the formation and the holding periods. I examine the contrarian profitability in the full sample period 1969-2014 and in different market states.

5.2.3.1 Contrarian Strategies for International Investors: Full Sample 1969-2014

I examine the international contrarian strategy initially, on the entire time series data. Investors the loser's countries and sell the winners countries. The winners and the losers' portfolios are constructed based on their past performances. They use 3 different formation periods 'F' and 3 different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.6, this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.6 panel A are formed immediately after the formation period. However, I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.6 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the table below, the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.6 Here]

The contrarian strategy can also be presented with the overlapping to support my initial findings and inform the reader on the strength of the test on return reversal. To illustrate these points, Table 4.2.6 reports the results for the whole sample period: the winner, the loser, and the contrarian portfolio (loser-winner) returns are reported for the 18 strategies. All the contrarian strategies' returns are positive and significant. The most successful contrarian strategy and selects stocks based on their previous performances over 48 months and then holds the portfolio for the next 48 months. This strategy yields 0.55% per month (6.80% per year) with a t-statistic of 11.30% and a p-value of 0.00 (Table 4.2.6 Panel A).

Investigating whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period did not improve the 48-month/48-month strategy performance as the equivalent holding period returns are slightly lower. When there is a time lag between the portfolio formation period and the holding period the 48-month/48-month yields 0.55% % per month (6.80% per year) with a t-statistic of 11.27 and a p-value of 0.00 (Table 4.2.6 panel B). This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns.

Given that the contrarian strategies' returns are positive in most of the cases and that the returns are highly significant in all cases, I suggest that the contrarian strategies are on average profitable internationally when using overlapping portfolios of stock indices, and that the loser portfolio outperforms the winner portfolio to generate positive average contrarian profits. I establish that the most profitable strategy is the 48-month/48-month (Table 4.2.6 Panel A) with an effective compounded return of 6.80% per year (0.55% per month). However, the 48-month/48-month (Table 4.2.6 Panel A) is different and less profitable than the 48-month/60-month documented with the non-overlapping strategies (Table 4.2.1 Panel A) (10.37% per year) and the 8% per year previously suggested by De Bondt and Thaler (1985).

This indicates that skipping a month lag between the formation and holding period do not increase the portfolios returns and using overlapping portfolio do improve the test on return reversal, but lessen the portfolio return. These findings have another notable aspect as they point to an observable pattern that shows that increasing the holding period does increase the portfolio return. The results remain comparatively greater than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable (5.60 % per year); conversely, the results with overlapping portfolio indicate signs of robustness for the long-term contrarian phenomenon internationally.

Furthermore, this part of the study contributes substantialy to the literature given that, I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to other approaches.

The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan's (2012), and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French's (1996) studies were conducted on US stocks only.

5.2.3.2 Contrarian Returns for International Investors: Established Markets

Next, I turn to a more stable sample period, I implement the contrarian strategies with overlapping portfolio in the 1969-2014 subsample, where all countries' indices start and end in the same date to avoid any blunder which may occur from non-synchronized starting dates among countries' indices. To implement the basic contrarian strategies on the sub-set 1969-2014 period (18 countries) at `t', I buy the loser countries and sell the winner countries. The winners and the losers’ portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 for different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.7 below; this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.7 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.7 Panel B. The average monthly returns of the winners and the losers’ portfolio are indicated in the table below the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.7 Here]

Contrarian analyses on established market reveal very interesting aspect of the reversal effect. Table 4.2.7 reports the results for the whole sample period of established market, the winner, the loser, and the contrarian portfolio (loser-winner) returns are reported for the 18 strategies. All the contrarian strategies’ returns are positive. These results show that, the contrarian strategies’ returns are positive in most of the cases, all strategies are significant. The most successful contrarian strategy selects stocks based on their previous performances over 48 months and then holds the portfolio for the next 48 months. This strategy yields 0.45% per month (5.59% per year), with a t-statistic of 11.28 and a p-value of 0.00 (Table 4.2.7 Panel A), when there is not time lag between the portfolio formation period and the holding period.

Examining whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period did not improve the 48-month/48-month strategy performance as the equivalent holding period returns are slightly lower. It yields 0.45% per month (5.59% per year) with a t-statistic of 11.21% and a p-value of 0.00 (Table 4.2.7 panel B). When there is a month lag between the formation period and the holding period. This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding month is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French (1996) suggested 1.16% average return per month for the loser portfolio, 0.42 % per month for the winner portfolio and 0.74% per month (9.25% per year) for the loser minus winner portfolio). However, the 48-month formation period remains profitable regardless of the holding period for both sets of strategies.

Given that the contrarian strategies returns are positive in most of the strategies and that the returns are highly significant in all cases, I may suggest that the contrarian strategies are on average profitable internationally, and that the loser portfolio outperforms the winner portfolio to generate positive average contrarian profits. I then establish that the most profitable strategy is the 48-month/48-month that does not skip a month (Table 4.2.7 Panel A); it yields an effective compounded return of 5.59% per year. The returns here are significantly lower than the 8% return per year suggested by De Bondt and Thaler (1985). In addition, these findings are essential and deviate from other studies in the sense that I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to other approaches. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return.

These results are also complementary given that Jordan's (2012) and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler's (1985), and Fama and French's (1996) studies were conducted on US stocks only. The results here highlight the fact that contrarian strategies returns are lower if investors apply the standard contrarian strategy with overlapping portfolios.

5.2.3.3 Contrarian Returns with Overlapping Portfolios since Globalisation

To ascertain whether the contrarian strategies remain profitable with overlapping portfolio after 1994, I examine an alternative set of contrarian overlapping portfolio, which are formed on the 1994-2014 subsamples (47 countries). At 't' I buy the loser countries and sell the winner countries. The winners and the losers' portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.21 below, and this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.8 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.8 Panel B. The average monthly returns of the winners and the losers’ portfolio are indicated in the Table 4.2.8. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from January 1994 to January 2014.

[Insert Table 4.2.8 Here]

The contrarian strategy return can also be influenced by the effect of the globalisation. Table 4.2.8 shows the results of the contrarian strategies implemented on the stock market indices of 47 countries for 1994 to 2014, which include the global finance crisis 2007-2008. It shows that the contrarian strategies remain profitable on average (9 out of 9 strategies) for the strategies without time lag and (9 out of 9 strategies) for the strategies with a month lag. All the returns are significant. The 48-month/48-month generates a positive and significant payoff 0,45% per month (5.59% per year) with a t-statistic of 5.43 and a p-value of 0.00 (Table 4.2.8 Panel A). Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period improves the 48-month/48-month strategy performance as the equivalent holding period returns are slightly greater. The loser portfolio outperforms the winner portfolio to generate a relatively higher return 0.45% per month with a t-statistic of 5.56 and a p-value of 0.00 when there is a time lag between the formation and the holding period (Table 4.2.8 Panel B).

This indicates that, even with the impact of the financial crisis and the globalization the contrarian strategies can still be profitable with the overlapping approach. The 1994-2014 period exhibits contrarian profit with the 48-month/48-month portfolio of countries' indices generating and effective return of 5.56% per year at its best (Table 4.2.8 Panel B); but the degree of profitability is considerably lower than the 8% return per year with the 36-month holding period presented by De Bondt and Thaler (1985). My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47% per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years.

In sum, contrarian strategies are quite profitable during the 1994-14 period. I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to other approaches. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. This study is also complementary given that Jordan's (2012) and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler’s (1985) and Fama and French’s (1996) studies were conducted on US stocks only.

5.2.3.4 Contrarian Returns with Overlapping Portfolios in Developed Countries

To better understand which of the developed and the emerging market may be driving the return on the global contrarian strategies, I implemented the contrarian strategy with overlapping portfolio on the developed countries subsample (23 countries) over 1969-2014. At `t' I buy the loser countries and sell the winner countries. The winners and the loser’s portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.9 below, this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.9 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.9 Panel B. The average monthly returns of the winners and the losers’ portfolio are indicated in Table 4.2.9

below, the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.9 Here]

Table 4.2.9 reports the contrarian results of the developed countries for the whole sample period, the winner, the loser, and the contrarian portfolio (loser-winner) returns are reported for the 18 strategies. The results in every strategy indicate that the contrarian strategies returns are positive and significant (9 out of 9 strategies) for the strategies without time lag and (9 out of 9 strategies) for the strategies with a month lag. The most successful contrarian strategy selects stocks based on their previous performances over 48 months and then holds the portfolio for the next 48 months. This strategy yields 0.59% per month (7.33% per year) with a t-statistic of 11.69 and a p-value of 0.00 when there is not time lag between the portfolio formation period and the holding period (Table 4.2.9 Panel A).

Studying how skipping a time lag affects the contrarian return, I find that skipping a month between the formation and the holding period improves the contrarian strategy. It yields 0.59% per month (7.33% per year) with the 48-month/48-month strategy when there is not time lag. It also generates 0.62% per month (7.66% per year) at it best with a t-statistic of (11.26) and a p-value 0.00 with the 60-month/36-month (Table 4.2.9 Panel B), when there is a month lag between the formation period and the holding period. This is in line with the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or 9.25% per year for the loser minus winner portfolio).

Given that the contrarian strategies returns are positive in most of the strategies and that the returns are highly significant, I may suggest that the contrarian strategies are on average profitable internationally for developed countries, and that the loser portfolio outperforms the winner portfolio to generate positive average contrarian profits. This also validates my initial result, and the most profitable strategy is the 60-month/36-month with a month lag. These results support my initial findings that, the contrarian strategies are consistently profitable internationally with overlapping portfolio, but generate significantly low effective return of 7.66% per year. Which is lower compared to De Bondt and Thaler's (1985) findings that suggest 8% per year contrarian return in the US market; this result helps reiterate the point that the long-term contrarian strategies that use overlapping portfolio are consistently profitable in developed countries. My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47% per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years.

Still, these findings are essential and deviate from previous contrarian studies in the sense that I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to other approaches. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan’s (2012) and De Bondt and Thaler’s (1985), and Fama and French’s (1996) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler’s (1985) and Fama and French’s (1996) studies were conducted on US stocks only.

5.2.3.5 Contrarian Returns with Overlapping Portfolios in Emerging market

I implement the contrarian strategies on the emerging market subsample (December 1987 to January 2014) given that the first emerging market enters the sample in December 1987.At `t' I buy the loser countries and sell the winner countries. The winners and the losers’ portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.10 below and this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.10 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.10 Panel B. The average monthly returns of the winners and the losers’ portfolio are indicated in the table, the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1987 to January 2014.

[Insert Table 4.2.10 Here]

The emerging market state is arguably significant in influencing the international contrarian strategies. Table 4.2.10 reports the contrarian strategies' results on emerging countries. By comparison, to those of the full sample and the developed countries, the contrarian strategies in emerging countries appear to be more profitable on average. 9 out of 9 strategies generate positive return for strategies without a time lag and 9 out of 9 strategies generate positive return for the contrarian strategies with a month lag. The most successful strategy selects stocks based on their previous performances over 48 months and then holds the portfolio for the next 36 months. This strategy yields 0.71% per month (8.91% per year) with a t-statistic of 0.7.64, and a p-value of 0.00 (Table 4.2.10 Panel A),

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period did not improve the 48-month/36-month strategy performance. It yields a return of 0.69% per month (8.65% per year) with a t-statistic of 7.46 and a p-value of 0.00 (Table 4.2.10 panel B). This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or 9.25% per year for the loser minus winner portfolio). They are consistent with studies such as De Bondt and Thaler (1985) in US stock market that suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post-ranking period. They also indicate a better contrarian return than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable (5.60 % a year) with earning above the risk-free rate; and that the long-term contrarian profits is not a robust phenomenon internationally.

My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47% per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years.

These findings are essential and deviate from other studies in the sense that I use deciles portfolio to demonstrate how trading on extreme losers and winners (deciles Portfolios), contrarian investors could generate superior return compared to other approaches. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return.

Given that the contrarian strategies' returns are all positive when there is not time lag between the portfolio formation period and the holding period, and that the returns are significant. I may suggest that the contrarian strategies are on average consistently profitable for emerging countries with overlapping portfolio, that the loser portfolio always outperforms the winner portfolio to generate positive average contrarian profits. However, contrary to the developed and the whole sample analysis, the 48-month/36-month generate the highest effective compounded return of 8.91% per year. They are also complementary given that Jordan (2012) and De Bondt and Thaler (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.2.3.6 Summary

The test of return reversal with overlapping portfolios based on past returns of countries' indices in international equity markets, indicate evidences of contrarian profitability. The 48-month/60-month strategy has shown to generate the highest effective contrarian return of 10.401% per year (0.828% per month) over the full sample period. However, the contrarian strategies are on average positives and the returns may vary considerably from one market condition to another. More importantly, the contrarian strategies remain on average profitable but not significant in the period post-1994 with the non-overlapping portfolios. These evidences also indicate that the contrarian strategies' returns are on average lower but significant with the overlapping approach. Moreover, the contrarian strategies remain profitable in emerging countries, but it is important to reiterate that on average they are more significant with overlapping portfolios.

Even more interesting, this thesis did not find evidence of consistent return continuation with the contrarian strategies among countries' indices when using overlapping portfolio and the contrarian strategies are highly profitable in emerging countries and that developed countries' contribution are less significant. These results are in line with Jordan's (2012) study suggested that suggested contrarian strategies are internationally profitable and that the long-term contrarian profits are not a robust phenomenon. I also emphasise the point that investors may earn extra returns over time by investing internationally as the global contrarian generates a return higher than the 8% per annum reported by De Bondt and Thaler (1985).

5.3 Contrarian strategies with Quintile Portfolios

5.3.1 Introduction

This section investigates the performances of the long-run contrarian strategy with quintile portfolio on the global equity market, based on countries' indices past performances. Consistent with the predictions of the overreaction hypothesis, that suggested that portfolios of prior "losers" do outperform prior "winners" three years after portfolio formation, the losing stocks earned about 25% more than the winners and 8% annually for 5 years post-ranking period even though the latter are significantly riskier (De Bondt and Thaler, 1985). This section also discusses the empirical results of my study based on raw return for both overlapping and non-overlapping portfolios, following the pure contrarian strategies approach and concludes with a discussion of these strategies' sub-period results.

Given the long research history in this field, I focus on a global coordinated contrarian phenomenon. I construct quintile portfolios and carefully re-examine the international evidence for the long-run reversal predictability in different market states. I also provide alternative explanations of the international profitability of the contrarian strategy. International contrarian investors will buy stocks in the losers' countries and sell stocks in the winners' countries that replicate indices performances or invest in index-trackers in these countries respectively to generate extra profit.

5.3.2 Contrarian Strategies with Non-overlapping Quintiles Portfolios

5.3.2.1 Contrarian Strategies for International Investors: Full Sample 1969-2014

To ascertain whether the global contrarian strategies based on quintile portfolio work in the global equity market, I implement the basic contrarian strategies, firstly, on the entire times series data. In period `t' I buy the losers' countries indices and sell the winners' countries indies. The winners and the losers' portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 for different holding periods 'H', where F equals 36, 48, and 60 months, and H equals 36, 48, and 60 months; thus, I have 9 strategies in total. The contrarian portfolios in Table 4.2.11 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.11 Panel B.

The average monthly returns of the winners and the losers' portfolio are indicated in the Table 4.2.11. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.11 Here]

Table 4.2.11 provides the estimated results of the contrarian strategies for the whole sample period; the winner, the loser, and the contrarian portfolio (loser-winner) returns are reported for the 18 strategies. All the contrarian strategies' returns are positives; 9 strategies are significant. The most successful contrarian strategy selects stocks based on their previous performances over 60 months and then holds the portfolio for the next 48 months. This strategy yields 0.71% per month (8.89% per year) with a t-statistic of 4.78 and a p-value of 0.00 when there is not time lag between the portfolio formation period and the holding period (Table 4.2.11 Panel A).

Testing out whether a time lag is beneficial between the formation and the holding period. I find that skipping a month between the formation and the holding period did not improve the 60-month/48-month strategy performance as the equivalent holding period returns are slightly lesser when the strategies skip a month between the formation and the holding period, it yields 0.70% per month (8.76% per year) with a t-statistic 5.70 and a P-value 0.00 (Table 4.2.11 Panel B). This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding months is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. This also points to greater returns given that Fama and French (1996) suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or 9.25% per year for the loser minus winner portfolio).

These results show that the contrarian strategies' is on average profitable; the 60-month formation period is exceptionally profitable in all cases. I then establish that the most profitable strategy is the 60-month/48-month that does not skip a month with an effective compounded return of 8.89% per year (Table 4.2.11 Panel A) and suggest that indices choice should be based on substantial range of performances.

Overall, the results in Table 4.2.11 validate the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They are consistent with studies such as

De Bondt and Thaler (1985) in US stock market that suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post-ranking period. They indicate a better contrarian return than Jordan’s (2012) study that suggested that contrarian strategies are internationally profitable (5.60% per year) with earning above the risk-free rate; and that the long-term contrarian profits is not a robust phenomenon internationally.

My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47% per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years. Moreover, my findings are essential in the sense that i use quintile portfolios to demonstrate how trading on quintile portfolios, the contrarian investors could generate significant return but lower return compared to the contrarian strategies based on deciles portfolios approaches. They are also complementary evidences given that Jordan's (2012), and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return, the losers and winners represented the 25% bottom and 25% top, and did not established the performance differences between quintile and deciles portfolios' approaches, while De Bondt and Thaler’s (1985) study were conducted on US stock only.

5.3.2.2 Contrarian Returns with Quintiles Portfolio in Established Markets

I implement the contrarian strategies in a more stable sample period (1969-2014), where all countries indices start and end in the same date to avoid any slip-up, which may occur from variation among the starting dates of countries indices, and to gauge the effect of the variation in the sample size.

To implement the basic contrarian strategies with quintile portfolios on the subsample1969-2014 (18 countries), at `t' I buy the loser countries and sell the winner countries. The winners and the losers’ portfolios are constructed based on their past performances. I used 3 different formation periods 'F' and 3 different holding periods 'H', where F equals 36, 48, and 60 months and H equals 36, 48, and 60 months as indicated in Table 4.2.12. Thus, I have 9 strategies in total. The contrarian portfolios in Table 4.2.12 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.12 Panel B.

The average monthly returns of the winners and the losers' portfolio are indicated in the table. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.12 Here]

Very interesting aspects of the reversal effect appear when analysing the contrarian strategies on established market. In Table 4.2.12., the results of the contrarian strategies with quintile portfolios on established market for the whole sample period reveal that, most of the contrarian strategies' returns are positive; 6 strategies are significant. The most successful contrarian strategy selects stocks based on their previous performances over 60 months and then holds the portfolio for the next 48 months. This strategy yields 0.44% per month (5.40% per year) with a t-statistic of 3.15 and a p-value of 0.02 when there is not time lag between the formation period and the holding period (Table 4.2.12 Panel A).

More importantly, I find that skipping a month between the formation and the holding period did not improve the 60-month/48-month strategy performance as the equivalent holding period returns are slightly lower, it yields 0.42 per month (5.10% per year) with a t-statistic of 3.37 and a p-value of 0.00 (Table 4.2.12 Panel B). This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding months is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French (1996) suggested 1.16% average return per month for the loser portfolio, 0.42 % per month for the winner portfolio and 0.74% per month (9.25% per year) for the loser minus winner portfolio).

Overall, these results show that the contrarian strategies' returns are positive. The loser portfolio outperforms the winner portfolio to generate positive average contrarian profits. I can establish that the most profitable strategy is the 60-month/48-month that does not skip a month (Table 4.2.12 Panel A); it yields and effective compounded return of 5.40% per year and when the strategy does skip a month the 60-month/48-month remains profitable and significant (Table 4.2.12 Panel B).

My findings are consistent between unbalanced sample and the established market sub-set as they suggest that the global contrarian strategy remains profitable after changing the sample size and constituents, and support De Bondt and Thaler's (1985) findings in US stock market.

They suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post- ranking period. These findings also support the initial tests and hypothesis that long-term contrarian strategies are profitable and indicate a better contrarian return than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable (5.60% per year) with earning above the risk-free rate; and that the long-term contrarian profits is not a robust phenomenon.

In addition, these findings are essential and deviate from other studies in the sense that I use quintiles portfolio to demonstrate how the portfolio size affect the contrarian return. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan's (2012), and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler’s (1985) and Fama and French’s (1996) studies were conducted on US stocks only.

5.3.2.3 Contrarian Returns with Quintiles Portfolio since Globalisations 1994-2014

I consider alternative set of contrarian portfolios, which are formed on the 1994-2014 subsamples (47 countries), given that, since MSCI launched the Emerging Market Index in 1988 it consisted of just 10 countries representing less than 1% of world market capitalization. From 1994 to 2014 the MSCI Emerging Market Index consist of 23 countries representing 10% of world market capitalization. The Index is now available for a number of regions, market segments or sizes and covers approximately 85% of the free float-adjusted market capitalization each of the 23 countries.

. At 't' I buy the winner countries and sell the loser countries. The winners and the losers’ portfolios are constructed based on their past performances. I use 3 different formation periods 'J' and 3 different holding periods 'K', where J equals 36, 48, and 60 months and K equals 36, 48, and 60 months as indicated in Table 4.2.13. Thus, I have 9 strategies in total. The contrarian portfolios in Table 4.2.13 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.13 Panel B. The average monthly returns of the winners and the losers’ portfolio are indicated in the table the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1994 to January 2014.

[Insert Table 2.13 Here]

In table 4.2.13., my attempt to examine the contrarian strategies on the stock market indices of 47 counties for 1994 to 2014, which include the global finance crisis 2007-2008 shows that the contrarian strategies remain profitable on average but none of the strategies' return is significant. The most successful contrarian strategy selects stocks based on their previous performances over 60 months and then holds the portfolio for the next 48 months. This strategy yields 0.59% per month (7.20% per year) with a t-statistic of 1.61 and a p-value of 0.25 (Table 4.2.13 Panel A).

Examining whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period, it yields 0.63% per month (7.85% per year) with a t-statistic of 2.06 and a p-value of 0.01 (Table 4.2.13 Panel B) which appears to be not significant and inconsistent with the overall findings. This is in line with the initial findings by Fama and French (1996) that suggested that when the preceding months are included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or 9.2504 per year for the loser minus winner portfolio).

This also indicates that, even though different market conditions and different periods exhibit contrarian profit, this return vary with the study time horizon, which may arise in the period post-globalisation as the evidences suggest here. However, I argue that the fact that these results are less significant can be due to the small number of observations generated with non-overlapping approach, as I do not have much power to detect the departure from zero. Therefore, I will not be quick to throw out the strategies, which are not significant or get too enamoured with the ones that appear significant.

Overall, the results in Table 4.2.13 validate the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They are consistent with other such as De Bondt and Thaler (1985) in US stock market that suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post-ranking period. They also indicate a better contrarian return than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable (5.60 per year) with earning above the risk free rate; and that the long-term contrarian profits is not a robust phenomenon internationally. My findings also present better return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47 per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years.

However, this thesis deviates from other studies in the sense that I use quintiles portfolio to demonstrate how the portfolio size affect the contrarian return. The effective yearly returns are calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. The findings are complementary given that Jordan (2012), and De Bondt and Thaler (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.3.2.4 Contrarian Returns with Quintiles Portfolios in Developed Market

I assess the contribution of the developed countries on global contrarian strategies, since the contrarian profit may differ from developed to emerging countries. I implement the contrarian strategy with quintile portfolios on the developed countries subsample (23 countries) over 1969-2014. At `t' I buy the winner countries and sell the loser countries. The winners and the losers' portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 as indicated in Table 4.2.14 below; this give a total of 9 strategies. The contrarian portfolios in Table 4.2.14 panel A are formed immediately after the formation period, but I also examine a second set of 16 momentum strategies that skip a month between the formation and the holding period as indicated in Table 4.2.14 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in, the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.14 Here]

The results in Table 4.2.14 show that the contrarian strategies' returns are profitable in developed countries, given that 8 strategies are significant. The most successful contrarian strategy selects indices based on their previous performances over 60 months and then holds them for the next 48 months. This strategy yields 0.58% per month (7.12% per year) with a t-statistic of 5.65 and a p-value of 0.00 when there is not time lag between the formation period and the holding period (Table 4.2.14 Panel A).

Testing out whether skipping a time lag is beneficial, I find that, skipping a month between the formation and the holding period improve the 60-month/48-month strategy performance as the equivalent holding period returns are slightly lower. It yields 0.56% per month (6.94% per year) with a t-statistic of 6.85 and a p-value of 0.00 (Table 4.2.14 Panel B). This contradicts the initial findings by Fama and French (1996) that suggested that, when the preceding months are included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points greater returns given that Fama and French suggested 1.16% average return per month for the loser portfolio, 0.42 % per month for the winner portfolio and 0.74% per month (9.25% per year) for the loser minus winner portfolio).

I suggest that the contrarian strategies are profitable internationally with respect to the time horizon and the length of the formation and the holding period. I establish that the most profitable strategy is the 60-month/48-month that does not skip a month; it generates an effective compounded return of 7.12% per year (Table 4.2.14 Panel A). My findings endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47 per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years.

Additionally, these findings are essential and deviate from other studies in the sense that I use quintiles portfolio to demonstrate how the portfolio size affect the contrarian return. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan's (2012) and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.3.2.5 Contrarian Return with Quintiles Portfolios in Emerging Market

Given that contrarian strategies are significantly profitable in the full sample and, on average, positive in different period, I will expect the contrarian strategies to be profitable in emerging market. It is understandable that there may be serious concern over the fact that emerging market might be on average illiquid and unstable and seriously segmented (Chan, et al., 2000) but this analysis is more interested in the practicality of the contrarian strategies than the market condition. To test the sensitivity of the contrarian strategies with quintile portfolios on the emerging market, I implement the contrarian strategies on the emerging market subsample (December 1987 to January 2014) given that the first emerging market enters the sample in December 1987.

At 't' I buy the loser countries and sell the winner countries. The winners and the losers' portfolios are constructed based on their past performances. I use 3 different formation periods 'J' and 3 different holding periods 'K', where 'J' equals 36, 48, and 60 months and 'K' equals 36, 48, and 60 months as indicated in Table 4.2.15 below. This gives a total of 9 strategies. The contrarian portfolios in Table 4.2.15 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.15 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the table, the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1987 to January 2014.

[Insert Table 4.2.15 Here]

The contrarian strategies result on emerging countries are reported in Table 4.2.15. By comparison, to those of the full sample and the developed countries, the contrarian strategies in emerging countries appear to generate positive returns, on average. 8 out of 9 strategies generate positive return for the contrarian strategies without a month lag and 8 out of 9 strategies generate positive return for the contrarian strategies with a month lag but none is significant. The 60-month/60-month is the most profitable strategy it yields 0.65% per month (8.13% per year) with a t-statistic of 3.84, and a p-value of 0.03 (Table 4.2.15 Panel A).

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period did not improve the 60-month/60-month strategy performance as the equivalent holding period returns are slightly lower. When there is not time lag between the portfolio formation period and the holding period, it yields a considerably but less return of 0.55% per month (6.80% per year) with a t-statistic of 3.60 and a p-value of 0.04 (Table 4.2.15 panel B) which is significant at 5% level. This indicates that, even though different market conditions and different time periods exhibit contrarian profit, the highest return observed in emerging market as the evidences suggest is 8.14% per year with the 60-month/ 60-month with a time lag. This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding months/year is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or 9.25 per year for the loser minus winner portfolio).

Overall, the results in Table 4.2.15 validate the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They are consistent with other studies such as De Bondt and Thaler (1985) in US stock market that suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post-ranking period. They indicate a better contrarian return than Jordan’s (2012) study that suggested that contrarian strategies are internationally profitable (5.60% per year) with earning above the risk-free rate; and that the long-term contrarian profits is not a robust phenomenon internationally.

My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47% per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years.

However, these findings deviate from other studies in the sense that I use quintiles portfolio to demonstrate how the portfolio size affect the contrarian return. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan’s (2012) and De Bondt and Thaler’s (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.3.2.6 Summary

I examined the profitability of the contrarian strategies with quintile portfolios based on past returns of countries indices in international equity markets. My findings indicate evidences of contrarian profitability. The contrarian strategies have shown to be profitable on average over the full sample period, and the 60-month/48-month strategy generates the highest return with the whole sample period this strategy yield 0.71% per month (8.89% per year) with a t-statistic of 4.78 and a p-value of 0.00 (Table 4.2.11 Panel A). Evidences also indicate that the contrarian strategies are highly profitable in emerging countries and that developed countries' contribution are significant.

Even more interesting this study did not find evidence of return continuation among countries indices but I must point out that the evidences are in line with Jordan's (2012) study that suggested that contrarian strategies are internationally profitable and that the long-term contrarian profits is not a robust phenomenon. I also emphasise the point that investors may earn extra returns over time by investing internationally as the global contrarian strategy generates a return slightly higher than the 8% per annum as reported by De Bondt and Thaler (1985). A direct implication of these results is that international investors will be able to beat the market using common investment strategy such as the global momentum with overlapping portfolios.

To increase the power of the test, I also perform similar analysis on contrarian strategies with overlapping portfolios where, contrarian deciles portfolio in any month holds indices ranked in the deciles in any of the previous J months.

5.3.3 Contrarian Strategies with Overlapping Portfolios Quintile Portfolios

5.3.4 Introduction

In this section, I examine whether contrarian strategies earn significant return after increasing the power of the test. I construct overlapping contrarian quintiles portfolios that in any particular month holds stocks ranked in those quintiles in any of the previous H ranking months. In sequence with the initial findings by Fama and French (1996) that suggested that when the preceding months are included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners do. I also test the contrarian strategies that sky a month between the formation and the holding periods. I examine the contrarian strategies profitability in the full sample 1969-2014 and in different market states.

5.3.4.1 Contrarian Strategies for International Investors: Full Sample 1969-2014

I start the analysis by implementing the basic contrarian strategies with overlapping quintile portfolios first, on the entire times series data. In period `t' I buy the losers countries and sell the winners countries' indices. The winners and the losers' portfolios are constructed based on their past performances. I use three different formation periods 'F' and three different holding periods 'H', where 'F' equals 36, 48, and 60 months, and 'K' equals 36, 48, and 60 months as indicated in Table 4.2.16 below, this give a total of 9 strategies. The contrarian portfolios in panel A are formed immediately after the formation period Table 4.2.16 Panel A, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.16 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the table the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.16 Here]

Table 4.2.16 reports the results for the whole sample period, the winner, the loser, and the contrarian portfolio (loser-winner) returns are reported for the 18 strategies. All the contrarian strategies' returns are positive; 13 strategies are significant. The most successful contrarian strategy selects stocks based on their previous performances over 60 months and then holds the portfolio for the next 48 months. This strategy yields 0.71% per month (8.89% per year) with a t-statistic of 4.77 and a p-value of 0.20 when there is not time lag between the portfolio formation period and the holding period (Table 4.2.16 Panel A).

Investigating whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period did not improve strategy return. The 60-month/48-month strategy yields 0.51% per month (6.28% per year) with a t-statistic of 15.91 and a p-value of 0.00 (Table 4.2.16 panel B) when there is a time lag between the portfolio formation period and the holding period.

Given that the contrarian strategies' returns are positive in most of the case and that the returns are highly significant in most cases, I suggest that the contrarian strategies are on average profitable internationally when using overlapping quintile portfolios of stock indices and that the loser portfolio outperforms the winner portfolio to generate positive average contrarian profits. I establish that, the most profitable strategy is the 60-month/48-month, when the strategy does not skip a month (Table 4.2.16 Panel A). It yields and effective compounded return of 8.89% per year but investor can also earn a return in the magnitude of 10.28% per year with the 48-month/60-month strategy that skip a month lag, which is different and more profitable than the 48-month/60-month documented with the non-overlapping strategies Table 4.2.16 Panel A (8.89% per year).

These findings are central since they indicate that skipping a month lag between the formation and holding period do not always increase the quintile portfolios returns and using overlapping portfolio do improve the test on return reversal, but lessen the portfolio return. These findings have another outstanding aspect as they point out the fact that overlapping quintile portfolio might be more profitable than deciles portfolio. The returns remain comparatively greater than De Bondt and Thaler’s (1985) proposed return of 8% per year and Jordan’s (2012) study that suggested that contrarian strategies are internationally profitable and yields 5.60% per year over three years; conversely the result with overlapping portfolio indicate signs of strength of the long-term contrarian phenomenon internationally.

Nonetheless, these findings are essential as I use quintiles portfolio to demonstrate how the portfolio size affect the contrarian return. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan’s (2012), and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler’s (1985) and Fama and French’s (1996) studies were conducted on US stocks only.

5.3.4.2 Contrarian Returns with Quintiles Portfolio in Established Markets

I turn to a more stable sample period, I implement the contrarian strategies with overlapping quintile portfolios in the 1969-2014 subsamples, where all countries' indices start and end in the same date to avoid any blunder, which may occur from non-synchronized starting dates among countries' indices. To implement the basic contrarian strategies on the established market subset 1969-2014 period (18 countries) at `t', I buy the loser countries and sell the winner countries. The winners and the losers' portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 for different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.17 below, this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.17 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.17 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the table below. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

[Insert Table 4.2.17 Here]

Table 4.2.17 reports the results for the whole sample period on established markets, the winner, the loser, and the contrarian portfolio (loser-winner) returns are reported for the 18 strategies. All the contrarian strategies' returns are positive. The most successful contrarian strategy selects stocks based on their previous performances over 60 months and then holds the portfolio for the next 36 months. This strategy yields 0.34% per month (4.13% per year) with a t-statistic of 9.93 and a p-value of 0.00 (Table 4.2.17 Panel A) when there is not time lag between the portfolio formation period and the holding period.

Examining whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period improve the 60-month/36-month strategy performance as the equivalent holding period returns are slightly greater, it yields 0.35% per month (4.21% per year) with a t-statistic of 10.30 and a p-value of 0.00 (Table 4.2.17 panel B). When there is a month lag between the formation period and the holding period, the 48-month formation period. It remains profitable regardless of the holding period for both set of strategies. This is in line with the initial findings by Fama and French (1996) that suggested that when the preceding months is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to greater returns given that Fama and French (1996) suggested 1.16% average return per month for the loser portfolio, 0.42 % per month for the winner portfolio and 0.74% per month (9.25% per year) for the loser minus winner portfolio.

Given that the contrarian strategies returns are positive in most of the strategies and that the returns are highly significant in all cases, I may suggest that the contrarian strategies are on average profitable for established market, and that the loser portfolio outperforms the winner portfolio to generate positive average contrarian profits. I then establish that the most profitable strategy is the 60-month/36-month that does not skip a month (Table 4.2.17 Panel). The returns here are significantly lower than the 8% return per year suggested by De Bondt and Thaler (1985). The results here emphasise the fact that contrarian returns are lower if investor apply the standard contrarian strategy with overlapping portfolios.

Although, these findings are critical in the sense that I use quintiles portfolio to demonstrate how the portfolio size affect the contrarian return. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan’s (2012) and De Bondt and Thaler’s (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.3.4.3 Contrarian Returns with overlapping quintiles portfolios since Globalisation

To ascertain whether the contrarian strategies with overlapping quintile portfolios remain profitable after 1994, I examine alternative sets of contrarian portfolio, which are formed on the 1994-2014 subsamples (47 countries). At `t' I buy the losers’ countries indices and sell the winners’ countries indices. The winners and the losers' portfolios are constructed based on their past performances. I use three different formation periods 'F' and three different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.18 below, and this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.18 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period Table 4.2.18 Panel B. The average monthly returns of the winners and the losers’ portfolio are indicated in the table the t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from January 1994 to January 2014.

[Insert Table 4.2.18 Here]

Table 4.2.18 shows the results of the contrarian strategies implemented on the stock market indices of 47 countries for 1994 to 2014, which include the global finance crisis 2007-2008. These results show that the contrarian strategies' returns are positive in most of the cases, 6 strategies are significant. The most successful contrarian strategy selects stocks based on their previous performances over 60 months and then holds the portfolio for the next 36 months. This strategy yields 0.36% per month (4.40 per year) with a t-statistic of 4.44 and a p-value of 0.00 (Table 4.2.18 Panel A).

Testing out whether skipping a time lag is beneficial, I find that skipping a month between the formation and the holding period improve the 60-month/36-month strategy performance. The equivalent holding period returns are slightly greater 0.37% per month (4.45% per year) with a t-statistic of 4.66 and a p-value of 0.00 (Table 4.2.18 Panel B) when there is a time lag between the formation and the holding period. This indicates that even with the impact of the financial crisis and the globalization, the contrarian strategies can still be profitable.

In addition, these findings are essential and deviate from other studies in the sense that I use quintiles portfolio to demonstrate how the portfolio size affect the contrarian return. The effective yearly return is calculated using the monthly-compounded return over 12 months rather than the arithmetic average of percentage return. They are also complementary given that Jordan's (2012) and De Bondt and Thaler's (1985) study did not look at the contrarian phenomenon as a generalized phenomenon. Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler (1985) and Fama and French (1996) studies were conducted on US stocks only.

5.3.4.4 Contrarian Return with Overlapping Quintiles Portfolios in Developed Countries

To better understand which of the developed and the emerging market may be driving the return on the global contrarian strategies, I implement the contrarian strategy with overlapping portfolio on the developed countries subsample (23 countries) over 1969-2014. At `t' I buy the loser countries and sell the winner countries. The winners and the loser's portfolios are constructed based on their past performances. I use 3 different formation periods 'F' and 3 different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.19 below, this give a total of 9 strategies. The contrarian portfolios in Table 4.2.19 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.19 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in the table below the t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.2.19 Here]

Table 4.2.19 reports the contrarian results of the developed countries for the whole sample period, the winner, the loser, and the contrarian portfolio (loser-winner) returns are reported for the 18 strategies. The results in developed countries indicate that all the contrarian strategies return are positive and significant (9 out of 9 strategies) for the strategies without time lag and (9 out of 9 strategies) for the strategies with a month lag. The most successful contrarian strategy selects stocks based on their previous performances over 60 months and then holds the portfolio for the next 36 months. This strategy yields 0.45% per month (5.54% per year) with a t-statistic of 12.11 and a p-value of 0.00 (Table 4.2.19 Panel A), when there is not time lag between the portfolio formation period and the holding period.

I also find that skipping a month between the formation and the holding period improve the 60-month/36-month strategy performance as the equivalent holding period returns are slightly greater. It yields 0.46% per month (5.70% per year) with a t-statistic of 12.56 and a p-value of 0.00 (Table 4.2.19 Panel B), when there is a month lag between the formation period and the holding period. This is in line with the initial findings by Fama and French (1996) that suggested that, when the preceding month is included in the test, short-term continuation tends to offset long-term reversal and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to a greater return given that Fama and French suggested 1.16% average return per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month (9.25% per year) for the loser minus winner portfolio.

Since the contrarian strategies returns are positive in most of the strategies and that the returns are highly significant. I may suggest that the contrarian strategies are on average profitable internationally for developed countries, that the loser portfolio outperforms the winner portfolio to generate positive average contrarian effective return of 5.69% per year. This results support my initial findings that, the contrarian strategies are consistently profitable internationally with overlapping quintile portfolio. In line with De Bondt and Thaler's (1985) findings that suggested 8% per year contrarian return in the US market and

Jordan's study which was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top. However, both study did not look at the contrarian phenomenon as a generalized phenomenon.

5.3.4.5 Contrarian Return with Overlapping Quintiles Portfolios in Emerging Market

I re-examined the contrarian strategies with quintile portfolio in the same manner as I did in developed countries, I implement the strategies on the emerging market subsample (December 1987 to January 2014) given that the first emerging market enters the sample in December 1987.At `t' I buy the loser countries and sell the winner countries. The winners and the losers' portfolios are constructed based on their past performances. I use three different formation periods 'F' and three different holding periods 'H', where 'F' equals 36, 48, and 60 months and 'H' equals 36, 48, and 60 months as indicated in Table 4.2.20 below and this gives a total of 9 strategies. The contrarian portfolios in Table 4.2.20 panel A are formed immediately after the formation period, but I also examine a second set of 9 contrarian strategies that skip a month between the formation and the holding period as indicated in Table 4.2.20 Panel B. The average monthly returns of the winners and the losers' portfolio are indicated in Table 4.2.20 below. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1987 to January 2014.

[Insert Table 4.2.20 Here]

Table 4.2.20 reports the contrarian strategies results on emerging countries. By comparison to those of the full sample and the developed countries, the contrarian strategies in emerging countries are positives and significant on average. 9 out of 9 strategies generate positive return without a time lag and 9 out of 9 strategies generate positive return for the contrarian strategies with a month lag. The 48-month/36-month is the most profitable strategy, it yields about 0.73% per month with a t-statistic of 10.59, and a p-value of 0.00 (Table 4.2.20 Panel A), when there is not time lag between the portfolio formation period and the holding period.

I also find that skipping a month between the formation and the holding period improve the 48-month/36-month strategy performance. The equivalent holding period returns are slightly lower 0.71% per month with a t-statistic of 10.19 and a p-value of 0.00 (Table 4.20 panel B) when there is a month lag between the formation period and the holding period. This contradicts the initial findings by Fama and French (1996) that suggested that when the preceding month is included in the test, short-term continuation tends to offset long-term reversal, and past losers have lower future returns than past winners for portfolios formed with up to four years past returns. It also points to a greater return than Fama and French (1996) propose returns of 1.16% per month for the loser portfolio and 0.42 % per month for the winner portfolio (0.74% per month or (9.25% per year) for the loser minus winner portfolio.

Given that, the contrarian strategies' returns are positive in all the strategies I may suggest that the contrarian strategies are on average more and consistently profitable for emerging countries with overlapping portfolio. The loser portfolios outperform the winner portfolio to generate an effective compounded contrarian return of 9.13% per year, but contrary to the developed and the whole sample analysis the 48-month/36-month generate the highest return.

Overall, the results in Table 4.2.20 validate the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They are consistent with studies such as De Bondt and Thaler (1985) in US stock market that suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post-ranking period. They also indicate a better contrarian return than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable (5.60% per year) with earning above the risk-free rate.

I using quintiles portfolio I demonstrate how the portfolio size affect the contrarian return which deviate from Jordan's (2012) and De Bondt and Thaler's (1985) given that they study did not look at the contrarian phenomenon as a generalized phenomenon. More importantly do not enphasis on the portfolios size. It is also essential to reiterate that Jordan's study was initially done on individual market index where stocks are sorted by their past 3-year buy-and-hold return and the losers and winners represented respectively the 25% bottom and 25% top, while De Bondt and Thaler's (1985) and Fama and French's (1996) studies were conducted on US stocks only.

5.3.4.6 Summary

I examined the profitability of the contrarian strategies using deciles and quintiles portfolios based on past returns of countries' indices in international equity markets. Taken individually the results with the non-overlapping decile portfolios validate the initial tests hypothesis that long-term contrarian strategies are profitable internationally. They indicate evidences of consistence contrarian profitability where the 48-month/60-month strategy generates a return as high 0.83% per month (10.40% per year) with the whole sample period. However, the contrarian returns tend to rise considerably when the strategy skips a time lag between the portfolio formation period and the holding period, the overall result is not exceptionally significant.

Evidences also indicate that; the contrarian strategies are highly profitable in emerging with a return as high as 1.37% per month (17.70% per year) with the 60-month/ 48-month strategy. The developed countries' contributions are less significant, still a consistent contrarian return of 0.93% per month (11.72% per year) could be observed in developed countries with the 60-month/48-month strategy when the strategy skips a time lag between the portfolio formation period and the holding period.

My findings also indicate that, contrarian strategies with non-overlapping quintile portfolios are profitable over the full sample period. The 48-month/60-month strategy generates a return as high as 0.71% per month (8.89% per year). These returns are not statistically significant on the average and vary considerably from one market condition to another. More importantly, the contrarian strategies remain on the average profitable and significant in the period post-1994. The contrarian strategies remain profitable in emerging countries, but it is important to reiterate that on average they are more statistically significant with overlapping portfolios than the non-overlapping portfolios.

Taken as a whole these evidences indicate that the contrarian strategies' yield on average higher return with the non-overlapping portfolio than the equivalent overlapping approaches for both deciles and quintiles portfolios and that the contrarian strategy are on the average considerably greater with deciles portfolios than quintiles portfolios.

These results demonstrate that, the contrarian strategies are consistently profitable internationally with both quintile and decile portfolio. They point to significantly higher returns compared to De Bondt and Thaler's (1985) study suggested that 3 to 5 years after a past performance based portfolio formation, losers' portfolios outperformed winners' portfolios by approximately 25% over 3 years and 8% annually for 5 years post-ranking period. They indicate a better contrarian return than Jordan's (2012) study that suggested that contrarian strategies are internationally profitable (5.60% per year) with earning above the risk-free rate; and that the long-term contrarian profits is not a robust phenomenon internationally

My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47 per year) in emerging market, and Richards's (1996) study that found 6.60% per year for 3 years holding period and 5.80% per year over 4 years.

So far, I have argued that contrarian strategy is on the average profitable in international market. However, from the theoretical point of view, there is reason to believe that contrarian trading is a risky process and therefore that it is only of limited effectiveness. In principle, any example of persistent mispricing is evidence of limited arbitrage (Barberis and Thaler, 2002). The problem is that while the profitability of the contrarian strategy could be interpreted as price deviation from fundamental value it required consistent analysis in different market states and time periods to provide evidence of inefficiency. Because the world has just experienced one of its worst bear markets since the great Depression, there is an even greater need to start studying contrarian performance in the past bull and bear markets to make long-term decisions about investing using the global contrarian strategy. By providing information on contrarian, performance over different market state and different period, investors can define a model of contrarian equilibrium with endogenous trading across different state of the economy based on their preference.

5.3.5 Contrarian Returns Following Bear and Bull Phases

To examine the extent to which contrarian performances are associated to the bull and bear phases I refer to the popular agreement that the bull markets are associated with persistently rising share prices, but it can be noted that there still does not exist a consensus as to the objective definition of a bull market (Gonzalez et al. 2005). This thesis utilizes a formal procedure to identify bear and bull phases in stock indices' series that indicate the meaningful time intervals corresponding to a bear or a bull phase. It then examines the magnitude of the contrarian profitability achieved following bull and bear markets using data from the MSCI World index, as it appears to be a good representation of the world equity markets.

Testing out whether the global contrarian strategy generates superior contrarian return following stock market state, this study examines how the performances of the optimum strategy 48-month/60-month are associated with different phases of the world equity market, because the bull and the bear markets are broad market movements and would best capture the impact of market state changes.

The bull and bear phases are defined based on the global market return (MSCI World Index) over various time horizons, and it is expected that the global momentum should earn more pronounced return following down markets. The sample period is divided into bear and bull phase following Siganos and Chelley-Steeley (2006) approach. This paper defines bull phase as the period when the market return is positive for 3, 6, 9 and 12 months before the test period, and the bear state when the market return is negative for 3, 6, 9 and 12 months before the test and the results are shown in the Table 21 below.

[Insert Table 4.2.21 Here]

Table 4.2.21 presents the bear and bull market performances between December 1969 and January 2014, and the average contrarian profits accomplished after bull and bear markets, and the 12 months' market performance of the defined phases. This study noted that the longer the duration employed to define the up and down states the smaller the number of bear and bull periods. The lowest the duration used to describe the down market generates the strongest the negative market return that arises in bear phase. The optimum contrarian strategy 48-month/60-month is associated with the 12-month duration where the bull market performance (-1.43%) is relatively higher than the equivalent bear market (1.09%) in absolute value and the bear frequency (25%) is the lowest while the bull frequency (75%) is the highest compared to another horizon (3, 6 and 9). These observations suggest that the contrarian strategy generates superior return when the market rises slowly in bull and/or fall quickly in bear phase as the high market performance indicates a high and positive change in Indices prices and inversely. Therefore, a forecast of a slow recovery could bike seen as good news for contrarian investors while the inverse is not necessary a bad news for global contrarian investors comparatively. These results are in line with Klein's (2001) study that suggested that higher price restores equilibrium because it induces more selling by investors who are locked into a given security, and causes less buying by investors who wish to acquire exposure to the risk characteristics of this security. The higher equilibrium price implies that expected returns in subsequent periods are lower. However, this study reiterates that the size of contrarian return will depend upon speed of the rising and the falling market phases.

To restate, the primary goal of this study is to test whether the contrarian strategy is profitable internationally and whether prices reversal effect is predictive. In other words, as I focus on indices that go through more extreme return experiences during the formation period, subsequent price reversals should be pronounced over the test period. De Bondt and Thaler

(1985) suggested that, an easy way to generate extreme observations for any given formation period is to compare the test period performances over time. Following this view, I examine whether the cumulative average return for various formation period (36, 48 and 60-month) grows consistently larger over the test period. I then identified when the subsequent reversal occurs during the test period, to consider whether there is a pattern among contrarian returns with different formation period over different holding periods (1, 3, 6, 12, 24, 36, and 60-month) as indicated in Table 4.2.22.

[Insert Table 4.2.22 Here]

Table 4.2.22 shows that none or little significant reversal pattern for formation period 36, 48 and 60-month in the first 2 years. As the cumulative average returns of holding periods as short as 2 year-period do not always grow larger. The results also indicate sign of growing return reversal pattern in period after 3 years for the 36 and 48-month formation periods but the 60-month formation period shows opposite effect as the cumulative average returns of the holding period after 3 years plunge lower. These results are broadly consistent with the prediction of the return reversal in international equity market. However, several aspects of the contrarian return internationally remain without adequate explanation.

[Insert Figure 2 Here]

In addition, Figure 25 also indicates that as investors move toward periods with the lowest past market performance the contrarian become highly profitable with all holding periods. The 48-month formation period yields negative payoffs at the end of every good market state with the 1-month holding period while the return with the 60-month holding period are positive regardless of the sub-period. Still most of the returns are realized by selecting stock based on their performances over previous 48 months and hold for horizon up to 60 months are positive. Furthermore, if the reversal effect survives the globalisation impact we should be able to detect this following a longitudinal analysis of the sub-period average contrarian return. Figure 2 also indicates that significant return come from period after 1994; this shows that the integration of equity markets together with the international correlation among markets do not synchronized the prices reversal effect around the world.

Overall these findings are in line with the thought that indicated that when past movement of the market has upward movement, most of the share prices have achieved gain, and investors become optimistic for the future. The stronger the achieved lagged market gains, the more optimism appears among traders, generating increasing reversal effect (Siganos and Chelley-Steley, 2006). Another possible explanation of the contrarian superior return is that; it is relatively less difficult to account for bad news than good news. This implies that investors react to bad news, by massive selling, thus overestimating bad news impact on prices, and subsequently revise their expectation and start buying back stock or invest after periods of bad news. This explanation means investors are not rational, that information is not always included in share prices and that it takes time to be fully included on the stock price, given that investors take time to reflect on bad news' impact.

5.3.6 Conclusion

I examine the profitability of the contrarian strategy internationally while considering the contrarian strategy as a global phenomenon over the period 1969 to 2014 and study the effect of the globalisation, and the change on the global financial market as I progress over time on the contrarian strategy profitability. I also take a step towards linking the global contrarian profitability to different phases (Bear and bull phases), and different period. Which in turn, helps enhance my understanding of the factors that drive contrarian return across different period and different market states. My analysis takes on particular significance given the association between lagged market movement (share prices) and investor's optimism that appears among traders, generating increasing reversal effect (Siganos and Chelley-Steley, 2006), and also has direct implication for predicting and controlling trading costs associated with asset allocation strategies.

Some of the findings are as follows: The contrarian strategies are highly profitable with the full sample 0.83 per month (10.40 per year). The contrarian strategies generate in emerging countries return as high as 1.37% per month (17.70% per year) with the 60-month/ 48-month strategy. The developed countries' contributions are less significant, still a consistent contrarian return of 0.93% per month (11.72% per year) could be observed in developed countries with the 60-month/48-month strategy when the strategy skips a time lag between the portfolio formation period and the holding period.

My findings also indicate that, contrarian strategies with non-overlapping quintile portfolios are profitable over the full sample period. The 48-month/60-month strategy generates a return as high as 0.71 per month (8.89% per year). These returns are not statistically significant on the average and vary considerably from one market condition to another. More importantly, the contrarian strategies remain on the average profitable and significant in the period post-

1994 but are not particularly distinctive, which imply that the reversal effect survive the globalisation impact and indicate that the integration of equity markets together with the international correlation among markets do not synchronized the prices reversal effect around the world given that.

Moreover, the contrarian strategies remain profitable in emerging countries, but it is important to reiterate that on average they are more statistically significant with overlapping portfolios than the non-overlapping portfolios.

Taken as a whole these evidences indicate that the contrarian strategies' yield on average higher with the non-overlapping portfolio than the equivalent overlapping approaches for both deciles and quintiles portfolios and that the contrarian strategy are on the average considerably greater with deciles portfolios than quintiles portfolios. A direct implication of these results is that international investors might be able to beat the market using common investment strategy such as the global contrarian.

Furthermore, there is not sign of consistent and predictable seasonal contrarian pattern over consecutive sub period with test horizons as long as 2 years. As the cumulative average returns of holding periods as short as 2 year-period do not always grow larger. The results also indicate sign of growing return reversal pattern in period after 3 years for the 36 and 48-month formation periods but the 60-month formation period shows opposite effect as the cumulative average returns of the holding period after 3 years plunge lower.

My work suggests a lush research agenda given that little theoretical work has been done on time-series movement of return reversal internationally, and there is no theory that link the contrarian strategy taken as global and generalized phenomenon, and the change in international equity market state. This implies that a model of contrarian equilibrium with endogenous trading across different market state would be desirable. I expect this work to serve and inspire research in these areas as it reiterates that the size of contrarian return will depend upon speed of the rising and the falling market phases.

Chapter 6: Impact of the Risks Factors on Global Momentum and Contrarian Strategies

6.1 Introduction

In this Chapter I examine for the first time the role of global risk factors in explaining profitability of the global momentum and contrarian strategies, I start by examining whether the momentum strategies earn significant return after adjusting for global risks given that, the risk explanation of the momentum strategies could be seen as validation test for the Efficient Market Hypothesis. I then examine whether the contrarian strategies earn significant profit after adjusting for global risk in line with Chan's (1988) suggestion that the contrarian profits are just normal compensation for investors bearing extra risk.

The results indicate a strong relation between variations in macroeconomic factor notably world industrial production and the adjusted momentum return. The evidence is that industrial production tends to contribute significantly in explaining the momentum return with a coefficient of 1.05, a t-statistic of 3.46 and a P-value of 0.00 when I control for global risks factors. This reveals that change in economy growth or in industries' output strongly affects the momentum profit, and indicates the ability of global factor to explain the momentum profit. In line with Cochrane's (2011) suggestions that markets are integrated across both countries and assets. Moreover, I find no systematic relation between variation in macroeconomic factor and the contrarian profit. The evidence is that significant adjusted contrarian returns remains after controlling consecutively for Fama and French risks, market state factors, macroeconomic risk factor and the joint effect of global risk factors.

6.2 Global Risks Impact on Momentum Strategy Payoff

In this section, I examine more formally the effect of systematic variation in global risks factors on the strength of the global momentum performance following Jegadeesh and Titman (1993), I focus on momentum performance because the momentum phenomenon is an anomaly not explained by risk premium. If change in momentum reflects change in risk factors, I will expect a significant relation between momentum profits and change in risk factor, consequently, no significant abnormal return after controlling for global risk factors.

6.2.1 Effect of Fama and French risk on Momentum Profits

I start the analysis by implementing test on Fama and French risks. I consider the optimum strategy that generates the highest returns and remains profitable in every horizon (9-month/3-month). This strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months, based on overlapping portfolios. The choice of the overlapping approach is to avoid statistical error, which may occur due to limited number of observations. The returns are further adjusted by the Fama-French's three-factor model (see equation below). I also report the regression result for 6, 9 and 12 months holding period, in Table 4.3.1 below. The t-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

$$Mom_t = \alpha_0 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + e_t \quad (28)$$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, and SMB_t(small minus big) is returns to long-short portfolios constructed using size in US market. $R_M - R_F$ is the market premium and β the factors loading are the slopes in the times-series regression.

[Insert Table 4.3.1 Here]

As shown in Table 4.3.1 Panel A, the momentum strategies have positive and consistent adjusted returns (Alpha) with all holding periods. The optimum strategy 9-month/3-month retains abnormal return of about 0.90% per month with a t-statistic of 4.82 and a P-value of 0.000 after adjusting for Fama and French risk. For the findings to be consistent in any period, I expect the abnormal return to be unswerving and significant over time. The evidence in Table 4.3.1 Panel A is strongly consistent with this explanation given that the adjusted momentum returns remain for 6-month holding period (0.70% per month), 9-month (0.60% per month) and 12-month (0.30% per month). Of particular interest, the size of the abnormal return decrease when I increase the holding period with the lowest return of 0.30% per month observed with the 9-month/12-month strategy suggesting that this abnormal return may disappear in the long-run. More importantly, I find that these adjusted returns are highly significant.

The SMB tends to contribute gradually and significantly, in reducing the size of the abnormal return in the long-run but the SMB effect is slightly moderated as the time goes given that the coefficient rises but oscillates significantly between -0.106 and -0.092. The effect of the HML is also noticeable at 9-month horizon. This pattern of behaviour is robust in Table 4.3.1

Panel B with the Fama and French risks when I substitute the excess return based on the MSCI world index (MKTRF) with the excess return on the US market (ERM).

The findings indicate that the global momentum adjusted return is consistent and different from zero in all horizon even with estimation method such as OLS (Appendix C13) and Newey and West procedure (Appendix C1 and C2) rejecting the null hypothesis that Alpha is equal to zero at 1% significance level. All this suggests that investors may earn extra return for accepting the strategies. These findings strongly support the argument that Fama-French's three-factor model is well specified for momentum portfolio. Given that, the Fama and French's three factor model do not explain the momentum profit, at least for the short to medium term. These findings are in line with Chordia and Shivahumar's (2005) and Fama and French's (1996) studies that suggested that the short-term returns continuation are primarily attributable to cross-sectional variation in the exposure of momentum portfolios to the earning based factor.

6.2.2 Effect of Market State Factors on Momentum profits

Since the predictability of the momentum strategies payoff might be affected by market state risk factors, I use a variety of measure as proxies of the market risk factors (liquidity factor (LIQ), Default spread ((DS), the Term spread (TS) and the market return (MKT)), to examine the role of such factors on the momentum strategies. I regress the momentum returns on the lagged market state. This approach indicates that the momentum returns are further adjusted to market state risk. The results are reported in Table 4.3.2 the regression is written as follow.

$$Mom_t = \alpha_1 + \beta_1 LIQ_{t-1} + \beta_2 DS_{t-1} + \beta_3 TS_{t-1} + \beta_4 MSCIW_{t-1} + e_t \quad (29)$$

Where: LIQ_{t-1} is the liquidity factor, DS_{t-1} is the Default spread, TS is the Term spread, and MKT_{t-1} is the return on the MSCI world indices price level and represent price levels at time t-1, the t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.3.2]

Table 4.3.2 shows that the momentum strategy has a positive and consistent adjusted returns (Alpha) for holding periods up to 9-month. The optimum strategy 9-month/3-month retains abnormal return of about 1.2% per month with a t-statistic of (2.01) and a P-value of 0.045 after adjusting for market state risk. For the findings to be consistent in any period, I expect the market state factors to be constant and significant over time. The evidence in Table 4.3.2 is consistent with this explanation in the short term given that the adjusted momentum returns remain for 6-month holding period (1.0% per month), and 9-month (0.40% per month). Of particular interest, the size of the abnormal return also decreases when I increase the holding period with the lowest return of -0.10% observed with the 9-month/12-month strategy. This later adjusted return is also non-significant suggesting that this abnormal return may disappear in the long-run. More importantly, the market return shows a significant coefficient of -0.033 with a t-statistic of -2.07 indicating that the market tendency may reduce the momentum profit by -0.033 for every unit change in market return. This pattern of behaviour is consistent with market risk factor as shown with estimation approach such as OLS (Appendix C14) and the Newey West procedure (please see appendix C2 and C4) rejecting the null hypothesis that Alpha is equal to zero at 1% significance level. This finding is central given that the momentum returns also follow similar outline given that they rely on performance of the determinants of the market to move in the short run and reverse in the long term in conformity with the expected market risk premium. This is also consistent with the modern asset pricing theories that indicate the countercyclical price of risk (Zang, 2005).

6.2.3 Effect of macroeconomic factor on momentum profits

The momentum strategies profit could reflect mispricing of macroeconomic variables (Chordia and Shivakumar, 2005) this implies that momentum profit would again be related to macroeconomic conditions. I test this assertion by regressing the momentum returns on the lagged macroeconomic variables. I also account for time variation through time dummy. I report the regression parameters result for each explanatory variable in Table 4.3.3. This table shows the result of the following monthly time-series regression.

(30) $$Mom_t = \alpha_2 + \beta_1 \Delta OP_{t-1} + \beta_3 WVOL_{t-1} + \beta_4 \Delta IP_{t-1} + e_t$$

Where: ΔOP_{t-1}, is the Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1 based on the MSCI world indices price level, and ΔIP_{T-1} is the monthly value of the US Industrial production at time t-1. I estimate the regression using the GMM model. The test statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.3.3 Here]

As for the intercepts (Alphas) that measure the abnormal profits of the global momentum strategy after adjusting for the exposure to market state factors, evidences show that none of the abnormal return is significant. The momentum strategy has inconsistent adjusted returns for all holding periods after adjusting for risk; this includes the optimum strategy 9-month/3-

month. Of particular interest, I find that industrial production tends to contribute significantly in explaining the momentum return with a coefficient of 0.989, a t-statistic of 3.18 and a P-value of 0.001 for the optimum strategy (9-month/3-month), this effect persists for horizon up to 6-month but diminishes considerably at 9-month and before disappearing at 12-month. The contribution of the market volatility is also noticeable for 6-month holding period. This result indicates that change in economy growth or in industry output strongly explains the momentum profit in the short to medium term, and indicates the ability of global factor to explain the momentum profit, for example all adjusted returns measured by Alpha become insignificant after adjusting the momentum return for macroeconomic risks, in line with Cochrane (2011) suggestions market are integrated across both countries and assets. This pattern of behaviour is consistent as shown with different estimation approach such as OLS (Appendix C15) and Newey and West procedure (please see appendix C5 and C6) rejecting the null hypothesis that Alpha is equal to zero at 1% significance level. One possible interpretation of this result is that there is a strong relation between change in economic state variable and the global momentum. These findings reject Liew and Vassala's (2000); Griffin et al. (2003) study that found that internationally macroeconomic risk cannot explain momentum profits. They contradict Jegadeesh and Titman's (1993) contention that irrational agents drive the momentum returns and raise the question to whether the momentum strategy taken as global coordinated and generalized strategy could have different feature.

Objectively these factors may not solely influence momentum profit. I therefore account for the joint impact of Fama and French risk, market state and macroeconomic risk factors on the global momentum profit.

6.2.4 Effect of Global Risk Factor on the Global Momentum Profit

To examine whether jointly Fama and French risks factors, market state factor, and macroeconomic risks factors affect the momentum payoff. I follow Avramov et al. (2015) approach. My examination is based on the following time-series regression specification. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model 3. I report the regression parameters result for each explanatory variable in Table 4.3.4.

(31) $Mom_t = \alpha_3 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_{10}\Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12}\Delta IP_{t-1} + e_t$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices price level and represent price levels at time t-1, ΔOP_{t-1} is the percent change of monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the percent change of monthly value of the US Industrial production at time t-1. The results are reported in Table 4.3.4. The test statistics are reported in the parentheses and the P-values are reported next.

[Insert Table 4.3.4 Here]

Table 4.3.4 reports the test results of the momentum portfolio returns regressed on the global risk factors. I begin the estimation with Fama and French risk factors, and then include market state and macroeconomic factors consecutively. Table 4.3.4 Models 1 and 2 show significant adjusted momentum returns of the momentum portfolio after adjusting the momentum return consecutively to the Fama and French risks and the market state factors. The coefficients associated with the macroeconomic risk factors are not particularly significant. More importantly, I find that industrial production contributes significantly in explaining the momentum return with a coefficient of 1.011, a t-statistic of 3.27 and a P-value of 0.001 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.3.4 Model 3). This effect persists when the test includes all risk factors where the momentum strategy yields about 1.051% abnormal return per month with a t-statistic of 3.46 and a P-value of 0.001. Implying that change in economy growth or in industry output strongly explains the momentum profit.

One possible interpretation of this result is that there is as strong relation between change in macroeconomic and the global momentum profitability. They indicate the ability of global factor to explain the momentum profit; in line with Cochrane (2011), suggestions that market are integrated across both countries and assets. I can confirm at this stage that if the momentum profits are improved by taking extra risk these risks do not or least partially do not derive from the Fama and French, and market state factor but there is a strong tendency of macroeconomic risk factors in explaining the momentum profit. These findings contribute in the debate by reinforcing Chordia and Shiva Kumar's (2000) study that suggested that momentum strategies profits are explained by common macroeconomic variables, implying that the profitability of the global momentum strategy could be due to variations in common macroeconomic factors and presumably change in risk. Also in line with Griffin et al. (2003), study demonstrated that average momentum profit is positive during GDP growth and even larger and positive with negative market return than positive market returns.

[Insert Table 4.3.5 Here]

Considering the seasonality of the relation between global risk factor and the momentum profitability as shown in Table 4.3.5, the momentum strategy has insignificant adjusted returns (Alpha) with all holding periods. The optimum strategy 9-month/3-month retains abnormal return of about 0.50% per month with a t-statistic of (0.71) and a P-value of 0.481 after adjusting for global risk. For the findings to be consistent in any period, I will expect the global risk factors to be unswerving over time. The evidence in Table 4.3.5 is strongly consistent with this explanation given that the adjusted momentum return remains insignificant abnormal return for the 6-month holding period (0.10% per month), 9-month (0.00% per month) and 12-month (-0.40% per month). Of particular interest the size of the abnormal return decreases when I increase the holding period with the lowest return of -0.40% observed with the 9-month/12-month strategy suggesting that this abnormal return not only disappear in the long run after controlling for global risk, global risks may induce a negative momentum payoff. This particular aspect attracts my curiosity given that I have a zero profit for horizon up to 9-month and a negative abnormal return at 12-month.

The effect of market volatility on momentum profit is also non-negligible at 9-month holding period. These findings indicate that the global momentum adjusted returns are not consistent due to the effect of macroeconomic risk. I may accept the hypothesis that Alpha is equal to zero at 9-month horizon. This pattern of behaviour is also confirmed with results using estimation method such as OLS (Appendix C16) and Newey and West procedure (please see appendix C7 and C8). The implication is that, as momentum investors hold on to their momentum portfolio the abnormal return diminishes gradually up to the point where the momentum profit alters from positive to negative payoff (between 9-month and 12-month holding period) due to the reduced contribution of macroeconomic factor such as the industrial production. These findings support Chordia and Shivakumar (2000) study that suggested that momentum strategies profits are explained by common macroeconomic variables, implying that the profitability of the global momentum strategy could be due to variations in common macroeconomic factors and presumably change in risks. Also in line with Griffin et al. (2003), study demonstrates that, average momentum profit is positive during GDP growth and even larger and positive with negative market return than positive market returns in the United States.

6.2.5 Crises Role on Momentum Profits

To examine how global risks factors, affect the momentum performance in crisis period, I regress a time series of momentum return in crisis period on the equivalent global risk factors in the same period. I also conduct separate regression with a dummies variables as additional variables to my initial regression model to control for the impact of crisis period, where a dummy variable takes the value one when the economy is in crisis mode and zero otherwise. My examination is based on the following regression specification. I report the first regression parameters result in Table 4.3.6. This table shows the result of the following monthly time-series regression.

(32) $$Mom_t = \alpha_4 + \beta_2(R_M - R_F)_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$$

Where: Mom_t is the momentum returns, HML_t (High minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size in US market, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices price level and represent price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and IP_{T-1} is the monthly value of the US Industrial production at time t-1.The t-statistics are also reported in the parentheses and the p-values are reported next. I report the parameter results for each type of crisis (Currency crisis, Stock market crash and banking crisis).

I consider all possible combinations of predictive risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). I report the regression parameters result for crisis period and non-crisis period in Table 4.3.6, 4.3.7 and 4.3.8.

[Insert Table 4.3.6, 4.3.7and 4.3.8 Here]

Table 4.3.6 reports the test result of the momentum portfolio returns regressed on Fama and French, market state and macroeconomic risk factors. I begin with the estimates of the regression for the currency crisis. I then examine the impact during stock market crash, and banking crisis and find that the adjusted momentum remains significant only during banking crisis with 4.30% per month, a t-statistic of 3.54 and a P-value of 0.000, this imply that global risk factor does not or at least partially explain the momentum profit during banking crisis. Industrial production remain the main driver of the momentum return in all other crisis. However, including all crisis (currency crisis banking crisis and stock market crash) in the sample as indicate in Table 4.3.7 shows that macroeconomic factors do explain the momentum profit. More importantly industrial production indicates significant impact on momentum profit Table 4.3.7 Model 3 and 4 with a coefficient of 0.975% per month, t-statistic (2.60) and a P-value (0.009) when all global risk factors are included in the analysis.

Further analysis with the subset of non-crisis Table 4.3.8 period indicate that the momentum returns remain after adjusting for Fama and French risks (Table 4.3.8 Model 1), with adjusted momentum return of 1.20% per month with a t-statistic of (4.28) and a P-value 0.000. More importantly industrial production remains the main driver of the abnormal return with a coefficient of 1.94, a t-statistic of 2.04 and a P-value of 0.042 when all risk factors are included (Table 4.3.8 Model 4) in non-crisis period. This result indicates that change in economy growth or in industry's output strongly affects the momentum profit. One possible interpretation of this result is that, there is a strong relation between change in macroeconomic variables and the global momentum. This reinforcing Chordia and Shivakumar's (2000) argument that momentum strategies profits are explained by common macroeconomic variables, and indicates the ability of global factor to explain the momentum profit, in line with Cochrane (2011) suggestions that market are integrated across both countries and assets classes.

I can confirm at this stage that the momentum profits can be improved by taking extra macroeconomic risk in non-crisis period, during currency crisis and stock market crash as indicated in Table 4.3.6. These results are compatible with a separate analysis that add crisis dummy as additional variable to the set of independent variables to capture the impact of individual crisis on momentum return, estimate with method such as the Newey and West procedure (please see appendix C9) following Avramov, et al. (2015). The results also show a strong influence of industrial production on the momentum profit in crisis periods. None of crisis shows significant abnormal return.

6.2.6 Business Cycle Role on Momentum Profits

To examine the joint effect of Fama and French risk factors, market state factor, and macroeconomic risk factors on momentum payoff follow business cycle. I follow Avramov et al.'s (2015) approach. My examination is based on the following time-series regression specifications. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). I report the regression parameters result in Table 4.3.9. This table shows the result of the following regression.

(33) $$Mom_t = \alpha_5 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_{10}\Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12}\Delta IP_{t-1} + e_t$$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolios that, is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, MKT_{t-1} is the MSCI world indices prices level, It represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.3.9 and 4.3.9 Here]

Table 4.3.9 model 1 indicates that the momentum strategy yields significant abnormal return of 1.10% per month with, a t-statistic of 5.61 and a P-value of 0.00 after adjusting for Fama and French risk. The subsequent analysis that includes market and economics state factors consecutively in Table 4.3.9 Models 2 to 4 indicates insignificant adjusted momentum returns. As of interest, the coefficient associated with the macroeconomic risk factor such as industrial production remains significant. This indicates that industrial production tends to contribute significantly in explaining the momentum return with a coefficient of 1.31, a t-statistic of 3.42 and a P-value of 0.00 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk (Table 4.3.9 Model 3). This effect persists with all risk factors included with a coefficient of 1.26, a t-statistic 3.21 and a P-value of 0.00. The default spread also show significant but lower effect on the momentum profit. This result indicates that change in economy growth or in industry's output strongly explains the momentum profit. One possible interpretation of this result is that there is a strong relation between change in economic state variable and the global momentum. That the default spread also contribute in explaining the momentum profit during economic expansion. I therefore confirm at this stage that if the momentum profits are improved by taking extra risk these risks do at least or partially derive from market state and macroeconomic factors.

Further analyses with the subset of contraction period (Table 4.3.10) indicate that momentum returns become negative after adjusting for macroeconomic risks (Table 4.3.10 Model 3), with adjusted momentum return (-1.30% per month), with a t-statistic of -2.12 and a P-value of 0.03. More importantly, one of the market risks factor do contribute to the momentum profit (TS). I also notice a high and significant level of the market volatility. I may suggest that the effect of economy growth or change in industrial production disappears during the contraction period. However, it is also important to suggest that the impact of market state factor become more noticeable.

6.2.7 Momentum Profits and Macro Risk Factor in Emerging Market

In addition to the global risk on momentum crisis following crisis and change in business cycle, I examine the influence of these factors on the global momentum in different markets' state. I examine whether jointly Fama and French risk factors, market state factor, and economic risk factors explain the momentum payoff in emerging market. I follow Avramov et al. (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results in Table 4.3.11.

(34) $Mom_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_{10}\Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12}\Delta IP_{t-1} + e_t$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI world indices price level and represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.3.11 Here]

As shown in Table 4.3.11 Models 1 and 2, significant adjusted momentum returns remain after adjusting the momentum profit consecutively for Fama and French risks and market state factors. While the abnormal return associated with the macroeconomic risk factor and the regression after controlling for global risk factor are not significant. More importantly, I find that industrial production tends to contribute significantly in explaining the momentum return with a coefficient of 1.36, a t-statistic of 3.27 and a P-value of 0.00 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.3.11 Model 3). This effect persists with all risk factors included with a coefficient of 1.04, a t-statistic 2.39 and a P-value of 0.02. This result also indicates that one unit change in industrial production will increase the momentum profit by 1.04. implying that change in economy growth or in industry's output strongly explains the global momentum profit, and shows the ability of global factor to explain the momentum profit, in line with Cochrane (2011) suggestions that markets are integrated across both countries and assets classes.

One possible interpretation of this result is that there is a strong and positive relation between change in macroeconomic variable and the global momentum. I therefore confirm at this stage that if the momentum profits are improved by taking extra risk these risks do derive in most case from macroeconomic risk factors. These findings contribute in the debate by reinforcing Chordia and Shivakumar (2000) study that suggested that momentum strategies profits are explained by common macroeconomic variables, implying that the profitability of the global momentum strategy could be due to variations in common macroeconomic factors and presumably change in risk. It is also in line with Griffin et al. (2003) that demonstrated that average momentum profit is positive during GDP growth and even larger and positive with negative market return than positive market returns. These results are also consistent with estimation approach such as the Newey West procedure (Please see Appendix C12).

6.2.8 Momentum Profits and Macro Risk Factor in Develop Market

To examine whether jointly Fama and French risk factors, market state factor, and macroeconomic risk factors explain the momentum payoff in develop market. I also follow Avramov et al. (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3); starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results Table 4.3.12. This table shows the result of the following monthly time-series regression.

(35) $$Mom_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_{10} \Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12} \Delta IP_{t-1} + e_t$$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, LIQ_{t-1}Is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, MKT_{t-1} is the MSCI world indices price level, It represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.3.12 Here]

As shown in Table 18 Models 1, 2 and 3 I record significant adjusted momentum returns after adjusting for Fama and French risks. While the coefficients associate with market state and macroeconomic risk factor and the regression after controlling for all global risk factor are not significant. More importantly, I find that industrial production contributes significantly in explaining the momentum return with a coefficient of 0.57, a t-statistic of 2.08 and a P-value of 0.038 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.3.12 Model 3). This effect persists with all risk factors included in the regression, with a coefficient of 0.71, a t-statistic 2.48 and a P-value of 0.01. This result also indicates that one unit change in industrial production will increase the momentum profit by 0.71, which is lower by comparison to 1.04 in emerging market. It also implies that change in economy growth or in industry's output strongly explains the global momentum profit, and indicates the ability of global factor to explain the momentum profit, in line with Cochrane (2011) suggestions that markets are integrated across both countries and assets classes.

One possible interpretation of this result is that there is a strong and positive relation between change in macroeconomic variable and the global momentum. I therefore confirm at this stage that if the momentum profits are improved by taking extra risk these risks do derive in most case from macroeconomic risk. However, the Term Spread contribution is not negligible given that it positively and significantly explains the momentum return at 1% level in develop market. These results are in line with Chordia and Shivakumar's (2000) study that suggested that momentum strategies profits are explained by common macroeconomic variables, implying that the profitability of the global momentum strategy could be due to variations in common macroeconomic factors and presumably change in risk. It is also in line with Griffin et al. (2003) that demonstrated that average momentum profit is positive during GDP growth and even larger and positive with negative market return than positive market returns. These results are also consistent with estimation approach such as the Newey West procedure (Please see Appendix C11).

6.2.9 Momentum Profits and Macro Risk Factor in Established Market

I examine the influence of these factors on the global momentum in established market. I follow Avramov et al.'s (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3); Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results in Table 4.3.13.

(36) $$Mom_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_{10} \Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12} \Delta IP_{t-1} + e_t$$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI world indices price level and represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.3.13 Here]

As shown in Table 4.3.13 Models 1, 2, and 3 significant adjusted momentum returns remain after adjusting of the momentum portfolio consecutively to the Fama and French risks and the market state factors. While the coefficients associated with the macroeconomic risk factor and the regression after controlling for global risk factor are not significant. More importantly, I find that industrial production to contribute significantly in explaining the momentum return with a coefficient of 0.59, a t-statistic of 2.17 and a P-value of 0.03 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.3.13 Model 3). This effect persists with all risk factors included with a coefficient of 0.68, a t-statistic of 2.50 and a P-value of 0.01. This result also indicates one unit change in industrial production will increase the momentum profit by 0.68, that change in economy growth or in industry's output strongly explains the global momentum profit, and indicates the ability of global factor to explain the momentum profit, in line with Cochrane's (2011) suggestions that markets are integrated across both countries and assets classes.

One possible interpretation of this result is that there is a strong and positive relation between change in economic state variable and the global momentum. I therefore confirm at this stage that if the momentum profits are improved by taking extra risk these risks do derive in most case from macroeconomic risk. These findings contribute in the debate by reinforcing Chordia and Shivakumar's (2000) study that suggested that momentum strategies profits are explained by common macroeconomic variables, implying that the profitability of the global momentum strategy could be due to variations in common macroeconomic factors and presumably change in risk. It is also in line with Griffin et al. (2003) that demonstrated that average momentum profit is positive during GDP growth and even larger and positive with negative market return than positive market returns.

6.2.10 Macro Risk Factor Impact on Momentum Profit During the Globalization Period 1994-2014

I examine whether jointly Fama and French risk factors, market state factor, and economic risk factors explain the momentum payoff during the globalization period. I follow Avramov et al (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3)' starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results on Table 4.3.14 this table shows the result of the following monthly time-series regression.

(37) $Mom_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_{10}\Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12}\Delta IP_{t-1} + e_t$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (High Minus Low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI the world indices price level and represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.3.14 *Here]*

As shown in Table 4.3.14 Models 1 and 2, significant adjusted momentum returns remain after adjusting the momentum portfolio return consecutively to Fama and French risks and market state factors. While the coefficients associate with the macroeconomic risk factor and the regression after controlling for global risk factor are not significant. The results indicate that industrial production contribute positively significantly in explaining the momentum return with a coefficient of 1.19, a t-statistic of 2.77 and a P-value of 1.01 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.3.14

Model 3). This effect persists when all risk factors included in the regression with a coefficient of 0.807, a t-statistic of 2.01 and a P-value of 0.04 (Table 4.3.14 Model 4). The results also indicate that one unit change in industrial production will increase the momentum profit by 0.81. implying that change in economy growth or in industry's output strongly explains the global momentum profit, and indicates the ability of global factors to explain the momentum profit, in line with Cochrane's (2011) suggestions that market are integrated across both countries and assets classes. The Term Spread also show significant but lower contribution to the momentum profit during the globalization period.

One possible interpretation of this result is that there is a strong and positive relation between change in macroeconomic factor such as industrial production, state variable such as change on term spread and the momentum profit. This in line with Chordia and Shivakumar's (2000) study that suggested that, momentum strategies profits are explained by common macroeconomic variables, implying that the profitability of the global momentum strategy could be due to variations in macroeconomic factors and presumably change in risk. It is also in line with Griffin et al. (2003) that demonstrates that average momentum profit is positive during GDP growth and even larger and positive with negative market return than positive market returns.

6.2.11 Effect of Global Risks Factors on Excess Momentum Profits

I finally examine the influence of these factors on the excess global momentum in other to access the comparative advantage of opting for the strategies. To examine whether jointly Fama and French risk factors, market state factor, and economic risk factors explain the momentum payoff. I follow Avramov et al. (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results Table 4.3.15.

(38) $Mom_t - R_{Ft} = \alpha_7 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_{10} \Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12} \Delta IP_{t-1} + e_t$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} Is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, MKT_{t-1} is the MSCI world indices prices levels, It represents prices levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} and is the yearly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.3.15 Here]

As shown in Table 4.3.15 Models 1 and 2 significant adjusted momentum returns remain after adjusting consecutively for Fama and French risks and market state factors. The coefficients associated with the macroeconomic risk factor and the regression that include all global risk factor are not significant. More importantly, I find that industrial production contributes significantly in explaining the momentum return with a coefficient of 0.10, a t-statistic of 3.28 and a P-value of 0.00 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.3.15 Model 3). This effect persists with all risk factors included in the regression with a coefficient of 1.04, a t-statistic 3.44 and a P-value of 0.00 (Table 4.3.15 Model 4). This result also indicates that one unit change in industrial production will increase the momentum profit by 1.035. implying that change in economy growth or in industry’s output strongly explain the global momentum profit, and indicates the ability of global factor to explain the momentum profit, in line with Cochrane’s (2011) suggestions that markets are integrated across both countries and assets classes.

One possible interpretation of this result is that there is a strong and positive relation between change in macroeconomic variable and the global momentum. I therefore confirm at this stage that if the momentum profits are improved by taking extra risk these risks do derive in most case from macroeconomic risk.

These findings contribute in the debate by reinforcing Chordia and Shivakumar’s (2000) study that suggested that momentum strategies profits are explained by common macroeconomic variables, implying that the profitability of the global momentum strategy could be due to variations in common macroeconomic factors and presumably change in risk. It is also in line with Griffin et al. (2003) that demonstrates that average momentum profit is positive during economy growth and even larger and positive with negative market return than positive market returns.

6.2.12 Summary

I examined the role of global risks factors in explaining the global momentum profit, and found a strong systematic relation between variations in macroeconomic factor, notably industrial production, and the adjusted momentum return. The evidence is that industrial production tends to contribute significantly in explaining the momentum return with a coefficient of 1.05, a t-statistic of 3.46 and a P-value of 0.00 when I control for all risk factor. This reveals that change in economy growth or in industry's output strongly affect the momentum profit, and indicates the ability of global risks factors to explain the momentum profit, in line with Cochrane (2011) suggestions market are integrated across both countries and assets classes. This positive relationship is quiet strong. For example, the findings survive with 6-month and 9-month holding period. Of particular interest, the abnormal return decease when I increase the holding period (0.10%), 9-month (0.00%) and 12-month (-0.40%) with the lowest return of -0.40% observed with the 9-month/12-month strategy. Suggesting that this abnormal return not only disappears in the long run after controlling for global risks, the global risks may induce a negative momentum payoff. This aspect attracts my curiosity given that I have a zero profit for 9 months' horizon and a negative abnormal return at 12-month.

The positive impact of macroeconomic risk factor on the global momentum profit is also significant when I examine the role of the risk factors in explaining the momentum profit in emerging countries, developed countries, established markets and globalization indicating that the findings are not limited. These findings on the association between macroeconomic risk and momentum abnormal indicate the need of studying the dynamic of the global momentum worldwide.

Examining the impact of crisis on the momentum, I refer to the possibility that stock market is an indicator of the state of the economy as suggested by Naes et al. (2011) given that the global momentum are based on stock market indices prices. I also find no substantial remaining momentum after account for the crisis and non-crisis period with the exception made on Banking crisis (4.30% per month) when taken solely. My findings also strongly support that industrial production contributes significantly in explaining the momentum return following business cycle expansion, and disappears with contraction in line with Chordia and Shivakumar (2002) who suggested that variation in momentum payoffs reflect time varying over the business cycle. A direct implication of these results is that the global momentum profit could be a compensation for global. international investors might be able to earn extra return by increasing their exposure to world risks factors in line with arguments that support Efficient Market Hypothesis.

6.3 Global-risk Factors Role in Explaining the Contrarian Strategy Payoff

Given the results obtained for the momentum, I now turn into the contrarian risks based explanation. Chan (1988) suggested that the abnormal returns earned with the contrarian strategy are just a normal compensation for risk related to the strategy. The risk-based explanation defends the efficient market hypothesis, suggesting that abnormal profits of trading strategies can be captured by asset pricing model or model misspecification. I examine whether the global contrarian strategy earn significant profit after adjusting for risk with the intuition that, examining more formally the effect of systematic variation in global risks factors on the strength of the global contrarian performance will provide more information. If changes in contrarian profit reflect changes in risk factors, I will expect a significant relation between contrarian profits and change in risk factor, consequently, no significant abnormal return after controlling for global risk factors.

6.3.1 Effect of Fama and French Risk on Contrarian Profits

I start the analysis by implementing test on Fama and French risks. I consider the optimum strategy that generates the highest returns and remains profitable in every horizon (48-month/48-month). This strategy selects stocks based on their previous performances over 48 months and then holds the portfolio for the next 48 months, based on overlapping portfolios. The choice of the overlapping approach is to avoid statistical error, which may occur due to limited number of observations. The returns are further adjusted by the Fama-French's three-factor model (see equation 39 below). I also report the regression result for 36, and 60 months holding period, in Table 4.4.1 below. The test-statistics are reported in the parentheses and the p-values are reported next. The sample period is from December 1969 to January 2014.

(39) $$Con_t = \alpha_0 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + e_t$$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, and SMB_t(small minus big) is returns to long-short portfolios constructed using size in US market. $R_M - R_F$ is the market premium and β the factors loading are the slopes in the times-series regression.

[Insert Table 4.4.1 Here]

As shown in Table 4.4.1 Panel A, the contrarian strategy has positive and consistent adjusted returns (Alpha) with all holding periods. The optimum strategy 48-month/48-month retains abnormal return of about 0.50% per month with a t-statistic of 13.11 and a P-value of 0.000 after adjusting for Fama and French risk. For the findings to be consistent in any period, I expect the Fama and French factors to be unswerving and significant over time. The evidence in Table 4.4.1 is strongly consistent with this explanation given that the adjusted contrarian return remains for 36-month holding period (0.60% per month), and 60-month (0.50% per month). Of particular interest, the sizes of the abnormal returns are relatively close when I increase the holding period suggesting that the contrarian strategies may generate consistent abnormal regardless of the holding period. More importantly, I find that these adjusted returns are highly significant. The SMB tends to contribute significantly to reduce the size of the abnormal return. The SMB effect is slightly moderated as the time goes given that the coefficient decreases and becomes less significant from -0.084 to -0.031. The effect of the MKTRF is also noticeable at 36-month horizon. This pattern of behaviour is strong in Table 4.4.1 Panel B with the Fama and French risks when I substitute the excess return based on the MSCI world index (MKTRF) with the excess return on the US market (ERM). The findings indicate that the global contrarian adjusted return is consistent and different from zero in all horizon. Rejecting the null hypothesis that Alpha is equal to zero at 1% significance level. All these findings imply that investor may earn extra return for accepting the strategies. They strongly support the argument that, the contrarian strategy can produce both market and CAPM-adjusted abnormal return with holding and testing periods, rankings from three to five years (Larkomaa, 1999). These findings are in line with Jegadeesh (1990), and De Bondt and Thaler (1985) who suggested that adjustment of the contrarian strategy return to risk could not explain the abnormal results. In addition, De Bondt and Thaler (1985) showed that portfolios based on market-adjusted excess returns do not differ with respect to market value. Therefore, these results challenge the hypothesis of weak-form market efficiency.

6.3.2 Effect of Market State Factor on Contrarian Profits

Since the predictability of the contrarian strategies payoff might be affected by market state risk factors, I use a variety of measure as proxies of the market risk factors (liquidity factor (LIQ), Default spread ((DS), the Term spread (TS) and the market return (MKT), to examine the role of such factors on the contrarian strategies. I regress the contrarian returns on the on the lagged market state factors. This approach indicates that the contrarian returns are further adjusted by the risk exposure to market state factors. I report the regression parameters result for each explanatory variable in Table 4.4.2 showing the results of the following monthly time-series regression.

(40) $$Con_t = \alpha_1 + \beta_1 LIQ_{t-1} + \beta_2 DS_{t-1} + \beta_3 TS_{t-1} + \beta_4 MKT_{t-1} + e_t$$

Where: LIQ_{t-1} is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS is the Term spread at time t-1, and MKT_{t-1} is the return on MSCI world indices. The test-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.2]

Table 4.4.2 reports the test result of the contrarian strategies return regress on market state factors. The contrarian strategy has a positive and consistent adjusted returns (Alpha) for all holding periods up to 60-month. The optimum strategy 48-month/48-month retains abnormal return of about 0.70% per month with a t-statistic of 7.04 and a P-value of 0.000 after adjusting for market state risks. For the findings to be consistent in any period, I expect the market state factors to be constant and significant over time. The evidence in Table 4.4.2 is consistent with this explanation given that the adjusted momentum returns remain for all holding periods. Of particular interest, the size of the abnormal return also decreases when I increase the holding period from 36 months to 48 months but remains constant thereafter. These adjusted returns are all significant suggesting that the contrarian abnormal return remains in the long run. More importantly, the default spread shows a significant and negative coefficient of -0.002 with a t-statistic of -3.16 and a P-value of 0.002 with the 60-month indicating that change in default risk may reduce the contrarian profit by -0.002 for every unit change in default spread. This pattern of behaviour is consistent in market risk factor rejecting the null hypothesis that Alpha is equal to zero at 1% significance level. This finding is central given that the contrarian return relies the on performance of the determinants of the market to reverse in the long term in conformity with the expected market risk premium. They are also consistent with the modern asset pricing theories that indicate the countercyclical price of risk (Zang, 2005). They are in line with Lakonishok et al.'s (1994) study that suggested that, there is little evidence to support that, value stocks are fundamentally riskier than glamour stocks. My findings are also consistent with Gregory et al.'s (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk.

6.3.3 Effect of Macroeconomic Factor on Contrarian Profits

The contrarian strategies profit could reflect mispricing of macroeconomic variables this implies that contrarian profit would again be related to future macroeconomic conditions. In this section I examine whether the global contrarian strategy earn significant profit after adjusting for risk. I regress the contrarian' returns on the lagged macroeconomic variables I also account for time variation through time dummy. I report the regression parameters' results for each explanatory variable in Table 4.4.3. This table shows the result of the following monthly time-series regression.

(41) $$Con_t = \alpha_2 + \beta_1 \Delta OP_{t-1} + \beta_3 WVOL_{t-1} + \beta_4 \Delta IP_{t-1} + e_t$$

Where: ΔOP_{t-1}, is the Oil price at time t-1, $WVOL_{t-1}$is the market volatility at time t-1 based on the MSCI world indices price level, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. I estimate the regression using the GMM model. The test statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.3 Here]

As for the intercepts (Alphas) that measure the abnormal profits of the global contrarian strategy after adjusting to macroeconomic factors, evidences show that all the abnormal returns are significant. The contrarian strategy has consistent adjusted returns for all holding periods after adjusting for risk. This includes the optimum strategy 48-month/48-month. Of particular interest, I find that industrial production tends to contribute significantly in reducing the contrarian return with a coefficient of -0.673, a t-statistic of -5.28 and a P-value of 0.000 for the optimum strategy (48-month/48-month), this effect persists for horizon up to 60-month. The contribution of the oil price is also noticeable for 60-month holding period. This result indicates a negative relation between economy growth and industry's output and the contrarian profit, and rejects the null hypothesis that Alpha is equal to zero at 1% significance level. One possible interpretation of this result is that there is none or little relation between change in economic state variable and the global contrarian. They are in line with Lakonishok et al.'s (1994) study that suggested that, there is little evidence to support that, value stocks are fundamentally riskier than glamour stocks. My findings are also consistent with Gregory et al.'s (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk.

Objectively these factors may not solely influence the contrarian profit as the study suggests. I therefore account for the joint impact of Fama and French risk, market state and macroeconomic risk factors on the global momentum profit.

6.3.4 Effect of Global Risk Factor on the Global Contrarian Profit

To examine whether jointly Fama and French risk factors, market state factor, and economic risk factors affect the contrarian payoff. I follow Avramov et al. (2015) risk analysis approach. My examination is based on the following time-series regression specification. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). I report the regression parameters' result for each explanatory variable in Table 4.4.4. This table shows the result of the following monthly time-series regression.

(42) $$Con_t = \alpha_3 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$$

Where: Con_t are the returns of the contrarian portfolio at time t, HML_t (high minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, LIQ_{t-1} is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, MKT_{t-1} is the MSCI world indices price level and represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The results are reported in Table 4.4. The test-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.4 Here]

As shown in Table 4.4.4 Models 1, 2 and 3 significant adjusted contrarian returns remain after controlling consecutively for Fama and French risks, market state risks, and macroeconomic risks. More importantly, when I control for the joint effect of the global risk factors, the contrarian strategy generates a statistically and significant abnormal return of 1.00% with a t-statistic of 6.58 and a P-value of 0.000 with the optimum strategy (48-month/48-month) Table 4.4.4 Model 4. The results also show that market volatility tends to contribute significantly in reducing the contrarian return with a coefficient of -0.686, a t-statistic of -5.16 and a P-value of 0.000 with the optimum strategy, when I control for macroeconomic risk exclusively (Table 4.4.4 Model 3). The market volatility effect persists even when I account for all risk factors with a coefficient of -0.639, a t-statistic of -4.75 and a P-value of 0.000. However, the market volatility impact solely cannot expunge the abnormal return. One possible interpretation is that global risk factors do not explain the contrarian profit. I can confirm at this stage that contrarian investors will not increase their profits by taking extra risk. However, there is a tendency of macroeconomic risk factors to be on average negatively related to the contrarian profit. These findings are in line with Lakonishok et al. (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks, consistent with Gregory et al. (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk. These results also contribute to the debate by reinforcing De Bondt and Thaler (1985) findings that claim that overreaction is predictive, and that adjustment of profits to the CAPM-model could not explain the abnormal returns. In addition, they show that portfolios based on market-adjusted excess returns do not systematically differ with respect to market value of equity, challenging the weak form of the efficient market hypothesis.

[Insert Table 4.4.5 Here]

Considering the seasonality of the relation between global risk factor and the momentum profitability. As shown in Table 4.4.5, the contrarian strategies have significant adjusted returns (Alpha) with all holding periods. The optimum strategy 48-month/48-month retains abnormal return of about 1.00% per month with a t-statistic of 6.58 and a P-value of 0.000 after adjusting for global risk. For the findings to be consistent in any period, I will expect the global risk factors to be unswerving over time. The evidence in Table 4.4.5 is strongly consistent with this explanation given that the adjusted momentum return remains insignificant for 36-month holding period (1.20% per month), and 60-month (0.90% per month). Of particular interest, the size of the abnormal return decrease when I increase the holding period with the lowest return of 0.90% per month observed with the 48-month/60-month strategy suggesting that this abnormal return may disappear in the long-run after controlling for global risk. This particular aspect attracts my curiosity given that investors will exploit such awareness to avoid sudden negative payoff and increase their profit. The negative effect of the default spread, market volatility and the change in SMB factors on contrarian profit are also non-negligible. These findings indicate that the global contrarian adjusted returns remain consistent after controlling the impact of macroeconomic risk rejecting the hypothesis that Alpha equal to zero in all horizon. This pattern of behaviour is also confirmed when I substitute the contrarian return with the contrarian excess return later in my analysis. The implication is that, as contrarian investors hold on to their contrarian portfolio the abnormal return diminishes gradually over time due to the negative contribution of global risk factor such as the default spread, market volatility and the change in SMB factors.

6.3.5 Crises Role in Explaining the Contrarian Profits

To examine how global risk factors, affect the contrarian performance in crisis periods, a time series of contrarian returns in crisis periods is regressed on the equivalent global risk factor in the same periods, I conduct this analysis with time dummies as endogenous variable to control the impact of time variation on the contrarian profit. My examination is based on the following regression specification. I report the regression parameters' result for Table 4.4.6. This table shows the result of the following monthly time-series regression.

(43) $$Con_t = \alpha_4 + \beta_2(R_M - R_F)_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$$

Where: Con_t is the contrarian returns, HML_t (High minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size in US market, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices price level and represent price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and IP_{T-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are also reported in the parentheses and the p-values are reported next. I report the parameter results for each type of crisis (Currency crisis, Stock market crash and banking crisis).

I examine individual crisis solely, then all crises together. I also consider all possible combinations of predictive risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). I report the regression parameters result for crisis period and non-crisis period subset variable in Table 4.4.6 to 4.4.8.

[Insert Table 4.6, 4.7and 4.8 Here]

Table 4.4.6 reports the test result of the contrarian portfolio returns regressed on Fama and French, market state and macroeconomic risk factors. I begin with the estimates of the regression for the currency crisis. I then examine the impact during stock market crash, and banking crisis, and find that the adjusted contrarian remains significant and positive during banking crisis with a coefficient of 1.40%, a t-statistic of 5.37 and a P-value of 0.000, and currency crisis with 4.20% per month, a t-statistic of 3.05 and a P-value of 0.002. However, the analysis in stock market crash shows a negative but significant abnormal return with -0.80% per month, a t-statistic of -2.82 and a P-value of 0.005. This implies that global risk factors at least partially do not explain the contrarian profit during currency and banking crises but the contrarian abnormal return could be wipe out during stock market crash due to the dominant negative effect of global risk factors. However, including all crisis (currency crisis, banking crisis and stock market crash) in the sample, Table 4.4.7 shows that macroeconomic factors do explain the momentum profit. More importantly, the default spread and the market return indicate significant and positive contribution to the contrarian profit Table 4.4.7 Model 2 and 4 with a coefficient of 0.005, t-statistic (3.14) and a P-value (0.002) for the default spread and 0.040%, a t-statistic of 2.75 and a P-value of 0.005 for the market return.

Further analysis with the subset of non-crisis period on Table 4.4.8 indicate that contrarian returns remain after adjusting for global risk (Table 4.8 Model 1 to 4), with adjusted momentum return. More importantly the HML remains the only positive and significant contributor to the contrarian return with a coefficient of 0.065, a t-statistic of 2.92 and a P-value of 0.004 when all risk factors are included (Table 4.4.8 Model 4) in non-crisis period. This result indicates that changes in market state factors and macroeconomic factors do not explain the global contrarian profit.

One possible interpretation of this result is that there is none or little relation between change in macroeconomic risk and the rise global contrarian, reinforcing De Bondt and Thaler's (1985) claim that overreaction is predictive, and that adjustment of profits to the risk could not explain the abnormal returns. I therefore confirm at this stage that the contrarian profits cannot be improved by taking extra macroeconomic risk in non-crisis period, during currency crisis and banking crisis. However, stock market crash may have significant impact on the profitability of the contrarian strategy.

6.3.6 Business Cycle Role on Contrarian Profits

To examine the joint effect of Fama and French risk factors, market states factors and macroeconomic risk factors on contrarian payoff following business cycle. I follow Avramov, Cheng, and Hameed's (2015) approach. My examination is based on the following time-series regression specifications. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). I report the regression parameters results in Table 4.4.9. This table shows the results of the following regression.

(44) $$Con_t = \alpha_5 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$$

Where: Con_t are the returns of the contrarian portfolio at time t, HML_t (High minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI world indices price level and represent price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.9 and 4.4.10 Here]

Table 4.4.9 reports the test result of the contrarian portfolio returns regressed on Fama and French, market state and macroeconomic risk factors. The results indicate that the adjusted contrarian returns are all significant for every combination of factors (Model 1-4). As of interest, the coefficients associate with the risk factor such as market volatility negative -0.665, a t-statistic of -3.59 and a P-value of 0.000. The HML factor coefficient is also negative -0.040, a t-statistic of -1.92 and a P-value of 0.055 (Table 4.4.9 Model 4). This effect persists when I control for macroeconomic factors solely with a coefficient of -0676, a t-statistic -3.67 and a P-value of 0.000 for market volatility and -0.034 with a test statistic of -

1.66 and a P-value of 0.096 for the HML factor. Indicating a negative relationship between contrarian return, market volatility and HML factor. However, the weight of the findings indicates that the contrarian abnormal return remains after adjusting for global risks. One possible interpretation of this result is that global risk factors do not explain the contrarian profit and consequently investors will not increase their profit by taking risk associate with the strategy if any exist during economic expansion.

Further analysis with the subset of contrarian returns during contraction periods Table 4.4.10 indicates that the contrarian abnormal returns become negative after adjusting for market state factors and macroeconomic risks (Table 4.4.10 Model 2 and 3), while the contrarian adjusted return is insignificant when all risk factors are included. More importantly the market volatility shows a negative relation with the adjusted return with a coefficient of -0.341, a t-statistic of (-3.27) and a P-value 0.001, the SMB factor also shows a negative and significant relation to the contrarian profit with a coefficient of -0.093, a t-statistic of (-2.08) and a P-value 0.037.

These results indicate that the contrarian profit may not remain after controlling for global and consequently global risk factor do explain the contrarian profit during economy contraction. The same Fama and French risks taken solely do explain the contrarian profit. I may suggest that while global risk factor have none or little impact on contrarian profit during expansion, the impact become noticeable during contraction allowing contrarian investor to take advantage of any change in global risk factors and even more precisely, change in Fama and French risks. These findings also reject Gregory et al. (2001) findings that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns could be a result of a compensation for market risk during contraction period.

6.3.7 Contrarian Profits and Global Risk Factor in Emerging Market

In addition to the effect of global risk on contrarian payoff following crisis and change in business cycle, I examine the influence of these factors on the global contrarian in different market states. To examine whether jointly Fama and French risk factors, market state factor, and economic risk factors explain the contrarian payoff in emerging market. I follow Avramov et al.'s (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results Table 4.4.11. This table shows the results of the following monthly time-series regression.

(45) $$Con_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$$

Where: Con_t are the returns of the contrarian portfolio at time t, HML_t (High minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1' DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices prices level. It represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.11 Here]

The results in Table 4.4.11 Models 1 to 4 show that significant adjusted contrarian returns remain after adjusting the momentum profit consecutively for Fama and French risks, market state factors and macroeconomic factor. More importantly, I find that market return tends to contribute positively significantly in explaining the momentum return with a coefficient of 0.038, a t-statistic of 2.69 and a P-value of 0.00 for the optimum strategy (48-month/48-month) when I control for market state risk factors exclusively (Table 4.4.11 Model 2). This effect persists with all risk factors included with a coefficient of 0.039, a t-statistic 2.75 and a P-value of 0.006. This result also indicates that one unit change in market return will increase the contrarian profit by 0.039. The same the coefficient associate with the industrial production is also positive and significant indicating that change in economy growth or in industry output may have also have a positive contribution on the contrarian profit, while all other significant factors show a negative coefficient.

One possible interpretation of this result is that global risk factors show opposite and conflicting relation to the contrarian profit and their combining effect do not explain the contrarian abnormal return. I can confirm at this stage that if the contrarian profits will not improve by taking extra risks in emerging market. These findings are in line with Lakonishok et al. (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks, consistent with Gregory et al. (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk. These results also contribute to the debate by reinforcing De Bondt and Thaler's (1985) findings that claim that overreaction is predictive, and that adjustment of profits to the CAPM-model could not explain the abnormal returns.

6.3.8 Contrarian Profits and Macro Risk Factor in Developed Markets

To examine whether jointly Fama and French risk factors, market state factor, and macroeconomic risk factors explain the contrarian payoff in developed countries. I also follow Avramov et al. (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results on Table 4.4.12. This table shows the results of the following monthly time-series regression.

(46) $$Con_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{T-1} + \beta_{10} WVOL_{T-1} + \beta_{11} \Delta IP_{T-1} + e_t$$

Where: Con_t are the returns of the contrarian portfolio at time t, HML_t (high minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI world indices price level and represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.12 Here]

Table 4.12 Models 1 to 4 shows significant adjusted contrarian returns after adjusting the contrarian portfolio consecutively for Fama and French risks, market state and macroeconomic risk factor. More importantly, I find that the liquidity factor, the default spread, and the term spread are positively related to contrarian, while the SMB and the HML factors are negatively related. The strategy generates a contrarian adjusted return of 0.40% per month with a t-statistic of 3.69 and a P-value of 0.000 for the optimum strategy (48-month/48-month) when I control for all global risk (Table 4.4.12 Model 4). This result also implies that the combine change in global risk factor do not explain the contrarian profit.

One possible interpretation of this result is that there is a limited relation between change in global risk factors and the global contrarian. I therefore confirm at this stage that the contrarian profits are not improved by taking extra risk in developed markets. These findings follow Lakonishok et al. (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks, consistent with Gregory et al. (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk. These results also contribute to the debate by reinforcing De Bondt and Thaler’s (1985) findings that claim that overreaction is predictive, and that adjustment of profits to the CAPM-model could not explain the abnormal returns.

6.3.9 Impact of Global Risks Factors on Contrarian Profit in established market

I examine the role of the global risk factors in explaining the global contrarian in established market. I follow Avramov et al. (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results Table 4.4.13. This table shows the results of the following monthly time-series regression.

(47) $$Con_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$$

Where: Con_t are the returns of the contrarian portfolio at time t, HML_t (high minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices price level, It represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.13 Here]

As shown in Table 4.4.13 Models 1, 2 and 3 significant adjusted contrarian returns remain after adjusting of the contrarian portfolio consecutively to the Fama and French risks, the market state factors, and the macroeconomic factor. More importantly, I find that when all factors are included, the contrarian strategy yields a statistically significant abnormal profit at 10% per month of 0.20% with a t-statistic of 1.74 and a P-value of 0.082 for the optimum strategy (48-month/48-month) Table 4.4.13 Model 4. This result also indicates a positive relation between the default spread, industrial production and the contrarian return while all Fama and French risk factors have a negative effect on the momentum profit (Table 4.4.13 Model 4) and implies that the combined change in global risk factors do not explain the contrarian profit in established market. One possible interpretation of this result is that there is a limited relation between change in global risk factors and the global contrarian.

I therefore confirm at this stage that the contrarian profits are not improved by taking extra risk in developed market. These findings follow Lakonishok et al.'s (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks, consistent with Gregory et al. (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk. These results also contribute to the debate by reinforcing De Bondt and Thaler (1985) findings that claim that overreaction is predictive, and that adjustment of profits to the CAPM-model could not explain the abnormal returns.

6.3.10 Effect of Global Risk Contrarian Profit Factor during the Globalization Period 1994-2014

I also examine whether jointly Fama and French risk factors, market state factor, and economic risk factors explain the contrarian payoff during the globalization period. I follow Avramov et al.'s (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results in Table 4.4.14. This table shows the results of the following monthly time-series regression.

(48) $Con_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$

Where: Con_t are the returns of the contrarian portfolio at time t, HML_t (High Minus Low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI world indices price level, It represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.14 Here]

As shown in Table 4.14 Models 1, 2 and 3 significant adjusted momentum returns remain after adjusting of the momentum portfolio consecutively to the Fama and French risks, the market state factors, and the macroeconomic factor. More importantly, I find that when all factors are included, the contrarian strategy yields a statistically significant abnormal profit at 1% of 1.70% per month with a t-statistic of 8.42 and a P-value of 0.00 for the optimum strategy (48-month/48-month) Table 4.4.14 Model 4. This result also indicates a negative relation between the market volatility and default spread, and the contrarian return. However, the combined change in global risk factors do not explain the contrarian profit in de globalization period. One possible interpretation of this result is that there is a limited relation between change in global risk factors and the global contrarian profit. Implying that the contrarian profits are not improved by taking extra risk during globalization period.

These findings follow Lakonishok et al. (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks, consistent with Gregory et al. (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk. These results also contribute to the debate by reinforcing De Bondt and Thaler's (1985) findings that claim that overreaction is predictive, and that adjustment of profits to the CAPM-model could not explain the abnormal returns.

6.3.11 Global Risks Impact on excess contrarian profits

In addition to the global risk effect following crisis and change in business cycle, I finally examine the influence of global risks factors on the excess global contrarian return in other to access the comparative advantage of opting for the strategies. To examine whether jointly Fama and French risk factors, market state factor, and macroeconomic risk factors explain the contrarian payoff. I follow Avramov et al.'s (2015) approach. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results in Table 4.4.15. This table shows the result of the following monthly time-series regression.

(49) $Con_t - R_{Ft} = \alpha_7 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_5 LIQ_{t-1} + \beta_6 DS_{t-1} + \beta_7 TS_{t-1} + \beta_8 MKT_{t-1} + \beta_9 \Delta OP_{t-1} + \beta_{10} WVOL_{t-1} + \beta_{11} \Delta IP_{t-1} + e_t$

Where: $Con_t - R_{Ft}$ is the excess return of contrarian strategy at time t, HML_t (high minus low) is the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t(Small minus big) are returns to long-short portfolios constructed using size, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI world indices price level, It represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the yearly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.4.15 Here]

Table 4.4.15 Models 1, 2 and 3 show significant adjusted contrarian excess returns after adjusting of the contrarian portfolio consecutively to the Fama and French risks, the market state factors, and the macroeconomic factor. More importantly, I find that when all factors are included in the regression, the contrarian strategy yields a statistically significant abnormal profit at 1% of 0.60% per month with a t-statistic of 4.98 and a P-value of 0.000 with the optimum strategy (48-month/48-month) Table 4.4.15 Model 4. This result also indicates a positive relation between the default spread, market volatility, the HML factor and the contrarian return and implies that the combined change in global risk factor do not explain the adjusted excess contrarian profit. One possible interpretation of this result is that there is a limited relation between change in global risk factors and the global contrarian profit. I therefore confirm that the contrarian profits are not improved by taking extra risk and that the results do not systematically differ with respect to either the return or the excess return on the global contrarian strategy. These findings follow Lakonishok et al. (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks, consistent with Gregory et al's (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk. These results also contribute to the debate by reinforcing De Bondt and Thaler's (1985) findings that claim that overreaction is predictive, and that adjustment of profits to the CAPM-model could not explain the abnormal returns.

6.3.12 Summary

I examined the role of global risk factor in explaining the global profit. I find no relation between variations in macroeconomic risk factors. Notably the evidence is that the contrarian strategy generates risk-adjusted profit of 1.00% with a t-statistic of 6.58 and a P-value of 0.000 with the optimum strategy. The results also show that market volatility tends to contribute significantly in reducing the contrarian return. This finding is quiet robust. For example, the finding survives during the banking crisis with 1.40% abnormal return per month, 4.20% per month during currency crisis. However, the exception is during stock market crash where the thesis records a negative abnormal profit. Further analysis indicates that contrarian returns remain after adjusting for global risks. 2.50% per month with subset of non-crisis period, 1.00% per month during the expansion period, 1.40% per month in emerging market, 0.40% per month in developed countries, 0.2% per month in established market, and 1.70% per month during the globalization period, 0.60% per month when I control the impact of global risks on excess contrarian return. However, the contraction subset shows insignificant abnormal return. A direct implication of these results is that international investors might be able to beat the market using common investment strategy such as the global contrarian, and the contrarian strategies profits are not compensation for risks.

6.4 Other Robustness Checks

It is important to determine whether global momentum and contrarian profits and specific risks are related across regions. If the global momentum profits are explained by global risks, and markets are internationally and regionally integrated, then one ought to expect a strong relation between regional (Emerging and Developed markets) risks factors and global momentum. From a purely empirical perspective, examining the relation between the global momentum profits and the global risk factors internationally and across regions enable one to examine whether global momentum profits is explained by a single global risk factor or instead are due to nearly independent regional risk factors.

6.4.1 Effect of Global Fama and French Three-Factor on the Global Momentum Profit

To examine whether jointly Fama and French risks factors, market state factor, and macroeconomic risks factors affect the momentum payoff. I based my examination on the following time-series regression specification. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include Global Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model 3. I report the regression parameters result for each explanatory variable in Table 4.5.1.

(50) $$Mom_t = \alpha_3 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 gHML_t + \beta_4 LIQ_{t-1} + \beta_5 DS_{t-1} + \beta_6 TS_{t-1} + \beta_7 MKT_{t-1} + \beta_8 \Delta OP_{t-1} + \beta_9 WVOL_{t-1} + \beta_{10} \Delta IP_{t-1} + e_t$$

Where: Mom_t are the returns of the global momentum portfolio at time t, HML_t (high minus low) is the equal-weight average of the return for the two high book-to-market portfolios for region minus the average of the returns for the two low book-to-market stocks, SMB_t(small minus big) is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices price level and represent price levels at time t-1, ΔOP_{t-1} is the percent change of monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the percent change of monthly value of the US Industrial production at time t-1. The results are reported in Table 4.4.1. The test statistics are reported in the parentheses and the P-values are reported next.

[Insert Table 4.5.1 Here]

Table 4.5.1 reports the test results of the momentum portfolio returns regressed on the global risk factors. I begin the estimation with the Global Fama and French risk factors, I subsequently include market state and macroeconomic factors consecutively. Table 4.5.1 Models 1 and 2 show significant adjusted momentum returns of the momentum portfolio after adjusting the momentum return consecutively to the Global Fama and French risks and the market state factors. The coefficients associated with the macroeconomic risk factors are not particularly significant in Table 4.5.1. More importantly, I find that industrial production contributes significantly in explaining the momentum return with a coefficient of 1.291, a t-statistic of 3.24 and a P-value of 0.001 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.5.1 Model 3). This effect persists when the test includes all risk factors where the coefficient associated with industrial production remains significant at 5% (0.983) with a t-statistic of 2.00 and a P-value of 0.045 and abnormal return is insignificant. This implyies that change in economy growth or in industry output strongly explains the momentum profit.

One possible interpretation of this result is that there is as strong relation between change in global macroeconomic risk and the global momentum profitability. They indicate the ability of global factor to explain the momentum profit; in line with Cochrane (2011), suggestions that market are integrated across both countries and assets. I can confirm at this stage that if momentum investors follow the 9-month/3-month they will outperform the market. Their profits could be improved by taking extra risk following change in industrial production. However, the Global Fama and French Three-Factor do not or least partially do not explain the momentum profit. This result also support Griffin et al.'s (2003) finding that average momentum profit is positive during GDP growth and even larger and positive with negative market return than positive market returns.

6.4.2 Effect of Global Fama and French Five-Factor on the Global Momentum Profit

Fama and French (2015) suggested that a five-factor model that adds profitability and investment factors to the three-factor model of Fama and French (1993) largely absorbs the patterns in average returns in the stock market. Given that the momentum strategies rely on the ability of the stock market to rise in the short term, I examine whether jointly Global Fama and French five-factor, market state factor, and macroeconomic risks factors affect the momentum payoff. I extend equation (50) by adding two additional factors (profitability and investment). My examination is based on the following time-series regression specification. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include the Global Fama and French Five-Factor, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model 3. I report the regression parameters result for each explanatory variable in Table 4.5.2.

(51) $$Mom_t = \alpha_3 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 LIQ_{t-1} + \beta_7 DS_{t-1} + \beta_8 TS_{t-1} + \beta_9 MKT_{t-1} + \beta_{10}\Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12}\Delta IP_{t-1} + e_t$$

Where: Mom_t are the returns of the global momentum portfolio at time t, HML_t (high minus low) is the equal-weight average of the return for the two high book-to-market portfolios for region minus the average of the returns for the two low book-to-market stocks, SMB_t(small minus big) is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios, RMW_t (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, CMA_t (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices price level and represent price levels at time t-1, ΔOP_{t-1} is the percent change of monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the percent change of monthly value of the US Industrial production at time t-1. The results are reported in Table 4.5.2. The test statistics are reported in the parentheses and the P-values are reported next.

[Insert Table 4.5.2 Here]

Table 4.5.2 reports the test results of the global momentum portfolio returns regressed on the global risk factors. I begin the estimation with global Fama and French Five-Factor, subsequently include market state and macroeconomic factors. Table 4.5.2 Models 1 and 2 show significant adjusted momentum returns (Alpha) of 0.007 with a t-statistic of 3.04 and a p-value of 0.002 after adjusting the momentum return the Global Fama and French Five-Factor, 0.002 with a t-statistic of 3.90 and a p-value of 0.000 after adjusting for market state factors (0.022). The coefficients associated with the macroeconomic risk factors are not particularly significant. More importantly, I find that industrial production contributes significantly in explaining the momentum return with a coefficient of 1.266, a t-statistic of 3.24 and a P-value of 0.001 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.5.2 Model 3). This effect persists when the test includes all risk factors. The adjusted return (Alpha) is not significant but industrial production show significant impact in explaining the momentum return with a coefficient of 0.936 a t-statistic of 2.29 and a P-value of -0.001. Implying that change in economy growth or in industry output strongly explains the momentum profit. One possible interpretation of this result is that there is as strong relation between change in macroeconomic and the global momentum profitability. These findings contribute in the debate by reinforcing Chordia and Shiva Kumar's (2000) study that suggested that momentum strategies profits are explained by common macroeconomic variables, implying that the profitability of the global momentum strategy could be due to variations in common macroeconomic factors and presumably change in risk. However, the Fama and French's profitability and the investment factors do not significantly affect the profitability of the momentum strategy momentum return.

6.4.3 Effect of Asia Pacific Market Fama and French Three-factor on Momentum Profits in Emerging Market

There is also a tendency for the average stock returns to rise relatively with book-to- ratio. Fama and French (2015) document evidence of such rise in Asia Pacific countries. Since the momentum return relies the on performance of the determinants of the market to rise in the short term. I examine whether jointly the global Fama and French Three-Factors (Fama and French Asia Pacific excluding Japan) market state factors, and the macroeconomic factors explain the momentum profit in emerging market. I consider all possible combinations of predictive risks factors. The predictive variables include all the Global Fama and French three-factors (Fama and French Asia Pacific excluding Japan), all market state factors, and all macroeconomic variables included in the previous equation (1-3) are considered. Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results in Table 4.5.3.

(52) $$Mom_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 LIQ_{t-1} + \beta_5 DS_{t-1} + \beta_6 TS_{t-1} + \beta_7 MKT_{t-1} + \beta_8 \Delta OP_{t-1} + \beta_9 WVOL_{t-1} + \beta_{10} \Delta IP_{t-1} + e_t$$

Where: Mom_t are the returns of the momentum portfolio in emerging market at time t, HML_t (high minus low) is the equal-weight average of the returns for the two high book-to-market portfolios for a region minus the average of the returns for the two low book-to-market portfolios, SMB_t(Small minus big) is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the big stock portfolio, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI world indices price level and represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.5.3 Here]

As shown (Table 4.5. 3. Model 1) when I control for the Fama and French risks exclusively the adjusted return become insignificant indicating the ability of the Fama and French risks factor to subsume the momentum profit in emerging market. In Table 4.5.3. Models 2, significant adjusted momentum returns (Alpha) of 0.034 with a t-statistic of 3.18 and a p-value of 0.001 remain after adjusting the momentum profit consecutively for Fama and French risks and market state factors. While the abnormal return associated with the macroeconomic risk factor and the regression after controlling for global risk factor are not particularly significant. More importantly, I find that industrial production tends to contribute significantly in explaining the momentum return with a coefficient of 1.832, a t-statistic of 2.31 and a P-value of 0.021 for the optimum strategy (9-month/3-month) when I control for macroeconomic risk exclusively (Table 4.5. 3. Model 3). However, when all risk factors included with the adjusted return become significant (0.026) with a t-statistic of 2.11 and a P-value 0.035 which could be interpreted as the dominant contribution of the market state factor. My intuition is that the impact of industrial production is still considerable but not enough to explain the momentum profit.

6.4.4 Effect of European Fama and French Five-Factor, TED and Euribor: OIS Spread on Momentum Profits in Develop Market

In this section, I follow the thought that different state of the economy might induce unprecedented liquidity shock and increase in credit risk in the European market (Aussenegg et al. 2016). More precisely the EURBOR_OIS is often considered as a market barometer of liquidity and widely use as measure of the level of liquidity in the European region

(Aussenegg et al., 2015). In addition, the average stock returns in Europe also tend to increase with the book-to-market ratio and the profitability are inversely related to investment (Fama and French, 2015). I extend my analysis by adding the Fama and French's profitability and the investment factors. I also consider an alternative measure of liquidity such as the EURIBOR: OIS Spread (difference between the rate at which European banks lend to each other (ERIBOR) and the overnight' risk free' swap rate (EONIA) among the same banks for 3-month period. Please see Appendix E4 for detailed definition.), given that this informs investor on whether risk is rising or falling in credit market and it is a good indicator of stress in the banking system.

I refer to the TED Spread or the difference between the London Interbank Offered Rate (Libor) and the 3-month Treasury Bill, given that rising TED Spread is commonly known as a bearish indicator and it is evidence that liquidity is being withdrawn from the financial market (Please see Appendix E4 for detailed definition). I consider all possible combinations of predictive risk factors. The predictive variables include all Fama and French Five-Factors, all market state excluding the U.S. liquidity factors. I include the EURIBOR: OIS and the TED Spread, and all macroeconomic variables included in the previous equations; starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (7). My examination is based on the following time-series regression specification. I report the regression parameters results Table 4.5.4. This table shows the result of the following monthly time-series regression.

(53) $$Mom_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + +\beta_6 EOIS_{t-1} + \beta_7 TED_{t-1} + \beta_8 DS_{t-1} + \beta_9 TS_{t-1} + \beta_{10} MKT_{t-1} + \beta_{11} \Delta OP_{t-1} + \beta_{12} WVOL_{t-1} + \beta_{13} \Delta IP_{t-1} + e_t$$

Where: Mom_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the equal-weight average of the return for the two high book-to-market portfolios for the region minus the average of the returns for the two low book-to-market stocks, SMB_t(small minus big) is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios, RMW_t (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, CMA_t (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, $EOIS_{t-1}$ (EURIBOR:OIS

Spread) is the difference between the rate at which European banks lend to each other (ERIBOR) and the overnight' risk free' swap rate (EONIA) among the same banks a 3 month period, TED_{t-1} Spread or the difference between the London Interbank Offered Rate (Libor) and the 3-month Treasury Bill at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, MKT_{t-1} is the MSCI world indices price level, It represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.5.4 Here]

In Table 4.5.4. Models 1, and 2 I record consecutively significant adjusted momentum returns of 0.005 with a t-statistic of 2.46 and a p-value 0.014 after adjusting for European Fama and French risks, 0.006 with a t-statistic of 2.37 after adjusting for the TED Spread. Indicating that the European Fama and French risk factor do not explain the momentum profit. Also, the TED Spread is and indicator of change in liquidity in the given the perceive risk in lending as interbank rates rise against risk-free treasury rate. Which imply that a change in liquidity risk will not explain the momentum profit in developed control while I refer to the TED Spread. Conversely Table 4.5.4. Model 3 insignificant adjusted return. The coefficients associate with The Euribor: OIS Spread is significant (1.334) with a t-statistic of 4.04 a p-value of 0.000 indicating that this factor may have significant impact on the momentum profit in developed market. The Euribor: OIS Spread inform us about how much trusts banks place in each other. One possible interpretation of this result is that rising or falling credit risks could explain the momentum profit in developed countries.

Moreover, controlling for the joint effect of market state factors including The TED Spread Table 4.5.4 Model 4 indicates insignificant adjusted return implying that the Term Spread could have significant impact on momentum profit in developed countries, while the joint effect of market state factors including the Euribor: OIS not explains the momentum profit indicating that additional market variable might reduce the power of the change in credit risk in explaining the momentum profit. In Table 4.5.4. Model 6 there are consistent evidence to suggest that macroeconomic risk factor explain the momentum profit given that the adjusted return (Alpha) become insignificant. More importantly I find that Euribor: OIS contribute in explaining the momentum profit in developed countries, when I control for all risk factors (Table 4.5.4 Model 7) the Euribor: OIS is associate with a coefficient of 1.242 with a t-statistic of 3.67 and a p-value of 0.000, while the Term Spread is associate with a coefficient of 0.192 with a t-statistic of 3.73 and a p-value of 0.000. The implication is that momentum investors could increase their profit following the credit risk when trading on developed country only. However, the Term Spread contribution is not negligible given that it positively and significantly explains the momentum return at 1% level in develop market, in line with Chordia and Shivakumar's (2000) study that suggested that momentum strategies profits are explained by common macroeconomic variables.

6.4.5 Summary

I examined whether global momentum profits and specific risks are related across regions (Emerging and developed). I also examine whether global momentum profits is explained by a single global risk factor or instead are due to nearly independent regional risk factors, and found no consistent relation between variations in Global Fama and French Risks factor and the momentum profit. To reiterate the U.S. Fama and French has similar effect on the global momentum profit. As the global Fama and French risk factors. Examining the joint effect of Global Fama and French Factor on momentum profit I find that industrial production remains significant in explaining the momentum profit. This factor is associate with a coefficient of 0.936, a t-statistic of 2.29 and a P-value of 0.022 when the Five Factors are included. This reveals that change in economy growth or in industry's output strongly affect the momentum profit as initially found. This do results are not specific to individual region. This is in line with Cochrane (2011) suggestions market are integrated across both countries and assets classes. However, studying the relation between specific risk factors and momentum profit in emerging and developed market show that Fama and French factors in Asia pacific excluding Japan could explain the momentum profit based on emerging countries only given that the adjusted return become insignificant. But, impact of the industrial production remains strongly noticeable when I control for both Fama and French factors and macroeconomic factor.

However, when I include market state factors in the equation this effect disappears indicating that the effect of market state factor reduces the power of the Fama and French Asia pacific Factor and the macroeconomic factor in explaining the momentum profit in emerging market. More importantly I find that both Euribor: OIS and the Term Spread contribute in explaining the momentum profit based on developed countries only, when I control for all risk factors. This positive relationship is quiet strong. For example, the Term Spread previously show the same effect when using U.S. instead of the European Fama and French Factor in the thesis.

The effect of macroeconomic cannot be ignore given that, when I control for both European Fama and French Factor and macroeconomic factor jointly the adjusted return (Alpha) become insignificant.

6.5 Global-risk factors Role in Explaining the Contrarian Strategy Payoff

The contrarian strategy has been shown to be profitable in U.S. and most developed countries. Jeegadesh and Titman (2001) show that the best performers appear to be no riskier than the worst performers. Therefore, standard risk adjustment will increase rather than decrease the return spread between past winners and past losers. I have shown that the global contrarian profits are not explained by global risks. However, if markets are internationally and regionally integrated, then one ought to expect a strong relation between risks factors and contrarian profit in various regions (Emerging and Developed markets). From a purely empirical perspective, examining the relation between the global contrarian profits and the global risk factors internationally and across regions enabling one to examine whether global contrarian profits are explained by a single global risk factor or instead are due to nearly independent country or regional risk factors.

6.5.1 Effect of Global Fama and French Three-Factor on the Global Contrarian Profit

To examine whether jointly the Global Fama and French Three-Factor, market state factor, and macroeconomic risks factors affect the global contrarian payoff, I based my examination on the following time-series regression specifications. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include the Global Fama and French risk factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model 3. I report the regression parameters result for each explanatory variable in Table 4.3.4.

(54) $$Con_t = \alpha_3 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 gHML_t + \beta_4 LIQ_{t-1} + \beta_5 DS_{t-1} + \beta_6 TS_{t-1} + \beta_7 MKT_{t-1} + \beta_8 \Delta OP_{t-1} + \beta_9 WVOL_{t-1} + \beta_{10} \Delta IP_{t-1} + e_t$$

Where: Con_t are the returns of the global contrarian portfolio at time t regress on the Global Fama and French Three-Factor, HML_t (high minus low) is the equal-weight average of the return for the two high book-to-market portfolios for region minus the average of the returns for the two low book-to-market stocks, SMB_t(small minus big) is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices price level and represent price levels at time t-1, ΔOP_{t-1} is the percent change of monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the percent change of monthly value of the US Industrial production at time t-1. The results are reported in Table 4.6.1. The test statistics are reported in the parentheses and the P-values are reported next.

[Insert Table 4.6.1 Here]

As shown in Table 4.6.1 Models 1, 2 and 3 significant adjusted contrarian returns remain after controlling consecutively for Global Fama and French risks, market state risks, and macroeconomic risks. More importantly, when I control for the joint effect of the global risk factors, the contrarian strategy generates a statistically and significant abnormal return of 0.010 with a t-statistic of 3.54 and a P-value of 0.000 with the optimum strategy (48-month/48-month) Table 4.6.1 Model 4. The results also show that market volatility tends to contribute significantly in reducing the contrarian return with a coefficient of -0.512, a t-statistic of -3.25 and a P-value of 0.001 with the optimum strategy 48-month/48-month. The effect of the term spread is also noticeable -0.195 with a t-statistic of 2.57 and a p-value of 0.010. When I control for macroeconomic risks exclusively (Table 4.6.1 Model 3), the market volatility effect persists with a coefficient of -0.750, a t-statistic of -5.86 and a P-value of 0.000. However, neither the market volatility, the term spread, nor oil price solely cannot expunge the contrarian abnormal return. One possible interpretation is that global risk factors including the Global Fama and French Three-Factor do not explain the contrarian profit. I can confirm at this stage that contrarian investors will not increase their profits by taking extra risk. However, there is a tendency of all risks factors to be on average negatively related to the contrarian profit. These findings are in line with Lakonishok et al. (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks, consistent with Gregory et al. (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk. These results also contribute to the debate by reinforcing De Bondt and Thaler (1985) findings that claim that overreaction is predictive, and that adjustment of profits to the CAPM-model could not explain the abnormal returns.

6.5.2 Effect of Global Fama and French Five-Factor on the Global Contrarian Profit

Referring to the Fama and French (2015) suggestion that a five-factor model that adds profitability and investment factors to the three-factor model of Fama and French (1993) largely absorbs the patterns in average returns. I extend my analysis by adding two additional factors (profitability and investment). My examination is based on the following time-series regression specifications. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French Five-Factors, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model 3. I report the regression parameters result for each explanatory variable in Table 4.6.2.

(55) $$Con_t = \alpha_3 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 LIQ_{t-1} + \beta_7 DS_{t-1} + \beta_8 TS_{t-1} + \beta_9 MKT_{t-1} + \beta_{10}\Delta OP_{t-1} + \beta_{11} WVOL_{t-1} + \beta_{12}\Delta IP_{t-1} + e_t$$

Where: Con_t are the returns of the momentum portfolio at time t, HML_t (high minus low) is the equal-weight average of the return for the two high book-to-market portfolios for region minus the average of the returns for the two low book-to-market stocks, SMB_t(small minus big) is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios, RMW_t (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, CMA_t (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is the MSCI world indices price level and represent price levels at time t-1, ΔOP_{t-1} is the percent change of monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the percent change of monthly value of the US Industrial production at time t-1. The results are reported in Table 4.6.2. The test statistics are reported in the parentheses and the P-values are reported next.

[Insert Table 4.6.2 Here]

As shown in Table 4.6.2 Models 1 and 2, I record significant adjusted contrarian returns after controlling consecutively for Fama and French risks and the market state risks. Table 4.6.3 Model 3 also show significant adjusted momentum return (Alpha) indicating global risk factors including the Global Fama and French Five-Factor do not explain the contrarian profit. However, when I control for the Global Fama and French Five-Factor exclusively the investment factor (CMA) become significant with a coefficient -0.002 with a t-statistic of -4.11 and a p-value of 0.000 so is the Profitability factor (RMW) with a negative coefficient -0.001 with a t-statistic of -1.68 and a p-value 0.000. Furthermore, when I control for the joint effect of the global risk factors, the contrarian strategy adjusted returns remains significant at 0.014 with a t-statistic of 9.71 and a P-value of 0.000 with the optimum strategy (48-month/48-month) Table 4.6.2 Model 4. The results also show that market volatility tends to contribute significantly in reducing the contrarian return with a coefficient of -0.616, a t-statistic of -5.11 and a P-value of 0.000 with the optimum strategy. The default spread also remains significant with a coefficient of -0.004, a t-statistic of -2.82 and a P-value of 0.005. Overall these results indicate that the contributions of the added risk factors (RMW and CMA) are not sufficient to expunge the abnormal return. One possible interpretation of this finding is that global risk factors do not explain the contrarian profit. I can confirm at this stage that contrarian investors will not increase their profits by taking extra risk. However, there is a tendency of macroeconomic risk factors to be on average negatively related to the contrarian profit. These findings are in line with Lakonishok et al. (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks, consistent with Gregory et al. (2001) study that found that, the contrarian excess returns persist even after controlling for size effects in stock returns and confirm that the contrarian returns are not compensation for market risk.

6.5.3 Effect of Asia Pacific Fama and French Three-factor on Contrarian Profit in Emerging Market

In addition to the effect of global Fama and French risks on contrarian profits, I examine the influence of these factors on the global contrarian in emerging market following Fama and French (2015) findings that average stock returns of Asia Pacific increase with the book-to-market ratio. Given that the contrarian return relies on the performance of the determinants of the market to rise in the long term. I examine whether jointly the global Fama and French Three-Factors (Fama and French Asia Pacific excluding Japan), market state factor, and economic risk factors explain the contrarian payoff in emerging market. I consider all possible combinations of predictive risks factors. The predictive variables include all the Fama and French Three-Factor in Asia Pacific excluding Japan, all market state factors, and all macroeconomic variables included in the previous equation (1-3). Starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (4). My examination is based on the following time-series regression specification. I report the regression parameters results in Table 4.6.3.

(56) $Mom_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 LIQ_{t-1} + \beta_5 DS_{t-1} + \beta_6 TS_{t-1} + \beta_7 MKT_{t-1} + \beta_8 \Delta OP_{t-1} + \beta_9 WVOL_{t-1} + \beta_{10} \Delta IP_{t-1} + e_t$

Where: Con_t are the returns of the contrarian portfolio in emerging market at time t, HML_t (high minus low) is the equal-weight average of the returns for the two high book-to-market portfolios for a region minus the average of the returns for the two low book-to-market portfolios, SMB_t(Small minus big) is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the big stock portfolio, $LIQ_{t-1}$is the liquidity factor at time t-1, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, $MKT_{t-1}$is MSCI world indices price level and represents price levels at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.6.3 Here]

The results in Table 4.6.3 Models 1 to 4 show that significant adjusted contrarian returns remain after adjusting the contrarian profit consecutively for Fama and French Three-Factor, market state factors and macroeconomic factor. More importantly, I find that market return tends to contribute positively significantly in explaining the contrarian return with a coefficient of -0.025 a t-statistic of -2.18 and a P-value of 0.029 for the optimum strategy (48-month/48-month) when I control for market state risk factors exclusively (Table 4.6.3 Model 2). This effect persists with all risk factors included with a coefficient of -2.24, a t-statistic 0.025 and a P-value of 0.003. This result also indicates that the default Spread significantly affects the contrarian return with coefficient of -0.006 a t-statistic of -4.93 and a P-value of 0.000 for the optimum strategy (48-month/60-month) Table 4.6.3 Model 3. This effect persists with all risk factors included with a coefficient of -0.009, a t-statistic -5.61 and a P-value of 0.000. The same the coefficient associated with the industrial production is also positive and significant, indicating that change in economy growth or in industry output may have also have a positive contribution on the contrarian profit.

This result indicates that global combining effect do not explain the contrarian return. The effect of industrial production in explaining the contrarian profit persist even after controlling the Global Fama and French Three-Factor in Asia pacific excluding Japan. I can confirm at this stage that if the contrarian investors will not improve their profit by taking extra risks in emerging market. These findings are in line with Lakonishok et al. (1994) study that suggested that, value stocks are not fundamentally riskier than glamour stocks.

6.5.4 Effect of Fama and French Five-Factor, TED and EURIBOR: OIS Spread on Contrarian Profits in Developed Market

Different states of the economy might induce unprecedented liquidity shock and increase in credit risk in the European market (Aussenegg et al. 2016) more precisely the EURBOR_OIS is considered as a market barometer of liquidity and widely used measure of the level of liquidity in the European region (Aussenegg et al., 2015). Furthermore, the average stock returns in Europe tend to increase with the book-to-market ratio and the profitability are inversely related to investment (Fama and French, 2015). Given that the contrarian relies on stock price to rise in the short term, I extend my analysis by adding the profitability and the investment factors. I also consider an alternative measure of liquidity such as the EURIBOR: OIS Spread (difference between the rate at which European banks lend to each other (ERIBOR) and the overnight' risk free' swap rate (EONIA) among the same banks a 3-month period. Please see Appendix E4 for detailed definition.), given that it informs investor on whether risk is rising or falling in credit market and it is a good indicator of stress in the banking system. I finally refer to the TED Spread or the difference between the London Interbank Offered Rate (Libor) and the 3-month Treasury Bill (Please see Appendix E4 for detailed definition.). Given that a rising TED Spread is a Bearish indicator and it is evidence that liquidity is being withdrawn from the financial market.

To examine whether jointly Fama and French Five-Factors, market state factor, and macroeconomic risk factors explain the contrarian payoff in develop market. I consider all possible combinations of predictive macroeconomic risk factors. The predictive variables include all Fama and French Five-Factors, all market state excluding the U.S. liquidity factors. Additionally, I add consecutively the EURIBOR: OIS and the TED Spread, and all macroeconomic variables included in the previous equation (1-3); starting with model (1) which drops all predictive macroeconomic risk variables and ending with all-inclusive model (7). My examination is based on the following time-series regression specification. I report the regression parameters results Table 4.6.4. This table shows the result of the following monthly time-series regression.

(57) $Con_t = \alpha_6 + \beta_1(R_M - R_F)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + + \beta_6 EOIS_{t-1} + \beta_7 TED_{t-1} + \beta_8 DS_{t-1} + \beta_9 TS_{t-1} + \beta_{10} MKT_{t-1} + \beta_{11} \Delta OP_{t-1} + \beta_{12} WVOL_{t-1} + \beta_{13} \Delta IP_{t-1} + e_t$

Where: Con_t are the returns of the contrarian portfolio at time t, HML_t (high minus low) is the equal-weight average of the return for the two high book-to-market portfolios for region minus the average of the returns for the two low book-to-market stocks, SMB_t(small minus big) is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios, RMW_t (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, CMA_t (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, DS_{t-1} is the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, MKT_{t-1} is the MSCI world indices price level, It represents price levels at time t-1, $EOIS_{t-1}$ (EURIBOR:OIS Spread) is the difference between the rate at which European banks lend to each other (ERIBOR) and the overnight' risk free' swap rate (EONIA) among the same banks a 3 month period, TED_{t-1} Spread or the difference between the London Interbank Offered Rate (Libor) and the 3-month Treasury Bill at time t-1, ΔOP_{t-1} is the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. The t-statistics are reported in the parentheses and the p-values are reported next.

[Insert Table 4.6.4. Here]

Table 4.12 Models 1 to 3 shows significant adjusted contrarian returns after adjusting the contrarian portfolio consecutively for Fama and French risks, market state and macroeconomic risk factor. More importantly, I find that the Fama and French Five-Factor, the TED Spread, and the Euribor: IOS factor do not explain the contrarian profit given that all adjusted contrarian profit remains significant. The default spread, and the term spread have no impact on the contrarian given that none of the coefficient are profitable (Table 4.6.4 Model 4 and 5). Market return also have significant effect in explaining the contrarian profit but these effects are not sufficient to expunge the abnormal profit. Controlling for macroeconomic factors (Table 4.6.4 Model 6 do not show sign of explaining the momentum profit. However, oil price show at least partially significant in explaining the contrarian profit with a coefficient of -0.010 a t-statistic of -2.41 and a p-value of 0.016. Market volatility also contributes in explaining the contrarian return with a coefficient of -0.434 with a t-statistic of -5.24 and a p-value 0.000. More importantly when the strategy generates a contrarian adjusted return of 0.005 per month with a t-statistic of 2.61 and a P-value of 0.009 for the optimum strategy (48-month/48-month) when I control for all global risks (Table 4.6.4 Model 7). This result also implies that the combined change in global risk factor do not explain the contrarian profit and indicates that momentum investors could not increase their profit following the credit or liquidity risk when trading on developed countries only.

6.5.5 Summary

In supplementary tests, I examined the role of global risk factor in explaining the global contrarian profit. I find no relation between variations in global risk factors and the contrarian profit. Notably the results show that the contrarian strategy generates risk-adjusted profit of 0.016 with a t-statistic of 9.01 and a P-value of 0.000 with the optimum strategy. When I control jointly for the Fama and French Five-Factor, the contrarian profit remains highly profitable (0.013) with a t-statistic of 9.71 and a p-value of 0.000. Referring to regional risk, I found that adjusting the contrarian strategy with global risk including the Fama and French Asia Pacific excluding Japan do not explain the contrarian profit in emerging market the adjusted contrarian profit is 0.012 with a t-statistic of 6.44 and the p-value of 0.000.

More importantly to examine of the impact European risk factor on contrarian profit, I consider the European Fama and French Five-Factor, the Euribor: IOS and the TED Spread given that different state of the economy might induce unprecedented liquidity shock and increase in credit risk in the European market (Aussenegg et al. 2016). More precisely the EURBOR_OIS is often considered as a market barometer of liquidity and widely used as measure of the level of liquidity in the European region (Aussenegg et al., 2015). I also consider the joint effect of all states and macroeconomic factors. The results indicate that the strategy generates a contrarian adjusted return of 0.005 per month with a t-statistic of 2.61 and a P-value of 0.009, consistent with this thesis initial findings that global risk factors do not explain the contrarian profit and indicate that contrarian investors could not increase their profit following the credit or liquidity risk when trading on developed countries only.

Chapter 7: Conclusion

7.1 Introduction

In this thesis, I indorse a better understanding of the dynamics of contrarian profitability by analysing the momentum and contrarian strategies internationally and across different market states (established Markets emerging market, developed countries, and during the globalization period). I also take a step towards linking the global momentum and contrarian profitability to different phases (Bear and bull phases), and different periods. This includes the effect of global chocks such as global financial crisis (banking crisis, currency crisis, and stock market crashes) on the momentum and the contrarian strategies profitability, which in turn, helps enhance my understanding of the factors that drive the momentum and the contrarian profit across different periods and different market states.

The Efficient Market Hypothesis suggests that price "fully reflect" available information (Fama, 1970). A direct implication of the Efficient Market hypothesis is that no investors should be able to beat consistently the market using common investment strategies. The profitability of the global momentum and contrarian strategies presented in this thesis demonstrated that trading on indices performances worldwide might provide more evidences of market inefficiency when international investors follow countries' indices performances. On the other hand, introducing the global contrarian strategies could add to the literature on stock market overreaction under the presumption that when investors react to unanticipated news, the price will initially be greater than it should be. There will be a subsequent price decline to the level justified by new information (De Bondt and Thaler, 1985).

By examining the global momentum and contrarian strategies with countries' past indices performances, I have shown that both momentum and contrarian strategies are consistent in producing excess returns using data from 47 countries assuming that investors can switch back and forth from one countries to another in designing a global strategy.

7.2 Summary

In Chapter 4 I find that the global momentum strategies are consistently profitable on the average over the full sample period 1969-2014, and the most successful momentum strategy selects stocks based on their previous performances over 9 months and then holds the portfolio for the next 3 months. This strategy yields 3% per month (42.57% per year) with a t-statistic of 4.50 and a p-value of 0.00. However, these returns vary considerably from one market condition to another. It yields 1.77% per month (23.43% per year) in established market, 2.17% per month (29.38% per year) in developed countries and 3.28% per month (47.29% per month) in emerging markets. More importantly, the momentum strategies remain on the average profitable in the period of post-globalisation but the optimum strategies generate a negative return. My evidences also stipulate that the momentum strategies' returns are on the average low with the overlapping approach. The optimum strategy selects stock based on their past 9 months' performances and hold for 3 months it yields 0.95% per month (12.01% per year).

After examining the 9-month/3-month strategy in different market states, I found that investors could achieve superior returns by adopting the momentum strategy after a bear phase; but there is a strong link between the rising market performances in bull market and the momentum profits. This strategy yields 2.65% per month (36.98% per year) during the bear market and 3.16% per (45.20% per year) in bull market. This indicates that the return(s) on the momentum strategy will depend upon speed of the falling and the rising market. More importantly, the momentum strategies' returns are high when the bull market performance is relatively higher than the equivalent bear market in absolute value.

In Chapter 5, I find that the contrarian strategies are highly profitable. The optimum strategy is the 48-month/60-month this strategy yields 0.83% per month (10.43 per year). The contrarian strategy generates return high as 1.38% per month (17.70% per year) in emerging market with the 60-month/ 48-month strategy. Developed countries' contributions are less significant, still a consistent contrarian' return of 0.93% per month (11.72% per year) could be observed in developed countries with the 60-month/48-month strategy when the strategy skips a time lag between the portfolio formation period and the holding period.

My evidences also instruct that the contrarian strategies' returns are on the average low with the overlapping approach. The optimum strategy selects stock based on their past 48 months' performances and holds for 48 months it yields 0.55% per month (6.80% per year). The contrarian strategies with non-overlapping quintile portfolios are the most profitable. The 48-month/60-month strategy generates a return as high as 0.71 per month (8.89% per year). More importantly, the contrarian strategies remain on the average profitable in the period post-1994 but the returns are not statistically significant on the average, which implies that the reversal effect survives the globalisation impact and indicates that the integration of equity markets together with the international correlation among markets do not synchronized the prices reversal effect around the world.

The contrarian strategies remain profitable in emerging countries, but I reiterate that on average they are less statistically significant with overlapping portfolios; the optimum strategy yields 0.71% per month (8.89% per year). Taken as a whole, these evidences indicate that the contrarian strategies yield on average higher return with the non-overlapping portfolio than the equivalent overlapping approaches for both deciles and quintiles portfolios and that the contrarian strategies are on the average considerably greater with deciles portfolios than quintiles portfolios.

At a more general level, the results present the global contrarian strategy as a highly profitable strategy and indicate the need for considerable care in constructing and evaluating the global contrarian internationally. Moreover, my analysis takes on particular significance given the association between lagged market movement (share prices) and investor's optimism that appears among traders, generating increasing reversal effect (Siganos and Chelley-Steley, 2006), and also has direct implication for predicting and controlling trading costs associated with asset allocation strategies.

It is important to reiterate that, the global momentum and contrarian strategies is profitable after accounting for transaction costs given that, on average, the contrarian strategies with non-overlapping portfolios are long-term strategies and result in a low turnover. The optimum strategy generates a return of 10.40% per annum while the portfolios are rebalanced with 48 months' intervals, and the optimum momentum strategy also result in a low turnover with 42.57% return per annum. Jegadeesh and Titman (1993), and Berkowitz, Logue and Noser (1988) estimate one-way transaction costs of 23 basis points for institutional investors suggesting that transaction cost of 0.5% per trade with a 6-month/6-month strategy is conservative. This implies an estimated transaction cost of 0.6% per annum which is not negligible, suggesting a contrarian profit of 9.8% per annum, and a momentum profit of 41.97 which does not undermine the high profitability of these strategies. However, investment firms will have to demonstrate that they have executed at the best possible trade condition conformably with the European regulation.

Furthermore, ETFs are easy to access and simple to use. They can achieve diversification through one trade, allowing access to different investment and cover a broad range of asset classes. They often have lower cost than many other type of investments funds helping investors to keep more of their earnings. For example, a world equity ETFs with 5% turnover rate might incur transaction cost amounting to just 0.4 basis points per year (Morningstar, 2016). ETF are flexible to investors' needs, whether they want to invest in developed markets like US and UK, in emerging market like India and China or in commodity such as Oil and Gold.

In chapter 6, I find a strong relation between variations in macroeconomic factor notably industrial production and the adjusted momentum return. The momentum strategies generate a risk adjusted return of 0.9% per month when I control for Fama and French risk with t-statistic of 4.82% and a P-value of 0.00. When I control for market states risks, it generates 1.31% per month with a t-statistic of 2.21 and a P-value of 0.02. However, the abnormal return disappears when I control for macroeconomic risk as the momentum generates 0.5% abnormal return per month with a t-statistic of 1.71 and a P-value of 0.241. The evidence is that industrial production tends to contribute significantly in explaining the momentum return with a coefficient of 1.05, a t-statistic of 3.46 and a P-value of 0.00 when I control for global risks factor. The effect persists when I control jointly for Fama and French risks, market states risk, and macroeconomic risk, where the momentum abnormal return is 0.5% per month with a t-statistic of 0.71 and a p-value of 4.481. This reveals that change in economy growth or in industry's output strongly affects the momentum profit. However, abnormal return remains insignificant for every holding period. Suggesting that macroeconomic risks are consistent in explaining the momentum strategy profits regardless of the of the strategy time horizon.

The impact of macroeconomic risk factors on the global momentum profit holds in emerging countries, developed countries, established market, and globalization period, given that all the abnormal returns are not significant when I control jointly for Fama and French risk, market states risk and macroeconomic risks. This indicates that the findings are not limited to a specified sample.

I also examine the impact of crisis on the momentum profit; referring to the possibility, that stock market could add as indicator of the state of the economy (Naes et al., 2011). My findings show that the abnormal momentum profits become insignificant return after controlling jointly for Fama and French risks market states risk and macroeconomic risk during crisis period the crisis and non-crisis period. The exceptionally momentum strategy generates significant abnormal when it is implemented during Banking crisis, it generates 4.30% return per month with a t-statistic of 3.54 and a p-value of 0.00.

My findings strongly support that, industrial production contributes significantly in explaining the momentum return following business cycle expansion and the abnormal return become negative during contraction, in line with Chordia and Shivakumar (2002) who suggested that variation in momentum payoffs reflects time varying over the business cycle. These findings help deal with one of the fundamental issue in finance, the Efficient Market Hypothesis that suggests that excess returns cannot be earned using investment strategies based on historical shared price or other historical data (Fama, 1970). As the results suggest following macroeconomic risks could lead to additional return. Macroeconomic risks tend to explain the momentum profit therefore; global momentum profit could be seen as a compensation for international investors for bearing macroeconomic risk.

I finally examine the role of global risk factor in explaining the global contrarian profit. The results show none or little relation between variation in global risk factors and the contrarian profit. The contrarian strategies generate a risk adjusted return of 0.6% per month when I control for Fama and French risk with t-statistic of 13.24 and a P-value of 0.00. When I control for market states risks, it generates 0.6% per month with a t-statistic of 6.30 and a P-value of 0.00. However, the abnormal return disappears when I control for macroeconomic risk as the contrarian generates 1.0% abnormal return per month with a t-statistic 9.08 and a P-value of 0.00. The effect persists when I control jointly for Fama and French risks, market states risk, and macroeconomic risk, where the contrarian abnormal return is 1.00% per month with a t-statistic of 6.58 and a p-value of 0.00. This reveals that change in global risk does not explain the momentum profit. Of particular interest, the abnormal return remains significant for every holding period. Suggesting global risks have no power in explaining the contrarian strategy profits regardless of the of the strategy time horizon.

The contrarian strategy remains profitable after adjusting for global risks in different market states. It generates a risk adjusted return of 1.4% per month with a t-statistic of 7.25 and a P-value of 0.00. In emerging countries, in developed countries I find 0.4% abnormal return with a t-statistic of 3.29 and a P-value of 0.00, countries, in established market it generates 0.2% per month with a t-statistic of 1.74 and a P-value of 0.08, and during the globalization period it earns 1.7% per month with a t-statistic of 8.42 and a P-value of 0.00. Given that all the abnormal returns are significant when I control jointly for Fama and French risk, market states risk and macroeconomic risks. This indicates that the findings are not limited to a specified sample.

I examine the impact of crisis on the contrarian profit; referring to the possibility, that stock market could add as indicator of the state of the economy (Naes et al., 2011). My findings show that the abnormal contrarian profits remain significant after controlling jointly for Fama and French risks market states risks and macroeconomic risks during crisis period and non-crisis period. Exceptionally, the contrarian strategy generates a negative abnormal return when it is implemented during stock market crash -0.80% return per month with a t-statistic of -2.82 and a p-value of 0.00. My findings also strongly support that global risk do not contribute significantly in explaining the contrarian return following non-crisis period it generates 2.5% per month with a t-statistic of 15.92 and a P-value of 0.000. This strategy also generates positive abnormal return expansion (1.00% per month) with a t-statistic of 4.72 and a P-value of 0.00. However, the abnormal return becomes insignificant during contraction, in line with Chordia and Shivakumar (2002) who suggested that variation in momentum payoffs reflects time varying over the business cycle.

For readers inclined to dismiss these findings at a global level, I offer a further check by examining whether global momentum profits and specific risks are related across regions (Emerging and developed) using global and regional risk factros. I test whether global momentum profits are explained by a single global risk factor or instead are due to nearly independent regional risk factors, and found no consistent relation between variations in Global Fama and French Risks factor and the momentum profit. To reiterate, the U.S. Fama and French has similar effect on the global momentum profit as the global Fama and French risk factors. The same, the contrarian strategy generates risk-adjusted profit of 0.016 with a t-statistic of 9.01 and a P-value of 0.000 with the optimum strategy. When I control jointly for the Fama and French Five-Factor, the contrarian profit remains highly profitable (0.013) with a t-statistic of 9.71 and a p-value of 0.000. Referring to regional risk I found that adjusting the contrarian strategy with global risk including the Fama and French Asia Pacific excluding Japan do not explain the contrarian profit in emerging market the adjusted contrarian profit is 0.012 with a t-statistic of 6.44 and the p-value of 0.000.

More importantly examining the impact of european risk factor on contrarian profit, I consider the European Fama and French Five-Factor, the Euribor: IOS and the TED Spread. I also consider the effect of all states and macroeconomic factors. The results indicates that the strategy generates a contrarian adjusted return of 0.005 per month with a t-statistic of 2.61 and a P-value of 0.009, consistent with this thesis's initial findings that global risk factors do not explain the contrarian profit and indicate that contrarian investors cannot increase their profit following the credit or liquidity risk when trading on developed countries only.

These findings also help deal with the fundamental issue in finance, the Efficient Market Hypothesis that suggests that excess returns cannot be earned using investment strategies based on historical shared price or other historical data (Fama, 1970). As the results suggest following macroeconomic risks could lead to additional return. Macroeconomic risks tend to explain the momentum profit consequently global momentum profit could be seen as a compensation for global macroeconomic risks. While the global contrarian profit is not necessary a compensation for contrarian investors bearing extra risks.

7.3 Contribution

This thesis main contribution relies of the fact that it provides evidences of the profitability of the global momentum and contrarian strategies worldwide. It explains how the profit of the momentum and contrarian strategies varies in different market states the extent to which the initial effect dissipates or ceases to affect the momentum and the contrarian strategies profitability. It presents the Global Momentum and Contrarian Strategies as highly profitable strategies and examines the role of global crisis in explaining the momentum and contrarian profits; the results are consistent between subsample periods.

I therefore contribute to several stands in finance. First, I promote new momentum and contrarian strategies by suggesting the use of countries' indices performances to momentum and contrarian portfolio selections. Investors can now move back and forth from one country to another in designing momentum or contrarian portfolios. My analysis includes a wider set of equity indices (47 countries indices), variety of parameters (3, 6, 9, and 12-month formation and holding periods for the momentum, and 36, 48, 60-month formation and holding periods for the contrarian), sub-periods' analysis, and event-time analysis by sub-period. These results contribute to the debate by reinforcing De Bondt and Thaler's (1985) findings that claim that overreaction is predictive, and that adjustment of profits to the CAPM-model could not explain the abnormal returns. In addition, they show that portfolios based on market-adjusted excess returns do not systematically differ with respect to market value of equity. Challenging the weak form of the Efficient Market Hypothesis that suggests that excess returns cannot be earned in the long run by using investment strategies based on historical shared price or other historical data (Fama, 1970).

This thesis provides evidence of greater return reversal internationally consistent with Jordan's (2012) study that suggested that contrarian strategies are internationally profitable, but reported return based on national indices of about 5.60% per year with earning above the risk-free rate. My findings also endow with a greater return than Malin and Bornholt's (2013) study that suggested 0.46% contrarian return per month (5.66% per year) in developed market and 0.68% per month (8.47 per year) in emerging market, and Richards's (1996) study that found 6.60% per year over 3 years holding period and 5.80% per year over 4 years.

Even more interesting, studying the global momentum do not show evidence of return continuation among countries indices. However, I must point out that my evidences are different from Chan, Hameed, Tong's (2000) study that suggested that momentum strategies are internationally profitable on the point of view US investor as they suggested that on average the momentum strategy generates 1% per month which is significantly lower than the average momentum return in this study (42.57% per annum). I also emphasise the point that investors earn extra returns by investing internationally as the global momentum generates a return of about three times higher than the return indicated on Jegadeesh and Titman (1993, 2001).

The thesis finally adds to the literature on the motivation behind the overreaction hypothesis by suggesting a highly profitable contrarian strategy. In line with the proposal that, if stock prices systematically overshoot, then their reversal should be predictable from past return data alone, with no use of any accounting data such as earnings.

A direct implication of my findings is that international investors could beat the market using common investment strategy such as the global momentum and the global contrarian strategies. The global contrarian strategies profits are not compensation for risks. While the global momentum profit could be explained by global risks. International momentum investors could earn excess return by increasing their exposure to global risks.

7.4 Limitations

The evidences on the global momentum and contrarian strategies seen as independent and profitable strategies with respect to Fama and French risks, market state risks, and macroeconomic risks are remarkable in international equity market. Still, the main issue that remain is however, how the global momentum and contrarian strategies perform in other asset classes. The same trading with the global momentum and contrarian strategies requires investors to either invest in ETFs or in individual stock in the maner that replicated loser and winner indices performances. The second investment approach might seem intricate for individual investors without siginificant knowledge of financial transaction. In addition, investing in individual stocks internationally implies that investor might sustain additional cost (Unknown) which are not discussed in this thesis. It also remains to be seen, whether both strategies might become independent risk factor in global asset pricing which are unresolved puzzle.

Moreover, it might be more interesting to study a longer period dating back to the nineteenth century or the Victorian Era characterized by the rapid change development in almost every domain. This includes advances in scientific, technological and medical knowledge, change in population growth and location, which deeply change countries' mood leading to optimism, economic boom and prosperity.

A more complete analysis could examine the ability of the global momentum and contrarian to converge. Balvers and Wu (2006) suggested that technological progress in one country implies that the country has a competitive advantage that grows relatively fast as the technology is implemented leading to a momentum profitability for this country. When the technology is imitated in other countries, the production levels converge, causing reversion in equity prices.

Figure 1 Momentum Strategy Return in Event Time

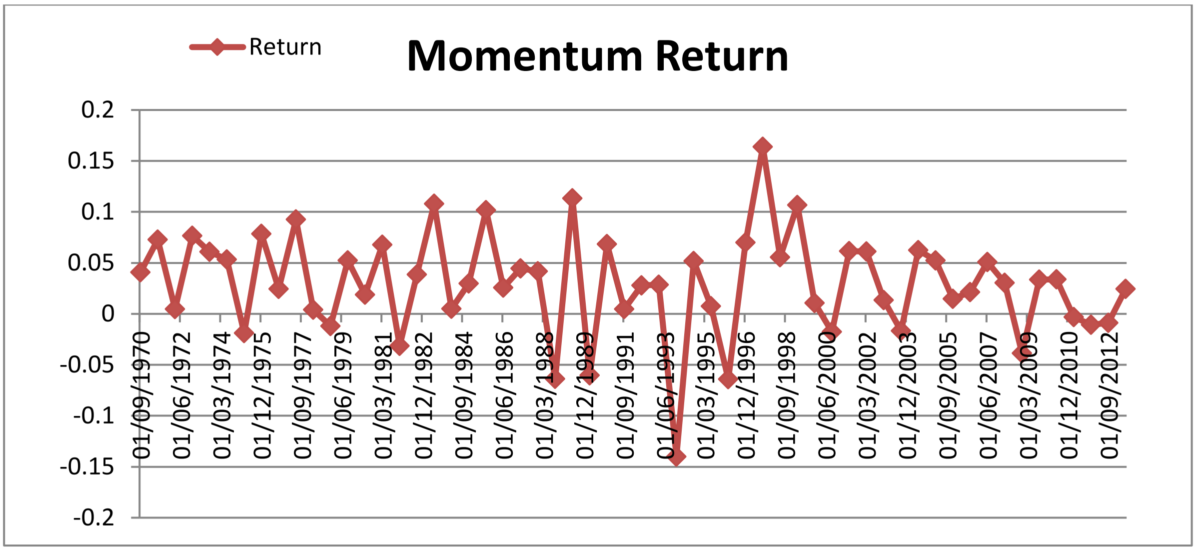


Fig 24 Shows the momentum returns, from December 1969 to January 2014. Note that the red line represents the average monthly return of the 9-month/3-month momentum strategy at different time periods.

Figure 2 Contrarian Strategies Periodical Brunt.

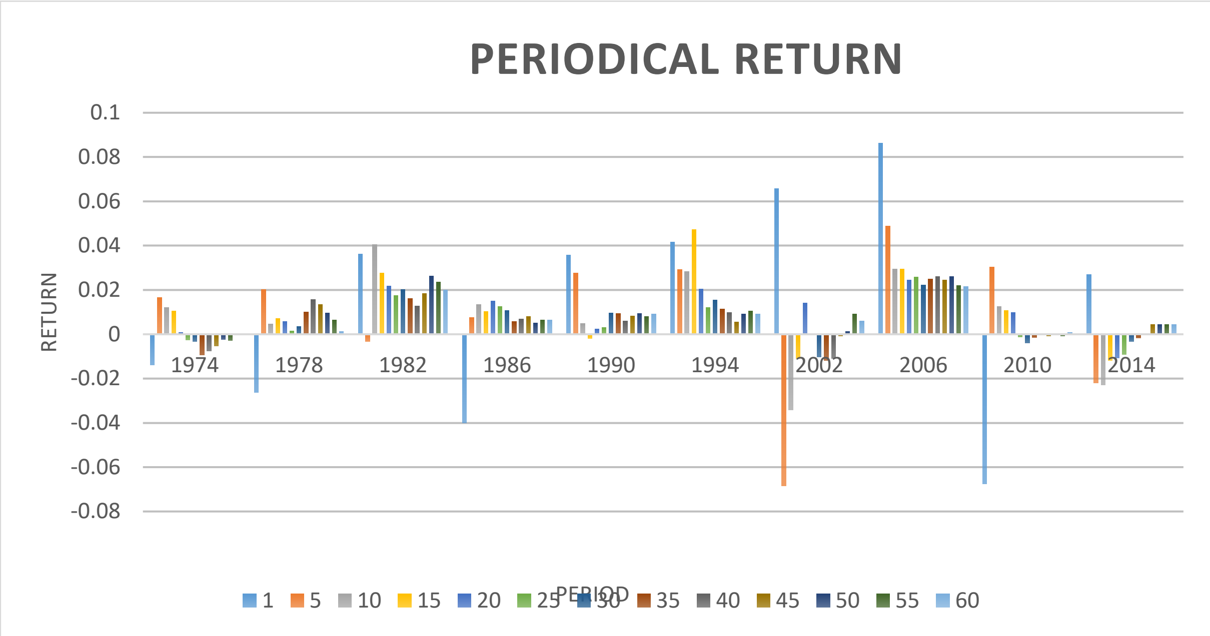


Fig 27 Shows the returns on the contrarian portfolio based on 48-month formation with various holding period (1 to 60 month) at the end of all portfolio formation period, from December 1969 to January 2014.

Table 3. 1 Monthly Return Characteristic of 47 Countries Indexes Price 1969-2014

Panel A: Monthly return characteristics of developed countries										
Name	(ID)	Start	End	Mean	Std	Skewness	Kurtosis	Shapiro-Wilk	Sig.
USA	(1)	31/12/1969	31/01/2014	0.54	0.04	-0.67	2.47	0.97	0.00
JAPAN	(2)	31/12/1969	31/01/2014	0.62**	0.06	-0.02	0.67	0.10	0.06
UK	(4)	31/12/1969	31/01/2014	0.49	0.06	0.29	5.53	0.95	0.00
Australia	(10)	31/12/1969	31/01/2014	0.40	0.07	-1.49	9.79	0.92	0.00
France	(11)	31/12/1969	31/01/2014	0.53	0.07	-0.47	1.46	0.98	0.00
Germany	(12)	31/12/1969	31/01/2014	0.58	0.06	-0.66	1.82	0.97	0.00
Italy	(15)	31/12/1969	31/01/2014	0.21**	0.07	-0.16	0.63	0.10	0.08
Canada	(20)	31/12/1969	31/01/2014	0.53	0.06	-0.89	3.54	0.96	0.00
Hong Kong	(21)	31/12/1969	31/01/2014	0.85	0.10	-0.53	7.15	0.92	0.00
Singapore	(23)	31/12/1969	31/01/2014	0.69	0.08	-0.52	5.92	0.93	0.00
Spain	(24)	31/12/1969	31/01/2014	0.31	0.07	-0.53	2.14	0.97	0.00
Switzerland	(25)	31/12/1969	31/01/2014	0.74	0.05	-0.40	1.33	0.98	0.00
Belgium	(27)	31/12/1969	31/01/2014	0.51	0.06	-1.22	8.19	0.92	0.00
Sweden	(29)	31/12/1969	31/01/2014	0.82	0.07	-0.49	1.38	0.98	0.00
Austria	(30)	31/12/1969	31/01/2014	0.48	0.07	-0.98	6.83	0.92	0.00
Ireland	(32)	31/12/1987	31/01/2014	0.18	0.07	-1.02	2.78	0.95	0.00
Netherlands	(33)	31/12/1969	31/01/2014	0.60	0.06	-0.82	2.76	0.96	0.00
New Zealand	(34)	31/12/1981	31/01/2014	0.37	0.07	-0.91	5.05	0.95	0.00
Norway	(35)	31/12/1969	31/01/2014	0.64	0.08	-0.86	2.97	0.96	0.00
Portugal	(37)	31/12/1987	31/01/2014	0.01	0.07	-0.42	1,80	0.98	0.00
Denmark	(39)	31/12/1969	31/01/2014	0.82	0.06	-0.49	2.35	0.98	0.00
Finland	(40)	31/12/1981	31/01/2014	0.92	0.09	-0.41	1.65	0.98	0.00
Israel	(42)	31/12/1992	31/01/2014	0.29	0.07	-0.47	0.89	0.97	0.00
Average				0.53	0.07	-0.61	3.44	0.96	0.01

Table 3. 2 Monthly Return Characteristic of 47 Countries Indexes Price 1988-2014

Panel B: Monthly return characteristics of Emerging countries									
China	(3)	31/12/1992	31/01/2014	0.21	0.10	-0.00	1.53	0.98	.00
Brazil	(5)	31/05/1987	31/01/2014	0.95	0.15	-1.38	10.87	0.89	.00
India	(6)	31/12/1992	31/01/2014	0.54***	0.09	-0.22	0.62	0.99	.20
Korea	(7)	31/12/1987	31/01/2014	0.46	0.10	0.19	3.02	0.97	.00
Russia	(8)	30/12/1994	31/01/2014	0.86	0.16	-1.19	6.03	0.93	.00
Turkey	(9)	31/12/1987	31/01/2014	0.44	0.16	-0.03	1.13	0.99	.00
Indonesia	(13)	31/12/1987	31/01/2014	0.62	0.13	0.18	5.21	0.92	.00
South Africa	(14)	31/12/1992	31/01/2014	0.62	0.08	-0.90	2.48	0.96	.00
Mexico	(16)	31/12/1987	31/01/2014	1.33	0.09	-0.99	3.49	0.95	.00
Taiwan	(17)	31/12/1987	31/01/2014	0.33	0.10	-0.06	1.65	0.98	.00
Thailand	(18)	31/12/1987	31/01/2014	0.39	0.11	-0.54	2.45	0.96	.00
Argentina	(19)	31/12/1987	31/01/2014	0.88	0.14	0.27	3.92	0.94	.00
Malaysia	(22)	31/12/1987	31/01/2014	0.50	0.08	-0.28	4.70	0.93	.00
Chile	(26)	31/12/1987	31/01/2014	0.89	0.07	-0.59	2.50	0.97	.00
Colombia	(28)	31/12/1992	31/01/2014	0.87	0.09	-0.43	1.20	0.98	.00
Egypt	(31)	31/05/1994	31/01/2014	0.86	0.93	-0.12	1.41	0.99	.02
Poland	(36)	31/12/1992	31/01/2014	0.84	0.13	0.50	5.79	0.94	.00
CZECH Rep	(38)	31/12/1994	31/01/2014	0.55	0.09	-0.75	2.29	0.97	.00
Hungary	(41)	30/12/1994	31/01/2014	0.65	0.11	-1.06	4.22	0.94	.00
Pakistan	(43)	31/12/1992	31/01/2014	0.10	0.11	-1.24	7.52	0.91	.00
SRI Lanka	(44)	31/12/1992	31/01/2014	0.35	0.10	0.58	3.30	0.95	.00
Morocco	(45)	31/12/1994	31/01/2014	0.47	0.06	-0.11	1.15	0.99	.03
Peru	(46)	31/12/1992	31/01/2014	0.95	0.09	-0.75	3.36	0.96	.00
Jordan	(47)	31/12/1987	31/01/2014	0.03	0.054	-0.44	3.05	0.96	.00
Average				0.61	0.14	-0.39	3.49	0.96	0.01

This table reports the descriptive statistic and normality test of individual countries. The sample is from 1969 to 2014. I test whether the returns of the 23 developed and 24 Emerging markets indices prices are normally distributed through their skewness, kurtosis. I use the mean and standard deviation to compare the two sets of countries. I used the Shapiro-Wilk test to confirm the normality of the distribution. The results are ** statistically significant for p>0.05 and ***statistically significant for p>0.1.

Table 3. 3 Momentum and Fama and French Risk Factors 1969-2014

Panel A. Descriptive Statistics

	Obs	Min	Max	Mean	Std	Skew	Kur	SW	P-value
ERM	517	-0.232	0.161	0.005	0.059	-0.547	2.000	4.954	0.000
SMB	517	-0.167	0.223	0.002	0.031	0.614	6.815	7.269	0.000
HML	517	-0.131	0.139	0.003	0.029	-0.015	2.596	5.763	0.000
MKTRF	517	-0.212	0.127	0.001	0.043	-0.774	2.210	5.969	0.000

Panel B. Correlation

	MKTRF	SMB	HML
MKTRF	1.0000		
SMB	0.1924	1.0000	
HML	-0.2045	-0.2333	1.0000

Panel C Variance Inflation Factor with MSCI World Index Excess Return

Variable	VIF	1/VIF
HML	1.090	0.919
SMB	1.080	0.924
MKTRF	1.070	0.936
Mean VIF	1.080	

Panel D Variance Inflation Factor with excess return on US market

Variable	VIF	1/VIF
ERM	1.170	0.855
HML	1.140	0.880
SMB	1.120	0.896
Mean VIF	1.140	

Panel E Serial correlation and heteroscedasticity

		Serial correlation					Breusch-Pagan	
Variable	LAG	AC	PAC	Q	Prob>Q		Prob>chi2	Chi2(1)
MKTRF	1	0.116	0.116	7.023	0.008		0.850	0.040
SMB	1	0.022	0.022	0.254	0.615			
HML	1	0.143	0.143	10.76	0.001			

This table reports the descriptive statistic, the correlation, the normality test, the variance inflation factor, Breusch-Pagan test for heteroscedasticity, and the standard Q test statistic for the time series of monthly value of excess return on the market (ERM), Small-Minus-Big Return (SMB), High-Minus-Low Return (HML), Risk-Free Return Rate (RF) and the Momentum Factor (MF). The sample period ranges from January 1970 to December 2013. I test whether the variables series are normally distributed through their Skewness, kurtosis. I use the mean and standard deviation to compare the variable. I used the Shapiro-Wilk test to confirm the normality of the distribution. The results are ** statistically significant for p>0.05 and ***statistically significant for p>0.1. I also test for any sign of multicollinearity through the variance inflation factor and the correlation coefficient.

Table 3. 4 Momentum Profit and Market State Factors 1969-2014

Panel A Descriptive Statistic

	Obs	Min	Max	Mean	Std	Skew	Kur	SW	P-value
LIQ	517	-0.461	0.201	-0.031	0.064	-1.580	6.849	8.625	0.000
DS	517	0.550	3.380	1.112	0.460	1.720	3.796	9.458	0.000
TS	517	-0.106	0.143	0.003	0.031	0.349	2.076	4.957	0.000
MSCI W	517	-0.211	0.133	0.006	0.043	-0.790	2.304	5.969	0.000

Panel B Correlation

	TS	LIQ	DS	MSCIW
TS	1.000			
LIQ	0.002	1.000		
DS	0.080	-0.099	1.000	
MKT	0.066	0.282	0.033	1.000

Panel C Variance Inflation Factor

Variable	VIF	1/VIF
TS	1.010	0.990
LIQ	1.100	0.909
DS	1.020	0.980
MKT	1.100	0.913
Mean VIF	1.060	

Panel D serial correlation and heteroscedasticity

		Serial correlation				Breusch-Pagan	
Variable	LAG	AC	PAC	Q	Prob>Q	Prob>chi2	Chi2(1)
TS	1	0.050	0.050	1.284	0.257	0.708	0.140
LIQ	1	0.097	0.098	4.936	0.026		
DS	1	0.961	0.963	480.53	0.000		
MKT	1	0.110	0.110	6.3294	0.012		

This table reports the results of the descriptive statistic, the correlation, the normality test, of the variance inflation factor, the Breush-Pagan test and the standard Q test statistic for the time series of monthly value of the liquidity factor (LIQ), Business cycle (NBER M), Default spread ((DS), the Term spread (TS) and the MSCI world index indices price level (MKT). The sample period ranges from January 1970 to December 2013. I test whether the variables series are normally distributed through their Skewness, kurtosis. I use the mean and standard deviation to compare the variable. I used the Shapiro-Wilk test to confirm the normality of the distribution. The results are ** statistically significant for p>0.05 and ***statistically significant for p>0.1. I also test for sign of multicollinearity through the variance inflation factor and the correlation matrix.

Table 3. 5 Momentum and Macroeconomic Factor 1969-2014

Panel A. Descriptive Statistics

	Obs	Min	Max	Mean	Std	Skew	Kur	SW	P-value
ΔOP	517	-0.400	0.500	0.006	0.084	-0.394	4.510	8.106	0.000
WVOL	517	-0.044	0.024	0.002	0.007	-1.200	0.214	7.793	0.000
ΔIP	517	0.003	0.039	0.007	0.004	3.586	20.385	11.131	0.000
ΔOP	517	-0.400	0.500	0.006	0.084	-0.394	4.510	8.106	0.000

Panel B Correlation

	WOP	IP
OP	1.000	
IP	0.065	1.000
MKTVOL	0.042	-0.199

Panel C VIF

Variable	VIF	1/VIF
ΔIP	1.050	0.955
WVOL	1.040	0.957
ΔOP	1.010	0.995
Mean VIF	1.030	

Panel D serial correlation and Heteroscedasticity

	Serial correlation					Breusch-Pagan	
Variable	LAG	AC	PAC	Q	Prob>Q	Prob>chi2	Chi2(1)
ΔOP	1	0.200	0.200	20.745	0.000	0.667	0.180
ΔIP	1	0.355	0.355	65.376	0.000		
WVOL	1	0.635	0.637	209.95	0.000		
ΔOP	1	0.200	0.200	20.745	0.000		

This table reports the results of the descriptive statistic, correlation coefficient, the normality test, of the variance inflation factor, Breusch-Pagan test and the standard Q test for the time series of monthly value of, Oil price (ΔOP), Market volatility (WVOL), and Industrial production (ΔIP). The sample period ranges from January 1969 to December 2014. I test whether the variables series are normally distributed through their Skewness, kurtosis. I use the mean and standard deviation to compare the variable. I used the Shapiro-Wilk test to confirm the normality of the distribution. The results are ** statistically significant for p>0.05 and ***statistically significant for p>0.1. I also test for signs of multicollinearity through the variance inflation factor and the correlation matrix.

Table 3. 6 Correlation on Risk Factors 1969-2014

	MKTRF	SMB	HML	TS	LIQ	DS	MKT
MKTRF	1.000						
SMB	0.192	1.000					
HML	-0.205	-0.233	1.000				
TS	0.123	0.072	0.029	1.000			
LIQ	0.066	0.063	-0.036	0.002	1.000		
DS	0.042	0.106	-0.048	0.080	-0.099	1.000	
MKT	0.113	0.165	0.062	0.066	0.282	0.034	1.000
∆OP	-0.002	0.022	0.076	-0.136	-0.000	-0.089	0.018
∆IP	0.096	-0.090	0.036	-0.110	0.069	-0.322	-0.031
WVOL	-0.192	0.056	-0.037	-0.008	-0.079	0.157	-0.074
	∆OP	∆IP	WVOL				
∆OP	1.000						
∆IP	0.065	1.000					
WVOL	0.042	-0.199	1.000				

Table 3. 7 Variance Inflation Factor and Breusch-Pagan on Risk Factor 1969-2014

Variable	VIF	1/VIF		Breusch-Pagan test	
				chi2(1)	Prob > chi2
∆IP	1.18	0.849		0.400	0.529
MKTRF	1.160	0.860			
DS	1.160	0.863			
MKT	1.150	0.872			
SMB	1.140	0.878			
HML	1.130	0.888			
WVOL	1.110	0.901			
LIQ	1.110	0.901			
TS	1.060	0.943			
∆OP	1.040	0.961			

Table 4.1. 1 Momentum Returns for International Investor: Full sample 1969-2014

		Panel A					Panel B			
J	K=	3	6	9	12	K=	3	6	9	12
3 Sell		0.42	0.50	0.36	0.45		0.40	0.29	0.30	0.49
3 Buy		0.94	0.93	1.02	0.89		1.02	1.14	1.08	0.90
3 Buy-Sell		0.52	0.43	0.66	0.44		0.62	0.85	0.79	0.41
		(1.33)	(1.64)	(3.07)	(2.43)		(1.67)	(3.35)	(3.73)	(2.24)
Sig		0.19	0.10	0.00	0.02		0.09	0.00	0.00	0.03
6 Sell		0.43	0.28	0.11	0.43		-0.35	-0.04	-0.01	0.42
6 Buy		1.04	1.04	0.92	0.78		0.80	1.16	0.78	0.72
6 Buy-Sell		0.62	0.76	0.81	0.34		1.15	1.21	0.79	0.29
		(1.16)	(2.11)	(2.64)	(1.40)		(2.33)	(3.61)	(2.63)	(1.20)
Sig		0.25	0.04	0.01	0.16		0.02	0.00	0.01	0.23
9 Sell		-0.97	-0.21	0.08	0.18		-0.19	-0.16	0.17	0.36
9 Buy		2.01	0.93	1.10	0.93		1.27	0.86	1.00	0.74
9 Buy-sell		2.98	1.14	1.02	0.76		1.46	1.02	0.83	0.38
		(4.50)	(2.72)	(2.70)	(2.18)		(2.36)	(2.23)	(2.02)	(1.18)
Sig		0.00	0.01	0.01	0.03		0.02	0.03	0.05	0.24
12 Sell		1.15	0.72	0.17	0.43		0.84	0.12	0.00	0.58
12 Buy		1.14	0.79	0.54	0.64		0.84	0.69	0.22	0.49
12 Buy-		-0.01	0.06	0.37	0.21		0.01	0.57	0.22	-0.09
Sell		(-0.64)	(0.12)	(0.88)	(0.50)		(0.01)	(1.24)	(0.57)	(-0.23)
Sig		0.99	0.91	0.38	0.62		0.99	0.22	0.57	0.82

This table reports the momentum strategies' returns implemented on 47 stock market indices. The sample is from 1969 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios return are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.1. 2 Momentum Returns for International Investors: Established Markets 1969-2014

	Panel A					Panel B			
J K=	3	6	9	12	K=	3	6	9	12
3 Sell	0.53	0.48	0.33	0.34		0.35	0.30	0.27	0.33
3 Buy	0.71	0.74	0.80	0.69		0.70	0.84	0.81	0.68
3 Buy-Sell	0.18	0.25	0.47	0.35		0.35	0.55	0.55	0.35
	(0.59)	(1.17)	(2.66)	(2.31)		(1.14)	(2.65)	(3.25)	(2.31)
Sig	0.55	0.24	0.01	0.02		0.26	0.01	0.00	0.02
6 Sell	0.34	0.32	0.04	0.25		0.05	0.06	-0.01	0.19
6 Buy	0.65	0.83	0.58	0.63		0.44	0.87	0.50	0.57
6 Buy-Sell	0.31	0.51	0.55	0.38		0.39	0.82	0.51	0.37
	(0.72)	(1.62)	(1.94)	(1.61)		(0.96)	(2.75)	(1.87)	(1.53)
Sig	0.47	0.11	0.06	0.11		0.34	0.00	0.06	0.13
9 Sell	-0.51	-0.12	0.20	0.24		-0.10	-0.05	0.27	0.35
9 Buy	1.26	0.63	0.79	0.73		0.94	0.48	0.75	0.62
9 Buy-sell	1.77	0.74	0.58	0.73		1.04	0.53	0.48	0.27
	(3.19)	(2.10)	(1.82)	(1.71)		(1.88)	(1.39)	(1.36)	(0.99)
Sig	0.00	0.04	0.07	0.09		0.06	0.17	0.19	0.33
12 Sell	0.500	0.52	0.08	0.30		0.67	0.15	0.05	0.39
12 Buy	0.93	0.66	0.29	0.62		0.78	0.55	0.14	0.48
12 Buy-Sell	43.26	0.14	0.25	0.32		0.11	0.40	0.09	0.09
	(0.57)	(0.26)	(0.51)	(0.80)		(0.16)	(0.86)	(0.24)	(0.25)
Sig	0.57	0.80	0.61	0.43		0.87	0.39	0.81	0.81

This table reports the momentum strategies' returns implemented on 18 established stock market indices. The sample is from 1969 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios return are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.1. 3 Momentum Returns since Globalisation 1994-2014

	Panel A					Panel B			
J K=	3	6	9	12	K=	3	6	9	12
3 Sell	0.03	0.01	0.14	0.19		0.05	-0.09	0.07	0.21
3 Buy	0.45	0.48	0.60	0.55		0.56	0.75	0.75	0.54
3 Buy-Sell	0.42	0.47	0.46	0.35		0.51	0.83	0.68	0.33
	(0.83)	(1.33)	(1.71)	(1.55)		(1.31)	(2.52)	(2.58)	(1.51)
Sig	0.41	0.19	0.09	0.12		0.20	0.01	0.01	0.13
6 Sell	0.04	0.11	-0.01	0.29		-0.17	-0.13	-0.04	0.30
6 Buy	0.20	0.71	0.54	0.57		0.75	0.93	0.65	0.59
6 Buy-Sell	0.16	0.60	0.54	0.28		0.92	1.05	0.69	0.28
	(0.25)	(1.39)	(1.96)	(0.89)		(1.86)	(2.80)	(2.16)	(0.89)
Sig	0.81	0.17	0.06	0.38		0.07	0.01	0.04	0.38
9 Sell	1.61	0.36	0.28	0.43		-0.55	-0.07	0.16	0.10
9 Buy	0.09	0.04	0.28	0.27		-0.36	0.37	0.37	0.11
9 Buy-sell	-1.52	-0.33	-0.00	-0.16		0.19	0.44	0.21	0.01
	(-1.82)	(-0.73)	(-0.01)	(-0.36)		(0.44)	(0.71)	(0.39)	(0.02)
Sig	0.08	0.47	0.99	0.72		0.67	0.49	0.70	0.98
12 Sell	1.34	0.14	-0.26	0.35		1.32	-0.23	-0.38	0.45
12 Buy	0.32	0.15	-0.01	0.28		1.29	0.57	0.05	0.23
12 Buy-	-1.02	0.01	0.26	-0.08		-0.03	0.79	0.42	-0.22
Sell	(-1.13)	(0.01)	(0.56)	(-0.14)		(-0.03)	(1.30)	(0.91)	(-0.44)
Sig	0.27	0.99	0.59	0.89		0.98	0.21	0.38	0.66

This table reports the momentum strategies' returns implemented on 47 stock market indices. The sample is from 1994 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios return are reported. The t-statistic are reported in the brackets and the results are statistically significant for p<0.05.

Table 4.1. 4 Momentum Return in Developed Countries 1969-2014

	Panel A					Panel B			
J K=	3	6	9	12	K	3	6	9	12
3 Sell	0.48	0.37	0.27	0.31		0.27	0.19	0.22	0.30
3 Buy	0.57	0.64	0.76	0.69		0.71	0.77	0.83	0.71
3 Buy-Sell	0.09	0.28	0.49	0.39		0.43	0.58	0.61	0.41
	(0.29)	(1.25)	(2.64)	(2.44)		(1.30)	(2.66)	(3.44)	(2.61)
Sig	0.77	0.21	0.01	0.02		0.19	0.01	0.00	0.01
6 Sell	0.38	0.23	0.00	0.19		0.05	-0.02	-0.00	0.15
6 Buy	0.67	0.81	0.64	0.68		0.43	0.86	0.56	0.62
6 Buy-Sell	0.30	0.58	0.64	0.49		0.38	0.89	0.57	0.47
	(0.70)	(1.96)	(2.47)	(2.23)		(0.93)	(3.16)	(2.33)	(2.11)
Sig	0.48	0.05	0.02	0.03		0.35	0.00	0.02	0.04
9 Sell	-0.83	-0.16	0.08	0.16		0.03	-0.07	0.17	0.32
9 Buy	1.34	0.63	0.85	0.77		0.96	0.57	0.80	0.68
9 Buy-sell	2.17	0.78	0.76	0.61		0.93	0.64	0.63	0.35
	(4.31)	(2.12)	(2.22)	(1.97)		(1.66)	(1.53)	(1.63)	(1.16)
Sig	0.00	0.04	0.03	0.05		0.10	0.13	0.11	0.25
12 Sell	0.48	0.15	-0.17	0.12		0.12	-0.34	-0.18	0.14
12 Buy	1.44	0.80	0.41	0.72		0.76	0.62	0.24	0.59
12 Buy-Sell	0.56	0.65	0.57	0.60		0.64	0.96	0.42	0.45
	(0.74)	(1.17)	(1.35)	(1.53)		(0.85)	(2.05)	(1.14)	(1.16)
Sig	0.46	0.25	0.19	0.13		0.40	0.05	0.26	0.25

This table reports the momentum strategies' returns implemented on 23 stock market indices of developed countries. The sample is from 1969 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios return are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.1. 5 Momentum in Emerging Countries 1988-2014

	Panel A					Panel B			
J K=	3	6	9	12	K=	3	6	9	12
3 Sell	0.76	0.84	0.36	0.64		0.63	0.35	0.29	0.75
3 Buy	0.10	0.13	0.44	0.63		-0.35	0.43	0.59	0.71
3 Buy-Sell	-0.66	-0.72	0.08	-0.01		-0.99	0.08	0.30	-0.05
	(-0.82)	(-1.38)	(0.19)	(-0.03)		(-1.31)	(0.15)	(0.76)	(-0.11)
Sig	0.41	0.17	0.85	0.98		0.19	0.87	0.45	0.90
6 Sell	0.06	0.74	0.88	1.22		-0.77	0.43	0.81	1.25
6 Buy	0.49	0.96	0.96	0.73		1.00	1.35	0.77	0.74
6 Buy-Sell	0.43	0.22	0.08	-0.49		1.78	0.92	-0.04	-0.51
	(0.36)	(0.31)	(0.14)	(-0.96)		(1.72)	(1.25)	(-0.06)	(-0.92)
Sig	0.72	0.76	0.89	0.34		0.09	0.22	0.95	0.36
9 Sell	-1.14	0.78	0.53	0.75		0.60	0.31	0.69	0.95
9 Buy	2.14	0.96	0.93	0.47		1.24	0.82	0.79	0.11
9 Buy-sell	3.28	0.18	0.41	-0.28		0.64	0.51	0.10	-0.84
Sig	(1.98)	(0.21)	(0.56)	(-0.37)		(0.47)	(0.62)	(0.14)	(-1.31)
	0.06	0.83	0.58	0.72		0.64	0.54	0.89	0.20
12 Sell	3.20	1.99	1.38	1.36		2.37	1.20	0.87	1.51
12 Buy	0.44	0.58	0.35	0.22		1.00	0.78	-0.04	0.18
12 Buy-	-2.76	-1.41	-1.03	-1.14		-1.37	-0.41	-0.91	-1.34
Sell	(-1.98)	(-1.26)	(-1.01)	(-1.09)		(-0.80)	(-0.44)	(-0.86)	(-1.51)
Sig	0.06	0.22	0.32	0.29		0.43	0.67	0.40	0.14

This table reports the momentum strategies' returns implemented on 24 emerging stock market indices. The sample is from 1983 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios return are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.1. 6 Momentum Returns with Overlapping Portfolios: Full sample 1969-2014

	Panel A					Panel B			
J K=	3	6	9	12	K=	3	6	9	12
3 Sell	0.43	0.41	0.29	0.40		0.47	0.34	0.29	0.47
3 Buy	0.90	0.91	1.03	0.88		0.81	0.98	0.99	0.82
3 Buy-Sell	0.47	0.50	0.74	0.48		0.34	0.64	0.71	0.35
	(2.17)	(3.53)	(6.31)	(4.95)		(1.63)	(4.37)	(6.02)	(3.51)
Sig	0.03	0.00	0.00	0.00		0.10	0.00	0.00	0.00
6 Sell	0.28	0.18	0.14	0.34		0.21	0.10	0.17	0.39
6 Buy	0.92	1.03	0.97	0.78		1.03	1.08	0.93	0.72
6 Buy-Sell	0.64	0.85	0.83	0.45		0.82	0.98	0.76	0.32
	(2.84)	(5.59)	(6.79)	(4.36)		(3.71)	(6.37)	(6.35)	(3.22)
Sig	0.00	0.00	0.000	0.00		0.00	4.19	0.00	0.00
9 Sell	0.14	0.05	0.17	0.36		-0.05	0.00	0.21	0.42
9 Buy	1.09	1.00	0.90	0.72		1.07	0.95	0.81	0.63
9 Buy-sell	0.95	0.95	0.73	0.37		1.12	0.95	0.60	0.21
	(4.16)	(5.97)	(5.70)	(3.35)		(5.05)	(5.97)	(4.75)	(1.93)
Sig	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.05
12 Sell	0.15	0.23	0.33	0.50		0.12	0.27	0.42	0.56
12 Buy	0.99	0.79	0.66	0.54		0.78	0.70	0.56	0.44
12 Buy-	0.84	0.56	0.33	0.04		0.66	0.44	0.14	-0.12
Sell	(3.47)	(3.44)	(2.51)	(0.33)		(2.84)	(2.76)	(1.06)	(-1.07)
Sig	0.00	0.00	0.01	0.74		0.00	0.01	0.29	0.28

This table reports the momentum strategies' returns with overlapping portfolio implemented on 47 stock market indices. The sample is from 1969 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.1. 7 Momentum Returns for International Investors: Established Markets 1969-2014

		Panel A					Panel B			
J	K=	3	6	9	12	K=	3	6	9	12
3 Sell		0.48	0.45	0.31	0.33		0.38	0.34	0.27	0.35
3 Buy		0.74	0.70	0.83	0.71		0.62	0.73	0.78	0.66
3 Buy-Sell		0.26	0.25	0.51	0.38		0.24	0.39	0.52	0.31
		(1.44)	(2.02)	(4.99)	(4.42)		(1.33)	(3.02)	(5.09)	(3.62)
Sig		0.15	0.04	0.00	0.00		0.18	0.00	0.00	0.00
6 Sell		0.37	0.23	0.15	0.22		0.32	0.14	0.13	0.22
6 Buy		0.93	0.92	0.86	0.72		0.88	0.90	0.80	0.66
6 Buy-Sell		0.56	0.69	0.71	0.51		0.56	0.77	0.67	0.44
		(3.01)	(5.38)	(6.91)	(5.60)		(2.99)	(5.80)	(6.52)	(4.89)
Sig		0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
9 Sell		0.11	0.04	0.08	0.17		0.01	-0.01	0.08	0.21
9 Buy		0.88	0.83	0.78	0.70		0.88	0.81	0.75	0.65
9 Buy-sell		0.77	0.78	0.71	0.53		0.86	0.82	0.66	0.44
		(3.99)	(5.94)	(6.65)	(5.75)		(4.57)	(6.22)	(6.30)	(4.74)
Sig		0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
12 Sell		0.11	0.19	0.24	0.34		0.18	0.23	0.30	0.40
12 Buy		0.74	0.71	0.69	0.64		0.68	0.70	0.67	0.61
12 Buy-Sell		0.63	0.52	0.46	0.30		0.51	0.47	0.37	0.20
		(3.18)	(3.81)	(4.17)	(3.13)		(2.65)	(3.53)	(3.43)	(2.09)
Sig		0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.04

This table reports the momentum strategies' returns with overlapping portfolio implemented on 18 established stock market indices. The sample is from 1969 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.1. 8 Momentum Returns with overlapping portfolios since Globalisation 1994-2014

	Panel A					Panel B			
J K=	3	6	9	12	K=	3	6	9	12
3 Sell	0.18	0.01	0.02	0.12		0.14	-0.07	-0.00	0.16
3 Buy	0.49	0.54	0.68	0.61		0.49	0.64	0.71	0.56
3 Buy-Sell	0.31	0.53	0.67	0.49		0.34	0.71	0.71	0.00
	(1.14)	(2.83)	(4.46)	(3.91)		(1.44)	(3.82)	(4.73)	(3.17)
Sig	0.26	0.01	1.34	0.00		0.15	0.00	0.00	0.00
6 Sell	-0.13	-0.07	-0.09	0.07		-0.17	-0.12	-0.05	0.16
6 Buy	0.69	0.82	0.77	0.64		0.90	0.91	0.76	0.61
6 Buy-Sell	0.82	0.89	0.86	0.57		1.07	1.03	0.81	0.45
	(2.80)	(4.37)	(5.01)	(4.05)		(3.72)	(5.02)	(4.91)	(3.20)
Sig	0.01	1.95	0.00	0.00		0.00	0.00	0.00	0.00
9 Sell	0.09	-0.08	0.01	0.17		-0.17	-0.12	0.04	0.21
9 Buy	0.97	0.81	0.69	0.58		0.94	0.75	0.64	0.49
9 Buy-sell	0.88	0.89	0.68	0.41		1.11	0.88	0.60	0.28
	(2.77)	(4.20)	(4.03)	(2.86)		(3.72)	(4.18)	(3.57)	(1.90)
Sig	0.01	0.00	0.00	0.00		0.00	0.00	0.00	0.06
12 Sell	-0.01	-0.05	0.05	0.20		-0.14	-0.06	0.09	0.25
12 Buy	1.02	0.76	0.59	0.49		0.79	0.64	0.48	0.40
12 Buy-Sell	1.03	0.81	0.54	0.29		0.93	0.70	0.39	0.15
Sig	(3.11)	(3.82)	(3.08)	(1.85)		(3.07)	(3.41)	(2.25)	(0.94)
	0.00	0.00	0.00	0.07		0.00	0.00	0.03	0.35

This table reports the momentum strategies' returns with overlapping portfolio implemented on 47 stock market indices. The sample is from 1994 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios returns are reported. The t-statistics are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.1. 9 Momentum Return with Overlapping Portfolios in Developed Countries 1969-2014

	Panel A					Panel B			
J K=	3	6	9	12	K=	3	6	9	12
3 Sell	0.42	0.35	0.22	0.27		0.37	0.28	0.19	0.29
3 Buy	0.69	0.67	0.81	0.71		0.61	0.69	0.79	0.67
3 Buy-Sell	0.28	0.31	0.59	0.44		0.25	0.41	0.60	0.37
	(1.49)	(2.49)	(5.67)	(5.12)		(1.29)	(3.10)	(5.80)	(4.12)
Sig	0.14	0.013	0.00	0.00		0.20	0.20	0.00	0.00
6 Sell	0.32	0.18	0.09	0.19		0.30	0.08	0.09	0.21
6 Buy	0.87	0.91	0.88	0.73		0.84	0.91	0.83	0.68
6 Buy-Sell	0.54	0.73	0.79	0.54		0.53	0.83	0.74	0.47
	(2.84)	(5.59)	(7.63)	(5.93)		(2.76)	(6.21)	(7.15)	(5.10)
Sig	0.00	0.00	0.00	0.00		0.01	0.00	0.00	0.00
9 Sell	0.16	0.02	0.05	0.17		0.01	-0.07	0.06	0.20
9 Buy	0.98	0.92	0.84	0.76		0.97	0.88	0.81	0.71
9 Buy-sell	0.82	0.90	0.79	0.60		0.96	0.94	0.74	0.51
	(4.25)	(6.85)	(7.33)	(6.19)		(5.01)	(6.97)	(6.80)	(5.17)
Sig	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
12 Sell	0.09	0.13	0.20	0.32		0.08	0.16	0.28	0.38
12 Buy	0.89	0.79	0.78	0.71		0.77	0.76	0.74	0.66
12 Buy-	0.79	0.66	0.58	0.40		0.68	0.60	0.46	0.29
Sell	(3.89)	(4.78)	(5.12)	(3.95)		(3.45)	(4.29)	(4.01)	(2.83)
Sig	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00

This table reports the momentum strategies' returns with overlapping portfolio implemented on 23 developed countries stock market indices. The sample is from 1969 to 2014. I form momentum portfolios (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios return are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.1. 10 Momentum Return with Overlapping Portfolios in Emerging Countries 1988-2014

	Panel A					Panel B			
J K=	3	6	9	12	K=	3	6	9	12
3 Sell	0.55	0.55	0.42	0.52		0.74	0.41	0.41	0.67
3 Buy	0.13	0.56	0.68	0.67		-0.01	0.70	0.71	0.68
3 Buy-Sell	-0.42	0.01	0.25	0.14		-0.76	0.29	0.30	0.00
	(-0.95)	(0.04)	(1.03)	(0.66)		(-1.77)	(0.97)	(1.21)	(0.02)
	0.34	0.97	0.30	0.51		0.08	0.33	0.23	0.98
6 Sell	0.57	0.47	0.55	0.75		0.40	0.44	0.59	0.85
6 Buy	0.58	0.86	0.83	0.60		0.92	1.04	0.73	0.59
6 Buy-Sell	0.01	0.39	0.28	-0.16		0.51	0.60	0.14	-0.26
	(0.03)	(1.30)	(1.16)	(-0.71)		(1.17)	(2.06)	(0.58)	(-1.15)
	0.98	0.20	0.25	0.48		0.24	0.04	0.56	0.25
9 Sell	0.37	0.30	0.43	0.68		0.30	0.25	0.50	0.77
9 Buy	0.69	0.58	0.44	0.23		0.53	0.49	0.32	0.07
9 Buy-sell	0.32	0.28	0.01	-0.45		0.23	0.24	-0.17	-0.70
	(0.69)	(0.87)	(0.05)	(-1.87)		(0.52)	(0.71)	(-0.63)	(-2.92)
	0.49	0.39	0.96	0.06		0.61	0.48	0.53	0.00
12 Sell	0.82	0.73	0.74	0.81		0.66	00.61	0.77	0.82
12 Buy	0.58	0.41	0.26	0.08		0.28	0.35	0.02	-0.05
12 Buy-	-0.24	-0.32	-0.48	-0.73		-0.38	-0.25	-0.75	-0.86
Sell	(-0.48)	(-0.96)	(-1.64)	(-2.84)		(-0.79)	(-0.73)	(-2.58)	(-3.47)
	0.63	0.34	0.10	0.00		0.43	0.47	0.01	0.00

This table reports the momentum strategies' returns with overlapping portfolio implemented on 23 emerging stock market indices. The sample is from 1987 to 2014. I form momentum portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 4 different formations and holding periods. The winner portfolios, the loser portfolios, and the winner minus loser portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for p<0.05.

Table 4.1. 11 Performance of Momentum Strategies in Event Time 1969-2014

(Period) Date	Monthly Return	(Period) Date	Monthly Return	(Period) Date	Monthly Return
(1) 30/09/1970	4.08	(21) 30/09/1985	10.18	(40) 31/12/1999	1.07
(2) 30/06/1971	7.28	(22) 30/06/1986	2.57	(41) 29/09/2000	-1.75
(3) 31/03/1972	0.46	(23) 31/03/1987	4.47	(42) 29/06/2001	6.15
(4) 29/12/1972	7.66	(24) 31/12/1987	4.18	(43) 29/03/2002	6.13
(5) 28/09/1973	6.09	(25) 30/09/1988	-6.37	(44) 31/12/2002	1.34
(6) 28/06/1974	5.32	(26) 30/06/1989	11.317	(45) 30/09/2003	-1.66
(7) 31/03/1975	-1.89	(27) 30/03/1990	-6.03	(46) 30/06/2004	6.26
(8) 31/12/1975	7.83	(28) 31/12/1990	6.84	(47) 31/03/2005	5.23
(9) 30/09/1976	2.45	(29) 30/09/1991	0.45	(48) 30/12/2005	1.48
(10) 30/06/1977	9.26	(30) 30/06/1992	2.80	(49) 29/09/2006	2.13
(11) 31/03/1978	0.41	(31) 31/03/1993	2.87	(50) 29/06/2007	5.07
(12) 29/12/1978	-1.21	(32) 31/12/1993	-13.99	(51) 31/03/2008	3.05
(13) 28/09/1979	5.25	(33) 30/09/1994	5.19	(52) 31/12/2008	-3.87
(14) 30/06/1980	1.89	(34) 30/06/1995	0.74	(53) 30/09/2009	3.36
(15) 31/03/1981	6.78	(35) 29/03/1996	-6.41	(54) 30/06/2010	3.39
(16) 31/12/1981	-3.14	(36) 31/12/1996	6.99	(55) 31/03/2011	-0.31
(17) 30/09/1982	3.85	(37) 30/09/1997	16.39	(56) 30/12/2011	-1.08
(18) 30/06/1983	10.79	(38) 30/06/1998	5.57	(57) 28/09/2012	-0.90
(19) 30/03/1984	0.51	(39) 31/03/1999	10.67	(58) 28/06/2013	2.46
(20) 31/12/1984	2.98				

This table reports the average momentum returns, winner minus loser, portfolio in each 3 month following the formation period (9) with the exception of the first 9month of the sample. The sample is from December 1969 to January 2014.

Table 4.1. 12 Description of the Bear and Bull Phases 1969-2014

	N0 of periods	% of total periods	Monthly/Market performance	9-month/3-month Performance
Panel A: Bear Phase				
3 months	60	33.70786	-0.01970	
6 months	28	31.46067	-0.01415	
9 months	21	35.59322	-0.01132	0.026575
12 months	11	25.00000	-0.01430	
Panel B: Bull phase				
3 months	118	66.2921	0.01361	
6 months	61	68.53932	0.01262	
9 months	38	64.40677	0.01282	0.031571
12 months	33	75.00000	0.01089	

Table 13 shows the number of bear and bull market over the full sample period, their frequency, market performances in different bear and bull horizon (3, 6, 9, 12) between December 1969 and January 2014, and the average momentum profits accomplished after bull and bear markets with the optimum strategy (9-month/3-month). The bear phase (Panel A) is the periods when the market returns (MSCI World Index) is negative for 3, 6, 9, and 12 months before the test period and the bull state (Panel B) is when the market return is positive for 3, 6, 9, and 12 months.

Table 4.2. 1 Contrarian Returns for International Investor: Full Sample 1969-2014

Panel A					Panel B		
J	K= 36	48	60	K=	36	48	60
3 6 Buy	0.67	0.78	0.83		0.62	0.74	0.77
36 Sell	0.60	0.63	0.49		0.61	0.52	0.40
36 Buy-Sell	0.06	0.15	0.34		0.01	0.21	0.37
	(0.20)	(0.45)	(1.12)		(0.04)	(0.67)	(1.33)
Sig	0.85	0.66	0.29		0.97	0.52	0.21
48 Buy	0.46	0.79	0.81		0.43	0.80	0.77
48 Sell	-0.07	-0.03	-0.01		-0.15	-0.08	-0.06
48 Buy-Sell	0.53	0.82	0.83		0.58	0.88	0.83
	(1.43)	(2.63)	(3.16)		(1.67)	(2.97)	(3.63)
Sig	0.19	0.03	0.01		0.13	0.02	0.00
60 Buy	0.92	0.76	1.09		0.77	0.70	1.08
60 Sell	0.28	0.15	0.56		0.20	0.14	0.52
60 Buy-sell	0.64	0.61	0.53		0.57	0.56	0.56
	(1.64)	(1.75)	(2.04)		(1.59)	(1.74)	(2.37)
Sig	0.15	0.12	0.09		0.16	0.12	0.056

This table reports the contrarian strategies' returns implemented on 47 stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistics are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 2 Contrarian Returns for International Investors: Established Markets 1969-2014

	Panel A				Panel B		
J	K= 36	48	60	K=	36	48	60
36 Buy	0.56	0.74	0.78		0.55	0.72	0.73
36 Sell	0.21	0.34	0.34		0.25	0.28	0.28
36 Buy-Sell	0.35	0.40	0.44		0.30	0.44	0.45
	(1.35)	(1.33)	(1.46)		(1.23)	(1.49)	(1.60)
Sig	0.20	0.21	0.17		0.24	0.16	0.14
48 Buy	0.55	2.93	0.69		0.51	0.68	0.68
48 Sell	-0.29	-0.16	-0.08		-0.29	-0.20	-0.08
48 Buy-Sell	0.84	0.83	0.769		0.80	0.89	0.76
Sig	(2.59)	(2.82)	(2.99)		(2.43)	(3.25)	(3.29)
	0.03	0.02	0.02		0.04	0.01	0.01
60 Buy	0.57	0.59	0.89		0.45	0.53	0.85
60 Sell	0.16	0.08	0.51		0.07	0.11	0.44
60 Buy-sell	0.40	0.51	0.37		0.38	0.41	0.41
	(1.23)	(1.82)	(2.39)		(1.32)	(1.69)	(2.93)
Sig	0.26	0.11	0.05		0.23	0.13	0.03

This table reports the contrarian strategies' returns implemented on 18 stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 3 Contrarian Returns since Globalisation 1994-2014

		Panel A				Panel B		
J	K=	36	48	60	K=	36	48	60
36 Buy		0.61	0.77	0.64		0.66	0.74	0.58
36 Sell		0.31	0.37	0.00		0.46	0.35	0.07
36 Buy-Sell		0.30	0.40	0.64		0.20	0.40	0.51
		(0.53)	(0.88)	(1.32)		(0.35)	(0.86)	(1.00)
Sig		0.63	0.43	0.30		0.74	0.44	0.39
48 Buy		0.33	0.84	0.97		0.49	0.09	0.97
48 Sell		0.36	0.71	0.71		0.43	0.68	0.75
48 Buy-Sell		-0.03	0.13	0.26		0.07	0.19	0.22
		(-0.10)	(0.33)	(0.77)		(0.18)	(0.43)	(0.51)
Sig		0.93	0.77	0.52		0.87	0.71	0.66
60 Buy		0.27	0.16	0.61		0.21	0.16	0.64
60 Sell		0.02	-0.38	0.05		-0.06	-0.45	0.03
60 Buy-sell		0.25	0.53	0.56		0.27	0.61	0.61
		(0.31)	(0.97)	(0.71)		(0.39)	(1.16)	(0.76)
Sig		0.79	0.43	0.61		0.74	0.36	0.58

This table reports the contrarian strategies' returns implemented on 47 stock market indices. The sample is from 1994 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 4 Contrarian Return in Developed Countries 1969-2014

		Panel A				Panel B		
J	K=	36	48	60	K=	36	48	60
36 Buy		0.65	0.84	0.87		0.62	0.83	0.83
36 Sell		0.30	0.38	0.35		0.33	0.31	0.29
36 Buy-Sell		0.34	0.46	0.53		0.29	0.52	0.54
		(0.90)	(1.33)	(1.63)		(0.73)	(0.01)	(1.77)
Sig		0.39	0.21	0.13		0.48	0.14	0.10
48 Buy		0.48	0.63	0.64		0.41	0.64	0.62
48 Sell		-0.04	-0.04	-0.01		-0.10	-0.10	-0.03
48 Buy-Sell		0.52	0.68	0.64		0.51	0.74	0.65
		(1.22)	(1.89)	(2.24)		(1.32)	(2.37)	(2.63)
Sig		0.25	0.09	0.06		0.22	0.04	0.02
60 Buy		0.89	0.88	1.00		0.83	0.84	1.00
60 Sell		-0.00	-0.05	0.44		-0.13	-0.01	0.36
60 Buy-sell		0.89	0.93	0.56		0.96	0.85	0.64
		(2.26)	(2.49)	(1.94)		(2.22)	(2.31)	(2.20)
Sig		0.06	0.04	0.10		0.06	0.05	0.07

This table reports the contrarian strategies' returns implemented on 23 stock market indices of developed countries. The sample is from 1969 to 2014. I form contrarian portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 5 Contrarian Return in Emerging countries 1988-2014

	Panel A			Panel B		
J	K= 36	48	60	K= 36	48	60
36 Buy	0.57	0.29	0.29	0.64	0.15	0.27
36 Sell	0.41	0.60	0.53	0.37	0.46	0.34
36 Buy-Sell	0.16	-0.31	-0.24	0.27	-0.31	-0.07
	(0.32)	(-0.37)	(-0.36)	(0.71)	(-0.37)	(-0.14)
Sig	0.76	0.72	0.73	0.50	0.72	0.90
48 Buy	0.74	1.51	0.79	0.64	1.46	0.78
48 Sell	-0.01	0.43	0.29	-0.43	0.37	0.23
48 Buy-Sell	0.76	1.09	0.50	1.07	1.09	0.55
	(2.37)	(3.38)	(2.78)	(3.30)	(3.08)	(3.89)
Sig	0.08	0.03	0.05	0.03	0.04	0.01
60 Buy	1.35	1.39	1.60	1.46	1.44	1.34
60 Sell	0.32	0.02	0.32	0.52	0.24	0.25
60 Buy-sell	1.02	1.37	1.29	0.94	1.20	1.93
	(2.13)	(5.15)	(3.22)	(1.64)	(3.16)	(2.87)
Sig	0.12	0.01	0.05	0.20	0.05	0.06

This table reports the contrarian strategies' returns implemented on 24 emerging stock market indices. The sample is from 1983 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 6 Contrarian Returns Developed and Emerging Markets Full Sample: 1969-2014

	Panel A				Panel B		
J	K= 36	48	60	K=	36	48	60
36 Buy	0.73	0.79	0.78		0.00746	0.80	0.79
36 Sell	0.31	0.29	0.33		0.30	0.29	0.33
36 Buy-Sell	0.42	0.50	0.46		0.44	0.56	0.46
	(7.18)	(10.02)	(10.99)		(7.63)	(10.33)	(11.10)
Sig	0.00	0.00	0.00		0.00	0.00	0.00
48 Buy	0.81	0.86	0.85		0.83	0.86	0.86
48 Sell	0.28	0.31	0.33		0.83	0.31	0.34
48 Buy-Sell	0.55	0.55	0.51		0.55	0.55	0.52
	(9.29)	(11.29)	(13.04)		(9.55)	(11.27)	(13.32)
Sig	0.00	0.00	0.00		0.00	0.00	0.00
60 Buy	0.84	0.84	0.87		0.84	0.85	0.88
60 Sell	0.34	0.34	0.36		0.33	0.34	0.37
60 Buy-sell	0.50	0.50	0.51		0.51	0.50	0.51
	(8.88)	(11.02)	(13.23)		(9.29)	(11.22)	(13.54)
Sig	0.00	0.00	0.00		0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping portfolio implemented on 47 stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 7 Contrarian Returns for International Investors: Established Markets 1969-2014

		Panel A				Panel B		
J	K=	36	48	60	K=	36	48	60
36 Buy		0.63	0.65	0.65		0.64	0.65	0.65
36 Sell		0.30	0.28	0.29		0.30	0.28	0.30
36 Buy-Sell		0.33	0.37	0.36		0.34	0.37	0.36
		(6.97)	(8.58)	(9.74)		(7.21)	(8.62)	(9.74)
Sig		0.00	0.00	0.00		0.00	0.00	0.00
48 Buy		0.67	0.69	0.68		0.68	0.69	0.70
48 Sell		0.24	0.23	0.28		0.24	0.24	0.29
48 Buy-Sell		0.43	0.45	0.41		0.44	0.45	0.41
		(9.44)	(11.28)	(12.42)		(9.59)	(11.21)	(12.53)
Sig		0.00	0.00	0.00		0.00	0.00	0.00
60 Buy		0.65	0.63	0.67		0.64	0.64	0.68
60 Sell		0.27	0.26	0.29		0.26	0.26	0.29
60 Buy-sell		0.37	0.38	0.38		0.38	0.38	0.38
		(8.13)	(9.69)	(11.88)		(8.33)	(9.90)	(12.17)
Sig		0.00	0.00	0.00		0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping portfolio implemented on 18 established stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 8 Contrarian Returns with overlapping portfolios since Globalisation 1969-2014

	Panel A			Panel B		
J	K= 36	48	60	K= 36	48	60
36 Buy	0.67	0.83	0.89	0.68	0.84	0.89
36 Sell	0.49	0.49	0.50	0.47	0.48	0.51
36 Buy-Sell	0.18	0.34	0.38	0.22	0.36	0.38
	(2.21)	(4.65)	(5.36)	(2.57)	(4.90)	(5.44)
Sig	0.03	0.00	0.00	0.01	0.00	0.00
48 Buy	0.80	0.96	0.96	0.82	0.96	0.96
48 Sell	0.42	0.50	0.51	0.41	0.50	0.52
48 Buy-Sell	0.38	0.45	0.44	0.40	0.45	0.44
	(4.04)	(5.43)	(5.81)	(4.44)	(5.56)	(6.03)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
60 Buy	0.97	1.01	0.97	0.99	1.01	0.98
60 Sell	0.55	0.60	0.54	0.57	0.60	0.56
60 Buy-sell	0.42	0.41	0.43	0.41	0.41	0.42
	(4.29)	(4.87)	(5.53)	(4.38)	(4.95)	(5.56)
Sig	0.00	0.00	0.00	0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping portfolio implemented on 47 stock market indices. The sample is from 1994 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 9 Contrarian Return with Overlapping Portfolios in Developed Countries 1969-2014

	Panel A			Panel B		
J K=	36	48	60	K= 36	48	60
36 Buy	0.67	0.72	0.71	0.69	0.73	0.72
36 Sell	0.22	0.22	0.24	0.21	0.22	0.24
36 Buy-Sell	0.45	0.50	0.48	0.47	0.51	0.48
	(7.75	(9.95)	(11.38)	(8.12)	(10.23)	(11.48)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
48 Buy	0.79	0.81	0.77	0.81	0.81	0.78
48 Sell	0.23	0.22	0.26	0.23	0.22	0.27
48 Buy-Sell	0.56	0.601	0.51	0.57	0.59	0.51
	(9.51)	(11.70)	(12.35)	(9.68)	(11.60)	(12.30)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
60 Buy	0.83	0.77	0.78	0.84	0.77	0.78
60 Sell	0.24	0.21	0.26	0.22	0.21	0.26
60 Buy-sell	0.60	0.56	0.51	0.62	0.56	0.52
	(10.89)	(12.22)	(12.57)	(11.26)	(12.37)	(12.78)
Sig	0.00	0.00	0.00	0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping portfolio implemented on 23 developed countries stock market indices. The sample is from 1969 to 2014. I form contrarian portfolios (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 10 Contrarian Return with Overlapping Portfolios in Emerging Countries 1988-2014

		Panel A				Panel B	
J	K= 36	48	60	K=	36	48	60
36 Buy	0.80	0.86	0.81		0.79	0.85	0.81
36 Sell	0.34	0.31	0.37		0.32	0.31	0.37
36 Buy-Sell	0.46	0.55	0.44		0.47	0.54	0.44
	(4.91)	(7.12)	(6.15)		(4.93)	(7.01)	(6.31)
Sig	0.00	0.00	0.00		0.00	0.00	0.00
48 Buy	0.87	0.92	0.87		0.87	0.92	0.86
48 Sell	0.16	0.26	0.32		0.17	0.28	0.34
48 Buy-Sell	0.71	0.66	0.54		0.69	0.63	0.52
	(7.64)	(8.94)	(7.84)		(7.46)	(8.92)	(7.84)
Sig	0.00	0.00	0.00		0.00	0.00	0.00
60 Buy	0.83	0.89	0.84		0.80	0.89	0.82
60 Sell	0.33	0.44	0.42		0.33	0.43	0.42
60 Buy-sell	0.50	0.45	0.42		0.47	0.46	0.40
	(6.26)	(6.97)	(6.98)		(5.97)	(7.50)	(6.73)
Sig	0.00	0.00	0.00		0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping portfolio implemented on 23 emerging stock market indices. The sample is from 1987 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formation and 3 different holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 11 Contrarian Returns Developed and Emerging Markets Full Sample: 1969-2014

Panel A					Panel B			
J	K=	36	48	60	K=	36	48	60
36 Buy		0.69	0.79	0.86		0.64	0.74	0.81
36 Sell		0.51	0.55	0.49		0.52	0.50	0.41
36 Buy-Sell		0.18	0.23	0.37		0.12	0.24	0.40
		(0.81)	(1.11)	(1.89)		(0.57)	(1.18)	(2.12)
Sig		0.43	0.29	0.08		0.58	0.26	0.06
48 Buy		0.35	0.62	0.74		0.39	0.68	0.75
48 Sell		0.02	0.08	00.16		-0.03	0.05	0.15
48 Buy-Sell		0.33	0.53	0.58		0.43	0.62	0.60
		(1.13)	(2.33)	(2.21)		(1.49)	(2.78)	(2.54)
Sig		0.29	0.04	0.06		0.17	0.02	0.03
60 Buy		0.67	0.68	0.92		0.56	0.66	0.92
60 Sell		0.02	-0.03	0.38		-0.02	-0.05	0.35
60 Buy-sell		0.65	0.71	0.54		0.58	0.70	0.57
		(2.51)	(4.78)	(3.75)		(2.69)	(5.70)	(4.36)
Sig		0.04	0.00	0.01		0.03	0.00	0.00

This table reports the contrarian strategies' returns implemented on 47 stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistics are reported in the brackets and the results are statistically significant for p<0.05.

Table 4.2. 12 Contrarian Returns for International Investors: Established Markets 1969-2014

	Panel A			Panel B		
J	K= 36	48	60	K= 36	48	60
36 Buy	0.49	0.65	0.75	0.47	0.66	0.73
36 Sell	0.33	0.54	0.56	0.38	0.52	0.51
36 Buy-Sell	0.16	0.10	0.19	0.09	0.14	0.22
	(0.95)	(0.62)	(1.10)	(0.53)	(0.85)	(1.35)
Sig	0.36	0.54	0.30	0.61	0.41	0.20
48 Buy	0.42	0.60	0.63	0.42	0.61	0.64
48 Sell	0.09	0.31	0.43	0.07	0.29	0.42
48 Buy-Sell	0.33	0.30	0.20	0.35	0.32	0.23
	(1.71)	(2.20)	(1.84)	(1.68)	(2.74)	(2.74)
Sig	0.12	0.05	0.10	0.13	0.02	0.03
60 Buy	0.60	0.68	0.88	0.54	0.67	0.88
60 Sell	0.23	0.24	0.48	0.19	0.25	0.42
60 Buy-sell	0.37	0.44	0.40	0.34	0.42	0.45
	(1.41)	(3.15)	(3.70)	(1.60)	(3.37)	(4.20)
Sig	0.20	0.02	0.01	0.15	0.01	0.57

This table reports the contrarian strategies' returns implemented on 18 stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 13 Contrarian Returns since Globalisation 1994-2014

	Panel A				Panel B			
J	K=	36	48	60	K=	36	48	60
36 Buy		0.47	0.62	0.42		0.50	0.55	0.36
36 Sell		0.38	0.37	-0.01		0.45	0.30	0.03
36 Buy-Sell		0.10	0.25	0.43		0.05	0.25	0.33
		(0.18)	(0.59)	(0.95)		(0.10)	(0.59)	(0.71)
Sig		0.86	0.59	0.41		0.93	0.59	0.52
48 Buy		0.41	0.82	0.93		0.48	0.82	0.93
48 Sell		0.23	0.59	0.64		0.28	0.57	0.68
48 Buy-Sell		0.18	0.23	0.29		0.20	0.24	0.25
		(0.62)	(0.51)	(0.69)		(0.54)	(0.51)	(0.52)
Sig		0.58	0.66	0.56		0.63	0.66	0.65
60 Buy		0.33	0.19	0.64		0.23	0.15	0.61
60 Sell		0.04	-0.40	0.22		-0.05	-0.48	0.20
60 Buy-sell		0.29	0.59	0.42		0.28	0.63	0.41
		(0.47)	(1.61)	(0.82)		(0.49)	(2.06)	(0.86)
Sig		0.68	0.25	0.56		0.67	0.18	0.55

This table reports the contrarian strategies' returns implemented on 47 stock market indices. The sample is from 1994 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 14 Contrarian Return in Developed Countries 1969-2014

	Panel A				Panel B		
J	K= 36	48	60	K=	36	48	60
36 Buy	0.51	0.72	0.81		0.52	0.74	0.80
36 Sell	0.40	0.54	0.52		0.43	0.52	0.47
36 Buy-Sell	0.13	0.18	0.28		0.09	0.22	0.32
	(0.60)	(0.91)	(1.43)		(0.43)	(1.144)	(1.72)
Sig	0.56	0.38	0.18		0.67	0.27	0.11
48 Buy	0.50	0.66	0.68		0.50	0.68	0.70
48 Sell	0.12	0.27	0.35		0.08	0.24	0.33
48 Buy-Sell	0.38	0.39	0.33		0.43	0.45	0.37
	(1.74)	(2.57)	(2.12)		(2.01)	(3.56)	(2.82)
Sig	0.12	0.03	0.07		0.08	0.01	0.02
60 Buy	0.63	0.73	0.88		0.62	0.73	0.89
60 Sell	0.12	0.15	0.42		0.08	0.17	0.36
60 Buy-sell	0.56	0.58	0.46		0.54	0.56	0.52
	(2.48)	(5.65)	(3.97)		(3.59)	(6.85)	(4.60)
Sig	0.04	0.00	0.00		0.00	0.00	0.00

This table reports the contrarian strategies' returns implemented on 23 stock market indices of developed countries. The sample is from 1969 to 2014. I form contrarian portfolio (buy past winners and sell past losers) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 15 Contrarian Return in Emerging Countries 1988-2014

	Panel A				Panel B		
J	K=	36	48	60	K=	36	48	60
36 Buy		0.76	0.55	0.65		0.74	0.44	0.55
36 Sell		0.56	0.59	0.50		0.58	0.51	0.41
36 Buy-Sell		0.20	-0.04	0.15		0.16	-0.06	0.13
		(0.65)	(-0.06)	(0.34)		(0.56)	(-0.10)	(0.40)
Sig		0.54	0.95	0.75		0.60	0.92	0.70
48 Buy		0.72	1,08	0.43		0.51	0.98	0.43
48 Sell		-0.46	0.06	-0.17		-0.73	0.06	-0.15
48 Buy-Sell		1.18	1.02	1.60		1,24	0.92	0.58
		(2.44995)	(2.06993)	(1.39)		(2.26)	(1.68)	(1.34)
Sig		0.07044	0.10723	0.24		0.09	0.17	0.25
60 Buy		1.02	0.85	0.01		1.26	0.99	0.98
60 Sell		0.32	0.16	0.44		0.60	0.40	0.43
60 Buy-sell		0.70	0.70	0.65		0.66	0.59	0.55
		(1.93)	(3.04)	(3.84)		(1.60)	(2.54)	(3.60)
Sig		0.15	0.06	0.03		0.21	0.08	0.036

This table reports the contrarian strategies' returns implemented on 24 emerging stock market indices. The sample is from 1987 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for p<0.05.

Table 4.2. 16 Contrarian Returns for International Investor: Full Sample 1969-2014

Panel A				Panel B		
J K=	36	48	60	K= 36	48	60
36 Buy	0.69	0.79	0.86	0.74	0.78	0.78
36 Sell	0.51	0.55	0.49	0.34	0.36	0.38
36 Buy-Sell	0.18	0.23	0.37	0.40	0.41	0.40
	(0.81771)	(1.11)	(1.89)	(9.08)	(11.67)	(13.58)
Sig	0.43	0.29	0.08	0.00	0.00	0.00
48 Buy	0.35	0.62	0.74	0.81	0.83	0.82
48 Sell	0.02	0.08	0.16	0.31	0.33	0.36
48 Buy-Sell	0.33	0.53	0.58	0.50	0.50	0.82
	(1.13)	(2.33)	(2.21)	(11.86)	(15.32)	(0.00)
Sig	0.28	0.04	0.05	0.00	0.00	0.00
60 Buy	0.67	0.68	0.92	0.89	0.88	0.87
60 Sell	0.02	-0.03	0.38	0.35	0.37	0.39
60 Buy-sell	0.65	0.71	0.54	0.54	0.51	0.48
	(2.51)	(4.77)	(3.75)	(13.23)	(15.91)	(16.67)
Sig	0.04	0.20	0.01	0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping quintile portfolios implemented on 47 stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 17 Contrarian Returns for International Investors: Established Markets 1969-2014

	Panel A			Panel B		
J	K= 36	48	60	K= 36	48	60
36 Buy	0.66	0.68	0.69	0.67	0.68	0.69
36 Sell	0.40	0.44	0.45	0.40	0.44	0.45
36 Buy-Sell	0.26	0.24	0.24	0.26	0.24	0.24
	(7.49)	(8.73)	(9.84)	(7.73)	(8.83)	(9.97)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
48 Buy	0.70	0.71	0.71	0.70	0.72	0.71
48 Sell	0.40	0.41	0.43	0.40	0.41	0.43
48 Buy-Sell	0.30	0.30	0.28	0.31	0.30	0.28
	(8.77)	(11.52)	(13.27)	(9.05)	(11.58)	(13.36)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
60 Buy	0.74	0.74	0.73	0.74	0.74	0.73
60 Sell	0.40	0.43	0.45	0.40	0.43	0.45
60 Buy-sell	0.34	0.31	0.28	0.35	0.31	0.28
	(9.93)	(12.36)	(13.61)	(10.31)	(12.70)	(13.93)
Sig	0.00	0.00	0.00	0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping quintiles portfolio implemented on 18 established stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 18 Contrarian Returns with Overlapping Quintiles Portfolios since Globalisation 1994-2014

	Panel A			Panel B		
J	K= 36	48	60	K= 36	48	60
36 Buy	0.57	0.71	0.76	0.58	0.71	0.77
36 Sell	0.46	0.47	0.47	0.44	0.46	0.47
36 Buy-Sell	0.10	0.24	0.29	0.14	0.26	0.30
	(1.41)	(3.68)	(4.96)	(1.85)	(4.07)	(5.19)
Sig	0.16	0.00032	2.10	0.067	0.00	0.00
48 Buy	0.70	0.83	0.83	0.72	0.83	0.84
48 Sell	0.41	0.48	0.48	0.40	0.45	0.49
48 Buy-Sell	0.29	0.35	0.35	0.32	0.37	0.35
	(3.68)	(5.77)	(5.77)	(4.08	(5.73)	(5.95)
Sig	0.03	0.00	0.00	0.00	0.00	0.00
60 Buy	0.89	0.93	0.89	0.90	0.93	0.89
60 Sell	0.52	0.58	0.55	0.53	0.58	0.56
60 Buy-sell	0.36	0.35	0.34	0.37	0.35	0.34
	(4.44)	(5.02)	(5.49)	(4.66)	(5.17)	(5.59)
Sig	0.00	0.00	2.72	0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping quintile portfolios implemented on 47 stock market indices. The sample is from 1994 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 19 Contrarian Return with overlapping portfolios in developed countries 1969-2014

	Panel A			Panel B		
J	K= 36	48	60	K= 36	48	60
36 Buy	0.67	0.71	0.71	0.69	0.72	0.72
36 Sell	0.34	0.38	0.40	0.34	0.38	0.40
36 Buy-Sell	0.33	0.33	0.32	0.35	0.34	0.32
	(9.03)	(11.61)	(12.73)	(9.55)	(11.93)	(12.97)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
48 Buy	0.00753	0.77	0.74	0.77	0.77	0.75
48 Sell	0.34	0.36	0.39	0.34	0.36	0.39
48 Buy-Sell	0.41	0.41	0.36	0.42	0.42	0.35
	(11.64	(15.06)	(14.93)	(12.06)	(15.10)	(14.86)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
60 Buy	0.82	0.79	0.77	0.82	0.80	0.77
60 Sell	0.36	0.39	0.42	0.36	0.39	0.42
60 Buy-sell	0.45	0.41	0.35	0.46	0.41	0.35
	(12.11)	(13.99)	(13.43)	(12.56)	(14.20)	(13.57)
Sig	0.00	0.00	0.00	0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping quintile portfolio implemented on 23 developed countries stock market indices. The sample is from 1969 to 2014. I form contrarian portfolios (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formations and holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 20 Contrarian Return with Overlapping Portfolios in Emerging Countries 1988-2014

	Panel A			Panel B		
J K=	36	48	60	K= 36	48	60
36 Buy	0.79	0.77	0.75	0.78	0.76	0.74
36 Sell	0.33	0.27	0.33	0.30	0.27	0.33
36 Buy-Sell	0.46	0.50	0.42	0.48	0.49	0.42
	(6.79)	(8.40)	(8.37)	(7.01)	(8.58)	(8.36)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
48 Buy	0.81	0.80	0.77	0.80	0.78	0.77
48 Sell	0.08	0.20	0.26	0.09	0.21	0.28
48 Buy-Sell	0.73	0.59	0.51	0.71	0.57	0.50
	(10.58)	(10.36)	(9.70)	(10.19)	(7.00)	(9.57)
Sig	0.00	0.00	0.00	0.00	0.00	0.00
60 Buy	0.73	0.75	0.72	0.72	0.74	0.71
60 Sell	0.29	0.33	0.35	0.29	0.34	0.35
60 Buy-sell	0.45	0.42	0.37	0.43	0.41	0.36
	(7.10)	(8.31)	(7.39)	(7.00)	(7.96)	(7.16)
Sig	0.00	0.00	0.00	0.00	0.00	0.00

This table reports the contrarian strategies' returns with overlapping quintile portfolio implemented on 23 emerging stock market indices. The sample is from 1987 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formation and 3 different holding periods. The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.2. 21 Description of the bear and bull phases 1969-2014

	N0 of periods	% of total periods	Monthly/Market performance	48-month/60-month Monthly/Performance
Panel A: Bear Phase				
3-month	60	33.71	-1.97	
6-month	28	31.46	-1.42	
9-month	21	35.59	-1.13	
12-month	11	25.00	-1.43	0.25(3.04)
Panel B: Bull phase				
3-month	118	66.29	1.36	
6-month	61	68.54	1.26	
9-month	38	64.41	1.28	
12-month	33	75.00	1.09	1.41(18.30)

Table 34 shows the number of bear and bull market over the full sample period, their frequency, the market performances in different bear and bull horizon (3, 6, 9, 12) between December 1969 and January 2014, and the average contrarian profits realized after bull and bear markets with the optimum strategy (48-month/60-month) in the format month(year). The bear phase (Panel A) is the periods when market return (MSCI World Index) is negative for 3, 6, 9, and 12 months before the test period and the bull state (Panel B) is when the market return is positive for 3, 6, 9, and 12 months.

Table 4.2. 22 Seasonal-Difference in Cumulative Average Returns of the Contrarian Strategies 1969-2014

J	Holding period returns					Yearly event time			
	1	3	6	9	12	Year2	Year3	Year4	Year5
36 Sell	4.56	2.24	1.39	1.02	0.87	0.76	0.66	0.77	0.83
36 Buy	3.44	2.18	0.60	0.94	0.68	0.45	0.60	0.63	0.49
36 Buy-Sell	1.12	0.06	0.79	0.08	0.19	0.30	0.06	0.14	0.34
	(0.44)	(0.06)	(1.08)	(0.12)	(0.30)	(0.70)	(0.20)	(0.45)	(1.12)
Sig	0.66	0.95	0.30	0.90	0.76	0.49	0.84	0.66	0.29
48 Sell	3.26	2.52	-0.18	-0.39	0.48	0.87	0.46	0.79	0.81
48 Buy	1.81	-0.96	-0.75	-1.36	-0.90	0.14	-0.07	-0.03	-0.01
48 Buy-Sell	1.45	3.48	0.57	0.96	1.39	0.73	0.53	0.82	0.83
	(0.93)	(3.12)	(0.44)	(0.98)	(2.13)	(2.12)	(1.43)	(2.62)	(3.15)
Sig	0.37	0.012	0.67	0.35	0.06	0.06	0.18	0.03	0.01
60 Sell	3.89	1.88	0.90	0.78	0.88	0.80	0.92	0.76	1.09
60 Buy	1.63	0.05	0.93	0.48	0.94	0.61	0.28	0.15	0.556
60 Buy-sell	2.26	1.84	-0.03	0.29	-0.06	0.19	0.64	0.61	0.53
	(0.59)	(0.93)	(-0.02)	(0.25)	(-0.06)	(0.52)	(1.64)	(1.75)	(2.04)
Sig	0.57	0.39	0.99	0.81	0.95	0.62	0.15	0.12	0.087

This table reports the contrarian strategies' returns with deciles portfolios implemented on 47 stock market indices. The sample is from 1969 to 2014. I form contrarian portfolio (buy past losers and sell past winners) based on past performance of stock market indices. I use 3 different formation and 8 holding periods (1, 3, 9, 6, 12, 24, 36, and 60 month). The winner portfolios, the loser portfolios, and the loser minus winner portfolios returns are reported. The t-statistic are reported in the brackets and the results are statistically significant for $p<0.05$.

Table 4.3. 1 Fama and French Risks Impact on Global Momentum Profit 1969-2014

Fama French Three factor with excess return on MSCI world index

	Panel A: FF 3-Factors Model			
	3-month	6-month	9-month	12-month
α_o	0.009***	0.007***	0.006***	0.003***
	(4.82)	(6.45)	(5.95)	(3.65)
	0.000	0.000	0.000	0.000
MKTRF	-0.002	-0.011	-0.002	0.031
	(-0.04)	(-0.37)	(-0.09)	(1.48)
	0.965	0.713	0.925	0.138
SMB	-0.027	-0.106**	-0.068*	-0.092***
	(-0.42)	(-2.34)	(-1.68)	(-2.87)
	0.672	0.019	0.092	0.004
HML	-0.116*	0.016	-0.106***	-0.018
	(-1.69)	(0.33)	(-2.91)	(-0.58)
	0.091	0.738	0.004	0.565

Panel B: Fama French Three Factor with US Excess Market Return

	Panel A: FF 3-Factors Model			
	3-month	6-month	9-month	12-month
α_o	0.009***	0.008***	0.006***	0.003***
	(4.79)	(6.39)	(5.94)	(3.49)
	0.000	0.000	0.000	0.000
ERM	-0.025	-0.018	-0.016	0.018
	(-0.54)	(-0.60)	(-0.67)	(0.86)
	0.588	0.546	0.504	0.391
SMB	-0.017	-0.103***	-0.066	-0.093***
	(-0.27)	(-2.29)	(-1.65)	(-2.90)
	0.788	0.022	0.100	0.004
HML	-0.127*	0.012	-0.114***	-0.018
	(-1.82)	(0.26)	(-3.11)	(-0.55)
	0.068	0.798	0.002	0.579

This table reports the regression result based on model (28). The returns of the momentum portfolio at time t and regressed on: *ERM and MKTRF* the excess market returns, *HML* (high minus low) the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, and *BMS* (small minus big) returns to long-short portfolios constructed using size in US market. Panel A provide the results with the excess return based on MSCI world index, while panel B are based on US excess return. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 2 Effect of Market State Risks on Global Momentum Profit 1969-2014

	Parameter				
	α_1	LIQ	DS	TS	MKT
3-Month	0.012**	0.025	-0.003	0.059	-0.021
	(2.01)	(0.67)	(-0.48)	(0.82)	(-0.40)
	0.045	0.502	0.629	0.412	0.686
6-Month	0.010***	0.020	-0.002	0.022	0.009
	(3.00)	(0.94)	(-0.70)	(0.48)	(0.29)
	0.003	0.347	0.486	0.633	0.773
9-month	0.004*	-0.017	0.000	0.020	-0.010
	(1.78)	(-0.95)	(0.15)	(0.60)	(-0.40)
	0.076	0.340	0.883	0.551	0.691
12-month	-0.001	-0.033**	0.002	0.047	0.012
	(-0.31)	(-2.07)	(1.19)	(1.93)	(0.52)
	0.759	0.038	0.236	0.054	0.606

This table reports the regression result based on model (29). Where: LIQ_{t-1} is the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS the Term spread at time t-1 and the MKT_{t-1} the MSCI world indices return at time t-1. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk the R-square are also reported. I also report the autocorrelation coefficient of the residual, the GMM statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 3 Effect of Macroeconomic Risk on Global Momentum Profits 1969-2014

	Parameter			
	α_1	ΔOP	ΔIP	$WVOL$
3-Month	0.003	-0.006	0.455	0.989***
	(0.92)	(-0.24)	(1.09)	(3.18)
	0.356	0.807	0.274	0.001
6-Month	0.002	-0.006	0.607**	0.669***
	(0.84)	(-0.31)	(2.13)	(3.29)
	0.400	0.760	0.033	0.001
9-month	0.002	0.003	0.262	0.275*
	(1.15)	(0.18)	(1.12)	(1.80)
	0.249	0.855	0.264	0.071
12-month	0.001	-0.002	0.236	-0.008
	(0.68)	(-0.24)	(1.32)	(-0.07)
	0.497	0.814	0.185	0.948

This table reports the regression result based on model (30). Where, ΔOP_{T-1}, is the change in Oil price at time T-1, ΔIP_{T-1} the change in monthly value of the US Industrial production at time T-1, and $WVOL_{T-1}$ the market volatility at time T-1 based on the MSCI world return. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. R-squares are reported. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 4 Effect of Global Risk Factor on Global Momentum Profit 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.009***	0.0131**	0.005	0.005
	(4.82)	(2.21)	(1.17)	(0.71)
	0.000	0.027	0.241	0.481
LIQ		0.026		0.016
		(0.69)		(0.43)
		0.489		0.670
DS		-0.004		0.000
		(-0.66)		(0.05)
		0.509		0.959
TS		0.071		0.088
		(0.98)		(1.20)
		0.327		0.232
MKT		0.005		0.015
		(0.09)		(0.29)
		0.927		0.771
ΔOP			-0.003	-0.007
			(-0.11)	(-0.27)
			0.911	0.784
$WVOL$			0.325	0.326
			(0.74)	(0.72)
			0.462	0.470
ΔIP			1.011***	1.051***
			(3.27)	(3.46)
			0.001	0.001
$MKTRF$	-0.002	-0.020	-0.039	-0.049
	(-0.04)	(-0.42)	(-0.78)	(-1.00)
	0.965	0.671	0.434	0.316
SMB	-0.027	-0.051	-0.011	-0.040
	(-0.42)	(-0.78)	(-0.18)	(-0.62)
	0.672	0.433	0.860	0.538
HML	-0.116*	-0.143**	-0.120*	-0.151*
	(-1.69)	(-2.01)	(-1.75)	(-2.12)
	0.091	0.045	0.079	0.034

This table reports the regression result based on model (31). Where: the dependent variable are the returns of the momentum portfolio at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (Small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. These regressions are based on model 1 to 4 specification. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 5 Global Risk Factor and Global Momentum Profit Seasonal Effect 1969-2014

	3-Month	6-Month	9-Month	12-Month
α_3	0.005	0.001	0.000	-0.004
	(0.71)	(0.20)	(0.12)	(-1.46)
	0.481	0.840	0.901	0.144
LIQ	0.016	0.021	-0.020	-0.031**
	(0.43)	(0.97)	(-1.17)	(-2.00)
	0.670	0.332	0.243	0.046
DS	0.000	0.002	0.002	0.003
	(0.05)	(0.45)	(0.76)	(1.50)
	0.959	0.651	0.449	0.134
TS	0.088	0.048	0.046	0.044
	(1.20)	(1.05)	(1.31)	(1.73)
	0.232	0.295	0.189	0.083
MKT	0.015	0.020	-0.005	0.025
	(0.29)	(0.61)	(-0.21)	(1.05)
	0.771	0.542	0.836	0.292
ΔOP	-0.007	-0.004	0.017	0.003
	(-0.27)	(-0.24)	(1.14)	(0.31)
	0.784	0.812	0.255	0.754
$WVOL$	0.326	0.610**	0.207	0.294
	(0.72)	(2.05)	(0.91)	(1.67)
	0.470	0.040	0.364	0.095
ΔIP	1.051***	0.650***	0.384**	0.092
	(3.46)	(2.94)	(2.26)	(0.68)
	0.001	0.003	0.024	0.494
$MKTRF$	-0.050	-0.019	-0.014	0.039**
	(-1.00)	(-0.56)	(-0.48)	(1.88)
	0.316	0.575	-0.48	0.060
SMB	-0.040	-0.101**	-0.062	-0.119***
	(-0.62)	(-2.16)	(-1.55)	(-3.58)
	0.538	0.031	0.122	0.000
HML	-0.151**	0.003	-0.108***	-0.028
	(-2.12)	(0.06)	(-3.00)	(-0.88)
	0.034	0.956	0.003	0.379

This table reports the regression result based on model (31). Where: the dependent variable R are the returns of the momentum portfolio (9-month/3, 6, 9, 12-month) at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, the SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, the DS_{t-1} the Default spread at time t-1, TS_{t-1} is the Term spread at time t-1, the MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 6 Effect of Global Risk Factors on Global Momentum Profit During Crisis Period

	Currency Crisis	Stock Market Crash	Banking Crisis
α_3	-0.025	-0.007	0.043***
	(-1.04)	(-0.58)	(3.54)
	0.299	0.562	0.000
LIQ	0.100**	-0.027	0.019
	(2.22)	(-0.44)	(0.30)
	0.026	0.662	0.764
DS	0.006	0.013	-0.028***
	(0.41)	(1.49)	(-3.44)
	0.683	0.137	0.001
TS	0.063	-0.104	0.001
	(0.47)	(-0.74)	(0.01)
	0.642	0.459	0.993
MKT	-0.267***	0.038	0.042
	(-2.90)	(0.44)	(0.50)
	0.004	0.663	0.619
ΔOP	0.016	0.043	-0.091***
	(0.34)	(1.09)	(-2.68)
	0.733	0.276	0.007
$WVOL$	1.638	-0.198	0.174
	(1.37)	(-0.33)	(0.38)
	0.170	0.742	0.707
ΔIP	2.436***	0.921*	-0.118
	(4.12)	(1.89)	(-0.20)
	0.000	0.059	0.839
$MKTRF$	-0.084	-0.003	-0.010
	(-0.86)	(-0.04)	(-0.13)
	0.390	0.967	0.897
SMB	0.125	-0.004	0.215
	(0.88)	(-0.04)	(1.32)
	0.381	0.968	0.187
HML	0.400**	-0.150	-0.339**
	(2.22)	(-1.24)	(-2.50)
	0.027	0.214	0.012

This table reports the regression result based on model (32). Where: the dependent variable R are the returns of the momentum portfolio during crisis periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return time t-1, ΔOP_{t-1}, the chance on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. For detailed definition of the crisis period please see Appendix E4. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 7 Effect of Global Risks on Global Momentum Profit in Crisis Period (all crisis)

	Model	Mode2	Model3	Model4
α_3	0.006**	0.020**	0.002	0.008
	(2.42)	(2.49)	(0.44)	(0.88)
	0.016	0.013	0.659	0.377
LIQ		0.028		0.017
		(0.64)		(0.37)
		0.523		0.710
DS		-0.010		-0.005
		(-1.61)		(-0.76)
		0.107		0.446
TS		0.027		0.042
		(0.31)		(0.47)
		0.756		0.638
MKT		0.076		0.638
		(1.16)		(1.22)
		0.245		0.222
ΔOP			-0.000	-0.016
			(-0.01)	(-0.51)
			0.991	0.613
$WVOL$			0.367	0.447
			(0.88)	(1.03)
			0.381	0.303
ΔIP			0.974**	0.975***
			(2.59)	(2.60)
			0.010	0.009
$MKTRF$	0.009	-0.024	-0.021	-0.044
	(0.19)	(-0.46)	(-0.38)	(-0.80)
	0.852	0.646	0.704	0.421
SMB	-0.000	-0.036	0.024	-0.018
	(-0.01)	(-0.47)	(0.30)	(-0.23)
	0.996	0.639	0.763	0.820
HML	-0.176**	-0.235***	-0.178**	-0.226***
	(-2.37)	(-2.99)	(-2.33)	(-2.75)
	0.018	0.003	0.020	0.006

This table reports the regression result based on model (32). Where: the dependent variable R are the returns of the momentum portfolio during crisis periods (all crisis) at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. For detailed definition of the crisis period please see Appendix E4. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 8 Effect of Global Risks on Global Momentum Profit During Non-Crisis Period

	Model	Mode2	Model3	Model4
α_3	0.012***	0.000	0.007	-0.005
	(4.28)	(0.01)	(0.72)	(-0.44)
	0.000	0.996	0.472	0.663
LIQ		-0.073		-0.086
		(-1.22)		(-1.50)
		0.221		0.134
DS		0.018**		0.018**
		(2.04)		(2.09)
		0.042		0.037
TS		0.171		0.236*
		(1.20)		(1.69)
		0.230		0.091
MKT		-0.303***		-0.257**
		(-2.96)		(-2.39)
		0.003		0.017
ΔOP			0.014	0.011
			(0.35)	(0.28)
			0.728	0.777
$WVOL$			0.362	0.214
			(0.22)	(0.13)
			0.830	0.900
ΔIP			1.194**	1.060**
			(2.37)	(2.04)
			0.018	0.042
$MKTRF$	-0.089	-0.117	-0.107	-0.129
	(-0.83)	(-1.04)	(-0.99)	(-1.14)
	0.407	0.301	0.320	0.256
SMB	-0.160	-0.072	-0.155	-0.089
	(-1.27)	(-0.59)	(-1.26)	(-0.75)
	0.204	0.553	0.206	0.450
HML	0.087	0.025	0.049	-0.035
	(0.58)	(0.17))	(0.34)	(-0.24)
	0.561	0.865	0.733	0.808

This table reports the regression result based on model (32). Where: the dependent variable R are the returns of the momentum portfolio during non-crisis periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, $MSCIW_{t-1}$ the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. For detailed definition of the crisis period please see Appendix E4. Non-criss period exclude all crisis periods from de sample 1969-2014. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 9 Effect of Global Risks on Global Momentum Profit During Expansion Period

	Model	Mode2	Model3	Model4
α_3	0.011***	-0.003	0.005	-0.006
	(5.61)	(-0.48)	(0.89)	(-0.82)
	0.000	0.629	0.373	0.414
LIQ		0.034		0.032
		(0.73)		(0.69)
		0.465		0.492
DS		0.015**		0.013**
		(2.32)		(1.97)
		0.020		0.049
TS		0.010		0.005
		(0.11)		(0.06)
		0.912		0.951
MKT		-0.000		0.036
		(-0.01)		(0.57)
		0.995		0.568
ΔOP			-0.006	-0.012
			(-0.20)	(-0.38)
			0.839	0.705
$WVOL$			0.381	0.158
			(0.54)	(0.22)
			0.591	0.826
ΔIP			1.314***	1.260***
			(3.42)	(3.21)
			0.001	0.001
$MKTRF$	-0.072	-0.058	-0.082	-0.066
	(-1.20)	(-0.97)	(-1.33)	(-1.07)
	0.228	0.334	0.183	0.284
SMB	-0.042	-0.040	-0.038	-0.049
	(-0.62)	(-0.59)	(-0.58)	(-0.73)
	0.535	0.555	0.563	0.463
HML	-0.147*	-0.146*	-0.137*	-0.148*
	(-1.79)	(-1.78)	(-1.69)	(-1.83)
	0.074	0.074	0.090	0.067

This table reports the regression results based on Equation (33) Where: the dependent variable R are the returns of the momentum portfolio during expansion periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. For detailed definition of the expansion period please see Appendix E4. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors with based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 10 Effect of Global Risks on Global Momentum Profit During Contraction

	Model	Mode2	Model3	Model4
α_3	-0.002	0.009	-0.013**	-0.005
	(-1.00)	(0.79)	(-2.12)	(-0.38)
	0.318	0.429	0.034	0.703
LIQ		-0.095*		-0.072
		(-1.78)		(-1.24)
		0.076		0.215
DS		-0.020***		-0.020***
		(-3.47)		(-3.76)
		0.001		0.000
TS		0.226*		0.271**
		(1.68)		(2.07)
		0.093		0.038
MKT		-0.168*		-0.184**
		(-1.85)		(-2.08)
		0.064		0.038
ΔOP			0.015	0.007
			(0.38)	(0.24)
			0.706	0.812
$WVOL$			0.647	1.256***
			(1.32)	(2.70)
			0.186	0.007
ΔIP			0.012	-0.521
			(0.03)	(-1.28)
			0.975	0.201
$MKTRF$	-0.036	-0.060	-0.051	-0.001
	(-0.42)	(-0.89)	(-0.49)	(-0.02)
	0.677	0.375	0.627	0.985
SMB	-0.206	-0.074	-0.151	-0.237
	(-1.36)	(-0.54)	(-0.92)	(-1.47)
	0.174	0.590	0.356	0.141
HML	0.039	-0.134	0.028	-0.090
	(0.29)	(-1.08)	(0.20)	(-0.71)
	0.769	0.282	0.842	0.477

This table reports the regression result based on model (33). Where: the dependent variable R are the returns of the momentum portfolio during contraction periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. Detailed definition of contraction period please see Appendix E4. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 11 Effect of Global Risks on Global Momentum Profit in Emerging Market 1988-2014

	Model	Mode2	Model3	Model4
α_3	0.008***	0.023***	0.003	0.012
	(3.62)	(3.68)	(0.52)	(1.52)
	0.000	0.000	0.600	0.129
LIQ		0.015		0.008
		(0.38)		(0.20)
		0.704		0.843
DS		-0.015**		-0.010
		(-2.49)		(-1.42)
		0.013		0.156
TS		0.066		0.080
		(0.62)		(0.72)
		0.536		0.470
MKT		-0.124**		-0.095
		(-2.15)		(-1.64)
		0.032		0.102
ΔOP			-0.010	-0.009
			(-0.45)	(-0.40)
			0.653	0.687
$WVOL$			0.410	0.506
			(0.74)	(0.93)
			0.458	0.355
ΔIP			1.361***	1.043**
			(3.29)	(2.39)
			0.001	0.017
$MKTRF$	-0.093*	-0.118**	-0.157**	-0.141**
	(-1.68)	(-2.10)	(-2.53)	(-2.31)
	0.093	0.036	0.011	0.021
SMB	-0.091	-0.038	-0.082	-0.037
	(-1.16)	(-0.53)	(-1.07)	(-0.51)
	0.247	0.598	0.286	0.609
HML	-0.110	-0.123	-0.139	-0.140
	(-1.27)	(-1.37)	(-1.64)	(-1.57)
	0.204	0.170	0.102	0.116

This table reports the regression result based on model (34) Where: the dependent variable R are the returns of the momentum portfolio in emerging market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 12 Effect of Global Risks on Global Momentum Profit in Developed Market 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.006***	0.003	0.000	-0.004
	(3.77)	(0.77)	(0.08)	(-0.75)
	0.000	0.442	0.937	0.456
LIQ		0.044		0.041
		(1.14)		(1.07)
		0.253		0.283
DS		0.003		0.005
		(0.70)		(1.17)
		0.483		0.243
TS		0.106*		0.117
		(1.88)		(2.11)
		0.060		0.035
MKT		0.033		0.042
		(0.71)		(0.92)
		0.476		0.356
ΔOP			-0.023	-0.017
			(-1.09)	(-0.83)
			0.275	0.409
$WVOL$			0.663	0.541
			(1.49)	(1.15)
			0.136	0.250
ΔIP			0.577**	0.707**
			(2.08)	(2.48)
			0.038	0.013
$MKTRF$	-0.061	-0.069*	-0.056	-0.071*
	(-1.46)	(-1.71)	(-1.34)	(-1.69)
	0.144	0.088	0.181	0.090
SMB	-0.018	-0.054	-0.007	-0.048
	(-0.32)	(-0.94)	(-0.13)	(-0.84)
	0.746	0.349	0.894	0.399
HML	-0.176***	-0.196***	-0.161**	-0.190***
	(-2.72)	(-2.90)	(-2.48)	(-2.81)
	0.007	0.004	0.013	0.005

This table reports the regression result based on model (35). Where: the dependent variable R are the returns of the momentum portfolio in develop market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 13 Effect of Global Risks on Global Momentum Profit in Established Market 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.007***	0.009**	0.009***	0.007
	(4.98)	(1.94)	(2.81)	(1.49)
	0.000	0.052	0.005	0.137
LIQ		0.050		0.048
		(1.45)		(1.41)
		0.148		0.158
DS		-0.002		0.001
		(-0.34)		(0.30)
		0.734		0.765
TS		0.074		0.089
		(1.25)		(1.49)
		0.213		0.135
MKT		0.054		0.054
		(1.12)		(1.14)
		0.261		0.253
ΔOP			-0.023	-0.027
			(-1.14)	(-1.33)
			0.255	0.183
$WVOL$			-0.344	-0.289
			(-0.97)	(-0.76)
			0.334	0.447
ΔIP			0.586**	0.684**
			(2.17)	(2.50)
			0.030	0.012
$MKTRF$	-0.002	-0.029*	-0.035	-0.059
	(-0.06)	(-0.68)	(-0.80)	(-1.35)
	0.952	0.495	0.425	0.178
SMB	-0.040	-0.074	-0.023	-0.054
	(-0.75)	(-1.33)	(-0.43)	(-0.95)
	0.451	0.183	0.666	0.343
HML	-0.132**	-0.161**	-0.132	-0.159**
	(-2.18)	(-2.51)	(-2.15)	(-2.44)
	0.029	0.012	0.032	0.015

This table reports the regression result based on model (36) Where: the dependent variable R are the returns of the momentum portfolio in established market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔOP_{t-1} the monthly oil price based world indices value at t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 14 Effect of Global Risks on Global Momentum Profit in Globalization 1994-2014

	Model	Mode2	Model3	Model4
α_3	0.008***	0.027***	0.003	0.016
	(3.53)	(4.16)	(0.61)	(2.07)
	0.000	0.000	0.539	0.039
LIQ		0.030		0.023
		(0.77)		(0.59)
		0.439		0.552
DS		-0.018***		-0.015**
		(-2.89)		(-2.06)
		0.004		0.040
TS		0.290***		0.336***
		(3.07)		(3.41)
		0.002		0.001
MKT		-0.022		0.021
		(-0.39)		(0.37)
		0.696		0.712
ΔOP			0.013	0.015
			(0.48)	(0.57)
			0.632	0.566
$WVOL$			0.422	0.767
			(0.74)	(1.25)
			0.460	0.210
ΔIP			1.189***	0.807**
			(2.77)	(2.01)
			0.006	0.044
$MKTRF$	-0.091	-0.151***	-0.181**	-0.172***
	(-1.53)	(-2.65)	(-2.59)	(-2.66)
	0.127	0.008	0.010	0.008
SMB	-0.0235	-0.018	-0.037	-0.038
	(-0.30)	(-0.26)	(-0.48)	(-0.57)
	0.764	0.794	0.633	0.569
HML	-0.105	-0.183*	-0.170*	-0.219
	(-1.16)	(-1.94)	(-1.92)	(-2.42)
	0.246	0.052	0.055	0.016

This table reports the regression result based on model (37) Where: the dependent variable R are the returns of the momentum portfolio during the globalization periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. Test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.3. 15 Global Risks Impact on Excess Return of the Global Momentum 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.006***	0.011*	0.001	0.002
	(2.97)	(1.87)	(0.16)	(0.24)
	0.003	0.061	0.876	0.809
LIQ		0.023		0.017
		(0.62)		(0.44)
		0.538		0.659
DS		-0.005		-0.001
		(-0.87)		(-0.18)
		0.384		0.858
TS		0.061		0.085
		(0.84)		(1.14)
		0.403		0.254
MKT		0.009		0.019
		(0.18)		(0.36)
		0.859		0.715
ΔOP			-0.004	-0.008
			(-0.18)	(-0.33)
			0.860	0.742
$WVOL$			0.432	0.469
			(0.98)	(1.04)
			0.327	0.297
ΔIP			0.100***	1.035***
			(3.28)	(3.44)
			0.001	0.001
$MKTRF$	0.003	-0.015	-0.030	-0.040
	(0.06)	(-0.33)	(-0.61)	(-0.83)
	0.950	0.738	0.544	0.409
SMB	-0.024	-0.048	-0.007	-0.040
	(-0.37)	(-0.75)	(-0.11)	(-0.61)
	0.709	0.451	0.909	0.541
HML	-0.120*	-0.155**	-0.125*	-0.160**
	(-1.77)	(-2.18)	(-1.83)	(-2.25)
	0.077	0.029	0.067	0.024

This table reports the regression result based on model (38) Where: the dependent variable $R_t - R_{Ft}$ is the excess returns of the momentum portfolio at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 1 Fama and French Risks Impact on Global Contrarian Profit 1969-2014

Fama and French Three Factor with Excess Return on MSCI World Index

	Panel A: FF 3-Factors Model		
	36-month	48-month	60-month
α_o	0.006***	0.005***	0.005***
	(13.24)	(13.11)	(15.46)
	0.000	0.000	0.000
MKTRF	0.024*	0.010	0.012
	(1.82)	(0.87)	(1.64)
	0.069	0.382	0.100
SMB	-0.084***	-0.031*	-0.001
	(-3.08)	(-1.74)	(-0.10)
	0.002	0.081	0.919
HML	-0.024	-0.01£	0.016
	(-1.15)	(-0.69)	(1.15)
	0.248	0.493	0.249

Panel B: Fama and French three Factor with US Excess Market Return

	Panel A: FF 3-Factors Model		
	36-month	48-month	60-month
α_o	0.006***	0.005***	0.005***
	(12.93)	(12.70)	(16.00)
	0.000	0.000	0.000
ERM	0.029**	0.004	0.009
	(2.14)	(0.37)	(1.21)
	0.033	0.713	0.228
SMB	-0.090***	-0.031	-0.002
	(-3.25)	(-1.75)	(-0.19)
	0.001	0.079	0.853
HML	-0.016	-0.014	0.016
	(-0.73)	(-0.74)	(1.11)
	0.466	0.457	0.267

This table reports the regression result based on model (39). Where: the dependent variable *R* are the returns of the contrarian portfolio at time t and regressed on, *ERM and MKTRF* the excess market returns, *HML* (high minus low) the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, *and BMS* (small minus big) returns to long-short portfolios constructed using size in US market. Panel A provide the results with the excess return based on MSCI world index, while panel B are based on US excess return. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 2 Markets States Risks Impact on Global Contrarian Profit 1969-2014

	Parameter				
	α_1	*LIQ*	*DS*	*TS*	*MKT*
36-Month	0.009***	0.012	-0.002**	0.008	0.004
	(7.54)	(1.34)	(-2.14)	(0.50)	(0.36)
	0.000	0.181	0.032	0.616	0.720
48-Month	0.007***	0.010	-0.006	0.005	0.008
	(7.04)	(1.36)	(-1.64)	(0.38)	(0.75)
	0.000	0.173	0.100	0.700	0.453
60-month	0.007***	-0.002	-0.002***	-0.003	0.011
	(9.02)	(-0.32)	(-3.16)	(-0.28)	(1.46)
	0.000	0.750	0.002	0.782	0.145

This table reports the regression result based on model (40). Where: LIQ_{t-1} is the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS the Term spread at time t-1 and theMKT_{t-1} the MSCI world indices return at time t-1. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk the R-square are also reported. I also report the autocorrelation coefficient of the residual, the GMM statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 3 Effect of Macroeconomic Risk on Global Contrarian Profits 1969-2014

	Parameter			
	α_1	ΔOP	ΔIP	*MKVOL*
36-Month	0.011***	0.006	-0.619***	-0.014
	(11.92)	(0.95)	(-6.23)	(-0.21)
	0.000	0.341	0.000	0.835
48-Month	0.010***	0.008	-0.673***	0.076
	(9.18)	(1.55)	(-5.28)	(1.19)
	0.000	0.122	0.000	0.233
60-month	0.008***	-0.007**	-0.367***	0.019
	(9.08)	(-2.00)	(-3.36)	(0.37)
	0.000	0.045	0.001	0.713

This table reports the regression result based on model (41) Where: ΔOP_{T-1}, is the change in Oil price at time T-1, $\Delta\, IP_{T-1}$ the change in monthly value of the US Industrial production at time T-1 and $MKVOL_{T-1}$ the market volatility at time T-1 based on the MSCI world return. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 4 Effect of Global Risk Factor on Global Contrarian Profits 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.006***	0.006***	0.010***	0.010***
	(13.24)	(6.30)	(9.08)	(6.58)
	0.000	0.000	0.000	0.000
LIQ		0.014*		0.006
		(1.86)		(0.88)
		0.063		0.382
DS		-0.001		-0.000
		(-1.09)		(-0.17)
		0.275		0.865
TS		0.004		0.0105
		(0.32)		(0.76)
		0.752		0.444
MKT		0.015		0.009
		(1.34)		(0.85)
		0.180		0.398
ΔOP			0.009*	0.009*
			(1.76)	(1.69)
			0.078	0.092
$WVOL$			-0.686***	-0.639***
			(-5.16)	(-4.75)
			0.000	0.000
ΔIP			0.080	0.078
			(1.23)	(1.06)
			0.220	0.290
$MKTRF$	0.024	0.011	-0.455	-0.456
	(1.82)	(1.04)	(-0.44)	(-0.45)
	0.069	0.297	0.656	0.651
SMB	-0.084***	-0.040**	-0.026	-0.033*
	(-3.08)	(-2.11)	(-1.48)	(-1.76)
	0.002	0.035	0.139	0.078
HML	-0.024	-0.020	-0.025	-0.031
	(-1.15)	(-1.11)	(-1.37)	(-1.68)
	0.248	0.265	0.171	0.093

This table reports the regression result based on model (42). Where: the dependent variable R are the returns of the contrarian portfolio at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return t-1, and ΔOP_{t-1}, the chance on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. These regressions are based on model 1 to 4 specification. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 5 Global Risk Factor and Global Contrarian Profit Seasonal Effect 1969-2014

	36-Month	48-Month	60-Month
α_3	0.012***	0.010***	0.009****
	(8.65)	(6.58)	(8.68)
	0.000	0.000	0.000
LIQ	0.011	0.006	-0.002
	(1.36)	(0.88)	(-0.41)
	0.175	0.382	0.681
DS	-0.001	-0.000	-0.002**
	(-0.69)	(-0.17)	(-2.58)
	0.489	0.865	0.010
TS	0.026	0.0105	-0.008
	(1.55)	(0.76)	(-0.72)
	0.120	0.444	0.470
MKT	-0.002	0.009	0.013
	(-0.17)	(0.85)	(1.57)
	0.862	0.398	0.117
ΔOP	0.010	0.009*	-0.009
	(1.54)	(1.69)	(-2.57)
	0.123	0.092	0.010
$WVOL$	-0.572***	-0.639***	-0.298***
	(-4.99)	(-4.75)	(-2.82)
	0.000	0.000	0.005
ΔIP	-0.020	0.078	-0.036
	(-0.28)	(1.06)	(-0.65)
	0.777	0.290	0.513
$MKTRF$	-0.004	-0.005	0.002
	(-0.33)	(-0.45)	(0.24)
	0.744	0.651	0.812
SMB	-0.080***	-0.033*	0.004
	(-2.88)	(-1.76)	(0.36)
	0.004	0.078	0.721
HML	-0.042*	-0.031*	0.011*
	(-1.93)	(-1.68)	(0.75)
	0.054	0.093	0.455

This table reports the regression result based on model (42). Where: the dependent variable R are the returns of the contrarian portfolio (9-month/3, 6, 9, 12-month) at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 6 Effect of Global Risk Factors on Global Contrarian Profit During Crisis Period 1969-2010

	Currency Crisis	Stock Market Crash	Banking Crisis
α_3	0.042***	-0.008***	0.014***
	3.05	-2.82	5.37
	0.002	0.005	0.000
LIQ	-0.019**	0.003	0.015
	-2.17	0.32	1.04
	0.030	0.751	0.296
DS	-0.035**	0.010***	-0.003**
	(-2.58)	(5.13)	(-2.15)
	0.010	0.000	0.031
TS	0.032	-0.018	-0.009
	(0.89)	(-0.74)	(-0.370
	0.371	0.462	0.709
MKT	0.014	0.012	0.032
	(0.48)	(0.70)	(1.73)
	0.633	0.483	0.083
ΔOP	0.009	0.017*	-0.019***
	(0.84)	(1.65)	(-2.14)
	0.399	0.099	0.032
$WVOL$	0.774**	-0.377***	-0.441**
	(1.89)	(-2.93)	(-2.46)
	0.059	0.003	0.014
ΔIP	0.134	0.2543309	0.1068137
	(0.49)	(2.43)	(0.95)
	0.623	0.015	0.343
$MKTRF$	-0.068***	-0.026	0.009
	(-4.92)	(-1.52)	(0.59)
	0.000	0.129	0.553
SMB	-0.053	-0.039**	0.022
	(-1.47)	(-1.81)	(0.58)
	0.143	0.070	0.559
HML	-0.058	-0.094***	-0.044
	(-1.18)	(-4.15)	(-1.56)
	0.238	0.000	0.119

This table reports the regression result based on model (44). Where: the dependent variable R are the returns of the contrarian portfolio during crisis periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return time t-1, ΔOP_{t-1}, the chance on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1.For detailed definition of the crisis period please see Appendix E4. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 7 Effect of Global Risks on Global Contrarian Profit in Crisis Period 1969-2010 (all crisis)

	Model	Mode2	Model3	Model4
α_3	0.005***	0.001	0.008****	0.001
	(8.25)	(0.37)	(5.67)	(0.38)
	0.000	0.710	0.000	0.701
LIQ		0.0140		0.010
		(1.33)		(1.04)
		0.185		0.299
DS		0.004**		0.005***
		(2.29)		(3.14)
		0.022		0.002
TS		-0.021		0.001
		(-1.06)		(0.06)
		0.290		0.954
MKT		0.048***		0.040***
		(3.16)		(2.75)
		0.002		0.006
ΔOP			0.001	0.005
			(0.12)	(0.56)
			0.903	0.574
$WVOL$			-0.399***	-0.303**
			(-2.85)	(-2.22)
			0.004	0.026
ΔIP			0.254***	0.336***
			(2.93)	(3.54)
			0.003	0.000
$MKTRF$	0.010	0.017	-0.006	-0.006
	(0.71)	(1.18)	(-0.51)	(-0.45)
	0.478	0.237	0.610	0.654
SMB	-0.052**	-0.069***	-0.032	-0.046**
	(-2.32)	(-3.08)	(-1.39)	(-2.04)
	0.020	0.002	0.165	0.041
HML	-0.060***	-0.077***	-0.064***	-0.079***
	(-2.71)	(-3.64)	(-3.10)	(-4.02)
	0.007	0.000	0.002	0.000

This table reports the regression result based on model (43) Where: the dependent variable R are the returns of the contrarian portfolio during crisis periods (all crisis) at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. For detailed definition of the crisis period please see Appendix E4. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 8 Effect of Global Risks on Global Contrarian Profit During Non-Crisis Period 1969-2010

	Model	Mode2	Model3	Model4
α_3	0.006***	0.019***	0.014***	0.025**
	(9.63)	(12.24)	(11.66)	(15.92)
	0.000	0.000	0.000	0.000
LIQ		-0.004		-0.001
		(-0.34)		(-0.07)
		0.736		0.941
DS		-0.01***		-0.014***
		(-9.37)		(-10.18)
		0.000		0.000
TS		0.001		-0.004
		(0.07)		(-0.19)
		0.948		0.852
MKT		-0.018		-0.013
		(-0.99)		(-0.83)
		0.321		0.406
ΔOP			0.009	0.009
			(1.43)	(1.38)
			0.151	0.167
$WVOL$			-1.037***	-0.959***
			(-7.11)	(-8.31)
			0.000	0.000
ΔIP			-0.221**	-0.193**
			(-2.24)	(-2.07)
			0.025	0.038
$MKTRF$	0.025	0.020	0.019	0.019
	(1.49)	(1.18)	(1.23)	(1.24)
	0.136	0.238	0.220	0.215
SMB	0.005	0.033	0.005	0.026
	(0.24)	(1.49)	(0.26)	(1.29)
	0.813	0.137	0.797	0.198
HML	0.092***	0.099***	0.057**	0.065***
	(3.46)	(4.26)	(2.25)	(2.92)
	0.001	0.000	0.024	0.004

This table reports the regression result based on model (43). Where: the dependent variable R are the returns of the contrarian portfolio during non-crisis periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, $MSCIW_{t-1}$ the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. For detailed definition of the crisis period please see Appendix E4. Non-criss period exclude all crisis periods from de sample 1969-2010. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 9 Effect of Global Risks on Global Contrarian Profit during Expansion Period 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.006***	0.005***	0.011***	0.010***
	(14.68)	(3.23)	(7.77)	(4.72)
	0.000	0.001	0.000	0.000
LIQ		0.009		0.004
		(1.19)		(0.50)
		0.236		0.616
DS		0.002		0.001
		(1.06)		(0.79)
		0.290		0.432
TS		0.008		0.007
		(0.43)		(0.40)
		0.665		0.691
MKT		-0.002		0.006
		(-0.16)		(0.40)
		0.875		0.686
ΔOP			0.006	0.006
			(0.84)	(0.87)
			0.400	0.382
$WVOL$			-0.676***	-0.665***
			(-3.67)	(-3.59)
			0.000	0.000
ΔIP			-0.028	-0.007
			(-0.31)	(-0.08)
			0.758	0.938
$MKTRF$	-0.005	-0.004	-0.010	-0.008
	(-0.38)	(-0.28)	(-0.73)	(-0.64)
	0.705	0.783	0.465	0.525
SMB	-0.018	-0.023	-0.022	-.028
	(-0.94)	(-1.18)	(-1.15)	(-1.40)
	0.349	0.236	0.249	0.161
HML	-0.023	-0.027	-0.034*	-0.040*
	(-1.12)	(-1.36)	(-1.66)	(-1.92)
	0.261	0.174	0.096	0.055

This table reports the regression results based on Equation (44). Where: the dependent variable R are the returns of the contrarian portfolio during expansion periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. For detailed definition of the expansion period please see Appendix E4. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors with based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 10 Effect of Global Risks on Global Contrarian Profit during Contraction 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.001	0.004**	0.006***	0.003
	(1.58)	(1.95)	(3.74)	(0.74)
	0.114	0.051	0.000	0.458
LIQ		0.015		0.016
		(1.28)		(1.62)
		0.202		0.105
DS		-0.000		0.002
		(-0.32)		(0.95)
		0.745		0.340
TS		0.003		0.009
		(0.13)		(0.41)
		0.898		0.685
MKT		0.029**		0.020
		(1.94)		(1.44)
		0.052		0.151
ΔOP			0.009	0.010
			(1.05)	(1.03)
			0.292	0.303
$WVOL$			-0.378***	-0.341***
			(-3.97)	(-3.27)
			0.000	0.001
ΔIP			0.027	0.092
			(0.30)	(1.04)
			0.766	0.299
$MKTRF$	0.034**	0.032*	0.011	-0.002
	(2.08)	(1.80)	(0.65)	(-0.11)
	0.037	0.071	0.517	0.911
SMB	-0.121***	-0.138***	-0.075*	-0.093*
	(-3.37)	(-3.27)	(-1.86)	(-2.08)
	0.001	0.001	0.063	0.037
HML	0.016	-0.001	0.002	-0.006
	(0.62)	(-0.04)	(0.05)	(-0.22)
	0.535	0.970	0.957	0.824

This table reports the regression result based on model (44). Where: the dependent variable R are the returns of the contrarian portfolio during contraction periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. For detailed definition of the contraction period please see Appendix E4. For the contraction period, all expansion periods are excluded from the sample 1969-2014 I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 11 Effect of Global Risks on Global Contrarian Profit in Emerging Market 1988-2014

	Model	Mode2	Model3	Model4
α_3	0.007***	0.014***	0.010***	0.014***
	(10.18)	(9.95)	(8.21)	(7.25)
	0.000	0.000	0.000	0.000
LIQ		-0.008		-0.009
		(-0.98)		(-1.03)
		0.328		0.304
DS		-0.007***		-0.005***
		(-5.70)		(-3.36)
		0.000		0.001
TS		-0.002		0.001
		(-0.11)		(0.03)
		0.911		0.976
MKT		0.038***		0.039***
		(2.69)		(2.75)
		0.007		0.006
ΔOP			0.001	0.000
			(0.18)	(0.04)
			0.854	0.967
$WVOL$			-0.404***	-0.311***
			(-3.41)	(-2.97)
			0.001	0.003
ΔIP			0.359***	0.158*
			(4.07)	(1.68)
			0.000	0.093
$MKTRF$	0.019	0.012	-0.007	0.000
	(0.98)	(0.73)	(-0.39)	(0.01)
	0.329	0.464	0.698	0.992
SMB	-0.088***	-0.056*	-0.069**	-0.057*
	(-2.64)	(-1.81)	(-2.28)	(-1.86)
	0.008	0.070	0.023	0.063
HML	-0.041	-0.056***	-0.046**	-0.057***
	(-1.63)	(-2.99)	(-2.01)	(-2.71)
	0.104	0.003	0.045	0.007

This table reports the regression result based on model (45). Where: the dependent variable R are the returns of the contrarian portfolio in emerging market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 12 Effect of Global Risks on Global Contrarian Profit in Developed Market 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.006***	0.004***	0.007***	0.004***
	(16.37)	(4.77)	(8.16)	(3.69)
	0.000	0.000	0.000	0.000
LIQ		0.016**		0.016**
		(2.15)		(2.06)
		0.031		0.040
DS		0.002**		0.002**
		(2.48)		(2.14)
		0.013		0.032
TS		0.024*		0.022*
		(1.85)		(1.69)
		0.065		0.091
MKT		0.007		0.007
		(0.67)		(0.69)
		0.505		0.492
ΔOP			-0.006	-0.005
			(-1.01)	(-0.88)
			0.315	0.380
$WVOL$			-0.062	-0.042
			(-0.73)	(-0.44)
			0.463	0.659
ΔIP			-0.033	0.026
			(-0.55)	(0.38)
			0.579	0.706
$MKTRF$	-0.001	0.000	-0.002	-0.003
	(-0.12)	(0.00)	(-0.22)	(-0.32)
	0.903	1.000	0.824	0.752
SMB	-0.050***	-0.066***	-0.045***	-0.059***
	(-2.26)	(-2.94)	(-2.04)	(-2.61)
	0.024	0.003	0.041	0.009
HML	-0.031	-0.042**	-0.025	-0.036*
	(-1.51)	(-2.22)	(-1.20)	(-1.83)
	0.131	0.027	0.231	0.067

This table reports the regression result based on model (46). Where: the dependent variable R are the returns of the contrarian portfolio in develop market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 13 Effect of Global Risks on Global Contrarian Profit in Established Market 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.005***	0.003***	0.005***	0.002*
	(13.71)	(2.93)	(5.14)	(1.74)
	0.000	0.003	0.000	0.082
LIQ		0.009		0.008
		(1.34)		(1.33)
		0.180		0.182
DS		0.002**		0.003***
		(2.04)		(2.97)
		0.041		0.003
TS		0.008		0.013
		(0.72)		(1.14)
		0.471		0.252
MKT		0.003		0.006
		(0.39)		(0.68)
		0.700		0.499
ΔOP			-0.005	-0.004
			(-1.11)	(-0.87)
			0.265	0.386
$WVOL$			-0.037	-0.072
			(-0.36)	(-0.69)
			0.717	0.490
ΔIP			0.082	0.166***
			(1.63)	(2.78)
			0.104	0.006
$MKTRF$	-0.012	-0.011	-0.012	-0.016**
	(-1.44)	(-1.36)	(-1.51)	(-2.02)
	0.151	0.174	0.131	0.043
SMB	-0.029**	-0.036***	-0.025*	-0.032**
	(-2.26)	(-2.68)	(-1.93)	(-2.45)
	0.024	0.007	0.054	0.014
HML	-0.019	-0.028*	-0.018	-0.031**
	(-1.32)	(-1.93)	(-1.21)	(-2.16)
	0.186	0.054	0.227	0.030

This table reports the regression result based on model (47). Where: the dependent variable R are the returns of the contrarian portfolio in established market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔOP_{t-1} the monthly oil price based world indices value at t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 14 Effect of Global Risks on Global Contrarian Profit in Globalization 1994-2014

	Model	Mode2	Model3	Model4
α_3	0.004***	0.012***	0.010***	0.017***
	(6.01)	(6.29)	(7.59)	(8.42)
	0.000	0.000	0.000	0.000
LIQ		-0.013		-0.014
		(-1.20)		(-1.41)
		0.229		0.159
DS		-0.008***		-0.007***
		(-4.59)		(-4.84)
		0.000		0.000
TS		-0.003		-0.018
		(-0.14)		(-0.95)
		0.891		0.344
MKT		-0.001		-0.015
		(-0.10)		(-1.35)
		0.922		0.176
ΔOP			0.006	0.000
			(0.96)	(0.00)
			0.339	0.998
$WVOL$			-0.680***	-0.577***
			(-5.45)	(-5.20)
			0.000	0.000
ΔIP			0.128	-0.158
			(1.36)	(-1.43)
			0.173	0.153
$MKTRF$	0.024	0.016	-0.029*	-0.003
	(1.44)	(1.14)	(-1.78)	(-0.21)
	0.151	0.254	0.075	0.835
SMB	-0.071**	-0.027	-0.004	-0.004
	(-1.98)	(-0.82)	(-0.11)	(-0.14)
	0.048	0.412	0.911	0.892
HML	0.069*	0.032	0.045	0.034
	(1.87)	(0.84)	(1.33)	(1.11)
	0.061	0.398	0.182	0.266

This table reports the regression result based on model (48). Where: the dependent variable R are the returns of the contrarian portfolio during the globalization periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. Test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.4. 15 Global Risks Impact on Contrarian Strategy Excess Return 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.001***	0.004***	0.005***	0.006***
	(3.77)	(4.71)	(5.37)	(4.98)
	0.000	0.000	0.000	0.000
LIQ		0.015*		0.008
		(1.93)		(1.05)
		0.053		0.296
DS		-0.003***		-0.018***
		(-3.19)		(-2.01)
		0.001		0.044
TS		0.007		0.011
		(0.59)		(0.91)
		0.555		0.361
MKT		0.018*		0.011
		(1.76)		(1.01)
		0.078		0.315
ΔOP			0.007	0.003
			(1.37)	(0.70)
			0.171	0.486
$WVOL$			-0.502***	-0.404***
			(-4.73)	(-3.65)
			0.000	0.000
ΔIP			0.087	0.020
			(1.43)	(0.29)
			0.152	0.771
$MKTRF$	0.023**	0.019**	0.008	0.008
	(2.33)	(2.09)	(0.85)	(0.89)
	0.020	0.036	0.396	0.376
SMB	-0.016	-0.025**	-0.012	-0.019
	(-0.91)	(-1.29)	(-0.66)	(-1.01)
	0.365	0.196	0.509	0.314
HML	-0.018	-0.032*	-0.029	-0.035*
	(-1.00)	(-1.82)	(-1.60)	(-1.95)
	0.319	0.069	0.109	0.051

This table reports the regression result based on model (49). Where: the dependent variable $R_t - R_{Ft}$ is the excess returns of the contrarian portfolio at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. Regression are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.5. 1 Effect of Global Fama and French Three-Factor on Global Momentum 1990-2014

	Model	Mode2	Model3	Model4
α_3	0.005***	0.010****	0.011***	0.010***
	11.05	10.34	9.14	3.54
	0.000	0.000	0.000	0.000
LIQ		0.004		0.040
		0.52		1.28
		0.606		0.200
DS		-0.006***		-0.001
		-6.22		-0.49
		0.000		0.621
TS		0.017		0.195**
		1.03		2.57
		0.304		0.010
MKT		0.005		0.089*
		0.44		1.86
		0.661		0.063
ΔOP			0.010**	0.010
			1.97	1.22
			0.049	0.223
$WVOL$			-0.750***	-0.512***
			-5.86	-3.25
			0.000	0.001
ΔIP			0.128	0.037
			1.57	0.25
			0.115	0.804
$MKTRF$	0.000	0.000	-0.000	-0.000
	1.25	1.29	-0.83	-0.94
	0.210	0.196	0.409	0.347
SMB	0.000	0.000	0.000	-0.001
	0.69	1.38	0.42	-1.45
	0.492	0.167	0.677	0.147
HML	-0.000	-0.000	-0.000	-0.001**
	-0.65	-1.65	-1.36	-2.26
	0.518	0.100	0.172	0.024

This table reports the regression result based on model (50). Where: the dependent variable are the returns of the global momentum portfolio at time t and regressed on global Fama and French tree-factor: HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (Small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. These regressions are based on model 1 to 4 specification. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.5. 2 Effect of Global Fama and French Five-Factor on Global Momentum Profit 1990-2014

	Model	Mode2	Model3	Model4
α_3	0.005***	0.011***	0.011***	0.014***
	11.30	10.53	9.37	8.69
	0.000	0.000	0.000	0.000
LIQ		0.005		0.003
		0.68		0.46
		0.494		0.647
DS		-0.006***		-0.004***
		-6.22		-2.82
		0.000		0.005
TS		0.014		0.010
		0.93		0.70
		0.350		0.483
MKT		-0.004		-0.011
		-0.37		-0.94
		0.714		0.346
ΔOP			0.008	0.006
			1.63	1.05
			0.103	0.293
$WVOL$			-0.698***	-0.616***
			-5.61	-5.11
			0.000	0.000
ΔIP			0.116	0.004
			1.40	0.04
			0.163	0.968
$MKTRF$	-0.000	-0.000	-0.000**	-0.000**
	-0.84	-1.17	-2.42	-2.26
	0.404	0.242	0.016	0.024
SMB	-0.000	0.000	-0.000	0.000
	-0.28	0.31	-0.63	0.05
	0.779	0.758	0.529	0.959
HML	0.001**	0.000	0.000	0.000
	2.06	0.89	0.78	0.60
	0.039	0.376	0.436	0.547
RMW	-0.001*	-0.001*	-0.001**	-0.001**
	-1.68	-1.65	-1.97	-1.98
	0.094	0.098	0.049	0.048
CMA	-0.002***	-0.002***	-0.001***	-0.001***
	-4.11	-3.71	-2.90	-2.93
	0.000	0.000	0.004	0.003

This table reports the regression result based on model (51). Where: the dependent variable are the returns of the global momentum portfolio at time t and regressed on the Fama and French Five-Factor: HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (Small minus big) returns to long-short portfolios constructed using size in the world market, RMW_t (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, CMA_t (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. These regressions are based on model 1 to 4 specification. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.5. 3 Effect of Fama and French Asia Pacific Excluding Japan on Emerging Momentum Profit in Emerging Market 1990-2014

	Model	Mode2	Model3	Model4
α_3	0.003	0.034***	0.003	0.026**
	0.74	3.18	0.34	2.11
	0.462	0.001	0.737	0.035
LIQ		0.090		0.078
		1.62		1.40
		0.106		0.163
DS		-0.031***		-0.022*
		-2.91		-1.70
		0.004		0.089
TS		0.208		0.259
		1.32		1.63
		0.186		0.103
MKT		-0.274**		-0.288***
		-2.45		-2.60
		0.014		0.009
ΔOP			0.050	0.063
			0.97	1.35
			0.332	0.177
$WVOL$			-0.258	-0.230
			-0.31	-0.26
			0.760	0.799
ΔIP			1.832**	1.128
			2.31	1.56
			0.021	0.118
$MKTRF$	-0.000	-0.000	-0.001	-0.001
	-0.33	-0.65	-1.30	-1.20
	0.742	0.519	0.193	0.232
SMB	0.000	0.001	-0.000	0.001
	0.20	0.80	-0.30	0.62
	0.844	0.423	0.762	0.535
HML	0.001	0.001	0.001	0.001
	0.66	0.94	0.91	0.94
	0.511	0.345	0.361	0.345

This table reports the regression result based on model (52) Where: the dependent variable *Mom* are the returns of the momentum portfolio in emerging market at time t and regressed on the Fama and French three-factor excluding Japan: HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.5. 4 Effect of European Fama and French Five-Factor, TED and EURIBOR: OIS Spread on Momentum Profit in Developed Market 1999-2014

	Model	Mode2	Model3	Model4	Model5	Model6	Model7
α_3	0.005**	0.006**	0.002	0.005	0.007*	-0.003	0.002
	2.46	2.37	0.78	1.08	1.78	-0.59	0.36
	0.014	0.018	0.435	0.280	0.075	0.552	0.716
TED		-0.016		-0.019			-0.006
		-0.67		-0.89			-0.37
		0.502		0.373			0.715
$EOIS$			1.334***		1.436***		1.242***
			4.04		3.47		3.67
			0.000		0.001		0.000
DS				0.001	-0.006		-0.005
				0.05	-1.67		-1.15
				0.963	0.095		0.252
TS				0.208***	0.193***		0.192***
				3.88	3.66		3.73
				0.000	0.000		0.000
MKT				-0.003	-0.001		-0.005
				-0.07	-0.02		-0.12
				0.947	0.983		0.901
ΔOP						-0.028	0.021
						-1.54	1.08
						0.124	0.281
$WVOL$						0.979*	0.550
						1.90	1.07
						0.057	0.284
ΔIP						0.360	0.046
						1.30	0.17
						0.195	0.865
$MKTRF$	-0.001**	-0.001***	-0.001***	-0.001**	-0.001**	-0.001**	-0.001***
	-2.34	-2.36	-2.48	-2.31	-2.36	-2.32	-2.05
	0.019	0.018	0.013	0.021	0.018	0.021	0.041
SMB	-0.001	-0.003***	-0.003***	-0.002**	-0.002**	-0.001	-0.002**
	-1.47	-3.26	-3.50	-2.45	-2.44	-1.48	-2.23
	0.143	0.001	0.000	0.014	0.015	0.140	0.025
HML	-0.002**	-0.003**	-0.003**	-0.004***	-0.003***	-0.002**	-0.003***
	-2.06	-2.75	-2.37	-3.29	-2.75	-2.05	-2.87
	0.040	0.006	0.018	0.001	0.006	0.040	0.004
RMW	0.000	-0.001	-0.001	-0.001	-0.000	-0.000	-0.001
	0.02	-0.63	-0.42	-0.53	-0.21	-0.09	-0.46
	0.980	0.529	0.676	0.596	0.834	0.926	0.649
CMA	0.001	0.002	0.002	0.003*	0.002	0.001	0.002
	0.60	1.36	1.23	1.76	1.52	0.61	1.49
	0.551	0.173	0.218	0.078	0.128	0.543	0.136

This table reports the regression result based on model (53). Where: the dependent variable R are the returns of the momentum portfolio in develop market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the $EOIS_{t-1}$ (EURIBOR:OIS Spread) is the difference between the rate at which European banks lend to each other (ERIBOR) and the overnight' risk free' swap rate (EONIA) among the same banks a 3 month period, TED_{t-1} Spread or the difference between the London Interbank Offered Rate (Libor) and the 3-month Treasury Bill at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.6. 1 Effect of Global Fama and French Three-Factor on Global Contrarian Profit 1990-2014

	Model	Mode2	Model3	Model4
α_3	0.005***	0.010***	0.009***	0.016***
	13.82	9.54	8.66	9.01
	0.000	0.000	0.000	0.000
LIQ		0.000		-0.031
		0.03		-1.55
		0.974		0.121
DS		-0.005***		-0.010***
		-4.74		-5.43
		0.000		0.000
TS		-0.005		-0.014
		-0.37		-0.23
		0.712		0.817
MKT		0.020**		0.020
		2.10		0.50
		0.036		0.614
ΔOP			-0.006*	-0.006
			-1.81	-1.20
			0.071	0.232
$WVOL$			-0.591***	-0.336**
			-4.30	-2.34
			0.000	0.019
ΔIP			0.014	-0.283***
			0.20	-3.05
			0.845	0.002
$MKTRF$	0.000	-0.000	-0.000	0.000
	1.34	-0.47	-0.83	0.28
	0.179	0.638	0.404	0.778
SMB	0.000	-0.000	-0.000	0.000
	0.09	-0.23	-0.61	0.55
	0.927	0.816	0.545	0.580
HML	0.000	-0.000	-0.000	-0.000
	0.14	-1.02	-0.72	-1.23
	0.887	0.307	0.473	0.219

This table reports the regression result based on model (54). Where: the dependent variable are the returns of the global momentum portfolio at time t and regressed on Global Fama and French Three-Factor: HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (Small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. These regressions are based on model 1 to 4 specification. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.6. 2 Effect of Global Fama and French Five-Factor on Global Contrarian Profit 1990-2014

	Model	Mode2	Model3	Model4
α_3	0.005***	0.011***	0.009***	0.013***
	12.88	9.24	8.79	9.71
	0.000	0.000	0.000	0.000
LIQ		0.001		0.001
		0.21		0.12
		0.834		0.908
DS		-0.006***		-0.005***
		-4.75		-3.91
		0.000		0.000
TS		-0.006		-0.003
		-0.37		-0.23
		0.713		0.821
MKT		0.018*		0.016
		1.70		1.64
		0.090		0.101
ΔOP			-0.006*	-0.007*
			-1.82	-1.77
			0.069	0.077
$WVOL$			-0.558***	-0.418***
			-4.15	-3.12
			0.000	0.002
ΔIP			0.023	-0.152*
			0.33	-1.91
			0.742	0.057
$MKTRF$	-0.000	-0.000*	-0.000	-0.000
	-0.86	-1.95	-1.55	-1.51
	0.389	0.051	0.121	0.132
SMB	-0.000	-0.000	-0.000	-0.000
	-1.00	-1.08	-1.27	-0.99
	0.317	0.278	0.205	0.321
HML	0.000*	0.000	0.000	0.000
	1.68	0.62	0.43	0.11
	0.092	0.533	0.666	0.912
RMW	-0.001	-0.001*	-0.000	-0.000
	-1.62	-1.80	-1.29	-1.39
	0.105	0.072	0.195	0.164
CMA	-0.001**	-0.001**	-0.000	-0.000
	-2.41	-2.05	-1.16	-1.26
	0.016	0.040	0.248	0.208

This table reports the regression result based on model (55). Where: the dependent variable are the returns of the global momentum portfolio at time t and regressed on the Fama and Frech Five-Factor: HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market in the global market, SMB_t (Small minus big) returns to long-short portfolios constructed using size in global market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return t-1, ΔOP_{t-1}, the change on monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the change on monthly value of the US Industrial production at time t-1. I estimate the parameters using the interactive version of the generalized method of moment's estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. These regressions are based on model 1 to 4 specification. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.6. 3 Effect of Fama and French Asia Pacific Excluding Japan on Contrarian Profit in Emerging Market 1990-2014

	Model	Mode2	Model3	Model4
α_3	0.005***	0.011***	0.005***	0.012***
	10.85	7.87	4.80	6.44
	0.000	0.000	0.000	0.000
LIQ		-0.014		-0.011
		-1.34		-1.11
		0.179		0.265
DS		-0.006***		-0.009***
		-4.93		-5.61
		0.000		0.000
TS		-0.010		-0.009
		-0.55		-0.49
		0.582		0.621
MKT		-0.025**		-0.030**
		-2.18		-2.24
		0.029		0.025
ΔOP			0.002	0.003
			0.30	0.52
			0.763	0.604
$WVOL$			0.010	0.119
			0.12	1.34
			0.908	0.181
ΔIP			-0.097	-0.248***
			-0.94	-2.76
			0.345	0.006
$MKTRF$	-0.000	-0.000	-0.000	-0.000
	-1.27	-1.31	-1.08	-0.72
	0.204	0.191	0.282	0.469
SMB	0.000	0.001**	0.000	0.001***
	1.32	2.25	1.30	2.66
	0.188	0.025	0.194	0.008
HML	0.000**	0.000**	0.000**	0.000*
	2.45	2.17	2.10	1.92
	0.014	0.030	0.035	0.054

This table reports the regression result based on model (56) Where: the dependent variable *Mom* are the returns of the momentum portfolio in emerging market at time t and regressed on the Fama and French Three-Factor excluding Japan: HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in Asia Pacific countries excluding Japan, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I also account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

Table 4.6. 4 Effect of European Fama and French Factor, TED and EURIBOR: OIS on Contrarian Profit in Developed Market 1999-2014

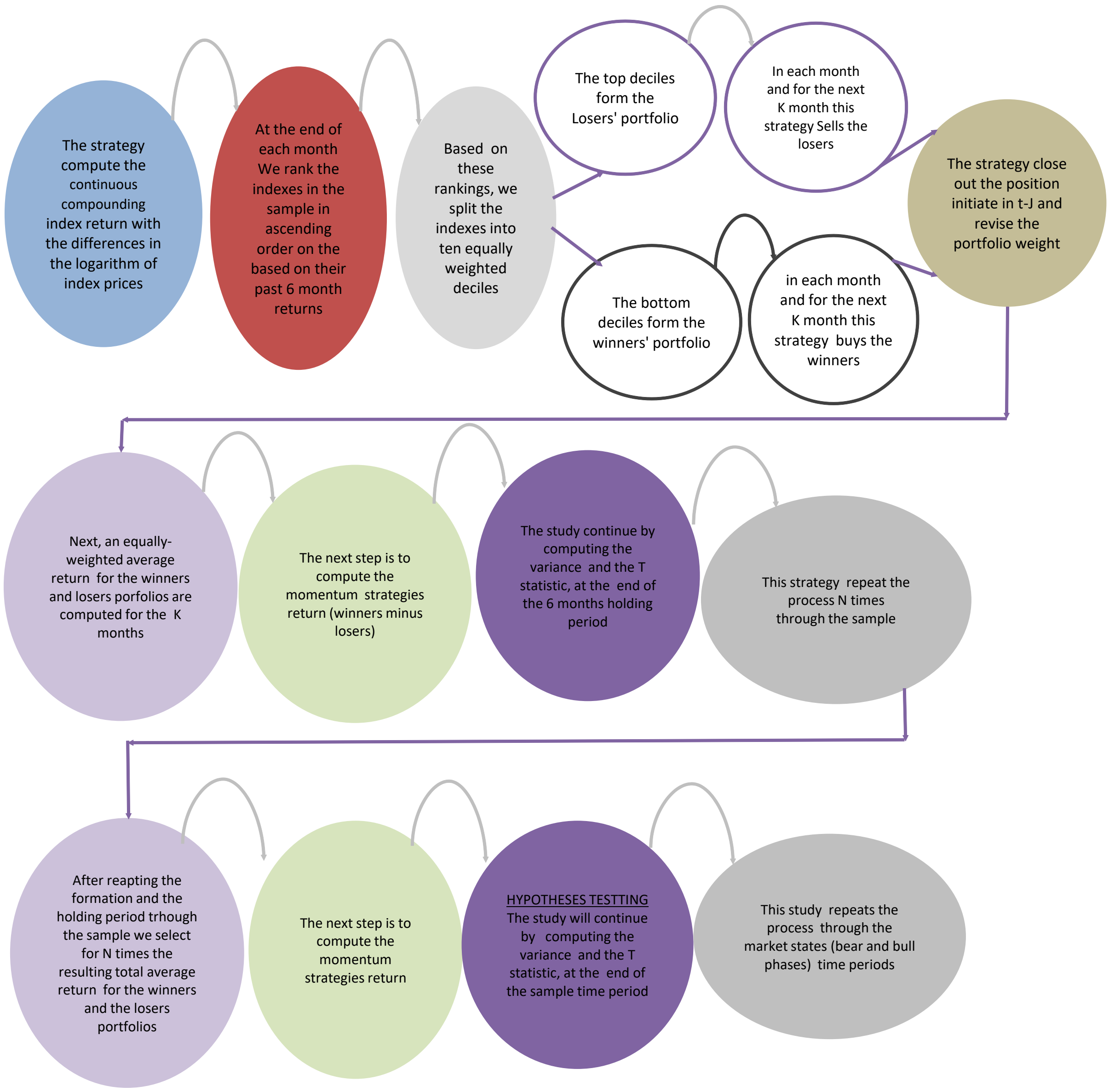
	Model	Mode2	Model3	Model4	Model5	Model6	Model7
α_3	0.006***	0.004***	0.004***	0.003***	0.003***	0.009***	0.005***
	12.37	7.27	5.96	3.19	3.32	10.07	2.61
	0.000	0.000	0.000	0.001	0.001	0.000	0.009
TED		0.004		0.001			0.063
		0.91		0.22			0.86
		0.361		0.827			0.392
$EOIS$			-0.013		0.009		0.144
			-0.15		0.08		0.73
			0.883		0.932		0.467
DS				0.000	0.000		0.002
				0.28	0.18		1.29
				0.779	0.857		0.198
TS				0.019	0.018		0.002
				1.08	1.06		0.13
				0.279	0.288		0.899
MKT				0.031**	0.031**		0.022*
				2.44	2.42		1.73
				0.015	0.015		0.084
ΔOP						-0.010**	-0.000
						-2.41	-0.01
						0.016	0.995
$WVOL$						-0.434**	-0.328**
						-5.24	-3.70
						0.000	0.000
ΔIP						0.076	0.144
						1.05	1.34
						0.294	0.181
$MKTRF$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1.42	1.46	1.57	1.34	1.39	0.81	0.68
	0.156	0.143	0.116	0.181	0.164	0.421	0.497
SMB	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1.00	0.98	0.96	0.03	0.05	0.87	0.08
	0.318	0.329	0.338	0.975	0.957	0.386	0.938
HML	-0.001**	-0.001**	-0.001**	-0.001**	-0.001***	-0.001**	-0.001***
	-2.04	-3.55	-3.29	-4.38	-4.04	-2.90	-3.87
	0.041	0.000	0.001	0.000	0.000	0.004	0.000
RMW	-0.001**	-0.001**	-0.001*	-0.001**	-0.001**	-0.001*	-0.001**
	-2.37	-2.09	-1.92	-2.35	-2.25	-1.94	-2.25
	0.018	0.037	0.055	0.019	0.024	0.052	0.025
CMA	-0.000*	-0.001**	-0.001*	-0.001**	-0.001**	-.001	-0.001
	-1.83	-2.46	-2.34	-2.06	-2.00	-0.89	-1.12
	0.067	0.014	0.019	0.040	0.045	0.372	0.263

This table reports the regression result based on model (57). Where: the dependent variable *Mon* are the returns of the momentum portfolio in develop market at time t and regressed on Fama and French Europe: HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in the region, SMB_t (small minus big) returns to long-short portfolios constructed using size in the region, RMW_t (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, CMA_t (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, $EOIS_{t-1}$ (EURIBOR:OIS Spread) is the difference between the rate at which European banks lend to each other (ERIBOR) and the overnight' risk free free' swap rate (EONIA) among the same banks a 3 month period, TED_{t-1} Spread or the difference between the London Interbank Offered Rate (Libor) and the 3-month Treasury Bill at time t-1, at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices return at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, and ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1. Regressions are based on model 1 to 4 specification. I estimate the parameters using the interactive version of the generalized method of moments estimation. I account for time variation through time dummies. I request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

8 Appendix A

8.1 Appendix A1

Momentum Flowchart



8.2 Appendix A2

6/6 Momentum strategy Breakdown structure

File: monthly returns ($r_{i,t}$) for each country (i) at month (t); multi-periods return ($R_{i,j}$) for each country (i) in (j) months.

1. Count the number of the countries = N_c
2. Divide by 10
3. Round to the nearest integer = N_p
4. Store, (that will be number of the winners and the losers in the winners and losers' portfolios).
5. Start at country i = 1, month t =1
6. Calculate sum of 6 monthly return$R_{1,6}$= $r_{1,1}$ + $r_{1,2}$ + ...+$r_{1,6}$
7. Go back to 5 continue with country i=2
8. Calculate sum of 6 monthly return $R_{2,6}$= $r_{2,1}$ + $r_{2,2}$ + ...+$r_{2,6}$
9. When all countries are finished, sum 6 monthly return $R_{Nc,6}$= sum last country
10. Rank sum 6 monthly return =$R_{1,6}$,$R_{2,6}$,...,$R_{Nc,6}$
11. Select countries in 1,...,N_p (top 10%) or winners (w_1, w_2,...,w_{Np}) and store
12. Select countries in N_c - N_p,..., N_c (bottom 10%)or losers (L_1, L_2,..., L_{Np}) and store
13. Start at winner1(w1), month t = 7
14. Calculate winner 1 average of 6 monthly return in the holding period (t = 7 to t = 12)$R_{w1,6}$= [$r_{w1,7}$ + $r_{w1,8}$ + ...+$r_{w1,12}$]/6
15. Go back to back to 13 continue with winner 2 (w2)
16. Calculate winner 2 average of 6 monthly return in the holding period (t = 7 to t = 12)$R_{w2,6}$= [$r_{w2,7}$ + $r_{w2,8}$ + ...+$r_{w2,12}$]/6
17. When all winners are finished sum 6 monthly return = $R_{w_{NP},6}$ = sum last winner
18. Calculate winners' portfolio (top 10%) average monthly return for the holding period (t = 7 to t = 12),$R_{W,1}$ = [$R_{w1,6}$+$R_{w2,6}$+…+$R_{w_{NP},6}$]/N_p
19. Go back to 13 start with Loser1(L1), month 7
20. Calculate Loser 1 average of 6 monthly return in the holding period (t = 7 to t = 12) $R_{L1,6}$= [$r_{L1,7}$ + $r_{L1,8}$ + ...+$r_{L1,12}$]/6
21. Go back to 13 continue with Loser2 (L2), month t = 7
22. Calculate Loser 2 sum of 6 monthly return in the holding period (t = 7 to t = 12) $R_{L2,6}$= [$r_{L2,7}$ + $r_{L2,8}$ + ...+$r_{L2,12}$]/6

23. When all Losers are finished sum 6 monthly return = $R_{L_{NP},6}$ = sum last Loser
24. Calculate Losers' portfolio (bottom 10%) average monthly return for the holding period (t = 7 to t = 12), $R_{L,1}$ = [$R_{L1,6}$+$R_{L2,6}$+…+$R_{L_{NP},6}$]/N_p
25. store
26. Go back to month t = 7
27. Start at country i = 1, month t = 7
28. Calculate sum of 6 monthly return (month t = 7 to t = 12) for country i = 1
    $R_{1,6}$= $r_{1,7}$ + $r_{1,8}$ + ...+$r_{1,12}$
29. Go back to 27 continue with country i=2-month t = 7
30. Calculate sum of 6 monthly return (month 7 to 12) = $R_{2,6}$= $r_{2,7}$ + $r_{2,8}$ + ...+$r_{2,12}$
31. When all countries are finished sum 6 monthly return, $R_{Nc,6}$= sum last country
32. repeat step 10 to 24
33. Store
34. Then repeat the formation and the holding period analysis through the sample period (N times) between 1969-2014
35. When all the winner portfolios are constructed, average monthly return of the holding period of the last winner is $R_{w,N}$
36. When all loser portfolios are constructed, average monthly return of the holding period of the last loser is $R_{L,N}$
37. Store
38. Calculate the average return of the winners' portfolio as of end of the sample period as AR_w = sum of all$R_{w,T}$ divide by (N) the number of the winner 6-month/6-month portfolios constructed over 1969-2014; where
    (T =1…N)AR_w= [$R_{w,1}$+$R_{w,2}$+…$R_{w,N}$]/N
39. Calculate the average return of the Losers portfolios as of end of the sample period as AR_L = sum of all $R_{L,T}$ divide by (N) the number of the Losers 6-month/6-month portfolios constructed over 1969-2014; where (T =1… N)AR_L= [$R_{L,1}$+$R_{L,2}$+…$R_{L,N}$]/N
40. Calculate the average momentum return as of end of period asAR_w - AR_L
41. Calculate the variance

$$S_M^2 = \left[\sum_{n=1}^{N}(R_w - AR_w)^2 - \sum_{n=1}^{N}(R_L - AR_L)^2/2(N-1)\right]$$

42. Calculate the T statistic $T_M = (AR_{w1} - AR_{L1})/\sqrt{2S_{M,t}^2/N}$

8.3 Appendix A3

MATLAB Programming

The winners and the loser's portfolios are constructed using MATLAB Programming; The Script files are provided in appendix 3 to 6. I also construct portfolios that skip one month between the formation and the holding period to evaluate the possibility that the momentum profits may arise because of the lead-lag relationship in indices prices in conformity with Jegadeesh and Titman (1993). To increase the power of the tests this, study finally constructs overlapping portfolios where the momentum portfolio in a given month holds stocks ranked in any of the previous six ranking months (Jegadeesh and Titman 2001).

The MATLAB Programming (Teamwork and training) that the study is referring to was organize in order to design a robust programme to compute and analyse the momentum and contrarian strategies returns in the course of this study. I am therefore grateful to Dr Natalia Bailey at the School of Economics and Finance who were involved in the design of the initial momentum flowchart (Appendix 1), the momentum strategy breakdown structure (Appendix 2) and the training in MATLAB programming by providing useful review comments and technical check during the progress of this study. More importantly I are delighted to reiterate that, I took this opportunity to learn a new skill in MATLAB Programming.

8.4 Appendix A4

Momentum Script-file

```
clearall
clc

%% Initial setup
r = xlsread('C:\Alain2\matdata.xlsx','Sheet3','b4:x532');
%r = xlsread('C:\Local\My Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=9; % J month calculation
per_hold=3; % K month calculation
p=(1:9)/10; % prob. for quantile code; Cut the returns of all countries into 10 (Deciles); if divided into 5 then command becomes: quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_mom=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

fort_for=t_start:per_for:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time t_for
r_adj=r(t_for:t_for+per_for+per_hold-1,:); % returns for formation and holding period (if you skip a month for holding period you need an extra element on T dimension)
fori=1:N;
ifr_adj(1,i)==-999
r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));
```

```
% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10 (Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=1+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

mom=w_p-l_p; % momentum

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_mom(t_for,1)=mom;
```

```
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_mom=sto_mom(~all(sto_mom == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners portfolios

% Average momentum return
a_mom=a_w_p-a_l_p;
% Variance
dif=sto_w_p-sto_l_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_w_p-a_l_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

8.5 Appendix A5

Momentum with time lag Script-File

```
clearall
clc

%% Initial setup
r = xlsread('C:\Alain2\matdata.xlsx','Sheet4','b3:y315');
%r = xlsread('C:\Local\My Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=9; % J month calculation
per_hold=3; % K month calculation
p=(1:9)/10; % prob. for quantile code; Cut the returns of all countries into 10 (Deciles); if divided into 5 then command becomes: quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_mom=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

fort_for=t_start:per_for:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time t_for
r_adj=r(t_for:t_for+per_for+per_hold,:); % returns for formation and holding period (if you skip a month for holding period you need an extra element on T dimension)
fori=1:N;
ifr_adj(1,i)==-999
r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));
```

```
% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10 (Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=2+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

mom=w_p-l_p; % momentum

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_mom(t_for,1)=mom;
```

```
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_mom=sto_mom(~all(sto_mom == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners portfolios

% Average momentum return
a_mom=a_w_p-a_l_p;
% Variance
dif=sto_w_p-sto_l_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_w_p-a_l_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

8.6 Appendix A6

Momentum with overlapping portfolios

```
clearall
clc

%% Initial setup
r = xlsread('C:\Alain2\matdata.xlsx','Sheet3','b4:av532');
%r = xlsread('C:\Local\My Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=9; % J month calculation
per_hold=3; % K month calculation
p=(1:9)/10; % prob. for quantile code; Cut the returns of all countries into 10 (Deciles); if divided into 5 then command becomes: quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_mom=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

fort_for=t_start:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time t_for
r_adj=r(t_for:t_for+per_for+per_hold-1,:); % returns for formation and holding period (if you skip a month for holding period you need an extra element on T dimension)
fori=1:N;
ifr_adj(1,i)==-999
r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));
```

```
% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10 (Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=1+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

mom=w_p-l_p; % momentum

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_mom(t_for,1)=mom;
```

```
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_mom=sto_mom(~all(sto_mom == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners portfolios

% Average momentum return
a_mom=a_w_p-a_l_p;
% Variance
dif=sto_w_p-sto_l_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_w_p-a_l_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

8.7 Appendix A7

Momentum with Time lag and overlapping portfolios

```
clearall
clc

%% Initial setup
r = xlsread('C:\Alain2\matdata.xlsx','Sheet3','b4:x532');
%r = xlsread('C:\Local\My Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=9; % J month calculation
per_hold=3; % K month calculation
p=(1:9)/10; % prob. for quantile code; Cut the returns of all countries into 10 (Deciles); if divided into 5 then command becomes: quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_mom=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

fort_for=t_start:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time t_for
r_adj=r(t_for:t_for+per_for+per_hold,:); % returns for formation and holding period (if you skip a month for holding period you need an extra element on T dimension)
fori=1:N;
ifr_adj(1,i)==-999
r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));
```

```
% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10 (Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=2+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

mom=w_p-l_p; % momentum

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_mom(t_for,1)=mom;
```

```
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;


end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_mom=sto_mom(~all(sto_mom == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners portfolios

% Average momentum return
a_mom=a_w_p-a_l_p;
% Variance
dif=sto_w_p-sto_l_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_w_p-a_l_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

9 Appendix B

9.1 Appendix B1

Contrarian with Non-overlapping decile portfolio

```
%% housekeeping
clear all
clc

%% Initial setup
r = xlsread('C:\Alain3\matdata.xlsx','Sheet2','b4:av532');
%r = xlsread('C:\Local\My
Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual
return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=36; % 36 month calculation
per_hold=36; % 36 month calculation
p=(1:9)/10; % prob. for quantile code; Cut the returns of all countries
into 10 (Deciles); if divided into 5 then command becomes:
quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_con=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

for t_for=t_start:per_for:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time
t_for
r_adj=r(t_for:t_for+per_for+per_hold-1,:); % returns for formation and
holding period (if you skip a month for holding period you need an extra
element on T dimension)
for i=1:N;
if r_adj(1,i)==-999
       r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));

% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10
(Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
```

```
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=1+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for
holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for
holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

con=l_p-w_p; % reversal

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_con(t_for,1)=con;
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_con=sto_con(~all(sto_con == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners
portfolios

% Average reversal return
a_con=a_l_p-a_w_p;
% Variance
dif=sto_l_p-sto_w_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_l_p-a_w_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

9.2 Appendix B2

Contrarian with decile portfolio and a month lag

```
%% housekeeping
clear all
clc

%% Initial setup
r = xlsread('C:\Alain3\matdata.xlsx','Sheet4','b4:av532');
%r = xlsread('C:\Local\My
Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual
return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=36; % 36 month calculation
per_hold=36; % 36 month calculation
p=(1:9)/10; % prob. for quantile code; Cut the returns of all countries
into 10 (Deciles); if divided into 5 then command becomes:
quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_con=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

for t_for=t_start:per_for:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time
t_for
r_adj=r(t_for:t_for+per_for+per_hold,:); % returns for formation and
holding period (if you skip a month for holding period you need an extra
element on T dimension)
for i=1:N;
if r_adj(1,i)==-999
       r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));

% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10
(Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
```

```
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=2+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for
holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for
holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

mom=l_p-w_p; % reversal

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_con(t_for,1)=con;
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_con=sto_con(~all(sto_con == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners
portfolios

% Average reversal return
a_con=a_l_p-a_w_p;
% Variance
dif=sto_l_p-sto_w_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_l_p-a_w_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

9.3 Appendix B3

Contrarian with overlapping decile portfolio

```
%% housekeeping
clear all
clc

%% Initial setup
r = xlsread('C:\Alain3\matdata.xlsx','Sheet2','b4:av532');
%r = xlsread('C:\Local\My
Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual
return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=36; % 6 month calculation
per_hold=36; % 6 month calculation
p=(1:9)/10; % prob. for quantile code; Cut the returns of all countries
into 10 (Deciles); if divided into 5 then command becomes:
quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_con=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

for t_for=t_start:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time
t_for
r_adj=r(t_for:t_for+per_for+per_hold-1,:); % returns for formation and
holding period (if you skip a month for holding period you need an extra
element on T dimension)
for i=1:N;
if r_adj(1,i)==-999
       r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));

% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10
(Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5); decile (1:9)/10
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
```

```
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=1+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for
holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for
holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

con=l_p-w_p; % reversal

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_con(t_for,1)=con;
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_con=sto_con(~all(sto_con == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners
portfolios

% Average reversal return
a_con=a_l_p-a_w_p;
% Variance
dif=sto_l_p-sto_w_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_l_p-a_w_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

9.4 Appendix B4

Contrarian with overlapping deciles portfolio and a month lag

```
%% housekeeping
clear all
clc

%% Initial setup
r = xlsread('C:\Alain3\matdata.xlsx','Sheet2','b4:532');
%r = xlsread('C:\Local\My
Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual
return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=36; % 36 month calculation
per_hold=36; % 36 month calculation
p=(1:9)/10; % prob. for quantile code; Cut the returns of all countries
into 10 (Deciles); if divided into 5 then command becomes:
quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_con=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

for t_for=t_start:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time
t_for
r_adj=r(t_for:t_for+per_for+per_hold,:); % returns for formation and
holding period (if you skip a month for holding period you need an extra
element on T dimension)
for i=1:N;
if r_adj(1,i)==-999
       r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));

% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10
(Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
```

```
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=2+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for
holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for
holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

con=l_p-w_p; % reversal

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_con(t_for,1)=con;
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_con=sto_con(~all(sto_con == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners
portfolios

% Average reversal return
a_con=a_l_p-a_w_p;
% Variance
dif=sto_l_p-sto_w_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_l_p-a_w_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

9.5 Appendix B5

Contrarian with Non-overlapping quintile portfolio

```
%% housekeeping
clear all
clc

%% Initial setup
r = xlsread('C:\Alain3\matdata.xlsx','Sheet2','b4:av532');
%r = xlsread('C:\Local\My
Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual
return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=36; % 36 month calculation
per_hold=36; % 36 month calculation
p=(1:4)/5; % prob. for quantile code; Cut the returns of all countries into
10 (Deciles); if divided into 5 then command becomes:
quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_con=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

for t_for=t_start:per_for:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time
t_for
r_adj=r(t_for:t_for+per_for+per_hold-1,:); % returns for formation and
holding period (if you skip a month for holding period you need an extra
element on T dimension)
for i=1:N;
if r_adj(1,i)==-999
       r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));

% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10
(Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
```

```
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=1+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for
holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for
holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

con=l_p-w_p; % reversal

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_con(t_for,1)=con;
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_con=sto_con(~all(sto_con == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners
portfolios

% Average reversal return
a_con=a_l_p-a_w_p;
% Variance
dif=sto_l_p-sto_w_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_l_p-a_w_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

9.6 Appendix B6

Contrarian with quintile portfolio and a month lag

```
%% housekeeping
clear all
clc

%% Initial setup
r = xlsread('C:\Alain3\matdata.xlsx','Sheet4','b4:av532');
%r = xlsread('C:\Local\My
Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual
return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=36; % 36 month calculation
per_hold=36; % 36 month calculation
p=(1:4)/5; % prob. for quantile code; Cut the returns of all countries into
10 (Deciles); if divided into 5 then command becomes:
quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_con=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

for t_for=t_start:per_for:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time
t_for
r_adj=r(t_for:t_for+per_for+per_hold,:); % returns for formation and
holding period (if you skip a month for holding period you need an extra
element on T dimension)
for i=1:N;
if r_adj(1,i)==-999
       r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));

% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10
(Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
```

```
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=2+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for
holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for
holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

mom=l_p-w_p; % reversal

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_con(t_for,1)=con;
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_con=sto_con(~all(sto_con == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners
portfolios

% Average reversal return
a_con=a_l_p-a_w_p;
% Variance
dif=sto_l_p-sto_w_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_l_p-a_w_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

9.7 Appendix B7

Contrarian with overlapping quintile portfolio

```
%% housekeeping
clear all
clc

%% Initial setup
r = xlsread('C:\Alain3\matdata.xlsx','Sheet2','b4:av532');
%r = xlsread('C:\Local\My
Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual
return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=36; % 6 month calculation
per_hold=36; % 6 month calculation
p=(1:4)/5; % prob. for quantile code; Cut the returns of all countries into
10 (Deciles); if divided into 5 then command becomes:
quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_con=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

for t_for=t_start:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time
t_for
r_adj=r(t_for:t_for+per_for+per_hold-1,:); % returns for formation and
holding period (if you skip a month for holding period you need an extra
element on T dimension)
for i=1:N;
if r_adj(1,i)==-999
       r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));

% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10
(Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5); decile (1:9)/10
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
```

```
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=1+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for
holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for
holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

con=l_p-w_p; % reversal

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_con(t_for,1)=con;
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_con=sto_con(~all(sto_con == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners
portfolios

% Average reversal return
a_con=a_l_p-a_w_p;
% Variance
dif=sto_l_p-sto_w_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_l_p-a_w_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

9.8 Appendix B8

Contrarian with overlapping quintile portfolio and a month lag

```
%% housekeeping
clear all
clc

%% Initial setup
r = xlsread('C:\Alain3\matdata.xlsx','Sheet2','b4:532');
%r = xlsread('C:\Local\My
Documents_QMUL\Alain2\matdata.xlsx','Sheet2','b4:av532'); % Load actual
return data
N=size(r,2); % number of countries: 47
T=size(r,1); % number of periods: 552 (1969-2014 monthly)
t_start=1; % Start of formation period
per_for=36; % 36 month calculation
per_hold=36; % 36 month calculation
p=(1:4)/5; % prob. for quantile code; Cut the returns of all countries into
10 (Deciles); if divided into 5 then command becomes:
quantile(s_C(:,2),(1:4)/5)

%%Storing
sto_l_p=zeros(T-per_for-per_hold,1);
sto_w_p=zeros(T-per_for-per_hold,1);
sto_con=zeros(T-per_for-per_hold,1);
sto_no_l=zeros(T-per_for-per_hold,1);
sto_no_w=zeros(T-per_for-per_hold,1);
sto_N_adj=zeros(T-per_for-per_hold,1);

%% Computations

for t_for=t_start:T-per_for-per_hold

% Adjustment of dataset to include all stock indices available at time
t_for
r_adj=r(t_for:t_for+per_for+per_hold,:); % returns for formation and
holding period (if you skip a month for holding period you need an extra
element on T dimension)
for i=1:N;
if r_adj(1,i)==-999
       r_adj(:,i)=-991;
end
end
B=-991*ones(size(r_adj,1),1);
r_adj1 = r_adj(:,~all(r_adj == repmat(B,1,N),1));

% Formation Period
r_for=r_adj1(1:per_for,:); % returns for formation period
N_adj=size(r_for,2);
ID=1:size(r_for,2); % ID of N countries in each period
R=cumsum(r_for,1); % Cumulative monthly returns
a_R=([ID; R(end,:)])'; % R matrix appended to ID and transposed
s_C=sortrows(a_R,2); % Ranked 6m returns (lowest to highest)
q = quantile(s_C(:,2),p); % Cut the returns of all countries into 10
(Deciles); if divided into 5 then
% command becomes: quantile(s_C(:,2),(1:4)/5)
s_Cl=s_C(:,2);
s_Cl(s_Cl>q(1,1))=0; % Select Losers
R_Cl = s_Cl(~all(s_Cl == 0,2),:);
```

```
ID_l=s_C(1:size(R_Cl,1),1); % ID of losers
no_l=size(ID_l,1); % Number of losers

s_Cw=s_C(:,2);
s_Cw(s_Cw<q(1,end))=0; % Select Winners
R_Cw = s_Cw(~all(s_Cw == 0,2),:);
ID_w=s_C(size(s_C,1)-size(R_Cw,1)+1:end,1); % ID of winners
no_w=size(ID_w,1); % Number of winners

% Holding Period
t_hold=2+per_for; % to skip one period you will have 2+per_for

rl_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_l'); % returns of losers for
holding period
m_rl=mean(rl_hold,1); % average returns of losers over holding period
l_p=mean(m_rl,2); % average loser portfolio return

rw_hold=r_adj1(t_hold:t_hold+per_hold-1,ID_w'); % returns of winners for
holding period
m_rw=mean(rw_hold,1); % average returns of winners over holding period
w_p=mean(m_rw,2); % average winner portfolio return

con=l_p-w_p; % reversal

% Save
sto_l_p(t_for,1)=l_p;
sto_w_p(t_for,1)=w_p;
sto_con(t_for,1)=con;
sto_no_l(t_for,1)=no_l;
sto_no_w(t_for,1)=no_w;
sto_N_adj(t_for,1)=N_adj;

end
sto_l_p=sto_l_p(~all(sto_l_p == 0,2),:);
sto_w_p=sto_w_p(~all(sto_w_p == 0,2),:);
sto_con=sto_con(~all(sto_con == 0,2),:);
sto_no_l=sto_no_l(~all(sto_no_l == 0,2),:);
sto_no_w=sto_no_w(~all(sto_no_w == 0,2),:);
sto_N_adj=sto_N_adj(~all(sto_N_adj == 0,2),:);

a_l_p=sum(sto_l_p,1)/size(sto_l_p,1); % Average return on losers portfolios
a_w_p=sum(sto_w_p,1)/size(sto_w_p,1); % Average return on winners
portfolios

% Average reversal return
a_con=a_l_p-a_w_p;
% Variance
dif=sto_l_p-sto_w_p;
a_p=sum(dif,1)/size(dif,1); % Average return on losers portfolios
v_dif=(dif-a_p).^2;
s_v_dif=sum(v_dif);
S_M_sq=(s_v_dif)/(2*(size(dif,1)-1));
% T-statistic
T_M=(a_l_p-a_w_p)/sqrt(2*S_M_sq/size(dif,1));
Pval=2*(1-tcdf(abs(T_M),size(dif,1)-1)); %check degrees of freedom
```

10 Appendix C

10.1 Appendix C1

Table 4.3.16 Effect of Fama and French Risks on Momentum Profit with Newey West Procedure 1969-2014

	Panel A: FF 3-Factors Model			
	3-month	6-month	9-month	12-month
α_o	0.010***	0.010***	0.008**	0.004***
	(3.58)	(4.66)	(4.57)	(2.64)
	0.000	0.000	0.000	0.009
MKTRF	-0.036	-0.029	-0.016	0.030
	(-0.67)	(-0.78)	(-0.50)	(1.29)
	0.501	0.433	0.619	0.199
SMB	-0.068	-0.118**	-0.079	-0.097***
	(-0.81)	(-2.26)	(-1.64)	(-2.76)
	0.416	0.024	0.101	0.006
HML	-0.116	0.009	-0.062	0.009
	(-1.51)	(0.17)	(-1.27)	(0.23)
	0.132	0.865	0.203	0.821
R^2/Adj-R^2	0.550/-0.030	1.350/0.770	0.950/0.360	1.590/1.000

This table reports the regression result based on model (28). Where: the dependent variable *R* are the returns of the momentum portfolio at time t and regressed on, *MKTRF* the excess market returns on MSCI world index, *HML* (high minus low) the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, and *BMS* (small minus big) returns to long-short portfolios constructed using size in US market. I estimate the parameters using the Newey West procedure. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey adjusted t-statistics are reported in the parentheses and the p-value next. The R-squares are also reported. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.2 Appendix C2

Table 4.3.17 Effect of Fama and French Risk on Momentum Profit with Newey West Procedure Estimation and Time Variation 1969-2014

	Panel A: FF 3-Factors Model			
	3-month	6-month	9-month	12-month
α_o	0.020	0.028***	0.037***	0.030***
	(1.60)	(3.76)	(5.11)	(14.39)
	0.110	0.000	0.000	0.000
MKTRF	-0.052	-0.025	0.004	0.046**
	(-1.00)	(-0.74)	(0.15)	(2.25)
	0.318	0.458	0.880	0.025
SMB	-0.023	-0.079*	-0.044	-0.076**
	(-0.32)	(-1.70)	(-1.27)	(-2.59)
	0.745	0.090	0.206	0.010
HML	-0.091	0.032	-0.072*	-0.017
	(-1.23)	(0.62)	(-1.87)	(-0.50)
	0.221	0.537	0.062	0.620
R^2/Adj-R^2	16.550/ 8.560	34.930/28.670	38.240/32.260	38.860/ 32.910

This table reports the regression result based on equation (28). Where, the dependent variable *R* are the returns of the momentum portfolio at time t and regressed on, *MKTRF* the excess market returns (based on MSCI world index), *HML* (high minus low) the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, *BMS* (small minus big) returns to long-short portfolios constructed using size in US market and the time dummy. I estimate the parameters using the Newey West procedure. I also account for time variation through time dummy. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey adjusted t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.3 Appendix C3

Table 4.3.18 Effect of Market State Pactor on Momentum Profit with Newey West Procedure 1969-2014

	Parameter					
	α_1	LIQ	DS	TS	MKT	R^2/Adj-R^2
3-Month	0.018**	0.102	0.029	-0.007	-0.017	0.830/0.060
	(2.24)	(1.17)	(0.62)	(-1.06)	(-0.26)	
	0.025	0.241	0.534	0.291	0.793	
6-Month	0.016***	0.047	0.013	-0.005	0.018	0.670/-0.110
	(2.81)	(0.81)	(0.55)	(-1.14)	(2.81)	
	0.005	0.416	0.584	0.254	0.005	
9-month	0.009**	0.024	-0.010	-0.002	-0.009	0.210/ -0.580
	(2.16)	(0.60)	(-0.48)	(-0.59)	(-0.28)	
	0.031	0.546	0.633	0.553	0.777	
12-month	0.003	0.026	-0.034*	-0.000	0.002	0.870/0.080
	(0.84)	(0.92)	(-1.77)	(-0.16)	(0.06)	
	0.402	0.359	0.078	0.869	0.952	

This table reports the regression result based on model (29). Where: LIQ_{t-1} is the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS the Term spread at time t-1 and theMKT_{t-1} the MSCI world indices price level and represent price levels at time t-1. I estimate the parameters using the Newey West procedure. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk the R-squares are also reported. The Newey adjusted t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.4 Appendix C4

Table 4.3.19 Effect of Market State Factor on Momentum Profit with Newey West Procedure Estimation and Time Variation 1969-2014

	Parameter					
	α_1	LIQ	DS	TS	MKT	R^2/Adj-R^2
3-Month	0.019	0.080	0.041	0.002	-0.035	16.610/ 8.430
	(1.01)	(0.97)	(0.84)	(0.15)	(-0.55)	
	0.315	0.335	0.399	0.882	0.580	
6-Month	0.030***	0.020	0.024	-0.001	0.026	34.500/ 28.050
	(2.69)	(0.41)	(1.04)	(-0.19)	(0.72)	
	0.007	0.683	0.300	0.846	0.475	
9-month	0.031***	-0.015	-0.000	0.007	0.008	37.950/31.800
	(3.32)	(-0.44)	(-0.00)	(1.23)	(0.28)	
	0.001	0.662	0.997	0.219	0.778	
12-month	0.020***	0.004	-0.022	0.008**	0.004	38.530/32.400
	(3.77)	(0.18)	(-1.41)	(2.02)	(0.18)	
	0.000	0.856	0.158	0.044	0.860	

This table reports the regression result based on model (29). Where: LIQ_{t-1} is the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS the Term spread at time t-1 and the MKT_{t-1} the MSCI world index price level and represent price levels at time t-1 and the time dummy. I estimate the parameters using the Newey West procedure. I also account for time variation through time dummy I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk the R-squares are also reported. The Newey adjusted t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.5 Appendix C5

Table 4.3.20. Effect of Macroeconomic Risk Factor on Momentum Profit with Newey west Procedure 1969-2014

	Parameter				
	α_1	ΔOP	ΔIP	$WVOL$	R^2/Adj-R^2
3-Month	0.005	-0.014	0.908	0.391	1.650/ 0.011
	(1.02)	(-0.48)	(2.54)	(0.70)	
	0.310	0.633	0.012	0.486	
6-Month	0.004	-0.021	0.548	0.572	1.550/ 0.970
	(1.26)	(-0.93)	(2.51)	(1.60)	
	0.209	0.354	0.012	0.111	
9-month	0.004	-0.016	0.276	0.327	0.750/0.160
	(1.62)	(-0.86)	(1.58)	(1.17)	
	0.106	0.388	0.114	0.243	
12-month	0.0008	-0.010	0.204	0.344	0.650/ 0.060
	(0.37)	(-0.84)	(1.29)	(1.45)	
	0.712	0.402	0.197	0.148	

This table reports the regression result based on model (30). Where: ΔOP_{t-1}, is the change in Oil price at time t-1,$\Delta\ IP_{t-1}$ the change in the monthly value of the US Industrial production at time t-1 and $WVOL_{t-1}$ the market volatility at time t-1 based on the MSCI world indices price level. I estimate the parameters using the Newey West procedure. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The R-squares are reported. The Newey adjusted t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.6 Appendix C6

Table 4.3.21. Effect of Macroeconomic Risk Factors on Momentum Profit with Newey West Procedure Estimation and Time Variation 1969-2014

	Parameter				
	α_1	ΔOP	ΔIP	$WVOL$	R^2/Adj-R^2
3-Month	0.012	0.002	0.770**	0.774	17.290/9.370
	(0.91)	(0.07)	(2.28)	(1.17)	
	0.365	0.947	0.023	0.244	
6-Month	0.023***	-0.005	0.300	0.075**	34.800/28.530
	(2.75)	(-0.23)	(1.37)	(2.08)	
	0.006	0.821	0.170	0.038	
9-month	0.037***	-0.007	-0.038	0.271	37.820/31.800
	(4.99)	(-0.45)	(-0.22)	(0.70)	
	0.000	0.653	0.826	0.487	
12-month	0.028***	-0.004	-0.178	54.247*	38.400/32.400
	(8.13)	(-0.35)	(-1.29)	(1.83)	
	0.000	0.726	0.196	0.068	

This table reports the regression result based on model (30). Where: ΔOP_{t-1} is the change in Oil price at time t-1, ΔIP_{t-1} the change in the monthly value of the US Industrial production at time t-1 and $WVOL_{t-1}$ the market volatility at time t-1 based on the MSCI world indices price level and time dummy. I estimate the parameters using the Newey West procedure. I account for time variation with time dummy. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk the R-squares are also reported. The Newey adjusted t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.7 Appendix C7

Table 4.3.22 Seasonal Effect of Global Risk Factor on Momentum Profit with Newey Procedure and Time Variation 1969-2014

	3-Month	6-Month	9-Month	12-Month
α_3	0.000	0.020*	0.030***	0.017***
	(0.02)	(1.71)	(2.93)	(2.66)
	0.980	0.089	0.004	0.008
LIQ	0.036	0.024	-0.000	-0.022
	(0.73)	(1.02)	(-0.02)	(-1.34)
	0.463	0.308	0.980	0.181
DS	0.009	0.003	0.005	0.007
	(0.80)	(0.40)	(0.97)	(1.57)
	0.426	0.693	0.331	0.117
TS	0.116	0.039	-0.008	0.007
	(1.37)	(0.82)	(-0.23)	(0.27)
	0.170	0.412	0.818	0.786
MKT	-0.017	0.036	0.018	0.009
	(-0.25)	(0.93)	(0.64)	(0.34)
	0.802	0.354	0.524	0.734
ΔOP	0.014	-0.003	-0.002	0.000
	(0.52)	(-0.14)	(-0.14)	(0.01)
	0.604	0.890	0.892	0.991
$WVOL$	0.750	0.782**	0.283	0.709
	(1.12)	(2.09)	(0.71)	(2.33)
	0.264	0.037	0.477	0.020
ΔIP	0.924***	0.336	0.012	-0.142
	(2.72)	(1.46)	(0.07)	(-1.00)
	0.007	0.144	0.946	0.319
$MKTRF$	-0.070	-0.025	0.006	0.051
	(-1.30)	(-0.71)	(0.22)	(2.55)
	0.195	0.477	0.829	0.011
SMB	-0.032	-0.101	-0.054	-0.091
	(-0.42)	(-2.04)	(-1.47)	(-2.89)
	0.673	0.042	0.143	0.004
HML	-0.100	0.022	-0.070	-0.009
	-1.21	(0.39)	(-1.73)	(-0.27)
	0.226	0.700	0.083	0.784
R^2/Adj-R^2	18.410/ 9.240	36.090/ 28.880	38.570/31.590	40.530/33.730

This table reports the regression result based on model (31). Where: the dependent variable R are the returns of the momentum portfolio (9-month/3, 6, 9, 12-month) at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{T-1}, the change in monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, OP_{t-1}, and ΔIP_{t-1} is the change in the monthly value of the US Industrial production at time t-1. I estimate the parameters using the Newey West procedure. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. I. The Newey t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.8 Appendix C8

Table 4.3.23 Effect of Global Risk Factors on Momentum Profit with Newey West Procedure and Time variation 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.020	0.020	0.012	0.000
	(1.60)	(1.09)	(0.94)	(0.02)
	0.110	0.278	0.350	0.980
LIQ		0.041		0.036
		(0.84)		(0.73)
		0.404		0.463
DS		0.001		0.001
		(0.09)		(0.80)
		0.931		0.426
TS		0.093		0.116
		(1.12)		(1.37)
		0.263		0.170
MKT		-0.025		-0.017
		(-0.38)		(-0.25)
		0.704		0.802
ΔOP			0.006	0.014
			(0.23)	(0.52)
			0.816	0.604
$WVOL$			0.700	0.751
			(1.04)	(1.12)
			0.298	0.264
ΔIP			0.794**	0.92***
			(2.39)	(2.72)
			0.017	0.007
$MKTRF$	-0.052	-0.060	-0.056	-0.070
	(-1.00)	(-1.14)	(-1.04)	(-1.30)
	0.318	0.253	0.299	0.195
SMB	-0.023	-0.028	-0.021	-0.032
	(-0.32)	(-0.38)	(-0.29)	(-0.42)
	0.745	0.703	0.775	0.673
HML	-0.091	-0.092	-0.100	-0.100
	(-1.23)	(-1.14)	(-1.31)	(-1.21)
	0.221	0.255	0.189	0.226
R^2/Adj-R^2	16.550/ 8.560	24.770/17.040	17.680/9.220	18.410/9.240

This table reports the regression result based on model (17). Where: the dependent variable R are the returns of the momentum portfolio during the globalization periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change in monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the change in the monthly value of the US Industrial production at time t-1 and time dummy. Regression are based on model 1 to 4 specification. I estimate the parameters using the Newey West procedure. I account for time variation through time dummy I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.9 **Appendix C9**

Table 4.3.24. Crisis Role on Momentum Profit with Newey West Procedure and Time Variation and Crisis Dummy 1969-2014

	Currency Crisis	Stock Market C	Banking Crisis	Business cycle
α_3	0.002	0.001	-0.001	-0.027
	(0.12)	(0.04)	(0.04)	(-1.62)
	0.903	0.966	0.966	0.106
Dummy	-0.001	-0.021	-0.003	-0.042***
	(-0.05)	(-1.07)	(-0.21)	(-3.41)
	0.957	0.286	0.834	0.001
LIQ	0.035	0.035	0.035	0.020
	(0.85)	(0.70)	(0.70)	(0.40)
	0.396	0.485	0.485	0.689
DS	0.009	0.009	0.009	0.020*
	(0.76)	(0.71)	(0.71)	(1.89)
	0.447	0.477	0.477	0.060
TS	0.114	0.114	0.114	0.111
	(1.40)	(1.23)	(1.23)	(1.31)
	0.162	0.221	0.221	0.192
MKT	-0.015	-0.015	-0.015	-0.040
	(-0.24)	(-0.20)	(-0.20)	(-0.58)
	0.809	0.840	0.840	0.562
ΔOP	0.014	0.014	0.014	0.023
	(0.47)	(0.49)	(0.49)	(0.87)
	0.635	0.623	0.623	0.383
$WVOL$	0.840	0.840	0.840	0.505
	(1.04)	(1.17)	(1.17)	(0.73)
	0.298	0.244	0.244	0.465
ΔIP	0.899**	0.899**	0.899**	0.696*
	(2.43)	(2.58)	(2.58)	(1.94)
	0.016	0.010	0.010	0.053
MKTRF	-0.065	-0.065	-0.065	-0.069
	(-1.08)	(-1.13)	(-1.13)	(-1.27)
	0.280	0.259	0.259	0.204
SMB	-0.028	-0.028	-0.028	-0.045
	(-0.34)	(-0.36)	(-0.36)	(-0.55)
	0.737	0.719	0.719	0.584
HML	-0.094	-0.094	-0.094	-0.073
	(-1.08)	(-1.12)	(-1.12)	(-0.87)
	0.279	0.263	0.263	0.387
R^2/*Adj*-R^2	17.780/8.410	17.780/8.410	17.780/8.410	19.970/11.160

This table reports the regression result based on model (32). Where: the dependent variable R are the returns of the momentum portfolio during crisis periods or during the contraction periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, KT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change in monthly Oil price at time t-1, $Wvol$ is the market volatility at time t-1, I added a crisis dummy and ΔIP_{t-1} is the change in the monthly value of the US Industrial production at time t-1. I estimate the parameters using the Newey West procedure. I also account for time variation through time dummy. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.10 Appendix C10

Table 4.3.25 Effect of Global Risk Factor on Momentum Profit in Globalization Period with Newey Procedure and Time Variation 1994-2014

	Model	Mode2	Model3	Model4
α_3	0.008	0.019	-0.002	0.004
	(0.77)	(1.36)	(-0.18)	(0.25)
	0.444	0.177	0.854	0.801
LIQ		0.034		0.029
		(0.67)		(0.57)
		0.507		0.566
DS		-0.014		-0.008
		(-0.98)		(-0.51)
		0.326		0.610
TS		0.242**		0.267**
		(2.41)		(2.56)
		0.017		0.011
MKT		-0.077		-0.078
		(-1.03)		(-0.99)
		0.305		0.326
ΔOP			0.024	0.029
			(0.75)	(1.06)
			0.453	0.290
$WVOL$			1.594*	1.770*
			(1.91)	(2.20)
			0.058	0.029
ΔIP			0.594	0.438
			(1.31)	(0.98)
			0.192	0.330
MKTRF	-0.159**	-0.166***	-0.169**	-0.172***
	(-2.57)	(-2.66)	(-2.48)	(-2.72)
	0.011	0.008	0.014	0.007
SMB	-0.060	-0.061	-0.109	-0.111
	(-0.70)	(-0.70)	(-1.20)	(-1.26)
	0.484	0.484	0.231	0.211
HML	-0.087	-0.090	-0.121	-0.115
	(-0.86)	(-0.77)	(-1.15)	(-0.97)
	0.393	0.443	0.253	0.335
R^2/*Adj*-R^2	23.810/ 16.040	27.610/18.560	25.910/17.090	29.840/19.820

This table reports the regression result based on model (37). Where: the dependent variable R are the returns of the momentum portfolio during the globalization periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{T-1}$ is the market volatility at time t-1, ΔOP_{t-1} the change in monthly oil price based world indices value at t-1, and ΔIP_{t-1} is the change in monthly value of the US Industrial production at time t-1. Regression are based on model 1 to 4 specification. I estimate the parameters using the Newey West procedure. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.11 Appendix C11

Table 4.3.226 Effect of Global Risk Factor on Momentum Profit in Developed Market with Newest Procedure 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.020	0.018	0.012	0.001
	(1.61)	(1.14)	(0.92)	(0.07)
	0.107	0.257	0.360	0.944
LIQ		0.041		0.037
		(0.89)		(0.79)
		0.376		0.428
DS		0.002		0.008
		(0.27)		(0.94)
		0.788		0.347
TS		0.135*		0.153**
		(1.92)		(2.16)
		0.056		0.031
MKT		-0.007		-0.003
		(-0.11)		(-0.05)
		0.910		0.962
ΔOP			-0.011	-0.002
			(-0.43)	(-0.08)
			0.666	0.937
$WVOL$			1.029*	1.087*
			(1.72)	(1.85)
			0.086	0.065
ΔIP			0.586**	0.731**
			(1.98)	(2.39)
			0.048	0.017
$MKTRF$	-0.070	-0.082*	-0.067	-0.084*
	(-1.50)	(-1.74)	(-1.41)	(-1.76)
	0.135	0.083	0.160	0.079
SMB	0.006	-0.008	0.004	-0.014
	(0.10)	(-0.12)	(0.06)	(-0.21)
	0.917	0.905	0.954	0.831
HML	-0.094	-0.101	-0.001	-0.102
	(-1.50)	(-1.50)	(-1.48)	(-1.48)
	0.135	0.134	0.141	0.139
R^2/Adj-R^2	15.010/6.870	16.120/7.300	16.180/7.570	17.640/8.390

This table reports the regression result based on model (35). Where: the dependent variable R are the returns of the momentum portfolio in develop market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change in monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the change in monthly value of the US Industrial production at time t-1 and time dummy. Regression are based on model 1 to 4 specification. I estimate the parameters using the Newey West procedure. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.12 Appendix C12

Table 4.3.27 Effect of global risk factor on momentum profit in emerging market with Newey procedure and time variation 1988-2014

	Model	Mode2	Model3	Model4
α_3	-0.038	0.003	-0.044	-0.020
	(-1.46)	(0.09)	(-1.62)	(-0.53)
	0.146	0.930	0.107	0.596
LIQ		0.068		0.059
		(0.89)		(0.76)
		0.375		0.447
DS		-0.036		-0.021
		(-1.33)		(-0.78)
		0.183		0.433
TS		-0.063		-0.037
		(-0.30)		(-0.18)
		0.762		0.860
MKT		-0.386***		-0.368***
		(-3.05)		(-2.95)
		0.003		0.004
ΔOP			0.048	0.035
			(0.85)	(0.66)
			0.395	0.513
$WVOL$			0.834	1.218
			(0.60)	(0.90)
			0.551	0.371
ΔIP			1.948*	1.332
			(1.83)	(1.37)
			0.069	0.172
$MKTRF$	-0.171*	-0.176*	-0.218*	-0.204*
	(-1.70)	(-1.76)	(-1.98)	(-1.88)
	0.090	0.079	0.049	0.061
SMB	-0.224*	-0.121	-0.239*	-0.146
	(-1.75)	(-0.92)	(-1.86)	(-1.09)
	0.082	0.359	0.064	0.276
HML	-0.057	0.045	-0.116	0.010
	(-0.38)	(0.26)	(-0.74)	(0.05)
	0.703	0.792	0.461	0.956
R^2/Adj-R^2	19.450/11.480	0.2413/ 15.390	21.790/13.100	25.230/15.670

This table reports the regression result based on model (34). Where: the dependent variable R are the returns of the momentum portfolio in emerging market at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, $MSCIW_{t-1}$ the MSCI world indices price level that represent price levels at time t-1, WOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔOP_{t-1} the monthly oil price based world indices value at t-1, ΔIP_{t-1} is the monthly value of the US Industrial production at time t-1 and time dummy. Regression are based on model 1 to 4 specification. I estimate the parameters using the Newey West procedure. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.13 Appendix C13

Table 4.3.28 Effect of Fama and French risk on Momentum Profit OLS Estimation

Panel A: Fama French Three-Factor with US excess Return 1969-2014

	Panel A: FF 3-Factors Model			
	3-month	6-month	9-month	12-month
α_o	0.010***	0.009***	0.008***	0.004***
	(4.42)	(6.10)	(5.96)	(3.31)
	0.000	0.000	0.000	0.001
ERM	-0.042	-0.034	-0.017	0.023
	(-0.79)	(-0.92)	(-0.57)	(0.91)
	0.430	0.361	0.572	0.363
SMB	-0.062	-0.113**	-0.076*	-0.098***
	(-0.81)	(-2.09)	(-1.77)	(-2.66)
	0.421	0.037	0.077	0.008
HML	-0.124	0.003	-0.065	0.0001
	(-1.52)	(0.05)	(-1.43)	(0.29)
	0.128	0.959	0.154	0.772
R^2/*Adj*-R^2	0.580/ -0.000	1.390/0.810	0.960/0.370	1.490/0.900

Panel B: Fama French Three factor with MSCI world excess return

	Panel A: FF 3-Factors Model			
	3-month	6-month	9-month	12-month
α_o	0.010***	0.010***	0.008***	0.004***
	(4.37)	(6.06)	(5.95)	(3.43)
	0.000	0.000	0.000	0.001
MKTRF	-0.036	-0.029	-0.016	0.030
	(-0.67)	(-0.78)	(-0.51)	(1.16)
	0.501	0.434	0.608	0.248
SMB	-0.068	-0.118**	-0.079*	-0.097***
	(-0.90)	(-2.22)	(-1.85)	(-2.66)
	0.369	0.027	0.065	0.008
HML	-0.012	0.009	-0.062	0.009
	(-1.46)	(0.17)	(-1.39)	(0.24)
	0.146	0.866	0.165	0.809
R^2/*Adj*-R^2	0.550/-0.030	1.350/ 0.770	0.950/ 0.360	1.590/ 1.000
AR (1)	0.183	0.091	0.120	-4.930

This table reports the regression result based on model (28). Where: the dependent variable *R* are the returns of the momentum portfolio at time t and regressed on, *ERM* the excess market returns on the US market, MKTRF the excess return on MSCI world index *HML* (high minus low) the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, *and BMS* (small minus big) returns to long-short portfolios constructed using size in US market. I estimate the parameters using OLS regression. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The t-statistics are reported in the parentheses and the p-value next. The R-squares are also reported. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.14 Appendix C14

Table 4.3.29 Effect of Market State Risk Factor on Momentum Profit OLS Estimation 1969-2014

	Parameter						
	α_1	LIQ	DS	TS	MKT	R^2/Adj-R^2	AR (1)
3-Month	0.018***	0.102	0.029	-0.007	-0.017	0.83/0.06	0.495
	(2.96)	(1.37)	(0.77)	(-1.36)	(-0.30)		
	0.003	0.171	0.440	0.174	0.763		
6-Month	0.015***	0.047	0.013	-0.005	0.018	0.670/ -0.110	0.691
	(3.60)	(0.89)	(0.51)	(-1.39)	(0.47)		
	0.000	0.372	0.611	0.166	0.636		
9-month	0.009***	0.024	0.572	-0.002	-0.009	0.210/ -0.580	0.715
	(2.69)	(0.57)	(-0.48)	(-0.67)	(-0.28)		
	0.007	0.572	0.633	0.503	0.778		
12-month	0.003	0.026	-0.034*	-0.000	0.002	0.870/ 0.080	0.700
	(1.06)	(0.74)	(-1.90)	(-0.18)	(0.06)		
	0.290	0.461	0.058	0.857	0.953		

This table reports the regression result based on model (29). Where: LIQ_{t-1} is the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS the Term spread at time t-1 and theMKT_{t-1} the return MSCI world indices price at time t-1. I estimate the parameters using OLS regression. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk the R-squares are also reported. I also report the autocorrelation coefficient of the residual, the t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.15 Appendix C15

Table 4.3.30 Effect of Macroeconomic risk factors on Momentum Profit with OLS Estimation

	Parameter					
	α_1	ΔOP	ΔIP	$WVOL$	R^2/Adj-R^2	AR (1)
3-Month	0.005	-0.014	0.908***	0.391	1.650/1.080	0.481
	(1.04)	(-0.51)	(2.92)	(0.70)		
	0.298	0.611	0.004	0.484		
6-Month	0.004	-0.021	0.548**	0.572	1.550/ 0.970	0.6832
	(1.33)	(-1.09)	(2.51)	(1.47)		
	0.183	0.274	0.013	0.143		
9-month	0.004*	-0.016	0.276	0.327	0.750/0.160	0.707
	(1.67)	(-1.03)	(1.57)	(1.04)		
	0.096	0.304	0.117	0.297		
12-month	0.001	-0.010	0.204	34.413	0.650/0.060	0.710
	(0.36)	(-0.77)	(1.36)	(1.28)		
	0.716	0.440	0.176	0.202		

This table reports the regression result based on model (30). Where: ΔOP_{t-1} is the change in Oil price at time T-1, ΔIP_{t-1} the change in monthly value of the US Industrial production at time t-1 and $WVOL_{t-1}$ the market volatility at time t-1 based on the MSCI world indices price level. I estimate the parameters using OLS regression. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk, the R-squares are reported. I also report the autocorrelation coefficient of the residual the t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

10.16 Appendix C16

Table 4.3.31. Seasonal Effect of Global Risk Factor on the Momentum Profit OLS Estimation

	3-Month	6-Month	9-Month	12-Month
α_3	0.000	0.020	0.000***	0.017
	(0.02)	(1.58)	(2.66)	(1.50)
	0.981	0.115	0.008	0.134
LIQ	0.036	0.024	-0.000	-0.022
	(0.92)	(0.97)	(-0.02)	(-1.34)
	0.360	0.331	0.983	0.182
DS	0.009	0.003	0.005	0.007
	(0.86)	(0.43)	(1.00)	(1.50)
	0.393	0.670	0.317	0.134
TS	0.116	0.039	-0.008	0.007
	(1.54)	(0.84)	(-0.22)	(0.22)
	0.124	0.402	0.825	0.825
MKT	-0.017	0.036	0.018	0.009
	(-0.30)	(1.01)	(0.66)	(0.38)
	0.767	0.314	0.509	0.704
ΔOP	0.014	-0.003	-0.002	0.000
	(0.50)	(-0.18)	(-0.15)	(0.01)
	0.614	0.856	0.881	0.991
$WVOL$	0.751	0.782*	0.283	0.709**
	(1.01)	(1.70)	(0.78)	(2.32)
	0.315	0.090	0.436	0.021
ΔIP	0.924***	0.336	0.012	-0.142
	(2.61)	(1.52)	(0.07)	(-0.97)
	0.009	0.129	0.945	0.334
MKTRF	-0.070	-0.025	0.006	0.051**
	(-1.25)	(-0.73)	(0.21)	(2.24)
	0.213	0.463	0.832	0.026
SMB	-0.032	-0.101**	-0.001	-0.001***
	(-0.40)	(-2.05)	(-1.40)	(-2.80)
	0.688	0.041	0.163	0.005
HML	-0.100	0.022	-0.070*	-0.009
	(-1.20)	(0.42)	(-1.72)	(-0.27)
	0.231	0.674	0.086	0.785
R^2/*Adj*-R^2	18.410/9.240	36.09/28.880	38.570/31.590	40.530/33.730

This table reports the regression result based on model (31). Where: the dependent variable R are the returns of the momentum portfolio (9-month/3, 6, 9, 12-month) at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change in monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the monthly change in the value of the US Industrial production at time t-1. I estimate the parameters using OLS regression. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

11 Appendix D

11.1 Appendix D1

Table 4.4.16. Effect of Global Risk Factors on Loser Profit with GMM Estimation Time Variation

	Model	Mode2	Model3	Model4
α_3	0.008***	0.013***	0.009***	0.012***
	(16.73)	(11.48)	(7.08)	(7.66)
	0.000	0.000	0.000	0.000
LIQ		0.002		0.002
		(0.19)		(0.18)
		0.851		0.856
DS		-0.004***		-0.004***
		(-4.52)		(-3.56)
		0.000		0.000
TS		0.002		0.003
		(0.11)		(0.23)
		0.914		0.817
MKT		0.031***		0.031**
		(2.41)		(2.38)
		0.016		0.017
ΔOP			0.011*	0.007
			(1.96)	(1.33)
			0.050	0.184
$WVOL$			-0.097	0.034
			(-0.64)	(0.23)
			0.525	0.815
ΔIP			0.119	0.022
			(1.56)	(0.26)
			0.119	0.791
$MKTRF$	0.009	0.004	0.003	0.003
	(0.69)	(0.32)	(0.25)	(0.26)
	0.491	0.751	0.804	0.793
SMB	-0.045***	-0.055***	-0.045***	-0.058***
	(-2.77)	(-3.30)	(-2.76)	(-3.38)
	0.006	0.001	0.006	0.001
HML	-0.053***	-0.068***	-0.057***	-0.067***
	(-2.68)	(-3.58)	(-3.09)	(-3.50)
	0.007	0.000	0.002	0.000

This table reports the regression result based on model (31). Where: the dependent variable R are the returns of the contrarian portfolio during the globalization periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the change in monthly Oil price at time t-1, $WVOL_{t-1}$ is the market volatility at time t-1, ΔIP_{t-1} is the change in the monthly value of the US Industrial production at time t-1 and time dummy. Regression are based on model 1 to 4 specification. I estimate the parameters using the Newey West procedure. I account for time variation through time dummy I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The Newey t-statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

11.2 Appendix D2

Table 4.4.17. Effect of Global Risk Factor on Winner Profit with GMM Method and Time variation 1969-2014

	Model	Mode2	Model3	Model4
α_3	0.002***	0.004***	-0.001	0.001
	(5.57)	(4.90)	(-1.53)	(0.53)
	0.000	0.000	0.127	0.594
LIQ		-0.022***		-0.022***
		(-2.96)		(-2.94)
		0.003		0.003
DS		-0.002***		-0.002***
		(-3.86)		(-3.69)
		0.000		0.000
TS		-0.011		-0.008
		(-1.00)		(-0.74)
		0.318		0.459
MKT		0.022**		0.026***
		(2.50)		(3.05)
		0.012		0.002
ΔOP			0.008	0.006
			(1.81)	(1.48)
			0.070	0.138
$WVOL$			0.417***	0.454***
			(3.80)	(4.21)
			0.000	0.000
ΔIP			0.099**	0.048
			(1.97)	(0.87)
			0.049	0.383
$MKTRF$	0.008	0.010	0.014	0.016*
	(0.87)	(1.13)	(1.55)	(1.75)
	0.387	0.259	0.121	0.080
SMB	-0.018	-0.009	-0.018	-0.015
	(-1.10)	(-0.57)	(-1.14)	(-0.94)
	0.273	0.571	0.254	0.349
HML	-0.004	-0.009	-0.005	-0.008
	(-0.26)	(-0.66)	(-0.42)	(-0.63)
	0.795	0.511	0.678	0.531

This table reports the regression result based on model (31). Where: the dependent variable R are the returns of the contrarian portfolio during the globalization periods at time t and regressed on, HML_t (high minus low) the return to portfolios that is long on high book-to-market stocks and short on low book-to-market stocks in US, SMB_t (small minus big) returns to long-short portfolios constructed using size in US market, the LIQ_{t-1} the liquidity factor at time t-1, DS_{t-1} the Default spread at time t-1, TS_{t-1} the Term spread at time t-1, MKT_{t-1} the MSCI world indices price level that represent price levels at time t-1, ΔOP_{t-1}, the monthly Oil price at time t-1, $WVOL_{T-1}$ is the market volatility at time t-1, ΔOP_{t-1} the change in monthly oil price based world indices value at t-1, and ΔIP_{t-1} is the change in monthly value of the US Industrial production at time t-1. Regression are based on model 1 to 4 specification. I estimate the parameters using the GMM method. I use the regression Alpha to measure the size of the abnormal return generated after adjusting for risk. The test statistics are reported in the parentheses and the p-value next. The results are* statistically significant at 10% for p<0.1, ** statistically significant at 5% for p<0.05 and ***statistically significant at 1% for p<0.01.

12 Appendix E

12.1 Appendix E1

Serial correlation

I then proceed with the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity to test if the estimated variance of the residuals from the model dependent on the values of the independent variables. The Breusch-Pagan test for conditional heteroscedasticity tests the null hypothesis of homoscedasticity. If the Chi Squared value is significant with p-value below an appropriate threshold (e.g. $p<0.005$) then the null hypothesis of homoscedasticity is rejected and heteroscedasticity assumed.

Ho: Constant variance (homoscedasticity)

H1: Heteroscedasticity

12.2 Appendix E2

Autocorrelation

I also test for serial correlation (autocorrelation) among the variable using the standard Q test statistic in STATA. If the test statistic is significant with p-value below an appropriate threshold (e.g. $p<0.005$) then the null hypothesis of no autocorrelation is rejected and the serial correlation present at range specified is assumed.

H0: Residuals are serially uncorrelated (no q order autocorrelation)

H1: Serial correlation present at range specified

12.3 Appendix E3

GMM Estimation Method

To test if the momentum profit can be explained by Fama and French risk, I regress the momentum return on Fama and French risk factors. I estimate the model using the interactive version of the generalized method of moments estimation. The model is a two-step GMM estimator to allow us to obtain parameter estimates based on the initial weight matrix, compute a new weight matrix based on those estimates, and then estimates the parameters based on that weight matrix. The instruments include the variable lists and the constant but I also account for time variation through time dummies. I specify weight matrix (wmatrix) type hac kernel to request for heteroscedasticity and autocorrelation consistent standard errors based on Bartlett kernel (Newey-West) with 1 lags. The choice of this matrix also allow us to control for non-normality. Using the linear combinations to fit my model, I type my equation as:

gmm (Momentum return -{xb: Variable list}-{b0}), instruments (instrumental variables) wmatrix (hac bartlett 1)

For example, my estimation for Fama and French risks is written as follow:

gmm (MO-{xb: ERM SMB HML}-{b0}), instruments (ERM SMB HML ***TIME DUMMY***) wmatrix (hac bartlett 1)

where gmm is the GMM command, MO is the momentum return, ERM the excess market returns, HML (high minus low) the return to portfolio that is long on high book-to-market stocks and short on low book-to-market stocks in US, BMS (small minus big) returns to long-short portfolios constructed using size in US market and TIME DUMMY (the time's dummies variables). ERM, SMB, HML and the time dummies are also the instruments for equation 1, the dummy variable are considered endogenous while other variables (ERM, SMB, and HML) are exogenous. The programme automatically includes the constant term b0 among the instruments. The results are given in the table below.

12.4 Appendix E4

Variable Definition

Price Risk Variable

Symbol	Variable	Definition	Source	ID
ERM	Excess Return on the Market	ERM (or Rm-RF) is the excess return on the market. It is calculated as the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate from Ibbotson, Associates, Ken French's web site http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/ (Percent change)	WRDS	Library: ff File: Factors_monthly
MKTRF	Excess Return on the MSCI world market	MKTRF (or %ΔMSCIW - RF) is the excess return on the market. It is calculated as the value-weight return of the MSCI World index minus the one-month Treasury bill rate	Own calculation	
SMB	Small-Minus-Big Return	SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios, SMB =1/3 (Small Value + Small Neutral + Small Growth)- 1/3 (Big Value + Big Neutral + Big Growth). SMB for July of year t to June of t+1 include all NYSE, AMEX, and NASDAQ stocks for which market equity data for December of t-1 and June of t, and (positive) book equity data for t-1, exists, from Ken French's web site. (Percent change)	WRDS	Library: ff File: Factors_monthly
HML	High-Minus-Low	Average return on the two value portfolios minus the average return on the two growth portfolios. HML=1/2(small value + Big Value -1/2(small Growth + Big Growth), from Ken French's website). (percent change)	WRDS	Library: ff File: Factors_monthly
RF	Risk-Free	Rate of one Month Treasury Bill	WRDS	Library: ff File: Factors_monthly

Market state variable

Symbol	Variable	Definition	Source	ID
LIQ	liquidity factor (PS_LEVEL)	Pastor-Stambaugh Level of Aggregate Liquidity (non-traded factor). PS_LEVEL basically correspond to equation numbers (5) in the published (JPE, 2003) version of the paper "Liquidity Risk and Expected Stock Returns".	WRDS	Library: ff Files: Liq_ps
TS	The term spread	difference between the average yield of Treasury bonds with more than 20 years to maturity and the average yield of T-bills that mature in three months. TS(t) = LGB(t) – TB(t-1), LGB(t) is the return on a portfolio of long-term government bonds obtained from WRSD; TB(t-1) is the lag average yield of the T-bills that matures in three months.	Own calculation	
LGB		LGB is the Index Level Associate with 20-year bond return (B20) obtained from the Center for Research in securities prices data files	WRDS	Library: Crspa File: cti
TB		TB is Index Level Associate with the 90 Day bill returns obtained from the Center for Research in securities prices data files	WRDS	Library: Crspa File: cti
DS	Default Spread	Difference between the average yield of bonds rated BAA by Moody’s and the average yield of bonds with a Moody’s rating of AAA. based upon the Federal Reserve Board’s H.15 release that contains selected interest rate for U.S.	Own calculation	
AAA	Moody’s Aaa Bon rate	Average yield of bonds rated AAA, based upon the Federal Reserve Board’s H.15 release that contains selected interest rate for U.S.	WRDS	Library: frb File: rates
BAA	Moody’s Baa Bon rate	Average yield of bonds with a Moody’s rating of BAA, based upon the Federal Reserve Board’s H.15 release that contains selected interest rate for U.S.	WRDS	Library: frb File: rates
MSCI World	Market Indices	Value-weighted MSCI world index prices level	DataStream	Mnemonic: TRVS1MB Code: S31ovJ
ΔMKT	Market return	ΔMKTt = ln(Pt)-ln(Pt-1), where Pt is the MSCI World index price at time t and Pt-1 is the world index prices at time t-1	Own calculation	

Economic Variable

Symbol	Variable	Definition or Source	Source	ID
OP	Oil price	Producer price index crude petroleum series obtain from the bureau of Labor Statistics	Bureau of Labour Statistics U.S. department of Labor Online available fromhttp://data.bls.gov/pdq/SurveyOutputServlet	Crude petroleum - WPU0561
VOL	Historical Volatility	Monthly standard deviation of daily returns (22 trading days per month).	Own calculation	
IP	Industrial Production	Total Industrial Production and Manufacturing Production index (SDDS+)	Online available from http://www.federalreserve.gov/releases/g17/download.htm	AIP_SA_IX
ΔIP	Percent change Industrial production	Monthly differences in the logarithm of the industrial production indexes $\Delta IP = \ln(IP_t)-\ln(IP_{t-1})$, IP_t is the industrial production index level at time t and IP_{t-1} is the industrial production index level at time t-1	Own calculation	
ΔOP	Percent change Oil Price	Monthly differences in the logarithm of the producer price index crude petroleum series (obtain from the bureau of Labor Statistics, U.S. department of Labor,) $\Delta OP = \ln(OP_t)-\ln(OP_{t-1})$, OP_t is the producer price index level at time t and OP_{t-1} is the producer price index level at time t-1	Own calculation	

Crisis

Symbol	Variable	Definition	Source	ID
NBER	Business cycle	Business cycle series is an interpretation of US Business Cycle Expansions and Contractions data provided by The National Bureau of Economic Research (NBER) is composed of dummy variables that represent periods of expansion (1) and recession (0).	Online available from http://www.nber.org/cycles/cyclesmain.html	
CC	Currency crisis	Annual depreciation versus the US dollar (or relevant anchor currency, historically the UK pound, the French franc, or German DM and presently the euro) of 15 percent or more. It is composed of dummy variables that represent periods of depreciation (1) and normal period (0)	Online available from http://www.carmenreinhart.com/data/browse-by-topic/topics/7/	
SMC	Stock Market crisis	Stock market crisis series is based on the bestselling *This Time Is Different: Eight Centuries of Financial Folly* by Carmen M. Reinhart & Kenneth S. Rogoff. Using data developed by Reinhart and Rogoff. It maps the cyclical history of financial crisis since 1810. it is composed of dummy variables that represent periods of crashes (1) and normal periods (0)	Online available from http://www.carmenreinhart.com/data/browse-by-topic/topics/7/	
BC	Banking crisis	Banking crisis are mark by two types of events: (1) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions; (2) if there are no runs, the closure, merging, takeover or large-scale government assistance of an important financial institutions. It is composed of dummy variables that represent periods of crisis (1) and normal period (0)	Online available from http://www.carmenreinhart.com/data/browse-by-topic/topics/7/	

Other Variables

Symbol	Variable	Definition	Source	ID
Euribo	Euribor	Euribor if the rate at which Euro interbank term deposits are offered by one prime bank to another prime bank within the EMU zone is calculated at 11:00 a.m. (CET) for spot value (T+2). The choice of banks quoting for Euribor is based on market criteria. These banks have been selected to ensure that the diversity of the euro money market is adequately refelected. Thereby making Euribor an efficient and representative benchmark.	Online available from https://www.emmi-benchmarks.eu/euribor-org/about-euribor.html	
Eonia	Eonia	Eonia (Euro OverNight Index Average) is the effective overnight reference rate for the euro. It is computed as a weighted averge of all overnight unsecured lending transactions in the interbank market, undertaken in the European Union and European Free Trade Association (EFTA) countries. The European Central Bank is the calculation Agent for Eonia.	Online available from https://www.emmi-benchmarks.eu/euribor-eonia-org/about-eonia.html	
EOIS	EURIBOR: OIS Spread	It is the difference between the rate at which European banks lend to eachother (EURIBOR) and the overnight 'risk free' swap rate (EONIA) among the same banks a 3-month period. EURIBOR (Euro InterBank Offered Rate) is an average of the rate each bank in the 43-member 'prime bank' panel reports that it would offer to the other banks. EONIA (Euro OverNight Index Average) is the average of swaps conducted between a 22-member panel at what each panel bank believes is the mid-market rate each day.	Own calculation	
TED	TED Spread	It is the difference between the LIBOR (London Interbank Offered Rate) and the 3 Month Treasury Bill.	Own calculation	
Libor	Libor	It is the average interbank interest rate at which a selection of banks on the London money market are prepared to Lend to one another. Libor comes in 7 manurities (from overnight to 12 months) and in 5 different currencies. The official Libor interest rates are announced once per working day at around 11:45 a.m. In the past, the BBA/IAE published LIBOR rates for 5 more currencies (Swedish hrona, Danish krone, Canadian dollar, Australian dollar and New Zealand dollar) and 8 more maturities (2 weeks, 4, 5, 7, 8, 9, 10 and 11 months).	Online available from http://www.global-rates.com/interest-rates/libor/libor.aspx	

13 Appendix F

13.1 Appendix F1

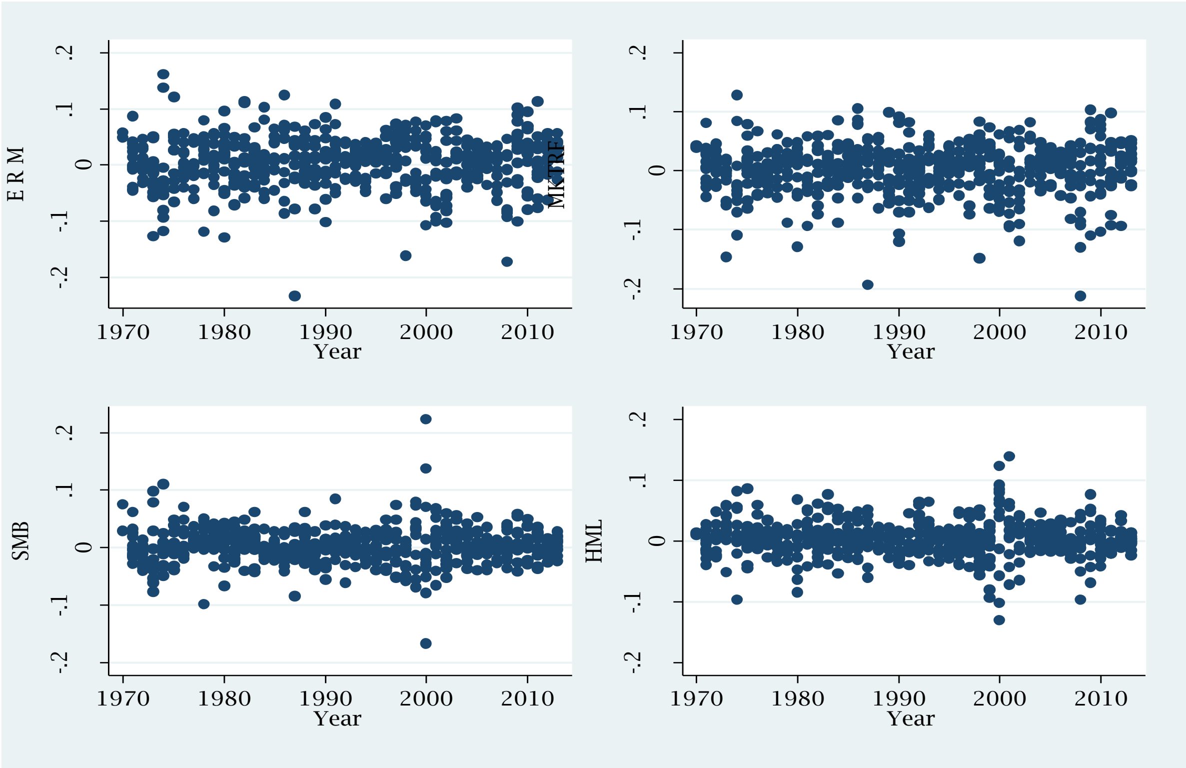
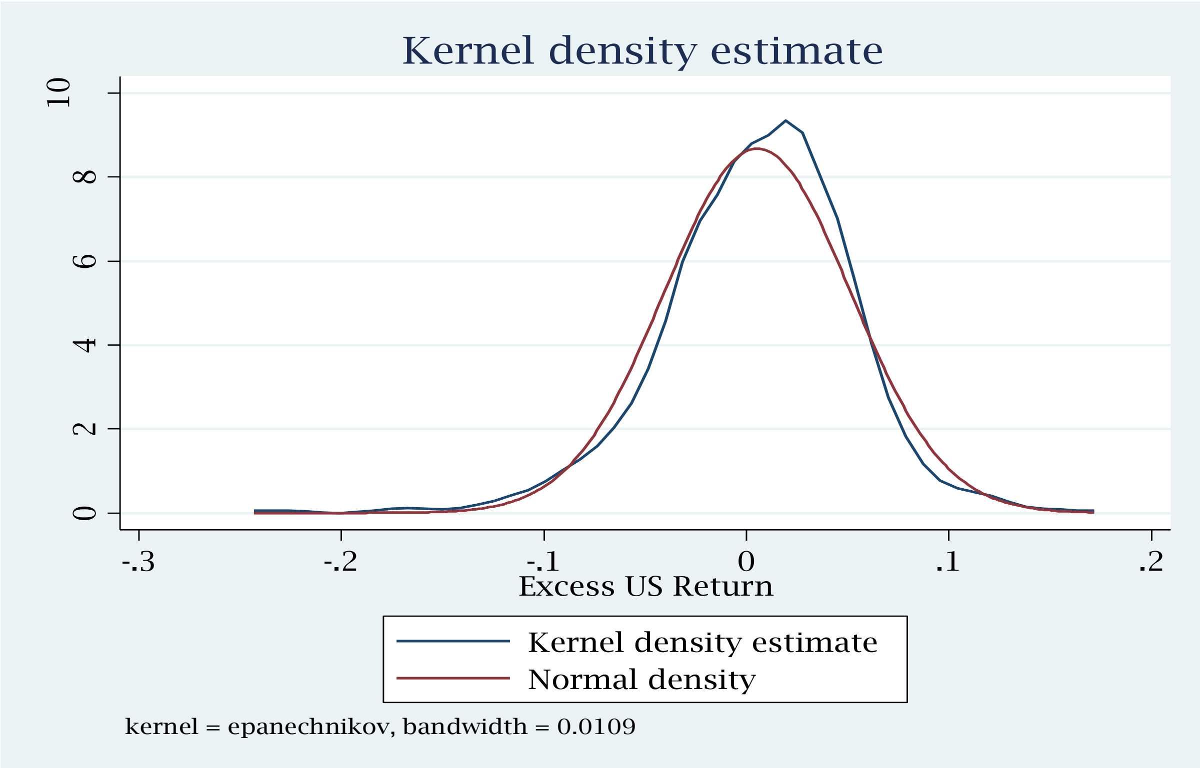


Figure 3 Fama and French Risk

Note: Each point corresponds to the average monthly entry of each individual Fama and French factors (ERM is the excess return on US return, MKTRF is the excess in MSCI world indices over the study period 1969-2014

13.2 Appendix F2

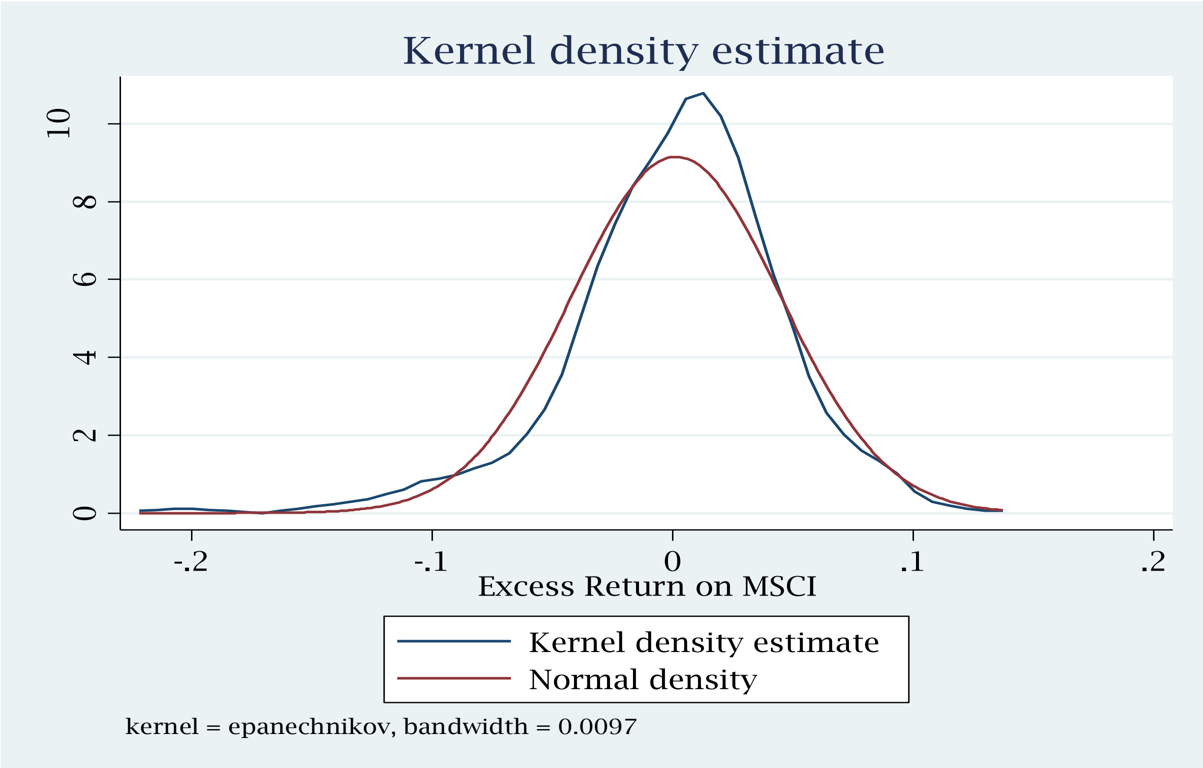
Figure 4 Excess Return on US market Distribution of Entry of the Historical Values



Note: Kernel density. The red line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing rate of the GDP growth

13.3 Appendix F3

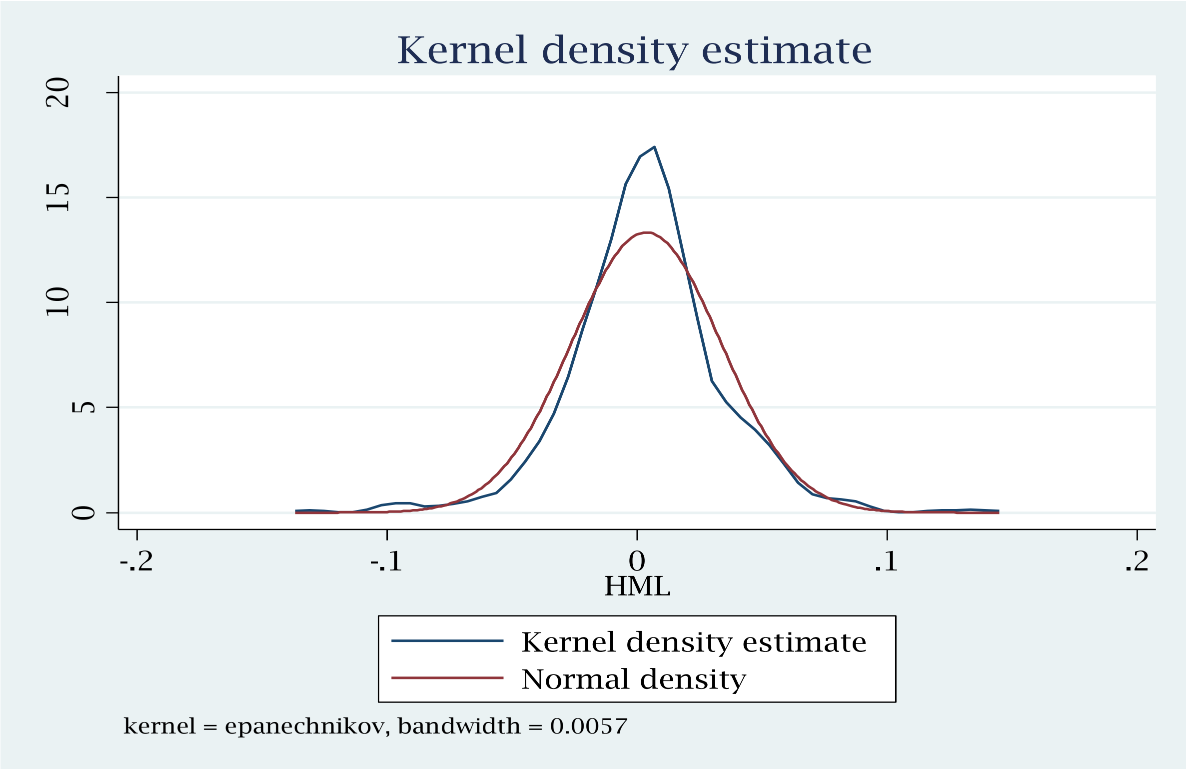
Figure 5 MSCI world Index Excess Return Distribution of Historical Values



Note: Kernel density. The red line represents the expected normal density and the black line is the excess in MSCI world indices distribution density. Each point corresponds to the monthly entry and existing rate of the excess return on MSCI world.

13.4 Appendix F4

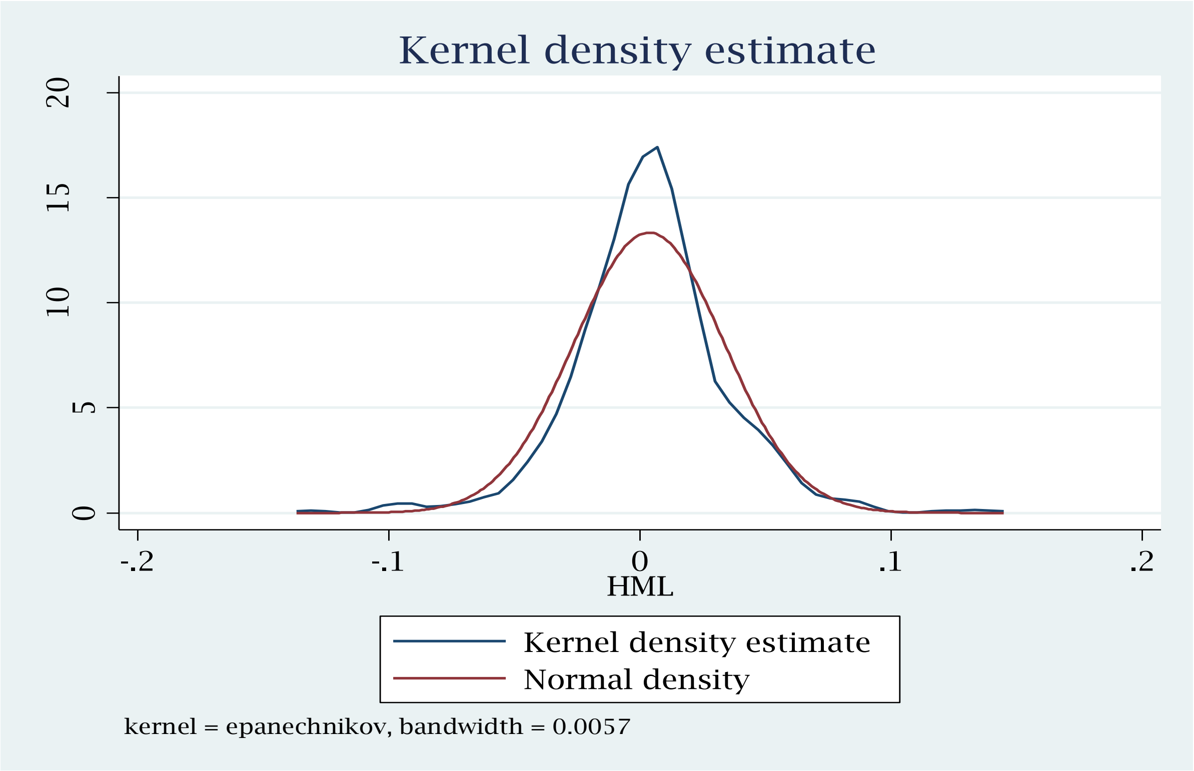
Figure 6 Distribution of Entry of the Historical Value of the SMB Factor



Note: Kernel density. The red line represents the expected normal density and the black line is the SMB distribution density. Each point corresponds to the monthly entry and existing rate of the SMB.

13.5 Appendix F5

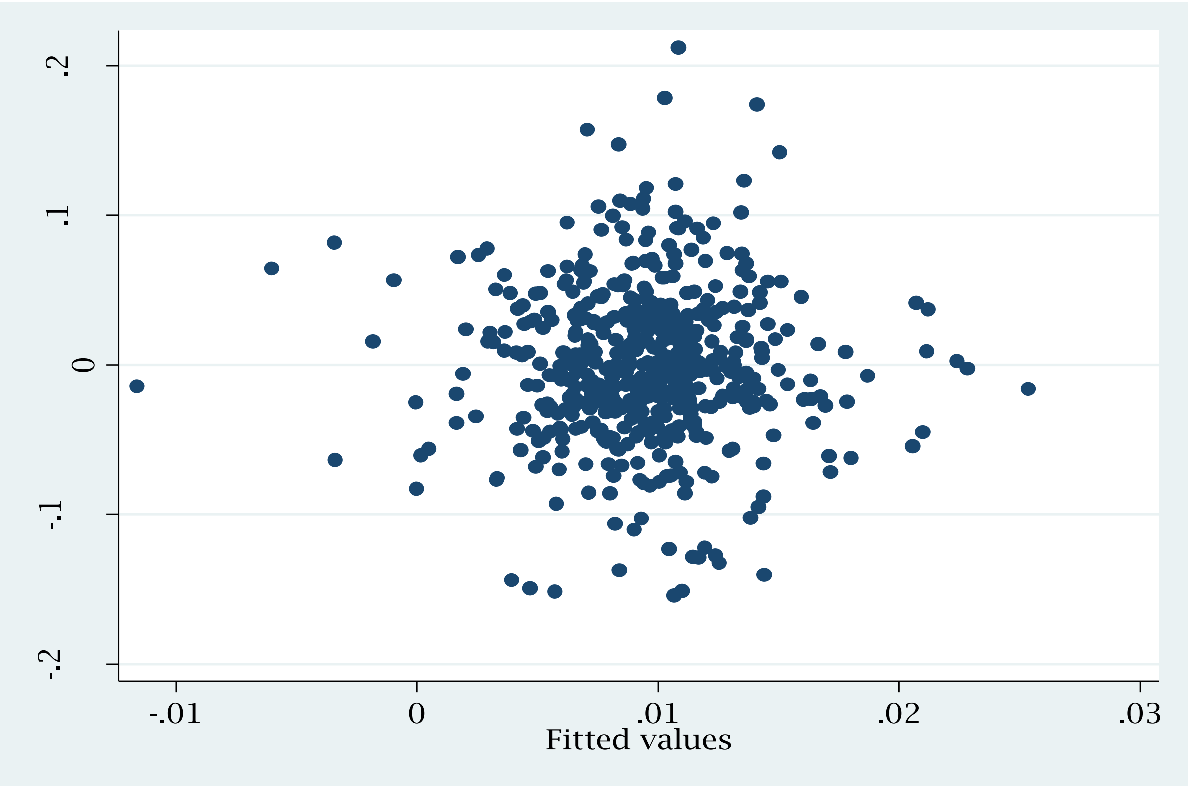
Figure 7 Distribution of Entry of the Historical Value of the HML Factor



Note: Kernel density. The red line represents the expected normal density and the black line is the HML distribution density. Each point corresponds to the monthly entry and existing rate of the SMB.

13.6 Appendix F6

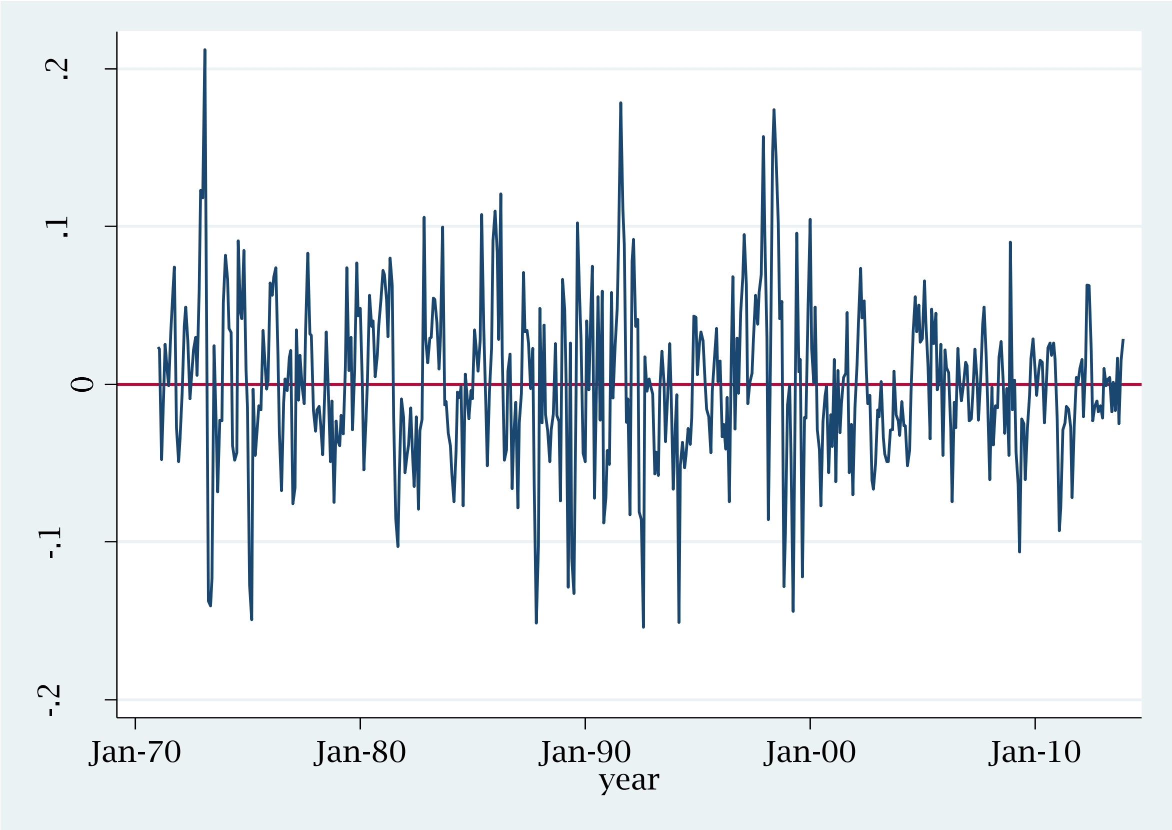
Figure 8 Residual and Fitted Values Plot Fama and French 3-Factor Model



Note: Figure 8 indicates the plots of the absolute of the residual Residual (vertical line) against the fitted values (horizontal line) after the momentum return regress on the Fama and French three factor model over the study period 1969-2014 (please see equation 14)

13.7 Appendix F7

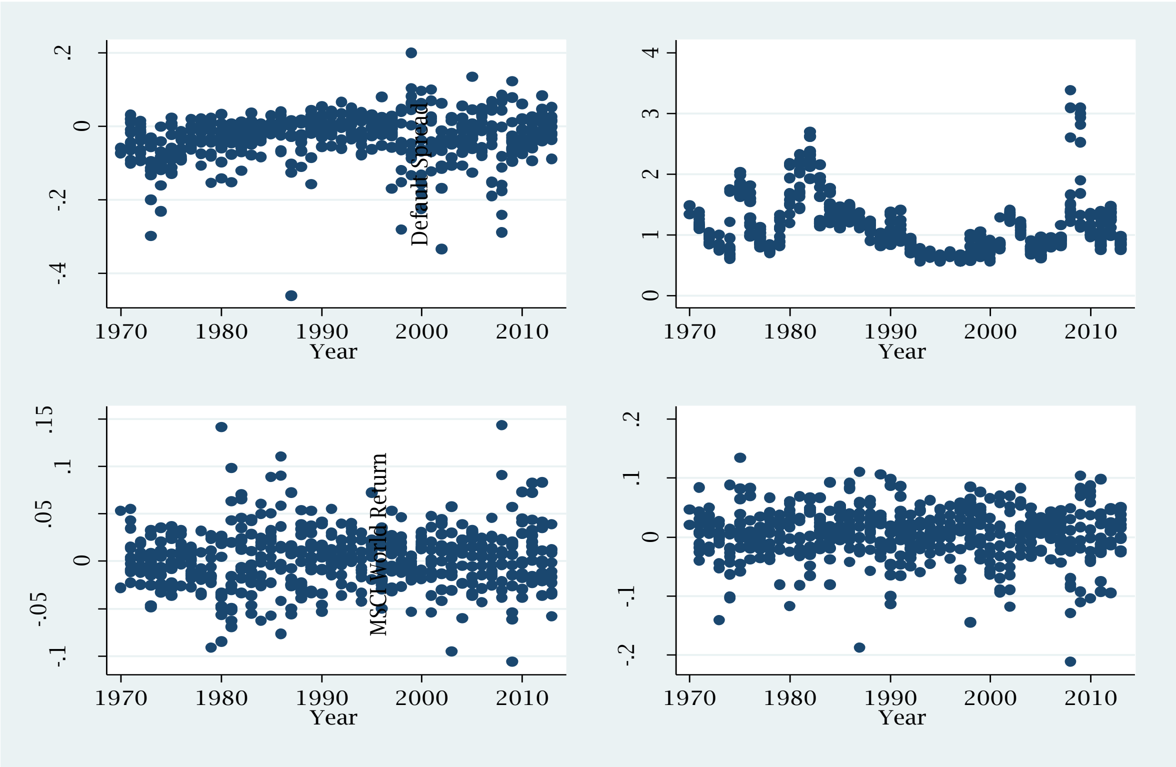
Figure 9 Residual Plot of the Fama and French 3-Factor Model



Note: Figure 9 shows the trend that corresponds to the average monthly entry of the residual after regressing the momentum return on the Fama and French risk factors (see equation 14) over the study period 1969-2014

13.8 Appendix F8

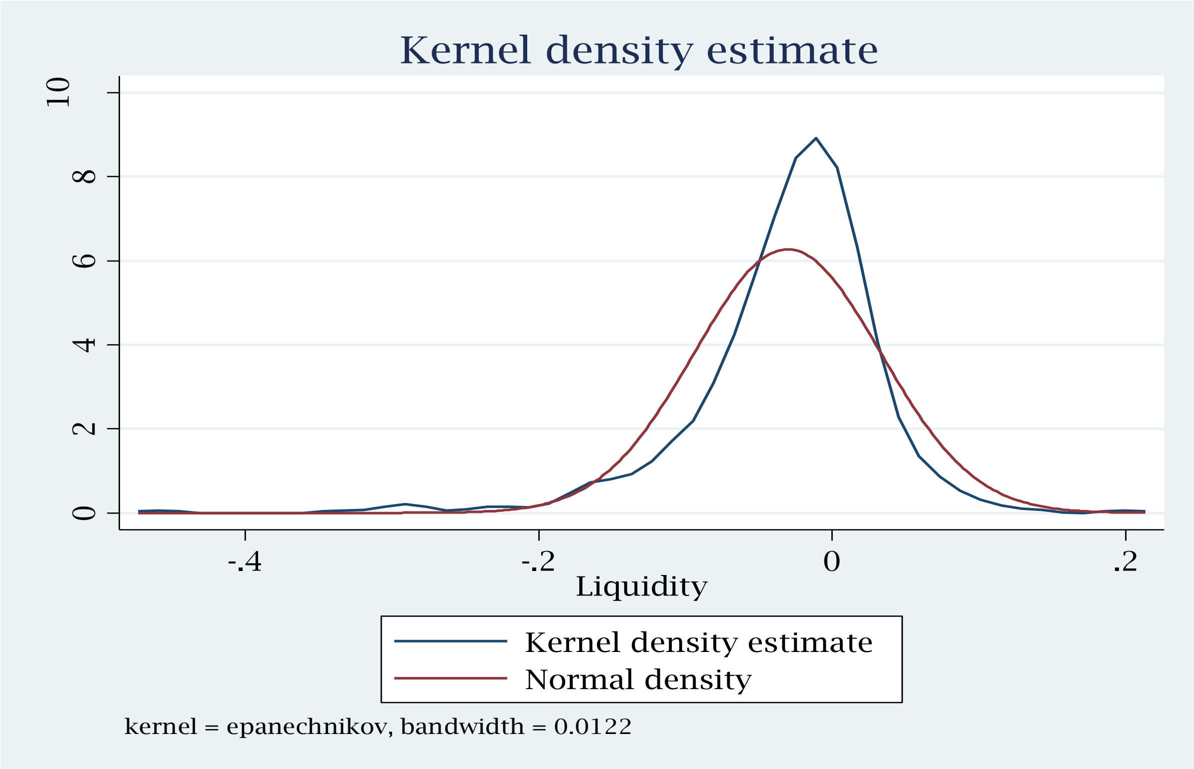
Figure 10 Scatter plot of Market State factor



Note: Each point corresponds to the average monthly entry of each individual market state factors (Liquidity, term spread, default spread, and return on the MSCI world index) as in the vertical line over the study period 1969-2014 in horizontal line.

13.9 Appendix F9

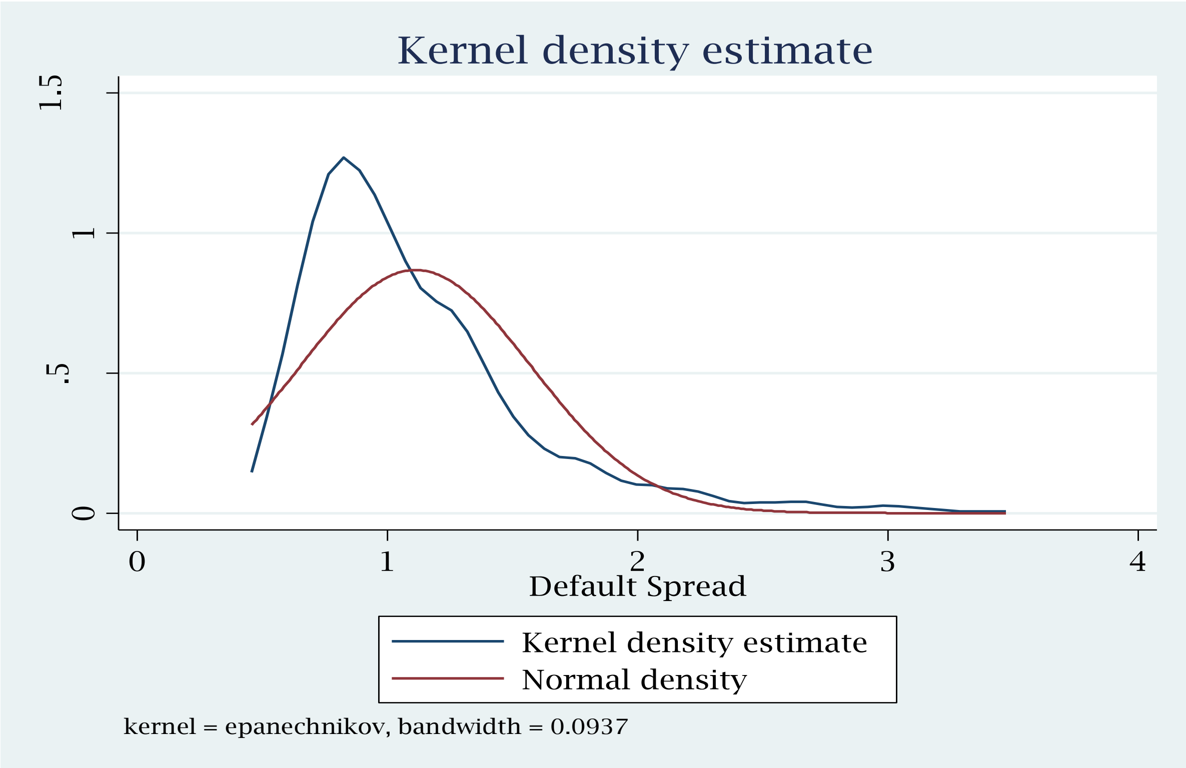
Figure 11 Distribution of Entry of the Historical Value of The Liquidity Factor



Note: Kernel density. The dotted line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing rate of the liquidity.

13.10 Appendix F10

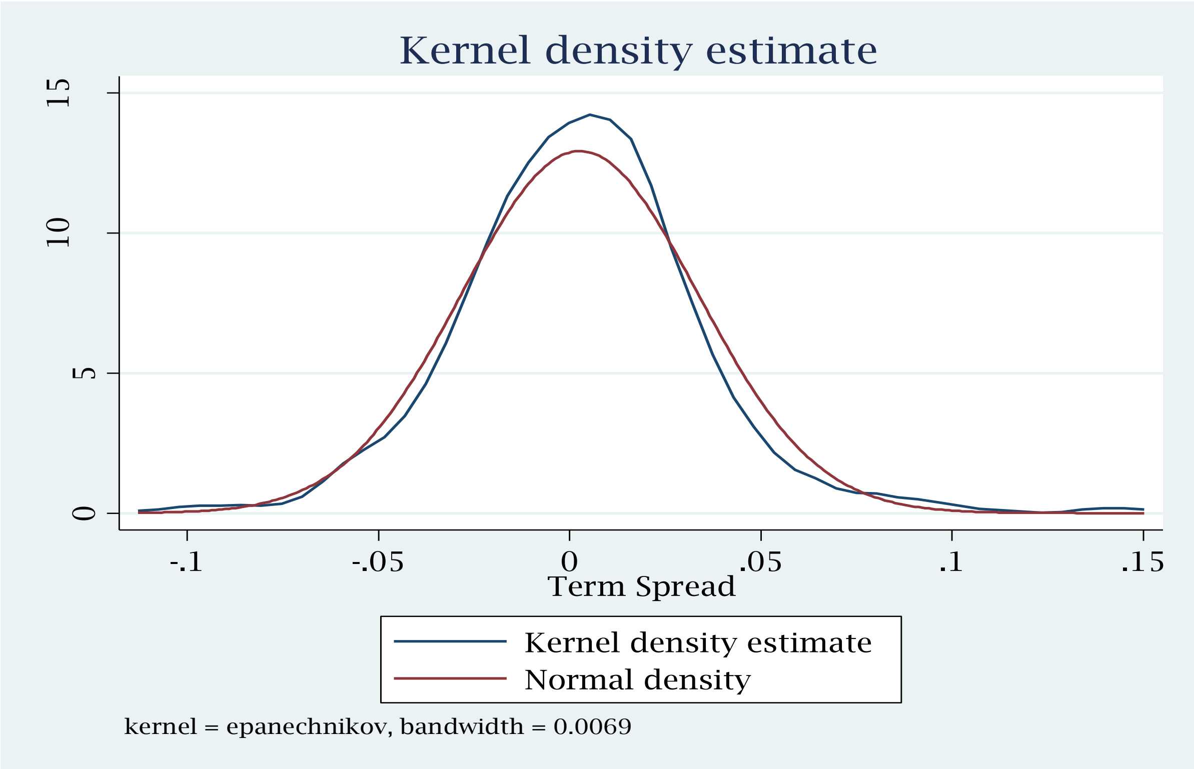
Figure 12 Distribution of Entry of the Vistorical value of the Default Spread Factor



Note: Kernel density. The dotted line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing rate of the Default Spread.

13.11 Appendix F11

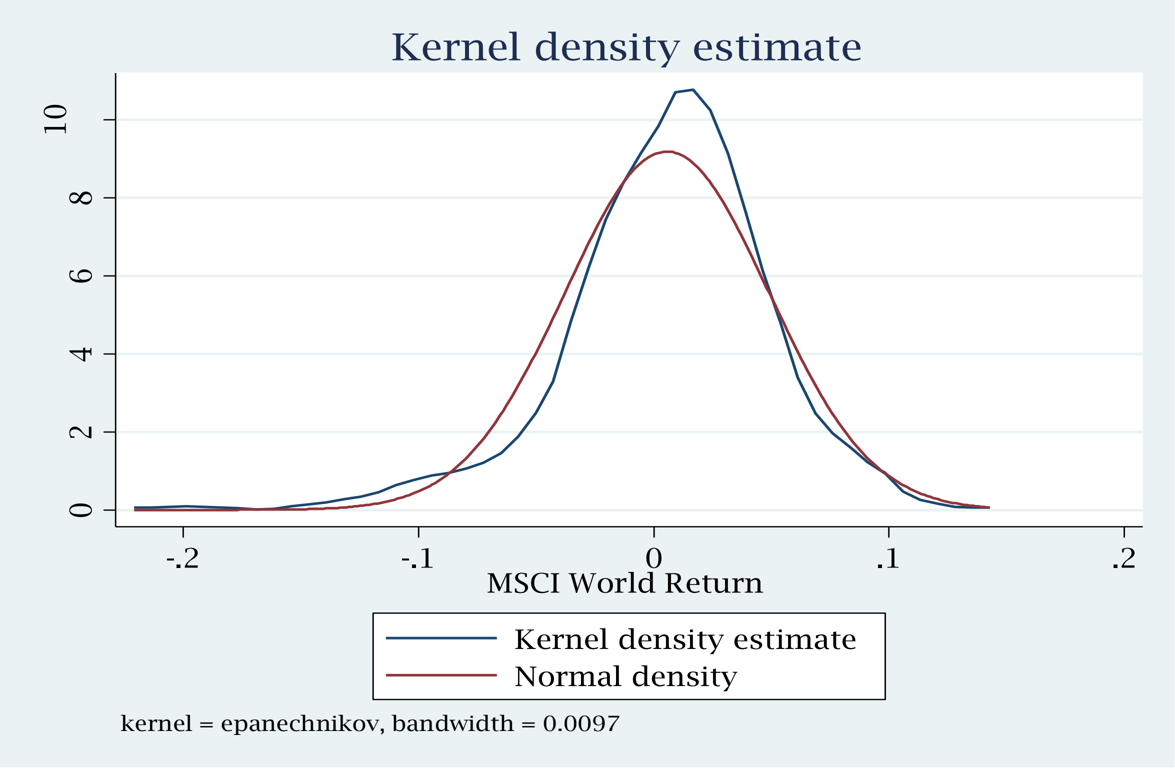
Figure 13 Distribution of Entry of the Historical Value of the Term Spread Factor



Note: Kernel density. The dotted line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing rate of the Term Spread.

13.12 Appendix F12

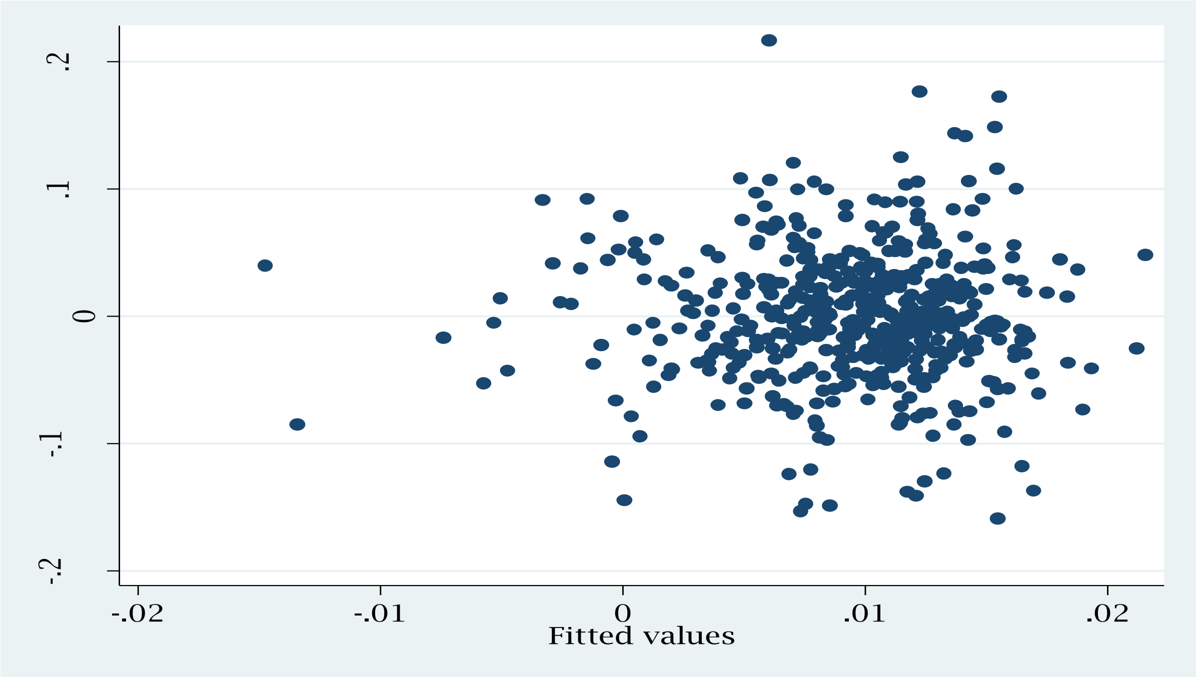
Figure 14 Distribution of Entry of the Historical Value of the Return



Note: Kernel density. The dotted line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing rate of return on the MSCI World index.

13.13 Appendix F13

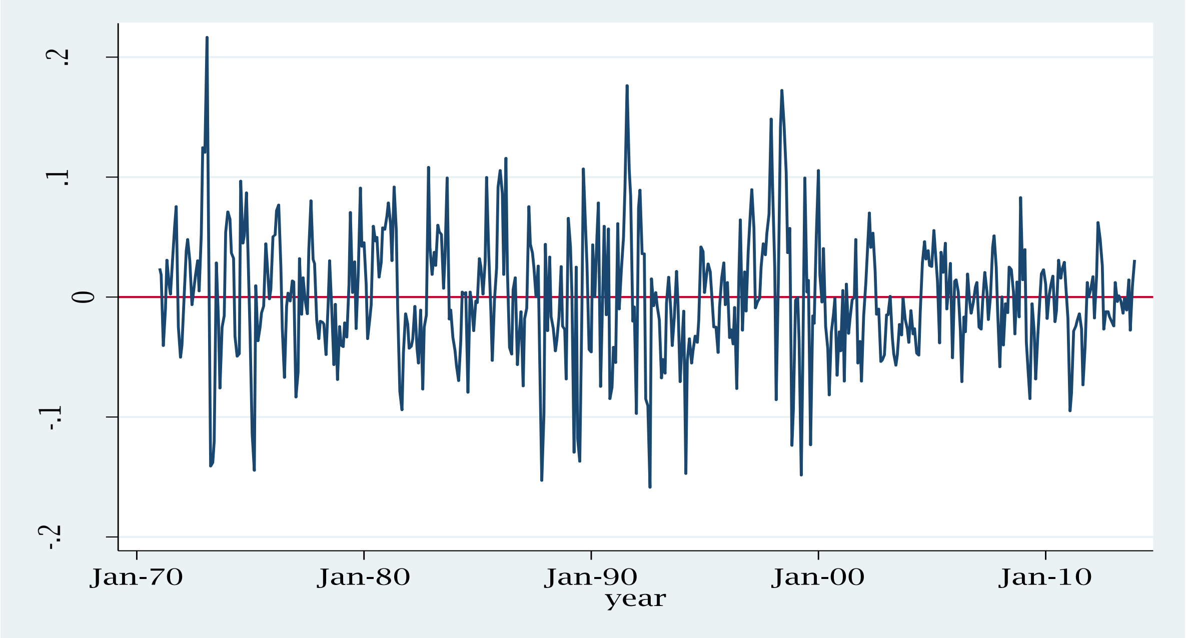
Figure 15 Residual Plot Market State Factor (heteroscedasticity)



Note: Figure 6 indicates the plots of the absolute value of the residual (vertical linee) against the fitted values (horizontal line) after the momentum return regress on the market state factor over the study period 1969-2014 (please see equation 15)

13.14 Appendix F14

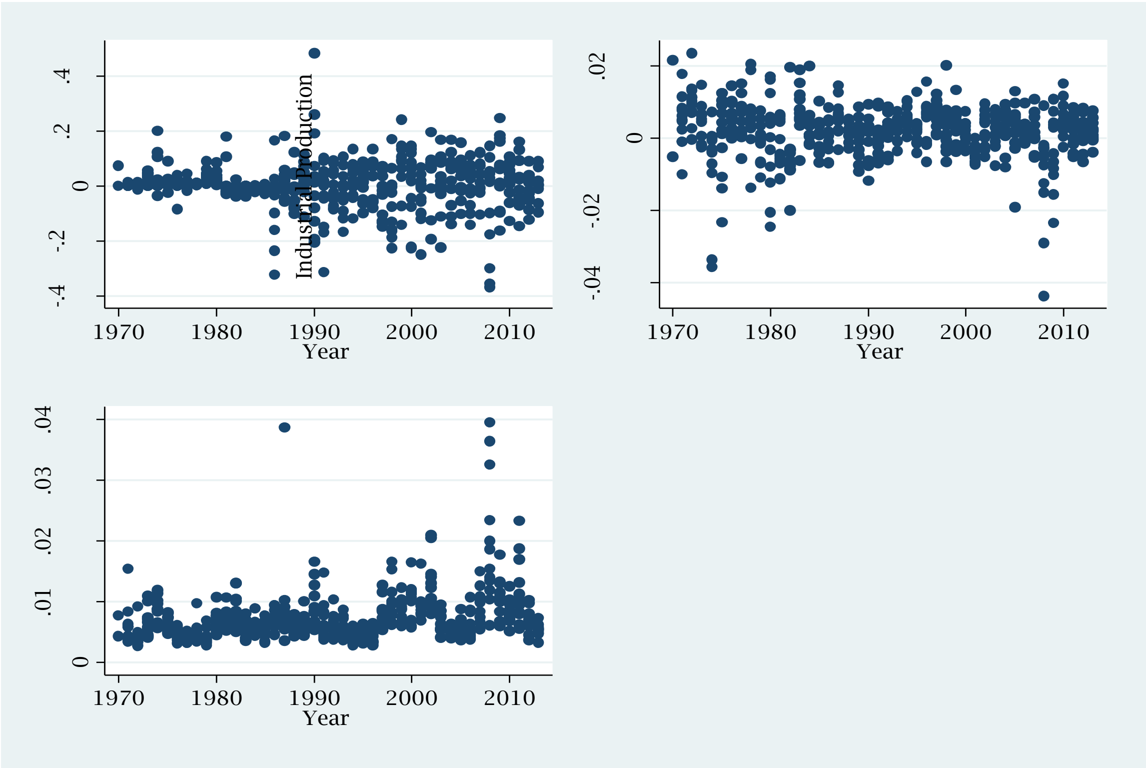
Figure 16 Residual Plot Market State Factor (Autocorrelation)



Note: Figure 14 shows the trend that corresponds to the average monthly entry of the residual after regressing the momentum return on the market state factors (see equation 15) over the study period 1969-2014

13.15 Appendix F15

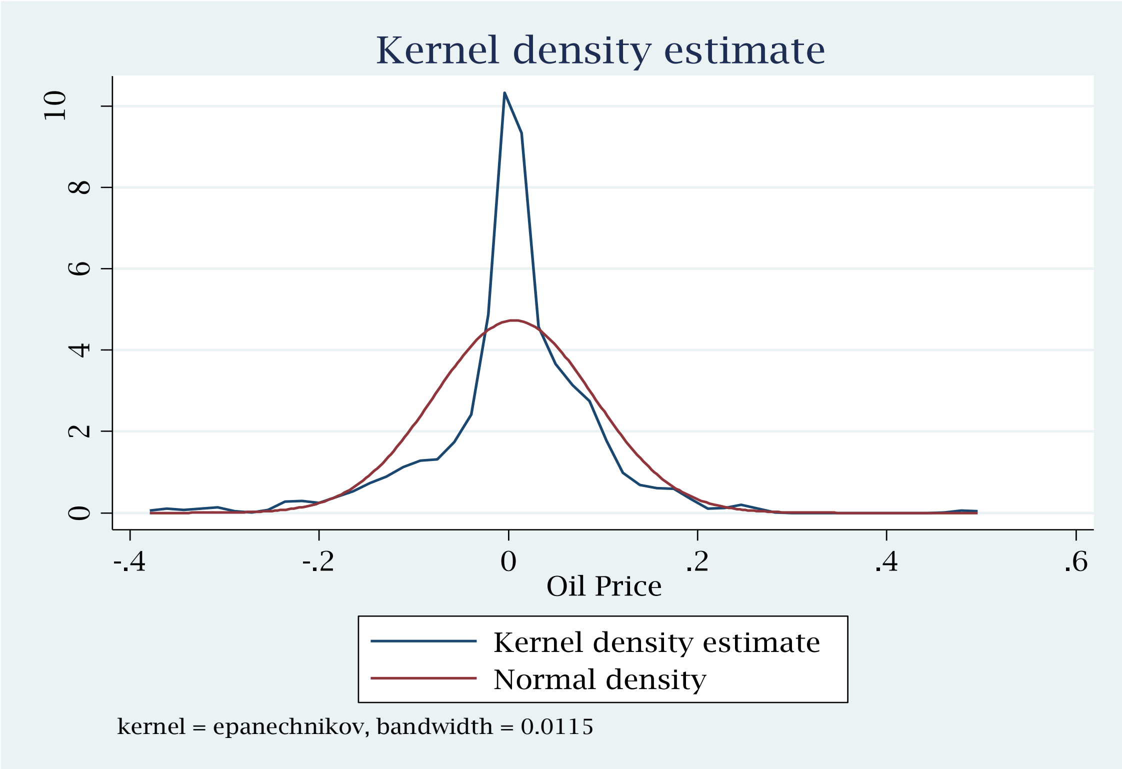
Figure 17 Scatter Plot of Macroeconomic Variables



Note: Each point corresponds to the average monthly entry of each individual macroeconomic variable (Oil price, industrial production, and world market volatility) as in the vertical line over the study period 1969-2014 (horizontal line).

13.16 Appendix F16

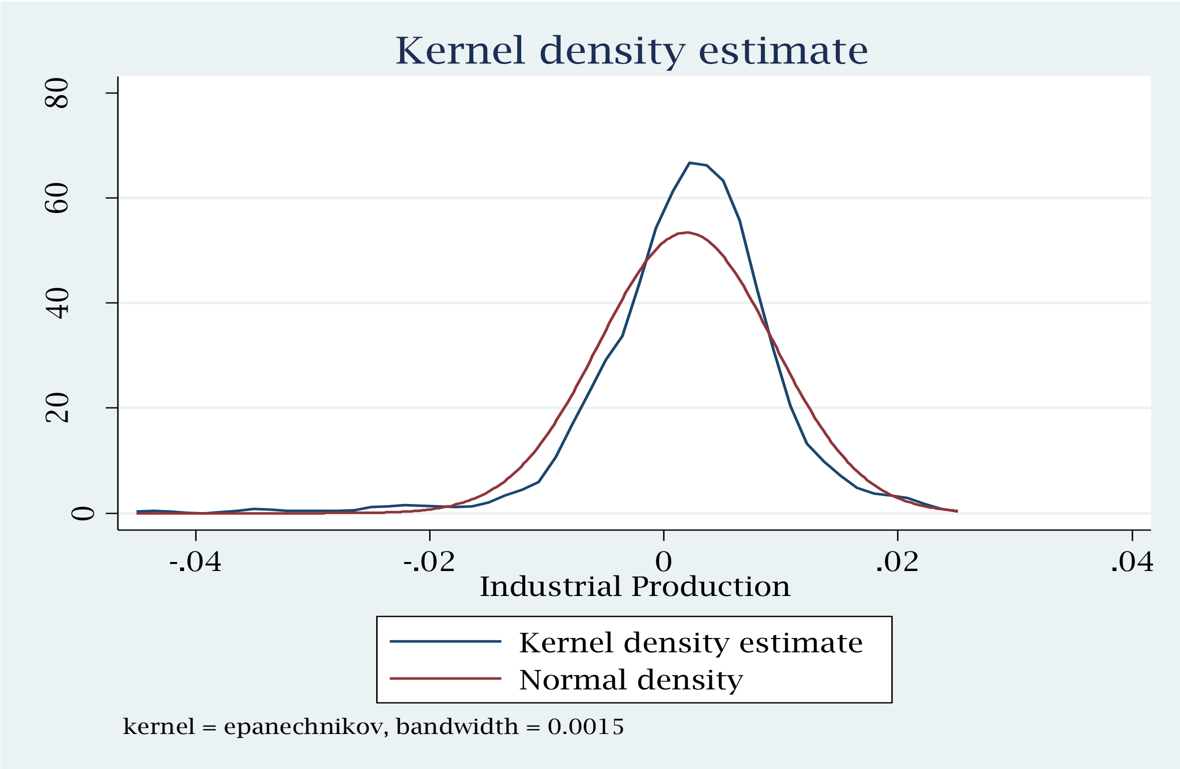
Figure 18 Distribution of Entry of the Historical Values of Oil Price



Note: Kernel density. The dotted line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing percent change in oil price.

13.17 Appendix F17

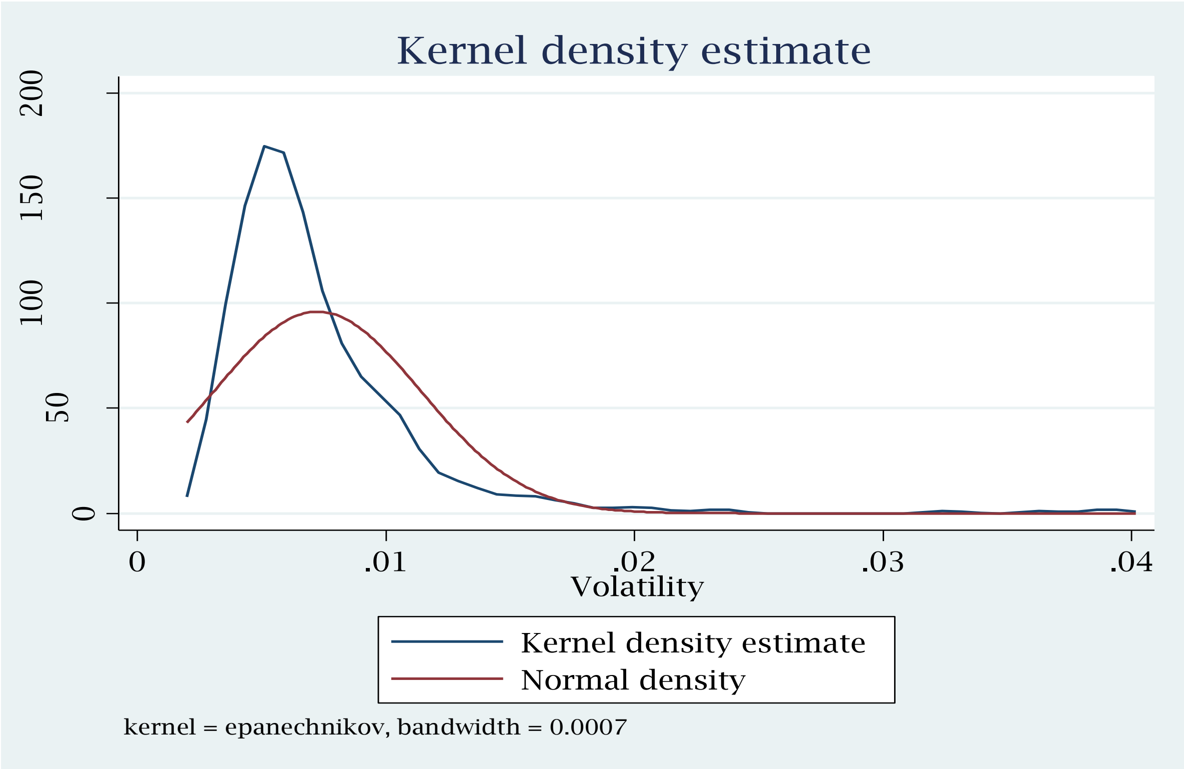
Figure 19 Distribution of Entry of the Historical Value of the Change on Industrial Production



Note: Kernel density. The dotted line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing percent change on industrial production.

13.18 Appendix F18

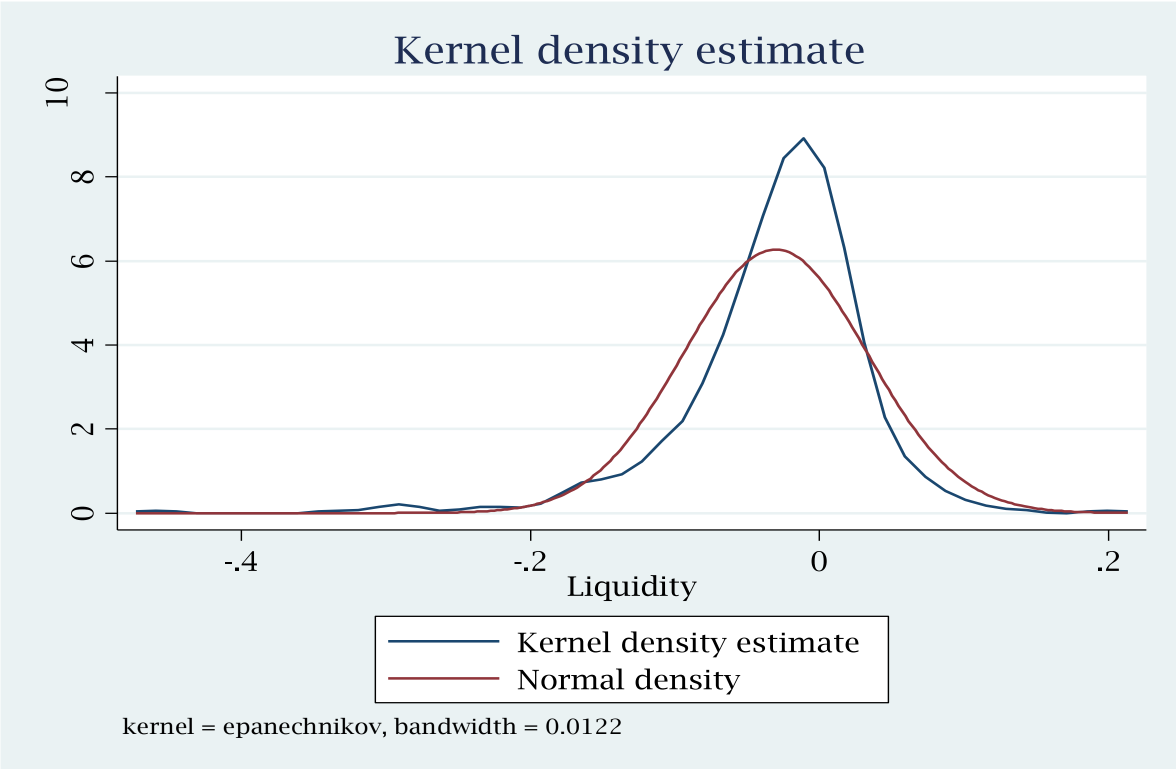
Figure 20 Distribution of Entry of the Historical Value of the Change on World Market Volatility



Note: Kernel density. The dotted line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing change on world market volatility.

13.19 Appendix F19

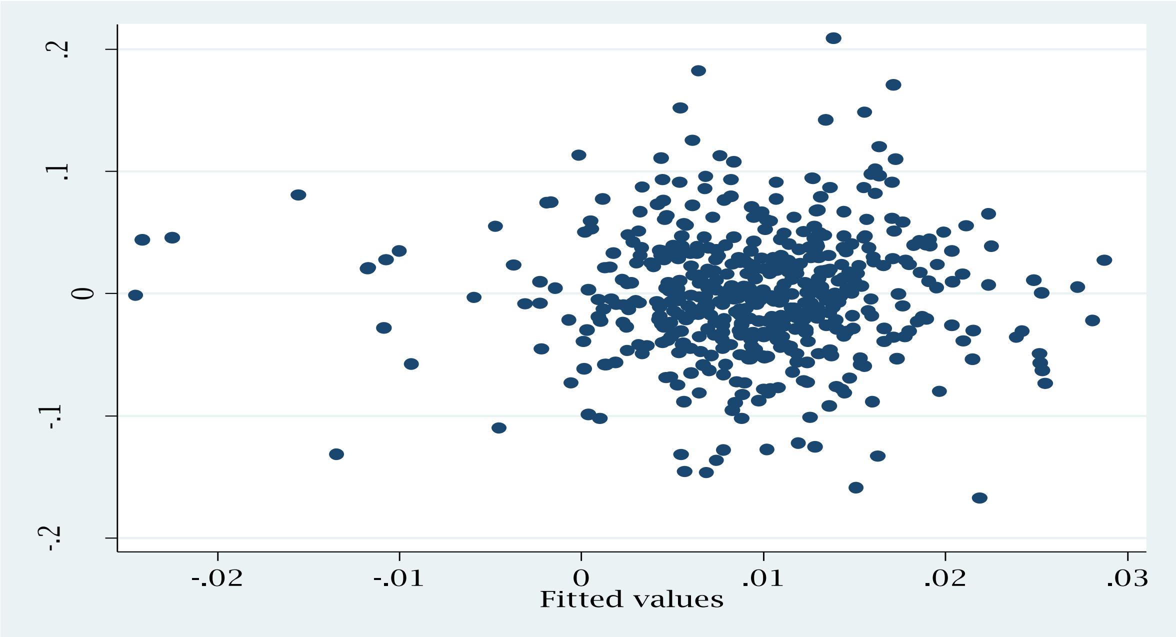
Figure 21 Distribution of Entry of the Historical Value of the Liquidity Factor



Note: Kernel density. The dotted line represents the expected normal density and the black line is the distribution density. Each point corresponds to the monthly entry and existing rate of the liquidity factor.

13.20 Appendix F20

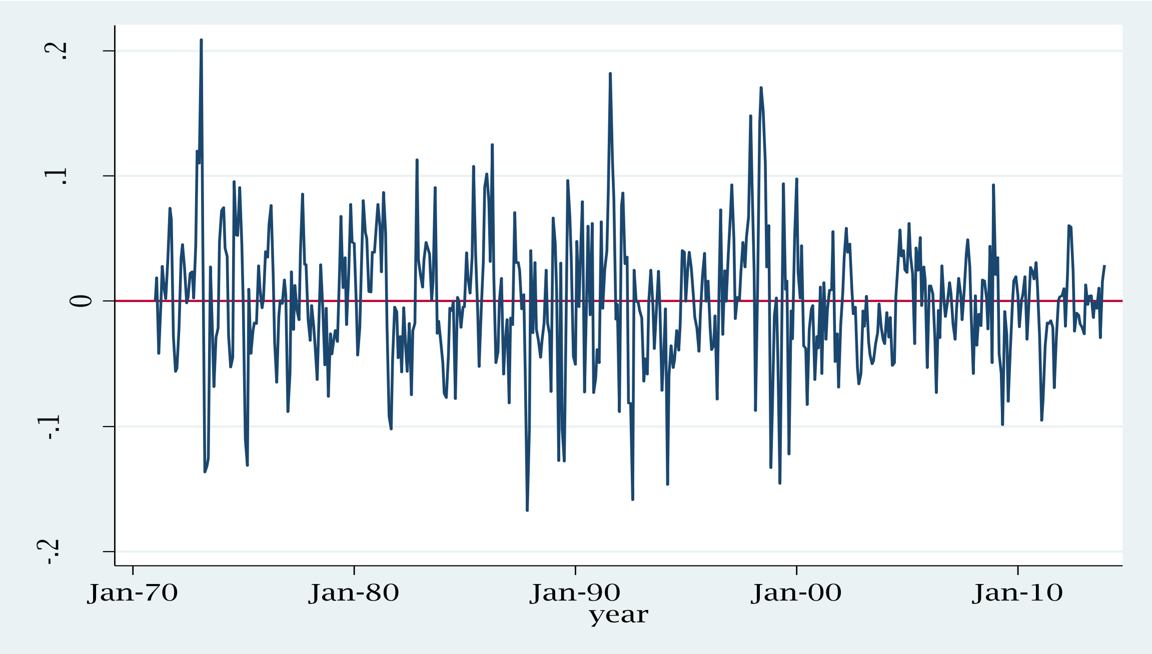
Figure 22 Residual Plot Macroeconomic Variable



Note: Figure 20 indicates the plots of the absolute value of the residual (vertical linee) against the fitted values (horizontal line) after the momentum return regress on the macroeconomic factors over the study period 1969-2014 (please see equation 16)

13.21 Appendix F21

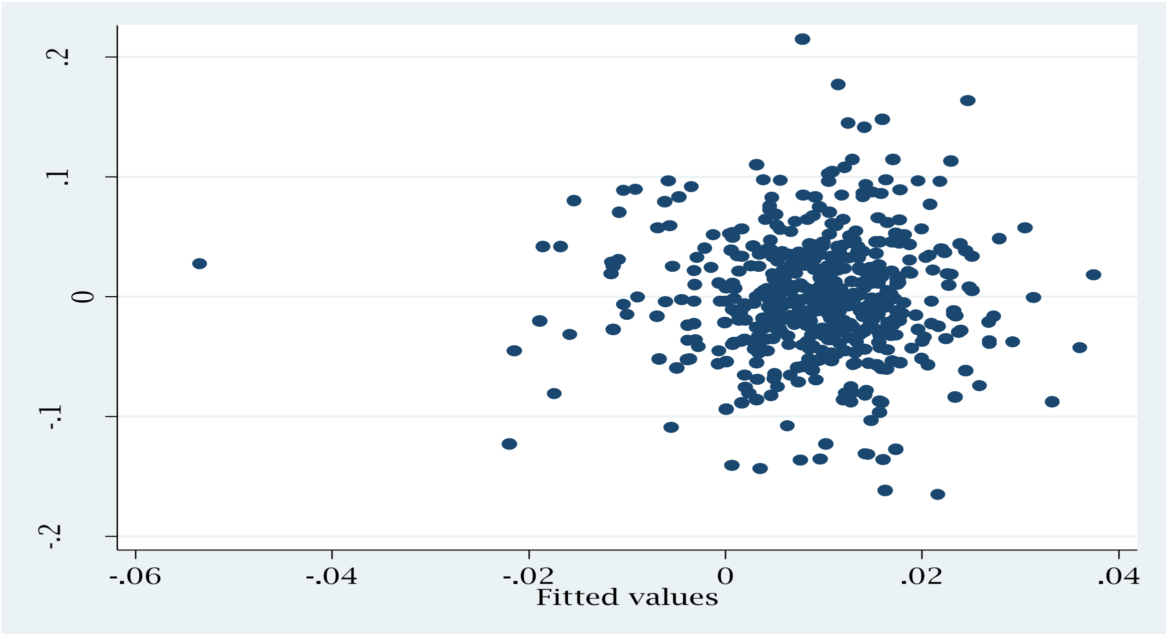
Figure 23 Residual Plot Macroeconomic Variable



Note: Figure 21 shows the trend that corresponds to the average monthly entry of the residual after regressing the momentum return on the market state factors (see equation 16) over the study period 1969-2014

13.22 Appendix F22

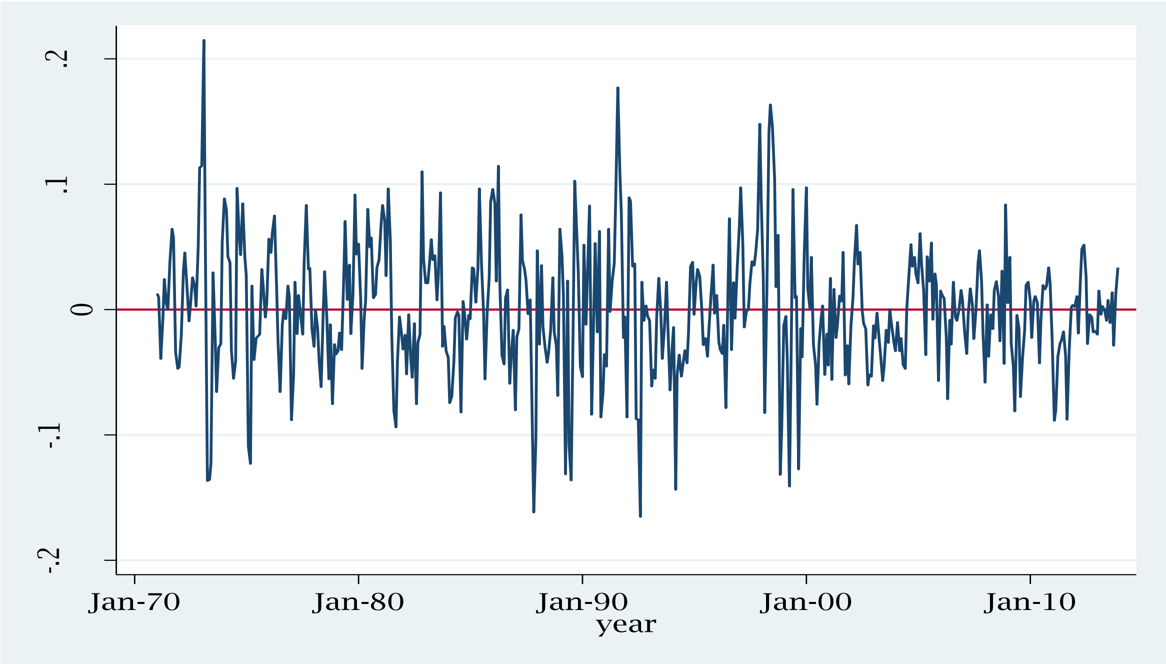
Figure 24 Residual plot Fama and Frech, Market Etate and Economic Variables



Note: Figure 22 indicates the plots of the absolute value of the residual (vertical linee) against the fitted values (horizontal line) after the momentum return regress on the Fama and French, market state and macroeconomic factors over the study period 1969-2014 (please see equation 17)

13.23 Appendix F23

Figure 25 Residual Plot Fama and French risk, Market State and Macroeconomic Variables



Note: Figure 21 shows the trend that corresponds to the average monthly entry of the residual after regressing the momentum return on the Fama and French, market state and macroeconomic factors jointly (see equation 17) over the study period 1969-2014

14 Appendix G

14.1 Appendix G1

Summary Momentum Literature Survey

Date	Author	Contribution	Limitation
1993	**Jegadeesh and Titman**	Strategies generate significant and positive abnormal return between 1965 and 1989 and are profitable for 3 to 12 month holding period. When considering the optimum portfolio of 6-month formation and 6-month holding period, the momentum strategy appears to be consistently profitable and can generate a profit of up to 1% as the winner portfolios keep winning and significantly outperform loser portfolios.	They suggested that this result cannot be explained by systematic risk or delay in stock price reaction to common factors. However, this study was conducted on individual stocks.
1995	**Grinblatt, Titman, and Wermers**	Examined the extent to which mutual funds purchase stocks based on their past returns as well as their tendency to exhibit herding behaviour. They found significant evidences suggesting that large number of mutual funds earned positive risk-adjusted abnormal returns and that 77% of mutual were momentum investors, they tend to buy past winners, but there is little evidence to suggest that these funds systematically sell past losers. They also reiterated that mutual funds that use the momentum strategy tended to perform better than others did and that there is little evidence to suggest that funds tended to buy and sell the same stocks at the same time.	This study is Limited to mutual fund. The paper characteriszes some of the investmentstartegies of mutual funds and anlyse hoe these strategies relate to realized performance.
1998	**Conrad and Kaul**	Studied the momentum strategies in the US NYSE and AMEX stock market with methods similar to Lo and Mackinlay (1990), and Lehmann (1990) from 1926 to 1989. The study decomposed securities' profits into two components, the cross-sectional variation and time-varying components with different formation and holding periods. They tested 120 trading strategies and found that 50% of them generate significant profits, they suggested that, on average both momentum and contrarian strategies were equally profitable respectively at medium-term (3 to 12 months) and short-term (1week to 1 month) and long-term (3 to 5 years) but they made the exception in for 1926-1947 period. They also demonstrated that the success of the momentum and contrarian strategies can also be attributed to the variation in mean returns.	Their results indicated that, event of random walk the momentum and contrarian strategies can still be profitable. This remains to be tested at a global level.
1999	**Moskowitz and Crinblatt**	Studied industries momentum while ranking their data into twenty different industries groups. They found that the momentum strategies do not generate significant profit for individual industry. However, when the strategies buy the winners and sell the losers industries they tend to be significantly profitable. They also found that, in the short term the industry momentum seems to be stronger than the stock momentum and that the momentum profit persists in the medium term but dissipate after 12 months. Furthermore, they suggested that, industries factor have undeniable impact on the momentum strategy profitability.	The paper study the momentum strategies in individual stock, with a focus on individual and randow industries. Their result indicated industry-based strategies is the more profitate. However, the study did not incated how this could be use by international investor.
2001	**Jegadeesh and Titman**	Reviewed the evidence of price earnings momentum and found that there is a substantial evidence to prove that stocks that perform well or badly over a 3 to 12-month period tend to continue to perform well or badly over the next 3 to 12 months. They suggested that the strategies that make use of this type of phenomenon are consistently profitable in the United States and most developed markets. They examined the returns of the winner and loser stocks in the month 13 to 60 and found that, the cumulative returns of momentum portfolio are negative, which is consistent with the behavioural theories. They advocate that there are substantial evidences to confirm that firm's and market characteristics can determine momentum strength but the profit size issue from these factors depend on the extent to which they are incorporated in the firm or the market activities.	The study focus on momentum with individual stocks.

Date	Author	Contribution	Limitation
2004	George and Hung	Adopted a different approach; they studied the momentum strategy with an investment strategy named “52-week high”. The strategy longs the winners and sorts the losers based on their previous month’s prices divided by their past 12 months’ highest price. They found that this strategy could generate higher momentum return compare to the Jegadeesh and Titman (1993) and the Moskowitz and Grinblatt (1999) strategies. After controlling for the size effect, the bid-ask bounce, and exclude the January return they found that the strategy profitability is two times the profit of previous momentum trading strategies, they concluded that, the 52-week high strategy predicts investors’ perception of the Losers and winners.	The paper did examine whether the “52-Week High” could apply to international investor.

		Risk Based Explanation of the Momentum and Contrarian profits	
Date	Author	Contribution	Limitation
2002	Goetzmam and Massa	Found that investors that consistently react to daily price perform at least as well as the factors based on stock market return and that momentum investor flows are more strongly related to returns, which confirms and displays a positive correlation between investment decision of the purchase momentum investors and sales contrarians and the same day return.	Nevertheless, the study was done on two years’ data only, with a restricted number of mutual funds.
2006	Sadka	Decomposes liquidity risk into variable and fixed components and found that the variable component is priced with an annual premium of about 6.5% in the context of momentum and post-earnings announcement, which indicates that liquidity risk, can explain between 40% and 80% of the cross-sectional variation of expected momentum and post-earnings announcement portfolio returns. He suggested that a substantial part of momentum returns can be viewed as compensation for unexpected variations in the aggregate ratio of informed traders to noise traders and the quality of information possessed.	The study did not examine the process by which noise and informed traders make this happens.

Date	Author	Contribution	Limitation
2008	Schumaker and Hsinchun	Suggested that, a strategy using both quantitative strategy and a full set of financial news articles would have a great return. Using one-week portfolio formation they were able to make 20.79 percent return and only 4.54 percent return with the contrarian over five weeks holding period and concluded that and hybrid strategy were more appropriate.	The study did not specify which proportion of each strategies is required for and optimum portfolio of momentum and contrarian strategy.
2008	Roberto et al.	Found a second effect momentum, which, offsets and indeed dominated the reversal after the initial 1-week reversal. They suggested that the longer-run momentum results do not extend to 1-week momentum, that the market's reactions to price movements without public news are not categorically different to price movement with public news, and that uncertainty is not related to momentum in 1-week returns.	A more completed study could provide supporting evidences of the second effect momentum internationally.
2009	Bulkley and Nawosah	Suggested that momentum might be rationale explained as a consequence of the cross-sectional variation of unconditional expected returns. Stocks with relatively high unconditional expected returns will on average outperform in both the portfolio formation and in the subsequent holding period. they evaluate this explanation by first removing unconditional expected returns for each stock from raw returns and then testing for momentum in the resulting series. They measure the unconditional expected return on each stock as its mean return in the whole sample period and find that the momentum effect disappears in demeaned returns.	The study is country specific and based on individual stock.
2010	Asem and Tiam	Investigated the effects of market reversals on momentum profits in accordance with asymmetric momentum profits in the down and the up markets. Their results indicate that, momentum profits are higher for up markets when the market continue to go up than when the market states change. The momentum profit tends to be larger when the market goes down as the mean momentum profit decreases from 2.09% per month when the market continues in UP states and to -0.01% when they transition DOWN. They suggested that these results are consistent with the effect of market transitions on momentum profits.	The study did not consider the momentum strategy as a global cordonated and generalised phenomenon, which could be done following the world market trend instead.
2011	Kelsey, Kozhan and Pang	Examined whether uncertainty is an asymmetry in momentum returns, with a model that includes three types of traders: arbitragers, uncertainty adverse traders and momentum traders, on bonds and stocks. They investigated separately winner and loser momentum returns on firms with different levels of uncertainty and suggested that momentum effect is stronger and more likely to last for losers with a greater level of uncertainty and that asymmetry between negative and positive momentum returns are more profound during the crisis periods.	The study did not examine the cultural on the risk perception. Be cause even in period of some investors in different countries might be more prone to risk or incertainty than others.
2013	Dobrynskaya	Studied the risk-based explanation of the momentum strategies internationally. He showed that the performance of past winners and past losers is asymmetric in states of the global market upturns and downturns, that the winners have higher downside market betas and lower upside market betas or risks than the losers and that the past winners are compensated by higher returns. More importantly while studying the momentum strategy between 1984 and 2013 he found that the global momentum had on average 13 percent per annum and suggested that the profitability of this strategy cannot be explained by the conventional risk measures (standard deviation, skewness or market beta) as they are all similar for the portfolio considered. His study includes additional indexes a year after their appearance but did not report what effect new entries have on the profitability of the global momentum and consequently their impact on they risk-based explanation of the momentum strategy	This paper did not consider the momentum strategy as a global cordonated and generalised phenomenon, which could be done following the world market trend instead.

		Firms Specific Risk Factors	
Date	**Author**	**Contribution**	**Limitation**
1991	Chan, Hamao and Lakonishok	Studied the cross-sectional differences in returns on Japanese stocks relative to Earnings Yield, Size, Book to market ratio, and cash flow yield from 1971 to 1988 and they found a considerable impact of the book to market ratio and cash flow yield on the expected returns in the Japanese market. That high E/P stocks outperform low E/P stocks with a difference of 0.40% per month between the top and the bottom quartiles. Small stocks achieve substantially higher returns than large stocks, with difference of 0.97% per month between the two extreme groups. Firms with large positive book to market ratios earn a premium of 1.10% over firms with low, positive book to market. The difference between the two extreme groups for the cash flow yield variable is 0.79%. They suggested that these results were consistent with the US findings of Jade, Keim, and Westerfield (1989).	Their findings are limited to the Japanese Market.
2002	Chordia and Shivakumar	Studied the importance of common factors and firm-specific information as source of momentum profit they divided the sample period into two economic environments: expansionary and recessionary periods. They examined the payoffs to momentum strategies in each of the environments and demonstrated that the profit on momentum strategies were explained by common macroeconomic variables that were related to the business cycle. The results of their analysis suggested that the momentum strategy payoffs are positive only during the expansionary periods when the marginal utility of returns it is likely to be lower. Even more each of the post war expansionary periods had positive momentum payoffs and the overall momentum payoffs are negative during recession.	A more completed study could examine the performance of the momentum in expansionary and recessionary periods globaly.
2007	Sagi and Seasholes	Tested whether firms' specific attributes predict future expected return, they examined how firms' specific attributes can be used to create "enhanced momentum strategies". They found that momentum strategies that use firms with high revenue growth volatility. Low cost, or valuable growth options outperform traditional momentum strategies by approximately 5% per year.	The study is based on individual stock.
2013	Hirshleifer, Hsu, and Li	Examined the relation between innovative efficiency firm's ability to generate patent and patent citations per dollar of research and development investment, and subsequent operative performance as well as stock returns. They found evidences that some firms' factors and market conditions, which may not be complimentary for the momentum strategies in one period, can be useful in different periods or in different market conditions. The strategies on average remain profitable even though some analysis always fail to validate this argument.	The aggregate effect of firm's ability to generate patent and patent citations per dollar of research and development investment, and subsequent operative performance as well as stock returns. Could have significant impact on the world economy. One might be curious to know how does it affect the global momentum profitability?
2014	Liu and Zhang	Examined whether momentum is connected to economic fundamental, using US stock market data and the neoclassical theory of investment as their fundamental starting point. They matched average livered investment returns to average stock returns across momentum portfolios, they found that for price momentum, the winner-minus-loser deciles has a small error (alpha) of 0.30% per month, which is only 2.65% of the average winner-minus-loser return of 1.26%. In addition, the mean absolute error across the deciles is 0.07%, which is 6.69% of the average deciles return of 1.03%. For earning momentum, the winner-minus loser decile has an alpha of -0.076%, which is 10.86 % of the average winner-minus-loser return of 0.705%. The mean absolute error across the deciles is 0.052%, which is only 4.12% of the average deciles return of 1.271%. The expected investment-to-capital growth is the most important component of momentum. Even more, they found that prices momentum starts at 1.665% per month in the first month after portfolio formation, fall to 1.095% in month six, converge to zero in month ten, and turn negative afterward. They suggested that managers align investment policies properly with the cost of capital, and that momentum might be consistent with this alignment, as their result did not prove rationality.	This paper did not explain the rationality behind manager's action with regard to alignment of investment policies. The might be internal or external factor that motivate manager's behaviour.

		Seasonality Effect	
Date	**Author**	**Contribution**	**Limitation**
2003	Oknev and White	Studied the profitability of the momentum strategies in foreign exchange markets and found that during the seventies and eighties the momentum strategies were highly profitable and continue throughout the nineties. They suggested that the momentum profits are not due to compensation for bearing time varying risk premium.	The study did not take into consideration the how change in market conditions could affect the size of the return on foreign exchange markets.
2004	Grinblatt and Moskowiz	Tax, avoidance behaviour drives much of the relation between past returns and expected returns in December and January while using a parsimonious stock ranking system derived from simple Fama-MacBeth cross-sectional regressions in their analysis. They claimed that seasonality is associated with past returns, and that when effective capital gains tax rates are expected to decrease the contrarian strategies become relatively less profitable. Similarly, when expected tax-code changes favour capital loss deferral, the opposite occurs. In such case, contrarian strategies become more profitable.	The test was conducted on the US stocks only while the tax system differs from one country to another.
2005	Shen, Szakmary and Sharma	Suggested that, the profitability of the momentum strategy generated in the short term tends to continue after December 1987. Nevertheless, after further analysis of the momentum phenomenon in the international market they found that there was no evidence to suggest that the profitability of the contrarian strategies persist in the long term.	The study contructed the momentum strategy with individual stock and did not examine the momentum as a global strategy.
2005	Levy and Post	Pointed out that there are practical considerations that reduce the likelihood of successful momentum strategies. First, the momentum strategies are likely to require high turnover of shareholdings with the effect that transaction cost are high. Second, the momentum effect is strong among small capitalisation stocks. Small capitalisation stocks tend to be illiquid, which makes high turnover impossible. Third, most of the return available from momentum strategies comes from taking short positions in poorly performing share.	Some of the featuere find in this study could test at a regional or global level, example, one could test if the global momentum strategy could be explained by illiquidity and trade volume
2006	Cooper, McConnell, and Ovtchinnikow	Tested whether, stock market returns in January are good predictors of returns over the next 11 months, whether it is reflection of investor sentiment. They claimed that the other January effect is not explained by investors' sentiment and that stock returns are surprisingly robust predictors of the market returns over the following 11 months. Given, that when the Centre for Research in Security Prices (CRSP) value-weighted Market returns (VW) in January is positive, the VW market return over the next 11 months' average is 14.8%. When the VW market return in January is negative, the VW market return over the next 11 months' averages is 2.92% and that the result cannot be explained by the presidential cycle in stock returns.	It is defficult to draw a conclusion with their, for example the January effect might explanation other investment sentiment, one might arguu that it is due to tax avoidance.

Date	Author	Contribution	Limitation
2009	Asness et al.	Studied the profitability of the momentum strategies across eight diverse market and asset classes and found that the momentum profits were consistent across asset classes. They suggested that common global risk characterized with a three-factor model could explain the momentum profit, and that global funding liquidity risk is a partial source of these patterns. They claimed that these findings present a challenge to existing behavioural and rational asset pricing theories that largely focus on US equities.	The channenge is that 8 countries individually are less like to represent the whole world, further study across region might provide different results.
2010	Gupta, Locke, and Scrimgeour	Investigated whether the industrial momentum and 52- week high momentum returns are superior to conventional momentum returns as claimed by Moskowiz and Grinblatt (1999), George, and Hwang (2004) and whether these returns are consistent under different approaches on a global basis. They found that for the industry momentum the highest profitability is observed in the Indian stock market with average monthly return of 0.60% above market. The return in the US market is comparatively lower, vis-à-vis other markets, but still profitable with a market excess return of 0.32% compared to 0.43% in the US stock market as suggested by Moskowitz and Grinblatt (1999). Those returns are negative for all countries except Japan, suggesting a reversal pattern in the loser portfolio. Both the industry and 52-week high strategies generate positive returns but neither is greater than the conventional momentum strategy as the traditional momentum strategy using three portfolio and value-weighted CAR approach is 0.58% compared to 38% for the 52-week high momentum.	This paper maintly focus on individual countries and industries, while the world is in the process of globalisation.
2011	Lui et al.	Studied the 52-week high momentum strategy in 20 major stock markets and found that the 52-week high momentum effect is robust in international markets. then out of twenty markets present evidence of a profitable 52-week high with ten having significantly positive profits. They also showed from the portfolio of cross-sectional regression analyses that the George and Hwang (2004) industry momentum effect is weaker after controlling for the 52-week high momentum effect. However, they also demonstrated that although the returns of these momentum strategies are highly correlated, the George and Hwang (2004) conditional momentum profits still exist.	The study do not say whether the momentum profit remains following the same pattern with risk factors.
2012	Menkhoff	Investigated the momentum strategies in foreign exchange market from January 1976 to January 2010. Compared to the stock market, the foreign exchange markets are more liquid and feature high transaction volumes and low transaction cost, they are populated with very large number of sophisticated professional investors, and there are no natural short-selling constraints that prevent the shorting of past loser assets to fully implement momentum strategies. The study's main contribution was to examine the economic anatomy of the momentum profits in the foreign exchange market. They started by forming currency portfolios where an investor is long in currencies with high past excess returns or winners short in currencies with low past excess returns or losers, they then considered the exchange rate in dollar. They found that these strategies yield high unconditional average excess returns of up to 10% per year, in contrast to explanation based on systematic risk. They also found evidence for under and overreaction in long-horizon momentum returns. They suggested that, cross-sectional currency momentum has very different properties from the widelystudied carry trade and is not highly correlated with returns of benchmark technical trading rules; however, there seems to be very effective limits to arbitrage that prevent momentum strategies from being easily exploitable in currency markets. As in Jegadeesh and Titman (2001), they found some evidence of return continuation and subsequent reversals over longer horizons of up to 36 months which is consistent with the under- and the overreaction hypothesis. They suggested that momentum effect in different asset classes might share a common source.	The paper did not examine if the origine of these sources have cross-sectional difference, in which case momentum might not be profitable in all place at the same time and momentum investors could take advantage of the time difference.

		Momentum in the Bond Market	
Date	**Author**	**Contribution**	**Limitation**
2005	Gebhart	Examined the relation between momentum in equities and corporate bonds. They claimed that, there is no evidence of momentum among investment grade corporate bonds. Instead, they suggested that corporate bonds under-react to information in past equity prices about changing default risk and indicated a significant reversal as winner's bonds over a three to twelve-month period underperform bonds that are losers over the same period by about 1% over the subsequent 12 months. Furthermore, the reversals appear to be the strongest among the riskiest bonds. They also found that there is a significant momentum spill over from equities to bond of the same firm. Firms earning high or low equity returns over the previous 3 to 12 months earn high or low bond returns over the next 3 to 12 months. Bonds of winners' portfolios outperform bonds of loser portfolios by approximately 1% over the following 12 months. However, this thesis examines the return base on month-end bid prices instead of the transaction prices.	The study found that there is a significant momentum spill over from equities to bond of the same firm. This can also be tested international to if there is disparities among countries.

		Momentum Strategies International Evidence	
Date	**Author**	**Contribution**	**Limitation**
1998	Rouswenhorst	He examined 12 European countries with an international portfolio that include The United Kingdom, the Switzerland, Sweden, Spain, Norway, The Netherlands, Italy, Germany, France, Denmark, Belgium, and Austria from 1980 to 1995 and found similar pattern. He found that the momentum strategies are as well as profitable in Europe as in United States, that the past winners outperformed the past losers by about 1% per month in the medium term and that the return continuation is present in all the countries after considering the firms' sizes.	However, the study did not examine whether international investors could take advantage of the momentum strategies in both market.
1999	Schireck et al.	Studied all major companies listed on the FSE from 1961 to 1991 and found that the momentum and contrarian strategies appeared to beat a passive approach that invested in the market index. They suggested that factors such as beta, risk, or firm size do not easily account for the results because several strategies require limited trading, that the implementation costs are modest which implies that the results are economically meaningful. From the behavioural finance point of view, they found that the results for Germany matched the findings for the United States even though equity markets are organized very differently and even though there are profound differences in the social, cultural, and economic environment. They pointed out the fact that general traits in human behaviour and psychology could overcome these differences and ultimately drive the speculative dynamics of asset prices in the world financial markets.	However, they did not explore other market as the US and the German are all developed market and may have similar economical characteristics.

Date	Author	Contribution	Limitation
1999	Fung	Studied the contrarian strategy in the Hong Kong's Heng Sang Index (HSI) while using winners and losers' portfolios formation period of 2 years. He found that, the loser portfolio significantly outperforms the winner portfolios by almost 10% a year. Which is significantly different from the approximately 8% reported by De Bondt and Thaler (1985) in the US equity market. However, the study reported different characteristics for the Hong Kong market, which include his difference in stock market capitalisation, high liquidity, the presence of a legal system and an accounting system, his similarity to the western standard, the dominance of mutual funds. Furthermore, Hong Kong market is also characterised by the fact that in most studies (the up-tick rule for short-selling was abolish after 25 March 1996 in Hong Kong), selling some of the winner portfolios may be difficult if not impossible.	However, the study did not explain how international investors could take advantage of these characteristics while moving his momentum portfolio between the Hong Kong markets and other markets to consistently profit from the global momentum and contrarian strategy.
2000	Chan et al.	Studied the profitability of the momentum strategies internationally the formed momentum portfolios based on past stocks' returns of individual stock market indices successively and examined whether theses strategies are useful for country selection. They examine how the profitability of international momentum sytraties is affected by exchange rate movement. Considering a US investor who implements momentum strategy that involves buying british stocks when the value of British stocks increase (in terms of U.S dollars). They found that the value of investor portfolio depends on how the equity and currency market affect each other. For example, if British pounds tends to appreciate following arise in the british equity market, the U.S. investor profits when he liquidates the british stock portfolio and convert to U.S. dollars. Similarly, if the value of British stocks tends to increase following british pound appreciation, the U.S. investor also profits. In both case, they suggested that the momentum profits do not come from return continuation in the equity market but from the interdependence between the currency and equity market. They also emphasised the link between momentum profit and trading volume and suggested that significant portion of the profit come from emerging markets as emerging markets are more predictable given the low liquidity.	The study was conducted with individual stocks, a global momentum could also be tested using countries indices. And the risk based explanation of the profit could refer to global risk factor
2002	Hameed and Kusnadi	Investigated the profitability of the momentum investment strategy in six Asian stock markets (Thailand, Taiwan, Korea, Singapore, Malaysia and Hong). They found that the momentum investment strategies do not yield significant momentum profits. They suggested that a diversified country-neutral strategy generates small but statistically significant returns of 0.37% per month over six month holding period and between 1981 and 1994 but after controlling for size and turnover they found that the country neutral profit dissipates. They concluded that factors that contribute to momentum phenomenon in the United State are not widespread in the Asian markets and that countries specifics characteristics effect are diversifiable internationally.	However, the study was limited to Asian stock market and did not include the contribution of other markets, as the momentum tends to be profitable in western countries as well as in countries with low liquidity.

Date	Author	Contribution	Limitation
2002	Liu and Ni	Studied the stock-return behaviour in the Chinese stock market. They found that short-term contrarian and intermediate-term momentum generate significant profits. After further analysis the suggested, that overreaction to firm-specifics information is the single source of short-term contrarian profits that, momentum profits are not distinct in the medium term, which is explained by the dominance of overreaction effect. They also reported that negative cross-serial correlation contributes to the momentum profits that large firms tend to lead small firms in holding periods 1 to 8 weeks, while the small firms lead large firms in the holding periods 12 to 26 weeks. They reported that with value-weighted portfolio strategies, the momentum profits become more distinct because of the unique lead-lag structure in China as the large firms lead the small firms in short horizon while the small firms lead the large firms in relatively longer horizon.	However, the study used the "A" shares, which are only accessible to local investors in China and did not said if the unique lead-lag effect can be seen as a sign to predict future momentum and contrarian profit.
2003	Hurn and Pavlov	Examined the momentum strategies in the Australian market, they analysed 200 stocks as the small were characterised by low liquidity issues; they established the existence of short to medium-term momentum. They found that momentum strategies yield significant profit of about 4.79% to 13% for the yearly holding period and they suggested that the result are even stronger for portfolio based within individual industries.	They advocated that these figures were consistent with the momentum in stock returns reported in international markets and that the contrarian strategy does not provide significant abnormal return over the same time-period but the result was only applicable on the Australian markets, as it does not give any indication of the worldwide momentum profitability.
2003	Former and Marhuenda	found sign of momentum and contrarian effects in the Spanish stock market. They concluded that momentum strategies could be profitable on the 12-month basis and that contrarian strategies offered profitable opportunities over 60-month periods but their analysis was restricted to the Spanish market and did not explore the global perspective.Momentum and contrarian strategies seem to be more effective where the degree of the market sensitivity is considered, Narajo and Porter (2010) studied the sources of cross-country co-movement of momentum returns across developed and emerging markets. They found that country-neutral momentum returns are significantly correlated across countries, the correlation is time varying and that co-movement among industries cannot explain the co-movement of country-neutral momentum returns	but the study did not explain how international investor could take advantage of the country-neutral momentum returns correlation effect.
2004	Griffin et al.	Extended jegadeesh and Titman (1993), Chan et al. (1996) study in the U.S in a global setting in 40 market for price momentum and 34 for earning momentum by analysing several key issues: the separated the long-side positions from the short-side positions; the interaction between price earnings momentum, the relation between individual countries nonentum strategies across markets; and momentum's sensitivity to global market condition, extreme events, and seasonolity. They Provided practical perspective for price and earnings momentum investing from 1975 to February 1995 in individual countries stock market internationally. They found that, momentum is potentially useful even for investors who are only able to take long positions. They also suggested that, ignoring transactions cost, an investor investing 1$ in European securities in 1975 would have earned $15.06 in low past 6-month return securities, as compared to $66.01 in market indices, or $192.66 in high past return securities as price and earnings momentum profits are large and positive on a global basis.	However, Griffin et al.'s (2004) portfolio construction follows Chan et al. (1996) approach and is based on the performance of individual stocks within countries indices. And do not claim to test a global strategy nor considering the momentum as a global coordinate and generalize phenomenon. They attempt to show that price and earnings momentum profits are large and positive on a global basis result in countries comparison. Still, they did not explain why these return differences occur during this period and if they are consistent over time.

Date	Author	Contribution	Limitation
2005	Gebhart	Examined the relation between momentum in equities and corporate bonds. They claimed that, there is no evidence of momentum among investment grade corporate bonds. Instead, they suggested that corporate bonds under-react to information in past equity prices about changing default risk and indicated a significant reversal as winner's bonds over a three to twelve-month period underperform bonds that are losers over the same period by about 1% over the subsequent 12 months. Furthermore, the reversals appear to be the strongest among the riskiest bonds. They also found that there is a significant momentum spill over from equities to bond of the same firm. Firms earning high or low equity returns over the previous 3 to 12 months earn high or low bond returns over the next 3 to 12 months. Bonds of winners' portfolios outperform bonds of loser portfolios by approximately 1% over the following 12 months.	However, this thesis examines the return base on month-end bid prices instead of the transaction prices.
2008	Mclnish et al.	Studied the sort-term momentum strategies in Asian pacific countries while taking into account the effects of trading activity, size/value characteristics, and asymmetric investor responses to news on stock market in Singapore, Thailand, Malaysia, Hong Kong, Korea, Taiwan, and Japan from 1990 to 2000. They provided evidences of trading strategies based on past price performance for 1, 2 and 4 weeks. They suggested that, trading strategies based on past price patterns are not effectively profitable in most pacific Basin markets and that trading strategies, that combining both winners and losers are not consistently profitable over a week, that in 5 out of seven countries, winners display price reversal patterns.However, they found that momentum profits are profitable only in Japan and Hong Kong. For the Japanese market, the results indicate that the winner stocks earn significant returns after adjusting for three-factor risk (0.30% per week for the traded stocks and 0.20% for the low volume). Which, are statistically significant and which contradict the findings of Lee and Swaminathan (2000) in United State that suggested that past volume helps to reconcile intermediate-horizon under-reaction and long-horizon overreaction effects.	he study did not test whether by combining momentum and contrarian, international investors will be able to generate consistent profit in Asian pacific countries and therefore worldwide.
2008	Naughton	Examined the momentum and strategies in Shanghai Stock Exchange, while considering the effect of trading volume in portfolio formation. They used different formation and holding periods; they discovered that momentum strategy can be profitable in the short-term and can provide long horizon positive returns in the Shanghai stock market between 1995 and 2005. They suggested that, investors could generate superior returns by investing in strategies unrelated to market movements. The same past trading volume does not provide a strong link between momentum and value strategies, as they did not find any clear pattern in stock returns between high volume portfolio and low volume portfolios.	However, they recorded that around earning announcement the momentum strategies earn high short-term returns but did not explain if this is linked to the country characteristics.
2010	Griffin et al.	investigated the common perception that emerging equity markets are widely thought to be places of substantial trading profits and weak- and semi-strong-form market inefficiencies when compared to developed markets. They examined the short-term reversal, and momentum strategies, and found that short-term reversal, and momentum strategies earn similar returns in emerging and developed markets.	The study did not establish when and while the momentum and contrarian strategies alter in these markets and whether there are similitude and divergence in the momentum and reversal behaviour in both market.

Date	Author	Contribution	Limitation
2015	Avramov et al.	Examined the role of liquidity for arbitrage, they examine the systematic relation between variation in market liquidity and the strength of the momentum anomaly. They found that the effect goes in the opposite direction. The evidence is that momentum profits are large (weak) when the market are highly liquid (illiquid). One standard deviation increase in aggregate maret illiquidity reduces the momentum profits by 0.87 per month, over the 1928-2011 period. To examine the predictive role of market illiquididity in explaining temporal variation in momentum payoffs the consider a time-series regression were the predictive variable include three aggregate measure of market condition in the prior month. This include the level of market illiquidity, the state of market return, the aggregate market volatility, the also include the Fama-French three factors and hey found that there is an identical predictive effect of the lagged market state variable on the profitability of the momentum strategy. Earning momentum payoffs are significantly lower following periods of low market liquidity, reducing market valuation, reducing market valuations and high market volatility. Their findings on the predictive effect of market illiquidity on momentum payoffs remains unchanged when they control for various measures of the macroeconomy. The liquidity is also robust to, and partially subsumes the recent evidence that momentum payoffs depend on enter-temporal variation in investor sentiment, as documented by stambaugh et al. (2012). When they extend the analysis to non-U.S. such Japan and ten countries establishing the Eurozone, they found similar evidence of significant time-variation in momentum payoffs in relation to market illiquidity.	The study was conducted with individual stocks, a global momentum could also be tested using countries indices. And the risk based explanation of the profit could refer to global risk factor
2016	Narayan and Phan	Examined the profitability of the momentum strategies in Islamic stocks. They controlled for stock characteristics, the state of the market, and the seasonal patterns and found that momentum strategies work for Islamic stocks, but are characteristic-dependent. They show that up and down phases of the market offer different degree of profitability and the risks factors do explain momentum profits.	The study was limited to Islamic stocks and specific countries and most Islamic countries have different regard to interest on capital investment, indicating that there might be some sort of cultural bias.

		Momentum Trading Strategies during Financial Crisis	
1999	Choe et al.	Tested whether foreign investors' activities affect stock return in Korea from November 30, 1996 to the end of 1997, period that match with the Asian crisis they used order and trade data and found that there are strong evidences of positive feedback trading and herding by foreign investors before the period of Korea's economic crisis. They recorded that, during the crisis period, herding falls and positive feedback trading by foreign investors mostly disappears. They suggested that, there were no evidence of destabilizing effect of the foreign investors on the Korea stock market over their study period as the market adjusted quickly and efficiently to large sales by foreign investors. These sales were not followed by negative abnormal returns.	but the study did not extend this analysis to other equity market, to show whether adjustment process and speed is consistent across markets worldwide or it is just a feature of the Korean market.
2003	Otchere and Chan	Txamined the overreaction phenomenon in the Hong Kong market from March 1996 to June 1998, which included the pre- and the post-Asian financial crisis and found that Hong Kong market overreacted to information prior to the Asian financial crisis period. They found that the overreaction tends to be more evident for winners than the losers. They also found evidence of the overreaction in the pre-financial crisis period but reported that abnormal return obtained by exploiting such phenomenon are economical insignificant after considering transaction cost. However, they indicated that after accounting for size effect, and the day-of-week effect, the results appear to be very significant. They advocated that the Chinese culture may have significant impact on investors' view of the market, as they tend to perceive risks differently and are less risk adverse and less likely to overreact.	This study did not show how this particular feature of the Chinese market could help international momentum and contrarian investors in global portfolio allocation.
2007	Muga and Santania	Examined the characteristics of the momentum effect in the Spanish stock market, with particular emphasis on the time stability aspect. The results reveal that there was not significant momentum during the 1990's that did not prove to be time-stable, since it had begun to fade by September 1997 coinciding with the pick of the stock market crisis. The momentum has been associated with small-size/ high-turnover stocks. The relation with size appears to be consistent with slow diffusion of information, as suggested by Hong et al. (2000).	These analyses could be extended to other markets worldwide.
2012	Chen et al.	Studied the momentum and the contrarian trading strategies in the Chinese stock market from 1995 to 2010. They examined the performance of the trading strategies following different markets states and found that contrarian strategies are more profitable down market, especially after 2007 during the economic downturn. They suggested that market conditions are good predictors of the size of the contrarian profit. They also found that no significant profit is generated from both strategies in the medium term, they reiterated that, for practitioners and investors in general, these results provide good forecasting indicator especially during the post-crisis period. After consideration of the microstructure effect on the one to two-month formation and holding periods they found that the contrarian strategies generate on average 0.2% per week and even greater in `up' market.	However, the study indicated that these results might not apply in developed markets.

14.2 Appendix G2

Contrarian Literature Survey

		Contrarian Trading and Profitability	
Date	**Author**	**Contribution**	**Limitation**
1964	Keynes	He suggested that the day-to-day fluctuations in the profits of existing investments is obviously transitory and non-significant character, and tends to have an altogether excessive, and even an absurd, influence on the market	the main principle is to go contrary to the general opinion. If everyone agreed about its merit, the investment is to dear and therefore become unattractive.
1981	Shiller	Investigated the excess volatility issue; he revised the Miller-Modigliani view of the stock prices and defined it as a constraint on the likelihood function of a price-dividend sample. He suggested that, at least over the last century, dividends simply do not vary enough to justify observed aggregate price movements.	He results remain strongly conclusive and serve as a benchmark for many more research on return reversal
1981	Kleidon	Found that stock price movements are strongly correlated with the following year's earnings changes he suggested a clear pattern of overreaction in spite of the observed trendiness of dividends, and reiterated that investors tend to attach disproportionate importance to short-run economic developments.	With regard the overreaction to the averreaction hypothesis this study was conclusive. But might need empirical test international.
1982	Kahneman	Suggested that in revising their beliefs, individuals tend to overweight recent information and underweight prior information. People seem to make predictions according to simple matching rule such as the predicted value is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impressions. This rule-of-thumb was named the representativeness heuristic, as it violates the basic statistical principal that the extremeness of predictions should be moderated given the concept of predictability.	overweighting recent information and underweighting prior information go against the overreaction hypotheisis because in overreaction investor do not statistically weigth in any information but instinctively overreact to new information.
1982	Arrow	Suggested that the work of Kahneman and Tversky materializes the accurate excessive reaction of investors to current information which is characterized in all the securities and future markets. Two specific examples of the research to which Arrow (1982) was referring are the excess volatility of security prices and the price earnings ratio anomaly.	He findings appear to be conclusive folling empirical research on excess volatility.
1982	Dreman	An alternative behavioural explanation for the anomaly based on investor overreaction is what Basu called the "price-ratio" hypothesis. Companies with very low P/E are thought to be temporarily "undervalued" because investors become excessive pessimistic after a series of bad earnings reports or other bad news. Once future earnings turn out to be better than the unreasonably forecasts, the price adjusts. Inversely companies with very high P/E are thought to be "overvalued," before falling in price	Conclusive, but the study focus on individual country only.
1985	De Bondt and Thaler	Study was undertaken to investigate the possibility that both market behaviour and the psychology of individual decision making are related by more than just appearance while referring to investor’s overreaction, which, is the hub of contrarian strategies.They suggested that, the term overreaction carries an implicit comparison to some degree of reaction that is considered appropriate. They attributed the appropriate reaction to one of which has a well-established norm of probability revision problems for which Bayes' rule prescribes the correct reaction to new information of how individuals actually respond to new data while referring to Kahneman et al., (1982) findings.	The study was conducted with individual stocks, the overreaction hypothesis could also be tested at a global level with countries indices.

Date	Author	Contribution	Limitation
1988	Dreman	suggested that the gentlest peer pressure could lead us to bad decision, even when the facts are straightforward and easy to distinguish. When the reality is complex and the situation is hard to read, "Social reality" the consensus of the group, no matter how unbelievable, can take a grip on the mind, and turn strong, rational, independent people into sheep. The psychological findings on group peer behaviour provide only a part of the answer. Investors, even professionals, are victim of important logical psychological failings. These psychological pressures affect decisions under conditions of uncertainty in a very predictable manner in the market place. The bottom line is that these powerful forces lead most people to make the same mistakes repeatedly. Understanding them is the best protection against flying with the crowd, and perhaps profiting from their mistakes instead. Dreman suggested that despite what many economist and financial theorists assume that, people are not good intuitive statisticians, particularly under difficult conditions. They do not calculate likelihood properly when making investment decisions, which, causes consistent errors.	It remains to understand why such mistakes occur so frequently. Once their nature is understood, a study can then explain how the contrarian strategies are anchored upon these intuitive statistical limitations.
1982	Kahneman and Tversky	suggested the most common of the cognitive biases call the "representativeness". They show that it is a natural human tendency to draw analogies and see identical situations where none exists. In the market, this means labelling two market environments, as the same when the actual resemblance is superficial. When people are providing with a little information and they tend to pull out a picture they are familiars with, though it may only remotely represent the current situation.	
1998	Dreman	recorded that in five trading days the Dow fell 742 points, culminating with 508 points decline on Black Monday, October 19. This wiped out almost $1 trillion of value, and many investors taking this heuristically shortcut cowered in cash, were caught up in the false parallel between 1987 and 1929. In recounting how often crashes occurred, Victor Niederhoffer, noted that after the panic of 1837 "Prices dropped to zero." he reiterated that the panic of 1857 was much more severe, but do not say whether in the latter panic sellers actually had to pay buyers to carry away their stocks or bonds. So crash and depression were not identical.Dreman (1998) established that, most buyers of hot IPOs in the 1980s and 1990s focused on the individual story and forgot that over 80% of these issues had dropped in price after the 1962 and 1968 market breaks. Here again, the prior probabilities, although essential, were ignored.	However, it is essential to reiterate that impact of psychological pressure apply to investors worldwide indicating the need of a global study.

		Anchoring and Hindsight Biases	
Date	**Author**	**Contribution**	**Limitation**
1998	Dreman	suggests that an investor in 1977 might have thought a price of $91 was too high for cascade Communications, a leader in PC networking, and that $80 was more appropriate. However, Cascade Communications was grossly overvalued at $91 and dropped to $22 before recovering modestly. The final bias is interesting. In looking back at past mistakes, researchers have found that, people believe that each error could have been seen much more clearly, if only they had not been wearing dark or rose-coloured glasses. The inevitability of what happened seems obvious in retrospect. "Hindsight" bias seriously impairs proper assessment of past errors and significantly limits what can be learned from experience.	I find that the implications of cognitive biases are enormous, in investment. The tendency to underestimate or ignore prior probabilities in decision-making is undoubtedly the most significant problem of intuitive prediction for investors.
		Contrarian Strategies and Investor Overreaction Hypothesis	
Date	**Author**	**Contribution**	**Limitation**
1998	Dreman	Investors Overreaction Hypothesis predicts that after earnings or other surprises, investments previously considered to be "best" underperformed, while those considered being "worst" significantly outperformed, as both regress towards a average valuation. The hypothesis also states that the maximum price swing is produced by negative surprise on "best" stocks and positive surprises on "worst." On the other hand, positive surprise on favoured stocks and negative surprise on out-of-favour stocks reinforcing events corroborate the market's opinion of these stocks and have a lesser impact on price movements than event-triggers. The overreaction hypothesis holds that even without the occurrence of an event trigger, the "best" and "worst" investments regress towards the market average. Because the Investor Overreaction Hypothesis is based on psychological principles, it is likely to apply in other markets and in field outside of investments and economics where risk and uncertainty exist. The Investor Overreaction Hypothesis makes these predictions: best stocks underperform the market, while "worst" stocks outperform. For long periods; Positive surprise boost "worst" stocks significantly more than they do "best" stocks; Negative surprise knock "best" stocks down much more than "worst" stocks; There are two distinct categories of surprise: "event triggers" (positive surprise on "worst" stocks, and negative surprises on "best"), and "reinforcing events" (negative surprise on "worst" stocks and positive surprises on "best"). Event triggers result in much larger price movements than do reinforcing events; the differences will be significant only in the extreme quintiles, with minimal impact on the 60% of stocks in the middle. The hypothesis states that overreaction occurs before the announcement of an earnings or other surprise. A correction of the previous overreaction occurs after the surprise. "Best" stocks move lower relative to market while "worst" stock move higher, for a relatively long time following a surprise. This may fall as commandants for contrarians, but it can be remembered that, all five predictions of the investor overreaction hypothesis have been confirmed earlier to a high level of statistical probability.	It is necessary to make a distinction between a contrarian strategy and other trading strategies. The risk on contrarian strategy is measured as the risk on a value investment strategy. The payoff on a contrarian investment strategy is therefore often referred to as a value premium. The contrarian strategy premium will be positive as long as the loser or the value indices yields a higher return than the winner indices or growing indices over a given time period.

		Types of Contrarian Strategies	
Date	**Author**	**Contribution**	**Limitation**
1994	Lakonishok	Argue that the expectations of futures stock return are an extrapolation of the past stock performance without taking into account the mean reversion effect. The implication is that past stock performance will be replicated in the future which are prompt to naive investor but the contrarian will always bet against this belief and therefore will buy the losers' stocks and sells the winners'	This approach of the contrarian investing requires stock market overreaction as investors will become exceptionally excited about previous winner stocks, and thus bid their prices up till these winner stocks become overpriced and trade above their fundamental values (Barberis and Thaler, 2002). Correspondingly, investors will also overreact to previous poor performing stock and therefore oversell the previous loser stocks until they become under-priced and trade below their fundamental values. When the overreaction is corrected, poor performing stock adjust to high return while well performing stock have a low return.
1998	Dreman	A second contrarian investment is known as the valuation measure strategy. This strategy includes analysis based on different ratios (share price or book and market value) that proxy for past performance or alternatively disclose information about market expectation. But the basic idea remains the same. Contrarian investment strategies suggest that loser stocks should be chosen on criteria such as poor past performance versus good past performance and inversely	It is therefore expected that the two types of contrarian strategies should perform well given that the two strategies involve classifying more or less the same stocks as losers and winners.

		Contrarian Investment Strategies Based on Prior Returns	
Date	**Author**	**Contribution**	**Limitation**
1985	De Bondt	Provided evidence of the anomaly of the price reversal in the US stock market. Their study was inspired by the behavioural psychology of Kahneman and Tversky (1982) that suggested that people tend to overweight recent information and underweight past data when dealing with probability revision. With reference to the stock market, they suggested that people behaviour would imply that the market would overreact to unexpected information or news, causing stock price to be mispriced from their fundamental values and then reverts in the futures, which make stock price reversal predictable from past returns. They reported that paradoxically, long-term past losers outperform long-term past winners over the subsequent three to five years' period. The losing stock earned about 0.694% per month more than the winners did over three years on the US stock market from 1926 to 1982, and suggested that the profitability of the contrarian strategies can be associated with investor's overreaction. They also demonstrated that risks measured, as betas could not explain why past losers after portfolio formation make higher excess returns.	The study was conducted on U.S. Stock only.
1987	De Bondt	Re-evaluated the overreaction hypothesis with regards to the time-varying risk premium and the market efficiency. They accounted for Chan's suggestions and estimated betas in the test period as opposed to the formation period. They found that the losers' portfolios are subject to higher beta than the winners' portfolio but they suggested that differences in betas sizes alone could not explain the losers' portfolio superior return.	The study was conducted on U.S. stock only
1988	Chan	Suggested alternative explanation of the overreaction hypothesis. He put forward the risk-based explanation of the return generated by contrarian strategy as the risk of the winner and the loser's stocks change over time. Using the same sample as De Bondt and Thaler (1985), he found a considerable change in betas from the formation to the holding period but suggested that the change in betas alone cannot explain the losers' portfolio excess return.	At a more general level it might possible to the loser's excess return if one is dealing macro data which are easy to observe, therefore a global strategy could be advantageous.
1990	Jeegadesh	Studied a reversal strategy that buys losers and sell winners based on their prior-monthly returns and holds them for one month over 1934 to 1987. They found that the contrarian strategy generated a profit of about 1.99% per month and 1.75% percent per month outside January, which appears striking and suggests to which extent security return can be predictable.	The study was conducted with individual stock and the results are countries specific.
1990	Zarowin	Suggested that the losers tend to be small and that small firms outperform large firms	
1990	Lehmann	Found that contrarian strategies portfolios chosen on the basis of the price changes during one-week exhibit contrarian behaviour in the following week. A relatively good performance of one week tends to be followed by a relatively bad performance the next week, and vice versa. Using securities listed on the New York and the American Stock Exchange from 1962, he found that the weekly mean return of the two one-week portfolio strategies were of opposite sign, and the mean return of the winner's portfolio were about one-half the magnitude of the mean return of the loser's portfolio. The sample correlation of the weekly return of the one-week portfolio strategies were large and positive (0.851) for the full-week strategy and 0.873 for the four-day strategy. A short position in the winner's portfolio had a large negative correlation with a long position in the loser's portfolio	The study did not specify if these findings could be relevant at a global level.

Date	Author	Contribution	Limitation
1990	Lo and Mackinlay	studied the contrarian strategies while using US market weekly data from 1962 to 1987 and found that the average weekly long-short profit generated by the contrarian strategy over the sample periods for all stocks is $1.69 with the average weekly long-short position of $152. In contrast, the sample of small stocks yields an expected profit of $4.53 per week, but required only $209 long and short each week. They divided the contrarian return into three aspects. In the first part, they identified the of-diagonals of auto covariance matrix also known as the cross-auto correlation among stock components. In a simple term it is the difference of autocorrelation amongst stock in a portfolio between the past and the current period. Which is also called lead-lag effect. When the lead-lag relation is positive, Lo and Mackinlay explain that, the short-term stock return reversal with a regular pattern is a consequence of the delayed reaction to common factor and not investor overreaction to news or stock prices as suggested by De Bondt and Thaler (1985). This imply that the contrarian strategies' profits result from the investor's overreaction to news and related information. The second aspect in explaining the return reversal is related to the auto correlation of individual stock during different periods. They assume that the negative autocorrelation show positive contribution to the contrarian strategy returns and can explain the market overreaction. Lo and Mackinlay concluded that stock return's time varying are good predictors of the contrarian portfolio return. The third aspect is the cross-sectional variation of the expected return of individual stocks. They found evidences of the volatility-clustering phenomenon that shows that large stocks return tended to lead small stocks with the lead lag effect, which, tend to have negative effect on the contrarian strategies return.	Overall findings contradict the traditional behavioural finance hypothesis as suggested by De Bondt and Thaler (1985) and Lehmann (1990).
1990	Jegadeesh	He suggested that the negative first-order serial correlation in monthly stock returns is highly significant and found that the difference between the risk-adjusted excess return on the extreme deciles portfolios is 2.49% per month over the period 1934 to 1987, 2.20% per month excluding January, and 4.37 % per month when the month of January is considered separately. It is also found that the difference between the risk-adjusted excess returns on the extreme deciles portfolios formed based on one-month lagged return is 1.99% per month over the sample period and 1.75% percent per month outside January.	However, Jegadeesh and Titman (1995) suggested that the cross-sectional analysis of profit was not good indicator for investor overreaction to news. By analysing firm-specific characteristics, they found that short-term contrarian profit could be explained by investor's overreaction to firm-specific information.
1992	Chopra	Investigated stock return overreaction on the NYSE stock returns from 1926 to 1986 with monthly and annually returns. Their method included event time-varying betas created on an estimate market compensation per unit beta risk basis, which, is relatively smaller compared to the Sharp-Lintner model adopted by Ball and Kothari (1989), they found that the losers outperform the winners by approximately 0.542% per month on annual return and 0.792% per month on monthly returns. They also demonstrated that size alone could not explain the contrarian return. They suggested that a mutual consideration of size, prior return and beta could explain the contrarian return to avoid omitted variable bias.	There is significant evidence today to demonstrate that size and, prior return and beta alone can not explain the contrarian return, their impact might vary from one market to anaother.
1994	Lakonishok	defined two categories of stocks those with bad past performances or value stocks and those with better past performance or glamour. They claimed that value stocks have been undervalued and glamour stocks have been overvalued. They then defined a contrarian strategy that buys values stock and sells glamour stocks based on whether the stocks have a high book-to-market, a high sales growth in the past and low price relative to cash flow and earnings. They found that, for a five year holding period between 1963 and 1990 value stocks could generate an excess of 0.83 to 0.916% per month compared to the glamour stocks and that the result cannot be explained by systematic risk.	but, the study was conducted on US stock only and did not looks at the global implication of this results.

Date	Author	Contribution	Limitation
1995	Clare and Thomas	Studied the reversal strategies in the UK market using 1000 stocks from 1955 to 1990. they examine the Overreaction Hypothesis. They found that losers outperform winners by approximately 0.142% per month. After controlling for firm size, they suggested that the overreaction hypothesis is linked to the size effect.	The study focus on individual country.
1996	Chan et al.	Complimented De Bondt and Thaler 's (1985) findings. They suggested that stock price over- or under-react to information and that winners and loser often show reversal patterns, which are consistent with the overreaction hypothesis.	Their findings are conclusive and support the overreaction hypothesis, which, however is not the only agument put forward to explain return reversal in equity market.
2002	Kulpman	re-evaluated the overreaction hypothesis with regards to the time-varying risk premium and the market efficiency. They accounted for Chan's suggestions and estimated betas in the test period as opposed to the formation period. They found that the losers' portfolios are subject to higher beta than the winners' portfolio but they suggested that differences in betas sizes alone could not explain the losers' portfolio superior return.	The study is country specific.
2007	Galariotis et al.	Found evidences of contrarian profitability in the London Stock Exchange listed stocks from 1964 to 2005. Using 64 strategies for 6531 stocks and controlling for key potential explanations of the strategies' profitability, they found that, the lowest size quintile outperforms the highest size quintile by a figure ranging from 0.7% per month for the 60-month formation period to 1.84% per month. They suggested that for each of the holding periods there is a clear tendency for returns to rise as the market capitalization falls.	The study focus on UK stock market only.
2009	Li et al.	Studied value and growth stocks in UK stock market from July 1969 to June 2006 and found that growth portfolio has low mean return of 0.81% per month, that the value portfolio has high mean returns of 1.39% per month, and that the value premium is 0.57% per month. They suggested that superior return or value premium of value stocks in UK are a result of high return volatility between 1963 and 2006.	The study focus on individual country
2010	Dissanaike and Kim-Ham	Studied the reversal strategies while referring to the residual income model. They used variety of variables to form contrarian portfolio, ranging from book-to-market, cash flow-to-price, earnings-to-price and past returns, to more sophisticated measures based on the Ohlson model and residual income model. They found that, most of the portfolio formation methods based on raw and size-adjusted returns yield economically important contrarian profits. They suggested that, the raw returns portfolios fall from 1.689% per month in the test period year 1 to 0.778% per month in test period year 2 and finally to 0.049% per month in test period year 3and suggested that book-to-market based contrarian model outperform the contrarian strategies based on accounting information. However, these studies were solely based on UK market.	Wu and Li (2011) did not explore whether this could apply at a global level when using countries' indices.
2011	Wu and Li	Investigated whether long-term contrarian performance on the UK market is driven low-priced stock and found that contrarian performance at low, middle, low price levels is positive. The suggested that low-priced stock are not fully responsible for contrarian performance and that the findings were consistent with the overreaction hypothesis.	Low-priced stock effect might have in aggregate a significant impact on the overall indice performance. I anticipate that similar effect could be observe internationaly. Therefore, could also explain the global momentum strategy.
2016	Doan et al.	examine the coexistence of momentum and contrarian strategies in the Australian equity market from 1992 to 201. They found that contrarian strategies prevail in the intermediate and long-term. They show that short-term contrarian strategies significantly outperform the simple buy-and-hold strategy of investing in the market index. the Australian mining sector undermines the momentum performances but enhance the contrarian strategies profitability.	However, their analysis was based on Australian stocks solely and the momentum and contrarian profits could not be explained by standard return-generating models.

		Contrarian Strategies in Emerging Markets	
Date	**Author**	**Contribution**	**Limitation**
1999	Choe et al.	Evidences of contrarian strategies were also reported in emerging market: Choe et al. (1999) tested whether foreign investor activities affect stock return in Korea from November 30, 1996 to the end of 1997, period that matches with the Asian crisis. They used order and trade data, and found that there are strong evidences of positive feedback trading and herding by foreign investors before during the period of Korea's economic crisis. They recorded that during the crisis period, herding falls, and positive feedback trading by foreign investors mostly disappears. They suggested that there was no evidence of destabilizing effect of the foreign investors on the Korea stock market over their study period as the market adjusted quickly and efficiently to large sales by foreign investors. These sales were not followed by negative abnormal returns. They suggested that the losers earn about 0.068% per month more than the winner for institutional order before the Korean crisis.	However, the study did not extend this analysis to other equity market, to show whether adjustment process and speed are consistent across markets worldwide or it is just a feature of the Korean market.
2002	Kang et al.	Studied the contrarian strategy in China using stock prices from the period of January 1993 to January 2000, testing methods similar to Lo and Mackinlay (1990), and found that there is a significant abnormal return for some short and medium term contrarian strategies. They reported up to 0.744% return for portfolio formed based on previous 1-week returns and held for 1-week and suggested that it was associated with overreaction to firm specific information in short term. In addition, they discovered that there was not a distinctive effect in medium term, which was explained by the dominance of overreaction effect.	but they were able to demonstrate that the negative cross-serial correlation can lead to contrarian profits. However, their analysis was based on data only accessible by local investors.
2003	Otchere and Chan	Examined the overreaction phenomenon in the Hong Kong market from March 1996 to June 1998 that includes the pre- and the post-Asian financial crisis and found that Hong Kong market overreacted to information prior to the Asian financial crisis period. They also found that the overreaction tends to be more evident for winners than the losers. They also found evidence of the overreaction in the pre-financial crisis period but reported that abnormal return obtained by exploiting such phenomenon are economically insignificant after considering transaction cost (0.124% per month). However, they indicated that after accounting for size effect and the day-of-week effect, the results appear to be very significant. They advocated that the Chinese culture may have significant impact on investors' view of the market as they tend to perceive risk differently and are less risk averse and less likely to overreact but this study did not show how this particular feature of the Chinese market could help international momentum and contrarian investors in global portfolio allocation.	They advocated that the Chinese culture may have significant impact on investors' view of the market as they tend to perceive risk differently and are less risk averse and less likely to overreact but this study did not show how this particular feature of the Chinese market could help international momentum and contrarian investors in global portfolio allocation.
2012	Chen et al.	Studied the contrarian trading strategies in the Chinese stock market from 1995 to 2010. They examined the performance of the trading strategies following different markets states and found that contrarian strategies are profitable following down market especially during the economic downturn. They suggested that market conditions are good predictors of the size of the contrarian profit. In addition, they found that no significant profit is generated from both strategies in the medium term. They reiterated that, for practitioners and investors in general, these results provide good forecasting indicator especially during the post-crisis period. After consideration of the microstructure effect on the one-to-two-month formation and holding periods they found that the contrarian strategy generates on average approximately 0.8% per month and even greater in `up' market.	However, the study indicated that these results may not apply in developed markets and did not examine the reversal as a global phenomenon.

		Contrarian Strategies International Evidences	
Date	**Author**	**Contrarian**	**Limitation**
2012	Jordan	Examined the profitability of the long-term contrarian strategy using 81 years of data from 1925 to 2005and found that the contrarian based on 36 month holding period generate approximately 0.492% return per month when analysing 8 countries and even greater 0.586 per month for 16 countries. He reported that the long-term contrarian anomaly disappears when time-varying alpha are considered. He suggested that the benefits from the trades on long-term reversal do not go against a strategy based on diversification, but the method used in the construction of the losers and winners' portfolios and the test are based on 25% lowest (losers) and the 25% top (winners) or adjust for return.	However, He reported contrarian results based on monthly stocks performance of 8 and 16 countries only.
2013	Malin and Bornholt	Studied the profitability of the contrarian strategies on international equity markets from January 1970 to January 2011, using recent short-term performance (monthly). They proposed the late-stage strategy that buys long-term losers with relatively good recent short-term performances and sells long-term winners with relative poor recent short-term performances. They found that, with the 60-month formation period in developed countries, past long-term losers gain an average of 1.31% per month over the 6-month holding period and that long-term winner's gain an average of only 0.86% per month over the same period. The difference between long-term losers and long-term winners is 0.46% per month with a t-statistic of 2.28. In emerging countries, the strongest pure contrarian profit using 60-month formation and 6-month holding period generate 0.68% per month with a t-statistic of 1.69. They also found that, for the late-stage strategies in developed countries the contrarian strategy generated 0.58% per month with a t-statistic of 2.48. In emerging market, they reported a return of 1.24% per month with a t-statistic of 2.47. They suggested that, the late-stage strategy is consistently more profitable than the traditional pure contrarian strategy. They suggested that the late-state strategies it provides significant evidences of reversal in long-term returns for both the developed and the emerging markets.	but the study did not look at the contrarian strategy as a global and generalize phenomenon following different market state (bear and bull) and did not test whether the short-term contrarian is also profitable.
1989	Zarowin	Examined firm's stock over 36 months relative to extreme earning years and found that the poorest earners do outperform the best earners. He was able to demonstrate that when poor earners are matched with good earners, there is not substantial evidence to suggest that the factor responsible for the overreaction phenomenon is the size and not investor's overreaction to earnings, this argument reject De Bondt and Thaler (1985) suggestion.	However, the study made use of market adjusted excess return and not risk adjusted and did not examine the long-term contrarian strategy as a global phenomenon.

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