ESSAYS ON STOCK SPLITS AND HERDING

by

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AUTHOR'S DECLARATION

I wish to declare this thesis, titled as "Essays on Stock Splits and Herding", submitted to the University of London in pursuance of the degree of Doctor of Philosophy (Ph.D.) in Economics is my own work.

Signed

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EXTENDED ABSTRACT

This thesis consists in an analysis of stock splits, and their relationship with dispersion of beliefs and herding.

Chapter 1 introduces the topics that I tackle throughout the thesis. In particular, I motivate the interest in herding and stock splits presenting the unifying interpretation line among each chapter.

Chapter 2 proposes a literature review on stock splits, focusing on the explanations that the theoretical literature suggests and the empirical evidence of the market reaction.

Chapter 3 reports the results of an empirical analysis around the time of a stock split on the relation between the dispersion of beliefs among investors and the market reaction and future performance of the splitting company. We provide empirical results on a sample of US splits which occurred from 1993 to 2004. They show that, at the time around the announcement of a split, the distribution of the analysts' forecasts changes in mean and dispersion. Moreover, an event study shows that the differences of opinion have an impact on the future performance of the splitting firms and on the motivations behind the event.

Chapter 4 focuses on a literature review of herding, and in particu-

lar on the empirical investigation of imitative behavior among institutional investors.

Chapter 5 examines the relation between herding and stock splits. By herding we mean the abnormal correlation of trades among institutional investors, according to the methodology developed by Sias (2004). We use data on the buying and selling activity of US institutional investors, from 1994 to 2005. The results show a significant level of convergence in the overall market, both for splitting and non-splitting companies. We decompose this effect into the contributions of several types of herding. We observe the significant impact of informational cascades on the splitting stocks sample, while reputational herding and characteristic preference have a relevant impact on the non-splitting sample. The evidence of informational content in the split event is confirmed by the stabilizing effect of herding we find in the future returns of splitting companies.

Chapter 6 concludes, summarizing the main results and contributions of the thesis.

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Chapter 1

Introduction

1.1 Motivation

Stock splits are still a puzzling phenomenon in the financial markets. They are corporate events that increase the number of shares outstanding of a company without direct observable effects on cash flows, ownership basis or risk characteristics. Despite their purely "cosmetic" effect on companies, the financial literature still shows no agreement on either the managers' motivations behind these events or the validity of the empirical evidence on the market reaction.

In this dissertation, we aim to investigate the phenomenon of stock splits in a new light, connecting the market reaction with the presence of imitative behaviour among institutional investors. The abnormal reaction of the market to the announcement of stock splits could in fact be correlated with an abnormal level of herding among the most professional of investors.

Herding is a social phenomenon that occurs when a group of individuals follow each others' behavior over a period of time, partly ignoring their own private information. It is an old concept that dates back to Keynes' beauty contest (1936), and that has evolved till today, when imitative behaviour is theorized in financial markets within fully rational setups. Furthermore, the research on herding is still divided into multiple theoretical approaches and, in particular, the empirical and theoretical literature is hard to reconcile.

As far as my knowledge, the link between the two fields of literature of herding and stock splits has not yet been investigated, while an unifying analysis could bring new light on the understanding of both phenomena. This dissertation, therefore, intends to fill this gap and to provide new insights on both the motivations to herd and the motivations behind the underreaction to the announcement of stock splits. We define our study as a cross-borders investigation of herding and stock splits linking the Self Selection hypothesis for stock splits to informational-based herding. In its essence, our contributions focus on the hypotheses that stock splits convey noisy but positive information to the market, and the investors' biased reaction could be partly explained by informational institutional herding around the announcement of the event.

From the empirical literature on the price impact of stock splits, there are evidence of abnormal trading activities before and after the announcement of the event. Even if this evidence does not find full agreement among researchers, it is consistent with both the hypotheses that managers use stock splits to realign the stock price to an optimal trading range, and that the event is recognized by the market as a signal of positive future expectations. An unifying theory, consistent with underreaction of the market after the event, is the Self Selection hypothesis of Ikenberry, Rankine and Stice (1996). Linking this empirical literature to the investigation of herding around the event could help in understanding the motivations to investors' underreaction after the announcement of stock splits.[1]

The empirical literature on herding is even more controversial, as many are the limitations on the analysis of imitative behaviour on real-functioning markets. Most of the researchers agree on a level of correlated behaviour among investors, that is consistent with institutions engaging in imitative behaviour in their trading activities. However, the investigation of the motivations to herd is still an hard task to perform. Looking at herding in splitting stocks would help to extrapolate useful insights on why investors are herding. In particular, because of the noisy informational content of the split, and the underreaction after its announcement, such event seems an ideal moment to test for the presence of herding due to the arrival of new signals. Due to noisy information to the market and uncertainty on both the occurrence and the change in value of the company, investors would tend to observe each other trades and, to ignore their private signals, engaging in informational-based herding.[2]

Moreover, the link between the two empirical investigation is played by the dispersion of beliefs among analysts. We are going to introduce the effect of difference of opinions both on the market reaction to splits and informational herding. On one side, a change in the distribution of the analysts' forecasts in mean and dispersion will help to investigate the informational content in the announcement of the event. On the

[1] The literature on stock splits will be reviewed in Chapter 2.

[2] Chapter 4 reviews the empirical literature on herding.

other side, the dispersion of beliefs is proxy for the reliability of the new information, and therefore, proxy for an environment prone to informational-based herding to arise.

The full picture is as follows.

According to the Self-Selection hypothesis (Ikenberry and Ramnath, 2002), managers split their shares because they have a preferred trading range price which they wish to realign their price to, as it is costly for the company, management and investors to lie in a lower range. Managers will therefore split their shares if they are optimistic about the future growth performance of the company, as much as necessary to hold the risk of the share price going below the lower limit of the trading range.

A positive market reaction to the announcement of a stock split is consistent with this theory, as the event conveys positive information. However, the split also conveys the optimism of the managers, which the market cannot perfectly evaluate. Hence, we observe a timid reaction, extended in the long run with increasing prices.

According to this theory and connecting it with the differences of opinion literature, we investigate the impact of the announcement of splits on market expectations and vice-versa, considering the following conjectures:

Conjecture 1 *Positive changes in mean of the forecasts estimates, negative changes in dispersion and correction of estimates error after the event will confirm a signalling model of splits.*

Conjecture 2 *If the stock split event is signalling positive information, we expect the market to react at the announcement with positive abnormal returns.*

Conjecture 3 *If the event conveys uncertain information, we expect prices to underreact and the abnormal returns to be related to the quality of the information, proxied by the dispersion of beliefs.*

The presence of informational content in the split event motivates the analysis of whether an abnormal level of informational-based herding is present at the announcement of the event. If the event, in fact, conveys positive information together with the optimism of managers, this is an ideal condition for informational-based herding to arise (Bikhchandani, Hirshleifer and Welch, 1992). Informational cascades arise when agents are facing decisions in uncertain environments. According to the model of Avery and Zemsky (1998), in financial markets, with an efficient price mechanism, cascades can still incur if there is at least a two-dimensional uncertainty. If investors are facing decisions when only uncertainty on the value of the asset is present, the efficient price mechanism and rational agents are enough to prevent cascades from forming. If, instead, we add a second dimension of uncertainty, then the market is uncertain not only of the new value but also whether the value of the stock has actually changed from the expectations, and in these conditions herding can arise. In particularly extreme cases, if we include a third dimension of uncertainty on the average accuracy of traders' information, herding can also result in grave mispricing effects.

We can assume that an event that conveys both positive information about a change in value of the company together with the optimism of managers is introducing at least a two dimensional uncertainty on the new value of the shares; whether the change in value really occurred or whether it was merely caused by the overconfidence of the management.

With this background, if the dispersion of beliefs can be considered as a proxy for the quality of the information that reaches the market, informational-based herding will be detected by a positive relation between herding and dispersion of beliefs.

Chan, Hwang and Mian (2005) examine the relation between herding of mutual funds and dispersion of analysts' earnings forecasts, showing that the level of herding in individual stocks is positively related to the dispersion measure. This is due to the fact that dispersion in analysts' forecasts is a measure of disagreement among security analysts, that indicates the level of reliability of the information available to market participants about the future prospects of a company. Empirical evidence also shows that forecast dispersion is positively associated with other measures of a firm's fundamental risk such as market beta, past earnings variability, and stock return variability (Diether, Malloy and Scherbina, 2002). Forecast dispersion also reveals additional dimensions of a firm's information risk not captured by other measures (Barron, Kim, Lim and Stevens, 1998).

The last implication is that, if investors herd because there is lack of reliable information about a firm, as in informational cascades or reputational herding models, we should observe a positive relationship between the level of herding and the dispersion in forecasts.[3]

Conjecture 4 *In the presence of informational based herding, we expect herding to be higher when the dispersion of beliefs among analysts is higher.*

[3] On the other hand, if mutual fund managers herd because they observe correlated signals, as is postulated in models of investigative herding *(*Hirshleifer, Subrahmanyam and Titman (1994)*),* we should observe a negative relationship between the level of herding and dispersion in analysts' forecasts.

If all the previous conjectures are verified, we expect a different level of herding between companies that split their stocks and companies that do not, and that this difference has an informational content, explained by the dispersion of beliefs among analysts.

1.2 Outline of the thesis

Chapter 2 introduces the main theories on stock splits, connecting them to the empirical evidence behind their validation. The empirical literature has observed abnormal behaviour of splitting companies in the period before the announcement of the event. Evidence of high rates of returns before the announcement, due to abnormal increases in earnings and dividends (Lakonishok and Lev, 1987) are consistent with the theory that managers seek to realign the per share price to a preferred range, given market and industry considerations.

Besides, there is evidence that markets react favorably to the announcement of the event, reporting positive excess returns (Ikenberry, Rankine and Stice, 1996). This positive market reaction has motivated the Signalling hypothesis, according to which, managers split in order to convey their favorable private information to the market.

Both these findings, altogether with the evidence that the market reaction is dragged in the long run, are consistent with the Self-Selection hypothesis (Ikenberry and Ramnath, 2002).

Chapter 3 is an empirical study on a sample of US stock splits from 1993 to 2005, based on the Self-Selection hypothesis. We investigate stock splits and the abnormal market reaction in the light of changes in market expectations. Firstly, we investigate the link between stock splits and market expectations, looking at changes in the distribution of the analysts' earnings forecasts around the announcement or the occurrence of stock splits. A positive change in mean and a negative change in dispersion would confirm the signaling model of stock splits (Brennan and Copeland, 1988b, Ikenberry, Rankine and Stice, 1996). The results show an increase in the mean, but also a slight increase in dispersion. Moreover, we analyze the link between stock splits and prices, with an event study on the market reaction after the announcement and the occurrence of stock splits. Estimating the normal returns with a four-factor model (Carhart, 1997), we observe significant abnormal returns for splitting companies after the events. These results confirm previous literature, which concludes that the stock split is interpreted by the market as an event carrying positive but noisy information.

The relation between noisy information and market reaction is verified by a final step, examining the link between market expectations and prices. We regress the CARs on the dispersion of beliefs, finding evidence of a positive relation between them.

The results of this chapter motivates the next, namely the analysis of the relationship between stock splits and informational-based herding.

Chapter 4 introduces the literature on institutional herding. The primary focus is on the empirical works, looking at the principal measures developed and the main findings on herding among institutional investors. Nevertheless, we briefly introduce the most important theoretical families of models.

The main question in the literature is whether herding among institutional investors can have an inefficient impact on the market variables and leads to excess volatility and market fragility. Most of the empirical evidence shows a positive correlation between the direction of herding and the future short term returns (Nofsinger and Sias, 1999), which is consistent with a positive stabilizing effect. However, recent papers show a destabilizing effect on prices, as herding helps to predict reversals in long term returns (Dasgupta, Prat and Verardo, 2010).

Theoretical and empirical literature on this subject are hard to connect, due to the lack of data on the private signals of the investors. In most empirical works, herding is therefore broadly defined in terms of correlated behaviour across individuals, independent of the underlying motivations to it and any coordination mechanism among agents. We will focus on the developments in this field of research, reviewing two of the most widely used measures of herding, with their subsequent improvements and applications: the Lakonishok, Shleifer and Vishny (1992) measure and the beta developed by Sias (2004).

Chapter 5 is an empirical analysis examining whether splitting companies are more susceptible to the herding phenomenon than the rest of the market and what the motivations are for this difference. Using the same sample of US splits from 1993 to 2005, we investigate the presence of market herding, proxied by the level of correlation among investors' decisions, applying the methodology developed by Sias (2004). The results show positive and significant correlations between the fraction of investors buying this quarter and the fraction in the previous quarter, in any period of analysis. Restricting the analysis to splitting stocks, we observe a tiny difference in the correlation coefficients. Cleaning this measure by the influence of common factors other than intentional herding, we see an increase in the difference between the two groups.

The last part of the analysis investigates the motivations behind this level of potential herding, consistently with the theoretical literature. In particular, we focus on the investigation of informational-based herding (Bikhchandani, Hirshleifer and Welch, 1992, Scharfstein and Stein, 1990) with respect to positive-feedback models (Gompers and Metrick, 2001, Grinblatt, Titman and Wermers, 1995). Imposing and testing specific hypotheses for each theoretical model, we discriminate the contributions of the different types to the overall correlation. We observe the strong presence of all these theoretical types, in particular, institutional investors tend to be affected by informational-based herding when trading on splitting companies and the difference in herding between the two groups is due, in the most part, to informational content and the dispersion of beliefs.

These results confirm the previous conjectures, yet, there is a significant and relevant part of the correlation that is not explained by these models.

Chapter 6 draws the conclusion of the thesis.

Chapter 2

A literature review on stock splits

2.1 Introduction

This chapter introduces the main theoretical and empirical literature on stock splits. A stock split is a corporate event that increases the number of shares outstanding in a company, without having a direct effect on the market capitalization or on the ownership basis.[1] Existing shares are divided into multiple shares distributed in proportion to the existing shareholders, yet the total dollar value of the shares remains

[1] Stock splits and stock dividends are a very old phenomenon, since the East India Company in the XVII century decided to split its dividend at the height of its trading success (Angel, 1997). However, except for some notable historical examples, splitting stocks became very popular at the beginning of the 20th century after the First World War, and has remained prevalent, especially in periods of boom markets.

the same as the pre-split amount. It is therefore defined as a "cosmetic" event. However, despite its simplicity, there is evidence that the announcement of a stock split is accompanied by puzzling effects and disagreement regarding the real motivations. Thus, although it is not clear why managers are willing to sustain the real costs of these financial manipulations, conversely, the market appears to react to some hidden information conveyed by the event. Moreover, the apparent market reaction tends to be incomplete and biased.

The field of literature that focuses on the "anomalies" of the Efficient Market Hypothesis is particularly vivacious in the analysis of whether the market's reaction to events-driven information is unbiased. The most fascinating among the self-selected corporate events is the stock split, because of its apparent lack of directly observable effects on companies' cash flows, ownership structure or risk characteristics. As such, it appears to be the purest kind of data for event studies on the efficiency of the markets, starting with the empirical analysis of Fama, Fisher, Jensen and Roll (1969).

Empirical and theoretical literature is well connected. However, there is not full agreement, both on the theoretical motivation that could explain all the anomalies around stock split announcements and on the methodologies required to investigate such anomalies.

Regarding the pre-split window, there is robust evidence of high rates of returns before the announcement, due to abnormal increases in earnings and dividends (Lakonishok and Lev, 1987; Asquith, Healy and Palepu, 1989). These price run-ups can be determined by the specific characteristics of the company or by a general good moment in the markets. In fact, the number of splits increases in periods of boom and optimism in the markets. In addition, the announcement is generally preceded by high and abnormal trading volumes, especially in the few months immediately before the declaration.

These findings in part motivate the development of the Trading Range hypothesis of stock splits, whereby managers seek to realign the per share price to a preferred range, which is determined by market and industry considerations.

Besides, splits can positively influence the wealth of shareholders. There is in fact evidence that markets react favorably to the announcement of the event, reporting positive excess returns (Grinblatt, Masulis and Titman, 1984, McNichols and Dravid, 1990, Bar-Yosef and Brown, 1977). Such behaviour is consistent with an event conveying good information. Some evidence shows that this abnormal performance does not only happen at the announcement, when the implicitly good information should become public and thus incorporated in the prices, but that there is also a positive reaction around the ex date (Eades, Hess and Kim, 1984, Lakonishok and Vermaelen, 1986, Grinblatt, Masulis and Titman, 1984, Lamoureux and Poon, 1987, Nayar and Rozeff, 2001). Moreover, we also observe also future abnormal increases in the future company earnings (Fama et al., 1969, McNichols and Dravid, 1990), even if there is not agreement on the cause- effect relationship between splits and earnings (Lakonishok and Lev, 1987, Huang, Liano and Pan, 2006).

The positive reaction of the market at the announcement of a stock split is consistent with the Signalling hypothesis, which posits that managers aim to convey favorable private information to the market about the positive future performance of a company.

We also report empirical findings of market reaction in the long run, which reveals that the market underreacts to the announcement of stock splits, as there is evidence of positive returns in the long run event-window (Ikenberry, Rankine and Stice, 1996, Ikenberry and Ramnath, 2002, Desai and Jain, 1997).[2] Their results are not incompatible with both the trading range hypothesis and the signalling hypothesis, as they also find as well both pre-event price run-ups and short term positive market reactions.

The Self-Selection hypothesis is consistent with all the previous findings as it assumes that managers prefer the stock to lie within a certain trading range price. However, as it is costly for it to lie below that level, only managers that are optimistic about the future performance of their companies will opt for splitting as a method of conveying their private information to the public. The market will then underreact both to the positive information about the companies, and also to the optimism of the management.

There is evidence of increasing analysts' coverage after the announcement of stock splits, due to higher profits or promotional activities by market makers (Brennan and Hughes, 1991). This result is consistent with the Attention hypothesis, which states that managers undertake stock splits in order to attract the attention of analysts and market makers. However, the documented rise in coverage is not significantly different from matching nonsplitting companies (Ikenberry and Ramnath, 2002).

Other theories are developed by the literature, but with weaker empirical support. The Tick- Preference hypothesis assume that the managers aim to maintain the relative tick size within a certain range.

[2] See the works of Barberis, Shleifer and Vishny (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) for a theoretical contribution on underreaction, to which the findings on splits are consistent.

Finally, the Tax- Timing option (Lamoureux and Poon, 1987) is based on the tax opportunities given to firms, that can compensate long term gains with short- term losses.

The outline of the chapter is as follows. Section 2 will review the main theoretical motivations of stock splits. Then, Section 3 will examine at the empirical methodologies developed by the literature in order to investigate the market reaction of splits. Finally, Section 4 will review the main empirical results, focusing in particular on the market reaction.

2.2 Theoretical motivations

There are two main questions which the literature focuses on: why managers spend effort and resources to manage the unit price of their stocks and why the market pays attention to it and subsequently reacts. There are various proposed theories, although none of them is able to comprehensively unify the empirical evidence and definitively answer both questions. In the following, we will briefly look at the main theories, such as: 1) the Trading Range hypothesis, 2) the Signalling hypothesis, 3) the Attention hypothesis, 4) the Self-Selection hypothesis, 5) the Tick Size hypothesis, and 6) the Tax-Timing hypothesis.

2.2.1 Trading Range hypothesis

The Trading Range hypothesis is one of the explanations most supported by academics and practitioners. It suggests that managers seek to realign the per share price to a preferred range, in view of market and industry considerations (Dennis and Strickland, 2003; Dhar, Shepherd and Goetzmann, 2004; Lakonishok and Lev, 1987; Muscarella and Vetsuypens, 1996; So and Tse, 2000).

At first, earlier surveys of the managers' motivations to split support this theory. Among the explicit reasons to split, managers cite the attempt to balance the preferences of different classes of investors, to improve the marketability and liquidity of the stocks (Baker and Powell, 1993, Baker and Gallagher, 1980), to improve the controllability of the company by obtaining a wider ownership by small investors and to answer to particular industry norms (So and Tse, 2000). Angel (1997) shows that the average price per share on the US markets has not changed on average between 1943 and 1994, which is consistent with the preference of management to remain within an optimal trading range.

This theory assumes that the announcement of a stock split is preceded by an abnormal increase in the share price such that it becomes too costly or inopportune to remain in a too high target of investors. At this moment, managers decide to optimize the level of their share price, considering the trade-off between the costs for big investors and institutions and the benefits for small investors. In fact, a lower price would imply higher brokerage fees for big investors who would be investing the same large amount of money in a higher number of shares. Conversely, it could decrease the transaction costs for small investors, increasing the liquidity and the marketability of stocks.

Empirical tests of this hypothesis investigate both prior-event price run-ups and the distance between the pre-split price of the company and the price of comparable firms.

Lakonishok and Lev (1987) construct a model where the target price is function of a market-wide average price, an industry-wide average price and the firm-specific price. The decision of managers then depends on the average level of prices in the market and industry, and the difference between the pre-split price and the benchmark median share price of companies with the same characteristics. Another condition consistent with the Trading Range hypothesis is a high split factor.[3] A small factor would not motivate the costly action by managers to split in order to move the share price within an optimal range. In particular, if managers expect prices to continue to rise after the split as well, the factor has to be sufficiently high to maintain the desired range for a long period of time.

Lakonishok and Lev (1987) test this model looking at whether the post-split price is dependent on the level of comparable environments, using a sample of splits from 1963 to 1982. At the same time, they check for signalling on future dividends as a control factor, examining the growth in earnings and in cash dividends.

Their results show an abnormal positive behaviour in the period preceding the splits, with statistically significant differences in the earnings growth rates between splitting and control companies. The differences widen as the date of the announcement approaches. Then they diminish in the post-split period and remain significant for only one year after the event. The same time pattern can be drawn for the price gap that exists before the split, which also narrows and then vanishes one year after the event. This confirms the hypothesis that a normal trading range is reached after the splits and that further abnormalities stop.

[3] The split factor is the ratio between the number of new shares issued for one old share.

In their analysis of the dividend growth rates, they also find the same pattern pre- and post-event, although it is less intense. In the post-split period, the differences in dividend growth rates are significant for the following five years, however they do narrow after the first period. This is motivated by the fact that expectations of a constant growth are theoretically unrealistic in a rational market. Taking this into consideration, splits can then be seen at most as reassuring signals that the market will stabilize and that there will be no price reversals in the near future, similar to the conclusions previously drawn by Fama et al. (1969).

Finally, systematic and significant differences in trading volumes appear one year before the split and peak at month zero. Again, these effects vanish in an event window within two months after the event. Thus, the announcement of the event generates a rise in trading volume, which is still abnormal but is lower than in the period preceding the split, and which is not permanent. This large volume can however be attributed to the unusual operational performance.

These relations are not universally verified by empirical research, as we have seen previously, and complications arise when researchers checked for improved marketability and liquidity, as we will see in the last section.

2.2.2 Signalling hypothesis

The Signalling hypothesis is based on the existence of asymmetric information between managers and investors on the future performance and perspectives of the company (Brennan and Copeland, 1988b; Huang, Liano and Pan, 2006; Leung, Rui and Wang, 2005; Louis and Robinson, 2003; McNichols and Dravid, 1990; Hwang, Keswani and Shackleton, 2005; Titman, 2002).[4]

Observing the positive reaction of the market at the announcement of a stock split, the Signalling hypothesis contends that managers aim to convey favorable private information to the market about the current value of the firm and positive expectations regarding future performance. This mechanism works under the assumption that obstacles exist to the management which signal false positive information, such as costs for the company or for actual and future shareholders. This can happen with the presence of costs in holding odd lots or especially with the presence of transaction costs (Brennan and Copeland, 1988b, McNichols and Dravid, 1990, Nayak and Prabhala, 2001).

The drawback of this approach is that it is not widely accepted which costs would deter managers from undertaking a stock split without real and correct positive information.

Brennan and Copeland (1988b) construct a model of signalling in a two period world, with rational agents and asymmetric information. The underlying assumption is that a split is costly for shareholders because transaction costs are a positive function of the stock price, therefore the exogenous brokerage fees structure makes it costly to trade in low-priced stocks. Hence, managers will undertake the decision only if they truly possess positive information to share with the market. Given this relationship, there exists an optimal price level which can minimize the transaction costs for the investors. However, because the split itself is costly, this minimization cannot be realized continuously, but managers find it opportune to split again when they have true private information to convey to the investors. In particular, it is both the decision to split the shares and the size of the factor that signal infor-

[4] In fact, it is usually included in the broader category of asymmetric information.

mation (Brennan and Copeland, 1988b, Brennan and Hughes, 1991). The model considers an optimization problem whereby managers seek to maximize their wage, which is dependent on the true value of the company, the transaction costs and the market assessment of the true value after the split. So managers must decide whether to split their share prices and at which split factor, given that they have private information, compared to investors, on the true value of the firm at the next period.

The Signalling hypothesis is less strongly supported in literature, when compared to other explanations, in particular when compared with the Trading Range hypothesis.

McNichols and Dravid (1990) test both for signalling and trading range motivations, in a sample of US splits from 1976 to 1983. They aim to verify the effectiveness of signalling, considering whether the stock split conveys information about future earnings and whether the split factor itself is the signal.[5] Starting from the notion of signalling from Spence (1973) and Riley (1979), they test for a fully revealing signalling equilibrium with perfectly rational agents if three conditions subsist: (i) the level of the signal (the stock split factor) should correspond to the unobservable information of the managers, (ii) the agents' inferences about the private information should correspond to the level of the signal and (iii) the agents' inferences should correspond to the level of the unobservable information.[6]

First of all, they test if the split factor effectively reflects managers' private information about future earnings. The private information is

[5] The underlying assumption is that the better the private information, the greater the split factor.

[6] In order to also check for the Trading Range hypothesis, the authors include the hypothesis that there exist costs if the pershare price lays in different price ranges, and these costs vary inversely with the private information of managers.

proxied by the analysts' earnings forecast error[7]. If a relation between the level of signal and private information exists, the explanatory power of the pre-split price and market value is higher than the private information of the manager. Hence, they analyze the unexplained residuals of the relation between the split factor choice and the pre-split share price and the market value of the firm's equity. From a Tobit regression model, they find strong support for the Trading Range hypothesis compared to the Signalling hypothesis. The findings are consistent with firms that set the split factor in order to achieve the median trading range of the market and the target is greater for larger firms.

Secondly, McNichols and Dravid (1990) test whether the inferences of the investors correspond to the signal. The former is measured as the security return prediction errors in the stock distribution announcement period. They find evidence of a positive correlation, decomposed into two components to address both the signal associated with the decision to split and the signal associated with the split factor.

Finally, the third relation between the inferences and the private information of managers consists of the opportune revision of beliefs by the investors after the signal, corresponding to the firm's future earnings. The revision of investors' beliefs is proxied by security return prediction error at the announcement of the split and the firm's future earnings are proxied by the earnings' forecast errors of analysts in the pre-split period. It should be noted that this relation is only partly verified.

[7] Analists' earnings forecasts error is computed as the difference between the annual earnings reported after the split and the median analysts' pre-split earnings forecast

2.2.3 Attention hypothesis

Related to the Signalling hypothesis and starting from the same assumption of imperfect information between managers and investors, another explanation is the Attention hypothesis (Grinblatt, Masulis and Titman, 1984, Brennan and Hughes, 1991). Here, managers splitting their stocks aim to attract the attention of analysts and brokers, above all, on underpriced firms and on small firms.

Consistently with this explanation, abnormal returns after the announcement of a split are bigger for small firms, which usually have lower analysts' coverage and less public information available to the market, and they increase with the post-split price. Besides, as the new coverage is usually tilted towards positive recommendations, a distortion can be caused by this structure of incentives.

Brennan and Hughes (1991) develop a model in which firms decide the unit price of their shares in order to influence and attract the attention of brokers. Managers with positive private information would find it more convenient to have third independent parties produce positive information about their companies, rather than sharing it directly with the investors. In actual fact, traders invest more easily in stocks that have been promoted by brokers (Merton, 1987). A higher number of earnings forecasts imply higher trading activities and higher brokerage fees. Because in Brennan and Hughes (1991)'s model, brokerage fees depend on the per-share price, managers can actually influence the number of earnings forecasts, and consequently of traders, changing the price through a split.

Evidence from Lakonishok, Shleifer and Vishny (1994) and Haugen (1995) supports this theory and also shows that splits are signals of underpricing to the market, suggesting in fact that the magnitude of market reaction should be positively correlated with the book-to-market ratio.

If the Attention hypothesis is true, any kind of split would cause a positive reaction given the enlargement of the analysts' coverage. Actually, as evinced by Woolridge (1983) the market reacts negatively to a reverse split announcements, and in this negative response it is possible to see the influence of different explanations, such as for example a component of bad signalling.[8] In addiction, Ikenberry and Ramnath (2002) find an increase in coverage for splitting firms but it is not significantly different from the control non-splitting firms.

2.2.4 Self-Selection hypothesis

The previous hypotheses are not necessarily directly opposing theories, as illustrated by the contradictory empirical evidence. There is room for interdependence between them and many authors have tried to create new unifying theories, in particular between the Signalling and the Trading Range hypotheses (McNichols and Dravid, 1990, Grinblatt, Masulis and Titman, 1984, Ikenberry and Ramnath, 2002).[9]

The most important of these unifying theories is the so called Self-Selection hypothesis (Ikenberry, Rankine and Stice, 1996), which introduces optimistic managers. Managers prefer the per-share price to lie within a trading range, but they also have to consider that being below

[8] A reverse split is a much more rare case, in which the number of shares is decreased instead of increased and the price is multiplied.

[9] The asymmetric version of the Trading Range hypothesis considers that managers use the private information they own in order to set the split factor and convey their information to the investors, but that there exist costs in falling below the lower limit of the preferable range. In this way, investors can make better inferences about the private information by observing the split factor and knowing that the managers cannot expect the price to stay far from certain inferior support.

this level is too costly both for the company and for the shareholders. For this reason, managers that expect a decline in the stock price would probably not undertake a split operation, whereas optimistic managers would be more likely to. This means that the positive information contained in the event is actually the optimism of the management about the future performance of the company.

Evidence of managers being affected by optimism and overconfidence can be found in behavioural economics literature and in its psychological background. It is probable that agents with expertise and professionalism can end up with decisions that are biased in terms of the inferred probability of success of their decisions or ability. Given this background, Ikenberry, Rankine and Stice (1996) and Ikenberry and Ramnath (2002) assume that managers are more likely to be biased towards optimism, as they are the experts and professionals in their company. This bias causes the market to underreact to the announcement of the event. Investors would timidly update their expectations because although they know that managers are signalling good private information, they are also aware that they are biased with optimism. Investors are therefore uncertain as to the weight to put on the event. Their acting with prudence would cause positive returns of adjustment would be caused in the long run.

Ikenberry, Rankine and Stice (1996) analyze a sample of 2-to-1 splits from 1975 to 1990 finding evidence of positive excess returns in the announcement period and in the long run, consistent with both the Signalling hypothesis and the underreaction literature.

Some of the results coming from their analysis confirm previous works, both on the Trading Range and the Signalling hypotheses. They observe pre-event price run-ups and abnormal returns, and a relation between general conditions of the market and the number of announcements. Moreover, they confirm that the post-split price[10], is close to the median of comparably sized firms, consistently with the Trading Range hypothesis. Besides, they find a positive reaction of the market in the post-event window, in accordance with the Signalling hypothesis and underreaction. More precisely, they find that favorable information is incorporated into the price in the long run, and within one year the positive excess returns are still not reversed. These results confirm the Self-Selection hypothesis and underreaction due to the optimism of the management. This is in contradiction to the findings of Fama et al. (1969) that consider the market reaction immediately unbiased and complete, Ikenberry, Rankine and Stice (1996) and then Desai and Jain (1997) support the idea of underreaction.[11]

Moreover, Ikenberry and Ramnath (2002) further reinforce these findings. Once it is proven that the market underreacts to stock splits, the next research question is to ascertain what the market is reacting to. Two possible explanations consider the contribution of analysts. Either, investors fail to anticipate new analysts' coverage, which is usually optimistic, or they are slow to revise their expectations about future performance (which analysts' forecasts are supposed to be proxies for).

The first hypothesis comes from the general suggestion that managers split their stocks in order to draw the attention of analysts and convey news to the markets. Ikenberry et al. dismiss this explanation

[10] Post-split price is measured as the pre-split price divided by the split factor (as the target).

[11] However, there has been some notable criticism regarding the empirical evidence on underreaction. The main objections are concerns about the spurious results of such analysis, about the joint test hypothesis problem, famously reported by Fama (1998) and due to the absence of a robust asset pricing model to accurately compare the abnormal returns.

of underreaction, because they find that the increase in the analysts' coverage after a stock split is not so relevant when compared to the rise in coverage by the benchmark firms.

Actually, the effect of analysts' forecasts appears to be more relevant in the creation of expectations, which is consistent with the Self-Selection hypothesis. This is because, as it is more likely that optimistic managers would split their stocks than pessimistic ones, they would also be more likely to want to draw the attention of analysts to their positive expectations about future returns. On the market side, both investors and analysts are slow to incorporate these optimistic expectations into their own earnings forecasts. This causes underreaction. The evidence of the authors validates this hypothesis. Considering the forecast accuracy, such as measuring the error between the estimation of the next annual earnings and the actual value, they find that analysts tend to underestimate future earnings of splitting firms even up until three days before the earnings release, when compared with a control group of firms.

2.2.5 Preferred Tick Size hypothesis

The Preferred Tick Size hypothesis starts from the trading range motivation, adding a different and more sophisticated explanation. In the markets in which the minimum price variation is fixed by the exchange rules, companies find it advantageous and are able to change their relative tick sizes in order to optimize it and benefit from its advantages (Angel, 1997, Harris, 1994, Arnold and Lipson, 1997). Mainly, the advantages of tick size are related to concepts of bounded rationality and the discreteness, and to the usage of heuristics that simplifies decisional problems.

According to Harris (1994), there are four main reasons for the optimal relative tick size to be different from zero. To begin with, discreteness reduces the cost of negotiating for investors because it simplifies the traders' information sets and the possible outcomes, reducing the time spent for a trade and the possibility of potential trading error costs. Secondly, a large tick size should encourage market makers to quote this stock and create liquidity, because of the rise in bid-ask spread, and should therefore provide incentives to brokers to cover and promote the company. Thirdly, it attracts the desired clientele. Finally, investors have incentives to use limit orders, because a high tick size enforces time and price priority with the advantage of increasing liquidity.

Schultz (2000) tests the previous assumptions on intra-day data. He finds that the number of trades cancelled because of errors decreases after the splits. Moreover, he reports a rise in the shareholder base, because brokers are incentivized to promote companies with a relatively higher tick size.

The drawbacks of a higher tick size can be found in the increase in transaction costs. Copeland (1979) reports a rise in the relative bid- ask spread after the event. It could have the opposite effect on liquidity and improve the competition among brokers, eroding the profit margins.

Also, Angel (1997) provides a similar model and an empirical test of this theory. He argues that an optimal relative tick size helps companies to balance the benefits of increased liquidity and the higher costs paid by liquidity demanders. However, Lipson and Mortal (2006) run a natural experiment, looking at any changes in the split activity when the minimum tick size changes in an exchange. Hence, they investigate the effect of splits in sub-periods delimited by changes in the absolute tick size. They do not find any significant difference across the tick-regime samples in ownership structure or trade size. Moreover, practitioners do not explicitly cite tick size among the motivations for splits.[12]

2.2.6 Tax- Timing option

The last theory we will consider is the Tax- Timing option (Lamoureux and Poon, 1987). This hypothesis is based on the US tax code in the '80s where preferential treatment was given to long term capital gain, and short term capital losses could be used to offset short term gains. Investors were willing to pay for a tax option component, therefore higher volatilities had higher values (Constantinides, 1984). Thus, the increase in volume succeeding a split, can have a positive impact on the noise and on the non-systematic risk. Because of the tax option, the rise in volatility from a split would increase the value of the firm and subsequently reduce the required rate of return. Therefore, stock splits are a mechanism for the management to raise the tax option value of stock. Furthermore, the nature of the stock clientele will change because tax exempt investors will find the stock less desirable.

However, it is important to note that after the changes in the US tax code in 1987, the number of splits on the markets did not decrease, as would have been expected if applying this theory (Dhatt, Kim and Mukherji, 1997).

[12] However, this can be implicit in their behavior and can be confused between causes and effects of the preferred trading range.

2.3 Methodology of empirical analysis on stock splits

We have seen the main explanations proposed by the literature regarding the stock splits phenomenon. However, there is no single hypothesis that meets the general acceptance of researchers and really answers the questions as to whether stock splits are informative to the markets and what kind of information the market reacts to. The explanations are too broad, and it is difficult to delineate widely acceptable elements and implications to test, and to directly observe the information to test them. We have seen many empirical works end up with completely opposite conclusions because of noisy proxies, different sampling decisions or dissimilar methodologies.

Mitchell and Stafford (2000) consider the effect of methodological or sampling differences on the conclusions drawn, particularly in regard to long term abnormal returns.

Also Byun and Rozeff (2003) analyze the contradictions among the empirical findings, looking at the impact of different methodologies and sampling decisions on detecting long run effects.[13]

We have seen that splits look like a very uncomplicated event for traders to analyze, because of the absence of direct links to company or market variables and due to the long history of the econometric methodology used to study the effects of corporate events, since Fama et al. (1969). The event study is the methodology developed to analyze the impact of exogenous events on the performance of the market,

[13] We concentrate on the empirical literature on abnormal returns that is the area of most interest for the following analysis, and not on the debate about risk or liquidity.

comparing the returns effectively verified after the splits, with the "normal performance" as if the splits had not occurred. The choice of the method and model to better measure these unconditional returns depends on the specifics of the analysis to be conducted and its function is crucial to adjust returns for the risk.

If the objective of the analysis is the short term abnormal returns, the econometrics of the event studies is well developed and leads to widely accepted inferences with a satisfactory power of the statistics.[14]

In fact, the risk adjustment in the short term is not much related to the choice of the model used to measure the normal returns, and a standard market model or a constant-mean model are sufficient, without the necessity of any sophistication (Brown, Lockwood and Lummer, 1985).

We will now consider some of the methods used by the empirical research on stock splits to test for unexpected components in returns in the short period around the announcement or the ex dates.

The first methodological choice is how to measure the abnormal performance. Given an event period t, where $t = 0$ is the date of the stock split, and a splitting company i, the abnormal return of i can be measured using market-model abnormal returns or market- adjusted abnormal returns. According to the former one, the abnormal performance is estimated in comparison with the return of a market portfolio. The expected return of company i at period t is estimated as:

$$R_{it}^{*} = \widehat{\alpha}_i + \widehat{\beta}_i R_{mt} \tag{2.3.1}$$

where R_{mt} is the return on a market index, usually either CRSP

[14] This methodology has its milestones in the works, among others, of Cambpell, Lo and MacKinlay (1998), Brown and Warner (1980/1985), Barber and Lyon (1986), Khotari and Warner (2006).

value- or equal- weighted indexes.

Then, the abnormal return is equal to the difference between the observed return for company i at time t, R_{it}, and the expected return, R^*_{it}, as:

$$AR_{it} = R_{it} - (\widehat{\alpha}_i + \widehat{\beta}_i R_{mt}) \qquad (2.3.2)$$

Market- adjusted abnormal returns models focus instead simply on the difference between the observed returns for security i in period t and the returns from a market index that represents the market portfolio performance, such as the CRSP value- or equal- weighted index or an S&P index for the same event period t, R_{mt}:

$$AR_{it} = (R_{it} - R_{mt}) \qquad (2.3.3)$$

Once the model to measure the abnormal returns has been chosen, another methodological choice considers the aggregation of the abnormal returns, whether cross-sectionally and/or in time series. In time series, there are two aggregation methods that both correspond to the changes in wealth around the stock split dates given by the strategy to buy the splitting stocks at the beginning of the event period τ_1 and then holding them through to the end of τ_2.

The Cumulative Average Residual method (CAR), recommended by Fama (1998) measures the abnormal performance as the sum of the average abnormal performances for each period in the event window:

$$CAR(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} w_t \cdot \overline{AR}_t \qquad (2.3.4)$$

The Buy-and-Hold approach (Lyon, Barber and Tsai (1999)) suggests to compound each security's return in the event period T, measuring the abnormal returns as the difference between the observed portfolio compounded returns and the normal portfolio compounded returns:

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{mt}) \tag{2.3.5}$$

The aggregation then consists of determining the performance measure BHAR as an average of the compounded abnormal returns:

$$\overline{BHAR} = \sum_{i=1}^{N} w_i \cdot BHAR_i \tag{2.3.6}$$

Fama et al. (1969) were among the first authors to use an event study methodology which is very similar to modern methods, analyzing a sample of stock splits in the US markets from 1927 to 1959. They use a standard market model approach to measure the abnormal performance of the splitting firms in order to separate the effects of market movements.

They pay attention to the behaviour of the cross-sectional averages of the estimated residuals in the months surrounding the split dates, from the 29th month before to the 30th month after the ex date. The market model regresses linearly the (log) monthly rate of returns on the individual security j on the corresponding monthly (log) returns for the market, represented by L_t:

$$\ln R_{jt} = \alpha_j + \beta_j \ln L_t + u_{jt} \tag{2.3.7}$$

They show that the assumptions of a linear regression model are satisfied and, in order to eliminate the specification error from the months in which the residuals are not zero (the months close to the event), the authors exclude these periods from the estimation window.[15]

The abnormal returns are then averaged and cumulated for the event window with the CAR approach, and then compared in groups, focusing on characteristics of the companies, such as the next increasing or decreasing released dividends.

The alternative approach is to directly compare the Buy-and-Hold returns on the splitting company's portfolio with some market indexes, usually the CRSP equal- or value- weighted indexes or the S&P indexes. Ikenberry, Rankine and Stice (1996) analyze the market reaction around the announcement of a sample of splits from 1975 to 1990. They measure 5-day market adjusted abnormal returns, as the difference between the 5-day holding period returns for the splitting firms and the 5-day holding period return on the CRSP value-weighted index. Significance levels are assessed using cross-sectional standard errors.

On the other side, for long run abnormal returns there are no completely satisfactory methods or well specified test statistics. It is especially unclear which return model is correct because the risk adjustment is a very delicate matter when we take into account an event window longer than one year. In a quite hopeless mood, Fama (1998, pag. 291) states that "all models for expected returns are incomplete descriptions of the systematic patterns in average returns." In the recent empirical analysis, the common choice is to include the asset pricing three-factor

[15] No serious serial dependence is found in the residuals, and they also verify for linearity and homoscedasticity. Instead, the normality assumption is not verified, because the distribution is closer to a stable Paretian family: in any case, the authors use the OLS as the estimation technique, which is still unbiased and consistent.

model from Fama and French (1993) or the four-factor model, with the addiction of momentum, from Carhart (1997).

Then, there are two main methods to measure the post-event risk adjusted performance in a modern event study (Khotari and Warner, 2006): the Characteristic- based matching approach (Barber and Lyon, 1997) and the Calendar Time portfolio approach (Jaffe, 1974, Mandelker, 1974).

The Characteristic- based matching approach (or buy-and-hold abnormal returns approach - BHAR) bypasses the problem of the correct asset pricing model, because it requires the determination of a benchmark of companies with similar characteristics, from which to compare the results of the splitting portfolio. These similar characteristics are usually identified by industry, size, book-to-market and momentum. Abnormal returns for the company i are then calculated as the differences between the total rate of return of the splitting stock i in event period T and the average of the benchmark portfolio total return for period T:

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{bt}) \tag{2.3.8}$$

The aggregation of the individual abnormal returns cross- sectionally can be measured by an equal- or a value- weighted average:

$$\overline{BHAR} = \sum_{i=1}^{\mathbf{N}} w_i \cdot BHAR_i \tag{2.3.9}$$

where $w_i = \frac{1}{N}$ in the case of equal weights or at the market value of stock i in the value- weighted average. On this regard, Fama (1998) suggests the value-weighted average, because it is a closer reflection of the realistic way that investors judge their portfolios, while Loughran and Ritter (2000) prefer the equal-weighted approach to spread the emphasis across all the companies.

The test statistics are usually constructed with the bootstrapping approach: the benchmark portfolios are replicated to produce random bootstrapped pseudo-portfolios in order to obtain the benchmark distribution (Barber and Lyon, 1997).

The Calendar Time portfolio approach (or Jensen's Alpha) instead requires the assumption of the validity of an underlying asset pricing model. In recent years, the most common choice has been the market model or the three-factor model of Fama and French (1993), or extended with the fourth factor as Carhart (1997).

At calendar period t, the average abnormal returns, CTAR$_t$, are calculated for all the sample firms that have announced a split. The CTAR$_t$ are equal to the difference between the period returns on the portfolio of event firms at calendar time t and the expected normal returns on the event portfolio at the same time t:

$$CTAR_t = R_{pt} - E(R_{pt}) \tag{2.3.10}$$

The normal return can for example be estimated using the four-factor model, therefore, the expected excess return would be equal to:

$$R_{pt} - R_{ft} = \alpha_i + \beta_1 (R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t + \varepsilon_{it} \tag{2.3.11}$$

where $(R_{mt} - R_{ft})$ is the excess return of the market portfolio on the risk free return, SMB_t, HML_t, $PR1YR_t$ are the excess returns on portfolios mimicking the size effect, the book-to- market and the momentum effects respectively. After regressing the monthly portfolio excess returns on the four variables, the intercept is the measure of excess performance.

The test statistics are calculated with the estimated parameters from the time series of monthly standardized CTARs.

As we can see, there are many choices to be made regarding the empirical research, concerning the asset pricing model to measure normal returns, the aggregation method and the weights for the average of abnormal returns, without considering sampling decisions. Byun and Rozeff (2003) analyze long historical data about stock splits to give unity to the methodology and the sampling and in order to test for market efficiency, trying to solve the contradictory results of previous analyses. Among others, Fama, Fisher, Jensen and Roll (1969), using a calendar time approach, confirm the absence of any abnormal behaviour, while Ikenberry, Rankine and Stice (1996), Desai and Jain (1997) and Ikenberry and Ramnath (2002) instead reach the opposite conclusions using a BHAR approach.

Byun and Rozeff (2003) use different approaches and choices to the sample periods from 1927 to 1996 and find no evidence of abnormal reaction. For example, they compare their analysis conducted with BHAR and value- weighted average abnormal returns with the analysis of Desai and Jain (1997) that instead use an equal- weighted BHAR approach.

The problem is even more complex, as Ikenberry, Rankine and Stice (1996) already positively check the robustness of their results using both the BHAR method and the Calendar Time approach. Using the benchmark technique of matching each splitting company with a control firm which displays the same characteristics of market capitalization, book-to-market and momentum, they find a significant positive drift that characterizes underreaction in a sample of splits from 1988 to 1997 (Ikenberry, Rankine and Stice (1996), Desai and Jain (1997) use the same method). These results are also confirmed by the second approach, using a Calendar Time method, that applies the three-factor model of Fama and French (1993) as a normal return model. In this case, the difference in results reached by Byun and Rozeff (2003) seems to be attributed to the construction of the benchmark portfolios, based solely on a size dimension in order to enlarge the sample.

2.4 Empirical evidence

We have seen that the first authors to study the phenomenon of stock splits using modern methods are Fama et al. (1969). Because of the simplicity of the stock split event, they aim to investigate the Efficient Market hypothesis and the process of price-adjustment after the arrival of new pieces of information. They find abnormal pre-event returns in the months surrounding a sample of US splits from 1927 to 1959, but they explained that this behaviour could still be consistent with the market efficiency theory.

In fact, according to their research, splits are usually preceded by a period of abnormally high rates of return (on both dividends and capital), which is especially concentrated in the two or three months before the occurrence. After the events the returns tend to become randomly distributed again with zero mean. This is consistent with the motivation felt, as the market interprets splits as good information, as an anticipation of substantial increases in dividends and then their stabilization to the new levels. In fact, dividend announcements usually occur at the time of, or just after, a split.

When this information takes into account the expectations of investors, the apparent price effects vanish. In recent years, Nayak and Prabhala (2001) document that about 54% of split announcement effects can be attributed to dividend information, however, the puzzling effect of stock splits also persists in empirical analysis which is clean of contamination from other distributions (Grinblatt, Masulis and Titman, 1984).

In addiction, but without a robust argument, Fama et al. (1969) consider that this adjustment process is so rapid that splits can in no way be used to increase trading profits, confirming the non-systematic-profits implication of the Efficient Market Hypothesis.

Other than Fama et al. (1969), many authors have carefully investigated the existence of real effects on some market variables around the announcement and other essential dates of the split, and in the long run. However, these effects are not exempt from criticism and are not universally accepted. We report a brief review distinguishing between pre-split evidence and post-split evidence.

2.4.1 Pre- event window

Regarding the pre-split window, there is general agreement about the evidence of abnormal activity. Indeed, we observe high rates of returns in the prices before the announcement, due to abnormal increases in earnings and dividends (Fama et al., 1969, Asquith, Healy and Palepu, 1989, Lakonishok and Lev, 1987). Fama et al. (1969) analyze 940 stock splits monthly data between 1927 and 1959, using a market model. They find an average excess return of 34% preceding the split. Lakonishok and Lev (1987) study more recent stock splits, from 1953 to 1982, which show evidence of a significant abnormal return (an average of 53% in the 5 years pre-event and 47% in the year prior to the split). Also, Asquith, Healy and Palepu (1989) uses a market- adjusted approach finding excess returns of 56.8% in the years 1970-1980.

In addition, the announcement of this event is preceded by high and abnormal trading volumes. Lakonishok and Lev (1987) evince a strong monotonic increase in the months closely preceding the announcement. This result is motivated by a general abnormal operational performance, but it is not a permanent effect as it dies out in the few months after the split.

These robust observations of pre-split price run-ups for splitting stocks, as we have seen, in part motivate the will of managers to realign the increasing prices to a normal trading range. This run-up can be determined by specific motivations of the company or by a general good moment in the markets: it is typical that the number of splits increases in periods of boom and optimism in the markets (Fama et al., 1969, Ikenberry, Rankine and Stice, 1996).

2.4.2 Post- event window

Regarding the empirical evidence on the behaviour of market variables after the announcement or realization of a split, there is much less agreement, especially given the issues surrounding the correct methodology to employ, on which proxies to use and given the delicate impact on the Efficient Market Hypothesis.[16]

[16] We focus in particular on the market reaction and effects on the performance of the company, as we did in the previous section. However, we will briefly consider

Splits are considered to influence the wealth of shareholders. Empirical papers have widely shown how investors in aggregate respond to splits. After the announcement of the splitting decision, markets react favorably, presenting positive excess returns (Grinblatt, Masulis and Titman, 1984, McNichols and Dravid, 1990, Fama et al., 1969, Bar-Yosef and Brown, 1977), similar to the response to an event conveying good information.

Fama et al. (1969) find no abnormal post-event returns in the months surrounding a sample of US splits from 1927 to 1959. After the events, these returns tend to be randomly distributed again with zero mean, and they explained that this behaviour can still be consistent with the market efficiency theory. In fact, when a split is announced, the market interprets it as an anticipation of substantial increases in dividends and of their stabilization at the new levels.

Grinblatt, Masulis and Titman (1984) use a mean-adjusted approach to measure the post-event abnormal return in a window of 43 days, for a sample of 244 events. They are clean from the effect of any other distribution announcements in the same time window. They assume that the mean of the stock returns is representative of the typical return around the event. They find average significant excess returns in the day of announcement (1.96%) and in the following day (1.33%).[17]

Ikenberry, Rankine and Stice (1996) find market- adjusted abnormal returns around the announcement. However, the market reaction to stock splits decreases over time (considering sub-periods of 5 years, from 1975 to 1990, from 4.26% to 2.02%). Moreover, they find evidence that the abnormal return is negatively related to the size of the com-

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the impact on risk, liquidity and ownership structure.

[17] They also find excess positive returns on the ex-date (0.69%) and the following day (0.52%).

pany, the post-split price and the book-to-market ratio. Therefore, low book-to-market and small capitalization firms benefit the most from the split announcement.

Other evidence shows that this abnormal performance does not only happen at the announcement, when the implicitly good information becomes public and is aggregated into the prices, but also that there is a positive reaction around the ex date (Eades, Hess and Kim, 1984, Lakonishok and Vermaelen, 1986, Grinblatt, Masulis and Titman, 1984, Lamoureux and Poon, 1987, Nayar and Rozeff, 2001). Lamoureux and Poon (1987) use a market return model in an estimation window of -250 to -130 days prior to the announcement of the event. They construct t tests with an estimator of the variance in the window -120 to -60 prior to the announcement. They find a statistically significant average excess return of 0.56% on the split ex-date.

Besides, there is even evidence of negative abnormal returns around the record date, motivated by the inconvenience of holding non-splitting shares between the record date and the ex date, as Nayar and Rozeff (2001).[18]

The significant market reaction is also evidenced in case of reverse splits. In this case, a negative abnormal returns follows the announcement of stock splits in the short run (Woolridge, 1983 reports an average of -7% return in the days around the event).

Other analyses measure the intensity of this reaction in the long run, suggesting that markets exhibit long term excess returns after the announcement.

[18] The record date is the day between the announcement and ex dates which determines the ownership rights to the new shares. Buyers who become possessors of the shares before the record date are entitled to receive the new ones, whereas buyers of unsplitting shares after the record date have the obligation to hand in the new shares to the old possessor.

Earlier studies reject the hypothesis of long run effects on prices. Fama et al. (1969) report no significant abnormality in the monthly excess returns following the ex-date of the split. Also Lakonishok and Vermaelen (1986) find no statistical difference between the returns of splitting firms and a control set of firms after the ex-date of the events.

The first authors to re-consider the hypothesis are Ikenberry, Rankine and Stice (1996) and Desai and Jain, 1997, who find evidence of underreaction. Ikenberry, Rankine and Stice (1996) use a buy-and-hold approach for the three years following a split. They compare the returns of an equal-weighted portfolio of splitting firms with a portfolio of similar non-splitting companies, similar in size and book-to-market. They use bootstrap to construct the empirical distributions for the significance test. They find a 7.93% significant difference in the average returns of splitting companies one year after the split announcement, and 12.15% in a three-year period post-event. Desai and Jain, 1997 also find evidence that justifies the hypothesis of an initially timid reaction by the market, that is slowly corrected, implying long run positive returns. Moreover, they find the same reaction, but with opposite signs, for reverse splits.

The evidence of underreaction implies that the information that is transmitted with the event is positively received. However, the reaction is not immediately complete and unbiased. The news is initially underweighted and the prices do not aggregate them at once, but they are adjusted in the long run with a positive abnormal drift.[19]

This is a very delicate point, because as we have seen, there is no agreement on the correct econometric methodology. Byun and Roz-

[19] See the works of Barberis, Shleifer and Vishny (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) for a theoretical contribution on underreaction, to which the findings on splits are consistent.

eff (2003) analyze stock splits from 1927 to 1996 using alternative methodologies, with the aim to homogenize the different studies and results. They find an average excess return of 3.74% from the ex-date of the split, using a buy-and-hold methodology with matching portfolios. Moreover, they confirm that the effect changes over time and the most significant average excess return is in the 1975 to 1990 window. Then, they use a calendar-time abnormal return (as Mitchell and Stafford, 2000) using both the three- factor model (Fama and French, 1993) and the four-factor model (Carhart, 1997) to estimate normal returns. In the first model they find significant abnormal returns, even though they are relatively small. However, when introducing the fourth factor, they do not find significant abnormal returns.

Another impact on the wealth of the shareholders consists of future abnormal increases in the company earnings. This was one of the main effects attributed to stock splits, as Fama et al. (1969), McNichols and Dravid (1990).

Yet, similarly in this case there is no agreement within academia. Lakonishok and Lev (1987) consider this rise in earnings more as a cause than an effect of a split, showing that the fast growth in the months preceding the announcement is quickly corrected in the few months after, so it does not persist in the long run. Moreover, Huang, Liano and Pan (2006) also recently report no significant abnormal earnings performance in the following five years.

Splits also appear to influence the risk of the shares. However, the effects on risk are still uncertain, because many empirical studies suggest different and sometimes opposite conclusions, according to the proxies used and the methodologies applied.

Dravid (1987), Ohlson and Penman (1985), Koski (1998) find a permanent increase in return volatility, estimating the daily return volatility as the expected squared daily returns. Likewise, Ohlson and Penman (1985) observe an increase in risk, measured as daily variance up until one year after the ex-date of the split, which is 30% on average. Brennan and Copeland (1988a) find that the systematic risk (as beta) of these stocks also increases.

Besides, doubts arose that the results could be induced by measurement error. Amihud and Mendelson (1986), Blume and Stambaugh (1983) show that bid-ask spreads and discreteness could induce upward biases in the measurement of volatility. Yet, Koski (1998) report an increase in realized volatility, clean of measurement errors. Another example of disagreement comes from Bar-Yosef and Brown (1977), who find a decrease in the systematic risk of the company.

Furthermore, the impact of stock splits on liquidity and marketability of the stocks has been carefully investigated. In fact, when managers are asked about the motivations behind the splitting decision, the main justifications they report consider improving liquidity and marketability of the shares and attracting a wider and more diversified pool of investors. Artificially decreasing the price of the stocks could make the shares more accessible to small investors, allowing them to trade more easily in round lots, or to take advantage from the improved liquidity. All of these effects consequently lead to increases in the value of the companies (Baker and Gallagher, 1980).[20]

However, this is a controversial matter and the conclusions of the academic empirical literature are not unified, as many different proxies for liquidity and marketability are used. Two main variables are tested for liquidity: relative bid-ask spread and trading volume.

[20] See for example the reccomendation of splitting stock from a financial analyst, cited in McNichols and Dravid (1990), p. 858.

Copeland (1979) finds an increase of 6.54% in the bid-ask spread in the 20 days after the split, from 1968 to 1976. The effect of this increase on liquidity is mixed. This rise directly decreases the liquidity of the stocks, and it is accompanied by simulated evidence of an increase in brokerage fees of 7.1%. Conversely however, higher spreads in fact encourage brokers to do research on these companies and increases the analysts' coverage (Brennan and Hughes, 1991 and Copeland, 1979). McNichols and Dravid (1990) add that this new coverage is often positive and can be positively adapted to the small companies' situations.

Other supportive evidence of the increase in bid-ask spread are Conroy, Harris and Benet (1990) and Schultz (2000). The former authors, for example, find an increase in the relative bid-ask spread, along with a decline in the absolute spread. Desai, Nimalendran and Venkataraman (1998) distinguish an adverse component from the bid-ask spread, finding an increase in both the relative spread and the adverse information component after the splits. Similarly, Gray, Smith and Whaley (2003) find that the order processing costs and inventory holding costs increase, but that the degree of market competitiveness decreases.

Other studies use trading volume and turnover as proxies for liquidity. Copeland (1979) finds that trading volume increases on a small sample of 25 splits. Lakonishok and Lev (1987) find an increase in monthly turnover around the split, in comparison with matching non-splitting companies, but it is more of a pre-event phenomenon that dies out in the two months after the announcement. Instead, adjusting the trading volume with general market trends, they observe a decline in adjusted volume, following the announcement.

Finally, there is evidence of changes in the ownership basis. The impact on the ownership structure is one of the explicit motivations for managers to split. In particular, splits can lead to an increase in the number of shareholders (Lamoureux and Poon, 1987, and Maloney and Mulherin, 1992) or to a change in the clientele of investors (Dhar, Shepherd and Goetzmann, 2004), although the change in the pool of investors is not clear. Some analyses show that splits are followed by an increase in the institutional ownership of the company both in terms of number of institutions owning the stocks and in the percentage of shares owned by the institutions (Maloney and Mulherin, 1992, Baker and Powell, 1993). However, there is not a significant difference between splitting firms and control firms.

Other studies show evidence of an increase in the number of uninformed and noise traders as well (Easley, O'Hara and Saar, 2001, Admati and Pfleiderer, 1988, Lipson and Mortal, 2006).

The impact on informational asymmetry is also unclear: Desai, Nimalendran and Venkataraman (1998) find a rise in adverse selection with a spread decomposition procedure, while Easley, O'Hara and Saar (2001) conclude that there is a small decrease in adverse selection.

Chapter 3

Price impact of stock splits and dispersion of beliefs

3.1 Introduction

The aim of this chapter is to offer a new perspective on understanding stock splits. We look at the market reaction to analyze whether the announcement of such events impacts on the distribution of the analysts' forecasts and whether the dispersion of forecasts impacts on the abnormal future performance.

As we have seen in the previous chapter, a stock split is a "cosmetic" corporate event, which does not directly result in changes in market capitalization or to the ownership basis. Yet, managers invest resources in splits, and the market subsequently reacts to their announcement, as we evince from the empirical literature.

In the light of the Self-Selection hypothesis, our study aims to investigate the underreaction to the announcement of a stock split, connecting it with the differences of opinion among investors.

The literature on differences of opinion investigates whether the disagreement among investors affects the future performance of stocks returns. Empirical evidence shows that dispersion of beliefs is associated with measures of fundamental risk, such as market beta and stock returns variability (Diether, Malloy and Scherbina, 2002). However, dispersion of beliefs detects also an informational risk, not captured by such measures. Chan, Hwang and Mian (2005) consider dispersion of beliefs as a proxy for the reliability of the information to the market. This is the approach relevant for our analysis, as higher disagreement among analysts implies poor quality of the information available to the market and therefore leading to higher returns. At the time of the event, investors are facing uncertainty on the reliability of the new information. The increase in dispersion, together with the increase in consensus and decrease in forecasts error, are consistent with the presence of a noisy signal in the event, that introduces a two-dimension uncertainty on the value and on analysts' accuracy.

Our paper aims to investigate the relation between the dispersion in analysts' forecasts and market returns at the announcement of a stock split. The idea underlying this project is that the distribution of the forecast dispersion changes after a split and thereby can help to predict future performance. In fact, assuming the presence of underreaction in the markets at the announcement of stock splits (leading to long run positive returns in the splitting company), our study evinces that the dispersion in analysts' estimates can contribute to explaining this mispricing.

The analysis is carried out on a sample of splits which occurred in the US markets from 1993 to 2005, extracted from the CRSP and the I/B/E/S databases, considering price data and analysts' estimates. We analyze three types of relations.

The first step is to analyze the link between stock splits and market expectations, looking at changes in analysts' earnings forecasts. Positive changes in mean and negative changes in dispersion will confirm a signalling model of splits. Therefore, we check for changes in the distribution of the analysts' forecasts around both the announcement and the occurrence of a split. The results show an increase in the mean of forecasts, but also a slight rise in dispersion after both the announcement and the occurrence of a split.[1] This result suggests that an informational content is present in the event, as the estimates error of analysts' earnings forecasts decreases after the announcement. In particular, before the event, these companies were underestimated, with a negative forecasts error, close to significance at 10%. After the event, the mis-estimation is corrected as the error is on average positive but clearly not significant. However, there is also an increase in uncertainty, especially on the quality of information conveyed by the event (Chan, Hwang and Mian, 2005). These results are consistent with the Self-Selection hypothesis and the propensity for optimism by the management of splitting companies. Optimistic managers cause uncertainty in the market on the extent of the positive new information in the event. Higher is the dispersion, poorer is the information available to the market, so that the signals are noisy and not completely reliable.

[1] The proxy for the differences of opinion is the ratio between the standard deviation of the earnings' forecasts and the absolute value of the mean of these estimates. Both the mean and the dispersion are measured in the 2 months before the split and in the two months after (+/- 45 days from/to the event). We checked if the effect on dispersion could be contaminated by the contemporaneous increase in coverage, using the ratio of the standard error of the estimates over the absolute mean of the forecasts. We find no different evidence.

The second link we investigate is the relation between stock splits and prices. Once we have evidenced whether a change in expectations effectively occurs, we carry out an event study on the future returns of the splitting companies. We estimate the CARs with a four-factor model (Carhart, 1997). We find that a positive reaction of the market at the announcement of the stock splits actually exists. In the 90 trading days following the event, the abnormal component cannot be explained by the four-factor model which we used for normal returns. These results confirm the hypothesis of underreaction of the market to the announcement of such events (Ikenberry and Ramnath, 2002).

The final link we investigate is the relation between market expectations and prices. We divide the sample into subgroups for prior dispersion, then test for the impact of prior dispersion on abnormal returns. We find evidence that a relation, however weak, exists. The CARs are compared among three groups and we find that high levels of dispersion, in both the announcement and ex date databases, have a positive effect on abnormal returns. We can conclude that the excess returns are partly explained by the dispersion that exists before the announcement of the splits. We also regress the future returns on the change in dispersion, using an Instrumental Variable approach. The instrument for the change in dispersion is the prior dispersion. We find a non-linear relation between the change in dispersion and future returns, while a positive relation is significant between prior dispersion and 5-month compounding returns. .

The layout of the paper is as follows. Section 2 reviews the empirical framework on underreaction to splits and on differences of opinion. Next, Section 3 introduces the sample and the methodology, and summarizes the empirical analysis. Finally, Section 4 concludes our findings.

3.2 Dispersion of beliefs and stock splits

In this study we aim to address the phenomenon of stock splits from the point of view of differences of opinion. We examine whether the literature on dispersion of beliefs could help us to gain a better understanding of the motivations behind the abnormal returns after the announcement of stock splits.

Recalling Ikenberry, Rankine and Stice (1996), they find evidence of positive excess returns in the announcement period and in the long run on a sample of 2-to-1 splits from 1975 to 1990. These findings are consistent with both the Signalling hypothesis of stock splits and the underreaction literature. In fact, in the long run, favourable information is incorporated into prices within one year, and the positive excess one-year returns are not reversed. This is consistent with the Self-Selection hypothesis and the presence of optimistic managers. The authors also confirm the Trading Range hypothesis, finding that post-split prices tend to be close to the median of comparably sized firms.[2]

Once found that the market underreacts to stock splits, Ikenberry and Ramnath (2002) deepen the analysis, investigating the theoretical motivations. They consider the analysts' contribution to this reaction either because investors fail to anticipate new analysts' coverage, which

[2] However, some criticism has been levelled at the empirical evidence on underreaction. The main objections are concerns about spurious results of such analysis, about the joint test hypothesis problem, famously reported by Fama (1998) and due to the absence of a robust asset pricing model to effectively compare abnormal returns.

is likely to be optimistic, or because investors are slow to revise their expectations about future performance (which analysts' forecasts are supposed to be proxies for). The first hypothesis comes from the general suggestion that managers split their stocks in order to draw the attention of analysts and convey news to the markets. Ikenberry et al. deny this explanation of underreaction. In fact, the increase in analysts' coverage after a stock split is not so relevant when compared to the rise in coverage they observe for benchmark firms. Actually, the role of analysts' forecasts is more relevant in the creation of expectations, which is consistent with the Self-Selection hypothesis. Optimistic managers are more likely to split their stocks, and they intend to draw the attention of analysts to their positive expectations about future returns. Conversely, both investors and analysts are slow in incorporating these expectations into their own earning forecasts, causing underreaction. The evidence of the authors validates the hypothesis. Considering the forecast accuracy, such as the error between the estimation of the next annual earnings and the actual value, they find that analysts tend to underestimate future earnings of splitting firms even until three days before the earnings release, in comparison with control firms.

We connect this evidence of underreaction with the literature on differences of opinions. The empirical evidence on the relation between returns and differences of opinion are still mixed. A first approach was originally developed by Miller (1977) with a static model, then developed in the following years by other authors, such as Diether, Malloy and Scherbina (2002), Liu, Xu and Yao (2004), Diether (2004). The dispersion of beliefs is a proxy for disagreement among investors and it can lead to a negative long-term mispricing, given the assumptions that there are two classes of agents, optimistic and pessimistic investors, and there are short-sale costs that prevent the pessimistic opinions to be revealed. A second branch of literature introduces heterogeneous beliefs maintaining the equilibrium of the Efficient Market Hypothesis. Diamond and Verrecchia (1987) and Hong and Stein (2003) suggest that also in markets where disagreement exists, there are mechanisms or perfectly rational agents that can maintain the prices at their efficient levels. In fact, rational investors take already into account the constraints to negative opinions to be revealed. Finally, a positive relation between dispersion and future long term returns exists in the model of Varian (1985) and Merton (1987), where the differences of opinion are interpreted by the investors in the market as a component of risk. In this case of higher disagreement, it needs to be compensated with higher future returns, so the asset prices are likely to be downward mispriced today for a higher returns in the long run. This model works assuming no constraints to short selling.

From the literature, it appears that the effect extrapolated from the dispersion of beliefs is still ambiguous, as partly due to risk premium, as Varian (1985) and Merton (1987) models, and partly due to disagreement, as Miller (1977) model. Our results can be motivated with a dominant influence of informational risk effect over the disagreement effect. In particular, we focus on informational risk on the quality of the new signal driving the positive effect between dispersion of beliefs and future returns (Chan, Hwang and Mian (2005)).

To conclude, few studies apply the literature on differences of opinion to corporate events. Diether (2004) analyses the underperformance in the long run of a sample of SEOs, motivating it with short sale constraints and differences of opinion. Then, Loughran and Ritter (2000) analyze the dispersion of beliefs around extreme events in the three years after new equity issuances. They find that these extreme events are accompanied by a great divergence of opinion among investors, proxied by the share turnover. Assuming Miller's hypothesis, this leads to poor future performance given evidence of short sale constraints in IPOs or SEOs.

3.3 The empirical analysis

3.3.1 The sample

In order to analyze the impact of the dispersion of analysts' beliefs in the future performance of splitting firms, we use a sample of stock splits which occurred in companies quoted on NYSE, AMEX and NASDAQ markets in the period from 1993 to 2005. The CRSP monthly and daily datasheets provide the market variables of the companies and the information regarding the declared stock splits, such as announcement and payment dates and adjustment factors. The I/B/E/S Detail dataset provides the estimates for the next fiscal year earnings, for each analyst, with an indication of the estimate dates, revision dates and actual EPS.[3] By merging these two datasheets we obtain a sample composed

[3] There are some concerns about the accuracy of some rounding and assumptions made in the construction of the I/B/E/S data, as Diether, Malloy and Scherbina (2002) and Baber and Kang (2002) explain. These authors consider a reporting inaccuracy in this database which is normally used for research on analysts' forecasts. Because data is adjusted retroactively for splits, there are two sorts of problems which can arise. Earnings are reported on the basis of the shares outstanding at their present level, rather than at their historical values, and this assumption ignores the fact that splits are usually done by companies with positive performances. This means that the stock prices of splitting companies contain ex-post positive information, and the subsequent comparison with non-splitting firms is distorted. The second problem is a rounding approximation that with long series of data can cause

of 2090 splits, corresponding to 1299 companies. The companies are selected if they had announced at least one split in the above period, according to the CRSP database, and have been covered by at least two analysts as reported in the I/B/E/S database.

The splits have been selected by firstly considering all the available data in both the CRSP and the I/B/E/S databases. Not all the splitting companies in the CRSP have coverage in the I/B/E/S, as these latter database tilted towards firms with the highest size and performance.[4] In particular, we are interested in cases with at least two analysts covering each company before the announcement or the occurrence of the splits and at least two analysts covering after the declaration date (or ex-date).

Other important assumptions in the construction of the database are in regards to the dates of the splits. In order to properly analyze

a misunderstanding of the behaviour of the variables and of the real manifestation of the phenomena. Regarding this data, these problems seem to be particularly relevant when attempting to make comparisons with non-splitting firms, and not as relevant if for example you are calculating the impact of some sort of variable on all the stocks in the market. In our particular case, focusing only on splitting companies, the sample is a homogenous set of firms and we assume that each of them incorporates the positive future expectations of the management about their future performance.

[4] It follows that the sample could underperform the negative cases in the markets and overperform the bigger and more profitable companies. Two considerations can alleviate this asymmetry. We have previously seen that optimistic managers are more likely to split, because managers who imagine a negative performance would probably not undertake a split operation due to the costs of lying below the preferred trading range in the future. This means that the positive information contained in a split is the optimistic expectations of the management (Grinblatt et al. 1984, McNichols and Dravid, 1990). For this reason, the problem of overperforming the more profitable companies, becomes less important, as the sample is still homogeneous. It is, in fact, concentrated only on splitting companies, which are more profitable and have more optimistic expectations about the future. In addition, La Porta (1996) shows that regardless of the concentration of big stocks in the I/B/E/S database, the performance of this portfolio is the same as the one composed of all the CRSP companies.

the market reaction, we need to have an indication of both the days of the announcement and the distribution of the new shares. Thus, we assume that the announcement corresponds to the declaration date and the occurrence to the payment date indicated by CRSP. In addition, the splitting companies should have at least twelve months of observations after the payment date in order to consider future performance and at least 250 days before the announcement date as estimation windows.

The sample of splits has been cleansed further by disregarding the cases in which other distribution events have been announced in the previous five days (as Grinblatt et al. (1984)). With this further selection, we eliminate the frequent cases in which splits are announced at the same time as dividend distributions (Fama et al. (1969)).

Once the sample of splits is identified, two distinct databases are constructed: one is composed using the market variables and the analysts' estimates around the declaration dates and the second one is composed using the variables around the payment dates of the splits. This distinction allows us to measure the effect on the markets both around the announcement and the occurrence of the split.

3.3.2 The methodology

The empirical analysis consists of three stages. First at all, we check for changes in market expectations around the announcement and the occurrence of a split. Once we have analyzed that a change in the distribution of analyst's forecasts effectively occurs, we carry out an event study to investigate the market reaction to the announcement of the event. Finally, we analyze the impact of the dispersion of forecasts estimates on future returns of the splitting companies.

Distribution of the analysts' forecasts

Looking at the market expectations, we focus on any changes in mean and dispersion after the announcement of the event. We focus in particular on the differences of opinion, proxied by dispersion in analysts' earnings forecasts, in order to test the following conjecture.

Conjecture 1 *Positive changes in mean of the forecasts estimates and negative changes in dispersion and estimates error after the event will confirm a signalling model of splits.*

We measure the dispersion of forecasts as the ration of the standard deviation of earnings forecasts to the absolute value of the mean of these estimates (Diether, Malloy and Scherbina, 2002). As a robustness check, we also use the standard error, instead of the standard deviation over the absolute value of the mean estimate. This correction prevents the simultaneous increase in coverage from affecting the change in dispersion. We estimate the dispersion in four groups: before the announcement date, after the announcement date, before the ex-date and after the ex-date. We also analyze the change in dispersion, defined as the difference between the dispersion levels preceding and following the event.

This stage of the analysis is carried out with monthly data from CRSP and I/B/E/S, given the non-uniformity in time of the distribution of the I/B/E/S estimates. We consider the estimates by any analyst in a window of two months before the announcement (or payment) dates of the splits and analogously the estimates by each analyst in a window of two months after the event. The window is chosen primarily to facilitate a suitable size of the sample. As a robustness check, we use a window of 30 days before (after) the announcement. If an analyst has published more than one forecast in each period, only the closest to the event date is considered in each window.

We also analyze the relation between the dispersion of analysts' forecasts and present and future compounded returns.

Conjecture 2 *The hypothesis of an existing relation between returns and dispersion will be broadly verified if moving from the smallest to the highest group of dispersion, we can observe a systematic variation in the average returns. According to our assumption of dispersion of beliefs as a proxy for the reliability of the information, or information risk, we expect upwards changes in the returns moving from stocks with low to high dispersion.*

We first reduce the variability of an analysis on the whole sample, distinguishing groups of dispersion (see Jegadeesh and Titman, 1993). Next, we construct three portfolios of companies with low, medium or high intensity of dispersion, considering prior dispersion, post dispersion or the change in dispersion. We assign the stocks to the corresponding portfolio and calculate the average returns for each.

This relation is also checked by introducing a second variable to catch whether there is any endogenous influence of size effect on the relation. In this two-way cut, the mean returns are calculated for portfolios derived from the intersection of dispersion groups and size groups. An increase in the differential between the returns of low and high dispersion groups as the size diminishes would confirm that the relation is even stronger for small firms (Diether, Malloy and Scherbina, 2002).

We also investigate whether the change in dispersion after the announcement of stock splits affects the future returns of the companies by regressing the compounded returns on the change in dispersion. We use a polynomial model, using the square and the square root of the change in dispersion as regressors:

$$\mathbf{R}_{i,n}^{(0,t)} = \alpha + \beta_{1,t}\Delta Disp_{i_n} + \beta_{2,t}(\Delta Disp_{i_n})^2 + \beta_{3,t}\sqrt{\Delta Disp_{i_n}} + \epsilon_{i_n} \quad (3.3.1)$$

where t goes from 0 to 12 months after the event and i_n identifies the company-split going from 1 to 2090. $R_{i_n}^{(0,t)}$ is the compounded return for the company n from the month 0 of the announcement until month t after the split i. $\Delta Disp_{i_n}$ is the change in dispersion of beliefs, measured as:

$$\Delta Disp_{i_n} = PostDisp_{i_n} - PriorDisp_{i_n} \quad (3.3.2)$$

where $PriorDisp_{i_n}$ is the dispersion of beliefs, measured in the two months before the event, while $PostDisp_{i_n}$ is the dispersion of beliefs, measured in the two months after the event.[5]

We use an Instrumental Variable approach. In fact, the change in dispersion is measured in a window from 2 months before to 2 months after the event. Therefore, the post period overlaps with the returns period. The instrument which we use for the change is the prior dispersion; given that it is a good and relevant instrument.

[5] From now on we omit the index n, identifying i with both the splitting company and the stock split.

We also separately regress the average compounded returns, from the month of the split to 12 months later on the prior dispersion:

$$\mathbf{R}_{i,n}^{(0,t)} = \alpha + \beta_t PriorDisp_{i_n} + \epsilon_i \tag{3.3.3}$$

and similarly on post dispersion:

$$\mathbf{R}_{i,n}^{(0,t)} = \alpha + \beta_t PostDisp_{i_n} + \epsilon_i \tag{3.3.4}$$

The event study

The second part of the analysis focuses more formally on the effect of dispersion in analysts' forecasts on the cross- section of stock returns after the announcements of the events.

Conjecture 3 *If the stock split event is signalling positive information, we expect the market to react to the announcement with positive abnormal returns.*

In this stage, our analysis follows the standard event study methodology. We use daily data from the CRSP database.[6] We analyze the impact of the events (assuming they are exogenous) on the performance of the market, comparing the returns effectively verified after the event

[6] The main references are Cambpell, Lo and McKinlay (1997), Brown and Warner (1985), Kothari and Warner (2006). Thus, the methodology in use today was broadly introduced by Fama et al. (1969) in their analysis on stock splits, and with regard to short term analysis it is still similar.

with the "normal performance" as if the split did not occur. The choice of the method and model to best measure the unconditional returns is crucial to adjust returns for the risk.[7]

We estimate the parameters of a normal return model using the four-factor model as Carhart (1997). Then, in the post event window, we use the previously estimated coefficients in order to predict the abnormal returns after the arrival of the news conveyed by the splits.

The choice of estimation window and event window has to be taken carefully. In the estimation of the parameters of normal returns we have to exclude any eventual implication in trading activities or expectations from the split itself and other splits of the same company.

Regarding the estimation window from t_1 to t_2 before the announcement, we consider the period of 230 days that starts at t_1= -250 and ends at t_2 = -20 days before the declaration date of the split. The left extreme has been chosen in order to sufficiently avoid any overlap between previous stock splits undertaken by the same company and any contamination of altered performances. The right extreme derives instead from previous empirical findings that revealed an abnormal trading activity in the 10 days prior to the event announcement (Maloney and Mulherin, 1992, Easley, O'Hara and Saar, 2001).

Regarding the event window from τ_1 to τ_2 after the announcement (or occurrence) dates, we take into consideration different lengths in order to permit different analyses of the effect of the event. Given that day 0 is the announcement of the event, we consider the cases of 2 trading days (from day 0 to day 1) and 6 trading days (from 0 to 5). The event window should be short enough to avoid any overlap among

[7] See Mitchell and Stafford (2000) for considerations on how methodological or sampling differences can have a huge impact on the results of the study. This is especially important regarding long term abnormal returns.

companies. We clean the sample of splits for events that have no other distributions in the event window until 5 days after the split. In the following analysis we will also look at longer post-event windows in the months after the split. Once the windows of analysis have been defined, abnormal returns are assumed to capture the event impact. The abnormal returns are estimated as the difference between the observed returns over the event window and the normal returns that would exist in the absence of any event.

The asset pricing model used is the four-factor model of Carhart (1997), in which the explanatory variables are excess returns on portfolios constructed to mimic for size, book-to-market, market return and momentum. This check for momentum is particularly important to detect a split effect, given the abnormal high returns in the period before the event.

The regression equation is then:

$$R_{it} = \alpha_i + \beta_{1,i} F_{mkret,t} + \beta_{2,i} F_{btm,t} + \beta_{3,i} F_{size} + \beta_{4,i} F_{mom,t} + \varepsilon_{it} \quad (3.3.5)$$

where R_{it} is the continuously compounded excess return of the splitting company i from day $t-1$ to day t of the estimation window. $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$ and $\beta_{4,i}$ are the risk sensitivities of the four explanatory factors, for company i, ε_{it} is the disturbance terms or the abnormal returns. $F_{mkret,t}$, $F_{size,t}$, $F_{btm,t}$, and $F_{mom,t}$ are the four explanatory variables corresponding to the excess returns on portfolios constructed to mimic the implicit risks respectively in market return, size, book-to-market and momentum for the period t.[8]

[8] Factor returns are downloaded from the FF website.

Then, for company i and event day τ, we define the estimated abnormal returns in the event window (τ_1, τ_2) as:

$$AR_{i\tau} = R_{i\tau} - E[R_{i\tau}|F_\tau] = e_{i\tau} \tag{3.3.6}$$

where τ corresponds to the days around the announcement of the event; $R_{i\tau}$ are the returns for company/event i at day τ; and F_τ is the matrix of the four factors observed in this event window.

We use the CAR method in order to aggregate the abnormal returns. Then, we determine the cumulative abnormal returns in the event window for three groups, classified on the basis of the level of prior dispersion measured before the announcement of the splits.

Cumulative abnormal returns and standardized cumulative abnormal returns are estimated for each security/event i through time (for the interval τ_1 to τ_2 within the event window):[9]

$$CAR_i(\tau_1\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \tag{3.3.7}$$

and

$$SCAR_i(\tau_1\tau_2) = \frac{CAR_i(\tau_1\tau_2)}{[\widehat{\sigma}_i^2(\tau_1\tau_2)]^{1/2}} \tag{3.3.8}$$

where $\widehat{\sigma}_i^2(\tau_1\tau_2) = \sigma^2(AR_{i,1})$ is the variance of one period's abnormal returns.

Next, the cumulative abnormal returns are also aggregated across the events i, from 1 to N, and time τ_1 to τ_2, as the cumulative average abnormal return in the event window from τ_1 to τ_2, or equivalently as the average of the cumulative abnormal returns for i:

[9] With a sufficiently large estimation window, the SCAR is asymptotically distributed as a standard normal.

$$\overline{CAR}(\tau_1\tau_2) = \sum_{\tau=\tau_1}^{\tau_2}\overline{AR}_\tau = \frac{1}{N}\sum_{i=i}^{N}CAR_i(\tau_1\tau_2) \tag{3.3.9}$$

The last important step is to test for zero cumulative average abnormal return. This test raises the issue of the independence of the abnormal returns. In fact, the test constructed as the cumulative average abnormal returns divided by the variance of the abnormal returns (which we performed in the standardized CAR) brings some problems of specification. This is because the assumption of no correlation among the one period abnormal returns is not verified and also because of the existence of time clustering.[10]

Therefore, we use the test statistics as:

$$T(\tau_1\tau_2) = \frac{\overline{CAR}(\tau_1\tau_2)}{[\widehat{\overline{\sigma}}^2(AR_t)]^{1/2}} \backsim N(0,1) \tag{3.3.10}$$

where as estimator of the standard deviation is the average of the variances of the single CAR$_i$, $\overline{\sigma}_i^2(\tau_1\tau_2)$:

$$\widehat{\overline{\sigma}}_i^2(AR_t) = \frac{1}{N^2}\sum\sigma_i^2(AR_t) \tag{3.3.11}$$

Another possible test constructed from the Standardized CAR is:

$$(\frac{N(T-4)}{T-2})^{1/2}\overline{SCAR}(\tau_1\tau_2) \tag{3.3.12}$$

where T is the length of the event window.

The statistics under the null have a standard normal asymptotic distribution.

[10] A solution for the problem of specification of these tests considers using the estimated variance of the observed returns of the portfolio of the splitting companies in a period far from the event.

Dispersion of beliefs and future performance

The final step consists in a cross-section regression analysis. We examine whether the abnormal returns after the events are related to the dispersion of analysts' forecasts as measured in the period before the splits.

Conjecture 4 *If the event conveys uncertain information, we expect prices to underreact and the abnormal returns to be related to the quality of the information, proxied by the dispersion of beliefs.*

In order to perform this analysis, we use the three portfolios previously constructed based on the level of dispersion in the two months before the announcement and we compare the portfolio abnormal returns in the event windows.

To take into account the other variables that can affect the abnormal returns, the following regression is also estimated as a linear function of the abnormal returns on dispersion, and on the four factors of size, book-to-market, market return and momentum:

$$AR_{i\tau} = \alpha_i + \beta_0 PriorDisp_i + \beta_1 F_{mkret,\tau} + \beta_2 F_{btm,\tau} + \beta_3 F_{size,\tau} + \beta_4 F_{mom,\tau} + \varepsilon_{i\tau} \tag{3.3.13}$$

$$AR_{i\tau} = \alpha + \beta X_\tau + \epsilon_{i,t} \tag{3.3.14}$$

where X_t includes the dispersion ratio, and the excess returns on the factors size, book-to-market, market return and momentum.

3.4 Empirical evidence

3.4.1 The sample and the descriptive analysis

Regarding the descriptive statistics of the sample of splits, Tables 1.1 and 1.2 show the number of splits per year and per split-factor and the average number of splits per company.

The splits occurred in the period from 1993 to 2003 with a peak in 1999 and a following decreasing trend over the subsequent years. This is consistent with Lakonishok and Lev (1987), as we see that the splits tend to occur most frequently when the markets are in expansion phases.

The split-factor is the number of additional shares issued per one old share. The great majority of splits occur at the round numbers of 0.5, 1, 2, and the split 2-to-1 accounts for nearly half of the sample. This is an "anomaly" inside the anomaly, because it does not seem that there is a fundamental rationale for managers to prefer round factors, neither when considering the Signalling hypothesis nor the Trading Range hypothesis. We do not find evidence for a tick size motivation in this preference, as the number of splits or the preference for round split-factors does not change significantly after the 1997 change in the rules of decimalization in the US exchange.

The median number of splits per company in the period and in our sample is 2. The number of splits per share is, however, even higher, if we consider the complete sample of events. The decrease that we find is due to the cleaning we carried out for other distributions. Indeed, some companies choose to split their stocks regularly and often these events are declared concurrently with dividend distributions.

Table 2 reports the market variables of the companies in the sample by year of announcement. We consider in particular the averages of prices, volume of trading, market capitalization and shares outstanding at the end of the month of the announcement and the compounded returns for the 12 months after the split, by year of announcement.

Next, we analyze the distribution of analysts' forecasts for the four groups: (i) before the announcement date, (ii) after the announcement date, (iii) before the payment date and (iv) after the payment date. We focus in particular on our proxy for the forecast dispersion; that is the ration of the standard deviation to the absolute value of the mean of the forecasts. We initially examine all the changes in the analysts' coverage before and after the announcement (occurrence) of the split, based on the number of analysts that provided one fiscal year earnings estimates for each split-firm (Table 3.1 and 3.2).

One of the hypotheses explaining why managers are willing to split their stocks considers that they wish to attract the attention (usually positive) of analysts (Brennan and Hughes, 1991). Looking at the analysts' coverage, the evidence actually shows an average increase in the number of analysts following the firms after the announcement of the split, from 7.76 to 8.84 (Table 3.1). This change is stressed and accentuated after the occurrence of the event, when the average number of analysts increases from 8.35 to 9.48. Considering the median values, in both databases there is an increase of one unit before and after the event, from 6 to 7 analysts for each company-split.

The increase in coverage is stressed even more, by the evidence that in the month of the split, the total number of forecasts of the annual earnings of the splitting companies is strongly higher than in the month before or in the month after the split (Table 3.2).

Then, regarding the forecasts of analysts after the splits, we see in Tables 4.1 and 4.2 that the mean of the estimated EPS for the earnings per share of the next fiscal year significantly increases, by 0.04 to 0.99$, while the estimation error considerably decreases to close to zero, from a significant error of -0.024 to a less significant -0.007$.

The estimation error is measured as the difference between the earnings forecasts and the actual values. It shows that analysts tend to underestimate companies' earnings in the window before the event while this is nearly corrected in the following period. This is consistent with the Signalling hypothesis and with the hypothesis that a split draws positive attention to the company.

Considering the variability of the forecasts, we measure the range of the analysts' forecasts in the two months before (and after) the announcement date (and payment date) of the events. As we can see in Table 5.1, there is a slight increase in the average range after the announcement date from 0.17 to 0.19, which is also confirmed by an augment in the median. The differences of opinion increase even more after the payment date, as we have seen happening to the coverage.

Then, the dispersion ratio is measured by the standard deviation of the estimates, scaled by the absolute value of the mean of their forecasts. It confirms the same results seen for the range, consisting of a slight increase in the average value after the split and in an increase in its volatility in both databases, announcement and ex date (Table 5.2). From unreported results, using the ration of the standard error to the absolute mean of the estimate does not change the pattern.

The change in dispersion, given by the difference between the prior and post dispersion ratios has therefore a positive average value. This means that we see a small raise in the disagreement among analysts after the splits. In the payment database, the average is still slightly positive, even though it is lower than in the announcement database (Table 7).

Moreover, we consider the average of the estimates and forecast error by group of dispersion. We distinguish three groups of low, medium and high dispersion. We notice a decreasing relation between dispersion and average estimate, for which both before and after the splits, higher dispersions are associated with lower average estimates. Considering the average error of underestimation, it tends to be higher in the medium groups of dispersion, both before and after the event. The pattern is evident in both announcement and payment databases (Tables 6.1 and 6.2).

3.4.2 Dispersion of analysts' forecasts and returns

In order to analyze the relation between dispersion and returns, firstly we divide the sample into subgroups to reduce the variability of the previous phase (Jegadeesh and Titman, 1993, Diether, Malloy and Scherbina, 2002).

We construct different portfolios on the basis of the degree of prior and post dispersion and the change in dispersion. The stocks are assigned to the corresponding portfolio based on their level of forecasts dispersion and we then calculate the average returns for each portfolio, checking for any corresponding trend in the average returns.

We observe a pattern between the dispersion in analysts' forecasts, both before and after the announcement of the event, and future performance. In particular, moving from the lowest to the highest dispersion group, the compounded returns increase, broadly confirming the hypothesis of dispersion as an element of uncertainty (Tables 8.1 and 8.2).

Considering the change in dispersion, as the change in disagreement around the stock splits, it seems that returns are positively related to it (Table 8.3). The highest and the lowest groups exhibiting a change in dispersion (that corresponds to the extreme positive or negative variations of dispersion around the event) have the highest returns. Therefore, it seems that the direction of the change in dispersion is not as relevant as its entity. High variations in dispersion, either towards convergence or divergence of opinion, lead to higher future returns, while small changes lead to smaller but still positive returns.[11] However, this relation is not symmetric and is not stable across the compounded returns examined. Furthermore, this relation weakens with longer returns, and the pattern is less evident in the last months of the analysis.

We further analyze this relation introducing a second variable to check if there is an endogenous effect related to size. In a two-way cut, the average returns are calculated for each portfolio deriving from the intersection of dispersion quantiles and size quantiles (Table 9). The expected effect is a decline in the difference between the returns of lower and higher dispersion quantiles as the size increases, but that there is still a positive relation. This would confirm that the relation between returns and dispersion should be stronger for small firms. In fact our results show that the higher the capitalization of the company, the lower the future positive returns, but that they still exhibit a relation between the dispersion influences and future performance. This means that the smaller the firm, the bigger the predicted effect of the dispersion on the returns.

[11] We will consider in the future the relation between the change in dispersion and the returns with the introduction of herding.

All these conclusions regarding the announcement database are not however evinced in the payment database, confirming that the informational risk increases around the stock only at the announcement of the event.

Then, we regress the compounded returns from 1 to 12 months after the split on the dispersion ratios, as equations (3.3.1), (3.3.3) and (3.3.4). Table 10 reports the results of the regressions for the announcement database.

Looking at the prior dispersion, we confirm the positive relation between returns and differences of opinion before the event, in concurrence with the preceding results. However, it is significant only at 5 months after the announcement. Post dispersion has a positive estimated coefficient as well, although it is never significant in any of the 12 regressions.

Finally, we see that the change in dispersion, computed in the windows of -2 + 2 months around the event declaration dates, is significantly impacting on the compounded returns until 8 months after the announcement. In particular, we observe a negative relation between the change and the returns. The relation is not linear. In fact, the square root is also a significant component for all the compounded returns until 8 months after the event, but also with a significance at 12 months.

3.4.3 The results of the event study

The results from the previous analysis motivate the next step of the event study of the market reaction around the splits, and the analysis of this reaction in the light of the differences of opinion. In fact, we have found evidence of a relation between returns and dispersion of analysts' forecasts and now we wish to examine both whether abnormality exists in the post event performance and whether this abnormality is related to the prior dispersion.

We estimate the abnormal returns and the CAR following the announcement of the event, as equations (3.3.6) and (3.3.7).

As we can see in Table 11, the CARs are significant in the event windows that include the day of the event and the following day. They are positive and slightly increasing as we enlarge the event windows, but not significant enough according to the test we have constructed. We estimate in particular five CARs considering five event windows, which we denote as the number of days in each window: CAR2 (from day 0 to 1), CAR6 (from 0 to 5), CAR31 (from 0 to 30), CAR61 (from 0 to 60) and CAR91 (from 0 to 90 days after). The results of the CARs are significant and positive, and this is evident both in the announcement and in the payment datasets.

Running the analysis by groups of prior dispersion, we use the dispersion in the 2 months before the announcement (and occurrence) of the split in order to estimate the CARs for each of the three groups and compare them. In Figures 1.1 and 1.2, we show the trends of the cumulative abnormal returns distinguishing the three classes of dispersion. The results are different between the announcement and payment dates.

For the announcement date, the group with medium dispersion has the highest abnormal returns, followed by the group with higher dispersion and then by the group with lowest dispersion.

However, for the payment date, the group with the highest dispersion are the ones with the highest cumulative abnormal returns. The difference in returns is especially large 50-60 days after the event. The group with the lowest dispersion (negative value on average) is the one with the lowest abnormal returns on most days. Especially in the first days after the event, we verify very low or even negative abnormal returns. These values increase, as in the other subsamples, 50- 60 days after the event.

In order to better discern this relation, we carry out cross-sectional regressions, in which the CARs are explained by the prior dispersion and the set of factors, as we can see in Tables 12.1 and 12.2. We find that the dispersion is not a significant explanatory variable of the CARs in the event window, where other factors are shown to be more important. Instead, when increasing the window of analysis, the dispersion becomes a significant explanatory variable, given a positive relation with the abnormal returns.

Finally, we look at the cumulative abnormal returns dividing into three groups by time period: before 1996, between 1996 and 2000, and after 2000, in order to investigate whether, in the different time periods, the reaction of the market changed in its intensity. In fact, as we can see in Figures 2.1 and 2.2, we observed that in the period from 1996 to 2000 we have the lowest impact of abnormal returns, while the most recent period is the one that evidenced the highest effects, especially in the longest windows.

3.5 Conclusions

This chapter is an analysis of the relation between the dispersion of beliefs among analysts at the time of a stock split and the market reaction and future performance of the company. The central idea of the chapter is to analyze whether, either around the announcement or the payment date of a split, the disagreement in the consensus of the analysts is a determinant of the future abnormal returns of the splitting companies.

Firstly, we have analyzed the relation between dispersion and returns in the subsample of firms that have split their stocks in the period from 1993 to 2004, extracting the data from the CRSP and I/B/E/S databases. We have found a positive relation between the average of the compounded returns in the twelve months following the event and the dispersion ratio, measured as the ration of the standard deviation of the analysts' forecasts to the mean of the forecasts in the two months before the event. The results come from the analysis on subgroups of companies, where the average returns for each group seems to increase, when moving from a lower to a higher dispersion.

From carrying out an event study on the announcement of the split, we have evinced that the returns in the days around the events and in the next three months exhibit an abnormal component not explained by the four-factor model. When the abnormal returns are aggregated in the event windows, we observe positive and increasing cumulative abnormal returns.

In addition, the cumulate abnormal returns through companies and time series are compared among the groups of dispersion ratio measured before the announcement of the splits. We can conclude that these excess returns are partly explained by the introduction of the dispersion that exists before the announcement of the event.

A rationale for this relation is the idea that dispersion of beliefs is an indicator of informational risk and therefore induces an increase in the returns. The positive drift we observe in the returns of splitting companies, and the increase in uncertainty around these stocks will be seen more in details in future chapters, in the light of a herding motivation.

3.A Appendix A

Tables 1.1 & 1.2
Descriptive Statistics of the Splits

1.1 The number of stock splits per year of announcement and per split-factor.

Year	Number of splits	< 3-to-2	3-to-2	< 2-to-1 and > 3-to-2	2-to-1	> 2-to-1
1993	228	12.04%	37.75%	0.00%	46.99%	3.21%
1994	156	9.76%	37.36%	0.00%	47.13%	5.74%
1995	202	4.44%	37.33%	0.00%	55.56%	2.66%
1996	244	7.02%	38.38%	0.00%	50.55%	4.06%
1997	246	7.73%	32.05%	0.39%	56.37%	3.48%
1998	220	3.38%	31.78%	0.42%	58.90%	5.51%
1999	255	3.69%	24.72%	0.00%	68.27%	3.32%
2000	226	1.26%	19.75%	0.00%	71.43%	7.56%
2001	105	7.55%	48.11%	0.00%	43.40%	0.94%
2002	103	8.53%	36.75%	0.85%	52.14%	1.71%
2003	105	9.83%	39.29%	0.00%	45.54%	4.46%
Total	2090	131	677	3	1191	88

1.2 The number of stock splits per company

Number of splits per company	Number of splits	Number of companies
1	787	787
2	685	343
3	313	104
4	162	41
5	73	15
6	26	4
7	34	5
10	10	1
Total	2090	1299
Median	2	
Mode	1	
Std. Deviation	1.42	
Range	9	

These tables show the main descriptive analysis carried out on the sample of splits. We present the frequencies of the splits by year of announcement and split- factor (***table 1.1*** *) and by the number of splits per company (* ***table 1.2*** *). The split- factor is extracted from the CRSP data, and it represents the number of new shares to old shares. It is estimated with the following formula:*

$$facpr = \frac{s(t) - s(t')}{s(t')}$$

where s(t) is the number of shares outstanding, t is a date after or on the distribution date for the split, and t' is a date before the split.
The number of splits per company is calculated from the firms in the final sample, considering their distribution in the period 1993 - 2004.

Table 2

Descriptive Statistics of the Companies

Year of announcement		12-months compounded returns	Price	Volume	Capitalization	Shares outstanding
1993	Mean	0.12	44.62	42,753	2,502,883	44,175
	St. dev	0.38	19.81	81,994	6,185,242	91,100
1994	Mean	0.33	54.00	54,492	3,360,036	50,927
	St. dev	0.60	61.48	88,820	8,723,626	97,582
1995	Mean	0.40	49.75	75,277	2,972,688	46,829
	St. dev	0.65	21.36	135,455	5,721,260	69,097
1996	Mean	0.27	51.51	68,256	4,188,622	62,539
	St. dev	0.49	23.74	128,755	10,400,000	128,120
1997	Mean	0.27	54.94	105,941	7,434,517	88,776
	St. dev	0.70	27.05	276,806	20,200,000	186,772
1998	Mean	0.33	59.46	129,907	9,648,895	113,671
	St. dev	1.23	29.51	353,254	23,100,000	214,864
1999	Mean	0.67	73.86	331,977	17,200,000	184,958
	St. dev	1.58	34.73	647,979	41,400,000	397,635
2000	Mean	-0.21	93.26	291,102	16,400,000	156,098
	St. dev	0.52	61.01	578,115	50,800,000	457,131
2001	Mean	0.18	51.33	149,944	7,684,072	109,596
	St. dev	0.47	22.20	243,519	32,100,000	367,151
2002	Mean	0.06	52.33	133,930	3,938,523	69,894
	St. dev	0.42	26.79	415,934	6,778,046	127,803
2003	Mean	0.37	48.95	202,809	6,339,919	108,080
	St. dev	0.52	23.27	658,726	27,600,000	521,855
Total	Mean	0.27	59.16	146,424	7,962,379	96,689
	St. dev	0.86	38.07	396,226	27,100,000	279,217

This table describes the market variables of the sample of splitting companies, by year of announcement. We consider the average compounded returns of the company in the 12 months after the splits, price (in dollars), market capitalization (in dollars), volume of trading (in number of shares) and shares outstanding (in number of shares) at the end of month in which the split is announced.

Tables 3.1 & 3.2

Descriptive Statistics of Analysts' Coverage

3.1 Descriptive Statistics of the analysts' coverage of the splitting firms before and after the event.

Number of ANALYSTS	before announcement	after announcement	before ex-date	after ex-date
Mean	7.76	8.84	8.35	9.48
Median	6	7	6	7
Std. Deviation	6.12	6.48	6.50	6.84
Minimum	2	2	2	2
Maximum	42	42	41	39

3.2 Total number of forecasts

Number of FORECASTS	announcement date	ex-date
Previous Month	7,192	8,624
Month of the event	11,336	10,302
Next Month	7,262	8,969

Table 3.1 *shows the number of analysts that cover each splitting company in the period preceding or following the split. The averages are weighted with the number of splits each firm has announced and are included in the sample. They are divided in the two databases of analysis: the announcement-date database and the payment-date database. We consider only the analysts that have made at least one estimate in the two months before or in the 2 months after the announcement or payment date of the event.* ***Table 3.2*** *shows the total number of forecasts in the month before the announcement or payment date of the event, in the month of the event, or in the month after the split.*

Tables 4.1 & 4.2

Mean of Analysts' Estimates and Estimates Error before and after the Splits.

Table 4.1. Mean of analysts' estimates and estimates error before and after the announcements.

Estimates	Mean		t- test	Est. Error	Mean		t- test
Before	0.9512	***	37.82	Before	-0.0244	***	-3.59
After	0.9958	***	38.50	After	-0.0069		-0.96
Difference	0.0446	***	12.84	Difference	0.0175	***	3.76

Table 4.2. Mean of analysts' estimates and estimates error before and after the payment dates.

Estimates	Mean		t- test	Est. Error	Mean		t- test
Before	0.9844	***	39.43	Before	-0.0119		-1.60
After	1.0136	***	37.66	After	0.0039		0.48
Difference	0.0292	***	6.61	Difference	0.0158	***	2.13

*These tables present the average forecasts estimates and estimates error before and after the announcement (**table 4.1**) and the payment date of the splits (**table 4.2**). The average forecasts estimates are the mean EPS forecasts for the next fiscal year, published in the two months before and two months after the announcement/payment dates. The estimates error is the mean of the difference between the forecasts estimates and the actual earnings per share.*

Tables 5.1 & 5.2
Range and Dispersion Ratio

5.1 Range of forecasts estimates before and after the announcement/payment date

RANGE	before announcement	after announcement	before exdate	after exdate
Mean	0.1669	0.1892	0.1675	0.1796
Std. Error of Mean	0.0132	0.0140	0.0132	0.0100
	***	***	***	***
Median	0.0475	0.0650	0.0492	0.0800
Std. Deviation	0.6047	0.6394	0.6031	0.4591
Variance	0.3656	0.4089	0.3637	0.2108
Skewness	14.66	18.27	15.61	17.64
Kurtosis	295.05	454.68	332.19	489.37
Range	15.70	18.48	14.85	14.60
Minimum	0.00	0.00	0.00	0.00
Maximum	15.70	18.48	14.85	14.60

5.2 Dispersion of forecasts estimates before and after the announcement date and the payment date

DISPERSION	before announcemet	after announcement	before exdate	after exdate
Mean	0.0828	0.0955	0.0782	0.0940
Std. Error of Mean	0.0110	0.0155	0.0093	0.0127
	***	***	***	***
Median	0.0242	0.0277	0.0230	0.0313
Std. Deviation	0.5013	0.7070	0.4234	0.5784
Variance	0.2513	0.4999	0.1793	0.3345
Skewness	24.14	25.87	21.93	24.19
Kurtosis	659.64	718.40	555.37	647.11
Range	15.46	22.11	12.17	16.69
Minimum	0	0	0	0
Maximum	15.46	22.11	12.17	16.69

The tables report the range and the dispersion of the forecasts estimates. The range is calculated for each stock split as the difference between maximum and minimum of all the estimates published by analysts in the two months before or after the event, both at the announcement or at the payment date (***table 5.1*** *). The dispersion ratio is computed for each split as the standard deviation of the estimates in the 2-month window, scaled by the absolute value of the mean of the same estimates (* ***table 5.2*** *).*

Tables 6.1 & 6.2

Mean of Analysts' Estimates and Estimates Error by Dispersion Groups

Table 6.1. Mean of analysts' estimates and estimates error before and after the announcements of the splits by dispersion groups

Forecasts estimates		Mean		t- test	Estimates Error		Mean		t- test
Before	Total	0.9512	***	37.82	Before	Total	-0.0244	***	-3.59
	Low dispersion	1.0882	***	33.17		Low dispersion	-0.0222	***	-3.77
	Medium	1.0083	***	30.58		Medium	-0.0414	***	-4.29
	High dispersion	0.7554	***	12.81		High dispersion	-0.0095		-0.56
After	Total	0.9958	***	38.50	After	Total	-0.0069		-0.96
	Low dispersion	1.1328	***	33.55		Low dispersion	-0.0119	*	-1.67
	Medium	1.0533	***	31.41		Medium	-0.0119		-0.93
	High dispersion	0.7997	***	13.13		High dispersion	0.0030		0.19

Table 6.2. Mean of analysts' estimates and estimates error before and after the splits by dispersion groups

Forecasts estimates		Mean		t- test	Estimstes Error		Mean		t- test
Before	Total	0.9844	***	39.43	Before	Total	-0.0119		-1.60
	Low dispersion	1.1723	***	37.67		Low dispersion	-0.0099		-1.18
	Medium	1.0616	***	31.03		Medium	-0.0370	***	-4.57
	High dispersion	0.7153	***	12.34		High dispersion	0.0118		0.62
After	Total	1.0136	***	37.66	After	Total	0.0039		0.48
	Low dispersion	1.2146	***	37.93		Low dispersion	0.0219		1.17
	Medium	1.0861	***	31.27		Medium	-0.0237	***	-3.17
	High dispersion	0.7360	***	11.39		High dispersion	0.0139		0.97

These tables present the average estimates and the average estimates errors by the dispersion ratio before and after the announcement (***table 6.1*** *) and the payment date of the splits (* ***table 6.2*** *). The estimates are the EPS forecasts for the next fiscal year averaged in the two months before or after the announcement/payment date. The estimates error is the mean of the difference between the forecasts and the actual earnings per share in the same windows.*

Table 7

Change in Dispersion

Change in dispersion among analysts' forecasts in the announcement and payment databases

		Change in dispersion - announcement date		Change in dispersion - ex date	
Mean (St. error)		0.0128	(0.017)	0.0158	(0.010)
T test		0.7361		1.5800	
95% Confidence Interval for Mean	Lower Bound	-0.0212		-0.0047	
	Upper Bound	0.0468		0.0362	
5% Trimmed Mean		0.0052		0.0081	
Median		0.0008		0.0036	
Variance		0.6280		0.2280	
Std. Deviation		0.7926		0.4771	
Minimum		-15.20		-7.03	
Maximum		20.16		15.76	
Range		35.36		22.79	
Interquartile Range		0.04		0.04	
Skewness (St. error)		10.985	(0.054)	19.099	(0.054)
Kurtosis (St. error)		434.684	(0.107)	674.839	(0.107)

The change in dispersion is computed as the difference between the dispersion computed in the 2 months before the event and the dispersion in the 2 months after the event, as announcement or payment date.

Tables 8.1, 8.2

Compounded Returns by Dispersion Groups (Announcement Database)

Table 8.1 Prior dispersion

Dispersion before the announcement		Compounded returns				
		Month 0	1 month	3 months	6 months	12 months
Low dispersion	mean	0.0515	0.0837	0.1246	0.1671	0.2086
	se(mean)	0.0050	0.0079	0.0135	0.0162	0.0250
	st. dev.	0.1319	0.2072	0.3574	0.4264	0.6603
Medium	mean	0.0763	0.1104	0.1586	0.2127	0.2991
	se(mean)	0.0057	0.0087	0.0138	0.0207	0.0341
	st. dev.	0.1500	0.2306	0.3633	0.5464	0.8992
High dispersion	mean	0.1050	0.1458	0.2063	0.2155	0.2878
	se(mean)	0.0081	0.0125	0.0221	0.0220	0.0377
	st. dev.	0.2132	0.3300	0.5833	0.5819	0.9953
Total	mean	0.0776	0.1133	0.1632	0.1984	0.2652
	se(mean)	0.0037	0.0057	0.0098	0.0114	0.0189
	st. dev.	0.1700	0.2626	0.4483	0.5228	0.8637

Table 8.2 Post dispersion

Dispersion after the announcement		Compounded returns				
		Month 0	1 month	3 months	6 months	12 months
Low dispersion	mean	0.0575	0.0751	0.0989	0.1430	0.2042
	se(mean)	0.0048	0.0071	0.0100	0.0142	0.0235
	st. dev.	0.1259	0.1880	0.2641	0.3759	0.6205
Medium	mean	0.0727	0.1151	0.1586	0.2005	0.2756
	se(mean)	0.0059	0.0090	0.0159	0.0188	0.0311
	st. dev.	0.1552	0.2388	0.4195	0.4969	0.8223
High dispersion	mean	0.1007	0.1452	0.2241	0.2379	0.2881
	se(mean)	0.0081	0.0127	0.0224	0.0248	0.0411
	st. dev.	0.2146	0.3356	0.5922	0.6554	1.0842
Total	mean	0.0770	0.1118	0.1606	0.1938	0.2560
	se(mean)	0.0037	0.0057	0.0098	0.0114	0.0189
	st. dev.	0.1702	0.2629	0.4487	0.5233	0.8639

Table 8.3 Change in dispersion

Change in dispersion		Compounded returns				
		Month 0	1 month	3 months	6 months	12 months
Low	mean	0.1029	0.1455	0.2058	0.2184	0.3121
	se(mean)	0.0107	0.0166	0.0305	0.0291	0.0524
	st. dev.	0.2182	0.3395	0.6229	0.5950	1.0722
2	mean	0.0690	0.0883	0.1075	0.1674	0.2434
	se(mean)	0.0067	0.0103	0.0149	0.0207	0.0364
	st. dev.	0.1363	0.2105	0.3037	0.4232	0.7444
3	mean	0.0592	0.0909	0.1213	0.1395	0.1960
	se(mean)	0.0073	0.0103	0.0146	0.0174	0.0301
	st. dev.	0.1487	0.2112	0.2983	0.3555	0.6160
4	mean	0.0628	0.0939	0.1451	0.2067	0.2598
	se(mean)	0.0068	0.0105	0.0192	0.0252	0.0397
	st. dev.	0.1389	0.2157	0.3918	0.5145	0.8107
High	mean	0.0909	0.1404	0.2232	0.2372	0.2687
	se(mean)	0.0093	0.0149	0.0257	0.0325	0.0487
	st. dev.	0.1899	0.3036	0.5245	0.6645	0.9957
Total	mean	0.0770	0.1118	0.1606	0.1938	0.2560
	se(mean)	0.0037	0.0057	0.0098	0.0114	0.0189
	st. dev.	0.1702	0.2629	0.4487	0.5233	0.8639

In these tables, the average compounded returns for the month of the announcement of the split until 12 months after the event are reported in groups of prior dispersion, as computed in the two months before the event (***table 8.1*** *), post dispersion, as computed in the two months after the event (* ***table 8.2*** *) and change in dispersion, as the difference between prior and post dispersion (* ***table 8.3*** *).*

Table 9

Compounded Returns after the Announcement by Dispersion Groups and Size Groups

Dispersion before the announcement	Market capitalization		Compounded returns				
			Month 0	1 month	3 months	6 months	12 months
Low	Small companies	mean	0.0876	0.1234	0.2103	0.2754	0.3030
		se(mean)	0.0119	0.0177	0.0328	0.0446	0.0554
	2	mean	0.0629	0.0996	0.1435	0.2136	0.2066
		se(mean)	0.0119	0.0160	0.0255	0.0351	0.0468
	3	mean	0.0327	0.0605	0.0547	0.0411	0.0607
		se(mean)	0.0114	0.0202	0.0325	0.0306	0.0440
	4	mean	0.0454	0.0784	0.1513	0.1628	0.2830
		se(mean)	0.0117	0.0169	0.0368	0.0365	0.0837
	Big companies	mean	0.0275	0.0546	0.0592	0.1329	0.1825
		se(mean)	0.0080	0.0166	0.0203	0.0286	0.0382
	Total	mean	0.0515	0.0837	0.1246	0.1671	0.2086
		se(mean)	0.0050	0.0079	0.0135	0.0162	0.0250
Medium	Small companies	mean	0.1152	0.1470	0.2129	0.2774	0.3298
		se(mean)	0.0145	0.0209	0.0283	0.0446	0.0683
	2	mean	0.0668	0.0988	0.1253	0.1276	0.1679
		se(mean)	0.0108	0.0192	0.0296	0.0350	0.0510
	3	mean	0.0793	0.1127	0.1484	0.2123	0.3839
		se(mean)	0.0141	0.0193	0.0330	0.0411	0.0906
	4	mean	0.0573	0.0892	0.1574	0.2497	0.3432
		se(mean)	0.0099	0.0158	0.0279	0.0598	0.0808
	Big companies	mean	0.0587	0.1001	0.1446	0.1904	0.2607
		se(mean)	0.0123	0.0214	0.0343	0.0480	0.0821
	Total	mean	0.0763	0.1104	0.1586	0.2127	0.2991
		se(mean)	0.0057	0.0087	0.0138	0.0207	0.0341
High	Small companies	mean	0.1529	0.2237	0.2694	0.2894	0.3655
		se(mean)	0.0188	0.0282	0.0400	0.0492	0.0730
	2	mean	0.1341	0.1791	0.2666	0.2537	0.2486
		se(mean)	0.0187	0.0285	0.0620	0.0453	0.0499
	3	mean	0.0700	0.1263	0.1896	0.2500	0.4535
		se(mean)	0.0154	0.0295	0.0424	0.0589	0.1302
	4	mean	0.0818	0.1140	0.1821	0.1828	0.2012
		se(mean)	0.0191	0.0281	0.0549	0.0425	0.0649
	Big companies	mean	0.0921	0.0951	0.1320	0.1116	0.1828
		se(mean)	0.0173	0.0242	0.0417	0.0487	0.0794
	Total	mean	0.1050	0.1458	0.2063	0.2155	0.2878
		se(mean)	0.0081	0.0125	0.0221	0.0220	0.0377

This table reports the average compounded returns for the month of the announcement of the split until 12 months after the event, in a two-way cut, by groups of prior dispersion and by company market capitalization.

Table 10
Regressions Results: Compounded Returns on Dispersion Ratios (announcement db)

Regressors		Dependent variables: Compounded returns after the announcement of the split											
		1 month	2 months	3 months	4 months	5 months	6 months	7 months	8 months	9 months	10 months	11 months	12 months
Model 1. Prior dispersion													
Prior	coeff.	-0.0461	0.1193	0.0942	-0.0354	0.1033	0.1100	0.0760	0.1932	0.2374	0.3546	0.2594	-0.0778
	st. error	0.0382	0.1354	0.0727	0.0419	0.0575	0.0858	0.1269	0.2106	0.3315	0.4442	0.4269	0.2049
						*							
Model 2. Post dispersion													
Post	coeff.	0.0061	0.0170	0.0055	0.0004	-0.0007	0.0082	0.0080	0.0170	0.0191	0.0281	0.0201	-0.0164
	st. error	0.0042	0.0208	0.0217	0.0132	0.0189	0.0188	0.0235	0.0344	0.0400	0.0510	0.0455	0.0192
Model 3. Change in dispersion													
Change	coeff.	0.0421	-0.5389	-0.4907	-0.2406	-0.4899	-0.7481	-0.7932	-1.2024	-1.2693	-1.5375	-1.2470	-0.4966
	st. error	0.0969	0.3229	0.2036	0.2171	0.2293	0.2308	0.4624	0.6718	1.0295	1.3659	1.3029	0.6761
			*	**		**	***	*	*				
Square root	coeff.	-0.0883	-0.6346	-0.5469	-0.3593	-0.4697	-0.8366	-0.7942	-1.2342	-1.2002	-1.2097	-1.1424	-0.9884
of change	st. error	0.2041	0.3032	0.2479	0.2244	0.2939	0.3102	0.4160	0.5752	0.8026	1.0467	1.0001	0.5648
			**	**			***	*	**				*
Square	coeff.	0.0214	0.1136	0.0734	-0.0028	0.0452	0.0788	-0.0037	0.0891	0.0779	0.0428	0.0852	0.1109
of change	st. error	0.0548	0.0788	0.0634	0.0678	0.0707	0.0802	0.1151	0.1382	0.1850	0.2420	0.2223	0.1431

This table reports the results of the regression of compounded returns on the dispersion ratios. Model 1 regresses separately each of the compounded returns from one month to 12 months after the announcement of the event on the prior dispersion. Prior dispersion is computed as the standard deviation of forecasts scaled by the absolute value of the mean, in the 2 months before the event announcement date. Compounded returns are computed aggregating daily returns from the CRSP dababase from 22 to 264 trading days after the event declaration date. Model 2 regresses compounded returns on post dispersion. Model 3 regresses a quadratic model of the compounded returns on the change dispersion (post-dispersion ratio - prior dispersion ratio).

Table 11
Cumulative Abnormal Returns

		Announcement date database			*Payment date database*			
	Window length T (in days)	Mean	t test	TEST(T)	Mean	Std. Err.	t test	TEST(T)
CAR(0,1)	2	.01557	15.25	15.18	.0048	.001000	4.84	5.49
CAR(0,5)	6	.01561	10.85	17.91	.0045	.001648	2.73	4.74
CAR(0,30)	31	.01593	4.96	18.94	.0076	.003465	2.18	7.80
CAR(0,60)	61	.02495	5.38	27.82	.0126	.004591	2.75	13.18
CAR(0,90)	91	.01678	3.00	18.41	.0020	.005459	.37	2.12

The table reports the Cumulative Abnormal Returns computed on five different event windows from the event day 0. CAR(0,b) are computed on a window from day 0 to day b after the event. TEST(T) is computed as the ratio between the CAR(0,b) and the standard error of the abnormal returns in the event window.

Figures 1.1 & 1.2
Abnormal Returns by Dispersion Groups

Figure 1.1 Announcement date database

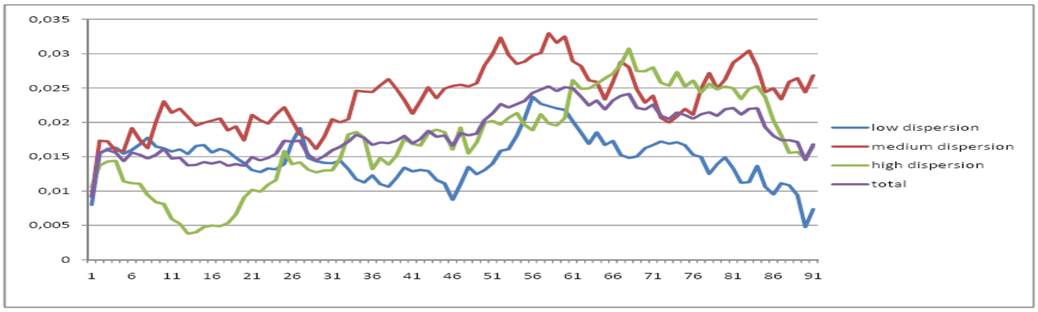
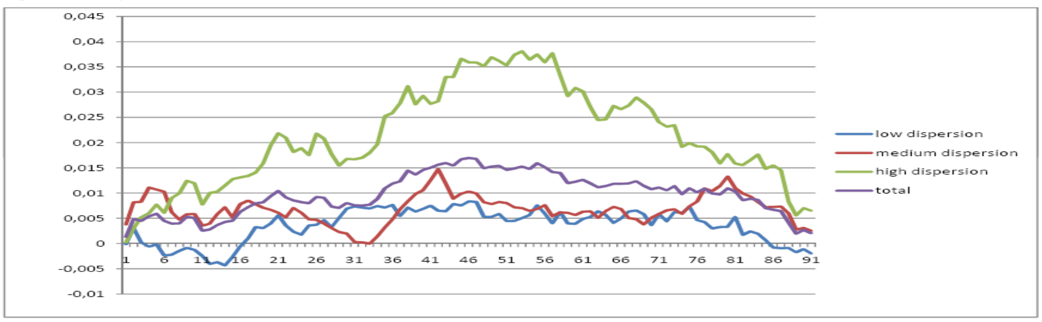


Figure 1.2 Payment date database



*In the figures we report the time series of the abnormal returns by prior dispersion, for the announcement date (**Figure 12.1**) and payment date (**Figure 12.2**) databases.*

Tables 12.1 & 12.2
Summary of the Regressions of the CARs on the Prior Dispersion

Table 12.1 Announcement date database

	CAR(0,1)		CAR(0,5)		CAR(0,30)		CAR(0,60)		CAR(0,90)	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Prior Dispersion	.0002	.977	-.020	.000	.056	.000	.096	.000	.117	.000
Market Return	.005	.008	.005	.000	.012	.000	.012	.000	.013	.000
Size	.008	.000	.006	.000	.012	.000	.017	.000	.017	.000
Book-to-market	.005	.049	.008	.000	.016	.000	.016	.000	.020	.000
Momentum	-.007	.000	-.008	.000	-.011	.000	-.011	.000	-.010	.000
Constant	.015	.000	.017	.000	.013	.000	.020	.000	.010	.000

Table 12.2 Payment date database

	CAR(0,1)		CAR(0,5)		CAR(0,30)		CAR(0,60)		CAR(0,90)	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Prior Dispersion	-.007	.315	.013	.035	.182	.000	.153	.000	.197	.000
Market Return	.006	.000	.008	.000	.013	.000	.015	.000	.015	.000
Size	.009	.000	.012	.000	.012	.000	.016	.000	.016	.000
Book-to-market	.004	.079	.008	.001	.019	.000	.024	.000	.026	.000
Momentum	-.004	.002	-.010	.000	-.011	.000	-.012	.000	-.010	.000
Constant	.005	.000	.004	.000	-.002	.095	.005	.000	-.008	.000

Tables 12.1 & 12.2 sum up the main results of the linear regressions of the cumulative abnormal returns on the prior dispersion and the four factors (market return, size, book-to-market and momentum) at the month of the event for both the announcement date database (***Table 12.1*** *) and the payment date database (* ***Table 12.2*** *). For each coefficient, the p-value is reported.*

Figures 2.1 & 2.2
CARs by Year Groups

Figure 2.1 Announcement date database

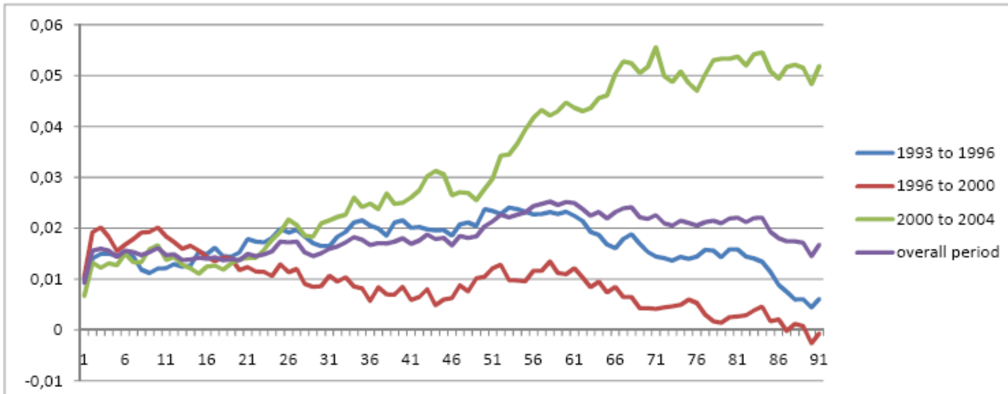
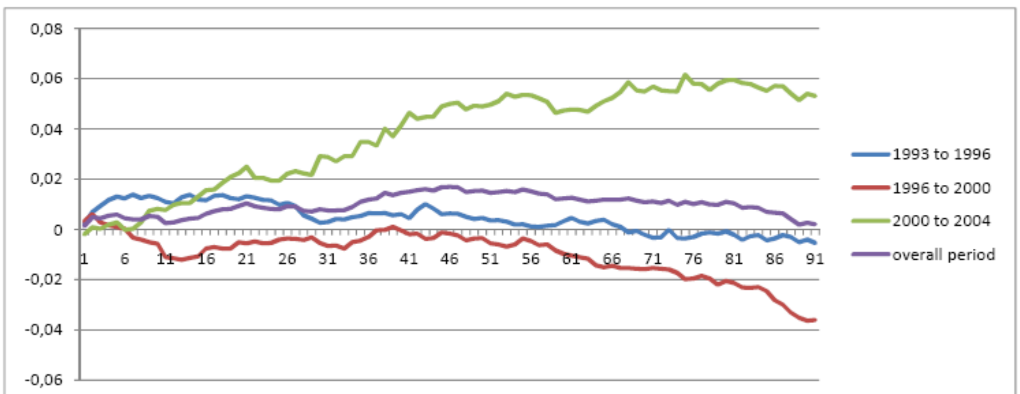


Figure 2.2 Payment date database



In these figures we report the time series of the abnormal returns by prior dispersion, for the announcement date (***Figure 2.1*** *) and payment date (* ***Figure 2.2*** *) databases.*

Chapter 4

An empirical literature review on herding

4.1 Introduction

This chapter introduces the literature on institutional herding. The primary focus is on the empirical works, looking at the principal measures developed and the main findings on herding among institutional investors. Nevertheless, it is necessary to briefly introduce the most important theoretical families of models.

The definition of herding does not find universal agreement, as it depends on the aim of the research. In the theoretical literature of rational social learning, herding is broadly defined as "a situation in which all agents take the same action after some date" (Chamley, 2003, pag. 5). In turn, the empirical literature mainly identifies herding with correlated trading (Lakonishok, Shleifer and Vishny, 1992).[1]

The main question in the literature is whether herding can have an inefficient impact on the market variables and lead to excess volatility and market fragility. Actually, most of the empirical and theoretical literature focuses on analyzing whether herding moves prices away from their fundamental values for long periods of time, or whether it helps the information aggregation to become more rapid and efficient. Many authors focus primarily on the behaviour of institutional investors. Given their growing importance, their acting as a herd could have a more visible and stronger impact on the market variables. Recent studies, in fact, document a relation between swings in institutional demand and same period stock returns and these swings can be aggravated by correlated trading among institutions (Grinblatt, Titman and Wermers, 1995; Wermers, 1999; Sias, Starks and Titman, 2001).

Most of the empirical evidence shows a positive correlation between the direction of herding and the future short term returns (Nofsinger and Sias, 1999). This is consistent with a positive stabilizing effect, whereby herding pushes prices closer to their efficient level. However, recent papers conversely show a destabilizing effect on prices, as herding helps to predict reversals in long term returns (Dasgupta, Prat and Verardo, 2010).

Theoretical and empirical literature is, however, notably hard to connect. In particular, empirical studies struggle to identify a clean measure of herding in real functioning markets.

The fundamental problem arises from its definition. In most empirical works, herding is defined in terms of correlated behaviour across

[1] For a comprehensive review of the theoretical literature, see Bikhchandani and Sharma (2000), Hirshleifer and Teoh (2003) and Chamley (2003).

individuals, independent of the underlying motivations to it. The strength of this approach lays on the clear and easy- to- test definition. The main weakness comes from the fact that this concept does not imply a coordination mechanism among agents. A correlated behaviour could, in fact, also appear when investors receive correlated information and act according to it, but are still acting independently of each other.

From the theoretical view, investors are not independent when they exhibit herding behaviour, but rather, they act in response to the decisions of other agents. The will of the individual to include other agents' actions in his evaluation process is the main attribute to true herding, which is also defined as "intentional herding" (Bikhchandani and Sharma, 2000).

This limitation of the empirical literature is difficult to solve because of the lack of data on private signals and on the communication that occurs among real agents. A proposed solution is to factor out the impact of fundamentals and examine whether specific assumptions behind the theoretical models are satisfied. This method provides a way of approximately distinguishing between intentional and unintentional herding.

Alternative approaches attempting to overcome this lack of data have been developed. We will briefly review some experimental studies in financial laboratories (as Anderson and Holt, 1997; Cipriani and Guarino, 2005, 2009; Park and Sgroi, 2008) and the estimation of structural models based on the assumptions of a specific theoretical herding type (as Cipriani and Guarino, 2010).

The first approach investigates the overall market, assuming that herding is a phenomenon more likely to occur in periods of stress. When big changes in prices happen, returns cluster more tightly around the market return if herding is present. This clustering is due to investors who do not discriminate enough between individual stocks.

Christie and Huang (1995) show that, in the presence of herding, returns will not differentiate enough from the overall market return. This leads to a rise in dispersion at a declining rate or even to a decrease if herding is relatively severe. Assuming that in periods of extreme market movements, herding tends to be higher, they find that the dispersion of equity returns is lower than average during stress periods.

Chang et al. (2000) also consider that equity returns could reveal the presence of herding, and, in particular, that the dispersion of returns is a traditional measure of it. In the presence of herding, the relation between dispersion of returns and market return tends to be non-linearly increasing or even decreasing. On the contrary, rational asset pricing models would predict a linear relation. The dispersion of returns would increase with the absolute value of the market return, since individual assets differ in their betas. Therefore, in periods of extreme price movements, if the dispersion of returns increases linearly, it provides evidence that herding is not occurring. A non-linear relation between dispersion and market price movement instead reveals the presence of some sort of imitative behaviour.

A second approach looks specifically at the behaviour of institutional investors. As the market clears itself between buyers and sellers, looking at a specific category of agents could show whether this group particularly buys or sells through the process of herding. The two earliest papers which investigate herding among institutional investors as a correlation of trading patterns are Kraus and Stoll (1972) and Friend, Blume and Crockett (1970). The first authors investigate herding as "parallel trading". They find little evidence of correlated behaviour in the monthly changes in holdings and weak evidence of a relationship between price changes and excess institutional demand in the same period of time. Friend et al. (1970) evince that mutual funds tend to buy stocks which were bought by successful funds in the previous quarter, confirming positive feedback strategies and correlated trading.

More recently, institutional herding has been proxied by large variations of stocks' holdings (Nofsinger and Sias, 1999; Dasgupta, Prat and Verardo, 2010). Most of the recent literature defines herding as the correlation between institutional decisions in the same period of time or in subsequent periods. We will focus on the developments in this field and review two of the most important measures of herding, with their subsequent improvements and applications: the Lakonishok, Shleifer and Vishny (1992) measure and the beta developed by Sias (2004).

The outline of the chapter is as follows. Section 1 will briefly introduce the main theoretical models of herding in financial markets. Section 2 will review the Lakonishok, Shleifer and Vishny (1992) measure of clustering and its improvements and applications. Section 3 will focus on Sias's methodology (2004) and its applications. Section 4 briefly points out other methodologies developed by the literature for this purpose.

4.2 The theoretical aspects of herding

In the theoretical literature, herding is characterized by a coordination mechanism. Different coordination mechanisms bring different forms of herding. A traditional distinction sets rational herding (see Devenow and Welch, 1996 and Chamley, 2003) against irrational herding (see De Long, Shleifer, Summers and Waldmann, 1991). In the first group of models, individuals observe others' behaviour and rationally follow their actions while they maximize their personal utility. Non-rational herding, in its extreme form, is instead based on psychological deviations from rationality and it considers agents who follow each other because they are driven by emotions, non-Bayesian expectations or widely-spread coordination rules of thumb. Lying somewhere between these two distinctions, are near-rational agents who use non-fully rational heuristics, which implies that they are utilizing the observation of other agents in their decision process.

Another proposed classification distinguishes between intentional herding and spurious herding (Bikhchandani and Sharma, 2000), having in mind the distinction between theoretical and empirical literature. Intentional herding assumes the will of individuals to renounce their private signals and follow others' decisions. This can bring inefficient outcomes as this type of behaviour is fragile and idiosyncratic, and subsequently, it may lead to excess volatility and systemic risk. Spurious herding, instead, does not require an intentional will. Similar behaviour among agents may be due to independent responses to their own private yet correlated signals. It may be driven by changes in fundamentals, thereby bringing an efficient outcome as it pushes prices towards their new correct values.

In the purpose of this review, we distinguish between informational-based models and positive-feedback models of herding in the financial markets.

The first category includes informational cascades, reputational herding and investigative herding. They are based on a strong theoretical background and in all models, herding is triggered by the arrival of new information. In informational cascades models, all agents optimize their personal utility, ignoring their own private signals and following the behaviour of prior agents. In reputational models, agents rationally follow the herd in order to positively affect their reputation. In investigative herding, agents act alike because the payoff resulting from following the same action increases with the number of agents adopting it.

The second category includes characteristic-based herding, momentum herding and investment style strategies. They are theories inducted by the evidence from the behaviour of institutional investors in real-functioning markets. The will of investors to trade alike, mimicking their peers, is based on sharing the same trading strategies based on the observation of past prices or companies' characteristics. Characteristic-based herding applies when investors show the tendency to hold the same stocks, because they share the same stock preferences. Momentum herding is a specific case of the former, for which investors co-move by buying stocks with high past returns and comove away from past losers stocks. Investment style is based more explicitly on behavioural components, as it occurs when investors categorize stocks in broad groups and allocate their investments among these "styles".

4.2.1 Informational cascades models

Informational cascades represent the widest family of models in the literature on herding which was originally proposed in the seminal works of Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992). In these earlier works, agents face the decision between investing and not investing in an uncertain project. They have access to imperfect public information, an imperfect binary private signal and the observation of previous agents' decisions. It is through the observation of others' behaviour that they can infer others' private signals. An informational cascade occurs when, given rationality, Bayesian expectations and the maximization of their expected utility, agents are better off ignoring their own private signals and conforming to the previous actions of their peers.

Herding occurs when the action of the agents is independent of their private signals. The presence of informational cascades is shown when all the agents herd and, period after period, private beliefs are not incorporated into their decisions.[2]

Thus, an informational cascade is a failure in the social learning process because it causes a block in the acquisition of public information. When a cascade starts, herding is present and private information is no longer incorporated in the behaviour that other agents can observe. Thus, an initial mistake will lead to all the other agents acting alike in taking the wrong decision, with the resultant public payoff being far from optimal. The probability of a wrong cascade is not negligible, as Bikhchandani et al. (1992) show. However, a cascade is fragile, idiosyncratic and path dependent. This is because all the agents are rational and any small informational shock can break the cascade and bring about a quick reversal in behaviour.

Avery and Zemsky (1998) adapt the basic model of informational cascades to the financial markets. In the earlier models the price is given and fixed, while in financial markets the price updates to reflect the publicly available information. According to Avery and Zemsky,

[2] An "invest cascade" will start when, given rationality and Bayes' rules, the agents decide to invest in the project following prior decisions whatever their own private signals are. A "reject cascade" is a series of non-investments, given the same conditions.

the presence of rational risk-neutral actors and of an informationally efficient price mechanic, provide enough conditions to prevent herding from arising. This is true if the only source of uncertainty in the market comes from the value of the asset (value uncertainty) and there are no market frictions.

Nevertheless, herding can still arise if agents face an additional source of uncertainty. In addiction to uncertainty as to the value of the asset, investors could also have imperfect information as to whether the value has changed from its initial expected value due to any informational shock (value uncertainty). With the introduction of this two-dimensional uncertainty, the model is consistent with the presence of herding, but there is little effect on prices, which remain efficient.

Finally, if we add uncertainty about the average accuracy of traders' information (composition uncertainty), not only does herding arise, but in turn it leads to inefficiency in prices, such as bubbles and crashes. In this situation, traders cannot be distinguished between well-informed and poorly informed traders. Consequently, herding destabilizes prices and causes severe mispricing or contrarian behaviour.

The empirical literature tests these models by mainly looking at conditions for imperfect information. More recently, a new microstructure approach has been developed.

In the first approach, the literature looks at market variables that could proxy for information availability. Traditionally, empirical investigations of this kind have used market capitalization. Grinblatt, Titman and Wermers (1995) and Wermers (1999) consider that informational cascades are more likely to occur when the information available to the market is noisier, such as in the case of small companies. Also, Sias (2004) consistently finds a significant level of clustering of trades for small companies, in comparison with larger firms.

Other than size, Chan, Hwang and Mian (2005) consider the dispersion of analysts' forecasts as an indicator of the quality of the information available to the market. They conclude that investors herd more in cases of highly divergent recommendations about a firm.

Similarly, Kremer (2010) uses trading volume of the stock as an indicator of the information quality or the stock return volatility.

Alternative recent approach aims to construct a theoretical microstructure model whose parameters could be easily estimated to test for informational cascades. Cipriani and Guarino (2010) find intraday herding among informed and uninformed traders. They find that this typology occurs on only a minority of days. However, on some particular days, it can heavily influence traders' behaviour and destabilize prices.

4.2.2 Reputational herding

An earlier family of informational based models considers career and reputational concerns. Economic incentives are particularly delicate in learning and decision processes when the external evaluation of performances is linked to a market benchmark.[3] Financial analysts and fund managers are ideal categories to test for reputational impact on their decisions. Applied to the financial markets, Scharfstein and Stein (1990) consider a one-period model in which managers rationally mimic the investment decisions of other managers in order to maximize their

[3] There is a vast literature on the effect of economic incentives on the investment choices of financial actors. Roll (1992) derives the portfolio choices of managers that are compensated relative to the S&P 1500, while Brennan (1993) builds an asset pricing model in which the benchmark-relative performance represents an extra factor.

reputation. If the abilities of managers are not immediately visible to their companies or their clients, conformity avoids being negatively evaluated. Although this behaviour is socially inefficient, it is rational from the perspectives of managers who are concerned about their careers in the labour market. The basic one-period model is constructed with one project to invest in and two managers. Managers can be of two types. "Smart managers" receive imperfect informative private signals and their signals are correlated. "Dumb managers" receive purely noisy and independent signals. However, neither the managers nor the market know the quality of the signals, so managers can use their investment decisions in order to manipulate the learning process of the market. The market can infer their ability ex post considering both the performance of the investment and the performance of the other manager. The first piece of information alone cannot bring a definite valuation, because of unpredictable components that could lead to the smart managers also showing a bad performance. Because smart managers receive correlated signals, if the managers mimic the prior agents on the "sharing the blame" principle, the market would infer that they have correlated signals. The authors prove that the manager that makes their decision last will conform to the first agent's behaviour, no matter what his private information or his ability may be. The tendency to herd will again lead to inefficiency in the market, because private signals are not incorporated in the public information.

Dasgupta, Prat and Verardo (2010) construct a multi- period model à la Glosten and Milgrom (1985) in which some of the traders are reputationally- concerned. With the introduction of reputational concerns, herding arises. Therefore, the price aggregation of information is limited and the prices will never converge to their true value. This conclusion is reached because managers do not have sufficient monetary incentives to trade according to their signals while the price becomes more and more precise. The endogenous reputational costs of acting as a contrarian strategy will be higher than the expected profit of exploiting the mispricing. Moreover, this theoretical model explains the empirical evidence that institutional herding is positively correlated with short-term returns, but negatively correlated with long- term returns.

Additionally, the authors also propose a correlation between reputational concerns and liquidity in the market. The increased presence of career-concerned managers will decrease the price informativeness, but it will improve the liquidity and the volatility of the market.

The literature finds supportive empirical evidence in different environments. De Bondt and Forbes (1999) conduct a survey study among analysts, evidencing the different factors that can help the development of imitative behaviour. From their results, they stress the role of the creation of a good reputation, the economic incentives system, the sharing of similar mental schemes, the payoff externalities in acquiring information and the likeliness of informational cascades.

By examining the behaviour of different classes of investors and stocks it is possible to draw more conclusions on reputational herding (Del Guercio, 1996; Bennett, Sias and Starks, 2003; Sias, 2004). According to Dasgupta, Prat and Verardo (2010), it is more likely to observe reputational herding by independent advisors and investment companies. Their clients are more attentive to reputation, so these institutions are more dependent on sudden changes in net flows because of reputation changes. Moreover, Scharfstein and Stein (1990) show that reputational concerns are more binding for stable stocks, because errors of evaluation are considered more severely if more information is publicly available. On the contrary, Sias (2004) evinces that herding is more accentuated for bank trust departments and insurance companies, as they are more likely to be connected to reputational concerns.

Finally, Lobão and Serra (2002) assume that different motivations for herding could also depend on the size of the fund. Managers of funds of similar size would have a higher incentive to adopt reputational herding, as they are risk adverse in preserving their reputation. Conversely, small funds would tend to adopt contrarian behaviour in order to distinguish themselves. However, Lobao and Serra do not verify these assumptions in their Portuguese sample of investors.

4.2.3 Investigative Herding

Investigative herding belongs to the wider class of payoff-esternalities models. Agents herd on the same action because their payoffs increase with the number of following agents who take the same decision.[4] In financial markets, payoff esternalities have been studied with regards to institutional investors who face information acquisition decisions.

Froot, Scharfstein and Stein (1992) and Hirshleifer, Subrahmanyam and Titman (1994) develop the concept of rational investigative herding. The two papers start from two different sets of assumptions, but they both conclude that agents herd on the information they choose to collect because their payoffs increase with the number of agents who are researching the same source. Froot et al. assume risk-neutral investors with exogenous short horizons. Hirshleifer et al. instead assume a sequential arrival of information and risk-adverse investors.

Froot et al. (1992) consider fully rational investors who trade on short-term horizons. Short-term risk-neutral speculators profit on us-

[4] There is a extensive literature of the applications of payoff esternalities in banking markets, but this is out of their scope of this chapter.

ing their private signals if the same information is gradually aggregated into the prices by the actions of following investors. Positive information externalities are realized when earlier investors reverse their trades, profiting from the slow and gradual updates of the prices. Earlier agents are constrained to reverse because of exogenous short horizons. However, in the aggregate market, these information externalities are not efficient. The traditional view of long-term investors considers negative informational spillovers that lead to contrarian behaviour and lead investors to equally study all the available sources of information. Short-horizon speculators instead have incentives to acquire information earlier if other agents are then acting alike. As a result, traders tend to focus on the same source of information, to the extent that they herd on a few types of sources, sometimes of poor quality, neglecting other pieces of information, which are often the fundamentals.

Hirshleifer et al. (1994) build a different model of investigative herding in which rational investors receive information at different times. This assumption implies positive externalities in acquiring and using the same piece of information. The earlier the investor receives his private signal, the higher his profit will be in exploiting it, given that other agents invest using the same source.

The sequential arrival of signals affects both the trading decisions and the information acquisition process. Early investors trade aggressively according to their private signals in an initial period. Then they partially reverse their trades as late-informed agents enter the market. Their actions induce prices to move gradually closer to the fundamental value, and the profit of reverse trading increases. The basic assumption is that earlier traders reverse their positions because they are risk-averse. They appear as short-term profit-seekers "leaders", while late-informed traders appear as "followers", because their trades are positively correlated with the former agents.

The sequential arrival of information also affects the information that investors are willing to acquire. They find it more attractive to invest in information that is followed by many investors. In this way, the first agents to acquire and use the information will profit by the price movement induced by late-informed investors and the reversal of the position. The effect is the same as in the Froot et al. (1992) model. Investors will herd in acquiring some information and in following some stocks, while they will neglect other stocks and other sources.

There is however, no agreement on the empirical evidence of these models. Researchers usually agree on the presence of herding caused by informational arrival, but it is a complex task to distinguish among the three types of informational-based herding.

Wylie (2005) concludes that investigative herding exists among UK funds. He confirms that herding is stronger for the smallest stocks and the largest stocks. Moreover, herding increases with the number of managers who trade a stock in a particular period. He assumes that the positive relation between herding and the number of managers is consistent with investigative herding, as it is with all other models of informational based herding.

Sias (2004) also tests for the presence of investigative herding. He finds evidence of informational based herding, but that it is predominantly caused by informational cascades rather than investigative herding. In order to distinguish between the two types, Sias assumes that the cross-sectional correlation between trades is more likely to occur in small stocks due to informational cascades, while in larger stocks it is more likely to be due to investigative herding. His results confirm the prevalence of cascades, as there exists a monotonic inverse relation between herding and market capitalization.

Finally, Choi and Sias (2009) find evidence of investigative herding when analyzing the behaviour of institutions at industry level rather than at stock-picking level.

4.2.4 Characteristic- based herding

The previous models are based on strong theoretical backgrounds, which are centred around rational social learning and informational arrival. Other motivations for herding have alternatively been induced from the evidence of the behaviour of institutional investors. In particular, starting from the "anomalies" of strategies not consistent with the basic dictates of the traditional finance paradigm, these models belong to the behavioural empirical literature.

As well as the considerations regarding the arrival of new information, herding can also be due to agents undertaking positive feedback strategies. Investors collectively trade according to feedback coming from the markets, which is by its nature past and stale information. There is evidence that these changes in market variables can attract the attention of investors and cause convergent behaviour (Barber and Odean, 2007).

A particular case in point is when institutional investors hold the same securities because they are attracted by the same asset characteristics (Falkenstein, 1996, Gompers and Metrick, 2001, Bennett, Sias and Starks, 2003). Gompers and Metrick (2001) focus on the motivation for the disappearance of the small-stocks premium in recent years. Therefore, they analyze the impact of changes in the institutional share of the market on the demand for stocks and prices. Institutional investors have had an increasing participation in US companies over the years and have consequently taken over the role of the "representative investor" in the markets. They have a different, stable demand for stock characteristics when compared with individual investors, thus a change in the representative actor brings changes in which stocks are more likely to be bought/sold and in their relative and absolute returns.[5]

Gompers and Metrick (2001) evince the impact of three main variables in institutional demand: prudence or regulations, liquidity of the stocks and the historical returns pattern. Institutional demand is positively correlated to liquidity of the stock (proxied by firm size, price per share, share turnover), company size, book-to-market, S&P membership and volatility. Instead, institutional investors tend to avoid investing in stocks with high past returns and high dividends.

Hence, the representative investor, in a market dominated by institutional investors, will cause a convergence of behaviour around large and stable companies, with low past returns.

Del Guercio (1996) focuses in particular on the effect of prudence. She looks at mutual funds and banks and finds evidence of a preference for "prudent" stocks. In fact, she concludes there is a stable demand for prudent characteristics, because institutional demand is positively related to age, yield, S&P membership and negatively related to volatility.

Moreover, Falkenstein (1996) evinces that mutual funds exhibit preference for highly liquid, transparent and volatile stocks. In fact, institutions turn over their portfolios and trade more often than individuals; therefore they are more sensitive to transaction costs. Their large orders lead to them preferably investing in stocks with large market capitalization and thick markets. Therefore, firm size, per share

[5] Given assumptions of imperfectly elastic demand and supply curves for stocks.

price and share turnover are proxies for this preference for liquidity. Historical returns patterns can also lead to cross-sectional variation in institutional ownership. Higher historical returns and preferences regarding risk and return could motivate investment in large companies, with high book-to-market and high past returns.

Finally, Persaud (2000) specifically underlines the behaviour of banks, considering that these institutions appear to share the same characteristics preference because they are regulated by the same authorities and they are induced to use the same risk management system. Systems such as VAR techniques could bring all banks to buy/sell the same typology of stocks in the same period of time.

4.2.5 Momentum strategies

A vast part of the literature on positive feedback strategies examines in particular the preference for stocks with high historical returns. Momentum trading consists of the strategy by institutional investors of buying stocks with high past returns and selling stocks that performed poorly in the past (Grinblatt, Titman and Wermers, 1995, Wermers, 1999). Evidence shows correlated decisions among institutions as empirical herding, due to the fact that most investors in the market apply the same strategy.

There are different reasons for institutional investors to engage in momentum trading. One set of reasons considers institutions as rational investors who act in consequence to irrational individual investors. Underreaction (Daniel, Hirshleifer and Subrahmanyam, 1998) as well as overreaction to information (De Long et al., 1991) can induce institutions to use positive feedback strategies. behavioural studies argue that institutions momentum trade in order to answer to uninformed investors who are subject to psychological biases. Individual investors engage in contrarian trading, because of the so-called "disposition effect", or the reluctance to realize losses (Barber, Odean and Zhu, 2009), and, therefore, institutions provide them with the necessary liquidity. Similarly, a conservative bias in individual investors causes them to underreact to information. As a consequence, prices do not immediately incorporate all the available information but rather this happens slowly over time (Hong and Stein, 1999), giving institutions the opportunity to exploit the mispricing, and so appearing as momentum traders (Barberis, Shleifer and Vishny, 1998).

There are other rational motivations for institutional investors to momentum trade. Due to agency problems in the money management industry, contrarian strategies would take too long to pay off (Lakonishok, Shleifer and Vishny, 1992). Also, because institutional investors avoid small capitalization stocks, this leads to momentum trading when they sell stocks whose large negative returns have reduced the market capitalization (Sias, 2007).

Another set of reasons considers institutions as directly subject to heuristic and not fully rational behaviour. They can be subject to the belief that trends are likely to continue or use window dressing in order to remove bad investments from the portfolio (Lakonishok, Shleifer, Thaler and Vishny, 1991).

Empirically, the evidence of the relation between demand of stocks and past returns, and the convergence of trading decisions, is mixed. We have previously seen Gompers and Metrick (2001) find evidence against momentum trading, while Falkenstein (1996) find a positive relation between high past returns and institutional demand.

Sias (2007) reviews the results of 11 papers on the topic. He reports nine papers that empirically support the presence of momentum trading. However, only two of them provide clear evidence (Bennett, Sias and Starks, 2003 and Chen, Hong and Stein, 2002). The author explains that the discrepancy is mainly due to the use of different methodologies. Some measures are influenced by the size of the company, therefore they mainly measure feedback trading in very large stocks. Other tests focus on the average institutional demand, whereas others on aggregate institutional demand. Works using the changes in the fraction of outstanding shares held by investors are using an aggregate concept. Average institutional demand is measured by the number of buyers related to the number of sellers. In addition, differences in the measure of institutional demand can affect the evidence of feedback trading. Some papers focus on changes in portfolio weights (Wermers, 1995) rather than changes in the number of shares traded (Lakonishok, Shleifer and Vishny, 1992). Using one or other of the definitions could even bring contradictory indications of the change in institutional demand. Finally, the lack of independence between current capitalization, lag returns and absolute value of measures of institutional demand further complicates the tests.

Sias (2007) homogenizes the methodology and tests a sample of US listed stocks from 1983 to 2003, finding strong presence of momentum trading in all but the largest stocks.

4.2.6 Style investing and behavioural models

Another case of convergence of behaviour which is not completely justifiable by rational motivations is the "style investing" proposed by Barberis and Shleifer (2003). They consider the psychological attitude of individuals who think in terms of categories and differences (Rosch and Lloyd, 1978). Therefore, even when they decide on investments, they tend to categorize securities in broad groups, such as by size, typology and fundamental values. Then they take decisions on how to allocate their funds among these groups (Bernstein, 1995). This attitude simplifies the choice problem of managers and, on the other hand, it helps investors to evaluate the activity of managers. The non-rationality of this behaviour, however, lies in the fact that when investors allocate their resources, they fail to consider the absolute performance of the stocks. They rather view the relative performance of a style of stock compared to another one, which in turn has likely effects on the prices and phenomenon such as fads and bubbles.

Barberis and Shleifer (2003) state three propositions from their model. Firstly, if investors are style-investing, there is comovement of returns among stocks that belong to the same style, which is not confirmed by comovement of fundamentals. In fact, prices of assets that are in the same style comove more than their cash flows do. The opposite is true among stocks of different styles that comove less than they should when considering the correlation between cash flows. Secondly, when assets change from one style to another, they exhibit a relative change in the intensity of the comovement of returns. They will comove more with the assets in the new style once added to the new group. On the contrary, their returns will comove less with the returns of the stocks in the previous group. Finally, the returns of stocks in the same style are positively correlated in the short-run and negatively correlated in the long run, even in terms of market adjusted returns.

Choi and Sias (2009) study the presence of style investing. They focus their attention to herding on industries, rather than single stocks, assuming industries proxy the different styles which investors are looking at. They find that the correlation between institutional demand for an industry and the previous quarter demand is an average of 40%. This result confirms that investors take their decisions looking at industries and herding on industry, rather than on single assets.[6]

4.3 Lakonishok, Shleifer and Vishny (1992)

Lakonishok, Shleifer and Vishny (1992) develop a measure of the convergence of behaviour among fund managers in trading securities. The assumption behind it is that, if investors follow each other over a period of time, they will end up being either primary buyers or sellers of a security in that period. Therefore, they measure the excess dispersion of trades of a subset of the market, either on the buy- or sell- side, over the same period of time.

They study the quarterly stocks holdings of 769 all-equity tax-exempt funds, from 1985 to 1989. They select a small subgroup of investors that is homogeneous enough to face similar decision problems. Money managers directly compete with each other, in terms of clients and evaluation. In addition, the subgroup has to be small enough to avoid the group of buyers in aggregate balancing the group of sellers in aggregate.

The main aim of Lakonishok, Shleifer and Vishny (1992) is to investigate whether institutional investors' trading patterns influence stock

[6] Other developments and empirical investigations on style investing are Teo and Woo (2004), Barberis, Shleifer and Wurgler (2005) and Froot and Teo (2008).

prices. They first assess the degree of correlation across money managers in buying and selling a given stock. Then, they examine the presence of positive feedback strategies when looking at the relationship between money managers' demand for a stock and its past performance. Finally, the core of the analysis is to investigate if herding and/or positive feedback strategies could destabilize the stock prices, testing the relationship between the excess demand by institutions and contemporaneous stock price changes.

4.3.1 Description of methodology

Technically, Lakonishok, Shleifer and Vishny (1992) consider the average tendency of investors to buy the same securities in the same quarter of the year, compared to an expected value in case of independence. Given a homogenous sample of fund managers, a stock i and a sub period t, the LSV herding measure is defined as:

$$LSV_{i,t} = |P_{i,t} - P_t| - AF_{i,t} \tag{4.3.1}$$

where: $P_{i,t}$ is the fraction of buyers, defined as the number of fund managers that have increased their holdings in security i in period t $(B_{i,t})$, over the total number of active managers that have traded stock i during period t (N_{it}), either buyers or sellers; P_t is the expected proportion of buyers, aggregated across all stocks traded in the quarter t. In some literature, it is computed as the average $P_{i,t}$ across the securities i, for the period t; or it is most commonly computed as $\frac{\sum B_{it}}{\sum N_{it}}$. $AF_{i,t}$ is an adjustment factor, estimated in case of independence where we assume that $B_{i,t}$ follows a binomial distribution with probability of success P_t and number of trials is equal to N_{it}.[7]

The adjustment factor is necessary in order to correct the upward bias introduced for securities traded by a small number of managers. It declines with the number of active investors, and, when $N_{i,t}$ is big enough, it equals zero.

In the null hypothesis of independence of behaviour, the measure of herding is zero, $H_{i,t} = 0$. The probability that an investor would buy stock i at time t is equal to P_t, and $|p_{i,t} - P_t| = AF_{i,t}$. Vice versa, values of $H_{i,t}$ significantly different from zero are interpreted as a convergence (or divergence) of behaviour. Hence, it measures the imbalance of buyers versus sellers, compared to the expected proportion of buyers.

Lakonishok, Shleifer and Vishny (1992) find weak evidence of herding, as 2.7% of imbalance trading on average, in their selected sample of US pension funds. In detail, they find that the correlation between trades is higher for smaller stocks against the larger companies (6.1% against 1.6%). This is consistent with the presence of informational based herding.

They do not find significant evidence of positive-feedback strategies, apart from with the smallest stocks.

Finally, they find a weak destabilizing effect on prices, given the tiny correlation between the excess demand for a stock in a given quarter and the contemporaneous change in price.[8]

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[7] *It is computed as:* $E(|P_{i,t} - P_t|) = \sum_{i=0}^{N_{it}} \binom{N_{it}}{i} P_{it}^{-i} (1 - P_t)^{N_{it}-i} \left| \frac{i}{N_{it}} - P_t \right|$.

[8] An accurate measure of the elasticities of demand for stocks would better examine the possibility of larger price impacts from small amounts of herding or positive-feedback strategies.

4.3.2 Limitations and further developments

The biggest limitation of the LSV measure is that it is not a measure of intentional herding, but rather of the clustering in trading patterns. If herding implies correlation of the trading decisions, the opposite cannot be said to be true. Correlation can have different motivations other than the intentional will to use others' trades in the decision process. According to this, the LSV measure is equal to zero in case of no-herding, but it could overestimate the phenomenon in cases where true herding exists.

Moreover, this correlation of trades is based on the strong assumption that investors can observe the decisions of others and can then use them in their trading decision process.

Other issues affect its interpretation, especially if the sample is not homogeneous and the securities have a thin market.

Lakonishok, Shleifer and Vishny (1992) do not consider the volumes of negotiations, but only the number of investors who trade them. This leads to an inaccurate reflection of the intensity of the phenomenon. The LSV measure does not pick up herding if the number of buyers and sellers is similar, but the amount of stocks bought are substantially different to the amount sold. This distinction seems particularly crucial if the aim of the work is to investigate the stabilization effect of herding on prices.

Addressing this issue, Wermers (1995) develops a measure of portfolio-change correlated trading. The intensity of the herding phenomenon is given by the change in the fraction of a stock in the investor's portfolio. Herding is measured as the comovement on the portfolio-weights assigned to each stock by different managers:

$$W_{t,\tau}^{I,J} = \frac{(\frac{1}{I})\sum_{n=1}^{I_t}(\Delta\omega_{i,t}^{I})(\Delta\omega_{i,t-\tau}^{J})}{\sigma^{I,J}(\tau)} \tag{4.3.2}$$

where: $\Delta\omega_{i,t}^{I}$ is the change in portfolio I's weight of stock i, during the period $t-1$ to t; $\Delta\omega_{i,t-\tau}^{J}$ is the change in portfolio J's weight of stock i, during the period $t-\tau-1$ to $t-\tau$; I_t is the number of stocks traded between period $t-\tau-1$ and t; $\sigma^{I,J}(\tau)$ is the time series average of the product of the cross- sectional standard deviations:

$$\sigma^{I,J}(\tau) = \frac{1}{T}\{\frac{1}{I_t}[\sum_{n=1}^{I_t}(\Delta\omega_{i,t}^{I})^2\sum_{n=1}^{I_t}(\Delta\omega_{i,t-\tau}^{J})^2]^{1/2}\} \tag{4.3.3}$$

Wermers finds a significant level of herding with this new measure of cross correlation. However, it introduces another distortion: managers with larger funds will tend to have a higher weight in the measure. Moreover, weights of stocks that increase in values tend to go up even without trades occurring.

Besides, Lakonishok, Shleifer and Vishny (1992) do not consider the direction of the herding phenomenon. Grinblatt, Titman and Wermers (1995) propose an improvement that distinguishes herding on the buy-side (herding into the stock) from herding on the sell- side (herding out of the stock), respectively:

$$BGTW_{(i,t)} = LSV_{i,t}|(p_{i,t} > p_t) \tag{4.3.4}$$

and

$$SGTW_{(i,t)} = LSV_{i,t}|(p_{i,t} < p_t) \tag{4.3.5}$$

They apply the distinction on a sample of US mutual funds finding on average little evidence of herding. Distinguishing between the buy- and sell- side allows them to conclude for the presence of positive feedback trading, even if it is a relatively small entity.[9]

Another improved measure is proposed by Oehler (1998), in order to distinguish between market-wide herding and stock-picking herding. Market or benchmark herding is identified as a mere consequence of market-wide effects; hence it is an irrelevant component to intentional herding. In fact, Oehler argues that market-wide net cash inflows/outflows should not lead to similar decisions in case of active fund management, while the LSV measure does not make this distinction. Stock-picking herding is the excess to this benchmark level.

Oehler proposed a measure of the excess demand of supply which has to be settled in the market, which represents only the market-wide herding:

$$O_{it} = |\frac{B_{it} - S_{it}}{B_{it} + S_{it}}| \tag{4.3.6}$$

More correctly, these measures are additionally cleaned, distinguishing only the effect of active funds:

$$O^{(A)} = |\frac{B_{it} - S_{it}}{N_{it}^{active}}| \tag{4.3.7}$$

[9] Moreover, they present a measure of herding by an individual fund to access the extent a fund runs with or against the crowd and how this is correlated with the performance. In fact, LSV does not consider the intertemporal trading behavior of a specific fund (Bikhchandani and Sharma, 2000).

where $N_{it}^{(A)}$ is the number of funds that allows for investments in stock i.

The stock-picking level of herding is the excess of the LSV measure once we adjust for the market-wide herding:

$$O_{it}^{(A)}(adj) = |(\frac{B_{it}}{N_{it}} - (P_t^{\text{buy}} - P_t^{\text{sell}})| - AF_{it}^{(A)} \tag{4.3.8}$$

where: P_t^{buy} (P_t^{sell}) is the average probability for a buying (selling) decision, and $AF_{it}^{(A)}$ is the adjustment factor that follows the same properties as LSV. It represents the expected value of $O_{it}^{(A)}$ in case of no herding, when $B_{it}(S_{it})$ follows a binomial distribution with parameters P_t^{buy} (P_t^{sell}) and N_{it}. Additionally, he controls for the difference between buying and selling decisions of the funds being a random decision process. It can be written as:

$$AF_{it}^{(A)} = |E[\frac{B_{it}}{N_{it}} - P_t^{\text{buy}}] - E[\frac{S_{it}}{N_{it}} - P_t^{\text{sell}}]| \tag{4.3.9}$$

Studying a sample of German mutual funds, Oehler finds strong evidence of herding due to the entire mutual fund industry facing cash inflows/outflows. However, not much stock-picking herding is left in excess to this market-wide benchmark.

Moreover, Wylie (2005) criticizes the assumptions under the null hypothesis of no herding. He argues that short-selling constraints and money manager heterogeneity can induce the measure to over-estimate herding where there is none.

Firstly, if institutional investors are subject to short sell constraints, the number of sellers for a stock- period cannot be higher than the number of managers who hold the stock at the beginning of the period. The distribution of sells is therefore truncated on the left.

Secondly, Lakonishok, Shleifer and Vishny (1992) simplify the distribution of trades in a stock-period. In the absence of herding, trades follow a Bernoulli distribution, where each trial is independent of all other trials and the probability of success P_t is invariant across all managers and stocks in a period t. They do not consider the specific propensity of the manager j to buy stock i in period t, represented by the parameter $p_{it}^{j} = \Pr ob(X_{it}^{j} = \text{buy}|X_{it}^{j} \in \{\text{buy, sell}\})$. In the LSV measure, the ex-ante probability of buyers is assumed to be constant across managers and companies, as $p_{it}^{j} = P_t, \forall i, j$, regardless for example of the initial holding in the stock or liquidity needs. If significant cross section variation is found, then the null of no herding is mistakenly rejected.

Wylie (2005) estimates the sampling distribution of LSV using a sample of UK funds. His evidence shows a level of unadjusted LSV similar to US studies, as 2.6% on average in the overall sample. However, in funds where managers cannot short sell stocks, the LSV is not calibrated to zero and 1.5% of the 2.6% of herding can be attributable to short-selling constraints. Then, checking the effect of cross-sectional variation among managers on the propensity to buy, its effect on the LSV measure in the UK market is small and negative.

Another issue is raised by Frey, Herbst and Walter (2007). They argue that the LSV measure is downwards biased because of the adjustment factor. Without the AF, the measure will overestimate the true level of herding in case of a small number of funds. However, it overcorrects leading to an underestimation of herding. Using a microstructure framework, they show that the LSV measure is unbiased only if the number of transactions per stock and period is very large. In cases of a smaller number of transactions the bias is function of the number of trades in a stock per period and the true level of herding.

This introduced bias has three main characteristics. Firstly it increases with the true level of herding. Secondly, it decreases with the number of trades in a stock and lastly, this decrease is more pronounced when true herding is higher. This bias implies in particular that differences between unequal subsets of the data might be affected solely by sample differences in the trading activity (such as the number of active funds itself or company size).

This criticism stimulates the development of an improved measure of clustering. Frey et al. (2007) build a structural model of investor transactions and herding consistent with the LSV measure. Then, they suggest an alternative measure of herding that works unbiasely in the same structural framework.

Defining the LSV measure as the excess dispersion in either buy or sell probabilities in a stock-quarter, there are three assumptions for a consistent model:

- under the null hypothesis of no herding, the probability of being a buyer of stock i at time t corresponds to the overall probability of buys during the period of analysis;

- herding is defined as deviation from the overall buy probability during the period;

- herding can be either on the buy or on the sell side.[10]

[10] In a consistent model the probability that the stock i is bought by a fund manager active in period t is:

$\pi_{it} = \pi_t + \iota_{it}\delta_{it}$,

where: π_t is the overall probability of buys in period t for all stocks; ι_{it} is an unobservable variable indicating whether herding is on the buy ($\iota_{it} = 1$) or sell side

Given the three assumptions and the microstructure model, the LSV measure can be written as:

$$LSV^*_{q,s} = |\frac{b_{it}}{n_{it}} - \widehat{\pi}_t| - E[|\frac{\widetilde{b_{it}}}{n_{it}} - \widehat{\pi}_t|; \widetilde{b}_{it} \sim B(\widehat{\pi}_t, n_{it}] \tag{4.3.10}$$

where: b_{it} is the number of buys transactions of stock i in period t; n_{it} is the total number of transactions for stock i in period t; and $\widehat{\pi}_t$ is the average proportion of buys to the total number of transactions in any stock in period t. This is the expected probability of a buy under the hypothesis of no herding. $E[|\frac{\widetilde{b_{it}}}{n_{it}} - \widehat{\pi}_t|; \widetilde{b}_{it} \sim B(\widehat{\pi}_t, n_{it}]$ is the adjustment factor, that represents the expected value of the dispersion of buys, assuming that the buys are binomially distributed. With n_{it} fund managers active in stock i - quarter t, the number of buys is the result of n_{it} draws from a Bernoulli distribution with success probability of π_t.

They propose an alternative measure, which uses the second moment of the excess dispersion of buyers:

$$FHW^2_{it} = ((\frac{b_{it}}{n_{it}} - \widehat{\pi}_t)^2 - E[(\frac{\widetilde{b_{it}}}{n_{it}} - \widehat{\pi}_t)^2; \widetilde{b}_{it} \sim B(\widehat{\pi}_t, n_{it})])\frac{1}{n_{it}(n_{it}-1)} \tag{4.3.11}$$

or alternatively:

$$FHW^2_{q,s} = \frac{(b_{it} - \widehat{\pi}_t n_{it})^2 - n_{it}\widehat{\pi}_t(1-\widehat{\pi}_t)}{n_{it}(n_{it}-1)} \tag{4.3.12}$$

In order to make it comparable with the original LSV, they use the square root of the aggregated herding measure.

($\iota_{it} = -1$), with equal probabilities; and δ_{it} is the true degree of herding in stock i - quarter t.

The authors prove that this new measure is an unbiased and consistent estimator of the parameter δ in their structural model.

However, while it excels over the LSV in measuring the level of herding in cases where it exists, it is not as reliable as the LSV under the null hypothesis of no herding. The authors suggest therefore the use of both measures. The LSV is a good first step to test for the presence of herding, because it is consistent and unbiased under the null hypothesis. The FHW can then be used as a good estimator of herding once the presence of correlated trading is tested.

Frey et al. (2007) apply the two measures on a set of German mutual funds, excluding passively managed funds, sorting the stocks per returns and market capitalization. They find evidence that the FHW measure is considerably higher than the LSV (2.8 times higher on average) and it monotonically increases when more funds trade in a stock. Then, the relative bias between LSV and FHW decreases with an increase in trading activity, which is consistent with the hypothesis that the LSV is downward biased for stocks with low trading activity.

Consistently, the relative differences between classes of stocks, is less pronounced under the FHW than under the LSV. Moreover, the FHW measure of herding is u- shaped when stocks are grouped by size.

4.3.3 Other applications

Despite the limitations, the empirical literature widely used the LSV measure to assess herding. Mainly because of its simplicity and intuitiveness, it has been applied to different markets, assets and countries. However, many studies show little evidence of herding among investors, especially in the US and the UK (Lakonishok, Shleifer and Vishny, 1992, Grinblatt et al., 1995, Wylie, 2005).

We classify the applications of the LSV measure considering:

- US or non-US markets;
- Stock or other securities markets;
- Quarterly or higher frequency data.

Earlier papers focus on investigating the US market, where data on quarterly stock holdings is widely available, given transparency regulations. However, little evidence of herding is found in the US market, which is consistent with Lakonishok, Shleifer and Vishny (1992).

Grinblatt et al. (1995) study a sample of 274 US mutual funds from 1974 to 1984, confirming the small intensity of the imitative phenomenon.

They focus on investigating momentum herding; therefore they classify the stocks based on their past performance. The results show a higher level of buy- herding for past winners stocks, and hence evidence for the use of positive feedback strategies in buying decisions. They do not find similar results for sell- herding for past losers.

Moreover, when they classify funds in homogenous groups based on investment style, they find even less evidence of herding in the different classes when compared with the average level. Finally, they assess a weak tendency at a fund level to run with or against the herd.

Wermers (1999) studies a larger and long term sample, looking at all US mutual funds from 1975 to 1994. The main aim of his work is to test the stabilizing effect on prices. First, he finds evidence of a slightly higher level of herding when compared to Lakonishok, Shleifer and Vishny (1992). Specifically, he shows that the LSV measure decreases with the trading activity (as defined by the number of traders) and it is negatively related to the market capitalization of the companies.

Then, he shows that this herding is beneficial to the market, as it pushes quickly prices close to their fundamental values. This conclusion is reached from the fact that stocks bought by herding have on average higher contemporaneous and future returns than stocks sold by herding, especially when considering small stocks, and this differential persists over time.

Looking at momentum strategies, Wermers confirms that buy herding is stronger in stocks with high past returns. However, sell herding is stronger and increases for companies with poor past performances, in contrast with Grinblatt et al. (1995). Window dressing considerations are excluded because there is no variation in sell herding across quarters in a year.

Brown et al. (2007) study the impact of analysts' recommendations on institutional herding. They apply the LSV measures and the Grinblatt et al. (1995) buy- sell distinction on a sample of funds from 1994 to 2003. They find evidence of interactions between analysts' revisions and mutual funds herding. An increase in consensus among analysts induces rises on buy- herding, while decline in consensus pushes sell-herding up. However, this documented level of herding has an inefficient effect on prices, inducing overreactions.

More recently, the focus of such analysis moved to the behaviour of other geographical markets, especially less developed markets. There are many contributions exploring the phenomenon of herding in several other countries and the phenomenon is usually documented to be at a higher level than in the US. Kim and Wei (2002a), Kim and Wei (2002b) were among the first authors to look at a market outside the US. They investigate the trading decisions of investors in Korea, finding higher level of herding among foreign institutional investors. In contrast, Kim and Nofsinger (2005) study institutional herding in Japan and although they find smaller herding than in the US, there is a higher price impact of herding on Japanese stocks. More recent papers use both the LSV and the FHW measures, as for example Blasco et al. (2009)) who study the Spanish market or Arouri et al. (2010) who investigate the French market.

There are several reasons for this difference. Informational opaqueness is higher in less developed markets. A difference in herding because of informational opaqueness can be linked closely to informational-based herding. Lobão and Serra (2002) test quarterly data in the Portuguese market, among 32 mutual funds between 1998 and 2000. They find a 4-5 times stronger level of herding (11.38% on average) than the one documented by previous studies in the US market, which is especially strong in terms of buying herding. Averaging the LSV in subgroups by the size of fund portfolio, they find that herding is higher for medium-sized funds and funds trading in a higher number of stocks. The motivation for this can be understood when considering that an excessive specialization will encourage a simplification of decision processes and lead to naive techniques. They also show that herding is correlated with the volatility and the sentiment of the market, being at its lowest in growing and volatile markets.

Walter and Weber (2006) link herding with the stage of development of the market, motivating the differences in markets with more incomplete regulatory frameworks and less transparent markets. They investigate herding behaviour in German mutual funds and they evince that German managers tend to herd more than their US peers and exhibit positive feedback trading patterns. They also find that a large proportion of apparent herding behaviour can be attributed to changes in the benchmark index composition. Oehler and Wendt (2008) also focus on the German market and they find a considerable amount of correlated behaviour in moments of wide cash inflows and outflows, which could be defined as unintentional herding.

The original works using the LSV measure are applied to the stock markets. Another extension is towards the behaviour of institutional investors in other securities markets.

Haigh, Boyd and Buyuksahin (2006) analyze daily data on future contracts from 1992 to 1994. They conclude that there is herding among investors in this sector, but that its effect is not destabilizing to the efficiency of the prices.

Oehler and Chao (2000) look at the behaviour of German investors in bond markets. They find a significant amount of herding, though of a much lower intensity than in the equity markets. Herding is highly dependent on the interest rates, and it influences the market by affecting the shape of the yield curve.

Recently, Barber, Odean and Zhu (2009) have applied this measure to investigate the behaviour of individual investors and the psychological and systematic biases that induce herding. They also evince that institutional investors are more likely to herd than individual investors, even if for different and more rational reasons.

In the earliest empirical tests applying the LSV measure, the most common data were quarterly stocks holdings from US institutional investors, as this was the most easily accessible data. Recently, studies have been proposed with higher frequency, such as weekly (Puckett and Yan, 2007), daily (Christoffersen and Tang, 2010) or intradaily data (Sharma, 2004).

Herding measures at a high frequency is much greater than quarterly evidence suggests. On an intradaily basis, Christoffersen and Tang (2010) find that the level of herding is twice the quarterly level (6.72% of buyers imbalance on average, in contrast with 3.04% measured on a quarterly basis). They find that herding increases with poorer information quality, confirming informational cascades at a high frequency. Puckett and Yan (2007) also find that weekly herding is 4.78% on average.

Herding might be understated using low frequency data, because many trades are completed within the period of analysis, therefore many trades which occurred due to herding, are not visible.

This will also make a difference when comparing different types of investors that act at different investment horizons. Informational cascades, for example, are usually short term phenomena because they can easily be broken by public information arrival. In these cases, they are not detected by quarterly data.

It is also difficult to correlate herding measures with stock-specific measures that change over the period. Sias et al. (2006) proposes an approach to use quarterly trading data and daily market data.

The proposed correct frequency to use in empirical analysis of herding is the average time between trades of a stock. The fact that larger stocks are subject to lower levels of herding could also be due to the frequency of data being much lower than the average time between trades.

Finally, there is a recent development of the literature that aims to deliver more comprehensive analyses of herding and its motivations. These studies use the LSV measure on regression analysis to analyze herding in the light of other stocks and market characteristics. Earlier examples are studies on the contribution to herding of size (Lakonishok, Shleifer and Vishny, 1992; Wermers, 1999), book- to- market (Grinblatt, Titman and Wermers, 1995) and performance measures (Kim and Wei, 2002a and Kim and Wei, 2002b). These studies help to complete the understanding of institutions that have a tendency to herd more around small and growth companies. More recently, Gelos and Wei (2002) find a negative correlation between herding and market transparency. Finally, Sharma, Easterwood and Kumar (2005) look at internet companies and conclude that these specific category of stocks exhibits a level of herding nearly double that of the rest of the market.

4.4 Sias' methodology (2004)

Sias (2004) proposes an alternative herding measure. He defines herding as the action of following each other into the same securities over a consecutive period of time. Therefore, the intertemporal cross-sectional correlation between the institutional demand measured this quarter and the previous quarter's demand, is proxy for herding. The underlying assumption is that, in the case of imitative behaviour, the buying decision of an investor is explained by the trading decisions undertaken in the previous period by the whole set of investors.

Once evidence of the presence of herding has been shown, Sias argues over its motivations and its impact on the efficiency of the market, taking into account momentum trading, company size, time and investor type. Moreover, he examines whether herding depends on institutional ownership and market liquidity.

4.4.1 Description of methodology

The methodology is based on the number of buyers over traders, as the LSV measure, rather than the dollar value of trades. The starting point is the fraction $P_{i,t}$ of institutional investors defined as buyers of stock i at the end of each quarter t over the number of traders. Then, the institutional demand for stock i at quarter t is standardized as:

$$\Delta_{i,t} = (P_{i,t} - \overline{P_t})/\sigma_t \tag{4.4.1}$$

where: $\overline{P_t}$ is the mean in the quarter t of the proportions $P_{i,t}$ across all companies; and σ_t is the standard deviation in the quarter t of the proportions $P_{i,t}$ across all stocks.

The potential level of herding is identified as the correlation β_t between the standardized institutional demand $\Delta_{i,t}$ of quarter t and its lag:

$$\Delta_{i,t} = \beta_t \Delta_{i,t-1} + \varepsilon_{i,t} \tag{4.4.2}$$

A positive correlation between the institutional demand and its lag is consistent with investors following the past behaviour of all the institutions in the market. Instead, a negative coefficient implies a contrarian attitude, such as if the institutional demand is still correlated with its past, but investors reverse from previous decisions.

Because of the standardization, this coefficient represents both the correlation between the standardized fraction this quarter and the previous consecutive one and the correlation between the institutional demand and its lag:

$$\beta_t = \rho(\Delta_{i,t}, \Delta_{i,t-1}) = \rho(P_{i,t}, P_{i,t-1}) \tag{4.4.3}$$

The estimated beta coefficient is the key measure for the level of intertemporal correlation between the investors' observed decisions. However, Sias (2004) further cleans it in order to distinguish between the correlation with the past decisions of the same investor and the past decisions of other investors.

In fact, the inertia of investing in the stocks already in a portfolio has to be cleared out. Reasons for this inertia could be related to transactions costs, including liquidity considerations (Grossman and Miller, 1988) or informed trading (Kyle, 1985). Investors build a position over time for fear of liquidity premiums on large orders; or else, investors exhibit a higher correlation with their own previous trades for fear of impacting too strongly on the price with the informational content of a large order.

We can consider the fraction of buyers as the sum of a series of dummy variables $D_{n,i,t}$ that assume value 1 if trader n is a buyer of i at quarter t, divided by the number of traders. Thus, we can rewrite the coefficient β_t as:

$$\beta_t = \left[\frac{1}{(I-1)\sigma_t\sigma_{t-1}}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{i,t}} \frac{(D_{n,i,t} - \overline{P_t})}{N_{i,t}} \sum_{n=1}^{N_{i,t-1}} \frac{(D_{n,i,t-1} - \overline{P_{t-1}})}{N_{i,t-1}}\right] \tag{4.4.4}$$

Then, rearranging the expression we solve for the beta as the sum of the two components:

$$\beta_t = \beta_t(1) + \beta_t(2) \tag{4.4.5}$$

- the "following themselves" component:

$$\beta_t(1) = \left[\frac{1}{(I-1)\sigma_t\sigma_{t-1}}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{i,t}} \frac{(D_{n,i,t} - \overline{P_t})(D_{n,i,t-1} - \overline{P_{t-1}})}{N_{i,t}N_{i,t-1}}\right] \tag{4.4.6}$$

- the "following others" component:

$$\beta_t(2) = \left[\frac{1}{(I-1)\sigma_t\sigma_{t-1}}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{i,t}} \sum_{m=1, m\neq n}^{N_{i,t-1}} \frac{(D_{n,i,t} - \overline{P_t})(D_{m,i,t-1} - \overline{P_{t-1}})}{N_{i,t}N_{i,t-1}}\right] \tag{4.4.7}$$

where: I is the total number of stocks in the analysis; N is the total number of institutional investors with open positions in any stock; σ_t is the standard deviation of the proportions of buyers of stocks i at time t; $D_{n,i,t}$ are dummy variables for each trader n that has increased his position on the stock i at the end of period t, and 0 otherwise; and $D_{m,i,t-1}$ are dummy variables that take value 1 if the investor m, with $m \neq n$, has increased his position in the stock i at the end of quarter $t-1$.

The first component represents the portion of correlation that results from inertia in the investors' decisions, who follow their own past in and out of the same securities. If $\beta_t(1)$ is positive (negative), the trading decisions in t are positively (negatively) influenced by the choice that the same investor took in $t-1$. Instead, if $\beta_t(1)$ is not significantly different from zero for each period, then investors act independently from their own past trading activities.

The second component estimates the portion of correlation that results from investor n following other agents m, with $m \neq n$, in their trading decisions. Thus, $\beta_t(2)$ represents more precisely the potential herding phenomenon. If it is significantly positive (negative), there is evidence of a convergence (divergence) of behaviour among the financial institutions.

Moreover, Sias distinguishes the correlation within the same investor type and with other investor types. We have previously seen that differences in the environments where financial institutions are working can influence their tendency to herd and determine who they are more likely to follow. Hence, this allows initial considerations on the different theoretical types of herding that are more likely to occur among certain categories of institution in comparison with others.

For this reason, the coefficients of correlation β_t^c for each investor type is defined as:

$$\Delta_{i,t}^c = \beta_t^c \Delta_{i,t-1} + \varepsilon_{i,t} \tag{4.4.8}$$

where $\Delta_{i,t}^c$ is the standardized fraction of buyers among the type c of investors, that is regressed on the lag demand of the sample of all investors.

Sias (2004) shows that the decomposition of the coefficient is still possible and it further permits to distinguish the correlation between similar institutions to the correlation between investors of different categories. The three additive components are in this case:

1. "following their own past trades":

$$\beta_t(1) = \left[\frac{1}{(I-1)\sigma^c_{it}\sigma_{i,t-1}}\right]\sum_{i=1}^{I}\left[\sum_{c=1}^{C_{i,t}}\frac{(D_{cit}-\overline{P^c_t})(D_{c,i,t-1}-\overline{P_{t-1}})}{C_{it}N_{i,t-1}}\right] \tag{4.4.9}$$

2a. "following other investors $m \neq n$, belonging to the same institutional category C":

$$\beta_t(2a) = \left[\frac{1}{(I-1)\sigma^c_{it}\sigma_{i,t-1}}\right]\sum_{i=1}^{I}\left[\sum_{c=1}^{C_{i,t}}\sum_{m=1,m\neq c,m\in C}^{C_{i,t-1}}\frac{(D_{cit}-\overline{P^c_t})(D_{m,i,t-1}-\overline{P_{t-1}})}{C_{i,t}N_{i,t-1}}\right] \tag{4.4.10}$$

2b. and "following other investors $m \neq n$, belonging to other categories else than C":

$$\beta_t(2b) = \left[\frac{1}{(I-1)\sigma^c_{it}\sigma_{i,t-1}}\right]\sum_{i=1}^{I}\left[\sum_{c=1}^{C_{i,t}}\sum_{m=1,m\notin C}^{N_{i,t-1}C_{i,t-1}}\frac{(D_{cit}-\overline{P^c_t})(D_{m,i,t-1}-\overline{P_{t-1}})}{C_{i,t}N_{i,t-1}}\right] \tag{4.4.11}$$

where: $D_{c,i,t}$ is a dummy variable that takes value 1 if the investor c, that belongs to the type C, is buyer of the security i over the period t; and $C_{i,t}$ is the number of financial institutions of type C that trade in stock i in quarter t. $\overline{P^c_t}$ is the average fraction of buyers over time t belonging to the type c; while $\overline{P_{t-1}}$ is the average fraction of buyers over time t for any type. σ^c_{it} is the standard deviation of the fraction of buyers of stock i in time t, belonging to the institutional type c, while $\sigma_{i,t-1}$ is the analogous standard deviation of the fraction of all buyers of any type, estimated for time $t-1$.

4.4.2 Further developments and applications

The limitations of this methodology are that again it does not completely isolate herding from a spurious non-intentional correlation. Sias partly addresses this problem, distinguishing between correlation with others' previous demand and the same investor's previous demand. However, this adjustment does not eliminate the effect of correlated signals to which the investors answer similarly but independently.

We will propose a solution to this issue in the next chapter, using the Fama and French (1993) and Carhart (1997) factors to correct for passive market strategies.

Moreover, this methodology only gives measures of herding per period, so it does not provide information at stock level.

Sias's measure has been applied by other researchers to the financial markets, mainly to stocks in the US markets.

Puckett and Yan (2007) use both the LSV measure and Sias's betas on the trades of 776 institutional investors, from 1999 to 2004 on weekly data. They find evidence of herding and destabilizing effects on the efficiency of prices, especially considering the sell-side. This result does not confirm the findings of older studies based on the LSV measure, which conclude that sell-herding has a stabilizing effect on prices. More recent studies, based on Sias' methodology consider behavioural reasons which bring inefficiency to the prices through herding. They do not find destabilizing on the buy- side. Buy-herding is instead stabilizing, considering the absence of price reversals after short-term buy herds.

Choi and Sias (2009) finds highly significant evidence of herding as cross- sectional correlation, when investigating the phenomenon at industry level, rather than at stock level. Moreover, they motivate it with correlated signals and style investing. They find that industry herding is due mainly to investigative herding, thus investors receive correlated signals at different times, and therefore it appears that late informed investors follow early informed ones.

This result is after correcting for underlying investors' flows. Following Dasgupta et al. (2010), they exclude the investors who are most subject to retail flows (mutual funds and independent advisors) and then look at the changes in portfolio weights rather than signs of trade.

They do not find evidence of momentum herding: institutional demand is independent of lag industry returns once controlling for lag demand.

4.5 Other methodologies

We have seen that the main limitations of the previous measures are the strong assumptions that a mere correlation of trades could be proxied for herding. For this reason, authors have tried to develop different methodologies to investigate the phenomenon more precisely, such as laboratory experiments, the estimation of microstructure models and econometric tests.

The limits of these methodologies lie in the econometrics robustness of the approaches, which restrict their agreement in the literature.

Experimental tests on artificial laboratories are one of the possible alternatives to the traditional clustering measures. They directly address the problem of lacking information on private signals, controlling exactly what information each trader receives, according to a theory.

They could directly test theories of herding, stating and assessing the assumptions and deviations.

Anderson and Holt (1997) is one of the first contributions to experimental tests of imitative behaviour. They found the presence of herding, but their model is not applicable to the financial markets because of the assumption of fixed price. The first contributions to experimental testing of herding in the financial markets are Drehmann, Oechssler and Roider (2005), Cipriani and Guarino (2005, 2009) and Park and Sgroi (2008).

Drehmann et al. (2005) and Cipriani and Guarino (2005) perform two similar experiments on a group of university students. They both test a model of informational cascades à la Avery and Zemsky (1998). Individuals have a choice between two actions, after receiving a binary signal and observing a moving price that efficiently incorporates the available public information. Both papers report that prices tend to exhibit lower volatility than expected and to revert to the mean. They found that informational cascades happen, but less often than predicted by the theory. Contrarian behaviour also happens, especially among subjects with high signals in moments of increasing prices.

Park and Sgroi (2008) test for both rational herding and rational contrarian behaviour in a multi-state multi-signal model, à la Park and Sabourian (2005). Their individuals are represented by a large sample of university students. They again found evidence of rational herding, however less than the theoretical expectations, as well as irrational herding.

A limitation of this approach is the validity of the sample of individuals they interview, as they are undergraduate students who will not pay directly the full consequences of the decisions they take during the experiment. The first issue is addressed by Alevy and Haigh (2006) and Cipriani and Guarino (2009). Alevy and Haigh (2006) experimentally compare the herding behaviour of students with that of CBOT traders. They find that students follow Bayesian rules more strictly, but that they do not perform better than professionals. In fact, professionals show a better use of the public information and they tend to use private information more than students do, limiting the probability of the rise of informational cascades. Professionals show their ability to learn throughout the game and to update the usage of the Bayes' rule according to the stage they are at in the game. However, despite the interesting results, Alevy and Haigh (2006) use a fixed payoff framework.

Cipriani and Guarino (2009) distinguishes themselves from the above paper because they test rational herding on a group of professionals and they use a model à la Avery and Zemsky (1998) with two states, two signals and a moving price that follows an efficient mechanism. They particularly focus on testing the hypothesis of herding the assumption of "event uncertainty". They find little evidence of rational herding among this group of real-world agents, and significantly they confirm the previous results from the sample of economics students.

Another recent alternative to the measures of clustering is developed by Cipriani and Guarino (2010). They build and estimate a sequential trading model of informational cascades, based on Avery and Zemsky (1998) and Glosten and Milgrom (1985). Traders take decisions on an asset of unknown value, trading against an uninformed market maker. On informational days, some agents receive a private signal of the changed value of the asset. On the other days, agents can still trade but only for non-informational reasons. The market maker is uninformed both on the change in the value of the asset and the type of investors, therefore he will tend to update the prices slowly, given space for informed traders to gain profit and informational cascades to arise.

The model parameters are then estimated using transaction data, as Easley, Kiefer and O'Hara (1997). They construct the likelihood function for the trading of the asset over several days, taking account of the signals, the updated probability of a buy or sell and the history of trades.

The results show the presence of buy (sell) herding in just 9% (11%) of the trading periods, particularly concentrated in some days, days in which herding also has a destabilizing effect on prices.[11]

Another approach developed by the literature is based on econometrics tools to detect dependence between trades. For this purpose, Patterson and Sharma (2007) utilize two different approaches on intradaily data based on econometrics tools. They use a bootstrapped runs test and a test of dependence between interarrival trade times. Using this method, they fail to find a relevant presence of herding and the market works efficiently. The level of herding they find is limited to very small stocks and it is not correlated with dispersion of opinion and analysts' recommendations.

[11] Other examples of the direct estimation of theoretical models are Welch (2000), who builds a structural model for analyst recommendations in which herding is a parameter influencing the transition probabilities between recommendations, and Hwang and Salmon (2004) who model how herding affects pricing in the CAPM.

Chapter 5

Stock splits and Herding

5.1 Introduction

This chapter addresses institutional herding in the specific occurrence of a stock split. One of the main concerns addressed by the literature on herding is the potential destabilizing effect of imitative behavior on prices. It is therefore interesting to examine whether herding has an impact on the market reaction to the announcement of a stock split. This event is still a puzzling phenomenon because of the abnormal market reaction following its announcement and occurrence (Lakonishok and Vermaelen, 1986, Ikenberry and Ramnath, 2002). The presence of imitative behavior could exacerbate suboptimal decisions in the functioning of the markets and the announcement reaction. On the other hand, a stabilizing herd behavior would help prices to aggregate more quickly any informational content that is driven by the event. The effect is particularly delicate if institutional investors are herding, given their growing presence and impact on the markets.

In the light of previous literature, that evince an informational content on the announcement of stock splits, we investigate whether companies that announce stock splits exhibit a systematic abnormal level of herding with respect to the rest of the market. The intensity of the phenomenon could help to explain the abnormal performance observed in the event window around the announcement.

The main data for the analysis are quarterly stocks holdings of US institutional investors, from Thompson Financial database, from 1994 to 2005. CRSP and I/B/E/S databases complete the information with market and analysts' data. We investigate institutional herding as proxy for market herding, defined as the correlation between trades among financial institutions over two consecutive periods of time (as Sias, 2004).

The analysis proceeds in three steps. First, we measure the level of correlation among investors' decisions both in the overall market and in a subsample of companies that have announced at least one stock split in the quarter. Then, we propose an analysis of the motivations of this behavior according to the theoretical literature and in particular to the motivations behind the difference in herding between spitting and non-splitting companies. Finally, we carry out some robustness checks. In particular, we control the estimated measure for a set of factors that, we assume, imply a nonvoluntary correlation and we investigate the stabilizing effect of herding on splitting stocks.

Before proceeding, we need to acknowledge the delicate challenges that the empirical literature faces in verifying both the presence and the causes of herding among investors in real-functioning markets. The empirical tests are usually based on the definition of institutional herding as the excess level of correlation with respect to a benchmark of independence. All the main measures of herding among institutional investors that we have reviewed in the previous chapter are based on this clear and easy-to-test definition. However, as it is true that herding implies correlated behaviour, this definition does not allow to investigate the coordination mechanism between agents, and therefore, it does not allow in itself to distinguish among different reasons to herd.

This issue is an hard task to solve in the empirical analysis of real-functioning markets, mainly because of the lack of data on the private signals and private communications between agents. As data on the inputs of the real decision processes of institution are difficult to access, the theoretical definition of herding, as the will of the individual to introduce other agent's decision in his evaluation process, is difficult to extrapolate.

One solution is to factor out the variables that could affect systematically the decisions of all the agents. This is partly done in the adjustment factor of the LSV measure (Lakonishok, Shleifer and Vishny, 1992). It is performed in our analysis controlling for variables that could determine correlated trades because of market conditions (four-factors Carhart, 1997).

We propose to use also different sets of variables to identify the presence of specific types of herding. It is an attempt to reach conclusions as accurate as possible on informational herding versus feedback strategies herding. However, it is not an entirely clean test, as both the four different types of herding and the sets of variables used are not completely disjoint one another.[1]

[1] Further research will focus on minimizing this limitation with a different methodology, using a microstructure models that could identify a cleaner impact of informational-based herding on the days around the announcement of a split.

The fact, however, that we are comparing two distinct groups, splitting and nonsplitting companies, and that the interest of the analysis is mostly on the difference between groups, could mitigate these limitations. Both samples share the same difficulties and lack of data, therefore we concentrate in extrapolating any interesting difference between the two categories of stocks.

Said so, the starting point in the measurement of the convergence of behavior among institutions is the methodology developed by Sias (2004), estimating the intertemporal correlation of the institutional demand. In the presence of herding, the trading actions observed in the previous quarter will help to explain this quarter's decisions.

We find that the first order serial correlations of the fraction of investors buying this quarter are always positive and highly significant in any period.[2] The phenomenon is particularly intense between 1998 and 2001. Restricting the analysis to splitting stocks, we observe a negligible difference on the average beta coefficients with respect to the non-splitting sample. Investors tend to herd slightly more when they trade on splitting companies in the subperiod from 1994 to 2001, while we observe a higher herding on non-splitting companies, even if still not significant, from 2002 onwards. In period of crisis, herding increases for nonsplitting companies, consistently with the literature. Splitting stocks are instead affected by market crises in their number, but not in the intensity of the herding phenomenon. This variation over time, and the negligible average difference between the two groups, motivates additional analysis. Firstly we take into account the effect of

[2] As a robustness check, we also use the methodology proposed by Lakonishov, Shleifer and Vishny (1992) that measures the convergent behavior in trading over the same period of time. The results confirm the presence of a correlation among investors decisions.

different trading activity among companies. We see that the correlation increases with the trading activity of the company and herding is more likely to occur among non-splitting stocks once we take out the effect of companies with thin markets. The difference between splitting and non-splitting companies is on average negative for all the restricted groups, reaching its minimum for highly traded firms.

We perform further analyses on the betas in order to account for the influence of factors other than intentional herding. In fact, if investors are exposed to similar market conditions, passive trading strategies and correlated information, they could exhibit clustered, but nonvoluntary, behavior. We factor out the effect of fundamentals and common public information, cleaning the estimated coefficients for the four factors of Carhart (1997): size, book-to-market, market return and momentum.

The empirical evidence shows that these factors are significant determinants of the institutional demand especially for non-splitting companies. Consistently with what stated above non-splitting stocks are more sensible to market conditions. Passive strategies based on the four factors account significantly in the trading activities on nonsplitting companies, while splitting stocks might tend to be more actively traded.Splitting companies appear to be less affected by unintentional factors, as the adjusted beta still accounts for 93% of the total correlation (against 85%).

The next part of the analysis aims to investigate the motivations behind the observed level of potential herding and the difference between splitting and non-splitting stocks. We impose and test specific assumptions for four theoretical reasons for herding in our samples. Hence, we construct a unifying model in order to estimate the contributions of each type to the overall herding.

We assume the most likely explanation for herding on stock splits is that it is informational-based, and our results are consistent with the presence of informational content in the split announcement and consequent underreaction of the market. We can also add that this underreaction is itself affected by trading on herd.[3]

Informational cascades can arise among Bayesian agents who face decisions in uncertain environments when they rationally ignore their noisy and imperfect private information. We therefore test empirically for the presence of informational-based herding, in the form of informational cascades (Bikhchandani, Hirshleifer and Welch, 1992, Avery and Zemsky, 1998) and reputational herding (Scharfstein and Stein, 1990, Dasgupta, Prat and Verardo, 2008), looking at market or company conditions for imperfect information (Wermers, 1999, Chan, Hwang and Mian, 2005). In order to proxy for critical information we use small market capitalization, high dispersion of analysts' forecasts and low analysts' coverage. In this case, the coefficients of the lag institutional demand are smaller than the overall Sias' beta, even if they are mostly positive and significant. This result confirms both the presence of informational-based herding and factors other than informational content.

For the splitting companies, we find that most of the general level of herding is explained by an informational component. This result is consistent with the theoretical literature on financial herding and

[3] A recent work by Green and Hwang (2009) connects the reason to split with a particular form of herding, such as style investing (Barberis and Shleifer, 2003. The authors consider how the market is attentive to the nominal price, therefore investors categorize stocks according to their price. This price-categorization could be one of the possible reason for managers to split their stocks. In our work, we have checked for reasons to herd as informational-based and characteristics-based, and price categorization would enter in this latter class, as institutional investors tend to commove towards stocks with high price.

the empirical literature on the market reaction to splits. In particular, according to the information cascades model developed by Avery and Zemsky (1998), when the market is uncertain about whether the value of the stock has changed from expectations, herding can arise. Moreover, if we combine this with uncertainty on the average accuracy of traders' information, it could link herding to mispricing effects. Once we account for informational factors, non-splitting stocks exhibit a much higher and more significant level of unexplained herding than splitting firms.

In particular we see that the difference in herding between splitting and non-splitting companies is explained predominantly by the dispersion of beliefs among analysts.

We then look more carefully to distinguish career and reputation concerns from informational cascades. Noisy environments can also induce rational managers to mimic the investment decisions of other managers in order to maximize their reputations (Scharfstein and Stein, 1990). According to Dasgupta, Prat and Verardo (2010), it more likely to observe reputational herding by independent advisors and investment companies. Therefore, we test for herding looking at the different institutional types and size-groups and the correlation of their trades within the same group or extra group.[4] We observe a high level of correlation inter-group, according to the size of the investor. In particular, the correlation of behavior is higher for big investors, where we assume reputational concerns are more binding. They also tend to herd more on splitting stocks, while small investors tend to cluster more easily

[4] Moreover, Scharfstein and Stein (1990), show that reputational concerns are more binding for stable stocks. Therefore, we alternatively look at stable stocks to give an indication of the presence of reputational concerns, proxied by big companies with high coverage from analysts.

around non-splitting companies.

Informational-based herding however does not explain all of the correlation for the overall market. In particular company size is positively related to herding, contradicting with informational-based herding. We test therefore for other motivations, such as positive-feedback strategies in the forms of characteristic herding (Falkenstein, 1996, Gompers and Metrick, 2001) and momentum strategies (Bennett, Sias and Starks, 2003, Grinblatt, Titman and Wermers, 1995, Wermers, 1999).

According to the former, investors collectively trade the same firms because they are attracted by the same company characteristics. Sharing this same strategy would cause convergent behavior towards the same companies. Gompers and Metrick (2001) find evidence that the institutional demand is positively correlated to the liquidity of the stock (proxied by firm size, price per share, share turnover), size, book-to-market, S&P membership and volatility. Instead, institutional investors tend to avoid investing in stocks with high past returns and high dividends. Regressing the institutional demand on its lag, interacted with the above regressors, we find that those variables have a significant impact on herding. Higher convergence of trades around large, more liquid stocks with low past returns stocks. However, on average there is still a positive component not explainable by characteristics motivations.

A specific case of positive feedback strategies is momentum trading, when investors buy stocks with high past returns and vice-versa. Evidence comes from the relation between demand of stocks and past returns. However, the evidence of such convergence is mixed, with many papers finding a weak presence of momentum trading and only a few which discover strong clear evidence (Sias, 2007, Bennett, Sias and Starks, 2003 and Hong and Stein, 1999). We find that momentum herding has little effect on imitative behavior and it does not impact on the difference in herding between splitting and non-splitting companies.

The final step is to test for the effect of herding on the future returns of companies. We observe that for the overall market and for non-splitting companies, herding does not have a significant impact on future returns. Conversely, the imitative behavior we observe for splitting stocks has a strong stabilizing effect on future returns. This result confirms the informational content that is included in the announcement of the event, and which the market reacts to. This is evidenced by the positive relation between institutional demand and consecutive two quarterly returns.

Yet, a significant part of the correlation among investors and of the difference between the subsamples is still not explained by these four types, suggesting that further studies can be carried out to better understand other motivations, probably irrational, to the phenomenon.

The remainder of this paper ensures as follows. Section 2 describes the methodology we use to detect, measure and motivate herding in our samples. Section 3 describes the data and discusses the main empirical results, whereas Section 4 reports the results of the robustness checks. Section 5 concludes offering some final remarks.

5.2 Measuring herding

For the empirical verification of herding among institutional investors, we start with the methodology proposed by Sias (2004). It consists of estimating the potential level of herding in quarter t as the correlation across companies between the standardized fraction of buyers of stock i in the quarter t on the analogous proportion in the previous period $t-1$:

$$\Delta_{i,t} = \beta_t \Delta_{i,t-1} + \varepsilon_{i,t} \tag{5.2.1}$$

where: $\Delta_{i,t}$ is the standardized institutional demand for stock at quarter t, computed as $\Delta_{i,t} = (P_{i,t} - \overline{P}_t)/\sigma_t$; $P_{i,t}$ is the fraction of institutional buyers of stock i at the end of quarter t; $\overline{P}_t$ is the mean in the quarter t of the proportions $P_{i,t}$ across the companies i; while σ_t is the standard deviation in the quarter t of the proportions $P_{i,t}$ across the stocks i.

A positive coefficient β_t is consistent with investors following the past aggregate behavior of all the institutional investors in the market, whereas a negative coefficient implies contrarian behavior.

First, we estimate the betas on the overall sample. Then, we replicate the quarterly estimations in each of the two subsamples of splitting and non-splitting stocks, first separately and then in a single model with a dummy variable.

In order to compute the beta in the subsamples we need to compute the institutional demand in the sample of splitting/non-splitting companies only, as respectively $\Delta_{i,t}^{(S)}$ and $\Delta_{i,t}^{(NS)}$. We therefore estimate a general level of herding as the $\beta_t^{(S)}$ from the equation:

$$\Delta_{i,t}^{(S)} = \beta_t^{(S)} \Delta_{i,t-1} + \varepsilon_{i,t}^{(S)} \tag{5.2.2}$$

$\Delta_{i,t-1}$ is computed on a different portfolio than $\Delta_{i,t}^{(S)}$, that consists of all the stocks traded in the previous period, splitting and non-splitting.

We have analogous general herding among non-splitting companies, for which $i \in NS$, as:

$$\Delta_{i,t}^{(NS)} = \beta_t^{(NS)} \Delta_{i,t-1} + \varepsilon_{i,t}^{(NS)} \tag{5.2.3}$$

Then, we test the equality of the betas in the two groups.

As a robustness check, we investigate the difference in herding between splitting and nonsplitting companies using another model specification that includes a binary variable $\delta_{i,t}^S$. The variable assumes value 1 if the company has announced at least one stock split in the quarter of interest and zero otherwise. We interact the dummy with the lag institutional demand. We regress, thence, the standardized fractions of buyers in period t on the fraction at end-of-quarter $t-1$ and on this interacted dummy, as:

$$\Delta_{i,t} = \beta_{0,t} \Delta_{i,t-1} + \beta_{1,t} \delta_{i,t}^S \Delta_{i,t-1} + \epsilon_{i,t} \tag{5.2.4}$$

A significant coefficient $\beta_{1,t}$ of the splitting dummy $\delta_{i,t}^S \Delta_{i,t-1}$ represents a significant difference in herding for splitting stocks when compared to the rest of the market.[5]

For a better understanding, we perform all the analysis in subsamples according to the number of traders, Trd_{it}. We restrict the sample to the securities with at least 10, 20, 50 or 100 traders per quarter respectively. This is an additional test to consider if the securities with

[5] We could have a bias here that derives from the influence of the number of institutional investors, which is different in the two groups. If this is the case, we should use another model that avoids any misinterpretation given by the different number of investors in the samples, as in Sias (2004). We will address this issue later, by looking at the number of traders.

too few traders could drive up the results from the true values.[6] Moreover, it homogenizes the samples for the number of investors trading in the company at time t.

5.2.1 Intentional herding

An initial issue arises when we consider that the beta does not provide any indication of the intentionality of the imitative behavior. Instead, one of the delicate points for the empirical investigation of herding is to distinguish unintentional comovements in the buying and selling decisions due to correlated or fundamental-driven signals.

Therefore, we assume that the determinants of non-intentionally correlated decisions are the market factors of Carhart (1997) (size, book-to-market, market return and one-year momentum factor). We assume they can proxy passive strategies and portfolio changes driven by variations on the fundamental characteristics of the market.

Thus, we estimate a measure of herding "conditional on the market conditions", across companies, regressing the previously estimated betas on the four market factors:

$$\beta_t = \alpha + \gamma_{HML} HML_t + \gamma_{SMB} SMB_t + \gamma_M R_{Mt} + \gamma_{MOM} MOM_t + \epsilon_t \tag{5.2.5}$$

where HML_t, SMB_t, $R_{\mathbf{Mt}}$ and MOM_t are the returns on value-weighted zero-investment factors that mimic portfolios for, respectively,

[6] In Sias (2004), the results of this additional test show that in the group of securities with at least 5 investors, the coefficients are even stronger, while in the other subgroups the number of investors per security does not alter the previous results. In our sample, we have already selected only stock-quarters with at least three traders.

book-to-market, company size, market returns and momentum, in quarter t.[7]

The coefficients of the factors indicate the proportion of the total beta ("Sias' beta") that is attributable to fundamental- driven clustering. While $\widetilde{\beta}_t = (\alpha + \epsilon_t)$ corresponds to the clean measure of intentional beta for the quarter t, that we call "beta adjusted".

Analogously, we distinguish between splitting stocks and non-splitting stocks and regress the previous model separately in the two samples, respectively:

$$\beta_t^{(S)} = \alpha^{(S)} + \gamma_{HML}^{(S)} HML_t + \gamma_{SMB}^{(S)} SMB_t + \gamma_M^{(S)} R_{Mt} + \gamma_{MOM}^{(S)} MOM_t + \epsilon_t^{(S)} \tag{5.2.6}$$

and

$$\beta_t^{(NS)} = \alpha^{(NS)} + \gamma_{HML}^{(NS)} HML_t + \gamma_{SMB}^{(NS)} SMB_t + \gamma_M^{(NS)} R_{Mt} + \gamma_{MOM}^{(NS)} MOM_t + \epsilon_t^{(NS)} \tag{5.2.7}$$

5.2.2 Testing for herding motivations

The next step of the analysis is to motivate herding and the difference in splitting and non-splitting stocks in the light of the theoretical literature.

We distinguish informational-based theories, such as informational cascades and reputational herding, and positive feedback theories, such

[7] The quarterly factors returns are downloaded from the Fama and French website.

as characteristic herding and momentum trading. At first, we consider separately each type, both for the overall sample and for the splitting/non-splitting groups. Later, a unifying model is constructed in order to distinguish simultaneously the impact of all the above types.

Informational - based herding

Both informational cascades and reputational herding models are based on the underlying hypothesis of partially noisy private signals. Therefore, we consider triggering conditions for noisy information such as small market capitalization, high dispersion of beliefs and low analysts' coverage. The first two following conjectures will detect informational-based herding of any kind, the third conjecture will instead distinguish a reputational component.

Conjecture 1 *In the presence of informational based herding, we expect herding to be higher for small stocks than for big stocks. This difference between small and big companies will detect both informational cascades and reputational concerns.*

This conjecture is consistent with much of the empirical literature, such as Grinblatt, Titman and Wermers (1995) and Wermers (1999).[8]

Conjecture 2 *In the presence of informational based herding, we expect herding to be higher when the dispersion of beliefs among analysts is higher.*

[8] On the contrary, a positive relation between size and herding will confirm the presence of correlated behavior which is caused only as a result of correlated signals received by the investors (Sias, 2004, Hirshleifer, Subrahmanyam and Titman, 1994).

This conjecture is consistent with the evidence from Chan, Hwang and Mian (2005) among individual and institutional investors.

We consider analysts' coverage as a proxy for the public information available to the market. We assume that the higher the public information, the lower weight investors then put on their own private signals and, in particular, the higher reputational concerns will be. To take out the effect of reputational herding, we consider the effect of coverage in inter-size groups.

Conjecture 3 *Coverage and the difference in inter-size groups between low and high analyst coverage can detect reputational concerns, distinct from informational cascades. Reputational concerns are higher when more public information is available to the market.*

This conjecture is consistent with Scharfstein and Stein (1990), for whom, stable stocks are more likely to raise reputational concerns.

In order to model conjectures 1, 2, and 3, we model the Sias' beta as a function of $X_{i,t-1}$, the matrix of C companies characteristics that proxy for informational-based herding:

$$\Delta_{i,t} = \beta_t(X_{i,t-1})\Delta_{i,t-1} + \epsilon_{i,t} \tag{5.2.8}$$

X_{t-1} includes: $size_{i,t-1}$, measured as the market capitalization of stock i in the quarter $t-1$; $dispersion_{i,t-1}$, as the ratio between the standard deviation of the earnings' forecasts and the standard error of the mean of these estimates, measured in the previous quarter $t-1$; $coverage_{i,t-1}$, as the number of analysts that have published at least a forecast on the company i in the previous quarter $t-1$; and

$(coverage * size)_{i,t-1}$, as the number of analysts following the company in the previous quarter among the same size group of companies.

Therefore, we regress the institutional demand on its lag, decomposing the total beta between the effect from the information quality proxies, $X_{i,t-1}$ and other factors:

$$\Delta_{i,t} = \beta_{NIH,t}\Delta_{i,t-1} + \sum_{c=1}^{C} \varphi_{c,t} X_{c,i,t-1}\Delta_{i,t-1} + \epsilon_{i,t} \tag{5.2.9}$$

The coefficients $\varphi_{\mathbf{c},t}$ are catching the effect of informational-based herding, in the form of informational cascades ($\varphi_{size,t}$, $\varphi_{dispersion,t}$ and $\varphi_{coverage,t}$) and reputational herding ($\varphi_{coverage*size,t}$).

Therefore, $\beta_{NIH,t}$ represents the remaining part of the total beta that cannot be attributed to informational contents, while $\beta_{IH,t} = (\beta_t - \beta_{NIH,t})$ represents the "Informational Beta".

An alternative test for reputational herding is the analysis per type and size of the investor portfolio. We expect reputational concerns to be more relevant when investors share the same trading strategies, the same clients and especially are subject to the same benchmark evaluation. Therefore, we distinguish between beta of the decisions of peer members of the same groups and beta of the overall group of investors.

Conjecture 4 *In case of reputational concerns, herding between investors belonging to the same class type will be considerably high compared to the total clustering of decisions among all investors.*

In order to test conjecture 4, we run the analysis in subsamples according to the investor type, and for each group we estimate the betas inter-type and extra-type, respectively "peer herding" and "general herding".

"Peer herding" is detected by $\beta^{(T)}_{p,t}$, that represents the coefficient between the institutional demand of type T with the past demand of peer investors belonging to the same type T:

$$\Delta^{(T)}_{i,t} = \beta^{(T)}_{p,t} \Delta^{(T)}_{i,t-1} + \varepsilon^{(T)}_{i,t} \tag{5.2.10}$$

"General herding" is instead represented by $\beta^{(T)}_{t}$, as the correlation between the demand of investor T with the past demand of all institutions of any type.

$$\Delta^{(T)}_{i,t} = \beta^{(T)}_{t} \Delta_{i,t-1} + \varepsilon^{(T)}_{i,t} \tag{5.2.11}$$

Similarly, the size of the investors could give information on the importance of reputational concerns (Lobão and Serra, 2002).

Conjecture 5 *If reputational herding is present, the correlation between trades of investors belonging to the same size class will be considerably high compared to the clustering of decisions among all investors. In particular, bigger investors will be more reputationally concerned than smaller investors.*

In order to test for Conjecture 5, we identify peer groups according to the size of the fund. Hence, we classify three groups, small, medium and large institutions according to the value of their portfolio and we reallocate the groups at the end of every quarter. The value of the portfolio of manager n is computed as the market value of all the stocks held in his portfolio in quarter t. As for the type analysis, we distinguish the correlation with the peer members of the same size class, $\beta_{p,t}^{(Sz)}$, and the correlation with any other institution, $\beta_t^{(Sz)}$:

$$\Delta_{i,t}^{(Sz)} = \beta_{p,t}^{(Sz)} \Delta_{i,t-1}^{(Sz)} + \varepsilon_{i,t}^{(Sz)} \tag{5.2.12}$$

and

$$\Delta_{i,t}^{(Sz)} = \beta_t^{(Sz)} \Delta_{i,t-1} + \varepsilon_{i,t}^{(Sz)} \tag{5.2.13}$$

Looking at the difference for splitting and non-splitting companies, we carry out all the previous analysis in the two samples, in order to test for the following conjecture.

Conjecture 6 *We expect the level of herding due to informational content to be higher for splitting stocks than for non-splitting stocks.*

Conjecture 6 is consistent with both the theory of Avery and Zemsky (1998) and the empirical evidence of underreaction of the market to the announcement of this event (Ikenberry and Ramnath, 2002).

We therefore regress all the previous models separately in the two subgroups. For each, we compute again the institutional demand, as demand for splitting/non-splitting stocks only, and we regress it on the lag demand for all stocks. In particular, for splitting stocks (and analogously for non-splitting stocks) we have:

$$\Delta_{i,t}^{(S)} = \beta_{NIH,t}^{(S)} \Delta_{i,t-1} + \sum_{c=1}^{C} \varphi_{c,t}^{(S)} X_{c,i,t-1} \Delta_{i,t-1} + \epsilon_t^{(S)}, \text{ where } i \in S \tag{5.2.14}$$

Also the analysis per type and investor size is performed separately in the two subsamples.

Finally, all the estimated coefficients are then adjusted with the Carhart factors.

Characteristic-based herding

Gompers and Metrick (2001) consider the impact of three main variables on the institution's demand for stocks: prudence or regulations, liquidity of the stocks and the historical returns pattern. In order to isolate the total level of herding by characteristic herding, we control for these variables which mirror the stock characteristics relevant for institutional investors. In particular, we use annual cash dividends per quarter and volatility of the stock as proxies for prudence; market capitalization, price per share and share turnover, for liquidity; and the returns over the previous year, for the historical pattern of returns.

Conjecture 7 *If the beta is due to characteristics preference, the relation between institutional demand and its lag is significantly explained by the variables in Gompers and Metrick (2001) In particular, we expect herding to be positively correlated with size, price, turnover and volatility, and negatively correlated with past returns and cash dividends.*

In order to test for this Conjecture 7, the total beta is therefore modelled as a function of $Z_{i,t-1}$:

$$\Delta_{i,t} = \beta_t(Z_{i,t-1})\Delta_{i,t-1} + \epsilon_t \tag{5.2.15}$$

where $Z_{i,t}$ is the vector of the Q characteristics that affect the institutional demand: $dividends_{i,t}$, $volatility_{i,t}$, $size_{i,t}$, $price_{i,t}$, $turnover_{i,t}$, and $momentum_{i,t}$ (as past year returns)

Hence, we regress the institutional demand on its lag, decomposing the relation between the effect of the characteristics of the company i at the quarter $t-1$ and other factors:

$$\Delta_{i,t} = \beta_{NCH,t}\Delta_{i,t-1} + \sum_{q=1}^{Q} \psi_{q,t} Z_{q,i,t-1}\Delta_{i,t-1} + \epsilon_t \qquad (5.2.16)$$

where: ψ_t is the vector of coefficients of the Q company characteristics, and $\beta_{NCH,t}$ is the remaining part of the Sias' beta that is not attributable to characteristics preference among investors, while we name $\beta_{CH,t} = (\beta_t - \beta_{NCH,t})$ the "Characteristics Beta".

We also analyze the impact of the equity ownership and the characteristic herding on the splits subsample. Thus, we carry out the analysis in the subgroup for splitting (and similarly for non-splitting stocks) and estimate the general level of herding as the relation between the institutional demand for splitting stocks on the lag demand for all stocks:

$$\Delta_{i,t}^{(S)} = \beta_{NCH,t}^{(S)}\Delta_{i,t-1} + \sum_{q=1}^{Q} \psi_{q,t}^{(S)} Z_{q,i,t-1}\Delta_{i,t-1} + \epsilon_t^{S}, \text{ where } i \in S \qquad (5.2.17)$$

The estimated betas $\beta_{NCH,t}$ so estimated are then adjusted for the Carhart factors.

Momentum herding

Institutional investors could also herd because there are momentum traders. If investors use momentum strategies, they would tend to buy the same stocks with past high returns and sell the same stocks with past poor performance. The presence of momentum therefore can be seen in the positive relation between the demand for stocks of quarter t and the past returns of the stocks. Thus, we take into consideration the possibility of a confounding effect in the beta coefficient, which comes from the fact that the past demand proxies last quarter returns if there is momentum among investors.

Conjecture 8 *If herding is due to momentum trading, the relation between institutional demand and its lag would be explained by the past quarter's returns. Higher past returns would explain higher correlation among investors.*

Following Sias (2007) freely, we model Conjecture 8 decomposing the total correlation between the past returns effect and other factors, adding the lag returns interacted with the lag demand, as:

$$\Delta_{i,t} = \beta_{NMT,t}\Delta_{i,t-1} + \rho_t R_{i,t-1}\Delta_{i,t-1} + \varepsilon_{i,t} \tag{5.2.18}$$

Therefore, $\beta_{NMT,t}$ is the remaining part of the correlation not explainable by momentum trading, while $\beta_{MT,t} = (\beta_t - \beta_{NMT,t})$ is the "Momentum beta".

We replicate the analysis for splitting and non-splitting companies. General herding for splitting companies is estimated from the following:

$$\Delta_{i,t}^{(S)} = \beta_{NMT,t}^{(S)}\Delta_{i,t-1} + \gamma_t^{(S)} R_{i,t-1}\Delta_{i,t-1} + \varepsilon_{i,t}^{(S)}, \text{ where } i \in S \tag{5.2.19}$$

The betas $\beta_{NMT,t}$ so estimated are then again adjusted for the Carhart factors.

The unifying model

Finally, we construct a model that simultaneously distinguishes the impact of the four different herding motivations and their effects on splitting and non-splitting companies.

We model the total beta from Sias as a function of all the previously stated explanatory variables:

$$\beta_t = f(\mathbf{X}_{i,t-1}, \mathbf{Z}_{i,t-1}, R_{i,t-1}) \tag{5.2.20}$$

and we regress the following model:

$$\Delta_{i,t} = \beta_{0,t}\Delta_{i,t-1} + \sum_{c=1}^{C} \varphi_{c,t} X_{p,i,t-1}\Delta_{i,t-1} + \sum_{q=1}^{Q} \psi_{q,t} Z_{q,i,t-1}\Delta_{i,t-1} + \rho_t R_{i,t-1}\Delta_{i,t-1} + \epsilon_{i,t} \tag{5.2.21}$$

The autocorrelation of the institutional demand is, thence, partitioned in three herding components. We recall that $X_{i,t-1}$ is the matrix of the variables that proxy informational cascades (size, dispersion of beliefs and analysts coverage) and reputational herding (coverage*size). The coefficients $\varphi_{c,t}$ would detect any Informational-based herding, either cascades or reputational herding. $Z_{i,t-1}$ is the matrix of variables that affect the stock preference of institutional investors (size, price, turnover, standard deviation of returns and past year return). The coefficient $\psi_{q,t}$ accounts therefore for the effect of any characteristic-based herding. $R_{i,t-1}$ is the momentum factor, proxied by the returns in the previous quarter, and the estimated ρ_t represents that part of the total correlation due to momentum strategies.

Then, $\beta_{0,t}$ is the remaining part of the original correlation that cannot be explained by any of the theories we considered so far. In order to attribute it to an intentional component, we clean it for the common factors that contribute to unintentional correlation, as:

$$\beta_{0,t} = \alpha_0 + \sum_{k=1}^{K} \gamma_k FF_{k,t} + \epsilon_{0,t} \tag{5.2.22}$$

where $\widetilde{\beta_{0,t}} = (\widetilde{\alpha}_0 + \widetilde{\epsilon_{0,t}})$ is the " beta adjusted" not explained by the theoretical types under examination.

We estimate the same model separately for splitting and non-splitting companies. We need to take into consideration, however, that the splitting sample is, in some quarters, too limited in size to be reliable enough.

5.3 Empirical results

5.3.1 Data description

In order to investigate institutional herding, we use the Thompson Financial database to access data from the quarterly reports of US stock holdings by financial institutions over a twelve year period. The sample period goes from 1994 to 2005. We consider all types of professional investment companies and advisors who are asked to fill the 13F form according to the SEC regulations. Information about the companies, such as stock splits data, prices and capitalization, are extracted by the CRSP daily database and aggregated per quarter. Data about the dispersion on analysts' forecasts and analysts' coverage is extracted from the I/B/E/S monthly database and again aggregated per quarter.

The overall sample is composed of 1,760 companies, traded by 3,690 investors. Other than due to the availability of data, we clean the sample considering: (i) any manager that holds at least one security for two consecutive quarters and (ii) any stock that has at least three investors trading it during the quarter. This sample represents the overall market, and the level of correlated decisions is our proxy for market herding.

We select the two subsamples of splitting and non-splitting stocks. We define a splitting stock if the company has announced at least one split in the quarter of analysis, according to the CRSP daily database. We have 1,602 announced events by 890 companies, with on average, 2.44 events per company. There are 3,252 investors with at least one of these companies in their portfolios. Non-splitting stocks are the remaining companies that have not had any split announcements in the quarter.[9]

The drawback of this definition is that we have a limited number of observations per quarter for the splitting companies' group. As shown in Table 1, we have on average 39 splits per quarter, ranging from a minimum level in the second half of 2002 and maximum in the second quarter of 1998. This distribution of events confirms the empirical

[9] We consider only one split per quarter per company. Only two companies announced two splits in the same quarter in our database.

literature that considers stock splits as a typical phenomenon of expansive phases. There are 9 "problematic" quarters with less than 20 observations.

We discuss some descriptive statistics on investors and companies in the two subsamples of interest.

Table 2 reports the average number of companies per investor (C_{nt}) and the average number of traders per company per quarter (Trd_{it}). The latter is the denominator of the fraction of buyers we will base our analysis on. Splitting stocks tend to have a higher average trading activity, compared to the more limited number of investors trading in non-splitting stocks. In fact, splitting stocks have an average of nearly 184 investors trading them per quarter, representing 95% of the investors holding these stocks in their portfolios. The alternative sample has an average of 147 traders, representing 85% of holders. This difference is consistent with the stock splits literature confirming the higher trading activities of stocks that decide to split their stocks.

We evince from this data that traders who invest in splitting stocks are on average bigger institutions, in terms of number of stocks traded in a quarter, C_{nt}. When a splitting company is included in their portfolio, investors tend to hold and trade in a higher number of stocks. We have on average 160 stocks in a portfolio that includes companies that announced stock splits in the quarter, compared to 127 in case of only non-splitting companies. Moreover, the splitting sample is slightly more homogeneous than the alternative one, in terms of smaller standard deviation and a narrower range of C_{nt}.[10]

Table 3 provides more details of the average number of institutions

[10] In unreported results, we have observed the same conclusions using the value of the portfolio held, instead of the number of stocks held.

trading in each stock in the samples. We classified the number of investors in five institutional types, defined as:

1. banks,
2. insurance companies,
3. investment companies,
4. independent investment advisors, and
5. other institutions, which includes foundations, university endowments, Employee Stock Option plans, internally managed pension funds and individuals who invests others' money.

The Thompson Database classification of the institutional investors is not always precise, especially between investment companies and independent advisors after 1998. In fact, in 1998 two different databases were merged leading to a change in the classification scheme and a massive transition from types 1-4 to 5. Considering the residual character of this class, we assume no real changes occur to type 5 after 1998 and we revert to the previous association as groups 1 to 4. Instead, we keep as valid, changes between types 1-4 or from 5 to any of the other classes. For new investors who are entered into the database after 1998 directly as class 5, we keep the observations as valid.[11]

We notice, as expected, the rise through the years in the number of institutions trading in the markets. This observation confirms the growing importance of these investors and the concerns around a change in the "representative investor" in modern markets. The average increase

[11] This correction is similar in spirit to Sharma (2004) and Sias, Starks and Titman (2001).

is primarily due to a strong rise in the number of independent advisors and in the residual category of "not defined".

Table 4 sums up the variables we use in the analysis. We can observe that the companies who are splitting stocks are on average predominantly bigger companies, with higher price per share, analysts' coverage and quarterly returns, when compared with the alternative sample. Therefore, the analysis on herding needs to be controlled by the effects of these variables as well, to isolate their effects in the difference of correlation between splitting stocks and the rest of the market.

Table 5 reports the covariance matrix of the variables of interest in the following analyses.

5.3.2 Sias' beta

The first step in the analysis is the estimation of the correlation coefficient between the standardized fraction of buyers of stock i at end of quarter t and the same fraction at the previous end of quarter $t-1$. We call this estimate the "Sias' beta". We first perform the regressions as in equations (5.2.1) for the overall sample, (5.3.3) and (5.2.2) for the splitting sample (analogously for non-splitting companies), in the 48 quarters from 1994 to 2005.

As we can see in Figure 1.1, the estimated correlations in the overall market are positive and statistically different from zero for all quarters. This result is consistent with the hypothesis that a level of herding exists in the trading decisions of institutional investors.[12]

[12] The results show levels of quarterly correlation much higher than Sias (2004). He studies the period from 1983 to 1997, considering all the investors who are required to fill-in the 13F reports in the US markets, and finds an average level of herding of 0.1755 (given the same assumption to consider only companies traded by at least 5 investors per quarter).

Table 6 documents that the beta is 0.457 on average across all the quarters, and it is highly significant, ranging from 0.346 in 2005 to 0.562 in 2000.

The results from the comparison between splitting and non-splitting companies are more complex.

General herding is higher than expected, implying that investors observe all the trades that occur in the past quarter. The average difference between splitting and non-splitting is negligible and not significant. Non-splitting companies exhibit positive and significant level of herding throughout the period, which is very close to the result for the overall market, which is 0.457 on average. Similarly, for splitting stocks, we also estimate positive and significant correlations for 36 out of 48 quarters. On average, the estimated coefficient for general herding in the group of interest is very close (0.467) to the alternative sample, but more volatile across the quarters. However, even if the difference in means is not statistically significant, the median results are clearly higher (0.471 against 0.442) for splitting companies.

As we can see graphically, investors tend to comove more on splitting companies in earlier years until 2001. Yet, in the years after 2001, the trend is inverted. We investigate the phenomenon in more detail breaking the analysis into three subperiods of four years each: 1994-1997, 1998-2001 and 2002-2005.

Averaging the betas within the subperiods, we observe that the highest level of herding occurs between 1998 and 2001. In this period we actually have the effect of a number of crises, confirming that herding is a phenomenon more likely to occur in moments of market stress. We see that the difference between splitting and non-splitting companies widens once we break the analysis into subperiods and it then decreases through the subsequent subperiods. Splitting stocks exhibit higher herding in the first and second subperiods, while non-splitting stocks have a higher level of correlated behavior in the third subperiod.[13] The tests on the averages are however still not significant.

This time pattern can be caused by market factors. The next step therefore is to cleanse the coefficients from common factors that could affect the decision process of institutional investors. We are then able to approximately discriminate between intentional and unintentional herding. We regress the estimated Sias's betas on the four factors of Carhart (1997) measured quarterly, as equations (5.2.5) and (5.2.6).

The last column of Table 6 reports the average standardized coefficients for the three samples. The factors are determinants of the herding phenomenon, but the average betas are still all considerably significant, and continue to represent almost all of the convergence of behavior. On average, the estimated adjusted beta is 0.448, as 98% of the total correlation measured by the average Sias' beta.

An interesting result is that the relative difference between splitting and non-splitting stocks rises once we adjust for common factors, especially for "general herding". In fact, the market factors seem to affect more the trading decisions on herd on non-splitting companies, for which the adjusted beta is on average smaller than the total correlation (0.447). Splitting stocks instead exhibit a level of correlation that is even higher once adjusted (0.506). Furthermore, the test on the means shows that the difference between the samples is significantly different from zero at 10%. It appears that non-splitting stocks are more affected by passive strategies, while common factors lead to contrarian behavior in trading splitting companies. In other words, when investors trade

[13] Unreported results.

on stocks that have announced at least one event in the quarter, they act actively against the information content in common factors. This observation could be affected either by the characteristics of splitting stocks and the tendency to announce more splits in moments of booms, or by private informational content in the split.

We conclude that, after adjusting for common factors, splitting companies exhibit a slightly higher level of herding in general terms, especially in the earlier years from 1994 to 2001. Later years show an opposite trend and investors then tend to herd on non-splitting stocks with higher intensity. These results need more investigation in order to understand what the determinants of this variation are, over time.

We continue investigating the phenomenon in more homogenous groups, in order to detect any bias that may derive from a different level of trading activity. We identify four subgroups considering the minimum number of traders, Trd_{it}, per company and quarter: at least 10, 20, 50 or 100 traders.

We report the results from the model specification that includes a dummy for splitting companies, interacted with the lag institutional demand, $\delta^S_{i,t}\Delta_{i,t-1}$. Then, we distinguish the correlation with past trades of stocks in the same group, from the correlation with past trades in all companies. We call them respectively "peer herding" and "general herding". In the splitting sample (analogously for the non-splitting companies), they are estimated respectively from:

$$\Delta^{(S)}_{i,t} = \beta^{(S)}_{0,p,t}\Delta^{(S)}_{i,t-1} + \beta_{1,p,t}\delta^S_{i,t}\Delta^{(S)}_{i,t-1} + \epsilon_{i,t} \tag{5.3.1}$$

and

$$\Delta^{(S)}_{i,t} = \beta^{(S)}_{0,t}\Delta_{i,t-1} + \beta_{1,t}\delta^S_{i,t}\Delta_{i,t-1} + \epsilon_{i,t} \tag{5.3.2}$$

We report the results in Table 7, distinguishing the three subperiods of analysis, and in Figures 2.

The general correlation is always highly significant and positive, and it increases with the minimum number of investors per company, except in the highest class. The averages in the restricted samples are always higher than in the unrestricted sample, ranging from 0.51 to 0.60. This result shows that low-traded companies (with 5 to 10 institutional investors per quarter) considerably lower the average level of herding. This gives us a hint that reputational herding is indeed present, when considering that according to the literature, it is more likely to occur in stable stocks, such as high-traded companies.

We can draw the same conclusions when we break the sample into three subperiods. We observe in the first period, a decline in all the groups and a clear positive relationship between trading activity and herding. The increase in the estimated coefficients in the second period is, in part, a general tendency, but is mostly due to an increase in herding on high-traded companies (0.6342).

"Peer herding" follows similar considerations. It is significantly smaller than the general correlation, in particular for medium traded companies. Investors mainly observe their peer's decisions, but they do not forget to keep an eye on all trades in all companies. Interestingly, high traded-companies exhibit a level of "peer herding" that is even stronger than the general phenomenon (0.5379 over 0.4916). This result shows herding behavior within the group, but contrarianism with the outside. However, when analyzing the subperiods, the relation between herding and trading activity is shown to be much weaker.

Looking at the average dummy coefficients for general herding, we observe that it is always negative and it is becomes increasingly negative as the minimum number of traders Trd_{it} increases. Moreover, it is significant (at 1%), when we focus the attention on companies traded by at least 20 or 50 traders per quarter. Therefore, the difference between splitting and non-splitting companies is at its highest (even slightly positive) for companies that are followed by a restricted number of investors, while it is at its lowest (significantly negative) for companies which are highly traded in the quarter (-0.1016).

Distinguishing by subperiod, we see that the dummy coefficient is still negative and highly significant in the medium-high groups of trading activity. In particular, the negative linear relation between the difference in splitting/non-splitting herding, and trading activity, is clear and highly significant for the last period, when high-traded splitting companies exhibit a level of -0.1906 when compared with non-splitting companies (0.536). We observed the highest level of herding in the years from 1998 to 2001, but the difference between splitting and non-splitting, therefore still negative, is not significant in any of the restricted samples.

In terms of peer herding, we observe the same pattern, but it is even stronger. The dummy coefficients are highly significant and negative for all groups with at least 10 traders per company. Especially high traded non-splitting companies exhibit a very high level of herding when compared to the same portfolio.

Summarizing, the subsampling per trading activity shows the noisy impact of companies with thin markets, where we observed a lower level of herding and for which the dichotomy splitting/non-splitting does not imply any strong difference in the intensity of the imitative behavior. Considering only medium- high traded companies, the level of herding increases with the number of investors, and trades on non-splitting companies are generally more affected by imitative behavior.

5.3.3 The Theoretical types of herding

The next step is to examine the impact of the four theoretical types of herding on the estimated correlation: informational cascades, reputational herding, characteristic herding and momentum trading.

Table 8 reports the average estimated coefficients for the variables in all the different models. In summary, when looking at the overall market, herding is mostly affected by all the variables we consider. It is positively affected by size, coverage, turnover, price, dividend and past returns. This confirms the presence of all the theoretical types we consider. They show a predominance of characteristic herding, especially as size and coverage have positive average coefficients. Non-splitting companies have results very similar to the overall market.

The splitting sample presents interesting results, which confirm the predominance of informational-based herding. In fact, the dispersion coefficient is on average positive and significant in the Informational-based models, detecting all of the Sias' correlation for the informational model. Higher is the dispersion of beliefs in the quarter preceding the split, higher is the level of herding. Characteristic-based herding is important as well. In fact, both in the Informational-based and in the Characteristic-based models, size is the predominant factor that affects herding for splitting companies the most, and we evince a positive relation.

We will now examine these results in more detail.

Informational- based herding

First at all, we check for the presence of informational-based herding. We regress the standardized fraction of institutions' buyers on its lag and on the set of variables which proxies for the quality of information available to the market.

We model the correlation of trades as a function of size, dispersion of earnings forecasts among analysts, coverage and coverage*size for the company i at the end of the quarter $t-1$. Thus, the estimated coefficient of the lag institutional demand now represents only that part of the correlation that cannot be explained with informational motivations. We call it the "Non-Informational beta" (Figure 1.2).

The lag institutional demand coefficients are always positive and significant for the overall sample and for the non-splitting companies (Table 9). The coefficients are smaller than the overall Sias' beta, being 0.40 on average for the overall market.

However, when looking at the signs of the other regressors, we see that they do not confirm conjectures 1 to 3, but rather, they imply the presence of characteristic-based herding.

Analyzing the splitting firms, we observe that the general level of herding has a very different pattern. It is significantly positive only in 10 quarters out of 18. In fact, the mean across quarters is actually negative but not significant. This average "Non-Informational beta" shows that investors even herd out of splitting companies for motivations other than informational cascades.[14]

We can conclude that most of the imitative behavior for splitting

[14] However, the range of the quarterly estimates is very wide and looking at the median, the value is closer (0.437) to the overall market and higher than for non-splitting companies (0.401).

stocks is due to the observation of past trades and is determined by informational content. In fact, the F tests on the four regressors provide evidence of the significance of these proxies for informational-based herding in most of the quarters. Moreover, the signs of the coefficients of the proxies all confirm conjectures 1 to 3 stated above, even if only dispersion is significant on average. The level of general herding for splitting companies is much lower than non-splitting firms, and the difference is significant.

Looking at the adjusted beta, which is cleaned from common factors, we substantiate the previous conclusions reached on the unadjusted estimates. General herding is even more negative on average once we cleanse for the common factors. However, it does not change the conclusions for unadjusted betas and non-splitting companies. Notably, the test for a positive difference in mean is even more significant (1%).

Characteristic-based and momentum herding

Once we observed the presence of informational-based herding for splitting stocks, we subsequently test for the presence of other types of herding, especially in the non-splitting sample.

We check first for characteristic herding, using the proxies for characteristics preference, such as size, price, turnover for company at the end of quarter t-1, annual dividend per quarter and return in the previous year. Then, the estimated coefficients of the institutional demand will be that part of the Sias' correlation that remains after the attribution of characteristic-based herding (Figure 1.3). We plot them per quarter and we observe that they are still positive and significant in 44 quarters for both the overall market and the non-splitting samples. For the splitting stocks, however, they tend to be more spread around the overall betas, but still significantly positive in 12 quarters.

On average the Non-Characteristics betas, not explainable by characteristics motivations, are still positive and highly significant (0.363 in the overall market), but smaller than the average Sias' beta and the Non-Informational beta (Table 10). Thus, this is consistent with the existence of characteristic-based herding. Moreover, looking at the regressors, we see that company characteristics have an important effect on convergence. The F tests on the regressors mainly reject the null of non- joint significance for all samples. Moreover, the signs of the coefficients are consistent with Conjecture 7 and we observe a tendency to herd towards large companies, with high price per share, high turnover and high dividends.

The average betas are again much smaller for the splitting companies, even being negative on average as opposed to the other samples. However, the results are weaker than informational-based herding, as the difference in means with non-splitting companies is not significant and there is a clear idea of the main sign of the estimated coefficients. The remaining correlation for splitting firms is actually positive in most of the significant quarters (9 out of 10). The F tests show a joint significance of the regressors in explaining the convergence of behavior. However, only size has a significant and positive coefficient, while all the other variables have signs contrary to the expectations of characteristic-based herding and are not significant.

The last type of herding we investigate is momentum trading. We extrapolate the effect of momentum strategies based on past returns (Figure 1.4 and Table 11).

Momentum has a smaller effect than the other types. The remaining beta is very close to the Sias' beta, for both the overall market and the non-splitting sample. The test on the average coefficient for past returns is usually significant, confirming that there is an impact of momentum herding in the two samples, even if it is small. However, it is not relevant for the splitting sample.

Looking in more detail, we find that for splitting companies, the remaining beta is slightly lower than the Sias' coefficient. However, in the majority of the quarters, the test on past returns is not significant, while the Non-Momentum coefficient is significantly positive in 34 quarters. When comparing the difference between samples, herding for splitting companies is slightly higher than for non-splitting, particularly when analyzing the median values. However, the difference in means is not significant.

The adjusted beta has interesting results after cleansing for passive strategies. In particular, general herding is much higher than the respective unadjusted average coefficient, to the extent that the difference in means between the samples is significant (at 1%). Therefore, once past returns are accounted for and the effect of passive strategies is cleared out, investors herd more on splitting companies for reasons other than momentum.

Unifying model and unifying conclusions

The unifying model aims to identify the contributions of each herding type. Yet, we can only rely on this model when considering the overall market and the specification with the interacted dummies. In fact, we cannot draw proper conclusions for the splitting sample, due to the limited size, especially in the last four years.

Table 12 reports the results of the model that includes all the proxies for informational-based herding, characteristics preference and momentum strategies, estimated on the overall sample.

The remaining beta is on average positive (0.366), and positively significant in 41 samples out of 48. This is interpretable as the convergence of behavior that remains after accounting for informational-based herding, characteristics and momentum strategies. It is still quite a high level when compared to the previous Sias' beta, therefore most of the correlation still cannot be explained by using the four main traditional theories.

We clean the estimated coefficients from the effect of common factors that could lead to an unintentional correlation, as equation (5.2.22). Looking at the estimated adjusted beta, they are on average slightly lower than the unadjusted value (0.333 on average), hence still positive and highly significant. This result shows that common factors have a small impact on the level of correlation, accounting for fundamental-driven clustering of the trades, yet still there is strong evidence of imitative behavior that we assume at this point is intentional.

We use F tests on the significance of the different sets of proxies. We can see that jointly, all the models (except for reputational herding, which we do not report), have an impact on the overall correlation. Characteristics and informational-based herding are especially significant determinants of the beta coefficient in all quarters. Momentum strategies are, conversely, much less important.

Then, we look at the results from the model specification that includes the set of dummies interacted with each of the regressors. The dummy coefficient on the lag institutional demand represents the difference in correlation that is not attributable to any of the four theoretical types. It is, on average, not significant and very small (0.008). Therefore there is no evidence of a difference in herding between splitting and non-splitting companies, after accounting for informational content, characteristics and momentum strategies.

When we break the analysis into subperiods of four years, we still see the time pattern on the average beta coefficient, which peaks in the second period, then decreases in subsequent years. Also, the dummy coefficient on the lag institutional demand maintains the same time pattern as the previous general analysis, as it decreases throughout the three subperiods. Its average however, is still never significant. Therefore, the time pattern also cannot be explained by the four theoretical types together.

We test each theory with an F test, both on the coefficients of the set of proxies and on the coefficients of the interacted dummies. We can see from the first tests that yet again, all types of herding are impacting on the correlation. Looking at the F test on the dummies, characteristic herding in particular accounts for the difference in imitative behavior which we observe between splitting and non-splitting firms. Informational cascades are also in part determinant of the difference, as the relative F tests are jointly significant in most quarters, even if the average p-value is 0.1331. Conversely, momentum herding, clearly does not impact on the differential in correlation.

The results on the difference between the two groups show that the model is well specified and detects all of the differences between splitting and non-splitting herding.

5.3.4 Robustness checks

Peer- herding versus general- herding

In addition we also test whether investing in splitting stocks is an investment style shared by the investors (as Barberis and Shleifer (2003)). If this is the case, institutions would imitate past trades in the same style more than the trades in all the companies. We therefore define "peer herding" as the correlation between the institutional demand for splitting stocks at time t on the demand for the same portfolio of splitting stocks at $t-1$. This definition distinguishes from the general level of herding we measured so far, as the correlation of the splitting institutional demand on the demand for all stocks in the previous period.

We have "peer herding" among splitting companies estimated as $\beta_{p,t}^{(S)}$ as:

$$\Delta_{i,t}^{(S)} = \beta_{p,t}^{(S)} \Delta_{i,t-1}^{(S)} + \varepsilon_{i,t}^{(S)} \tag{5.3.3}$$

where S is the set of companies that had announced at least a split in the quarter t, for which stock $i \in S$.

$\Delta_{i,t}^{(S)}$ is computed from the mean and standard deviation of P_{it} among the group of splitting stocks, as: $\Delta_{i,t}^{(S)} = (P_{i,t}^{(S)} - \overline{P}_{t}^{(S)})/\sigma_{t}^{(S)}$. Analogously, $\Delta_{i,t-1}^{(S)}$ is computed on the same portfolio of splitting stocks in period $t-1$.

A corresponding definition applies to the non-splitting companies. "Peer herding" among non-splitting companies, for which $i \in NS$, is estimated as $\beta_{p,t}^{(NS)}$ as:

$$\Delta_{i,t}^{(NS)} = \beta_{p,t}^{(NS)} \Delta_{i,t-1}^{(NS)} + \varepsilon_{i,t}^{(NS)} \tag{5.3.4}$$

The same distinction is carried out in all the previous models. Peer herding is computed respectively for informational-based herding, characteristic-based herding and momentum herding, as:

$$\Delta_{i,t}^{(S)} = \beta_{p,ICH,t}^{(S)} \Delta_{i,t-1}^{(S)} + \sum_{c=1}^{C} \varphi_{c,t}^{(S)} X_{c,i,t-1} \Delta_{i,t-1}^{(S)} + \epsilon_t^{(S)}, \text{ where } i \in S \quad (5.3.5)$$

$$\Delta_{i,t}^{(S)} = \beta_{p,NCH,t}^{(S)} \Delta_{i,t-1}^{(S)} + \sum_{q=1}^{Q} \psi_{q,t}^{(S)} Z_{q,i,t-1} \Delta_{i,t-1}^{(S)} + \epsilon_t^{S}, \text{ where } i \in S \quad (5.3.6)$$

and

$$\Delta_{i,t}^{(S)} = \beta_{p,NMT,t}^{(S)} \Delta_{i,t-1}^{(S)} + \gamma_t^{(S)} R_{i,t-1} \Delta_{i,t-1}^{(S)} + \varepsilon_{i,t}^{(S)}, \text{ where } i \in S \quad (5.3.7)$$

Analyzing the (unreported) results, we see that it does not add much understanding to the previous conclusions. Therefore, when trading in splitting stocks, investors observe the trades that happen in all the stocks in the market portfolio, without identifying splitting stocks as a specific investment style.

The only point to stress is the result for informational-based herding. The average peer beta is lower than Sias's beta on the same sample but still positive, while we have seen that the general beta decreases to zero (0.419 on average for peer herding). Besides, the quarterly betas are positive in 12 out of 13 significant quarters. This decrease in value from the Sias' beta still has a positive significance, but confirms that only a small amount of peer-herding can be explained by the informational proxies when compared to the general level of imitative behavior.

The splitting dummy model specification

In all the previous case, we investigate the difference in herding between splitting and non-splitting companies and also employ another model specification that includes a binary variable $\delta^S_{i,t}$. The variable assumes value 1 if the company has announced at least one stock split in the quarter of interest and zero otherwise. We interact the dummy with the lag institutional demand and regress, thence, the standardized fractions of buyers in period t on the fraction at end-of-quarter $t-1$ and on this interacted dummy, as:

$$\Delta_{i,t} = \beta_{0,t}\Delta_{i,t-1} + \beta_{1,t}\delta^S_{i,t}\Delta_{i,t-1} + \epsilon_{i,t} \tag{5.3.8}$$

The estimated coefficients of the splitting dummy are significantly negative in 7 quarters of analysis and positive in 5.The average coefficient of the binary variable across all the quarters is then very close to zero and not significant.

Averaging the dummy coefficients in the 3 subperiods, it shows a similar time pattern as the previous overall analysis. In the first two subperiods, the average of the estimates is positive (0.048 and 0.047 respectively) but not significant. In the third period, it is instead negative (-0.092), but still not significant on average (Tables 13 and 14). In the years, from 2002 to 2005, the dummy coefficients are significant in 7 quarters out of 48 and mainly negative. Besides, both the maximum and minimum of the beta coefficients are in this third subperiod.

We use the same specification as in all the other cases, including as many interacted dummies as the number of regressors.

For informational-based herding, we interact the dummy with the proxies we use for the quality of information. We interpret these coefficients of the interacted dummies as the difference in herding between the two subsamples that is explainable by informational content, while the dummy interacted only with the lag demand is the part of the difference in herding that is not explained by the proxies:

$$\Delta_{i,t} = \beta_{NIH,0,t}\Delta_{i,t-1} + \beta_{NIH,1,t}\delta_{i,t}^{(S)}\Delta_{i,t-1} + \sum_{k=1}^{K}\varphi_{k,t}^{(S)}X_{k,i,t-1}\Delta_{i,t-1} + \epsilon_t \tag{5.3.9}$$

We look at the coefficient of the dummy interacted with only the lag demand, $\beta_{NI,1,t}$. These coefficients are equally positive and negative in 6 out of the 12 significant quarters, confirming that informational content accounts for most of the difference in herding in the two groups. The average of the estimates across all quarters is smaller than the general Sias' analysis, negative and not significant. Also, as an average in each of the three subperiods, the average dummy coefficient is never significant, even though it shows the same pattern of decrease through the periods. It is in fact slightly positive in the years 1994 to 1998 (0.037), while it is negative in the third period (-0.066). This confirms that this time pattern is still not of informational content. However, it is less pronounced, as we cannot reject the null that the interacted dummies are not jointly significant.

Looking at characteristic herding, we interact the dummies with the companies' variables we identified as important characteristics for institutional demand. We estimate:

$$\Delta_{i,t} = \beta_{NCH,0,t}\Delta_{i,t-1} + \beta_{NCH,1,t}\delta^{(S)}_{i,t}\Delta_{i,t-1} + \sum_{k=1}^{K}\psi_{0,k,t}Z_{k,i,t-1}\Delta_{i,t-1} + \epsilon_t \tag{5.3.10}$$

Looking at the dummy interacted with only the lag demand, the estimated average coefficient $\beta_{NCH,1,t}$ is negative and not significant on average, confirmed by the quarterly evidence that only 7 quarters are significantly positive, while 13 are negative. Averaging in each of the three subperiods, we observe again that the average dummy coefficient decreases throughout the years. In particular, it is negative and significant in the third period, as investors herd more on non-splitting companies, once cleaned by the effect of characteristics. This supports the previous considerations that the difference between splitting and non-splitting companies is not explainable by characteristics preference.

Looking at momentum herding, we regress the following model:

$$\Delta_{i,t} = \beta_{NMH,0,t}\Delta_{i,t-1} + \beta_{NMH,1,t}\delta^{(S)}_{i,t}\Delta_{i,t-1} + \gamma_{0,t}R_{i,t-1}\Delta_{i,t-1} + \gamma_{1,t}R_{i,t-1}\delta^{S}_{i,t}\Delta_{i,t-1} + \varepsilon_{i,t} \tag{5.3.11}$$

The splitting dummy coefficient follows $\beta_{NMH,1,t}$ the same pattern as in the first Sias' analysis. Its average is very close to zero, even if positive in 7 out of 12 significant quarters. When analyzing the subperiods, we find that again the dummy coefficients decrease across the groups, but it is never significant on average. The F test on the dummies interacted with the past returns, shows that the difference in correlation does not come from momentum strategies.

Analysis per type and size of the investor

In the Informational-based herding model we added one variable that could address the distinction between informational cascades and reputational herding. However, the coefficient of size*coverage is negative for overall market and non-splitting companies, contrary to conjecture 3. For splitting stocks, the sign is confirming the conjecture, but it is not significant on average.

Therefore, before rejecting the presence of reputational herding, we investigate it in more detail, looking at homogeneous groups of investors. We consider, as peers, investors with the same portfolio size or belonging to the same institutional type.

Looking at the size of the investors, we classify three groups according to the value of the managed portfolio. We distinguish between herding inter-group ("peer-herding") or extra-group ("general herding"). We see the presence of reputational herding when examining both the difference between general and peer herding and the difference with the Sias' estimate for the overall sample of investors. In each group, we separately regress the models specified with an interacted dummy variable for splitting companies. Table 15 and Figure 3 report the average coefficients from the specification which includes a dummy for stock splits.[15]

The average betas clearly increase with the size of the investor, confirming that the biggest institutions are the ones who tend to herd more. We find that in any group, the estimated coefficients are smaller than the original beta estimates in the complete set of investors. This means that herding increases when we consider all the interactions among

[15] Therefore we restrain from considerations on the general level of herding, reporting only in regard to non-splitting versus splitting stocks.

groups of investors, thus, there is a relevant part that cannot be explained by reputational concerns. Larger investors exhibit the lowest differences with the original average measure, confirming the presence of reputational concerns for big investors rather than for smaller agents, even if it cannot be the predominant explanation for this behavior.

However, for both large and small investors, a considerable part of the imitative behavior comes from "peer herding", therefore reputational considerations seem to be a plausible explanation, but not the only one. The difference between the two specifications appears higher when observing medium size investors. These traders are influenced mainly by the decisions of their peers but also in part by their observations of other groups, as the difference between general and peer herding confirms.

Looking at the subperiods, the betas are only higher in the years from 1998 to 2001 for the largest investors. Therefore, the higher intensity of the herding phenomenon in the second subperiod seems to be driven by reputational concerns among big investors.

With regards to the difference between splitting and non-splitting companies, we look at the dummy coefficients. The average estimated dummy coefficient is negative (-0.992) and significant for small investors, yet it is positive and significant on average for bigger institutions (0.0513). Therefore, big investors tend to herd more on splitting stocks, while small investors tend to cluster more easily around non-splitting companies.

Again, peer and general herding are very similar; therefore we can conclude that the same type of herding is affecting both splitting and non-splitting companies, when we consider the size of the fund as an indication of reputational concerns.

This pattern could partly motivate the differences we observe in the three subperiods. In earlier years before 2002, the impact of bigger institutions is particularly strong and herding is slightly higher for splitting companies. We can therefore explain the difference, in part, by the influence of reputational considerations, as we have seen a tendency for big investors to herd more as they imitate the actions of their peers, and that they herd more on splitting companies.

In the third period, the dummy for smaller investors is particularly negative and significant. In this period the average negative difference we observe in the wide analysis is mainly driven by small investors, who herd more intensively on non-splitting stocks.

Furthermore, the analysis per type of investor could bring to light the presence of reputational herding. The investors with the highest level of correlation are banks and institutions belonging to the residual category of "not defined". This correlation is due to their observations of the peer members of the group and from their observations of other categories, as there is a quite distinct difference between peer herding and general herding among this type of investor. Instead, for investment companies and independent advisors, most of the correlation is inter group. This suggests that reputational considerations may be more binding for mutual funds than for banks.

Considering the dummy coefficients, we see that, on average, investors who herd the most cluster especially on non-splitting companies. Therefore banks and "not defined" institutions show a negative and significant difference between splitting and non-splitting companies. This is particularly the case when considering insurance companies. They herd more on splitting companies when they observe the behavior of all the previous investors, while they herd more on non-splitting companies according to their peers. This result shows a clear difference in the type of herding underlying the correlation. In particular, it reveals that reputational concerns are more binding for non-splitting companies.

Looking at the subperiods, the average results are dragged by the most recent years' data. Earlier years show a different pattern. Between 1994 and 1997, insurance companies exhibit a highly positive and significant difference (0.1071), therefore herding on splitting companies is one third of the overall correlation higher than in the alternative group. The result is equally strong, but reversed in sign for the residual category of investor (-0.1282). The average differences are mainly negative, apart from the one exception of mutual funds. Insurance companies are still particular, and the dummies in both general herding and peer herding are significant, though of opposite sign. In the years 1998-2001, four categories tend to herd more on the group under analysis. Investment companies and "not defined" investors in particular, show a higher and significant difference to herd on splitting companies (respectively 0.1171 and 0.1186 higher than non-splitting companies). Only banks still have a negative coefficient, however this is not significant. This will motivate the results in the second subperiod, where splitting stocks exhibit a slightly higher level of herding, due particularly to mutual funds. For the residual group, peer herding is still high for splitting companies and highly significant (at 1%), considering that the main part of the difference in herding for both subgroups comes from herding with the peer members of the same class. The third subperiod presents an inverted pattern. Four out of five institutional classes exhibit higher herding for non-splitting companies. The only exception is independent advisors, who have a positive but not significant difference. For mutual funds, we see that the dummy coefficient has an inverted sign between general and peer herding. Even if not significant, it confirms that investing in either splitting or non-splitting stocks has different reputational concerns.

Summarizing, we confirm the presence of reputational concerns, but not their predominance over informational cascades. Banks tend to herd more on non-splitting companies, with the data being especially strong in the third period. Investment companies are among the institutions that herd the least, but they are more influenced by their peer decisions and tend to herd substantially on splitting companies, dragging the results, especially in the second subperiod. Moreover, herding on splitting companies versus non-splitting companies seems to be affected differently by reputational concerns in insurance companies and mutual funds. In particular, they seem to be particularly careful in observing their peers when trading non-splitting companies.

The stabilizing effect of herding

We conclude by analyzing whether herding has a stabilizing effect on the future performance of the stocks and whether this effect is different between splitting and non-splitting companies.

Past literature exhibits a positive relation between institutional demand and same quarter or previous quarter returns and is weakly positive when correlated with future returns (see for example Nofsinger and Sias, 1999; Grinblatt, Titman and Wermers, 1995 and Sias, 2004). A negative relation between demand and subsequent returns will be consistent with a destabilizing effect on prices due to herding.

Moreover, the evidence of a destabilizing role of herding on future returns confirms the presence of intentional imitative behavior such as irrational or positive feedback strategies. A reversal in the prices after the herding measurement period will be consistent with this hypothesis. Alternatively, either an intentional correlation due to informational motivations or a fundamental-driven correlation will bring the prices closely and quickly towards the true value, bringing a stabilizing effect (Sias, 2004).

Therefore, we regress the institutional demand on the past quarter, the same period, and on the two consecutive quarter's returns after the measurement period (as reported in Table 16).

Consistent with the literature, we observe a positive relationship between institutional demand and past quarter and same quarter returns for the overall market and for non-splitting companies. We do not conclude for any similar relationship for the splitting companies.

Instead, interestingly, we observe a positive and highly significant relation between institutional demand and returns in the two following quarters for splitting firms (0.3704 and 0.3692 respectively). This is consistent with a stabilizing effect on prices for splitting companies due to herding. According to Sias (2004), such a positive relation is further evidence of the presence of informational-based herding.

5.4 Conclusions

With this empirical paper we aim to contribute to the understanding of stock splits and their market reaction, in the light of the impact of herding, or correlated trading decisions among institutional investors.

We have found evidence of positive and significant correlation in each quarter of analysis. Also, cleaning for intentional correlation, we have found that most of the correlation is not attributable to the four factors, namely size, market return and book-to-market, that proxy for unintentional or spurious herding.

Distinguishing between herding in splitting and non-splitting companies in the overall case, we do not evince a significant difference on average. However, the difference in correlation decreases over the three four-year subperiods, going from a positive but not significant average in the subperiod 1994 - 1998, to a negative (but still not significant) average in 2002-2005.

This time pattern motivates more detailed analyses, and we can see that the difference in herding is negative and becomes increasingly negative when we restrict the sample to high-traded stocks.

The presence of informational-based herding, especially for splitting companies, is also confirmed by observing the relation between institutional demand and future returns. Moreover, the positive relation we find between institutional demand for splitting firms and their future returns in the following two quarters, is consistent with the stabilizing effect of herding. On the contrary, we do not report any significant relationship between institutional demand and future returns in the non-splitting sample or in the overall market.

Our results are therefore consistent with the presence of informational content in the split event and to the underreaction of the market. We should also note however, that this underreaction is affected by trading on herd.

Still a significant part of the correlation among investors and of the difference between the subsamples is not explained by these four types, suggesting that further studies should be carried out to better understand other motivations, probably irrational, to the phenomenon. Moreover, further development of this research will focus on investigating both the change in herding and its impact on the future performance of the company on the days around the announcement of stock splits.

5.A Appendix B

Table 1.

Number of Observations per quarter and Splitting/Nonsplitting Subsamples.

Quarters	Number of companies per quarter: Splitting companies	Number of companies per quarter: Nonsplitting companies		
1994q1	39	931	*Noumber of Splits*	1,602
1994q2	22	950	*Number of Companies*	1,760
1994q3	20	950	*Number of Investors*	3,690
1994q4	23	960		
1995q1	18	973	*Number of Splits per quarter*	
1995q2	38	968	mean	39.05
1995q3	49	973	std. dev.	13.32
1995q4	43	1000	min	7
1996q1	41	1014		(in 2002-3)
1996q2	55	1022	max	65
1996q3	24	1063		(in 1998-2)
1996q4	39	1059	Q1	32
1997q1	42	1081	median	39
1997q2	23	1120	Q3	47
1997q3	64	1088		
1997q4	35	1146	*Number of Splits per company*	
1998q1	25	1159	mean	2.39
1998q2	65	1148	std. dev.	1.27
1998q3	29	1196	min	1
1998q4	19	1214	max	8
1999q1	58	1190	Q1	1
1999q2	44	1230	median	2
1999q3	34	1252	Q3	3
1999q4	32	1263		
2000q1	46	1258		
2000q2	42	1285		
2000q3	46	1283		
2000q4	15	1335		
2001q1	23	1328		
2001q2	29	1334		
2001q3	18	1350		
2001q4	22	1365		
2002q1	34	1364		
2002q2	51	1366		
2002q3	7*	1422		
2002q4	8*	1428		
2003q1	15	1423		
2003q2	16	1431		
2003q3	33	1419		
2003q4	34	1423		
2004q1	47	1416		
2004q2	34	1439		
2004q3	26	1455		
2004q4	32	1458		
2005q1	48	1444		
2005q2	40	1454		
2005q3	37	1464		
2005q4	18	1486		

This table reports the number of observations per quarter for the two subsamples; splitting and nonsplitting companies. We consider a splitting company to be any firm that has announced at least one stock split in the quarter of analysis, subject to the availability of all the necessary data and with at least 5 traders per quarter.
We also reports some descriptive statistics of the number of splits per quarter and per company.

** quarters for which it is not possible to estimate the restricted theoretical models.*

Table 2.

Quarterly Number of Companies Traded per Investor and Number of Investors per Company.

Average number of companies traded, C_{nt}

Year	Nonsplitting stocks	Splitting stocks
1994	80.40	127.37
1995	86.34	119.85
1996	87.95	130.52
1997	96.55	132.19
1998	97.77	143.41
1999	116.24	150.86
2000	117.99	168.19
2001	111.86	221.00
2002	119.13	255.66
2003	159.53	180.73
2004	163.50	150.06
2005	157.04	173.10
Overall period	126.96	159.49
Mean	126.96	159.49
Std. dev.	219.69	214.35
Min	1	1
Max	1,495	1,459
Q1	24	45
Median	55	80
Q3	116	169

Average number of active investors, Trd_{it}

Year	Nonsplitting stocks	Splitting stocks
1994	88.85	91.43
1995	95.05	119.32
1996	95.82	132.18
1997	107.58	129.99
1998	117.51	148.60
1999	129.02	198.36
2000	152.30	237.54
2001	160.39	235.74
2002	172.38	192.35
2003	184.77	169.82
2004	199.43	200.84
2005	205.73	214.12
Overall period	147.35	183.92
Mean	147.35	183.92
Std. dev.	154.51	173.11
Min	3	3
Max	1,327	1,229
Q1	53	76
Median	103	132
Q3	185	234

These tables report, for splitting and nonsplitting companies, the number of companies traded by institutional investor in a quarter, C_{nt} *(table 2.1), and the number of institutions trading in a company per quarter,* Trd_{it} *(table 2.2). Computed per quarter, they are averaged per year or overall period. We also report some descriptive statistics of the two variables for the overall period.*

Table 3.

Average Number of Investors per Institutional Type.

Nonsplitting stocks

Year	Banks	Insurance companies	Investment companies	Independent advisors	Not defined	All types
1994	221	78	68	815	78	1,260
1995	216	80	59	927	86	1,368
1996	201	76	97	979	79	1,432
1997	195	79	97	1,124	93	1,588
1998	204	82	95	1,227	128	1,736
1999	200	73	87	1,282	209	1,851
2000	193	67	88	1,310	350	2,008
2001	189	67	84	1,282	376	1,998
2002	173	61	78	1,209	570	2,091
2003	170	61	73	1,083	788	2,175
2004	163	58	71	1,080	984	2,356
2005	156	59	68	1,083	1,179	2,545
Overall	338	104	113	1,758	1,376	3,689

Splitting stocks

Year	Banks	Insurance companies	Investment companies	Independent advisors	Not defined	All types
1994	215	73	64	702	69	1,123
1995	214	71	56	803	71	1,215
1996	199	69	91	856	74	1,289
1997	194	73	92	983	76	1,418
1998	203	76	91	1,088	100	1,558
1999	198	66	82	1,140	168	1,654
2000	191	64	84	1,147	234	1,720
2001	180	60	79	1,077	276	1,672
2002	160	52	72	942	352	1,578
2003	166	52	64	938	560	1,780
2004	159	53	66	970	734	1,982
2005	152	47	64	955	865	2,083
Overall	332	99	111	1,646	1,064	3,252

Overall market

Year	Banks	Insurance companies	Investment companies	Independent advisors	Not defined	All types
Overall	338	104	113	1,759	1,376	3,690

This table reports the average number of investors in a quarter for the splitting/ nonsplitting samples, per year and per institutional type. The institutional type classification is adapted from the Thompson Financial database, correcting from issues arising at the end of 1998. In particular, we do not consider as valid any changes of classification from types 1 - 4 to type 5 that occurred at the end of 1998. In those cases, we keep as fixed until 2005 the category to which the institution was assigned before 1998. Any other changes are considered as valid.

Table 4

Stocks Characteristics.

Variables	Nonsplitting companies				Splitting companies			
	Mean	St. error of the mean	Median	Number of observations	Mean	St. error of the mean	Median	Number of observations
Size	5,866,644	86,358.30	1,044,035	60,291	9,363,908	788,877.00	1,587,120	1,642
Price	23.86	0.10	19.63	60,291	25.35	0.44	22.02	1,642
Shares outstanding	208,366	2,626.99	57,448	60,292	329,619	23,820.18	79,478	1,642
Volume	1,265,912	19,169.42	299,200	60,291	2,496,553	192,711.40	552,620	1,642
Turnover	7.30	0.05	4.30	60,291	9.93	0.37	5.62	1,642
Book-to-market	87.88	43.02	6.67	32,061	5.87	0.14	4.50	1,405
Dividends	0.11	0.00	0.03	60,292	0.05	0.00	0.01	1,642
Coverage	39.89	0.18	27.00	50,763	48.45	1.26	32.00	1,425
Dispersion among analysts	7,190	4,423.53	0.14	49,895	0.15	0.01	0.12	1,420
Institutional ownership	60.28%	0.00	61.77%	60,291	64.31%	0.01	65.03%	1,642
Quarterly returns	0.05	0.00	0.04	60,286	0.18	0.01	0.12	1,642
Standard deviation of returns	0.03	0.00	0.02	60,279	0.03	0.00	0.02	1,642

The table reports the main descriptives of the company variables we use in the following analysis. Size of company is measured as the market capitalization at the end of the previous quarter; price-per-share, shares outstanding, volume, turnover, and book-to-market are measured at the last day of the quarter. They are all extracted from the CRSP daily database. Coverage is the number of distinct analysts that have published forecasts of the annual company's earnings in the quarter; and dispersion is the ration of standard error to the absolute value of the mean of the analysts' earning forecasts, aggregated per quarter. They are extracted by the I/B/E/S database. Institutional ownership is the ration of institutional holdings on the shares outstanding, as reported by Thompson database. Returns are measured as compounded quarterly returns from the daily CRSP returns; standard deviation of returns is computed on the daily returns in the quarter.

Table 5.

Covariance Matrix of the Regressors.

	N_{it}	Trd_{it}	Price	Size	Turnover	Volume	Returns	Coverage	Dispersion	Book-to-market	Dividends
N_{it}	1										
Trd_{it}	0.9964	1									
Price	0.4998	0.489	1								
Size	0.7564	0.773	0.3157	1							
Turnover	-0.0618	-0.0464	-0.0117	-0.0642	1						
Volume	0.4377	0.4563	0.0149	0.4563	0.2494	1					
Returns	-0.038	-0.0326	0.0879	0.0011	0.0388	-0.0065	1				
Coverage	0.5221	0.5297	0.2126	0.3034	0.1576	0.3904	-0.0492	1			
Dispersion	-0.002	-0.0016	-0.0006	-0.0015	0.0107	0.0023	0.0272	0.0027	1		
Book-to-market	-0.0022	-0.0027	0.0088	-0.0024	-0.0034	-0.0031	-0.0074	-0.0072	-0.0001	1	
Dividends	0.1049	0.0957	0.1117	0.0508	-0.0494	-0.0071	-0.0077	-0.0002	-0.0018	0.0067	1

The table reports the covariance matrix of the regressors we use in the last part of the analysis. N_{it} is the number of institutions that hold the company i in their portfolio in quarter t, Trd_{it} is the number of active traders in stock i at quarter t, Size of company is measured as the market capitalization at the end of the previous quarter; price-per-share, volume, turnover, and book-to-market are measured at the last day of the quarter. They are all extracted from the CRSP daily database. Coverage is the number of distinct analysts that have published forecasts of the annual company's earnings in the quarter; and dispersion is the ration of standard error to the absolute value of the mean of the analysts' earning forecasts, aggregated per quarter. They are extracted by the I/B/E/S database. Returns are measured as compounded quarterly returns from the daily CRSP returns.

Figure 1.

Estimated coefficients of the lag institutional demand

Figure 1.1
Sias' Betas per Quarter

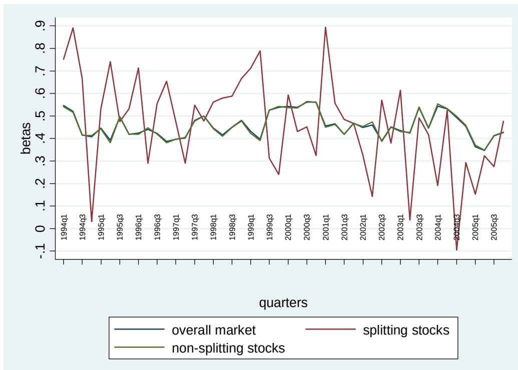


Figure 1.2
Non-Informational Betas per Quarter

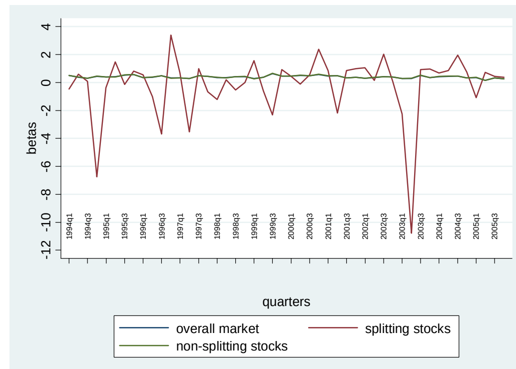


Figure 1.3
Non-Characteristic-based Betas per Quarter

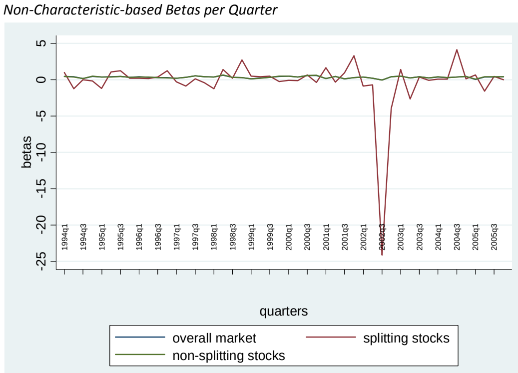
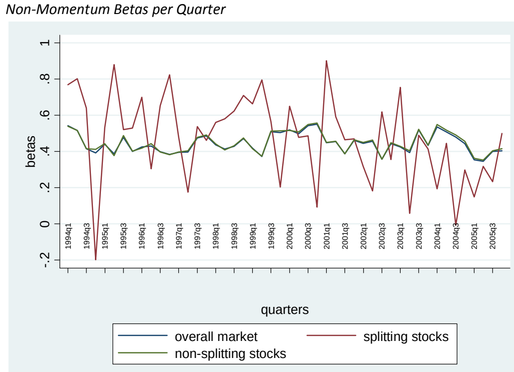


Figure 1.4
Non-Momentum Betas per Quarter



The graphs show the quarterly estimated coefficients of the institutional demand lag from the first quarter of 1994 to the last quarter of 2005, in the four restricted models. Figure 1.1 reports the Sias's beta, as the institutional lag coefficient in the Sias's model, equation 5.2.1. Figure 1.2 reports the coefficients of the lag institutional demand in the Informatinal-based model, equation 5.2.9. Figure 1.3 reports the estimated coefficients of the lag demand in the Characteristic based model, equation 5.2.16. Finally, Figure 1.4 reports the estimates in the Momentum Herding model, equation 5.2.18. We distinguish the three samples: overall market, splitting stocks and non-splitting stocks and the regressions are run separately in each subsample and in each quarter.

Table 6.

Sias' models

1) Overall market: *Dependent variable: $\Delta_{i,t}$*

	Mean			t	median	min	max	Q1	Q3	Significant	Significant	Beta Adjusted		
Variables	estimated		se							pos. qrts.	neg. qrts.	mean		se
$\Delta_{i,t-1}$	0.457	***	0.008	56.66	0.447	0.346	0.562	0.417	0.498	48	0	0.448	***	0.0079

2) Splitting companies: *Dependent variable: $\Delta^{S}_{i,t}$*

	Mean			t	median	min	max	Q1	Q3	Significant	Significant	Beta Adjusted		
Variables	estimated		se							pos. qrts.	neg. qrts.	mean		se
$\Delta_{i,t-1}$	0.467	***	0.031	14.87	0.481	-0.095	0.894	0.318	0.590	36	0	0.506	***	0.0302

3) Non-splitting companies: *Dependent variable: $\Delta^{NS}_{i,t}$*

	Mean			t	median	min	max	Q1	Q3	Significant	Significant	Beta Adjusted		
Variables	estimated		se							pos. qrts.	neg. qrts.	mean		se
$\Delta_{i,t-1}$	0.457	***	0.008	55.97	0.448	0.348	0.564	0.417	0.499	48	0	0.447	***	0.0080
Test: Beta S = Beta NS	t= 0.2920 (0.7714)											t= 1.8910 (0.0640)		

The table reports the summary statistics of the coefficients of the lag institutional demand (Sias' Betas) estimated in each quarter of analysis, from 1994 to 2005, for the models based on Sias (2004). Institutional demand $\Delta_{i,t}$ is the fraction of buyers of stock i at quarter t. It is firstly regressed on the lag institutional demand $\Delta_{i,t-1}$ for the overall market (Model 1). Model 2 regresses the institutional demand computed on the sample of splitting companies on the lag demand for all stocks. Analogously, Model 3 regresses the same model on the sample of nonsplitting companies. The t- values reported are computed from the standard error of the estimates series. The numbers of significant quarters are identified with a 10% of significance level. The last column considers the Beta adjusted, as the lag coefficients, once controlling for the four factors à la Cahart (1997). We finanly report the statistic and the p-value of the test on difference between splitting and nonsplitting samples.

* 10%, ** 5%, *** 1% of significance level.

Table 7.

Average Sias' Beta Coefficients per Number of Traders.

NO. TRADERS		General- herding						Peer- herding					
		Beta			Splitting dummy			Beta			Splitting dummy		
		Mean		t	Mean		t	Mean		t	Mean		t
all periods	>= 10 traders	0.510	***	55.04	-0.041		-1.27	0.489	***	56.01	-0.029		-0.95
	>= 20	0.564	***	47.22	-0.091	***	-2.86	0.508	***	53.55	-0.060	***	-2.14
	>= 50	0.600	***	42.42	-0.102	***	-3.08	0.510	***	49.55	-0.100	***	-2.99
	>= 100	0.554	***	32.49	-0.073		-1.61	0.518	***	55.45	-0.155	***	-5.07
1994-1997	>= 10 traders	0.521	***	37.59	0.005		0.12	0.493	***	41.34	0.006		0.16
	>= 20	0.624	***	47.60	-0.093	*	-1.91	0.539	***	46.54	-0.070	**	-1.94
	>= 50	0.653	***	37.01	-0.137	***	-2.46	0.549	***	43.78	-0.157	***	-2.87
	>= 100	0.492	***	14.72	0.014		0.13	0.538	***	45.46	-0.118	***	-2.12
1998-2001	>= 10 traders	0.539	***	35.13	-0.011		-0.28	0.517	***	33.66	0.008		0.21
	>= 20	0.588	***	40.07	-0.058		-1.50	0.528	***	33.32	0.001		0.03
	>= 50	0.654	***	39.95	-0.034		-0.80	0.536	***	34.71	0.000		0.00
	>= 100	0.634	***	23.44	-0.042		-0.71	0.547	***	33.92	-0.086	*	-1.82
2002-2005	>= 10 traders	0.470	***	32.40	-0.118		-1.53	0.456	***	31.36	-0.102		-1.38
	>= 20	0.481	***	33.23	-0.121	*	-1.64	0.457	***	32.42	-0.110	*	-1.63
	>= 50	0.495	***	35.81	-0.134	*	-1.91	0.445	***	34.43	-0.141	***	-2.18
	>= 100	0.536	***	40.60	-0.191	***	-3.14	0.468	***	35.64	-0.260	***	-5.46

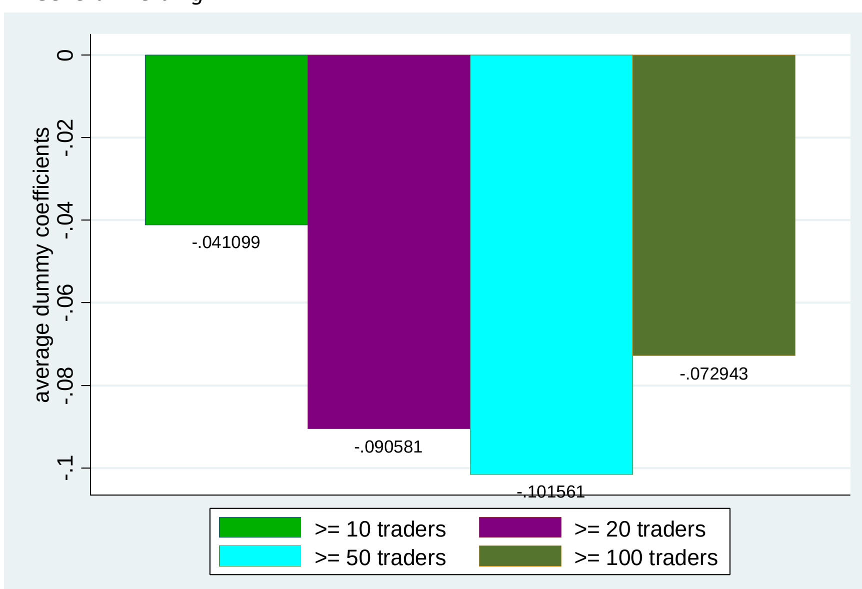
The table reports the summary statistics of the quarterly coefficients of the lag institutional demand $\Delta_{i,t-1}$ (Sias's Betas) and the splitting dummy coefficients estimated in subgroups based on the number of traders per company in the quarter. Institutional demand $\Delta_{i,t}$ (as fraction of buyer of stock i at quarter t) is regressed on the lag institutional demand $\Delta_{i,t-1}$ and a dummy for splitting companies interacted with the lag demand itself. The t- values reported are computed from the standard error of the estimates series.

* 10%, ** 5%, *** 1% of significance level.

Figures 2.1 & 2.2
Splitting Dummies per Number of Traders.

Figure 2.1 Peer- herding

Figure 2.2. General- herding



The following graphs represent the average estimated coefficient of the dummy for split. Peer herding is the correlation of the institutional demand for splitting (nonsplitting) stocks with the previous quarter demand for the same portfolio. General herding is the correlation between the institutional demand for splitting(nonsplitting) and the previous quarter demand for all stocks.

Table 8.

Average Estimated Coefficients for all Models.

1) Overall market — Dependent variable: $\Delta_{i,t}$

Variables	*Sias' model*			*Informational- based*			*Characteristic- based*			*Momentum*			*Unifying model*		
	mean		t	mean		t	mean		t	mean		t	mean		t
$\Delta_{i,t-1}$	0.4737	***	57.01	0.4138	***	29.60	0.3702	***	18.84	0.4654	***	57.57	0.3740	***	15.95
Dispersion*$_{t-1}$				-0.0132		-1.37							-0.0079		-0.96
Coverage*$_{t-1}$				0.1071	***	10.80							0.1014	***	11.05
Size*Coverage*$_{t-1}$				-0.0769	***	-6.42							-0.0706	***	-6.23
Size*$_{i,t-1}$				0.1456	***	12.16	0.0958	***	16.02				0.1372	***	11.44
Price*$_{i,t-1}$							0.0701	***	7.96				0.0520	***	6.65
Turnover*$_{i,t-1}$							0.0368	***	3.90				0.0039		0.48
StDeviation of returns*$_{i,t-1}$							-0.0181		-1.04				-0.0303		-1.48
Returns*$_{i,t-4}$							0.0028		0.48				0.0052		1.01
Dividends*$_{i,t-1}$							0.0116	**	2.14				0.0210	***	3.69
Returns*$_{i,t-1}$										0.0510	***	6.70	0.0498	***	6.45

2) Splitting companies — Dependent variable: $\Delta^{S}_{i,t}$

Variables	*Sias' model*			*Informational- based*			*Characteristic- based*			*Momentum*			*Unifying model*		
	mean		t	mean		t	mean		t	mean		t	mean		t
$\Delta_{i,t-1}$	0.4170	***	14.63	-0.2413		-0.79	0.2405		1.63	0.4278	***	13.02	0.2155		0.23
Dispersion*$_{t-1}$				0.4378	**	2.01							-2.1512		-0.96
Coverage*$_{t-1}$				0.1728		1.30							0.3278		0.81
Size*Coverage*$_{t-1}$				0.4031		0.97							-2.8701		-1.21
Size*$_{i,t-1}$				-0.1744		-0.43	0.2979	***	4.82				3.4335		1.23
Price*$_{i,t-1}$							-0.1120		-1.16				-2.0436		-1.13
Turnover*$_{i,t-1}$							-0.0514		-0.60				-0.5519		-1.27
StDeviation of returns*$_{i,t-1}$							0.1340		1.25				3.3859		1.04
Returns*$_{i,t-4}$							0.0172		0.46				-0.0276		-0.42
Dividends*$_{i,t-1}$							-0.0218		-0.35				-0.0623		-0.28
Returns*$_{i,t-1}$										-0.0283		-1.19	-0.0867		-1.12

3) Nonsplitting companies — Dependent variable: $\Delta^{NS}_{i,t}$

Variables	*Sias' model*			*Informational- based*			*Characteristic- based*			*Momentum*			*Unifying model*		
	mean		t	mean		t	mean		t	mean		t	mean		t
$\Delta_{i,t-1}$	0.4749	***	56.68	0.4155	***	29.15	0.3721	***	18.70	0.4660	***	56.34	0.3759	***	16.04
Dispersion*$_{t-1}$				-0.0139		-1.40							0.1378		-1.02
Coverage*$_{t-1}$				0.1071	***	10.93							-0.0086	***	11.13
Size*Coverage*$_{t-1}$				-0.0801	***	-6.25							0.1010	***	-6.18
Size*$_{i,t-1}$				0.1467	***	11.65	0.0935	***	15.23				-0.0732	***	11.17
Price*$_{i,t-1}$							0.0708	***	7.92				0.0526	***	6.81
Turnover*$_{i,t-1}$							0.0392	***	3.99				0.0082		0.94
StDeviation of returns*$_{i,t-1}$							-0.0211		-1.19				-0.0336	*	-1.64
Returns*$_{i,t-4}$							0.0035		0.60				0.0056		1.09
Dividends*$_{i,t-1}$							0.0115	**	2.09				0.0214	***	3.87
Returns*$_{i,t-1}$										0.0530	***	6.74	0.0522	***	6.44

*The table reports the average standardized coefficients of all the variables used in the five models. (1) Sias' model regresses the institutional demand $\Delta_{i,t}$ on its lag $\Delta_{i,t-1}$ only. (2) Informational- based models regress the institutional demand on its lag and a set of proxies for the quality of information, such as size, dispersion, coverage and size*coverage at the previous quarter. (3) The Characteristic- based model regresses the institutional demand on its lag and a set of company characteristics, such as size, price, turnover, standard deviation, returns of stocks and quarterly dividends, measured at the previous quarter. (4) The Momentum model regresses the institutional demand on its lag and the previous year returns. (5) The Unifying model regresses the institutional demand on all the previous variables. The significance is attributed estimating the t statistics from the time series of the beta estimates.*

** 10%, ** 5%, *** 1% of significance level.*

Table 9.

Informational-based Models

1) Overall market: *Dependent variable: $\Delta_{i,t}$*

Variables	Mean estimated		se	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	0.400	***	0.014	29.40	0.397	0.145	0.641	0.334	0.466	48	0	0.379	***	0.013
F test: informational herding				p value:	0.0002	0.0000	0.4972	0.0000	0.0058	43	-			

2) Splitting companies: *Dependent variable: $\Delta^{S}_{i,t}$*

Variables	Mean estimated		se	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	-0.195		0.332	-0.59	0.437	-10.786	3.398	-0.561	0.892	10	8	-0.473		0.324
F test: informational herding				p value:	0.0750	0.0000	0.9963	0.0033	0.4242	24	-			

3) Non-splitting companies: *Dependent variable: $\Delta^{NS}_{i,t}$*

Variables	Mean estimated		se	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	0.404	***	0.014	28.85	0.401	0.143	0.648	0.330	0.470	48	0	0.382	***	0.013
F test: informational herding				p value:	0.0002	0.0000	0.4830	0.0000	0.0142	41	-			
Test: Beta S = Beta NS		t=	-1.81	(0.0773)								t= -2.63	(0.0114)	

*The table reports the summary statistics of the coefficients of the lag institutional demand $\Delta_{i,t-1}$ estimated in each quarter of analysis, from 1994 to 2005, for four Informational-based Models. Model (1) regresses the institutional demand $\Delta_{i,t}$ (as fraction of buyer of stock i at quarter t) on the lag institutional demand for the overall market and the interacted variables that account for the lags of size, dispersion among analysts, coverage and size*coverage. Model (2) is regressed only on splitting companies, while Model (3) is regressed on non-splitting companies. The t-values reported are computed from the standard error of the estimates series. The numbers of significant quarters are identified with a 10% of significance level. For the F tests of the theoretical types of herding we report statistics on the quarterly p-values.*

** 10%, ** 5%, *** 1% of significance level.*

Table 10.

Characteristic-based Models

1) Overall market: *Dependent variable: $\Delta_{i,t}$*

Variables	*Mean estimated*		*se*	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	0.363	***	0.019	18.74	0.379	-0.011	0.653	0.291	0.447	44	0	0.340	***	0.017
F test: Characteristic herding				p value:	0.0000	0.0000	0.1054	0.0000	0.0006	47	-			

2) Splitting companies: *Dependent variable: $\Delta^{S}_{i,t}$*

Variables	*Mean estimated*		*se*	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	-0.303		0.541	-0.56	0.127	-24.108	4.168	-0.326	0.664	9	1	-0.295		0.499
F test: Characteristic herding				p value:	0.0067	0.0000	0.7919	0.0001	0.2490	31	-			

3) Non-splitting companies: *Dependent variable: $\Delta^{NS}_{i,t}$*

Variables	*Mean estimated*		*se*	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	0.368	***	0.020	18.60	0.386	-0.023	0.660	0.285	0.453	43	0	0.341	***	0.017
F test: Characteristic herding				p value:	0.0000	0.0000	0.0924	0.0000	0.0008	48	-			
Test: Beta S = Beta NS		t=	-1.24	(0.2210)								t= -1.27		(0.2087)

The table reports the summary statistics of the coefficients of the lag institutional demand $\Delta_{i,t-1}$ estimated in each quarter of analysis, from 1994 to 2005, for four Characteristics Herding Models. Model (1) regresses the Institutional demand $\Delta_{i,t}$ (as fraction of buyer of stock i at quarter t) on the lag institutional demand for the overall market and the interacted variables that account for the lags of size, price, turnover, standard deviation of returns, quarterly returns and annual dividend per quarter. Model (2) is regressed only on splitting companies, while Model (3) is regressed on nonsplitting companies. The t- values reported are computed from the standard error of the estimates series. The numbers of significant quarters are identified as having a 10% of significance level. For the F tests of the theoretical types of herding, we report statistics on the quarterly p-values.

** 10%, ** 5%, *** 1% of significance level.*

Table 11.

Momentum Models

1) Overall market: *Dependent variable: $\Delta_{i,t}$*

Variables	*Mean estimated*		*se*	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	0.445	***	0.008	56.65	0.438	0.346	0.552	0.400	0.483	48	0	0.437	***	0.008
F test: Momentum herding				p value:	0.0214	0.0000	0.9951	0.0013	0.2857	28	-			

2) Splitting companies: *Dependent variable: $\Delta^{S}_{i,t}$*

Variables	*Mean estimated*		*se*	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	0.475	***	0.035	13.49	0.495	-0.197	0.901	0.311	0.645	34	0	0.535	***	0.033
F test: Momentum herding				p value:	0.4085	0.0001	0.9599	0.2300	0.6525	9	-			

3) Non-splitting companies: *Dependent variable: $\Delta^{NS}_{i,t}$*

Variables	*Mean estimated*		*se*	*t*	*median*	*min*	*max*	*Q1*	*Q3*	*Significant pos. qrts.*	*Significant neg. qrts.*	*Beta Adjusted mean*		*Beta Adjusted se*
$\Delta_{i,t-1}$	0.449	***	0.008	56.05	0.443	0.353	0.557	0.404	0.491	48	0	0.440	***	0.008
F test: Momentum herding				p value:	0.0222	0.0000	0.9944	0.0005	0.3502	29	-			
Test: Beta S = Beta NS		t=	0.72	(0.4737)								t= 2.81		(0.0070)

The table reports the summary statistics of the coefficients of the lag institutional demand $\Delta_{i,t-1}$ estimated in each quarter of analysis, from 1994 to 2005, for four Momentum Models. Model (1) regresses the Institutional demand $\Delta_{i,t}$ (as fraction of buyer of stock i at quarter t) on the lag institutional demand for the overall market and the interacted variables that account for the lags of quarterly returns. Model (2) is regressed only on splitting companies, while Model (3) is regressed on nonsplitting companies. The t- values reported are computed from the standard error of the estimates series. The numbers of significant quarters are identified as having a 10% of significance level. For the F tests of the theoretical types of herding, we report statistics on the quarterly p-values.

** 10%, ** 5%, *** 1% of significance level.*

Table 12.

Unifying Model

1) Overall market with splitting dummy *Dependent variable: $\Delta_{i,t}$*

Variables		Mean estimated		se	t	median	min	max	Q1	Q3	Significant pos. qrts.	Significant neg. qrts.
$\Delta_{i,t-1}$	all quart.	0.363	***	0.023	15.91	0.399	-0.004	0.705	0.243	0.454	41	0
	1994-1997	0.375	***	0.041	9.05	0.406	0.025	0.705	0.275	0.464	13	0
	1998-2001	0.427	***	0.036	11.92	0.431	0.176	0.657	0.360	0.531	14	0
	2002-2005	0.286	***	0.035	8.23	0.303	-0.004	0.463	0.190	0.417	14	0
$\delta_{i,t}\Delta_{i,t-1}$	all quart.	0.008		0.036	0.24	-0.024	-0.569	0.708	-0.151	0.107	4	5
	1994-1997	0.061		0.071	0.86	-0.037	-0.211	0.708	-0.136	0.204	1	0
	1998-2001	0.033		0.037	0.89	0.070	-0.257	0.299	-0.071	0.102	1	1
	2002-2005	-0.069		0.070	-0.97	-0.106	-0.569	0.485	-0.255	0.067	2	4

F test: Informational herding	p value:	0.0017
F test: Characteristic herding	p value:	0.0026
F test: Momentum herding	p value:	0.0331
F test: Splitting Informational herding	p value:	0.1331
F test: Splitting Characteristic herding	p value:	0.0094
F test: Splitting Momentum herding	p value:	0.3925
F test: Splitting All motivations	p value:	0.0006

*The table reports the summary statistics of the coefficients of the lag institutional demand $\Delta_{i,t-1}$ estimated in each quarter of analysis, from 1994 to 2005, for the Unifying Model. It regresses the Institutional demand $\Delta_{i,t}$ (as fraction of buyer of stock i at quarter t) on the lag institutional demand for the overall market and the interacted variables that account for the lags of size, dispersion among analysts, coverage, size*coverage, price, turnover, standard deviation of returns, quarterly returns, annual dividend per quarter and past returns, and a set of splitting dummies interacted with all the previous regressors. The t- values reported are computed from the standard error of the estimates series. The numbers of significant quarters are identified as having a 10% of significance level. For the F tests of the theoretical types of herding, we report statistics on the quarterly p values.*

** 10%, ** 5%, *** 1% of significance level.*

Table 13.

Average Estimated Coefficients for all Models (dummy specifications)

Dependent variable: $\Delta_{i,t}$

Overall market with splitting dummies

Variables	*Sias' model*			*Informational- based*			*Characteristic- based*			*Momentum*			*Unifying model*		
	mean		t	mean		t	mean		t	mean		t	mean		t
$\Delta_{i,t-1}$	0.4743	***	56.79	0.4116	***	28.68	0.3671	***	18.52	0.4655	***	56.47	0.3709	***	15.66
Dispersion*$_{t-1}$				-0.0134		-1.38							-0.0092		-1.07
Coverage*$_{t-1}$				0.1095	***	11.05							0.1035	***	11.31
Size*Coverage*$_{t-1}$				-0.0814	***	-6.05							-0.0768	***	-6.49
Size*$_{i,t-1}$				0.1549	***	11.67	0.1027	***	17.80				0.1476	***	12.09
Price*$_{i,t-1}$							0.0726	***	8.02				0.0550	***	6.99
Turnover*$_{i,t-1}$							0.0406	***	4.26				0.0096		1.14
StDeviation of returns*$_{i,t-1}$							-0.0174		-0.98				-0.0305		-1.51
Returns*$_{i,t-4}$							0.0030		0.51				0.0075		1.51
Dividends*$_{i,t-1}$							0.0109	**	1.98				0.0196	***	3.45
Returns*$_{i,t-1}$										0.0534	***	6.72	0.0514	***	6.22
$\delta_{i,t}\Delta_{i,t-1}$	-0.0009		-0.19	-0.0034		-0.65	-0.0050		-1.03	0.0000		0.00	-0.0014		-0.26
$\delta_{i,t}$*Dispersion*$_{t-1}$				0.0262	***	2.52							-0.0378		-0.73
$\delta_{i,t}$*Coverage*$_{t-1}$				-0.0090		-0.96							-0.0324		-1.26
$\delta_{i,t}$*Size*Coverage*$_{t-1}$				0.0798		1.30							-0.0989		-0.65
$\delta_{i,t}$*Size*$_{i,t-1}$				-0.0630		-1.04	0.0157	***	2.74				0.1257		0.89
$\delta_{i,t}$*Price*$_{i,t-1}$							0.0031		0.31				0.0406		1.12
$\delta_{i,t}$*Turnover*$_{i,t-1}$							0.0013		0.19				0.0242		1.18
$\delta_{i,t}$*StDeviation of returns*$_{i,t-1}$							0.0139	*	1.93				0.0065		0.40
$\delta_{i,t}$*Returns*$_{i,t-4}$							0.0041		1.30				0.0055		1.26
$\delta_{i,t}$*Dividends*$_{i,t-1}$							-0.0109	*	-1.83				-0.0200	***	-2.61
$\delta_{i,t}$*Returns*$_{i,t-1}$										-0.0124	***	-2.72	-0.0151	***	-2.45

*The table reports the standardized coefficients of all the variables used in the five models. (1) Sias' model regresses the institutional demand $\Delta_{i,t}$ on its lag $\Delta_{i,t-1}$ only. (2) Informational- based models regress the institutional demand on the lag demand and a set of proxies for the quality of information, such as size, dispersion, coverage and size*coverage at the previous quarter. (3) The Characteristic- based model regresses the institutional demand on its lag and a set of company characteristics, such as size, price, turnover, standard deviation, returns of stocks and quarterly dividends, measured at the previous quarter. (4) The Momentum model regresses the institutional demand on its lag and the previous year returns. (5) The Unifying model regresses the institutional demand on all the previous variables. The significance is attributed estimating the t statistics from the time series of the beta estimates.*

** 10%, ** 5%, *** 1% of significance level.*

Table 14.

Average Estimated Betas for All Models per Subperiod (dummy specifications)

Dependent variable: $\Delta_{i,t}$

Overall market with splitting dummies

Variables		*Sias' model*			*Informational- based*			*Characteristic- based*			*Momentum*			*Unifying model*		
		mean		t	mean		t	mean		t	mean		t	mean		t
$\Delta_{i,t-1}$	all quart.	0.453	***	55.36	0.398	***	28.33	0.360	***	18.42	0.445	***	55.38	0.363	***	15.91
	1994-1997	0.438	***	34.83	0.401	***	18.63	0.369	***	14.73	0.434	***	34.10	0.375	***	9.05
	1998-2001	0.474	***	33.13	0.435	***	17.61	0.371	***	8.64	0.462	***	33.24	0.427	***	11.92
	2002-2005	0.447	***	30.15	0.357	***	14.85	0.342	***	10.34	0.438	***	29.53	0.286	***	8.23
$\delta_{i,t}\Delta_{i,t-1}$	all quart.	0.001		0.04	-0.005		-0.15	-0.021		-0.64	0.006		0.17	0.008		0.24
	1994-1997	0.048		1.09	0.037		0.67	0.035		0.59	0.047		0.81	0.061		0.86
	1998-2001	0.047		1.34	0.013		0.30	0.042		1.08	0.055		1.58	0.033		0.89
	2002-2005	-0.092		-1.23	-0.066		-0.87	-0.139	***	-2.32	-0.084		-1.18	-0.069		-0.97

*The table reports the standardized coefficients of the lag institutional demand and the dummy interacted with such lag, in the five models. (1) Sias' model regresses the institutional demand on its lag. (2) Informational- based models regress the institutional demand on the lag demand and a set of proxies for the quality of information, such as size, dispersion, coverage and size*coverage at the previous quarter. (3) The Characteristic- based model regresses the institutional demand on its lag and a set of company characteristics, such as size, price, turnover, standard deviation, returns of stocks and quarterly dividends, measured at the previous quarter. (4) The Momentum model regresses the institutional demand on its lag and the previous year returns. (5) The Unifying model regresses the institutional demand on all the previous variables. The significance is attributed estimating the t statistics from the time series of the beta estimates.*

** 10%, ** 5%, *** 1% of significance level.*

Table 15.

Average Beta Coefficients per Institutional Type and Size of Institutional Portfolio.

INVESTOR TYPE		General- herding						Peer- herding					
		Beta			Splitting dummy			Beta			Splitting dummy		
		Mean		t	Mean		t	Mean		t	Mean		t
all period	banks	0.401	***	32.99	-0.085	***	-2.44	0.334	***	29.99	-0.090	***	-2.71
	Insurance co.	0.241	***	15.86	0.051		1.55	0.172	***	12.02	-0.038		-1.22
	Investment co.	0.209	***	12.83	0.043		1.25	0.194	***	13.32	0.031		0.80
	indip. advisors	0.312	***	24.60	0.011		0.36	0.272	***	16.73	0.022		0.80
	not defined	0.409	***	30.46	-0.055	*	-1.66	0.330	***	20.90	-0.029		-0.85
1994-1997	banks	0.426	***	22.82	-0.073		-1.32	0.342	***	16.39	-0.074		-1.35
	Insurance co.	0.226	***	17.89	0.107	*	1.83	0.163	***	9.93	-0.043		-0.74
	Investment co.	0.195	***	10.07	0.047		0.82	0.203	***	13.43	-0.017		-0.25
	indip. advisors	0.358	***	37.62	0.011		0.22	0.339	***	30.74	0.019		0.43
	not defined	0.455	***	21.69	-0.128	***	-2.33	0.379	***	15.77	-0.058		-0.93
1998-2001	banks	0.435	***	21.86	-0.018		-0.49	0.376	***	30.51	-0.032		-0.59
	Insurance co.	0.314	***	10.16	0.047		1.05	0.215	***	6.32	0.043		0.99
	Investment co.	0.279	***	10.58	0.117	***	4.57	0.265	***	13.50	0.038		0.68
	indip. advisors	0.353	***	26.87	0.008		0.13	0.311	***	25.67	0.011		0.22
	not defined	0.393	***	17.51	0.119	***	2.24	0.280	***	11.38	0.124	***	2.35
2002-2005	banks	0.341	***	20.17	-0.163	***	-2.08	0.286	***	16.37	-0.163	***	-2.65
	Insurance co.	0.181	***	8.66	-0.002		-0.03	0.140	***	7.93	-0.114	***	-2.12
	Investment co.	0.154	***	5.15	-0.036		-0.45	0.114	***	4.61	0.072		0.91
	indip. advisors	0.224	***	10.31	0.016		0.27	0.165	***	5.10	0.036		0.69
	not defined	0.379	***	16.43	-0.157	***	-4.00	0.331	***	11.44	-0.155	***	-3.50

INVESTOR SIZE		Beta			Splitting dummy			Beta			Splitting dummy		
		Mean		*t*	*Mean*		*t*	*Mean*		*t*	*Mean*		*t*
all period	small investors	0.304	***	42.12	-0.122	***	-3.22	0.311	***	38.19	-0.099	***	-2.74
	medium	0.388	***	39.40	-0.009		-0.34	0.338	***	32.33	0.010		0.37
	big	0.391	***	37.73	0.062	*	1.89	0.375	***	34.98	0.051		1.46
1994-1997	small investors	0.312	***	28.22	-0.007		-0.11	0.285	***	27.30	-0.018		-0.31
	medium	0.406	***	33.04	-0.054		-1.16	0.353	***	28.45	-0.073	***	-2.52
	big	0.396	***	26.28	0.103	*	2.00	0.375	***	23.26	0.119	***	2.25
1998-2001	small investors	0.297	***	19.12	-0.118	***	-2.61	0.298	***	24.17	-0.059		-1.48
	medium	0.397	***	19.36	0.073		1.60	0.352	***	15.93	0.090	***	2.26
	big	0.428	***	29.08	0.096	***	2.61	0.415	***	27.43	0.068	***	2.35
2002-2005	small investors	0.301	***	27.97	-0.241	***	-3.22	0.349	***	24.20	-0.221	***	-2.85
	medium	0.362	***	22.10	-0.048		-0.96	0.310	***	17.70	0.014		0.24
	big	0.350	***	18.42	-0.013		-0.17	0.335	***	17.18	-0.033		-0.39

The table reports the summary statistics of the quarterly coefficients of the lag institutional demand (Sias's Betas) estimated in subgroups based on investor type and size of the investor portfolio per company in the quarter. Institutional demand (as fraction of buyer of stock i at quarter t) is regressed for each group on the lag institutional demand and a dummy for splitting companies interacted with the lag demand itself. The t- values reported are computed from the standard error of the estimates series.

** 10%, ** 5%, *** 1% of significance level.*

Figure 3.

Splitting Dummy Coefficients per Investor Type and Portfolio Size.

Figure 3.1 Peer herding: by size of investor portfolio

Figure 3.2 Peer herding: by type of investors

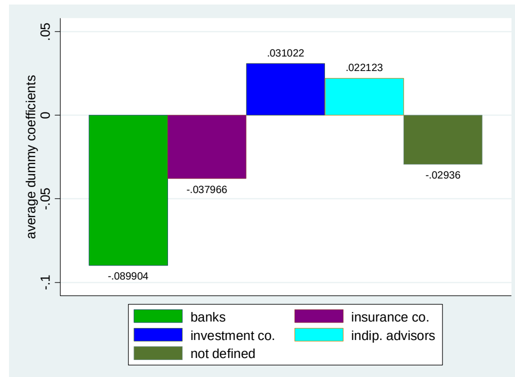


Figure 3.3 General herding: by size of investor portfolio

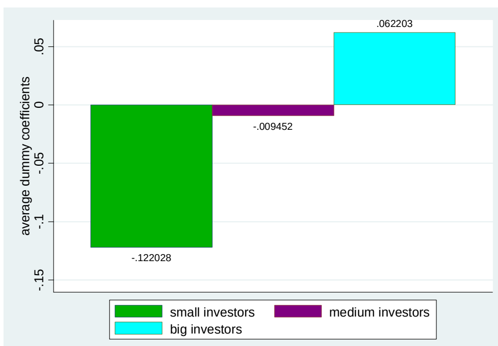
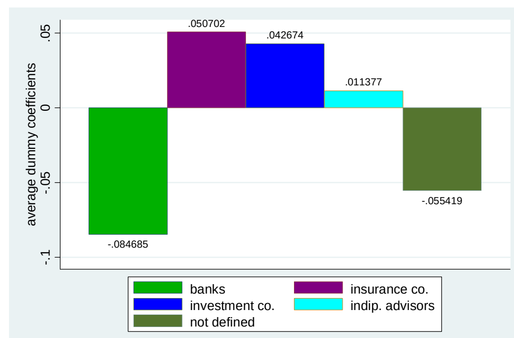


Figure 3.4 General herding: by type of investors



The following graphs represent the average dummy coefficient per splitting stocks herding compared to nonsplitting firms by size and type of investors. Peer herding is the correlation of institutional demand per splitting /nonsplitting stocks with the previous quarter demand for the same portfolio. General herding is the correlation between the institutional demand for splitting / nonsplitting and the previous quarter demand for all stocks.

Table 16.

Stabilizying Effect Models

1) Overall market: *Dependent variable: $\Delta_{i,t}$*

Variables	Mean estimated		se	t	min	max	Significant pos. qrts.	Significant neg. qrts.
$\Delta_{i,t-1}$	0.4468	***	0.0079	56.58	0.3671	0.5551	44	0
Ret_{t-1}	0.2271	***	0.0382	5.95	-0.3108	0.7938	24	1
Ret_{t}	0.3402	***	0.0357	9.54	-0.1692	0.8111	30	0
Ret_{t+1}	0.0028		0.0338	0.08	-0.5477	0.5919	9	6
Ret_{t+2}	0.0146		0.0303	0.48	-0.4089	0.4309	7	4
Ret_{t+4}	-0.0237		0.0277	-0.86	-0.4560	0.3506	3	5

2) With splitting dummy: *Dependent variable: $\Delta_{i,t}$*

Variables	Mean estimated		se	t	min	max	Significant pos. qrts.	Significant neg. qrts.
$\Delta_{i,t-1}$	0.4477	***	0.0081	55.23	0.3664	0.5552	44	0
Ret_{t-1}	0.2292	***	0.0383	5.98	-0.3110	0.7936	24	1
Ret_{t}	0.3418	***	0.0358	9.54	-0.1520	0.8263	31	0
Ret_{t+1}	0.0034		0.0338	0.10	-0.5477	0.5925	9	6
Ret_{t+2}	0.0128		0.0303	0.42	-0.4056	0.4318	7	4
Ret_{t+4}	-0.0249		0.0280	-0.89	-0.4952	0.3502	3	5
$\delta_{i,t}\Delta_{i,t-1}$	-0.0160		0.0308	-0.52	-0.5032	0.4991	4	7

3) Splitting companies: *Dependent variable: $\Delta^{S}_{i,t}$*

Variables	Mean estimated		se	t	min	max	Significant pos. qrts.	Significant neg. qrts.
$\Delta_{i,t-1}$	0.4057	***	0.0470	8.63	-0.3454	1.4248	26	0
Ret_{t-1}	0.0819		0.2240	0.37	-5.0132	3.2220	9	3
Ret_{t}	0.0035		0.2140	0.02	-5.2177	2.8125	8	1
Ret_{t+1}	0.3704	***	0.1760	2.11	-1.8904	3.7678	8	2
Ret_{t+2}	0.3692	***	0.1794	2.06	-3.5798	3.3968	7	1
Ret_{t+4}	0.1201		0.1904	0.63	-4.1861	3.9397	4	5

4) Non-splitting companies: *Dependent variable: $\Delta^{NS}_{i,t}$*

Variables	Mean estimated		se	t	min	max	Significant pos. qrts.	Significant neg. qrts.
$\Delta_{i,t-1}$	0.4484	***	0.0081	55.18	0.3633	0.5552	44	0
Ret_{t-1}	0.2212	***	0.0395	5.61	-0.3450	0.8020	23	1
Ret_{t}	0.3420	***	0.0369	9.27	-0.2119	0.8572	31	0
Ret_{t+1}	-0.0015		0.0342	-0.04	-0.5669	0.6303	10	6
Ret_{t+2}	0.0100		0.0301	0.33	-0.3770	0.4235	5	4
Ret_{t+4}	-0.0337		0.0289	-1.17	-0.4689	0.3463	3	5

The table reports the summary statistics of the coefficients of the lag institutional demand estimated in each quarter of analysis, from 1994 to 2005, for four Stabilizing Models. Model (1) regresses the institutional demand (as fraction of buyer of stock i at quarter t) on the lag institutional demand for the overall market and past quarter, same quarter, following two quarters and following year returns. Model (2) regresses the institutional demand on its lag, the previous set of investors and a set of splitting dummies interacted with all the regressors. Models (3) and Model (4) regress the same as Model (1) in only the splitting sample and nonsplitting sample respectively. The t- values reported are computed from the standard error of the estimates series. The numbers of significant quarters are identified with a 10% of significance level.

** 10%, ** 5%, *** 1% of significance level.*

Chapter 6

Conclusions

The present thesis consists of the analysis of stock splits and their impact on the market. We analyze this peculiar event, connecting it to changes in expectations of the market and to the level of herding among institutional investors.

In Chapter 2, we review the main theories on stock splits. Among them, we particularly focus on the empirical research on the Self-Selection hypothesis from Ikenberry and Ramnath (2002). According to the Self-Selection hypothesis, managers split their shares because they have a preferred trading range price they wish to realign their share price to, as it is costly for the company, the management and investors to lie in a lower range. Therefore, managers will split their shares if they are optimistic regarding the future growth performance of the company, so as to reduce the risk of the price going below the lower limit of the trading range. A positive market reaction to the announcement of a stock split is consistent with this theory, as the event conveys positive information. However, the split also conveys the optimism of the managers, which the market cannot perfectly evaluate. Hence, we observe a timid reaction, extended in the long run with increasing prices.

According to this theory and connecting it with the differences of opinion literature, in Chapter 3 we investigate the relation between the announcement of a split, changes in market expectations and the market reaction. In a sample of US stock splits from 1993 to 2005, we find evidence of signalling content in the announcement of the event. In fact, we observe positive changes in average forecasts estimates, coverage and decreases in the estimates error. However, we also observe a tiny increase in dispersion, which is consistent with a higher level of uncertainty in the market. An event study on the market reaction after the event suggests that the market reacts to positive informational content hidden in the split announcement, in the days immediately following the event, and also in a window of 90 days afterwards. A final verification shows that there is a positive relation between CARs and dispersion of beliefs, validating the hypothesis that dispersion of beliefs can be considered as a proxy for the quality of information that reaches the market.

The presence of informational content together with an increase in dispersion motivates the hypothesis of a relationship between stock splits and informational-based herding. According to the Self-Selection hypothesis, the event, in fact, conveys positive information together with the optimism of managers. This is an ideal condition for informational-based herding to arise (Bikhchandani, Hirshleifer and Welch, 1992, Avery and Zemsky, 1998), as the event conveys positive information about a change in value of the company but also uncertainty as to whether the change has really occurred or is merely caused by the overconfidence of the management. Chapter 4, therefore, proposes a review of the literature on herding, with particular focus on the empirical methodologies to detect and measure herding, which are then used in the empirical investigation of herding on splitting companies.

In Chapter 5, we analyze any abnormal level of herding in splitting companies in the quarter of the event announcement. Using a sample of US splits from 1993 to 2005, we investigate the presence of institutional herding, applying the methodology developed by Sias (2004). Estimating the first order serial correlation of the institutional demand for splitting companies, we first observe the potential presence of herding among all types of institutional investors. In particular, splitting stocks exhibit a slightly higher difference in the correlation coefficients in the period from 1998 to 2001. The difference in herding appears clearer once we factor out the effect of common market factors, such as the four-factors of Carhart (1997). After detecting the presence of herding, we impose and test specific hypotheses for informational-based herding (Bikhchandani, Hirshleifer and Welch, 1992, Scharfstein and Stein, 1990) and positive-feedback herding (Gompers and Metrick, 2001, Grinblatt, Titman and Wermers, 1995). We observe the strong presence of all theoretical motivations of herding. In particular though, we confirm that institutional investors tend be affected by informational-based herding when trading on splitting companies. Using the dispersion of beliefs among analysts as a proxy for informational-based herding, we observe that the difference in imitative behaviour between the two groups is mostly explained by informational content.

In conclusion, the results of the study confirm the presence of informational content in the announcement of the event, together with an additional source of uncertainty which originates from the optimism of managers. This two-dimensional uncertainty in the event causes the level of herding among institutional investors to be slightly higher for splitting companies in relation to the rest of the market, and in particular to be motivated by informational-content.

Besides the informative results of this study and the light we have drawn on the relation between stock split, dispersion of beliefs and herding, there are still some further improvements to be made, which could help to refine the future research into the analysis and impact of stock splits. In particular, a significant and relevant part of institutional herding is still not explainable by the models that we have applied in this research. This remaining unexplained imitative behaviour should be investigated in more depth to discern whether other, as yet unspecified, motivations are involved.

Moreover, the methodology we have used presents some drawbacks in its ability to distinguish between intentional and nonintentional herding. New methodologies would need to be considered and developed to take into account these issues, so as to further refine our understanding of the impact of this still puzzling "cosmetic" event.

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