Credit Ratings and Predictability of Stock Return Dynamics of the BRICS and the PIIGS: Evidence from a Nonparametric Causality-in-Quantiles Approach[#]

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Abstract

This paper provides a novel perspective on the predictive ability of credit rating announcements over stock market returns and volatility using a novel methodology that formally distinguishes between different market states that can be characterized as bull, bear and normal market conditions. Using data on the credit rating announcements published by the three well-established credit rating agencies and data on BRICS and PIIGS stock markets, we show that the stock markets react heterogeneously, and in quantile-specific patterns, to rating announcements with more persistent and widespread effects observed for PIIGS stock markets. The effect of rating announcements is generally stronger and more widespread in the case of the volatility of returns, implying significant risk effects of these announcements. Finally, we show that the effect of the aggregate ratings is driven mostly by rating upgrades rather than downgrades, implying asymmetry in the predictive ability of rating announcements during good and bad times. Overall, our findings show that predictive models can be greatly enhanced by disaggregating the overall rating announcements and taking into account nonlinearity in the relationship between rating announcements and stock return dynamics.

Keywords: Stock Markets Returns and Volatility; Credit Ratings; Nonparametric Quantile Causality; BRICS; PIIGS.

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1. Introduction

Numerous studies in the literature have examined the predictability of return and volatility dynamics in financial markets. A number of alternative predictors related to domestic and international financial, macroeconomic, institutional, behavioral, and financial/economic uncertainty have been used in both in- and out-of-sample tests (for detailed literature reviews, see Rapach et al., 2005; Rapach and Zhou 2013; Aye et al., 2017). Clearly, predictability of return and volatility is an important issue for practitioners as these statistics serve as basis for portfolio management and capital budgeting decisions. For academics, predictability of returns is a matter of market efficiency relating to the informational content of certain variables with predictive power that can be exploited to generate abnormal returns.

The predictability of financial market movements often becomes more challenging with the existence of credit rating agencies (CRAs) who are tasked with the responsibility of assessing the credit quality of the sovereign nation or financial asset and make timely (or sometimes untimely) announcements about the confirmation or change of the rating. In practice, the rating announcements of the CRAs are often used by investors in their portfolio allocation and market timing decisions. Clearly, CRAs play a crucial role in broadening the financial market as the markets for structured products would not have developed unless the credit assessment of these products were performed and offered by the CRAs. For instance, of the total bond value outstanding, structured finance products accounted for 8.56% in 1985. This increased by nearly four times to 35.58% in December 2008, before declining to 25.26% in December 2015.[1] However, the global financial crisis of 2008 has questioned the credibility of CRAs as they failed to correctly assess and disclose inherent asset specific risks, therefore, leaving the financial system hanging off the cliff. The report published by the financial stability forum in 2008 highlights the methodological shortcomings in risk assessment procedures employed by CRAs as well as conflicts of interests in the rating process as factors that led to the underestimation of the risks associated with the structured products.[2]

Given the significant role played by the CRAs in providing sovereign credit assessment and the outlook on the local economic fundamentals and considering that CRAs played a vital role in the financial crisis, this paper applies a novel methodology developed by Balcilar et al. (2018) to examine the predictive ability of the credit rating announcements published by the three well-

[1] The aggregate structured finance and total bond outstanding balances were obtained from Securities Industry and Financial Markets Association (SIFMA). The reports can be accessed at the following web link: http://www.sifma.org/research/statistics.aspx.
[2] Also see Becker (2011) who notes that the credit rating agencies played a key role in the formation of the credit bubble that led to the collapse of financial system.

established credit rating agencies over stock market returns and volatility. The higher (kth)-order causality-in-quantiles approach of Balcilar et al. (2018) employed in the empirical analysis allows us to formally distinguish between normal, bull and bear market conditions as represented by the quantiles of the conditional distribution of returns and volatility, thus provide a more comprehensive insight to the effects of CRA announcements on stock market return dynamics.

In our empirical analysis, we focus on the BRICS (Brazil, Russia, India, China, and South Africa) and the PIIGS (Portugal, Italy, Ireland, Greece, and Spain) economies as the former group represents major emerging markets, while the latter includes fragile developed markets. With the onset of the great financial crisis of 2007/2008, the U.S. government inevitably bailed out several financial institutions in order to avoid a destructive domino effect on the financial system. Following the collapse of Lehman Brothers in September 2008 and the intensification of the financial crisis with its impact stretching as far as Europe, several EU states agreed to commit large resources to support financial institutions (Sgherri and Zoli, 2009, Gerlach, et al. 2010).[3] It was around the same time when the sovereign spread across most member states also started to rise.[4] To make things worse, on November 5th 2009, Greece revealed its budget deficit at 12.7% of gross domestic product (GDP) which was over four times higher than the 3% "(convergence) criteria" set by the EU. This was coupled with the enormous debt burden for this country, amounting to 113% of GDP – nearly double the 60% of GDP "criteria" set by the EU. The list of heavily indebted countries that didn't meet the "(convergence) criteria" also included Portugal, Italy and Spain, who saw their sovereign spreads over German Bunds to rise significantly following the first Greek bailout in May 2010. Doestz and Fischer (2010) note that the volatility in sovereign bond spread is indicative of a rise in market perception of default probability.

In May 2010, José Manuel Barroso, the then President of the European Commission, harshly criticized the three main credit ratings agencies, noting that "deficiencies in their working methods have led to ratings being too cyclical, too reliant on the general market mood rather than on fundamentals – regardless of whether market mood is too optimistic or too pessimistic", (Barroso, 2010). Against this background, given the significant volatility in spreads and increased probability of default for these five economies viz. Portugal, Ireland, Italy, Greece and Spain (also known as PIIGS) and the role CRA played before and around the onset of the great financial crisis as well as the EU sovereign debt crisis, we also include PIIGS in our empirical

[3] See https://europa.eu/rapid/press-release_MEMO-09-111_en.htm for a comprehensive overview of national measures adopted as a response to the financial and economic crisis.
[4] For instance, with the nationalization of Anglo Irish Bank in January 2009, the sovereign spread for Ireland skyrocketed from 30 basis points in March 2008 to 300 basis points in January 2009 (Mody and Sandri, 2011).

analysis. The comparative analysis of these two groups of countries allows us to determine whether these economies are equivalently sensitive to ratings announcements given the fact that PIIGS countries are backed by a major economic union (EU) and most BRICS countries are highly sensitive to commodity price fluctuations as they are either major exporters or importers of commodities. This comparison becomes particularly interesting considering that the BRICS emerging economies displayed a significant resilience to the shocks from the financial crisis, while the developed economies in the PIIGS bloc failed to insulate themselves from the global recession. To that end, analyzing the degree of vulnerability to the shocks from the rating announcements of the CRAs can enlarge our understanding of the dynamics of the relationship between fragile advanced economies and emerging market economies as well as the role CRAs play as a driver of stock market dynamics.

Our tests show that the relationship between ratings announcements and stock market dynamics is in fact highly nonlinear and quantile-specific for most countries. The stock markets are found to react heterogeneously to ratings announcements with more persistent and widespread effects observed for PIIGS stock markets, implying that being part of a large economic union does not lessen the impact of ratings changes on stock market dynamics. We also find that the effect of rating announcements is generally stronger and more widespread in the case of volatility of returns, implying significant risk effects of these announcements. Finally, additional tests show that the predictability of return and volatility via credit ratings is primarily driven by rating upgrades rather than downgrades. Overall, our findings show that predictive models can be greatly enhanced by disaggregating the overall rating announcements and taking into account nonlinearity in the relationship between ratings announcements and stock return dynamics. The rest of the paper is organized as follows: Section 2 provides a brief review of the literature, Section 3 presents the quantile-based methodology, while Sections 4 and 5 discuss the data and empirical findings respectively. Finally, Section 6 concludes.

2. Literature Review

A number of studies in the literature have analyzed the effect of credit rating announcements of well-established CRAs on bond-yield spreads as well as stock market returns. The seminal study by Cantor and Packer (1996) investigates the predictive ability of rating announcements in explaining the cross-section of sovereign bond yields. They note that these announcements have immediate effects on market pricing for non-investment grade issues. Reisen and von Maltzan (1999) examine the links between sovereign credit ratings and dollar bond yield spreads for a number of emerging markets and find that the CRAs have a significant effect on government bond yield spreads. Furthermore, they find that this effect is more pronounced when a country is put on review for a downgrade. Brooks et al. (2004) examine the aggregate stock market impact of sovereign rating changes and find that, relative to rating upgrades, rating downgrades have a significant negative wealth impact on market returns. Pukthuanthong-Le et. al. (2007) later argue that the rating agencies provide financial markets with new tradable information and that changes in outlook significantly affect both bond and stock markets. More recently, Afonso et al. (2012) further support these findings and show that the changes in both credit rating notations and outlook have a significant effect on government bond yield spreads with the effect being more pronounced in the case of negative announcements.

Another strand of the literature has looked at the cross-border contagion (spillover effect) of the sovereign rating announcements on the financial markets of the neighbouring countries. For instance, Kaminsky and Schmukler (2002) examine whether changes in ratings of assets from one country trigger contagious fluctuations in other countries and find that rating changes of bonds in one emerging market trigger shifts in both yield spreads and stock returns in other emerging economies. Gande and Parsley (2003) study the effect of a sovereign credit rating change of one country on the sovereign credit spreads of other countries and show that rating change in one country has a significant effect on sovereign credit spreads of other countries, implying spillover effects of rating changes. Using intraday market and sovereign ratings data for nine countries in Asia-Pacific region over the 1997-2001 period, Treepongkaruna and Wu (2012) find that currency and stock markets react somewhat heterogeneously to rating announcements with stock markets found to be more responsive to rating news than currency markets. From a different angle, Christopher et al. (2012) investigate the permanent and transitionary effects of sovereign credit ratings on time-varying stock and bond market correlations with respective regional markets for nineteen emerging countries. They find that sovereign ratings and outlook announcements tend to be positively related to regional stock market co-movements, suggesting that there are positive rating spillover effects whereby rating upgrades provide obvious benefits for neighbouring countries in the region. All the above studies, however, have mainly relied on either the event study methodology, Granger causality, or vector autoregression (VAR) methodology for their empirical analysis.

Against this backdrop, we use the nonparametric causality-in-quantiles test recently proposed by Balcilar et al. (2018) to examine, for the first time, the predictability of returns and volatility of the BRICS and the PIIGS based on credit ratings of the three main rating agencies, namely Moody's Investor Services, Standard & Poor's and Fitch Ratings. We approach predictability from the perspective of causality, however, by focusing on quantile-based predictability patterns, thus allowing us to relate the effects of CRA announcements to market conditions that can be characterized as bear, bull or normal markets. It must be noted that one could have also used nonlinear causality tests (for example, Heimstra and Jones (1994) and Diks and Panchenko (2005, 2006)) and GARCH type models to analyze the impact of credit ratings on returns and/or volatility. However, these approaches rely on conditional-mean based estimations, and hence fail to capture the entire conditional distribution of returns and volatility – something we can do with our approach. In the process, our test is a more general procedure to detect causality in both returns and volatility simultaneously at each quantile of their respective conditional distributions. Hence, we are able to capture existence or non-existence of causality at various market states, i.e. bear (lower quantiles), normal (median) and bull (upper quantiles), in these stock markets. To that end, being a more general test, our method is more likely to pick up causality when conditional mean-based tests might fail to do so. Finally, since the model does not require the determination of the number of regimes as in a Markov-switching model, and can test for causality at each point of the conditional distribution characterizing specific regimes, our test also does not suffer from any misspecification in terms of specifying and testing for the optimal number of regimes.

3. Methodology

This section provides a brief description of the quantile based methodology that we use to detect nonlinear causality via a hybrid approach developed by Balcilar et al. (2018) based on the frameworks of Nishiyama et al. (2011) and Jeong et al. (2012). The nonparametric causality-in-quantiles test combines elements of the test for nonlinear causality of *k*-th order developed by Nishiyama et al. (2011) with the causality-in-quantiles test developed by Jeong et al. (2012) and, hence, can be considered to be a generalization of the former. The causality-in-quantile approach has the following three novelties: Firstly, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series, which could prove to be particularly important as it is well known that stock returns display nonlinear dynamics (Caraiani, 2012) - a fact we show to hold in our data as well. Secondly, via this methodology, we are able to test not only for causality-in-mean (1st moment), but also for causality that may exist in the tails of the joint distribution of the variables. This is particularly important if the dependent variable has fat-tails – something we show in our empirical analysis to exist for returns of the BRICS and PIIGS countries. Finally, we are also able to investigate causality-in-variance and, thus, study higher-order dependency. Such an investigation is important because, during some periods, causality in the conditional-mean may not exist while, at the same time, higher-order interdependencies may turn out to be significant.

Let y_t denote stock returns and x_t denote the predictor variable, which in our case is the numerical value associated with a credit rating by a particular rating agency (as described in detail in the Data section).[5] Formally, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The (non)causality in the q-th quantile hypotheses to be tested are:

$$H_0:\ P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \tag{1}$$

$$H_1:\ P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \tag{2}$$

Jeong et al. (2012) show that the feasible kernel-based test statistics has the following format:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{3}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{4}$$

with $L(\bullet)$ denoting the kernel function.

Balcilar *et al.* (2018) extend Jeong et al. (2012)'s framework, based on Nishiyama et al. (2011), to the *second* (or higher) moment which allows us to test the causality between the credit rating and stock return volatility. In this case, the null and alternative hypotheses are given by:

$$H_0:\ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1, \quad k = 1,2,\dots,K \tag{5}$$

$$H_1:\ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1, \quad k = 1,2,\dots,K \tag{6}$$

The causality-in-variance test can then be calculated by replacing y_t in Eqs. (3) and (4) with y_t^2. As pointed out by Balcilar et al. (2018), a rescaled version of $\hat{J}_T$ has the standard normal distribution. Testing approach is sequential and failing to reject the test for $k = 1$ does not automatically lead to no-causality in the *second* moment; one can still construct the test for $k = 2$. The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a

[5] Note that the write-up of this section, due to the technical details, relies heavily on the discussion of the econometric methodology in Balcilar et al. (2018).

lag order of one based on the Schwarz Information Criterion (SIC). We determine h by the leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

4. Data

We use daily data for Morgan Stanley Capital International (MSCI) total return stock market indexes (in USD) for the BRICS and PIIGS countries over the period of 1992 to 2016. Daily data are used in order to capture the dynamic, short-term effect of rating announcements on stock returns and volatility. CRA data includes the credit ratings by three agencies, namely Moody's Investor Services, Standard & Poor's and Fitch Ratings. The data is sourced from Datastream maintained by Thomson Reuters. We work with returns, obtained as the first-differences of the natural logarithmic values of the indices expressed in percentage, while the squared values of returns are used to measure the volatility of returns.

Sovereign credit ratings are measures used to assess the probability of default or creditworthiness of a national government, thus can be considered as an indicator of a government's willingness and ability to pay its debt based on the terms it was issued. The most widely recognized international rating agencies, whose ratings we use in this study, include Fitch, Moody's Investor Services (Moody's), and Standard & Poor's (S&P), as these agencies dominate almost the entirety of the market that can be classified as an oligopoly (Blaurock, 2007). Each rating agency uses a different individual scale on its ratings scheme, but they do have vast similarities as well –a summary of the rating scales is provided in Table 1(a). As shown in the table, the ratings are graded in an ordinal order based on various economic, social and political factors. The historical information on the ratings of a particular country by each of the three rating agencies is obtained from Bloomberg.

We employ historical long-term sovereign ratings for foreign currency denominated debt to generate the independent variables to be used in our empirical analyses. Brooks et al. (2004) note that foreign currency ratings consistently have greater market impact on asset returns. In addition, these authors note that that while there is not a 100 percent correspondence between local or foreign currency ratings, a change in one still triggers a change in the other, 75 percent of the time. Similar to Cantor and Packer (1996), Gande and Parsley (2005), Ferreira and Gama (2007), Christopher et al. (2012) and Teixeira et al. (2018), we use a standard linear rating transformation to generate the time series of ratings for each country. Separate daily rating time series for a particular country is generated by assigning the appropriate numerical value of a particular rating on and after the day that it is implemented up until any subsequent revision is made. More specifically, along the lines of Teixeira et al. (2018), we assign a numerical value of 20 to prime-rated bonds and 0 to default as described in Table 1(b).

[INSERT TABLE 1]

Table 2 presents the summary statistics for stock index returns (Table 2a) and for the numerical credit ratings from the three agencies (Table 2b). The table also notes the sample periods considered, with the start and end dates purely driven by data availability. Greece is the only country in the sample with negative mean return, most likely driven by the significant economic problems this country has faced over the past decade, while Russia has experienced the greatest return volatility as a major commodity exporter in the sample, thanks to the prolonged uncertainty experienced in the oil market, particularly following the global crisis. The negative mean return for Greece and high stock market volatility for Russia is accompanied with the widest range of credit ratings observed for these countries (Table 2b). For our context of causality-in-quantiles, all return series are found to be skewed to the left, with excess kurtosis, resulting in non-normal distributions, as indicated by the strong rejection of Jarque-Bera statistic at 1 percent level of significance. The heavy-tails of the distributions of returns provide preliminary support for the use of the causality-in-quantiles test in the empirical analysis. Figures 1 and 2 present the time series graphs for stock market returns and credit rating series, respectively.

[INSERT TABLE 2 and FIGURES 1 AND 2]

5. Empirical Results

5.1 Preliminary Tests

Before we discuss the findings from the causality-in-quantiles tests, for the sake of completeness and comparability, we first provide the findings from the standard linear Granger causality test, with lag-lengths determined by the SIC. As shown in Table 3, barring the case of Greece under the credit ratings provided by Fitch, and S&P, the standard linear Granger causality tests yield no evidence of causality running from any of the credit ratings to the stock returns of the remaining BRICS and PIIGS countries at the conventional 5 percent level of significance. Therefore, based on standard linear tests, one would incorrectly conclude no significant credit rating effects on the stock markets of these countries.

[INSERT TABLE 3]

Given the insignificant results obtained from linear causality tests, we next formally examine the presence of nonlinearity in the relationship between the stock returns and the credit ratings of the three agencies. Nonlinearity, if present, would further motivate the use of the nonparametric quantile-in-causality approach as the quantile-based test would formally address nonlinearity in the relationship between stock returns and credit ratings. For this purpose, we apply the Brock *et al.,* (1996, BDS) test on the residuals from the return equation involving lagged values of returns and that of the credit ratings, with the lags determined by the SIC. Table 4 presents the results of the BDS test of nonlinearity for the relationship between stock market returns and credit ratings. As shown in Table 4, we find strong evidence, at highest level of significance, for the rejection of the null of *i.i.d.* residuals at various embedded dimensions (*m*), providing strong evidence of nonlinearity in the relationship between returns and the three credit ratings. This evidence indicates that, the findings based on the linear Granger causality test, presented in Table 3, cannot be deemed robust and reliable. Given the strong evidence of nonlinearity in the relationship between returns and credit ratings, we now turn our attention to the causality-in-quantiles test, which is robust to linear misspecification due to its nonparametric (i.e., data-driven) approach. In addition, our approach also allows us to test whether the ratings capture predictive information over volatility in these stock markets.

[INSERT TABLE 4]

5.2 Quantile Causality Tests

Table 5 presents the findings from the causality-in-quantiles tests for stock returns and volatility of the 10 stock markets emanating from the credit ratings of the three agencies. Quantiles that range between 0.1 and 0.9 are presented in columns with the findings for each of the three rating agencies presented in rows. Table 5a (5b) present the causality tests for stock market returns (volatility) with the rejection of the null hypothesis of no causality at 5% level of significance indicated by the * symbol in each cell. The findings in both panels of Table 5 suggest that credit ratings indeed have a significant effect on stock market dynamics; however, the effect can be highly nonlinear and quantile-specific for some countries. In general, the effect of credit ratings is more prevalent on the volatility of returns with stronger and more consistent findings across different markets and quantiles, implying significant risk effects of the CRA announcements. The effect of ratings is also quite consistent across the three rating agencies examined, suggesting that the information reflected by rating announcements, irrespective of the source agency, are priced in the market, thus capturing new tradable information (Pukthuanthong-Le et. al., 2007).

Examining PIIGS stock markets, Portugal, Ireland and Greece are found to be the most vulnerable economies to rating annoucements with significant causality observed across all quantiles of the conditional distribution of stock market returns and volatility. Observing consistent causal effects across all quantiles in the case of these countries reflect the economic vulnerability and debt issues these three fragile European nations have experienced over the past decade. In the case of Spain, however, the causality effect is limited to market volatility and mostly concentrated on the quantiles above the median, suggesting that rating announcements have contributed to higher market volatility in this market. Considering the findings in Kaminsky and Schmukler (2002) and Gande and Parsley (2003), it is possible that the volatility effect on the Spanish market reflects volatility spillover effects from rating announcements for Portugal, Ireland and Greece. Interestingly, Italy stands out as the only country in the sample with no significant causality observed between rating announcements and stock market returns or volatility. This finding is consistent with Linciano (2004) who also reports moderate or statistically insignificant stock price reactions to rating change announcement for this country. In our case, the insignificant results may be due to relatively lower variation in the credit ratings for this country compared to the other PIIGS nations (Table 2b) which might have made it relatively easier for investors to build their expectations on rating changes.

It can also be argued that the finding of non-causality in the case of Italy could be due to sigificant mispricing (undervaluation) in the Italian stock market relative to the average stock market valuation of the PIIGS economies. In fact, Italy's stock market capitalization as a percentage of the GDP was 34.72% compared to the average valuation of nearly 50% for all the PIIGS economies. With this undervaluation, we conjecture that the stock market will remain relatively immune from the shocks of the ratings announcements, particularly when compared to markets that are significantly overvalued relative to the size of the economy. On the other hand, considering the government debt levels, one of the importatnt determinants of credit rating decisions (e.g. Reusens and Croux, 2017), one can expect the stock market of the country with significant debt levels to be more sensitive to sovereign rating announcements. Of all the PIIGS economies, we observe that Italy had the second highest government debt as a percentage of the GDP (i.e. the average government debt was 121.22% of the GDP since the onset of the financial crisis).[6] Our findings, therefore, suggest that despite the higher levels of the government debt and significant undervaluation, Italian stock market has remained relatively immune to shocks from the rating announcements. To that end, the findings point to the role of mispricing as a determinant of the market's reaction to ratings announcements.

In the case of the emerging BRICS nations, South Africa stands out as the most vulnerable nation with significant causality on both stock market return and volatility consistently across all

[6] The average stock market capitalization as a percentage of the GDP and the average government debt as a percentage of the GDP are calculated using data from the World Bank Database.

quantiles. While causality on returns is generally weaker and/or quantile-specific for Russia, India and China, we observe that the effect of rating announcements is more consistent on market volatility and particularly at quantiles above the median, implying risk effects of rating announcements in these stock markets. Interestingly, Brazil is found to be the least sensitive BRICS nation to rating announcements with the exception of Moody's rating at several quantiles. It is possible that the market had already anticipated ratings announcements for this country long before the announcement, thus rendering our tests insignificant. Overall, the quantile-based tests provide novel insight that cannot be captured by the misspecified linear causality tests reported in Table 3 and suggest that credit ratings contain predictive value over return and volatility in most of the stock markets examined, while the predictive ability is concentrated more on market volatility.

[INSERT TABLE 5]

5.3 Asymmetric Effect of Upgrades and Downgrades

Having presented evidence of significant causality from credit ratings to stock market return dynamics, we next examine whether the predictive power of credit ratings is primarily driven by rating upgrades or downgrades. For this purpose, we create two dummy variables corresponding to an upgrade and downgrade such that the variable takes a value of 1 if there is an upgrade (downgrade) and zero if there is a downgrade (upgrade) or if the rating remains unchanged. We then multiply the numerical rating values with the dummies to come up with the corresponding upgrade or downgrade in ratings. Tables 6 and 7 present the findings from quantile causality tests for ratings upgrades and downgrades, respectively. Panels a and b present the findings for stock market returns and volatility, respectively. Understandably, when there were no upgrades or downgrades for a particular country based on the ratings of a specific rating agency over the period under consideration, we do not have results for those cases.

Consistent with the earlier findings for the overall ratings, we observe that the effect is generally more persistent on volatility than returns although significant causality is also observed in the case of returns. The insignificant results for Italy and Brazil still hold suggesting that the finding of non-causality is not driven by asymmetric effects of downgrades and upgrades. Examining the findings for rating upgrades and downgrades reported in Tables 6 and 7, we observe significant causal effects of credit ratings in both cases. Interestingly, however, we see broader significance patterns in the case of rating upgrades in Table 6, compared to the findings for rating downgrades in Table 7. There are also instances when causality does not exist for the overall ratings (Table 5), but does under an upgrade for certain quantiles (e.g. Russia, China). The relatively stronger findings observed in the case of rating upgrades seem to contradict with several previous studies that report significant stock market reactions observed primarily in the case of rating downgrades (e.g. Hu et al, 2016; Li et al., 2006; Brooks et al. 2004).[7] However, there is also evidence in the literature showing that the stock market reaction to rating upgrades as well as downgrades is significant, particularly since the introduction of Regulation Fair Disclosure (Jorion et al, 2005). This is also supported by the earlier finding in Hseuh and Liu (1992) of significant abnormal stock price movements in response to both bond rating downgrades and upgrades.

Given the mixed evidence in the literature, one possible explanation for the stronger findings observed in the case of upgrades is that rating upgrades are generally harder to anticipate by market participants and includes a greater degree of surprise component compared to anticipated downgrade announcements, thus leading to stronger effects on stock market returns and volatility. On the other hand, when times are bad, it is easier for investors to anticipate a ratings downgrade which makes the effect on market dynamics more limited relative to an upgrade. Indeed, the literature suggests that short sellers are often able to successfully identify firms with credit rating downgrades (Henry et al., 2015) and that investors might use previous downgrades as an indication of a subsequent downgrade (e.g. Lando and Skodeberg, 2002). To that end, relatively weaker results observed in the case of rating downgrades is not necessarily inconsistent with the evidence in the literature and points to the information inefficiencies associated with the effect of downgrade announcements on stock market returns. Nevertheless, the findings suggest that there is value added in terms of predictability by disaggregating the overall rating announcements and analysts must take into account the asymmetric effects of upgrades and downgrades in forecasting exercises.

[INSERT TABLES 6 AND 7]

6. Conclusion

This paper provides a novel perspective to the predictive ability of credit rating announcements over stock market returns and volatility using a novel methodology that formally distinguishes between different market states that can be characterized as bull, bear and normal market conditions. Using data on the credit rating announcements published by the three well-established credit rating agencies (Moody's Investor Services, Standard & Poor's and Fitch Ratings) and employing the nonparametric causality-in-quantiles test of Balcilar et al. (2018), we examine, for

[7] Also see, Norden and Weber (2004) who observe a significant abnormal performance in the expected direction around negative rating events, but insignificant market reactions around positive events.

the first time, the predictability of returns and volatility of the BRICS and the PIIGS stock markets based on the credit ratings announcements.

While standard, linear causality tests yield largely insignificant results, our tests show that the relationship between ratings announcements and stock market dynamics is in fact highly nonlinear and quantile-specific for most countries. Quantile-based tests show that the major emerging markets (BRICS) and the fragile developed markets (PIIGS) react heterogeneously to ratings announcements. Interestingly, ratings announcements are found to have more widespread effects over PIIGS stock markets, implying that being part of a large economic union does not lessen the impact of ratings changes on stock market dynamics.

Causality is generally found to be more prevalent and stronger on return volatility than returns and mostly concentrated on the quantiles above the median, suggesting that rating announcements contribute to higher market volatility, an issue policy makers should consider in order to mitigate the negative effects of these announcements on their stock markets. This is particularly the case for Portugal, Ireland and Greece that are found to be the most vulnerable PIIGS nations with significant causality observed across all quantiles of the conditional distribution of market returns and volatility. At the same time, Italy stands out as the only country in the sample with no significant causality observed, neither in the case of returns nor in the case of volatility. Similarly, South Africa stands out as the most vulnerable BRICS nation with significant causality observed on both stock market return and volatility consistently across all quantiles.

Finally, additional tests show that predictability via credit ratings is primarily driven by rating upgrades rather than downgrades. We argue that rating upgrades are relatively harder to anticipate by market participants, leading to greater causal effects while, in bad times, there is greater anticipation towards a downgrade, thus lessening the impact of a downgrade on stock market return dynamics. Overall, our findings show that predictive models can be greatly enhanced by disaggregating the overall rating announcements and taking into account nonlinearity in the relationship between ratings announcements and stock return dynamics.

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Table 1(a): Rating scales of Moody's, S&P and Fitch.

Moody's	S&P	Fitch	Description
Aaa	AAA	AAA	Prime
Aa1, Aa2, Aa3	AA+, AA, AA-	AA+, AA, AA-	High grade
A1, A2, A3	A+, A, A-	A+, A, A-	Upper medium grade
Baa1, Baa2, Baa3	BBB+, BBB, BBB-	BBB+, BBB, BBB-	Lower medium grade
Ba1, Ba2, Ba3	BB+, BB, BB-	BB+, BB, BB-	Non-investment/speculative grade
B1, B2, B3	B+, B, B-	B+, B, B-	Highly speculative
Caa1, Caa2, Caa3	CCC+, CCC, CCC-	CCC	Extremely speculative
Ca	CC	CC	Imminent default
C	R, SD, D	C, RD, D	Default

Source: Website of the three rating agencies.

Table 1(b): Numerical conversion of the sovereign credit ratings.

	Rating Scale										
	20	19	18	17	16	15	14	13	12	11	10
Moody's	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1
S&P	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+
Fitch	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+

	Rating Scale									
	9	8	7	6	5	4	3	2	1	0
Moody's	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca	C
S&P	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	R, SD, D
Fitch	BB	BB-	B+	B	B-	CCC	CC	C	RD	D

Note: The rating provided by the three main rating agencies i.e., Moody's, Standard and Poor's (S&P) and Fitch is converted into a numerical scale from 0 (worst) to 20 (best).

Table 2a: Summary statistics and sample periods for stock market returns.

Country	Mean	Std. dev.	Median	Min	Max	Skew-ness	Kurtosis	Jarque -Bera
Brazil (31/12/1992 - 24/02/2016)	0.0002	0.024	0.0006	-0.183	0.167	-0.213	8.977	0.000*
Russia (07/10/1996 to 22/04/2016)	0.0003	0.046	0.0003	-2.003	1.913	-2.129	1263.955	0.000*
India (31/12/1992 to 08/04/2015)	0.0003	0.017	0.0002	-0.147	0.195	-0.154	10.286	0.000*
China (26/07/1993 to 31/03/2016)	0.0002	0.019	0.0000	-0.143	0.157	0.117	9.428	0.000*
South Africa (03/10/1994 to 06/05/2016)	0.0001	0.017	0.0005	-0.136	0.124	-0.361	8.321	0.000*
Portugal (31/12/1992 to 18/09/2015)	0.0000	0.013	0.0001	-0.130	0.118	-0.151	9.437	0.000*
Italy (31/12/1992 to 05/12/2014)	0.0001	0.016	0.0003	-0.109	0.125	-0.051	7.837	0.000*
Ireland (31/12/1992 to 13/05/2016)	0.0001	0.016	0.0002	-0.189	0.136	-0.649	13.438	0.000*
Greece (31/12/1992 to 22/01/2016)	-0.0003	0.022	0.0000	-0.243	0.172	-0.263	10.601	0.000*
Spain (31/12/1992 to 19/02/2016)	0.0002	0.016	0.0003	-0.112	0.160	0.038	9.348	0.000*

Note: * indicates rejection of null hypothesis of normality at 1% level of significance.

Table 2b: Summary statistics for credit rating series

Country	Rating	Mean	Std. dev.	Median	Min	Max	Skew-ness	Kurtosis	Jarque-Bera *p*-value	Sample period
Brazil	S&P	9.003	1.899	8.000	6.0	12.0	0.243	1.526	0.000	30/11/1994 to 17/02/2016
	Moody's	8.418	2.307	7.000	6.0	12.0	0.467	1.575	0.000	31/12/1992 to 24/02/2016
	Fitch	8.102	1.654	8.000	6.0	12.0	0.678	2.172	0.000	01/12/1994 to 04/04/2011
Russia	S&P	9.213	3.920	11.000	0.0	13.0	-1.257	3.532	0.000	10/04/1996 to 26/01/2015
	Moody's	10.310	2.774	11.000	5.0	13.0	-0.744	2.212	0.000	07/10/1996 to 22/04/2016
	Fitch	9.729	2.971	10.000	4.0	13.0	-0.731	2.224	0.000	07/10/1996 to 16/01/2012
India	S&P	10.063	0.798	10.000	9.0	11.0	-0.114	1.577	0.000	31/12/1992 to 26/09/2014
	Moody's	10.369	0.906	11.000	9.0	11.0	-0.794	1.692	0.000	31/12/1992 to 08/04/2015
	Fitch	10.303	0.751	10.000	9.0	11.0	-0.561	1.965	0.000	08/03/2000 to 18/06/2012
China	S&P	14.101	2.058	13.000	12.0	17.0	0.325	1.413	0.000	26/07/1993 to 31/03/2016
	Moody's	15.158	1.237	15.000	13.0	17.0	0.426	1.583	0.000	26/07/1993 to 02/03/2016
	Fitch	14.669	0.858	14.000	14.0	16.0	0.690	1.710	0.000	11/12/1997 to 12/04/2011
South Africa	S&P	11.451	1.285	11.000	9.0	13.0	-0.072	1.760	0.000	03/10/1994 to 04/12/2015
	Moody's	12.272	1.076	12.000	11.0	14.0	0.159	1.701	0.000	03/10/1994 to 06/05/2016
	Fitch	11.208	1.699	12.000	9.0	13.0	-0.275	1.400	0.000	22/09/1994 to 13/01/2012

Table 2b (cont.d)

Country	Rating	Mean	Std. dev.	Median	Min	Max	Skew-ness	Kurtosis	Jarque-Bera *p*-value	Sample period
Portugal	S&P	15.596	3.209	17.000	9.0	18.0	-1.351	3.132	0.000	31/12/1992 to 18/09/2015
	Moody's	16.050	3.309	18.000	8.0	18.0	-1.757	4.503	0.000	31/12/1992 to 25/07/2014
	Fitch	17.438	1.370	18.000	10.0	18.0	-3.922	18.554	0.000	10/08/1994 to 24/11/2011
Italy	S&P	16.686	1.852	18.000	11.0	19.0	-1.404	3.881	0.000	31/12/1992 to 05/12/2014
	Moody's	16.824	1.642	17.000	12.0	18.0	-1.893	5.947	0.000	31/12/1992 to 14/02/2014
	Fitch	17.261	0.480	17.000	14.0	18.0	0.518	2.927	0.000	10/08/1994 to 27/01/2012
Ireland	S&P	17.793	2.422	18.000	13.0	20.0	-0.992	2.651	0.000	31/12/1992 to 05/06/2015
	Moody's	17.452	3.515	19.000	10.0	20.0	-1.189	2.846	0.000	31/12/1992 to 13/05/2016
	Fitch	19.064	1.807	20.000	13.0	20.0	-2.534	8.566	0.000	10/10/1994 to 27/01/2012
Greece	S&P	11.304	4.163	11.000	0.0	16.0	-0.997	2.988	0.000	31/12/1992 to 22/01/2016
	Moody's	11.695	5.337	13.000	0.0	16.0	-1.216	3.024	0.000	31/12/1992 to 25/09/2015
	Fitch	13.141	2.785	15.000	1.0	16.0	-1.802	6.476	0.000	13/11/1995 to 17/12/2012
Spain	S&P	17.662	2.680	18.000	11.0	20.0	-1.616	4.228	0.000	31/12/1992 to 02/10/2015
	Moody's	17.664	2.900	18.000	11.0	20.0	-1.362	3.497	0.000	31/12/1992 to 9/02/2016
	Fitch	18.962	1.024	19.000	12.0	20.0	-1.219	5.837	0.000	10/08/1994 to 07/06/2012

Note: Jarque-Bera *p*-value corresponds to the null hypothesis of normality.

Table 3. Linear Granger Causality Test.

Country	Rating	*F*-stat	*p*-value
Brazil	S&P	1.821	0.177
	Moody's	3.195	0.074
	Fitch	0.215	0.643
Russia	S&P	0.397	0.529
	Moody's	0.187	0.666
	Fitch	0.254	0.614
India	S&P	0.524	0.469
	Moody's	0.171	0.679
	Fitch	0.401	0.526
China	S&P	0.626	0.429
	Moody's	0.789	0.374
	Fitch	0.070	0.792
South Africa	S&P	0.380	0.538
	Moody's	0.956	0.328
	Fitch	1.331	0.249
Portugal	S&P	2.141	0.144
	Moody's	0.207	0.650
	Fitch	2.313	0.128
Italy	S&P	0.302	0.582
	Moody's	1.146	0.285
	Fitch	1.015	0.314
Ireland	S&P	3.097	0.079
	Moody's	2.168	0.141
	Fitch	0.495	0.482
Greece	S&P	4.875	0.027
	Moody's	2.665	0.103
	Fitch	5.880	0.015
Spain	S&P	0.013	0.910
	Moody's	0.206	0.650
	Fitch	0.363	0.547

Note: * indicates rejection of the null that credit ratings does not Granger cause stock returns at 5 percent level of significance.

Table 4. BDS test of nonlinearity.

Country	Rating	Dimension				
		2	3	4	5	6
Brazil	S&P	15.705***	19.967***	23.870***	26.669***	29.355***
	Moody's	16.385***	21.521***	25.512***	28.449***	31.530***
	Fitch	15.964***	19.784***	23.291***	25.827***	28.246***
Russia	S&P	21.858***	27.043***	30.801***	33.984***	37.791***
	Moody's	20.150***	25.358***	29.029***	32.278***	35.898***
	Fitch	19.337***	24.352***	27.891***	31.108***	34.907***
India	S&P	16.441***	20.557***	23.623***	26.238***	29.054***
	Moody's	16.590***	20.820***	23.957***	26.563***	29.427***
	Fitch	14.502***	18.125***	21.123***	23.798***	26.524***
China	S&P	17.746***	22.247***	26.084***	29.664***	33.068***
	Moody's	17.786***	22.201***	26.131***	29.702***	33.095***
	Fitch	13.240***	16.962***	20.350***	23.557***	26.576***
South Africa	S&P	15.165***	20.948***	24.334***	27.464***	30.165***
	Moody's	15.209***	21.332***	24.881***	28.183***	30.977***
	Fitch	15.338***	21.631***	25.573***	29.047***	32.006***
Portugal	S&P	18.618***	23.247***	26.574***	29.070***	31.764***
	Moody's	18.412***	22.994***	26.197***	28.545***	30.980***
	Fitch	17.065***	21.834***	25.359***	28.011***	30.401***
Italy	S&P	14.248***	19.819***	23.614***	26.947***	30.003***
	Moody's	14.139***	19.806***	23.727***	27.108***	30.259***
	Fitch	15.093***	21.288***	25.538***	29.206***	32.693***
Ireland	S&P	20.699***	27.203***	30.935***	34.093***	36.960***
	Moody's	20.747***	27.214***	30.868***	33.980***	36.766***
	Fitch	20.168***	27.132***	31.200***	34.820***	38.076***
Greece	S&P	20.499***	26.619***	30.737***	34.438***	38.439***
	Moody's	20.352***	26.510***	30.522***	34.266***	38.262***
	Fitch	15.455***	21.222***	25.288***	28.741***	32.355***
Spain	S&P	16.240***	21.251***	24.843***	28.569***	31.751***
	Moody's	16.223***	21.369***	24.988***	28.697***	31.934***
	Fitch	15.690***	21.025***	24.824***	28.646***	31.925***

Note: The table provides the results of Brock *et al.,* (1996, BDS) test of nonlinearity in the relationship between stock market returns and the credit ratings of the three agencies. *m* stands for the number of (embedded) dimensions which embed the time series into *m*-dimensional vectors, by taking each m successive points in the series. Value in cell represents BDS *z*-statistic; *** indicates rejection of *i.i.d.* residuals at 1 percent level of significance.

Table 5a: Quantile causality (Returns)

Country	rating	Quantile																
		0.1	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**
Brazil	S&P	0.91	0.92	0.92	0.88	1.05	1.19	1.23	1.23	0.62	0.51	0.67	0.82	1.00	1.13	1.00	0.83	0.97
	Moody's	1.30	1.51	1.37	1.22	1.35	1.45	1.42	1.47	0.92	0.88	1.13	1.72	2.05*	2.40*	2.24*	2.00*	1.91
	Fitch	1.17	1.23	0.91	1.01	1.06	0.89	0.75	0.50	0.28	0.35	0.57	0.62	0.57	0.87	0.89	0.98	1.16
Russia	S&P	4.83*	5.87*	6.49*	5.04*	4.09*	2.49*	1.53	0.69	0.33	0.54	1.47	2.68*	3.77*	4.99*	6.09*	8.97*	8.79*
	Moody's	4.82*	5.32*	6.36*	5.13*	3.92*	2.28*	1.59	0.99	0.41	0.71	1.69	2.49*	3.83*	4.72*	5.79*	8.97*	7.64*
	Fitch	2.85*	3.72*	5.42*	4.70*	3.87*	2.84*	1.77	1.04	0.51	0.41	0.80	1.50	2.32*	3.25*	4.77*	7.94*	6.25*
India	S&P	3.86*	3.72*	4.23*	3.96*	4.30*	4.61*	4.83*	4.43*	4.58*	5.34*	6.08*	6.06*	5.45*	5.82*	5.59*	4.70*	3.94*
	Moody's	2.53*	2.51*	2.93*	2.86*	3.26*	2.95*	2.91*	2.24*	1.90	3.21*	2.89*	3.08*	3.07*	3.36*	3.05*	4.03*	3.83*
	Fitch	3.47*	3.03*	2.56*	2.06*	2.03*	2.05*	1.88*	1.90	2.03*	1.94	1.75	1.49	2.11*	2.79*	3.04*	3.17*	3.19*
China	S&P	1.06	1.33	1.51	0.80	0.69	0.80	0.71	0.64	0.57	0.71	0.94	1.12	1.31	1.58	1.70	2.11*	1.58
	Moody's	1.03	1.26	1.50	0.88	0.76	0.90	0.79	0.74	0.68	0.81	1.02	1.18	1.26	1.59	1.65	2.03*	1.54
	Fitch	1.78	2.19*	1.77	1.37	0.88	0.67	0.47	0.44	0.30	0.38	0.77	1.36	1.70	2.36*	3.04*	2.80*	1.85
South Africa	S&P	5.42*	6.75*	7.88*	5.88*	5.36*	4.38*	3.19*	2.76*	3.49*	4.03*	5.05*	6.31*	6.76*	7.99*	7.14*	6.44*	4.74*
	Moody's	5.56*	8.10*	10.3*	8.18*	8.17*	6.56*	5.16*	4.52*	5.51*	7.24*	8.41*	10.2*	9.71*	11.0*	8.95*	7.75*	5.02*
	Fitch	6.15*	9.52*	10.6*	8.25*	7.35*	5.65*	4.31*	3.65*	4.61*	6.39*	8.33*	10.8*	11.8*	13.3*	10.8*	9.59*	6.44*
Portugal	S&P	6.97*	9.86*	9.98*	10.6*	10.3*	8.30*	6.47*	5.26*	2.80*	2.75*	3.39*	4.86*	5.82*	7.57*	8.24*	6.53*	5.68*
	Moody's	5.50*	6.76*	6.57*	6.89*	6.57*	5.77*	4.88*	4.21*	2.76*	2.99*	3.97*	4.56*	4.55*	4.86*	5.03*	4.21*	4.16*
	Fitch	4.91*	6.13*	5.32*	5.46*	4.85*	4.74*	3.93*	3.30*	2.19*	2.42*	3.26*	3.42*	3.33*	3.44*	3.55*	3.12*	2.94*
Italy	S&P	0.10	0.13	0.12	0.11	0.06	0.01	0.01	0.01	0.01	0.01	0.01	0.03	0.06	0.11	0.15	0.13	0.07
	Moody's	0.03	0.05	0.04	0.03	0.03	0.02	0.01	0.01	0.00	0.01	0.02	0.06	0.11	0.18	0.23	0.15	0.07
	Fitch	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01
Ireland	S&P	4.77*	4.63*	5.72*	5.09*	4.73*	4.65*	4.05*	4.48*	3.61*	3.84*	4.02*	4.11*	4.35*	4.07*	4.20*	4.41*	3.71*
	Moody's	4.10*	4.10*	4.75*	4.27*	3.17*	3.40*	2.67*	3.03*	2.37*	2.52*	2.42*	2.80*	3.14*	3.62*	3.91*	4.30*	3.84*
	Fitch	4.86*	5.19*	5.58*	4.87*	3.66*	3.39*	2.33*	2.92*	2.43*	2.36*	2.39*	2.87*	3.38*	3.89*	4.24*	5.13*	3.92*
Greece	S&P	9.15*	11.6*	11.3*	9.62*	7.26*	6.31*	4.82*	4.26*	4.85*	5.88*	5.72*	5.44*	5.41*	6.45*	6.76*	6.83*	6.90*
	Moody's	6.73*	8.76*	9.17*	8.18*	6.67*	6.27*	5.15*	4.48*	4.97*	4.95*	4.67*	5.12*	5.66*	6.38*	6.70*	7.22*	6.39*
	Fitch	2.32*	2.23*	2.38*	1.64	1.12	0.86	0.65	0.45	0.26	0.09	0.07	0.11	0.26	0.63	0.95	1.09	1.34
Spain	S&P	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Moody's	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fitch	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: * indicates rejection of null hypothesis of no causality-in-quantiles at 5% level of significance.

Table 5b: Quantile causality (Volatility)

Country	rating	Quantile																
		0.1	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**
Brazil	S&P	0.03	0.04	0.01	0.00	0.00	0.01	0.03	0.04	0.15	0.13	0.11	0.10	0.10	0.06	0.04	0.02	0.01
	Moody's	0.01	0.01	0.01	0.04	0.06	0.15	0.20	0.30	0.43	0.52	0.42	0.49	0.45	0.36	0.25	0.21	0.13
	Fitch	0.10	0.11	0.05	0.03	0.04	0.05	0.04	0.02	0.01	0.01	0.04	0.05	0.05	0.06	0.06	0.06	0.11
Russia	S&P	0.56	1.28	2.38*	4.77*	5.98*	8.71*	11.2*	11.8*	14.1*	14.5*	14.9*	16.3*	17.9*	19.1*	16.1*	13.8*	8.23*
	Moody's	3.16*	3.28*	5.12*	7.41*	8.39*	11.6*	14.2*	15.8*	18.4*	18.9*	20.6*	20.5*	22.3*	21.1*	17.0*	14.8*	10.8*
	Fitch	2.03*	2.16*	3.40*	5.29*	5.90*	7.03*	9.91*	11.7*	12.4*	12.5*	13.6*	13.8*	15.7*	15.1*	13.1*	12.0*	7.91*
India	S&P	1.85	2.99*	3.45*	4.69*	3.63*	3.18*	3.90*	4.71*	4.16*	4.15*	3.30*	3.86*	4.32*	3.54*	3.80*	3.89*	2.82*
	Moody's	0.80	0.94	0.93	0.90	0.94	1.35	1.72	1.85	1.48	1.08	1.23	1.16	1.31	1.31	1.34	0.97	0.81
	Fitch	0.17	0.18	0.33	0.59	0.82	1.45	2.26*	2.50*	2.98*	5.32*	4.87*	6.23*	6.39*	6.74*	8.32*	6.99*	5.85*
China	S&P	1.07	1.29	1.47	2.17*	3.22*	3.59*	5.38*	6.63*	6.19*	7.08*	10.1*	9.42*	7.44*	6.63*	6.08*	6.16*	5.00*
	Moody's	1.32	1.47	1.52	1.86	2.79*	3.19*	3.92*	4.83*	4.53*	5.46*	7.83*	7.81*	6.90*	6.08*	5.58*	5.30*	4.09*
	Fitch	0.78	0.82	1.48	1.87	3.19*	3.58*	4.88*	5.29*	5.75*	7.34*	8.35*	8.11*	7.71*	6.72*	6.41*	3.79*	2.24*
South Africa	S&P	2.73*	4.73*	7.99*	9.73*	12.1*	15.5*	17.7*	18.1*	21.6*	21.0*	22.0*	21.4*	23.4*	21.6*	16.3*	14.3*	11.8*
	Moody's	4.27*	6.43*	9.94*	13.0*	15.0*	17.4*	20.0*	17.6*	21.0	17.4*	17.9*	16.0*	16.3*	13.2*	9.77*	7.06*	4.97*
	Fitch	4.38*	6.99*	11.9*	15.0*	17.2*	20.6*	22.2*	22.5*	25.8*	22.7*	21.6*	21.0*	22.6*	19.1*	14.1*	10.8*	8.23*
Portugal	S&P	4.70*	7.54*	9.55*	11.6*	16.1*	18.1*	17.8*	18.0	19.0*	19.9*	17.5*	13.8*	13.2*	11.3*	10.1*	8.05*	5.67*
	Moody's	2.68*	3.64*	5.05*	6.76*	9.04*	8.71*	8.49*	9.38*	9.27*	8.80*	7.95*	6.89*	7.59*	6.68*	5.79*	5.10*	3.88*
	Fitch	2.90*	3.21*	4.58*	5.86*	6.82*	7.02*	6.25*	6.53*	6.25*	5.50*	5.23*	5.06*	5.57*	5.47*	4.39*	3.89*	2.72*
Italy	S&P	0.00	0.00	0.01	0.00	0.01	0.04	0.06	0.05	0.07	0.09	0.13	0.13	0.10	0.10	0.08	0.09	0.07
	Moody's	0.02	0.01	0.01	0.01	0.02	0.05	0.06	0.05	0.06	0.07	0.07	0.11	0.09	0.06	0.04	0.04	0.02
	Fitch	0.05	0.07	0.10	0.18	0.29	0.35	0.49	0.63	0.60	0.56	0.59	0.66	0.64	0.62	0.55	0.44	0.26
Ireland	S&P	1.90	3.19*	4.18*	5.24*	6.07*	6.17*	6.08*	6.41*	6.77*	5.77*	5.25*	6.30*	7.06*	6.31*	6.58*	4.94*	3.17*
	Moody's	1.67	2.40*	3.80*	5.56*	6.03*	6.20*	5.86*	6.95*	7.22*	6.61*	5.80*	6.30*	6.19*	5.03*	5.37*	4.60*	3.22*
	Fitch	1.51	2.74*	3.63*	4.95*	5.84*	6.30*	5.75*	7.04*	7.80*	7.47*	6.41*	7.79*	7.48*	6.61*	7.34*	5.91*	4.03*
Greece	S&P	0.54	1.00	1.39	2.21*	2.80*	3.79*	5.36*	7.65*	8.86*	10.2*	12.7*	15.5*	14.7*	17.9*	16.5*	15.1*	10.2*
	Moody's	0.33	0.57	1.10	1.90	2.36*	3.18*	4.42*	6.60*	7.72*	8.86*	10.9*	13.0*	11.6*	13.8*	14.2*	12.1*	8.24*
	Fitch	1.00	1.55	1.61	2.64*	2.88*	3.70*	4.77*	5.21*	6.19*	7.55*	8.40*	8.58*	8.03*	7.69*	8.13*	6.49*	5.76*
Spain	S&P	0.92	1.04	1.79	2.82*	3.26*	4.53*	5.64*	6.09*	7.12*	6.87*	8.50*	8.09*	7.30*	6.81*	5.22*	4.52*	3.01*
	Moody's	0.21	0.20	0.67	1.44	1.05	1.06	0.94	1.43	2.02*	2.55*	3.56*	4.36*	3.50*	2.74*	2.50*	3.12*	2.45*
	Fitch	0.93	1.14	1.50	3.20*	4.89*	6.65*	7.72*	9.46*	12.2*	13.6*	16.8*	15.9*	12.3*	10.9*	9.49*	8.89*	6.64*

Note: * indicates rejection of null hypothesis of no causality-in-quantiles at 5% level of significance.

Table 6a: Quantile causality (Returns) under ratings *upgrade*

Country	rating	Quantile																
		0.1	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**
Brazil	S&P	1.19	1.83	1.95	2.19	1.65	1.46	1.00	0.60	0.24	0.18	0.48	0.69	0.97	1.35	1.26	1.39	1.61
	Moody's	2.00*	2.54*	2.08*	1.85	1.43	1.23	0.88	0.81	0.53	0.77	1.22	2.05*	3.23*	3.92*	3.87*	3.73*	3.86*
	Fitch	1.13	1.06	0.88	0.92	0.96	0.79	0.68	0.43	0.37	0.38	0.56	0.65	0.48	0.64	0.79	0.81	1.01
Russia	S&P	2.71*	3.29*	3.57*	4.28*	4.73*	3.38*	2.86*	1.98*	1.73	1.81	0.89	0.72	1.24	2.00*	2.49*	3.56*	4.67*
	Moody's	6.65*	9.65*	11.0*	8.97*	7.72*	4.29*	2.87*	1.62	0.69	0.51	0.99	2.43*	4.04*	5.79*	6.91*	10.4*	8.72*
	Fitch	4.07*	3.77*	4.17*	4.37*	4.65*	2.77*	1.78	1.00	0.47	0.41	0.73	2.15*	3.32*	4.44*	5.53*	6.07*	7.62*
India	S&P	3.36*	2.75*	2.55*	2.33*	3.33*	3.88*	4.43*	3.64*	3.63*	5.92*	6.21*	6.19*	5.70*	6.58*	5.69*	5.40*	4.46*
	Moody's	2.89*	2.72*	3.16*	3.08*	3.55*	3.21*	3.10*	2.40*	1.85*	3.41*	2.96*	3.02*	2.94*	3.29*	2.98*	4.03*	4.05*
	Fitch	2.05*	2.13*	1.86	1.53	1.63	1.37	1.51	1.27	1.42	1.82	1.66	1.76	2.49*	2.86*	2.80*	2.87*	2.57*
China	S&P	1.62	2.02*	2.12*	0.89	0.72	0.62	0.42	0.30	0.27	0.48	0.72	0.96	1.22	1.41	1.46	1.95	1.57
	Moody's	1.03	1.11	0.98	0.67	0.45	0.38	0.28	0.17	0.23	0.46	0.92	1.20	0.93	1.14	1.15	1.61	1.35
	Fitch	1.07	1.28	0.90	0.59	0.46	0.45	0.47	0.51	0.33	0.46	0.93	1.40	1.59	1.88	2.47*	2.34*	1.57
South Africa	S&P	6.20*	7.65*	8.89*	6.37*	5.83*	4.58*	3.32*	2.50*	2.66*	3.66*	4.70*	6.75*	6.87*	8.84*	8.29*	7.29*	5.32*
	Moody's	5.43*	7.48*	8.67*	6.39*	5.46*	5.26*	4.06*	3.88*	5.62*	8.19*	9.79*	12.4*	10.5*	12.8*	11.2*	9.11*	5.48*
	Fitch	4.69*	7.37*	8.40*	6.58*	6.07*	4.53*	3.47*	3.43*	4.18*	5.98*	7.81*	9.97*	10.4*	11.4*	8.67*	7.53*	4.85*
Portugal	S&P	6.25*	8.33*	7.00*	6.06*	6.36*	5.80*	4.70*	4.04*	2.61*	2.98*	3.97*	4.87*	5.36*	6.56*	7.66*	6.59*	5.55*
	Moody's	4.36*	5.16*	5.04*	4.80*	5.00*	4.37*	3.70*	3.45*	2.23*	2.60*	3.68*	4.11*	3.99*	3.72*	4.34*	3.59*	3.39*
	Fitch	4.17*	5.37*	4.58*	4.96*	4.44*	4.47*	3.79*	3.22*	2.07*	2.26*	3.10*	3.18*	3.15*	3.27*	3.57*	3.00*	2.84*
Italy	S&P	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Moody's	0.04	0.08	0.07	0.03	0.03	0.03	0.03	0.02	0.00	0.01	0.02	0.07	0.12	0.23	0.25	0.17	0.10
	Fitch	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01
Ireland	S&P	5.11*	4.90*	5.90*	5.35*	4.26*	4.10*	3.31*	3.65*	3.15*	3.59*	3.48*	3.53*	3.77*	3.95*	4.47*	5.83*	5.39*
	Moody's	5.00*	4.95*	5.51*	4.89*	3.62*	3.62*	2.72*	3.06*	2.41*	2.54*	2.35*	2.58*	3.09*	3.95*	4.56*	5.82*	5.38*
	Fitch	3.70*	3.56*	4.00*	3.61*	2.78*	2.56*	1.86	2.57*	2.22*	1.96*	1.91	2.33*	2.37*	2.49*	2.76*	3.35*	2.63*
Greece	S&P	6.25*	7.78*	7.60*	6.37*	5.00*	4.60*	3.72*	3.54*	3.85*	5.00*	5.01*	4.42*	4.45*	5.18*	5.27*	5.40*	5.39*
	Moody's	4.99*	6.55*	7.12*	6.44*	5.13*	5.20*	4.19*	3.79*	4.04*	4.02*	4.18*	4.09*	4.02*	4.84*	4.81*	5.44*	4.92*
	Fitch	1.03	0.78	0.64	0.41	0.29	0.24	0.18	0.07	0.02	0.04	0.08	0.06	0.10	0.17	0.24	0.29	0.43
Spain	S&P	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Moody's	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fitch	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: * indicates rejection of null hypothesis of no causality-in-quantiles at 5% level of significance.

Table 6b: Quantile causality (Volatility) under ratings *upgrade*

Country	rating	Quantile																
		0.1	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**
Brazil	S&P	0.03	0.03	0.10	0.18	0.19	0.18	0.26	0.28	0.37	0.38	0.30	0.32	0.30	0.33	0.22	0.11	0.04
	Moody’s	0.02	0.03	0.14	0.22	0.29	0.42	0.53	0.66	0.75	0.87	0.69	0.82	0.84	0.79	0.68	0.54	0.32
	Fitch	0.11	0.12	0.07	0.05	0.07	0.10	0.04	0.03	0.01	0.01	0.04	0.04	0.04	0.03	0.02	0.01	0.01
Russia	S&P	0.12	0.30	1.35	1.83	2.75*	4.75*	5.41*	6.34*	6.34*	7.24*	8.35*	8.84*	9.55*	10.5*	11.2*	8.85*	5.91*
	Moody’s	2.83*	3.04*	4.99*	7.41*	9.17*	13.6*	16.6*	18.3*	21.9*	22.1*	24.6*	24.1*	25.6*	23.7*	18.8*	17.4*	11.9*
	Fitch	1.90	1.93	3.32*	4.58*	5.59*	6.63*	8.02*	9.34*	9.07*	9.29*	10.4*	10.6*	11.2*	11.2*	10.3*	9.23*	5.88*
India	S&P	0.89	1.69	1.99*	2.10*	1.66	1.76	1.94	2.18*	1.91	2.63*	2.34*	2.73*	3.20*	2.81*	3.13*	3.32*	2.58*
	Moody’s	0.80	0.94	0.93	0.90	0.94	1.35	1.72	1.85	1.48	1.08	1.23	1.16	1.31	1.31	1.34	0.97	0.81
	Fitch	0.11	0.20	0.30	0.46	0.56	1.39	1.62	1.60	1.70	3.23*	2.85*	3.62*	3.57*	3.58*	4.70*	4.05*	3.18*
China	S&P	1.08	1.29	1.47	2.17*	3.22*	3.59*	5.38*	6.63*	6.19*	7.08*	10.1*	9.42*	7.44*	6.63*	6.08*	6.16*	5.00*
	Moody’s	1.11	0.86	0.67	0.50	0.90	1.14	0.71	0.75	0.69	0.58	0.99	0.89	0.81	0.68	0.48	0.54	0.39
	Fitch	0.74	0.53	0.91	1.16	2.00*	2.18*	3.31*	3.76*	3.75*	5.21*	6.10*	6.32*	6.30*	5.57*	5.19*	3.02*	1.60
South Africa	S&P	2.25*	4.00*	7.69*	9.11*	11.1*	15.0*	16.5*	17.2*	21.8*	22.1*	23.1*	22.9*	24.7*	23.1*	17.8*	15.6*	12.5*
	Moody’s	2.76*	4.42*	7.93*	10.5*	12.4*	16.5*	17.0*	14.7*	19.7*	17.4*	17.6*	17.1*	17.2*	14.3*	11.7*	9.23*	7.22*
	Fitch	4.38*	6.99*	11.7*	15.0*	17.2*	20.6*	22.2*	22.5*	25.8*	22.7*	21.6*	21.0*	22.6*	19.1*	14.1*	10.8*	8.23*
Portugal	S&P	3.55*	4.49*	6.00*	7.98*	11.0*	9.94*	9.10*	9.93*	10.9*	10.9*	10.5*	8.86*	8.87*	8.27*	7.18*	6.43*	4.91*
	Moody’s	2.24*	2.68*	3.46*	4.49*	5.68*	4.80*	4.45*	5.28*	4.38*	3.74*	3.40*	3.34*	3.27*	2.86*	2.72*	2.82*	1.96*
	Fitch	2.64*	2.81*	3.99*	5.26*	6.01*	5.94*	5.06*	5.52*	5.57*	4.57*	4.18*	4.17*	4.44*	4.11*	3.24*	2.91*	1.86
Italy	S&P	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Moody’s	0.03	0.03	0.02	0.02	0.02	0.04	0.05	0.06	0.09	0.11	0.11	0.17	0.13	0.08	0.08	0.08	0.06
	Fitch	0.05	0.06	0.09	0.16	0.28	0.37	0.48	0.60	0.61	0.58	0.58	0.66	0.66	0.61	0.51	0.44	0.24
Ireland	S&P	1.72	3.11*	4.22*	5.40*	6.28*	6.30*	6.43*	7.19*	7.89*	7.55*	7.21*	9.28*	10.6*	10.6*	10.4*	8.14*	5.81*
	Moody’s	1.67	2.74*	4.24*	6.27*	6.82*	6.95*	6.61*	7.93*	8.73*	8.76*	7.88*	9.14*	9.62*	9.17*	9.03*	7.52*	5.35*
	Fitch	0.95	1.71	2.21*	3.12*	3.42*	3.79*	2.89*	3.51*	3.42*	2.55*	1.82	2.24*	2.18*	1.43	2.23*	1.86	1.25
Greece	S&P	0.57	1.32	1.98*	2.65*	3.35*	4.26*	5.49*	7.47*	9.10*	11.1*	12.8*	16.5*	17.5*	20.2*	17.4*	15.3*	10.5*
	Moody’s	0.21	0.25	0.41	0.48	0.65	0.86	1.01	1.39	1.97*	2.47*	3.25*	5.17*	5.17*	6.24*	6.28*	5.94*	4.86*
	Fitch	0.92	1.43	1.18	2.05*	1.95	2.73*	3.30*	3.41*	3.62*	4.09*	4.08*	4.27*	4.32*	4.08*	3.96*	3.14*	2.68*
Spain	S&P	0.34	0.50	0.95	1.64	1.54	2.20*	2.77*	3.58*	4.12*	3.89*	4.15*	4.67*	4.79*	4.45*	3.69*	3.05*	2.73*
	Moody’s	0.17	0.16	0.73	1.60	1.08	1.31	1.30	1.94	2.52*	2.52*	2.80*	2.80*	2.26*	2.02*	1.51	1.42	1.62
	Fitch	0.67	0.51	0.67	1.34	1.69	2.03*	1.93	2.38*	3.34*	4.07*	5.31*	5.48*	4.42*	3.23*	2.28*	1.70	1.36

Note: * indicates rejection of null hypothesis of no causality-in-quantiles at 5% level of significance.

Table 7a: Quantile causality (Returns) under ratings *downgrade*

Country	rating	Quantile																
		0.1	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**
Brazil	S&P	1.21	1.81	1.74	1.96	1.63	1.63	1.16	0.65	0.21	0.22	0.55	0.75	0.89	1.08	1.05	1.16	1.29
	Moody's	1.46	1.76	1.52	1.42	1.28	0.98	0.76	0.46	0.20	0.33	0.59	0.92	1.46	1.75	1.59	1.40	1.55
	Fitch	0.96	0.94	0.81	1.15	1.02	0.95	0.53	0.43	0.18	0.22	0.36	0.55	0.87	1.31	1.16	1.31	1.60
Russia	S&P	1.35	1.43	1.29	0.95	1.47	1.43	1.50	1.14	1.17	2.34*	2.70*	2.28*	2.23*	2.34*	2.29*	3.23*	2.25*
	Moody's	3.90*	6.14*	6.87*	6.03*	5.85*	3.62*	2.38*	1.28	0.47	0.40	0.42	0.76	1.39	2.25*	3.39*	5.06*	5.06*
	Fitch	1.61	1.51	1.42	1.58	2.07*	1.31	0.92	0.50	0.34	0.33	0.47	0.75	1.25	1.54	1.94	2.16*	2.75*
India	S&P	2.62*	2.68*	3.20*	2.97*	3.66*	3.11*	3.35*	2.08*	2.36*	3.41*	3.57*	3.60*	3.39*	3.88*	3.21*	3.63*	3.04*
	Moody's	3.54*	3.36*	3.85*	4.04*	4.55*	4.01*	3.66*	2.47*	1.80	3.23*	2.63*	2.82*	2.71*	3.23*	3.05*	4.01*	3.62*
	Fitch	2.16*	2.47*	2.18*	1.64	1.58	1.27	1.28	0.90	0.88	0.87	0.92	0.87	1.61	2.13*	2.20*	2.38*	2.25*
China	S&P	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Moody's	1.01	1.17	1.27	0.77	0.58	0.62	0.52	0.47	0.47	0.69	0.95	1.11	1.11	1.39	1.47	1.91	1.45
	Fitch	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
South Africa	S&P	3.28*	3.56*	5.13*	4.14*	3.78*	3.48*	2.73*	2.10*	1.48	1.85	1.95	2.11*	2.75*	3.32*	3.07*	2.04*	2.29*
	Moody's	3.49*	3.96*	5.55*	4.25*	4.16*	3.46*	2.62*	1.98*	1.29	1.70	1.77	2.06*	2.78*	3.41*	3.13*	2.48*	2.38*
	Fitch	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Portugal	S&P	6.63*	9.34*	8.20*	7.04*	6.50*	5.78*	4.61*	3.92*	2.46*	2.78*	3.52*	4.83*	5.23*	6.90*	8.44*	7.23*	6.18*
	Moody's	6.57*	7.81*	7.63*	7.31*	6.33*	5.77*	4.46*	4.19*	2.21*	2.53*	3.22*	4.25*	4.47*	5.15*	6.46*	5.19*	4.86*
	Fitch	5.88*	7.25*	6.49*	6.16*	4.90*	4.70*	3.92*	3.31*	1.64	1.99*	2.60*	3.27*	3.46*	3.98*	4.74*	4.05*	3.87*
Italy	S&P	0.05	0.09	0.08	0.07	0.04	0.01	0.01	0.01	0.01	0.01	0.02	0.04	0.08	0.11	0.15	0.13	0.07
	Moody's	0.05	0.07	0.05	0.02	0.02	0.03	0.04	0.03	0.01	0.00	0.01	0.05	0.08	0.16	0.17	0.12	0.08
	Fitch	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01
Ireland	S&P	6.82*	6.54*	6.48*	5.24*	4.31*	3.36*	2.48*	2.97*	2.34*	2.01*	2.29*	2.57*	3.11*	4.65*	5.28*	6.51*	5.94*
	Moody's	6.83*	5.85*	5.93*	4.96*	4.09*	3.31*	2.37*	2.70*	2.29*	1.88	2.38*	2.63*	2.85*	4.14*	4.80*	5.96*	5.53*
	Fitch	6.62*	7.05*	6.57*	5.57*	4.37*	3.69*	2.47*	2.98*	2.28*	1.87	1.93	2.22*	2.84*	4.09*	5.20*	6.82*	5.52*
Greece	S&P	6.53*	7.90*	8.08*	6.77*	5.34*	4.38*	3.48*	2.64*	2.14*	2.81*	2.84*	3.22*	3.04*	4.56*	5.40*	6.10*	6.41*
	Moody's	3.96*	4.68*	5.04*	4.68*	3.85*	3.63*	3.34*	3.10*	3.22*	3.47*	3.17*	3.50*	3.34*	3.85*	3.90*	4.18*	4.11*
	Fitch	0.84	0.71	0.60	0.45	0.31	0.21	0.17	0.11	0.06	0.05	0.12	0.10	0.13	0.20	0.23	0.29	0.35
Spain	S&P	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Moody's	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Fitch	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: * indicates rejection of null hypothesis of no causality-in-quantiles at 5% level of significance.

Table 7b: Quantile causality (Volatility) under ratings *downgrade*

Country	rating	Quantile																
		0.1	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**
Brazil	S&P	0.07	0.08	0.16	0.23	0.21	0.15	0.18	0.19	0.16	0.18	0.12	0.15	0.14	0.18	0.08	0.03	0.01
	Moody's	0.03	0.05	0.13	0.16	0.15	0.18	0.21	0.23	0.24	0.22	0.14	0.15	0.13	0.12	0.10	0.06	0.02
	Fitch	0.06	0.02	0.03	0.06	0.11	0.06	0.12	0.18	0.24	0.23	0.06	0.06	0.05	0.05	0.05	0.02	0.02
Russia	S&P	0.10	0.34	0.24	0.90	1.38	1.86	2.55*	2.49*	3.84*	3.41*	3.07*	3.70*	4.24*	4.10*	2.66*	2.86*	2.21*
	Moody's	4.18*	4.02*	6.14*	9.60*	11.2*	14.8*	18.0*	20.5*	24.0*	25.8*	28.8*	29.1*	32.0*	31.9*	26.7*	24.0*	17.8*
	Fitch	2.60*	2.94*	4.66*	7.22*	9.37*	10.3*	12.0*	14.9*	14.4*	14.6*	17.2*	17.2*	20.1*	22.0*	21.2*	20.2*	13.0*
India	S&P	1.27	1.83	1.55	2.23*	1.65	2.03*	2.89*	2.89*	2.13*	1.20	1.08	1.00	1.06	0.81	0.81	0.77	0.94
	Moody's	0.89	1.17	0.91	1.53	1.19	1.90	2.43*	2.37*	1.76	1.39	1.32	1.23	1.41	1.16	1.39	1.06	0.71
	Fitch	0.10	0.15	0.25	0.31	0.53	0.94	1.06	1.07	1.71	2.44*	2.07*	2.73*	3.06*	3.71*	4.16*	3.09*	2.59*
China	S&P	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Moody's	1.32	1.47	1.52	1.86	2.79*	3.19*	3.92*	4.83*	4.53*	5.46*	7.83*	7.81*	6.90*	6.08*	5.58*	5.30*	4.09*
	Fitch	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
South Africa	S&P	0.14	0.22	0.47	0.75	0.63	0.74	1.24	0.82	1.14	0.82	0.60	0.58	0.26	0.40	0.40	0.58	0.55
	Moody's	0.45	0.80	1.35	1.71	2.43*	2.41*	3.15*	2.15*	2.73*	1.90	1.90	1.59	0.95	0.86	0.95	0.90	0.76
	Fitch	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Portugal	S&P	3.81*	4.53*	5.65*	6.10*	9.86*	9.08*	8.02*	9.42*	12.1*	13.0*	12.5*	10.5*	10.8*	10.6*	9.6*	8.2*	6.3*
	Moody's	2.86*	3.65*	4.86*	4.83*	6.83*	7.59*	6.19*	6.91*	7.79*	7.93*	7.04*	5.66*	6.11*	5.68*	5.34*	5.27*	2.94*
	Fitch	2.62*	3.23*	4.18*	3.68*	4.95*	5.86*	4.56*	4.56*	5.05*	5.16*	4.90*	4.17*	4.13*	4.44*	4.75*	4.27*	2.37
Italy	S&P	0.00	0.00	0.00	0.01	0.01	0.04	0.05	0.04	0.07	0.08	0.09	0.11	0.08	0.08	0.04	0.05	0.03
	Moody's	0.02	0.02	0.01	0.01	0.01	0.03	0.03	0.03	0.05	0.06	0.07	0.12	0.10	0.06	0.07	0.06	0.06
	Fitch	0.04	0.06	0.09	0.18	0.28	0.33	0.46	0.58	0.55	0.49	0.53	0.58	0.56	0.54	0.45	0.36	0.18
Ireland	S&P	0.75	1.56	1.51	1.20	1.35	1.53	1.76	2.55*	3.51*	3.82*	3.78*	4.42*	6.51*	6.80*	7.65*	7.62*	5.51*
	Moody's	0.88	1.46	1.71	1.15	1.03	1.27	1.57	1.84	2.62*	3.12*	3.03*	3.36*	4.90*	4.91*	6.06*	6.45*	4.46*
	Fitch	1.16	2.11*	2.13*	1.52	1.58	1.86	2.23*	2.65*	3.63*	4.20*	4.39*	5.45*	6.10*	6.86*	8.06*	8.03*	5.85*
Greece	S&P	0.23	0.54	0.80	1.30	1.70	1.96*	1.98*	3.30*	4.10*	4.85*	4.90*	7.06*	7.25*	8.09*	8.51*	6.39*	4.80*
	Moody's	0.12	0.73	0.85	2.65*	3.11*	3.59*	4.61*	4.62*	4.77*	4.54*	5.13*	4.44*	3.08*	3.07*	3.04*	2.08*	1.05
	Fitch	0.63	0.73	0.92	1.52	1.49	1.94	2.22*	3.01*	2.73*	3.44*	3.77*	4.22*	4.04*	4.26*	4.65*	4.44*	3.92*
Spain	S&P	0.34	0.54	0.65	1.10	1.51	2.66*	3.21*	4.87*	6.28*	7.47*	10.2*	12.9*	11.0*	10.8*	10.2*	10.7*	8.4*
	Moody's	0.15	0.17	0.28	0.67	0.56	0.81	1.01	1.78	2.35*	3.43*	5.12*	6.46*	5.25*	4.56*	4.20*	4.78*	4.22*
	Fitch	0.19	0.17	0.30	0.54	0.66	0.93	1.18	2.13*	3.11*	4.47*	6.72*	8.65*	6.90*	5.97*	5.87*	4.97*	4.28*

Note: * indicates rejection of null hypothesis of no causality-in-quantiles at 5% level of significance.

Figure 1: Time series graphs of daily returns series.

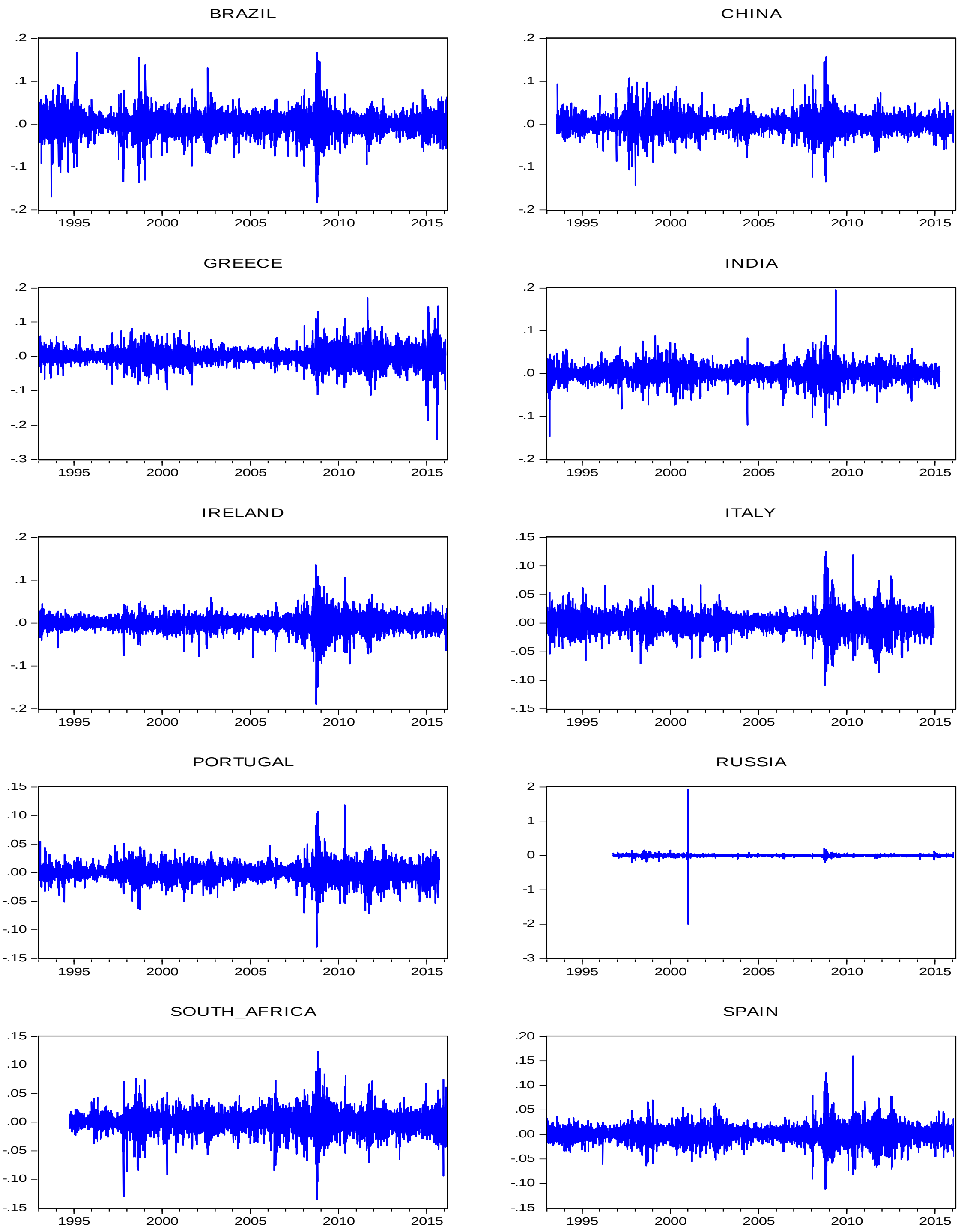

Figure 2: Time series graphs of credit ratings by S&P, Moody's and Fitch