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Country Risk Ratings and Stock Market Returns in BRICS Countries: A Nonlinear Dynamic Approach

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Abstract

This study examines the linkages between BRICS stock market returns, country risk ratings and international factors via Non-linear Auto Regressive Distributed Lags models (NARDL) that allow testing the asymmetric effects of changes in country risk ratings on stock market returns. We show that BRICS countries exhibit quite a degree of heterogeneity in the interaction of their stock market returns with country-specific political, financial and economic risk ratings. Positive and negative rating changes in some BRICS countries are found to have significant implications for both local stock market returns as well as commodity price dynamics. While the commodity market acts as a catalyst for these emerging stock markets in the long-run, we also observe that negative changes in the country risk ratings generally command a higher impact on stock returns, implying the greater impact of bad news on market dynamics. Our findings suggest that not all BRICS nations are the same in terms of how they react to ratings changes and how they interact with global market variables.

JEL classification : C32, F21, G32.

Keywords: Asymmetric responses; NARDL models; Stock market returns; Country risk ratings.

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1. Introduction

Since 2001, when Jim O’Neill coined the acronym BRIC for Brazil, Russia, India and China, this group of countries has experienced spectacular growth rates, especially in the period 2001-2010, and has played an increasingly important role in the world economy.¹ In fact, BRICS nations represent 41.3% of the total global population and 20.2% of total global GDP. Furthermore, from January 1988 to September 2015, the excess returns of emerging markets have been higher than in developed markets, while emerging market stock returns have a low correlation with developed market returns (Harvey, 2012), providing international investors with favorable risk and return tradeoffs and risk diversification opportunities. These characteristics explain, for example, why BRICS countries are large recipients of global investment flows, receiving 20% of the world FDI inflows and comprising about 24.6% of gross equity market capitalization (World Bank, 2015).

In the framework of standard asset pricing theories (Sharpe, 1964; Lintner, 1965), investment decisions are not only determined by expected stock returns, but by the volatility dynamics as well. To that end, BRICS stock markets have been subject to different risks over the last two decades. First, and due to the increasing integration across global markets, BRICS stock market returns are affected by international risk factors, such as the global financial crisis of 2007-2009 or the fluctuations in global commodity prices as this group countries represent some of the major commodity exporters and importers globally. Second, since these countries are not completely integrated with the world market (Errunza and Losq, 1985), domestic factors and country risk ratings also play an important role in their local stock market returns. This paper aims to test the validity of these considerations in a comprehensive framework that links country specific risk factors and key global factors in a parsimonious model. The country-specific risk factors are represented by three risk ratings: (i) political risk, which includes information on government stability, socioeconomic conditions, investment profile, internal and external conflict,

¹ In 2010, South Africa joined this group of countries and formed the BRICS.

corruption, democracy and bureaucracy; (ii) financial risk, which measures foreign debt service over GDP, current account over exports of goods and services, months of imports cover and exchange rate stability; (iii) economic risk, which provides evidence on per capita GDP, real GDP growth, annual inflation rate, budget deficit over GDP and current account over GDP. In this context, the objective of this paper is to analyze the linkages between stock market returns, country risk ratings and international factors in each of the BRICS countries using a parsimonious framework via Non-linear Auto Regressive Distributed Lags (NARDL) models. Clearly, such an examination is of interest to not only emerging market investors in their market timing strategies in and out of these major emerging markets, but also for domestic stakeholders in the management of local and global risks in the local market.

This paper contributes to the literature on international finance in several ways. First, we analyze each of the BRICS economies separately, allowing for heterogeneity in the response of each country to each global or individual risk indicator. To that end, in contrast with most studies in the literature that analyze BRICS markets as a whole, our analysis enlarges our understanding of the idiosyncratic characteristics of these key emerging markets. Second, and as far as the methodology is concerned, the NARDL specification employed in this paper allows us to jointly model the long- and short-run asymmetries in the relationships among the variables. As Shin et al. (2013) note, this methodology has two main advantages. First, it allows to simultaneously estimate long and short-run asymmetries. Second, it provides a straightforward way of testing both long- and short-run symmetry restrictions. Finally, the analysis of the dynamic long- and short-run linkages among the country-specific and global risk factors provides further insight to the findings from various strands of the literature that deal with issues including international transmission of shocks or contagion (e.g. Forbes and Rigodon, 2002), risk management (e.g. Scholes, 2000) and international portfolio diversification (e.g. Grubel, 1968).

Our findings suggest that BRICS countries exhibit quite a degree of heterogeneity in the interaction of their stock markets returns with country-specific financial, political and economic risk factors, while the most prevalent effects are observed in the case of China. We observe that symmetry, in both the short and long run, is largely rejected for all country-specific risk factors, suggesting that positive and negative changes in political, financial and economic risk ratings yield asymmetric impact on stock market returns as well as global variables. We also observe quite a degree of interaction among country-specific risk factors as well, particularly for Brazil and India, consistently across the financial, political and economic risk rating factors.

Our estimations indicate that positive and negative rating changes in some BRICS countries, particularly Brazil, China and Russia, have significant implications for both local stock market returns as well as commodity price dynamics. This finding is indeed interesting meaning that ratings changes in BRICS nations can have effects beyond financial markets, leading to spillover effects over commodities. At the same time, we observe that, in the long-run, the commodity market acts as a catalyst for these emerging stock markets as opposed to developed stock markets. We also observe that negative changes in the country risk ratings generally command higher coefficient estimates in absolute value, implying the greater impact of bad news on market variables. Particularly, the Chinese stock market stands out in its long-run equilibrium relationship with country rating changes, while no significant effects are observed for India and Brazil.

Finally, shocks in financial and political ratings are found to have negative long-run effects on the stock market, regardless of the sign of the shock, while an opposite effect is observed for economic ratings. While some of the results can be attributed to the informational inefficiencies and mis-pricing present in these stock markets, our findings clearly suggest that not all BRICS nations are the same in terms of how they react to ratings changes and how they interact with

global market indicators. From an investment perspective, our findings can be used as a guideline for global investors in their market timing strategies towards emerging stock markets.

The remainder of the paper is structured as follows: Section 2 provides the literature review. Section 3 describes the methodology and the construction of the NARDL model. Section 4 presents the data and the empirical results, and finally, Section 5 provides concluding comments and policy implications.

2. Literature Review

The empirical analysis carried out in this paper is related to various strands of the literature. One is the literature that deals with international equity correlations and portfolio diversification (e.g. Erb et al., 1994) as our analysis provides insight to the relationship between emerging stock market returns and global factors including returns for advanced stock markets. In an early study, Erb et al. (1994) find that cross-equity correlations in the G-7 countries are affected by the business cycle, while Longin and Solnik (1995) later document an increase in cross-country correlations during volatile periods. De Santis and Gerard (1997) also find evidence of asymmetric correlations in up and down markets, consistent with the evidence by Longin and Solnik (2001) and Ang and Bekaert (2004) who document higher return correlations in bear markets. We approach these considerations from a different angle and estimate the short and long-run asymmetric relationships between the stock returns for each BRICS country and the developed stock returns. By doing so, we determine not only which emerging country exhibits a greater degree of comovement with developed markets, but also provide insight to the dynamic nature of this comovement over the business cycles.

As mentioned earlier, the NARDL model employed in this study is specified to account for both country-specific and international risk factors as determinants of stock market returns. The relationship between stock market return and risk has been widely analyzed in the literature with

various studies examining alternative proxies for risk at both the country and global levels. The nature of the risk-return relationship and the channels with which risk relates to returns, however, remains an open question. Harvey (1995a, b), for example, find that both the mean and volatility of returns are higher in emerging than in developed countries. Focusing on 40 national equity markets, out of which 19 were emerging countries, Erb et al. (1995) show that country credit ratings are correlated with future equity returns and volatility. Erb et al. (1996) later argue that higher expected returns are associated with higher risk components, while Kaminsky and Schmukler (2001) find that changes in sovereign ratings have an impact on country risk and stock returns. Harms (2002) further supports these arguments and shows that political risk is an important determinant of stock market returns. Similarly, Bekaert and Harvey (1997) point out the greater role political risk plays in driving emerging market returns compared to its effect on developed markets. Further supporting this findings, Bilson et al. (2002) use data for a sample of 17 emerging and 18 developed markets and show that political risk is important in explaining return variation in emerging markets, but not in developed markets. Later, the significant role played by political risk factors on emerging market returns is further supported by numerous studies including Ramcharran (2003), Girard and Omran (2007), and Lehkonen and Heimonen (2015) using various data periods and country samples. Recently, focusing on BRICS stock markets, Balcilar et al. (2017) use the geopolitical risk index developed by Caldara and Iacoviello (2016) and show that BRICS nations exhibit heterogeneous exposures to geopolitical risks while Russia bears the greatest risk exposure to geopolitical uncertainties.

Finally, our study also contributes to the strand of the literature that deals with the relationship between oil price shocks and stock market returns (e.g. Hamilton, 1983; Kang and Ratti, 2013). On that aspect, BRICS countries provide an interesting mix of emerging stock markets as it includes some of the major net oil importers (China and India are two of the largest

oil importers) and exporter countries (Russia, Brazil), which allows for a comparative analysis of the stock and oil market relationship across heavy importers and exporters.

It must be noted that there are three papers in the literature, noteworthy of mention, that have also looked, using different methodologies, into the interactions across BRICS stock returns, country risk ratings and global risk factors, and have detected statistically significant relationships in the short- and long-horizons. For example, Mensi et al. (2016) analyse the asymmetric relationship between BRICS stock returns and country risk ratings via a dynamic panel smooth threshold regression (PSTR) model.² Liu et al. (2013) estimate a multivariate momentum threshold autoregression (MTAR) model and examine the relationship between stock markets for each of the five BRICS countries and country risk ratings, with the latter paper being an extension of the ARDL approach taken by Hammoudeh et al., (2013) to analyze the impact of credit ratings on the BRICS in a linear framework.³ The main advantage of our methodology from those of Hammoudeh et al. (2013), Liu et al. (2013), and Mensi et al. (2016) is that the NARDL model allows us to examine the presence of asymmetric effects in the short- and long-run relationships among the variables of interest. The main advantage of this approach is that it allows us to examine the asymmetric interactions across the variables by distinguishing between the positive and negative changes in the explanatory variables via partial sums. This procedure then allows us to capture the hidden cointegration, which is not possible with standard methods. By doing so, this paper provides a more comprehensive insight to the long and short run effects of the increases and decreases (i.e., positive and negative shocks) in country-specific risk factors and global factors on stock returns. Hence unlike the MTAR model of Liu et al., (2013), we do not study the asymmetric speed of adjustment to long-run equilibrium following positive and negative shocks, but the short- and long-run impact of positive and negative shocks of country-risk ratings on short and long-run

² Mensi et al., (2017) also used this approach to carry out a similar analysis for Gulf Cooperation Council (GCC) countries.

³ Sari et al., (2013) have also used the ARDL model to study the impact of country risk ratings on the Turkish stock market.

behavior of the stock market. Given our objective of analyzing the role of positive and negative shocks in short and long-runs, we understandably, also deviate from the PSTR approach of Mensi et al., (2016). These authors aim to analyze nonlinear short-run relationship between stock returns and country-risk ratings by allowing for regime-switching in a panel set-up. Thus in the process, they try to capture the asymmetric effect of the predictors on upper (bull) and lower (bear) regimes of stock returns, with the transition across the regimes being brought about based on an observable threshold variable in a smooth-fashion rather than in an abrupt-manner (based on the outcome of an unobservable regime variable) as in a Markov-switching model. To the best of our knowledge, this is the first paper to use a NARDL approach to study the asymmetric short and long-run effects of increases and decreases in country-risk ratings. Next, we explain the specification of the NARDL model.

3. Methodology

The empirical analysis adopted in this paper is based on the Nonlinear Autoregressive Distributed Lag (NARDL) model recently developed by Shin et al. (2014). This approach is designed to examine the presence of asymmetric effects in the short- and long-run relationships among variables of interest, in our case the three BRICS's country risk rating factors, their respective national stock market returns as well as two global factors, namely, the commodity index and the MSCI developed country index. The NARDL model is an asymmetric extension of the linear autoregressive distributed lag (ARDL) cointegration model developed by Pesaran et al. (2001) by taking account of short and long run asymmetric behavior in the model. To capture the asymmetric behavior across the variables, Shin et al. (2014) split the explanatory variables into their positive and negative partial sums as follows: $x_t = x_0 + x_t^+ + x_t^-$. Here, the two components x_t^+ and x_t^- are, respectively, positive and negative partial sums of x_t , such as

$$x_t^+ = \sum_{i=1}^t \Delta x_i^+ = \sum_{i=1}^t \max(\Delta x_i, 0) \text{ and } x_t^- = \sum_{i=1}^t \Delta x_i^- = \sum_{i=1}^t \min(\Delta x_i, 0) \quad (1)$$

This approach of partial sum decomposition was initially used by Granger and Yoon (2002) and Schorderet (2001) to examine the presence of asymmetric cointegration. The advantage of this decomposition is that positive and negative partial sums reflect, respectively, the increase and decrease of the explanatory variable. The NARDL model including both decomposed asymmetric variables and symmetric variables has the following error correction form

$$\Delta y_t = c + \rho y_{t-1} + \theta_w w_{t-1} + \theta_x^+ x_{t-1}^+ + \theta_x^- x_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + \sum_{j=0}^{q-1} (\varphi_{w,j} \Delta w_{t-j} + \varphi_{x,j}^+ \Delta x_{t-j}^+ + \varphi_{x,j}^- \Delta x_{t-j}^-) + \varepsilon_t \quad (2)$$

where $x_t = x_0 + x_t^+ + x_t^-$ is a $k \times 1$ vector of exogenous regressors entering the model asymmetrically, while w_{t-1} is an $m \times 1$ vector of other exogenous regressors entering the model symmetrically. ρ and θ_w are the symmetric long-run parameters while θ_x^+ and θ_x^- are the asymmetric long-run parameters.⁴ Similarly, $\varphi_{w,j}$ are the symmetric short-run coefficients while $\varphi_{x,j}^+$ and $\varphi_{x,j}^-$ are the asymmetric short-run coefficients. The latter two coefficients denote the short-run adjustments to the positive and negative shocks affecting the asymmetric regressors. γ_i are the autoregressive parameter and ε_t is i.i.d. zero mean random variable with finite variance σ_ε^2 . Finally, p and q represent the respective lag orders for the dependent variable y_t and the exogenous variables w_t and x_t in the distributed lag component.

If the coefficients associated with the partial sum variables in the short run, the long run or both differ significantly, then an asymmetric impact on the dependent variable can be established. In addition, one can compute the symmetric and the asymmetric positive and negative long-run coefficients, respectively as follows

$$L_w = \frac{-\theta_w}{\rho}, L_{x^+} = \frac{-\theta_x^+}{\rho} \text{ and } L_{x^-} = \frac{-\theta_x^-}{\rho} \quad (3)$$

⁴ The parameter ρ is assumed to be negative in order to have a cointegration relationship among the variables.

such that the statistical significance of these coefficients provides insights about the long-term relationships between the dependent variable and the respective independent variables. Positive sign of these coefficients indicates that positive or negative shocks in the exogenous variables have positive or negative long run effect, respectively, on the dependent variables while negative sign implies opposite effects.

As mentioned earlier, the NARDL model offers many benefits over traditional methods investigating the cointegration relationship, such as Engle and Granger (1987), Johansen and Juselius (1990), etc. An important advantage of the NARDL model is that it allows testing for long and short run asymmetries between the independent and dependent variables. Furthermore, it has the ability to combine I(0) and I(1) regressors, allowing us to capture the hidden cointegration which is not possible with standard methods.⁵ Finally, it performs better when testing for cointegration relationships in small samples compared to alternative cointegration procedures (Romilly et al., 2001).

In our empirical analysis, we consider the following regressions of the NARDL based error correction model presented in Equation 2. As explained earlier, we use the NARDL model to investigate the possible existence of both the long- and short-run asymmetries in the response of each dependent variable to positive and negative changes in risk rating factors.

$$\text{Model 1: } y = CM, \quad w = (S, SD), \quad x = (P, F, E) \quad (4a)$$

$$\text{Model 2: } y = S, \quad w = (CM, SD), \quad x = (P, F, E) \quad (4b)$$

$$\text{Model 3: } y = P, \quad w = (CM, S, SD), \quad x = (F, E) \quad (4c)$$

$$\text{Model 4: } y = F, \quad w = (CM, S, SD), \quad x = (P, E) \quad (4d)$$

$$\text{Model 5: } y = E, \quad w = (CM, S, SD), \quad x = (P, F) \quad (4e)$$

$$\text{Model 6: } y = SD, \quad w = (CM, S), \quad x = (P, F, E) \quad (4f)$$

where S is the BRICS stock index; P, F and E are the BRICS political, financial, and economic risk rating factors, respectively; CM is the commodity index and SD is the MSCI

⁵ According to Granger and Yoon (2002), two time series are hidden cointegrated if their positive and negative components are cointegrated with each other.

developed country stock index. The variables are measured in natural logarithm. Since the data is on monthly frequency, the maximum order of the lags in the NARDL model is chosen to be 12.

The estimation procedure adopted in this paper is as follow: Models 1-6 presented in Equations 4a-4f are estimated for each BRICS market one at a time. For each model, following Shin et al. (2014), we start with the maximum lag order $p_{\max} = q_{\max} = 12$ and then drop all insignificant stationary regressors sequentially. Next, we test the presence of cointegration among the variables of the final specification to identify the long-run relationships between the dependent and the independent variables. To achieve this, the significance of the lagged levels of the variables in the underlying NARDL model specification is tested using the F-statistic (denoted as FPSS test) where the null hypothesis of no cointegration is that the coefficients on the level variables are jointly equal to zero. For example, the null hypothesis for Model 1 in Equation 4a is stated as $H_0 : \rho = \theta_S = \theta_{SD} = \theta_P^+ = \theta_P^- = \theta_F^+ = \theta_F^- = \theta_E^+ = \theta_E^- = 0$.

4. Data and Empirical Results

4.1 Data

We use Political Risk Services (PRS)'s International Country Risk Guide (ICRG) composite, economic, financial and political risk ratings for the five BRICS countries over the monthly period of January, 1995 to December, 2015 (i.e., a total of 252 monthly observations). For the same period and frequency, we sourced the MSCI developed countries stock index and the dollar-denominated MSCI equity return indexes of the BRICS countries. Denominating the stock market indices in US dollars helps us to eliminate the effect of local inflation and national exchange rate fluctuations. We also use the S&P GSCI commodity spot price index, since these markets are large consumers and producers in the global commodity markets. Note the same start and end periods across the BRICS countries are determined purely by data availability and to ensure comparability of results based on the sample size.

The ICRG of PRS creates the composite country risk ratings comprised of the political risk (PR) ratings; financial risk (FR) ratings and economic risk (ER) ratings. The PR accounts for 50 percent of the composite risk ratings, while each of the other two ratings have a weight of 25 percent each of the composite. It is important to note that the greater the number of points assigned for a risk ratings factor, the lower the risk measured by that factor. The PR rating group identifies 12 political risk indicators covering government stability to conflict, corruption, democracy and bureaucracy. The five indicators with the highest weight and assigned 12 points each are: Government Stability; Socioeconomic Conditions; Investment Profile; Internal Conflict and External Conflict. All the remaining indicators have six points each, barring, Bureaucracy Quality, which is assigned four points. The total number of points for the PR group is 100. The FR group includes five financial risk indicators, with each of them assigned 10 points to make up a total of 50 points. The five indicators are: Foreign Debt Service/GDP; Current Account/ Exports of Goods and Services; Months of Imports Cover; Exchange Rate Stability. Finally, the ER group also includes five economic risk indicators, with a total point of 50 also assigned for this group like the FR group. The five ER indicators are: GDP per Capita; Real GDP Growth, Annual Inflation Rate; Budget Deficit/GDP; Current Account/GDP.

Figure A1 in the Appendix presents the time-series graphs of the data used in the study. The first five graphs show the risk ratings in the BRICS countries. The risk rating levels and variations differ from one country to another. In particular, the composite, economic and financial risk ratings for China exhibit remarkably low variation over time, especially from 1998 onwards. Unlike China, Russia's risk ratings exhibit much greater variation. Examining the stock price dynamics of developed and BRICS markets as well as the S&P GSCI commodity spot price index, we generally observe that all BRICS countries have experienced an upward trend in their stock market indices over the whole sample period with the exception of China.

The descriptive statistics presented in Table A1 in the Appendix show that the highest mean and median values in composite, economic and financial risk ratings are observed in China, while the highest mean and median values of political risk rating are in South Africa. Therefore, the comparison of the mean values for country ratings suggests that among the BRICS countries, China is the least economically and financially risky country while South Africa is the least politically risky country. On the other hand, Brazil has the lowest mean and median values in terms of composite and financial risk ratings, while India experiences the lowest mean and median values for both economic and political risk ratings. These observations suggest that Brazil is the most financially risky country while India is the most economically and politically risky country. However, examining the coefficient of variation values, i.e. the ratio of standard deviation to mean, we can see that the higher values are observed in Russia for all four risk categories, suggesting that Russia experiences the highest historical volatility for all country risk ratings, possibly making it harder for global investors to come up with economic forecasts for this major economy.

We also observe that almost all the risk ratings series have negatively skewed distributions (except China for the composite risk index and South Africa for both composite and political risk indexes), indicating that there is greater probability of large increases in risk levels (i.e., decreases in risk ratings) than decreases. Significant high kurtosis values are observed only for China's economic and financial risk ratings implying fatter tails than a normal distribution for these two risk measures, while significant low values are obtained for India's composite and financial risk ratings, China's political risk rating and South Africa's composite risk rating. This implies that the distribution of the above-mentioned risk factors is concentrated towards the mean and has skinny tails. These observations are further supported by the JB statistics, indicating rejection of the normality assumption at the conventional significance levels for the four risk factors in all BRICS countries except for China's composite risk rating.

4.2 Empirical Results from the NARDL Models

We begin our analysis by testing the presence of the long-run cointegrating relationship among variables in Models 1-6 presented in Equations 4a-4f. As mentioned earlier, we test the significance of the lagged levels of the variables in each underlying NARDL model using the F-statistic (denoted as FPSS test) where the null hypothesis of no cointegration is that the coefficients on the level variables are jointly equal to zero. Table 1 reports the results of the FPSS tests for each model across the BRICS stock markets presented in different columns.

Examining the results for Model 2 in Equation 4b where the stock market index is the dependent variable, we observe that the FPSS test statistics are highly significant only in the case of China and Russia, implying a long-run equilibrium relationship between the stock market index, the commodity index, the MSCI developed country index and the positive and negative changes in the economic, financial and political risk ratings. On the other hand, when the political risk rating is used as a dependent variable, we observe evidence of a long-run cointegrating relationship for Brazil, India and Russia only, while the same result holds for Brazil, India and South Africa when financial risk rating is the dependent variable. However, taking the economic risk rating as a dependent variable produces evidence of a long-run relationship for all BRICS countries except China. These findings suggest that BRICS countries exhibit quite a degree of heterogeneity in the interaction of their stock market returns with country-specific financial, political and economic risk factors, while the most prevalent effects are observed in the case of China and Russia. However, quite a degree of interaction is also observed across country risk factors as well, particularly for Brazil and India, consistently across the financial, political and economic risk rating factors.

In the case of commodity returns specified as the dependent variable, as specified in Model 1, we observe a long-run cointegrating relationship in the case of Brazil, China and Russia only. This is not unexpected as these countries represent major exporters and importers in our sample. Sudden shocks in the country-specific risk factors for these major players can significantly affect

commodity return dynamics. Interestingly, however when the MSCI developed stock market index is the dependent variable (Model 6), Brazil and Russia drop out and are replaced by South Africa, implying greater integration of this BRICS nation along with China with the world stock markets. While it is not surprising to observe a significant interaction between positive and negative changes in country specific risk factors for China and global stock market movements as this country is a key catalyst for global market dynamics, it is interesting that South Africa also yields significant results, possibly due to the degree of integration of this emerging market with global stock markets. Next, we examine the findings for the NARDL models.

The estimation results for the NARDL models for each BRICS stock market is presented in Table 2. As noted earlier, the main focus of this study is the possible existence of both long-run and short-run asymmetries in the response of BRICS stock market returns to positive and negative changes in risk rating factors. For this purpose, we report for each country, only the estimation results for Model 2 in Equation 4b where the stock market return is the dependent variable. The results for the remaining models are not reported for brevity and are available upon request. As noted earlier in the model description, L_{x^+} and L_{x^-} ($x = P, F$ and E) are the asymmetric positive and negative long-run coefficients and L_{CM} and L_{SD} are the symmetric long-run coefficients for the commodity and global stock markets. We use the Wald test statistic denoted by WLR_x in the table to test long-run symmetry represented by the null hypotheses $H_0: L_{x^+} = L_{x^-}$. Similarly, WSR_x is the short-run asymmetry test statistic based on the Wald test for the additive short-run symmetry formulated by the null hypothesis: $H_0: \sum_{j=0}^{q-1} \varphi_{x,j}^+ = \sum_{j=0}^{q-1} \varphi_{x,j}^-$.

The BDM test based on the co-integration test statistic by Banerjee et al. (1998) confirms the earlier FPSS test results, indicating cointegration in all considered equations for each country with the exception of Model 2 for Russia and Model 6 for China and South Africa⁶. Examining the

⁶ Results of the BDM test for all equations are available upon request.

symmetric long-run coefficients in Table 2, we observe quite a degree of heterogeneity across the BRICS stock markets. One commonality, though, is that the commodity market seems to have a more consistent long-run equilibrium relationship with BRICS stock markets compared to that with developed stock markets, implied by significant estimates for L_{CM} across all BRICS markets with the exception of Brazil. This confirms our prior argument that commodity market movements indeed act as a systematic catalyst for stock market movements in this bloc of major global importer and exporters. Interestingly, the L_{CM} values are estimated to be positive regardless of the importer or exporter classification, implying a positive long-run relationship between the commodity and BRICS stock markets. Considering that oil carries a significant weight in the commodity index, a positive trend in commodity markets may indicate improving demand for energy (and other raw materials for production) due to favourable global economic fundamentals, which also means good news for emerging countries as investors would be more willing to divert their funds into emerging stock markets in order to ride the wave of global growth expectations. On the other hand, a significant long-run equilibrium relationship with developed stock markets is only observed in the case of India, with weaker results for South Africa. These observations imply that, in the long-run, the commodity market acts as a catalyst for these emerging stock markets as opposed to developed stock markets.

Looking at the asymmetric impact of country rating changes, once again, we observe that BRICS stock markets exhibit heterogeneity in their long-run relationship with country risk ratings, with the strongest asymmetric effects observed in the case of China. We generally reject symmetry in both the short- and long-run, implying that positive and negative changes in political, financial and economic risk ratings yield an asymmetric impact on stock market returns. We also observe that negative changes in the country risk ratings generally command higher coefficient estimates in absolute value, implying the greater impact of bad news on stock market dynamics. This can be a manifestation of informational inefficiencies plaguing these emerging markets as investors over-

react to bad news, either due to possible herding effects that are more prevalent during bad times or due to loss aversion by investors.

Focusing on the findings for China, we see that shocks in political and financial ratings have a negative long-run effect on its stock market return, regardless of the sign of the shock, implied by negative estimates for L_{P+} , L_{P-} , L_{F+} , and L_{F-} for this country. The negative effect on the stock market may be a manifestation of the increased uncertainty these shocks bring to the market as retail investors who dominate this emerging stock market scramble to make sense of what the rating change truly means in terms of future growth expectations. In fact, we observe a similar negative effect of rating changes in the case of Russia and partially in South Africa as well, regardless of the sign of the change. To that end, the prevalent negative effect of financial and political rating changes may be due to informational inefficiencies in the stock market that hinders the processing of new information in a fundamental way, thus leading investors to take a cautious stand in their investments.

Finally, we do not observe any significant asymmetric effects of rating changes in the case of Brazil and India. The insignificant results observed for India is in fact consistent with the recent finding by Balcilar et al. (2017) that India is the most resilient BRIC nation to geopolitical risks with no significant causality effects observed on its stock market returns. Overall, our findings point to heterogeneity in the way BRICS stock markets react to country risk rating changes with the strongest effects observed in the case of China and in the case of negative rating changes. Furthermore, we observe the effect of these rating changes are not limited to stock markets only, but spills over to the commodity market as well.

5. Conclusions

This study examines the interactions of stock market returns with country risk ratings and global risk factors via a Non-linear Auto Regressive Distributed Lags (NARDL) specification that

allows testing the presence of asymmetric effects in the short- and long-run relationships. We capture asymmetric cointegration by differentiating between positive and negative changes in country-specific risk factors measured by the political, financial and economic risk ratings. Focusing on the major emerging stock markets in the BRICS, we analyze the linkages between local stock market returns, country risk ratings and international factors, including commodity and developed stock markets.

Our findings suggest that BRICS countries exhibit quite a degree of heterogeneity in the interaction of their stock markets with country-specific financial, political and economic risk factors, while the most prevalent effects are observed in the case of China. We observe that symmetry, in both the short- and long-run, is largely rejected for all country-specific risk factors, suggesting that positive and negative changes in political, financial and economic risk ratings yield an asymmetric impact on stock market returns as well as global variables, particularly commodity returns. While some degree of heterogeneity is observed in how financial, economic and political risk ratings interact in the long-run, our findings suggest that positive and negative rating changes in some BRICS countries have significant implications for both local stock market returns as well as commodity price dynamics. Particularly, the Chinese stock market stands out in its long-run equilibrium relationship with country rating changes, while no significant effects are observed for India and Brazil.

Interestingly, shocks in financial and political ratings are found to have negative long-run effects on BRICS stock returns, regardless of the sign of the shock, while an opposite effect is observed for economic ratings. While some of the results can be attributed to the informational inefficiencies and mis-pricing present in these stock markets, our findings clearly suggest that not all BRICS nations are the same in terms of how they react to ratings changes and how they interact with global market indicators. From an investment perspective, our findings can be used as a

guideline for global investors in their market timing strategies towards emerging stock markets as well as in their predictive models for commodity markets.

As part of future research, it would be interesting to extend our analysis using a quantile-based NARDL model of Greenwood-Nimmo et al., (2013), which will allow us to study the impact of increases and decreases in country-risk ratings over the entire conditional distribution of the stock returns, i.e., its various regimes, without having to explicitly categorize the number of regimes.

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Table 1: FPSS tests.

	Brazil	China	India	Russia	South Africa
Model 1	4.097**	5.247***	3.292	5.192***	2.772
Model 2	3.384*	6.581***	1.734	5.495***	2.747
Model 3	4.935***	2.973	5.664***	9.238***	2.902
Model 4	8.381***	3.288	5.146***	3.523*	6.833***
Model 5	4.113**	3.283	4.816***	8.649***	5.230***
Model 6	3.310	4.326**	2.098	2.040	4.573**

Note: This table presents the results of the FPSS tests for the presence of a long-run cointegrating relationship among the variables in Models 1-6 provided in Equations 4a-4f. The null hypothesis of no cointegration is that the coefficients on the level variables in each respective model are jointly equal to zero. Pesaran et al. (2001) tabulate the critical values for the FPSS test for $k=5$, as 3.35, 3.79 and 4.68 at 10, 5 and 1 percent levels, respectively.⁷ ***, ** and * represent significance at the 1, 5 and 10 percent levels respectively.

⁷ For the bounds testing procedure, two sets of critical values are provided. The upper critical bound assumes that there is a cointegration relationship among the variables, while the lower critical bound assumes that no cointegration relationship exists between the variables. If the F-statistic is greater than the upper level critical value, then the null hypothesis of no-cointegration is rejected (i.e. all variables are cointegrated). Conversely, if the computed F-statistic falls below the lower bound critical value, then the null hypothesis cannot be rejected (i.e. no cointegration). Finally, if the F-statistic falls between the bounds, the test is inconclusive.

Table 2. Nonlinear ARDL estimation results for stock market returns.

Brazil			China			India		
Variable	Coeff.	S.E.	Variable	Coeff.	S.E.	Variable	Coeff.	S.E.
c	0.464	0.511	c	-0.095	0.252	c	-0.370	0.239
S_{t-1}	-0.020	0.024	S_{t-1}	-0.089***	0.020	S_{t-1}	-0.055**	0.027
CM_{t-1}	0.044*	0.026	CM_{t-1}	0.128***	0.032	CM_{t-1}	0.038*	0.023
SD_{t-1}	-0.033	0.026	SD_{t-1}	-0.055	0.042	SD_{t-1}	0.067*	0.039
P_{t-1}^+	-0.192	0.175	P_{t-1}^+	-0.222	0.135	P_{t-1}^+	0.091	0.111
F_{t-1}^+	-0.134**	0.054	F_{t-1}^+	-0.339*	0.173	F_{t-1}^+	0.339*	0.179
E_{t-1}^+	-0.027	0.077	E_{t-1}^+	0.563*	0.287	E_{t-1}^+	-0.235	0.202
P_{t-1}^-	-0.359*	0.202	P_{t-1}^-	-0.590**	0.269	P_{t-1}^-	0.090	0.131
F_{t-1}^-	-0.075	0.102	F_{t-1}^-	-0.651	0.649	F_{t-1}^-	0.225	0.137
E_{t-1}^-	-0.062	0.088	E_{t-1}^-	1.230***	0.251	E_{t-1}^-	-0.123	0.114
ΔS_{t-1}	-0.120**	0.048	ΔCM_t	0.318***	0.089	ΔS_{t-5}	-0.125**	0.050
ΔS_{t-2}	-0.111**	0.049	ΔCM_{t-4}	-0.378***	0.091	ΔS_{t-7}	-0.124**	0.048
ΔCM_t	0.179**	0.071	ΔCM_{t-7}	-0.243**	0.093	ΔCM_t	0.227***	0.075
ΔSD_{t-1}	1.144***	0.092	ΔCM_{t-10}	-0.250***	0.090	ΔCM_{t-8}	-0.218***	0.075
ΔP_{t-6}^+	-0.838**	0.353	ΔSD_{t-1}	1.142***	0.114	ΔSD_{t-1}	0.726***	0.091
ΔP_{t-10}^+	0.844**	0.349	ΔSD_{t-7}	0.324***	0.114	ΔSD_{t-4}	0.190**	0.088
ΔP_{t-11}^+	1.000***	0.375	ΔSD_{t-8}	0.338***	0.114	ΔSD_{t-5}	-0.235***	0.088
ΔP_{t-12}^+	-0.712**	0.349	ΔP_{t-2}^+	1.410**	0.552	ΔSD_{t-9}	0.202**	0.089
ΔF_{t-1}^+	0.373**	0.159	ΔF_{t-6}^+	1.415***	0.480	ΔP_{t-3}^+	-0.687**	0.295
ΔF_{t-11}^+	-0.391***	0.149	ΔE_{t-10}^+	1.098**	0.483	ΔP_{t-7}^+	0.732**	0.293
ΔE_{t-3}^+	0.407**	0.177	ΔF_{t-3}^-	2.632**	1.185	ΔP_{t-9}^+	-0.792***	0.296
ΔE_{t-6}^+	0.574***	0.204				ΔF_t^+	0.936**	0.442
ΔP_{t-1}^-	0.969**	0.484				ΔF_{t-6}^+	0.821**	0.401
ΔF_{t-7}^-	0.430***	0.162				ΔF_{t-10}^+	-1.049***	0.386
ΔF_{t-11}^-	0.860***	0.185				ΔP_{t-11}^-	1.106***	0.337
ΔE_{t-3}^-	0.447**	0.188				ΔF_{t-9}^-	1.180***	0.453
ΔE_{t-5}^-	0.496**	0.196				ΔE_t^-	0.519**	0.241
						ΔE_{t-1}^-	1.090***	0.246
						ΔE_{t-7}^-	-0.633***	0.234
						ΔE_{t-12}^-	-0.716***	0.243
Long-run effects						L_{CM}	0.688**	0.297
L_{CM}	2.214	2.436	L_{CM}	1.434***	0.391	L_{SD}	1.234**	0.501
L_{SD}	-1.660	2.726	L_{SD}	-0.611	0.537	L_{P^+}	1.656	1.995
L_{P^+}	-9.626	16.577	L_{P^+}	-2.484*	1.357	L_{F^+}	6.201	4.793
L_{F^+}	-6.705	9.345	L_{F^+}	-3.803**	1.705	L_{E^+}	-4.301	5.027
L_{E^+}	-1.364	4.728	L_{E^+}	6.313**	2.983	L_{P^-}	1.655	1.971
L_{P^-}	-18.026	25.062	L_{P^-}	-6.618*	3.775	L_{F^-}	4.116	3.246
L_{F^-}	-3.755	7.658	L_{F^-}	-7.303	6.644	L_{E^-}	-2.244	2.079
L_{E^-}	-3.120	6.054	L_{E^-}	13.790***	4.067			
Statistics and Diagnostics								
BDM	-0.818		BDM	-4.537**		BDM	-2.040	
WLR_P	0.247	[0.620]	WLR_P	1.275	[0.260]	WLR_P	0.000	[0.999]
WLR_F	0.304	[0.582]	WLR_F	0.292	[0.589]	WLR_F	0.779	[0.379]
WLR_E	0.350	[0.555]	WLR_E	2.963	[0.087]	WLR_E	0.194	[0.660]
WSR_P	0.548	[0.460]	WSR_P	6.518	[0.011]	WSR_P	9.183	[0.003]
WSR_F	16.788	[0.000]	WSR_F	0.919	[0.339]	WSR_F	0.350	[0.555]
WSR_E	0.011	[0.916]	WSR_E	5.161	[0.024]	WSR_E	0.237	[0.627]
\bar{R}^2	0.524		\bar{R}^2	0.466		\bar{R}^2	0.518	
$SC(12)$	13.373	[0.342]	$SC(12)$	15.598	[0.210]	$SC(12)$	8.053	[0.781]
RRT	5.155	[0.023]	RRT	0.020	[0.886]	RRT	0.267	[0.605]
JB	4.644	[0.098]	JB	31.498	[0.000]	JB	0.239	[0.887]
HT	43.365	[0.000]	HT	0.122	[0.727]	HT	0.010	[0.921]

Table 2 (continued). Nonlinear ARDL estimation results for stock market returns.

Russia			South Africa		
Variable	Coeff.	S.E.	Variable	Coeff.	S.E.
c	-0.208	0.346	c	0.260*	0.143
S_{t-1}	-0.103***	0.029	S_{t-1}	-0.119***	0.027
CM_{t-1}	0.132***	0.038	CM_{t-1}	0.028*	0.015
SD_{t-1}	0.017	0.055	SD_{t-1}	0.032*	0.019
P_{t-1}^+	0.089	0.151	P_{t-1}^+	0.072	0.095
F_{t-1}^+	0.134	0.183	F_{t-1}^+	0.017	0.072
E_{t-1}^+	-0.226**	0.091	E_{t-1}^+	0.164*	0.088
P_{t-1}^-	0.196	0.228	P_{t-1}^-	0.206*	0.117
F_{t-1}^-	-0.340**	0.138	F_{t-1}^-	-0.122*	0.072
E_{t-1}^-	0.062	0.059	E_{t-1}^-	0.171**	0.072
ΔS_{t-1}	0.105**	0.049	ΔCM_t	0.146***	0.052
ΔS_{t-10}	0.110**	0.044	ΔSD_{t-1}	0.611***	0.071
ΔCM_t	0.242**	0.119	ΔP_t^+	-0.708**	0.294
ΔSD_{t-1}	1.355***	0.155	ΔP_{t-4}^+	-0.660**	0.292
ΔP_{t-7}^+	-0.950**	0.422	ΔP_{t-9}^+	0.970***	0.296
ΔF_t^+	-0.869***	0.328	ΔP_{t-1}^-	-1.029**	0.416
ΔF_{t-10}^+	-0.860***	0.326	ΔP_{t-10}^-	-1.083**	0.419
ΔE_{t-7}^+	0.382**	0.177	ΔF_{t-3}^-	-0.386**	0.162
ΔP_t^-	2.624***	0.433	ΔF_{t-5}^-	0.353**	0.155
ΔF_t^-	1.271***	0.258	ΔE_{t-12}^-	0.655***	0.189
ΔF_{t-4}^-	0.989***	0.246			
ΔF_{t-5}^-	-1.049***	0.302			
ΔF_{t-8}^-	-0.521**	0.234			
ΔF_{t-12}^-	-0.735***	0.274			
ΔE_{t-1}^-	-0.519***	0.137			
ΔE_{t-3}^-	0.424***	0.127			
ΔE_{t-5}^-	0.557***	0.163			
ΔE_{t-10}^-	0.288**	0.134			
Long-run effects					
L_{CM}	1.289***	0.351	L_{CM}	0.236**	0.115
L_{SD}	0.168	0.509	L_{SD}	0.269*	0.143
L_{P^+}	0.869	1.356	L_{P^+}	0.606	0.809
L_{F^+}	1.305	1.701	L_{F^+}	0.141	0.599
L_{E^+}	-2.194**	0.983	L_{E^+}	1.374*	0.768
L_{P^-}	1.908	2.003	L_{P^-}	1.730*	0.992
L_{F^-}	-3.304*	1.727	L_{F^-}	-1.024*	0.584
L_{E^-}	0.600	0.610	L_{E^-}	1.434***	0.533
Statistics and Diagnostics					
$FPSS$	5.495***		$FPSS$	2.747	
BDM	-3.598		BDM	-4.488**	
WLR_P	0.242	[0.623]	WLR_P	1.997	[0.159]
WLR_F	4.252	[0.040]	WLR_F	34.555	[0.000]
WLR_E	5.881	[0.016]	WLR_E	0.007	[0.932]
WSR_P	31.652	[0.000]	WSR_P	4.941	[0.027]
WSR_F	4.434	[0.036]	WSR_F	0.020	[0.887]
WSR_E	1.053	[0.306]	WSR_E	12.053	[0.001]
\bar{R}^2	0.617		\bar{R}^2	0.487	
$SC(12)$	12.230	[0.427]	$SC(12)$	9.651	[0.647]
RRT	2.735	[0.098]	RRT	3.550	[0.060]
JB	5.720	[0.057]	JB	3.491	[0.175]
HT	0.334	[0.564]	HT	30.155	[0.000]

Notes: L_{x^+} and L_{x^-} are the asymmetric positive and negative long-run coefficients, with $x=P, F$ and E . L_{CM} and L_{SD} are the symmetric long-run coefficients. WLR_x denotes the Wald test for long-run symmetry by testing the null hypothesis $H_0: L_{x^+} = L_{x^-}$. WSR_x denotes the Wald test of the additive short-run symmetry by testing the null hypothesis: $H_0: \sum_{j=0}^{q-1} \phi_{x,j}^+ = \sum_{j=0}^{q-1} \phi_{x,j}^-$. BDM refers to the co-integration test statistic

by Banerjee et al. (1998). Pesaran et al. (2001) tabulate the critical values of tBDM, for $k=5$, as -3.86, -4.19 and -4.79 at 10, 5 and 1 percent levels, respectively. R-Bar denotes the adjusted R-square. SC(k) refers to the Godfrey (1978) test for kth order serial correlation. RRT denotes the Ramsey (1969) RESET test of functional form. JB denotes the Jarque-Bera (1980) test statistic for normality. HT is the MicroFit test for heteroscedasticity. p-values for tests are given in square brackets. ***, ** and * represent significance at the 1, 5 and 10 percent levels respectively.

Appendix. Detailed specification of the NARDL models estimated:

The NARDL models provided in Equations 4a-4f can be presented in detailed form as

(1)

$$\Delta CM_t = c + \rho_{CM} CM_{t-1} + \theta_S S_{t-1} + \theta_{SD} SD_{t-1} + \theta_P^+ P_{t-1}^+ + \theta_P^- P_{t-1}^- + \theta_F^+ F_{t-1}^+ + \theta_F^- F_{t-1}^- + \theta_E^+ E_{t-1}^+ + \theta_E^- E_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta CM_{t-i} + \sum_{j=0}^{q-1} \varphi_{S,j} \Delta S_{t-j} + \sum_{j=0}^{q-1} \varphi_{SD,j} \Delta SD_{t-j} + \sum_{j=0}^{q-1} (\varphi_{P,j}^+ \Delta P_{t-j}^+ + \varphi_{P,j}^- \Delta P_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{F,j}^+ \Delta F_{t-j}^+ + \varphi_{F,j}^- \Delta F_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{E,j}^+ \Delta E_{t-j}^+ + \varphi_{E,j}^- \Delta E_{t-j}^-) + \varepsilon_t$$

(2)

$$\Delta S_t = c + \rho_S S_{t-1} + \theta_{CM} CM_{t-1} + \theta_{SD} SD_{t-1} + \theta_P^+ P_{t-1}^+ + \theta_P^- P_{t-1}^- + \theta_F^+ F_{t-1}^+ + \theta_F^- F_{t-1}^- + \theta_E^+ E_{t-1}^+ + \theta_E^- E_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta S_{t-i} + \sum_{j=0}^{q-1} \varphi_{CM,j} \Delta CM_{t-j} + \sum_{j=0}^{q-1} \varphi_{SD,j} \Delta SD_{t-j} + \sum_{j=0}^{q-1} (\varphi_{P,j}^+ \Delta P_{t-j}^+ + \varphi_{P,j}^- \Delta P_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{F,j}^+ \Delta F_{t-j}^+ + \varphi_{F,j}^- \Delta F_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{E,j}^+ \Delta E_{t-j}^+ + \varphi_{E,j}^- \Delta E_{t-j}^-) + \varepsilon_t$$

(3)

$$\Delta P_t = c + \rho_P P_{t-1} + \theta_S S_{t-1} + \theta_{SD} SD_{t-1} + \theta_{CM} CM_{t-1} + \theta_F^+ F_{t-1}^+ + \theta_F^- F_{t-1}^- + \theta_E^+ E_{t-1}^+ + \theta_E^- E_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta P_{t-i} + \sum_{j=0}^{q-1} \varphi_{S,j} \Delta S_{t-j} + \sum_{j=0}^{q-1} \varphi_{CM,j} \Delta CM_{t-j} + \sum_{j=0}^{q-1} \varphi_{SD,j} \Delta SD_{t-j} + \sum_{j=0}^{q-1} (\varphi_{F,j}^+ \Delta F_{t-j}^+ + \varphi_{F,j}^- \Delta F_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{E,j}^+ \Delta E_{t-j}^+ + \varphi_{E,j}^- \Delta E_{t-j}^-) + \varepsilon_t$$

(4)

$$\Delta F_t = c + \rho_F F_{t-1} + \theta_S S_{t-1} + \theta_{SD} SD_{t-1} + \theta_{CM} CM_{t-1} + \theta_P^+ P_{t-1}^+ + \theta_P^- P_{t-1}^- + \theta_E^+ E_{t-1}^+ + \theta_E^- E_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta F_{t-i} + \sum_{j=0}^{q-1} \varphi_{S,j} \Delta S_{t-j} + \sum_{j=0}^{q-1} \varphi_{CM,j} \Delta CM_{t-j} + \sum_{j=0}^{q-1} \varphi_{SD,j} \Delta SD_{t-j} + \sum_{j=0}^{q-1} (\varphi_{P,j}^+ \Delta P_{t-j}^+ + \varphi_{P,j}^- \Delta P_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{E,j}^+ \Delta E_{t-j}^+ + \varphi_{E,j}^- \Delta E_{t-j}^-) + \varepsilon_t$$

(5)

$$\Delta E_t = c + \rho_E E_{t-1} + \theta_S S_{t-1} + \theta_{SD} SD_{t-1} + \theta_{CM} CM_{t-1} + \theta_F^+ F_{t-1}^+ + \theta_F^- F_{t-1}^- + \theta_P^+ P_{t-1}^+ + \theta_P^- P_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta E_{t-i} + \sum_{j=0}^{q-1} \varphi_{S,j} \Delta S_{t-j} + \sum_{j=0}^{q-1} \varphi_{CM,j} \Delta CM_{t-j} + \sum_{j=0}^{q-1} \varphi_{SD,j} \Delta SD_{t-j} + \sum_{j=0}^{q-1} (\varphi_{F,j}^+ \Delta F_{t-j}^+ + \varphi_{F,j}^- \Delta F_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{P,j}^+ \Delta P_{t-j}^+ + \varphi_{P,j}^- \Delta P_{t-j}^-) + \varepsilon_t$$

(6)

$$\Delta SD_t = c + \rho_{SD} SD_{t-1} + \theta_S S_{t-1} + \theta_{CM} CM_{t-1} + \theta_P^+ P_{t-1}^+ + \theta_P^- P_{t-1}^- + \theta_F^+ F_{t-1}^+ + \theta_F^- F_{t-1}^- + \theta_E^+ E_{t-1}^+ + \theta_E^- E_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta SD_{t-i} + \sum_{j=0}^{q-1} \varphi_{S,j} \Delta S_{t-j} + \sum_{j=0}^{q-1} \varphi_{CM,j} \Delta CM_{t-j} + \sum_{j=0}^{q-1} (\varphi_{P,j}^+ \Delta P_{t-j}^+ + \varphi_{P,j}^- \Delta P_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{F,j}^+ \Delta F_{t-j}^+ + \varphi_{F,j}^- \Delta F_{t-j}^-) + \sum_{j=0}^{q-1} (\varphi_{E,j}^+ \Delta E_{t-j}^+ + \varphi_{E,j}^- \Delta E_{t-j}^-) + \varepsilon_t$$

where S is the stock index, P is the political risk rating factor, F is the financial risk rating factor, E is the economic risk rating factor, CM is the commodity index and SD is the MSCI developed country index. All variables are measured in natural logarithm. The coefficients ρ and θ_s , $s = CM, SD$ and S, are the symmetric long-run coefficients. θ_a^+ and θ_a^- , $a = P, F$ and E, are the asymmetric long-run coefficients. $\varphi_{s,j}$, $s = CM, SD$ and S, are the symmetric short-run coefficients while $\varphi_{a,j}^+$ and $\varphi_{a,j}^-$, $a = P, F$ and E, are the asymmetric short-run coefficients of the NARDL model. γ_i is the autoregressive parameter and ε_t is i.i.d. zero mean random variables with finite variance σ_ε^2 . Since the data is on monthly frequency, the maximum order of the lags in the NARDL model is chosen to be 12.

Figure A1: Time series plots of data

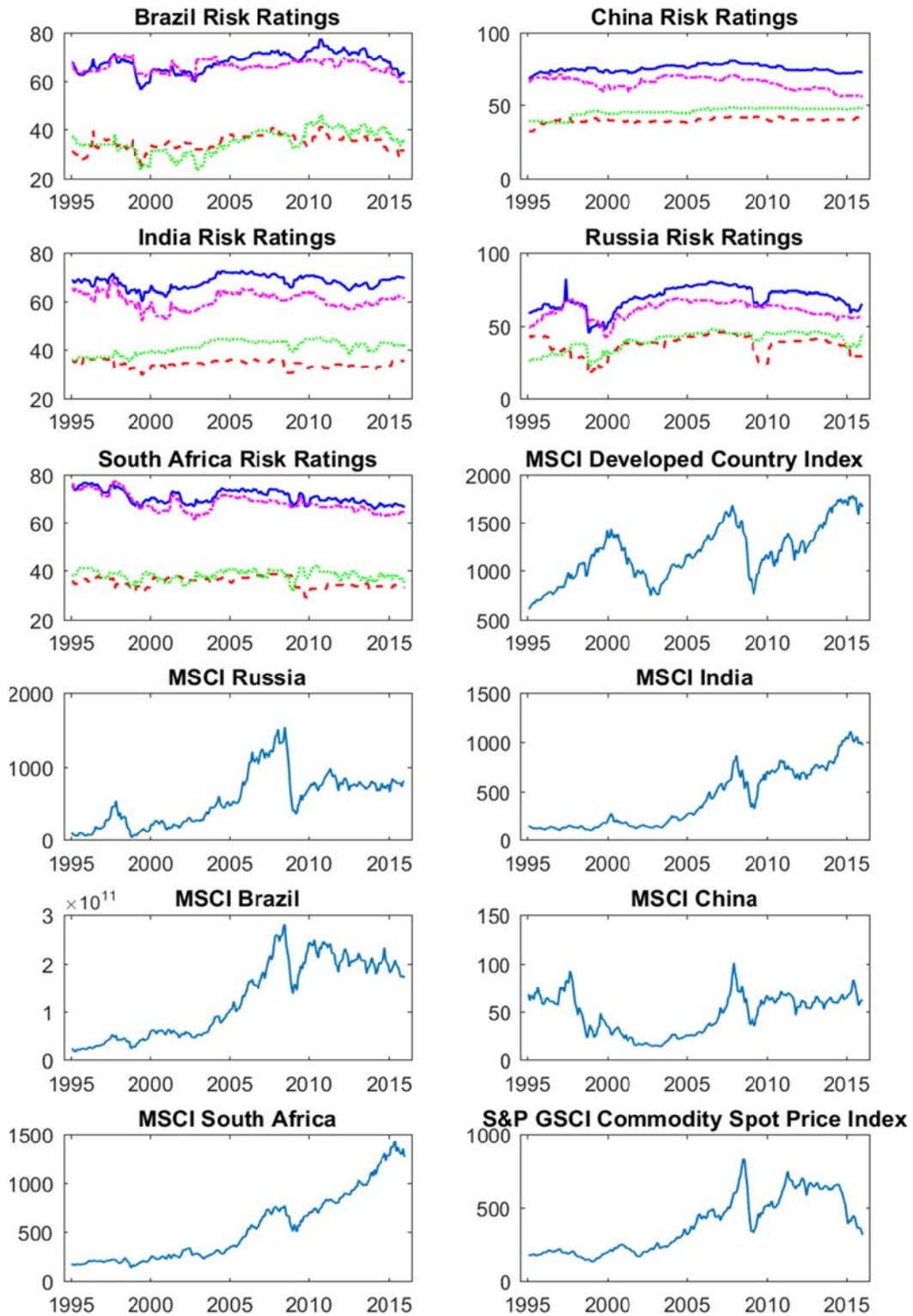


Table A1. Summary Statistics for country ratings.

Variables	Mean	Median	Maximum	Minimum	Standard Deviation	CV	Skewness	Kurtosis	Jarque-Bera	Probability
Brazil_CR	67.855	68.250	77.250	56.540	4.061	0.060	-0.375	2.624	7.382	0.025
Brazil_ER	34.655	35.000	41.000	25.060	2.988	0.086	-0.487	3.139	10.179	0.006
Brazil_FR	35.050	35.000	45.500	23.500	4.849	0.138	-0.318	2.583	6.085	0.048
Brazil_PR	66.000	66.000	71.000	59.500	2.546	0.039	-0.246	2.475	5.438	0.066
Brazil_MSCI	1.25E+11	1.12E+11	2.81E+11	1.66E+10	8E+10	0.640	0.142	1.425	26.910	0.000
Russia_CR	68.717	70.000	82.000	45.000	7.820	0.114	-0.829	3.342	30.101	0.000
Russia_ER	36.830	38.500	45.500	16.000	6.639	0.180	-1.048	3.410	47.848	0.000
Russia_FR	39.579	42.500	47.500	22.000	6.439	0.163	-0.871	2.554	33.934	0.000
Russia_PR	60.893	62.000	69.000	42.000	5.768	0.095	-0.818	3.329	29.258	0.000
Russia_MSCI	554.690	520.846	1539.354	31.221	362.081	0.653	0.486	2.445	13.141	0.001
India_CR	67.909	68.500	72.500	60.030	2.622	0.039	-0.301	2.329	8.514	0.014
India_ER	34.091	34.000	37.500	29.560	1.600	0.047	-0.318	2.417	7.828	0.020
India_FR	41.161	41.500	45.000	35.500	2.722	0.066	-0.434	1.898	20.667	0.000
India_PR	60.536	61.000	69.000	52.000	3.252	0.054	-0.274	2.580	5.007	0.082
India_MSCI	424.631	287.242	1111.045	100.851	300.412	0.707	0.535	1.892	24.942	0.000
China_CR	75.087	74.625	80.500	68.500	2.414	0.032	0.136	2.501	3.396	0.183
China_ER	39.541	39.500	42.000	32.000	1.713	0.043	-1.714	8.717	466.571	0.000
China_FR	45.435	46.000	48.500	38.000	3.040	0.067	-1.402	3.947	91.973	0.000
China_PR	65.177	66.000	71.000	56.000	4.254	0.065	-0.575	2.274	19.434	0.000
China_MSCI	47.751	54.250	100.662	13.752	20.537	0.430	-0.084	1.894	13.147	0.001
South Africa_CR	70.699	70.000	76.500	65.500	2.834	0.040	0.262	1.866	16.401	0.000
South Africa_ER	35.141	35.500	38.500	29.000	2.047	0.058	-0.373	2.606	7.476	0.024
South Africa_FR	38.069	38.000	42.000	31.500	1.996	0.052	-0.493	2.955	10.236	0.006
South Africa_PR	68.139	67.500	77.000	61.500	3.640	0.053	0.558	2.585	14.861	0.001
South Africa_MSCI	538.146	375.284	1432.465	137.224	355.219	0.660	0.789	2.501	28.738	0.000
Developed Markets_MSCI	1184.746	1178.420	1779.307	608.263	294.215	0.248	0.173	2.225	7.559	0.023
S&P GSCI Commodity Spot Price Index	379.791	348.328	832.304	131.751	188.518	0.060	0.422	1.801	22.587	0.000

Note: The table presents the summary statistics for monthly composite (CR), economic (ER), financial (FR) and political (PR) risk ratings for the five BRICS countries over the period of January 1995 to December 2015. x_MSCI represents the stock market index for country x. CV is the coefficient of variation