



Universidade do Minho
Escola de Economia e Gestão

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**FINANCIAL CONTAGION IN THE BRICS
STOCK MARKETS**
An empirical analysis of the Lehman Brothers
Collapse and European Sovereign Debt Crisis



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Master thesis in Monetary, Banking and Financial Economics

Supervisor:

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“It always seems impossible until it's done.”

Nelson Mandela

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Abstract

Purpose – The purpose of this research is to analyze and extend the study of contagion for BRICS Emerging Stock Markets in the context of the last two international financial crises: the Lehman Brothers Bankruptcy Crisis and the European Sovereign Debt Crisis. We investigate changes in the relationship and the co-movements between BRICS markets in response to international shocks that are originated in advanced markets like USA and Europe.

Methodology approach – Employing data of daily stock market indices of BRICS countries, this research tests for contagion, examining the interactions and characteristics of price movements of BRICS stock markets by applying a three-step Methodology: cointegration analysis, causality and VECM/Gonzalo-Granger statistic and variance decomposition methodology on stock returns as a measure of perceived country risk.

Findings – The results exhibit that both long-run cointegration relationships and short-run Granger causality relationships patterns exist between BRICS stock markets. Furthermore, these relations have drastically changed (amplified) during turbulent periods compared with tranquil period, pointing towards the occurrence of contagion phenomenon among BRICS markets during the last two crises. These results suggest that the benefits of portfolio diversification were significantly decayed during both crises and, consequently, diversification was not beneficial during either crisis.

Implications – The findings imply an increasing degree of global market integration due to quick dissemination of global shocks originating from the USA and the Euro Zone, and swift recovery which can be attributed to the increased resilience, consistent with the moderated level of domestically driven risk in the BRICS markets. Moreover, the results bring major implications for international portfolio diversification and policy makers, since these markets serve as an important alternative investment destination for global portfolio diversification. Furthermore, changes in the USA and the Euro Zone indices affect BRICS stock markets in the short-run, which implies that these markets may act as a leading indicator for investing in BRICS markets.

Keywords: Financial Contagion, BRICS Stock Markets, VAR Models, Financial Crises.

Resumo

Objetivo - O objetivo desta pesquisa é analisar e estender o estudo do contágio para os Mercados Emergentes dos BRICS, no contexto das duas últimas crises financeiras: a crise originada pela falência do *Lehman Brothers* e a crise das Dívidas Soberanas na Zona Euro. São analisadas as mudanças no relacionamento e os movimentos nos mercados de ações dos BRICS em resposta a choques internacionais provenientes de mercados desenvolvidos (EUA e a Europa).

Metodologia - Utilizando os dados diários dos índices de ações dos BRICS, o contágio é testado, examinando as interações e as características dos movimentos de preços destes mercados, aplicando uma metodologia em três passos: análise da cointegração, causalidade e estatística VECM/Gonzalo-Granger e a metodologia de decomposição da variância para os retornos de ações como uma medida de percepção do risco país.

Resultados - Os resultados exibem as relações de cointegração de longo prazo e os padrões de relacionamento de causalidade de curto prazo entre os BRICS. Estas relações foram fortemente amplificadas durante os períodos turbulentos em comparação com os períodos tranquilos, apontando para a ocorrência do fenômeno de contágio entre os BRICS durante as duas últimas crises. Revelando assim, uma significativa deterioração dos benefícios de diversificação em ambas as crises e, conseqüentemente, uma diversificação pouco benéfica para os investidores.

Implicações - As conclusões inferem um crescente grau de integração global dos mercados devido à rápida disseminação de choques globais originários dos países desenvolvidos, assim como, uma rápida recuperação que pode ser atribuída ao aumento da resiliência, consistente com o nível moderado de risco nacional dos BRICS. Os resultados trazem importantes implicações para a diversificação de investimentos e para os decisores políticos, uma vez que, os mercados de ações dos BRICS servem como um importante destino de investimento alternativo para a diversificação de *portfolios* globais. Evidenciam também, que alterações nos mercados de ações americanos e europeus afetam os BRICS no curto prazo, o que sugere que estes mercados podem atuar como um indicador de liderança para o investimento nos mercados de ações dos BRICS.

Palavras-chave: Contágio Financeiro, Mercado de Ações dos BRICS, Modelos VAR, Crises Financeiras.

Contents

Acknowledgments	ii
Abstract	iii
Resumo	iv
List of Tables and Figures	vii
List of Abbreviations	viii
1 Introduction	1
2 Literature Review	4
2.1 Contagion Phenomenon: Definition, Theories, Transmission and Measurement.....	4
2.1.1 What is Financial Contagion?	5
2.1.2 Causes and Transmission of Contagion.....	7
2.1.3 Contagion: Testing and Measurement.....	9
3 Data & Methodology	12
3.1 Data	12
3.1.1 Variable Transformation.....	14
3.1.2 Descriptive Statistics.....	14
3.2 Methodology.....	15
3.2.1 Testing for Stationarity	15
3.2.2 Vector Autoregressive Model	17
3.2.3 Johansen Cointegration Approach.....	19
3.2.3.1 Trace Test.....	19
3.2.3.2 Dynamic Bivariate Cointegration Analysis.....	20
3.2.4 Granger Causality Approach	22
3.2.4.1 Shock Transmission Direction.....	22
3.2.4.2 Common Factors/Price-Discovery/Permanent-Transitory Decomposition.....	24
3.2.4.3 VECM: Unveiling Two Types of Causality	26
3.2.5 Variance Decomposition: Exposure to External Shocks	27
4 Results	29
4.1 Contagion Windows Definition	29
4.2 Revealing the Contagion Process.....	33
4.3 Measuring Countries Degree of Exposure to the Contagion Process	39
4.4 Three-steps Results: Summary of the Major Findings.....	40
5 Conclusions	42
References	45
Appendixes	50

Appendix I: GDP Growth Rate for BRICS Emerging Markets.....	50
Appendix II: GDP Growth Rate for Developed Economies.....	51
Appendix III: The Evolution of FDI Inflows in BRICS Countries.	52
Appendix A: BRICS and USA Stock Markets – Individual Log-Level Representation.....	53
Appendix B: BRICS Vs USA Stock Markets - Log-Level Representation.	54
Appendix C: BRICS and USA Stock Markets - Percentage Daily Returns.....	55
Appendix D: Raw Data from Thomson Reuters Datastream.	56
Appendix E: Data Transformation in Log-Level.	57

List of Tables and Figures

Tables

Table I - Economic Forecast for BRICS Emerging Markets.....	1
Table II - Fundamentals Causes of Contagion.....	8
Table III - Possible Explanation for Contagion.....	9
Table 1 - Variables Explanation	12
Table 2 - Descriptive Statistics.....	15
Table 3 - Unit Root Tests.....	17
Table 4 - Contagion Window Summary.....	33
Table 5 - Results from Cointegration Test/Gonzalo-Granger Statistics.....	34
Table 6 - Rate of Exposure to the Contagion Process.....	40
Table 7 - Three-step Methodology: Summary Results from both Crises.....	41

Figures

Figure 1 - Movement of BRICS and USA Stock Market Indices from January 2003 to October 2016.....	13
Figure 2 - Framework of the Granger Causality Methodology.....	22
Figure 3 - Graphical Representation of the Contagion Windows.....	30
Figure 4 - Graphical Moving Average Representation of the Rolling Indicator.....	32
Figure 5 - Short/Long-run Connections Representation for the Tranquil and the Turbulent Periods.....	36

List of Abbreviations

AIC - Akaike Information Criterion	MA - Moving Average
ADF - Augmented Dickey-Fuller Test	MSCI - Morgan Stanley Capital International
ARCH - Autoregressive Conditional Heteroskedasticity	ML - Maximum Likelihood
ARMA - Autoregressive Moving Average Model	OLS - Ordinary Least Squares
BRA - Brazil	PP - Phillips and Perron Test
BRICS - Brazil, Russia, India, China and South Africa	R - Return
CAD - Current Account Deficit	RI - Rolling Indicator
CDS - Credit Default Swaps	RUS - Russia
CHI - China	SAF - South Africa
ECM - Error Correction Mechanism	SIC Schwarz Information Criterion
ECT - Error Correction Term	SMI - Stock Market Index
EU - European	SR - Stock Return
ESDC - European Sovereign Debt Crisis	S&P - Standard and Poor's
FEVD - Forecast-Error Variance Decomposition	US - United States
FD - First Difference	USA - United States of America
FDI - Foreign Direct Investment	VAR - Vector Autoregressive Model
GARCH - Generalized Autoregressive Conditional Heteroskedasticity	VARMA - Vector Autoregressive Moving Average Model
GDP - Gross Domestic Product	VECM - Vector Error Correction Model
GFC - Global Financial Crisis	
GG - Gonzalo-Granger Test	
HQ - Hannan-Quinn Information Criterion	
IID - Independently and Identically Distributed	
IND - India	
JB -Jarque-Bera Test	
K - Kurtoses	
LBBC - Lehman Brothers Bankruptcy Crisis	
LM - Lagrange Multiplier Test	

1 Introduction

The acronym BRIC was first suggested by Jim O'Neill¹ in 2001, in his publication “*Building Better Global Economic BRICs*”. The initial four countries – Brazil, Russia, India and China corresponded to BRIC. They were the rising stars of the Emerging Markets due to their large size, population and ambitious to become world’s leading economies propelled by their audacious growth. In April 2011, South Africa joined the group as a full member², in the 2011 summit in Sanya, China. Hence, the group was renamed BRICS – to reflect the group’s expanded membership. Fifteen years later, after a Global Financial Crisis (GFC)³, the expectations about the BRICS countries as the world’s leading emerging markets economies, still holds as the growth engines of the world economy, today and in the future (Bonga-Bonga, 2015; O’Neill, 2013).

Table I Economic Forecast for BRICS Emerging Markets.

Countries	2010	2015	2020	2025	2030	2035	2040	2045
	2015	2020	2025	2030	2035	2040	2045	2050
Brazil	4.1	3.8	3.7	3.8	3.9	3.8	3.6	3.4
Russia	3.8	3.4	3.4	3.5	3.1	2.6	2.2	1.9
India	5.9	5.7	5.7	5.9	6.1	6.0	5.6	5.2
China	5.9	5.0	4.6	4.1	3.9	3.9	3.5	2.9
South Africa	3.6	3.3	3.3	3.1	3.3	3.3	3.3	3.3

Note: BRICS real GDP growth (%): 5-year period average according to Wilson and Purushothaman (2003).

Wilson and Purushothaman (2003) predicted that over the next 50 years the BRIC economies (without South Africa) could become a much larger force in the world economy. They expect the total nominal GDP just for the four BRIC countries to reach \$128 trillion in 2050, compared to \$66 trillion for the G7 countries at that time. Just the four BRIC countries are expected to account for 41% of the world's stock market capitalization by 2030, when China is expected to overtake the United States in equity market capitalization, thus becoming the largest equity market in the world. This rampant growth of the BRICS countries has substantial effects for the capitalization of their stock markets as well as for their financial dependence with other stock markets (Mensi, Hammoudeh,

¹ Chief economist at Goldman Sachs Asset Management. See O’Neill (2001).

² Recently, several studies have added South Africa to the BRIC group as this country has also a fast-growing economy, experiences rapid financial market development and sophistication, and is globally recognized as a source possessing sophisticated professional services and financial expertise (Liu, Hammoudeh, & Thompson, 2013; Zhang, Li, & Yu, 2013). This financial influence is capable to transmit financial shocks in great degree and magnitude to the other BRICS countries (Bonga-Bonga, 2015). South Africa is also known as one of the world's largest producer of some strategic commodities (e.g., gold, platinum, and chrome) which are critical resources to support domestic and global economic growth. Thus, the presence of South Africa in the BRICS group provides opportunities to establish a dedicated investment strategy in terms of economic diversification opportunities, particularly in Africa (Mensi et al., 2014).

³ The US Subprime Crisis in August 2007 and the collapse of the Lehman Brothers in September 2008, sparked a GFC that affected the real sector and caused a rapid, synchronized deterioration in most major economies (Gentile & Giordano, 2012, 2013). Subsequently, the effects caused the Eurozone Sovereign Debt Crisis, which served as a catalyst towards further investigation of the contagion and spillover effects among the USA, Eurozone, Emerging Markets and Asian stock markets. These interdependencies could provide evidence whether there is a seemingly growing integration in international markets with important implications for portfolio diversification. Only a limited number of studies are available on the contagion effects of the US subprime crisis and its repercussions (Bekiros, 2014).

Reboredo, & Nguyen, 2014; Visalakshmi & Lakshmi, 2016). BRICS's economies have matured hastily and are becoming increasingly more integrated with the most developed economies in terms of trade and investment⁴.

In the past three decades, various countries have been hit by severe financial crises: the Mexican "Tequila Crisis" in 1994, the East Asian Crisis in 1997, the Russian Crisis in 1998, the Argentinean Crisis in 2002, the United States of America (USA) Subprime in 2007 and the Lehman Brothers Bankruptcy Crisis (LBBC) in 2008 and, more recently, the European Sovereign Debt Crisis (ESDC) in 2010/2011. All these financial crises started in a specific country and region in the globe and, subsequently, their effects spread to other countries and regions. Such transmission of shocks is dubbed *contagion* (Bonga-Bonga, 2015). Notwithstanding, the contagion term is not consensual, this research follows the largest body of the empirical literature based on the Forbes and Rigobon (2002) designation, where *contagion is defined as a significant increase of cross-market linkages after a shock to one country or a group of countries*. This contagion effect undermines the purpose of the portfolio diversification, revealing the situation where markets that were assumed to be weakly associated before a shock are subsequently found to be strongly associated in such a way that diversification across markets fails to shield the investors from the unsystematic risk (Gentile & Giordano, 2012, 2013). This definition indicates that, if two markets present a high degree of co-movement during periods of stability and continue to be highly correlated after a shock to one market, this indicates interdependence⁵ rather than contagion.

A comprehensive understanding of the financial market contagion is extremely important to address how its mechanisms work, to understand and assess its importance and take efficient policy measures. Regarding to these matters, there are policy implications associated with fundamentals-driven and contagion-driven movements, two broad concepts defined in the literature (Claessens, Dornbusch, & Park, 2001; Dornbusch, Park, & Claessens, 2000; Forbes & Rigobon, 2001; Gentile & Giordano, 2012, 2013; Masson, 1998). In the first one, measures must be taken by the policymakers to improve fundamentals. In the second one, if markets have fallen due to contagion, then the priority should be to improve market sentiments with credible policy actions. Contagion entails an intensification or change in the transmission of shocks among markets and it requires a structural break, leading to the identification of tranquil and turbulent periods⁶. Therefore, the transmission mechanisms during a crisis are forcibly different from those in a stable period (Gentile & Giordano, 2012).

⁴ The BRICS together constitute more than a quarter of the world's land area, more than 40% of the world's population and about 15% of global GDP (see Appendix I and II). The growth potentials in those culturally and geographically disparate countries are based on diverse attributes. Brazil is a resource-rich country, with resources such as coffee, soybean, sugar cane, iron ore and crude oil. Russia is well known for its massive deposits of oil, natural gas and minerals. India has a rising manufacturing base and is a strong service provider. China has a highly skilled workforce at low wage cost and it is considered to be the factory of the world. South Africa, the smallest of the five BRICS countries by land mass and world GDP contribution, is the world's largest producer of platinum and chromium, and holds the world's largest known reserves of manganese, platinum group metals, chromium, vanadium and aluminum-silicates (New Delhi, 2012).

⁵ When co-movements do not increase significantly after a shock, then any continued high level of market correlation indicates strong connections among the countries that exist worldwide (Gentile & Giordano, 2012).

⁶ Contagion occurs when there is a significant increase in cross-market co-movements after a shock to one country or a group of countries beyond what would be justified by fundamentals (Dornbusch et al., 2000). This definition of contagion is not possible to explain just looking for the fundamentals (such as trade or macroeconomic policy between countries). On the contrary, the presence of contagion assumes that the transmission of shocks is made possible through the *Investor's anticipation*, which can cause contagion due to a *shift* in the investor-behavior (Gentile & Giordano, 2012, p. 15), changing the flow of international portfolio investments (*flight-to-quality* phenomenon) in such a manner that it cannot be explained by economic fundamentals. For example, a crisis in one emerging market country can trigger investors to withdraw funds from many emerging markets without considering the fundamental economic differences between them (Bonga-Bonga, 2015).

This research enriches the literature by focusing the study on the great importance that the effects of contagion in the financial crises across BRICS countries can reveal based on the magnitude of the interaction among them and what they represent globally. The focus of this research is pointed towards the LBBC and the ESDC in order to identify if there was contagion transmission to the BRICS countries and the implications of this phenomenon due to the great impact that both crises had in the behavior of the investors, which brought massive inflows of foreign direct investment (FDI)⁷ to the BRICS countries, trying to hedge their investments (Nistor, 2015).

To achieve this goal, we implemented a three-step methodology that capture the different patterns of contagion transmission across BRICS countries stock markets, following Baig and Goldfajn (1999), Beirne and Gieck (2012), Gentile and Giordano (2012, 2013), Fourie and Botha (2015) and Boubaker, Jouini, and Lahiani (2016). The Johansen cointegration test to detect the cross-market connections in the long-run, allowing the identification of signs of contagion and the detection of the so called “*contagion Windows*” by looking direct in the data without any kind of previous assumptions; the Granger causality/Vector error correction model (VECM), which captures new significant short connections among the BRICS countries after a financial shock, allowing also the identification of which country propagates the impulses of contagion (*leading countries*) and which country is the target of contagion (*follower countries*); the last step is dedicated to the rate of involvement indicator, which identifies the most vulnerable countries, measuring how much of the domestic risk is explained by innovations in other BRICS countries.

Our results clearly reveal an increase in the long-run connections among BRICS stock markets jointly with changes in the causality patterns, which have changed in the turbulent periods compared to the tranquil periods. The evidence suggests that contagion effects strongly influenced the BRICS stock markets over both crises. These results also reveal that BRICS countries were not able to provide portfolio diversification, indicating that both crises affected their stock markets, revealing different degrees of vulnerabilities among them.

This empirical research is organized as follows. Section 2 contains a literature review, Section 3 describes the data and the econometric methodology, which is followed by Section 4, the core section, which presents the empirical results. Section 5 concludes.

Keywords: Contagion Effect, BRICS Stock Markets, VAR Models, Financial Crises.

⁷ See Appendix III.

2 Literature Review

2.1 Contagion Phenomenon: Definition, Theories, Transmission and Measurement

“(...) countries have become so interdependent in both good and bad times that contagion is extremely difficult to stop. Many measures aimed at minimizing contagion provide only a temporary reprieve and can aggravate contagion risks through other channels.”

(Forbes, 2012, p. 1)

The different definitions of contagion, how it is measured, what causes contagion, how it is transmitted and why, is extremely important to understand so as to evaluate this phenomenon correctly and develop policy responses efficiently. Blaming financial crisis on contagion remains an elusive concern, highly contagious among politicians and economists. Without a clear understanding of financial contagion and the mechanisms through which it works, we can neither assess the problem nor design appropriate policy measures to control for it (Moser, 2003). Such understanding is needed to identify the economic implications both for implementing policies and for investors, who need to understand the nature of changes in stock markets to evaluate the potential benefits of international portfolio diversification and the analytical assessment of risks.

Despite the significant theoretical and empirical interest of financial contagion, there is still no consensus about whether cross-country propagation of shocks through fundamentals⁸ should be considered contagion. Hence, we need to differentiate between *pure contagion*⁹ and shock propagation through fundamentals¹⁰. Some have suggested *transmission* (Bordo & Murshid, 2000; Lakshmi, Visalakshmi, & Shanmugam, 2015); *spillovers* (Brito & Pérez-Quirós, 2015; Dungey & Martin, 2007; Masson, 1998, 1999; Muratori, 2014); *interdependence* (Forbes & Rigobon, 2001, 2002, Gentile & Giordano, 2012, 2013) or *fundamentals-based contagion*¹¹ (Bonga-Bonga, 2015;

⁸ Financial, real and political links, constitute the *fundamentals links* of an economy (Gentile & Giordano, 2012; Moser, 2003). The first ones exist when two economies are connected through the international financial system. Real links are fundamental economic relationships between countries. These links have usually been associated with international trade, but other types of real links, like foreign direct investment across countries, may also be present. Finally, political links are the political relationships between countries. Although this link is much less stressed in the literature, when a group of countries share an exchange rate arrangement – a common currency in the case of the euro area countries – crises tend to be clustered (Gómez-Puig & Sosvilla-Rivero, 2014).

⁹ Masson (1998) defines *pure contagion* as an unanticipated situation. Claessens et al. (2001) and Gentile and Giordano (2012) define *pure contagion* in the sense of Masson's only when the transmission process itself changes when entering crises periods: when a crisis in one country may conceivably trigger a crisis elsewhere for reasons unexplained by macroeconomic fundamentals – perhaps because it leads to *shifts* in market sentiment, or changes the interpretation given to existing information, or triggers herding behavior.

¹⁰ The theories based on fundamentals channels are the oldest, and the general idea is that links across countries exist because the countries' economic fundamentals affect one another. These theories are usually based on standard transmission mechanisms, such as trade, monetary policy, and common shocks (e.g., oil prices), according Gentile and Giordano (2012, 2013).

¹¹ Fundamentals-based contagion refers to the transmission of shocks that is due to real and financial linkages or fundamental relationship of any kind, such as trade or macroeconomic policy, between countries (Bonga-Bonga, 2015; Dornbusch et al., 2000; Forbes & Rigobon, 2001; Masson, 1998).

Kaminsky & Reinhart, 1998). This differentiation is defined by Moser (2003), indicating that shocks propagation through fundamentals is the result of an optimal response to external shocks, which is not considered a source of pure contagion. For instance, a crisis in one country can cause disturbances in the equilibrium of other countries, causing an adjustment in the financial and real variables to a new equilibrium. In that case, financial market responses only anticipate and reflect changes in fundamentals, accelerating the adjustment to a new equilibrium, just transmitting and not causing the changes in the equilibrium. In other words, rather than causing a crisis, financial markets responses bring the crisis forward, being an example of fundamentals-based contagion rather than pure contagion (Moser, 2003).

In order to explain whether cross-country propagation of shocks is related or not by the fundamentals, market imperfections is the path to follow and understand. Having said that, two groups can be used to differentiate the *mechanisms of pure contagion* according to Moser (2003):

1. *Information Effects* – information is costly, imperfections and asymmetries can bring difficulties to assess fundamentals correctly. This situation can generate uncertainty among market participants, causing a miscomprehension of the true state of a country's fundamentals¹². A crisis elsewhere might lead them to reassess the fundamentals of other countries and cause them to sell assets, to call in loans, or to stop lending to these countries, even if their fundamentals remain objectively unchanged (Gentile & Giordano, 2013; Moser, 2003; Zouhair, Lanouar, & Ajmi, 2014). Goldstein (1998) affirms that a crisis in one country may serve as a *wake-up call* for market participants if it causes them to take a closer look at fundamentals similar to those in the country affected by the crisis¹³. Contagion occurs if the market participants find problems or risks that were not detected before (Gentile & Giordano, 2013).
2. *Domino Effects* – this group explains that a crisis in one country spreads to others as a result of the financial connections, direct or indirectly, in three possible different ways: by counterparty defaults; portfolio rebalancing related to liquidity constraints and portfolio rebalancing related to capital constraints. For more detail see (e.g., Gentile & Giordano, 2013, p. 202; Moser, 2003).

2.1.1 What is Financial Contagion?

Contagion phenomenon generally is used to describe the spread of market disturbances from one country to another¹⁴. In its broadest sense, therefore, financial contagion is related with the propagation of adverse shocks that have the potential to trigger financial crises. The core of the matter is to identify potential propagation mechanisms and define those that represent contagion (Moser, 2003). In spite of the greatest relevance of the

¹² Investors do not know enough about the countries in which they invest and therefore try to infer future price changes based on how the rest of the market is reacting. The relatively uninformed investors follow the supposedly informed investors, and all the market moves jointly (Gómez-Puig & Sosvilla-Rivero, 2014). For example, a crisis in one emerging market country can trigger investors to withdraw funds from many emerging markets without taking into account the fundamental economic differences between them (Bonga-Bonga, 2015; Gentile & Giordano, 2012, 2013).

¹³ The literature offers a few reasons indicating why crisis elsewhere could lead to a revaluation of the fundamentals. For instance, the signal extraction failures, wake-up call, expectations interactions, moral hazard plays and membership contagion (Moser, 2003).

¹⁴ The process can be observed through co-movements in exchange rates, stock prices, sovereign spreads and capital flows (Gentile & Giordano, 2012).

contagion phenomenon, there is still no consensus on either the definition or the transmission channels of financial contagion. As a first step, it is helpful to understand what contagion does not mean and what it does mean.

The World Bank (2016) distinguishes three definitions of financial contagion: *broad*, *restrictive* and *very restrictive*.

The *broad definition*: it is vague and generalist, this definition was used in the earliest stages of the research on contagion phenomenon. Under this approach, contagion is the cross-country transmission of shocks or the general cross-country spillover effects during the crisis (Gentile & Giordano, 2012, 2013). Furthermore, this definition also claims that contagion can take place during both “good” times and “bad” times, indicating that contagion does not need to be related to crises. However, contagion has been emphasized during crisis periods. Using the broad definition is difficult, since it does not provide a framework to work with, no triggering event is involved and, a priori, no underlying relationships are supposed. Within this definition, recent works about spillovers propagation can be seen in the research of Diebold and Yilmaz (2008). Corsetti, Pericoli, and Sbracia (2001) specify that contagion occurs when a country-specific shock becomes “regional” or “global”, which fits also the broad definition of contagion.

The *restrictive definition*: it is suitable in more recent literature, where contagion is the transmission of shocks from one country to others or the cross-country correlation, beyond what would be explained by fundamentals or common shocks¹⁵. This definition is usually referred to as *excess co-movement*¹⁶, commonly explained by *herding behavior*. The research of Eichengreen, Rose, and Wyplosz (1996) and Bekaert, Harvey, and Ng (2005) can be fit into this definition. For instance, Masson (1998, 1999) defines contagion as a transmission of crises that cannot be identified with observed changes in macroeconomic fundamentals. Therefore, the restrictive definition of contagion does not need any type of link among countries, implying that contagion should be explained by causes beyond any fundamentals links, namely, herd behavior, financial panics, or switches of expectations across instantaneous equilibria (Corsetti et al., 2001).

The *very restrictive definition*: it implies an increase in the linkages after a crisis, when cross-country correlations increase during “crisis times” relative to correlations during “tranquil times”, therefore, this can only be due to factors unrelated to fundamentals, since they cannot change in a short period of time (Gentile & Giordano, 2012, 2013). In fact, Dornbusch et al. (2000) and Forbes and Rigobon (2002) argue that contagion is a significant increase in cross-market co-movements after a (negative) shock to one country (or group of countries). This definition is known sometimes as “*shift-contagion*”¹⁷. Forbes and Rigobon (2001) reinforce that this notion of contagion excludes a constant high degree of co-movement in a crisis period, otherwise markets would be just

¹⁵ Fundamentals causes of contagion include macroeconomic shocks that have repercussions on an international scale and local shocks transmitted through trade links, competitive devaluations, and financial links (Gentile & Giordano, 2012, 2013).

¹⁶ That means a correlation that remains even after controlling for fundamentals and common shocks. Herding behavior is usually said to be responsible for co-movement beyond that explained by fundamentals linkages (Gentile & Giordano, 2012).

¹⁷ Our definition of “*shift contagion*” following Gentile and Giordano (2012), relies on a significant increase in cross-market co-movements after a shock, which is not related with fundamentals linkages (such as financial, real or political). The only transmission channel that could explain *contagion* is the *behavioral* one.

interdependent¹⁸. There is contagion only if cross-market co-movements increase significantly after the shock¹⁹. Any continued high level of market correlation suggests strong linkages between the two economies that exist in all states of the world. This definition implies the presence of a tranquil, pre-crisis period, requiring that contagion effects are to be differentiated from “normal” transmission of shocks across countries, usually defined as interdependencies (Bae, Karolyi, & Stulz, 2003; Corsetti, Pericoli, & Sbracia, 2005; Forbes & Rigobon, 2002; Gentile & Giordano, 2012, 2013; Gómez-Puig & Sosvilla-Rivero, 2014). In addition, Edwards (2000) asserts that contagion reflect a situation in which the effect of an external shock is larger than what was expected by experts and analysts, implying that contagion has to be differentiated from the “normal” transmission of shocks across countries.

Currently this *very restrictive* definition reveals two major advantages: firstly, it provides a straightforward framework for testing whether contagion occurs or not by comparing co-movements between two markets (such as cross-market correlations coefficients) during a relatively stable period with co-movements immediately after a shock or crisis, which does not require a specification of a structural representation for stock returns. Secondly, it allows distinguishing between permanent and temporal mechanisms of crises transmission. Identifying if the propagation of a crisis is due to permanent or temporal mechanisms has important implications for designing public policy responses (Bejarano-Bejarano, Gomez-Gonzalez, Melo-Velandia, & Torres-Gorron, 2015). There are several researches based on this definition²⁰.

This empirical research uses the *very restrictive* definition of contagion, because it provides an alternative explanation for transmission of crisis, namely interdependence, allowing one to answer the questions: *Is there contagion or interdependence? Do the periods of highly correlated market movements provide evidence of contagion? Does the cross-market relationship change during periods of crisis?* Our main goal is to try to answer these questions in the context of both crises (LBBC and ESDC) from the perspective of the BRICS countries stock markets.

2.1.2 Causes and Transmission of Contagion

The literature divides the concept of contagion into two broad categories (Bonga-Bonga, 2015; Dornbusch et al., 2000; Forbes & Rigobon, 2001; Masson, 1998; Pritsker, 2000), namely, *fundamentals-based*²¹ and *investor-behavior contagions*. The first category emphasizes spillovers that result from the normal interdependence among

¹⁸ Regarding the extreme definition of contagion phenomenon, for instance, the research of Bae, Karolyi, and Stulz (2000, 2003) consider extreme return shocks across countries as evidence for contagion.

¹⁹ A contagious event cannot occur in the absence of a shock, indicating that a large shock should occur (Caporin et al., 2013; Constâncio, 2012).

²⁰ See, for example, Forbes and Rigobon (2002), Pericoli and Sbracia (2003), Samarakoon (2011), Constâncio (2012), Kalbaska and Gałkowski (2012), Gentile and Giordano (2012, 2013), Bejarano-Bejarano et al. (2015), and Luchtenberg and Vu (2015).

²¹ *Fundamentals-based contagion* is caused by “monsoonal effects” and “linkages”. Monsoonal effects – are random aggregate shocks that hit a number of countries in a similar way (such as a major economic shift in industrial countries, a significant change in oil prices or changes in US interest rates) that may adversely affect the economic fundamentals of several economies simultaneously and, therefore, may cause a crisis (Eichengreen et al., 1996; Masson, 1998). Linkages – are normal interdependencies, such as those produced by trade and financial relations between countries and which can easily become a carrier of crisis (Kaminsky & Reinhart, 2000; Masson, 1998).

market economies, referring to the transmission of shocks that is due to real and financial linkages or fundamentals relationship of any kind, such as trade or macroeconomic policy, between countries. These forms of co-movements would not indicate contagion, according to the *restrictive* and *very restrictive* definition of contagion, which is adopted in this research. According to Gentile and Giordano (2012), fundamentals linkages cannot change suddenly in a few months after a shock has occurred. Hence, that is considered interdependence.

The second category involves a financial crisis that is not linked to observed changes in macroeconomics or other fundamentals but is solely the result of a change in investor behavior which alters the flow of international portfolio investments in such a manner that it cannot be explained by economic fundamentals. Under this definition, contagion arises when a co-movement occurs, even when there are no global shocks and interdependence and fundamentals are not factors. For example, a crisis in one emerging market country can trigger investors to withdraw funds from many emerging markets without taking into account the fundamental economic differences between them²² (Bonga-Bonga, 2015). If the transmission force is based on the irrational behavior of the market agents, known as “*irrational*” phenomena²³, then even countries with good fundamentals can be seriously affected, in this case we have contagion. On the other hand, if the crisis is transmitted through stable fundamentals linkages, then only countries with fragile economic fundamentals will be affected while those with good fundamentals can be protected. In that case, we have only interdependence (Gentile & Giordano, 2012).

Table II Fundamentals Causes of Contagion²⁴.

<i>Fundamentals-based</i>	<i>Investor's behavior</i>
1) Common shocks	1) Liquidity problems
2) Trade links and competitive devaluations	2) Information asymmetries and costs
3) Real and financial links	3) Multiple equilibriums
4) Macroeconomic policies	4) Changes in the rules of the game

The degree of financial market integration determines how immune to contagion countries are²⁵. The spread of a crisis depends on the degree of financial market integration²⁶. The higher the degree of integration, the more extensive could be the contagious effects of a common shock or a real shock to another country. Conversely, countries that are not financially integrated, because of capital controls or lack of access to international financing,

²² This event is known as “*Fight-to-quality phenomenon*” and refers to a sudden shift in investment behaviors in a period of financial turmoil where investors try to sell assets perceived as risky and instead purchase safe assets. An important feature of *flight-to-quality* is an insufficient risk taking behavior by investors. Though excessive risk taking can be a source of financial crisis, insufficient risk taking can severely dislocate credit and other financial markets during the financial crisis. These shifts in portfolio investments result in further negative shocks to the financial sector. In accordance to this phenomenon demand for 10-year US Treasuries and gold increased during the recent financial turmoil (Kazi & Wagan, 2014).

²³ This can occur in the form of speculative attacks, financial panics, herd behavior, loss of confidence, and increased risk aversion (Gentile & Giordano, 2012, 2013).

²⁴ Macroeconomics causes. See for example, Dornbusch et al. (2000) and Claessens et al. (2001).

²⁵ For example, Chinese and Indian economies are relatively closed and feature state-controlled capital markets, meaning that their development strategy is based on domestic industrialization catering to export markets. However, the Brazilian and Russian economies are based on natural resources and are much more open and currently subject to relatively less state control (Zouhair et al., 2014). South Africa is also based on natural resources and is much more open and currently subject to relatively less state control. In fact, is the most liberalized financial market in the BRICS countries (Bonga-Bonga, 2015).

²⁶ Despite its many advantages, in the short-term, financial liberalization is often accompanied by a wave of financial crises, many of which have taken a systemic extent and hit, in particular, the newly liberalized economies (Ben Rejeb & Boughrara, 2015). This Integration increased interdependence causes extreme negative events in one country to quickly affect others. These extreme negative events, and their joint coincidence across countries, have increased over time, creating substantial challenges for countries affected by contagion (Forbes, 2012).

are by definition immune to contagion (Dornbusch et al., 2000). This is correct because of our very restrictive definition, however, it might not be true for other definitions of contagion.

The initial literature has generally been divided as to whether transmission through real or financial channels constitutes contagion. Forbes and Rigobon (2001, 2002), Gentile and Giordano (2012) argue that the theoretical literature of contagion could be split into two groups: *crisis-contingent* and *non-crisis-contingent* theories.

Table III Possible Explanation for Contagion.

<i>Crisis-Contingent Theories</i>	<i>Non-Crisis-Contingent Theories</i>
1) Multiple equilibria ²⁷	1) Trade
2) Endogenous liquidity shocks	2) Policy coordination
3) Political contagion	3) Country reevaluation
4) Random global monetary shocks	4) Random real global shocks

The first one is related to the financial linkages, explaining why transmission mechanisms change during a crisis and therefore why a shock leads to an increase in the cross-market linkages. On the other hand, the second one is related to the real linkages, if transmission mechanisms are the same during a crisis as during more stable periods, and therefore cross-market linkages do not change (increase) after a shock. Theories belonging to the second group may be interpreted as interdependence rather than contagion²⁸.

2.1.3 Contagion: Testing and Measurement

Gentile and Giordano (2012, 2013) describe *contagion* as the amount of co-movement among asset prices which exceeds what is explained by fundamentals, since fundamentals cannot change in a few months. They argue that a degree of extreme connection or asymmetry that goes beyond interdependencies must be present in order for contagion to be present.

Research on contagion range from testing conditional correlation to contagion of bond spreads, sovereign ratings, credit default swaps (CDS) spreads, stock market returns, differences in interest rates, common trends and cycles, monetary policy and currency market (Bianconi, Yoshino, & Machado de Sousa, 2013; Caporin, Pelizzon, Ravazzolo, & Rigobon, 2013; Fourie & Botha, 2015; Gentile & Giordano, 2012, 2013, Gómez-Puig & Sosvilla-Rivero, 2014, 2011; Matos, Oquendo, & Trompieri, 2015)²⁹. For instance, Forbes and Rigobon (2001) discriminated empirically between contagion and interdependencies by testing whether or not cross-market correlation increases statistically significantly in crisis periods. If that is the case, *crisis-contingent* theories have a point, otherwise, interdependencies are responsible for the spread of crisis. Furthermore, Forbes and

²⁷ Multiple equilibria, occurs when a crisis in one country is used as a “sunspot” variable for other countries (Forbes & Rigobon, 2001). For example, Masson (1998) and Gentile and Giordano (2013) show how a crisis in one country could coordinate investors’ expectations, shifting them from a good to a bad equilibrium for another economy and thereby cause a crash in the second economy.

²⁸ For more detail, see, for example, Forbes and Rigobon (2002). As said before, the transmission of shocks through the first two linkages (financial and real) is considered as interdependence or spillovers (Gentile & Giordano, 2012).

²⁹ And others (Aloui, Aïssa, & Nguyen, 2011; Andenmatten & Brill, 2011; Ang & Chen, 2002; Baur, 2012; Beirne & Gieck, 2012; Bonga-Bonga, 2015; Boubaker et al., 2016; Campbell, Forbes, Koedijk, & Kofman, 2006; Constâncio, 2012; Favero & Giavazzi, 2000; Forbes, 2012; Forbes & Rigobon, 2001, 2002; Khalid & Kawai, 2003; Pontines & Siregar, 2007; Saghalian, 2010; Suleimann, 2003; Zouhair et al., 2014).

Rigobon (2002) argue that simple correlation are biased due to the presence of heteroskedasticity, endogeneity, and omitted variables³⁰. After correcting for these statistical problems for the case of the 1994 Mexican crisis, the 1997 Asian Crisis, and the 1987 USA stock market crash, they found only *interdependence*, no *pure contagion*³¹.

Andenmatten and Brill (2011), following Forbes and Rigobon (2002) methodology, also performed a bivariate test for contagion to examine whether the co-movement of sovereign CDS premium increased significantly after the beginning of Greek debt crisis in October 2009. The findings revealed that in European countries, both contagion and interdependence occurred. In addition, Baig and Goldfajn (1999) in the context of the Asian crisis, using the same methodology, performed a cross-market correlation for exchange rates, stock returns, interest rates, and sovereign bond spreads. The findings for sovereign spreads highlighted strong evidence of contagion and high correlation among exchange rate, stock returns and interest rates co-movements. They conclude that spreads directly reflecting the risk perception of financial markets, indicating that pure contagion may be the result of the behavior of investors or other financial agents (Claessens et al., 2001).

Extending the study related to the 1997 Asian crisis, Khalid and Kawai (2003) using the Granger causality and Impulse responses methodology for nine East Asian countries, tested for contagion based on three main financial markets indicators: foreign exchange rates, stock market prices and interest rates. The empirical evidence, however, did not find strong support for contagion.

Bonga-Bonga (2015) provides evidence of contagion phenomenon by analyzing financial contagion between South Africa and its BRICS equity market from December 1996 to May 2012, the initial period corresponds with the liberalization of a number of BRICS equity markets. By applying a conditional correlation framework, they find evidence of cross-transmission and dependence between South Africa and Brazil. Furthermore, the research also ascertained that South Africa is more affected by crises originating from China, India and Russia than these countries are by crises from South Africa. Furthermore, Matos et al. (2015) performed a test to identify common trends and cycles between BRIC's stock markets, providing evidence of contagion effect, with Brazil and China financial markets playing a leading role in the transmission of contagion. They conclude that worldwide investors should consider reactions in Chinese and Brazilian markets during a crisis as a predictor of other BRIC reactions through *the contagion channel*³², while policy makers should remain attentive to the level of contagion observed, given its relevance when evaluating the effectiveness of interventions and financial assistance packages after crisis.

A wide range of empirical techniques has been used to quantify contagion in the literature. For instance, Forbes (2012) refers tools to measure contagion range from cross-market correlations analysis (Forbes & Rigobon, 2001, 2002) to probability analysis (Constâncio, 2012; Eichengreen et al., 1996; Gómez-Puig &

³⁰ During times of increased volatility (i.e., in time of crisis) estimates of correlation are biased upward. If co-movement tests are not adjusted for that bias, contagion is too easily detected.

³¹ After they have adjusted the correlation coefficient, taking in account the changes in volatility. Notwithstanding, Corsetti, Pericoli, and Sbracia (2005) have contested this methodology, indicating that this conclusion cannot be empirically generalized.

³² Trade, banks/lending institutions, portfolio investors and wake-up calls/fundamentals reassessment (Forbes, 2012).

Sosvilla-Rivero, 2014, 2011) to latent factor/GARCH models (Bekaert, Ehrmann, Fratzscher, & Mehl, 2011; Bekaert et al., 2005; Dungey & Yalama, 2010) to extreme values/co-exceedance/jump (Bae et al., 2003; Berger & Pukthuanthong, 2012; Boyer, 2006; Forbes, 2012) and VAR models³³ (Beirne & Gieck, 2012; Favero & Giavazzi, 2002; Fourie & Botha, 2015; Gentile & Giordano, 2012, 2013; Matos et al., 2015; Syriopoulos et al., 2015).

More related to our approach, Boubaker et al. (2016) use VAR-VECM to measure contagion between US stock market and developed and emerging stock markets during the Subprime crisis in September 2008. They provided significant evidence of contagion effects between the US stock market and the developed and emerging equity markets after the global financial crisis. Beirne and Gieck (2012) use a global VAR to measure interdependence and contagion across bonds, stocks and currencies for over 60 economies during periods of crisis. Their analysis reveals that shocks to equity markets typically originate in the US and that bond market shocks tend to originate in the Eurozone. Gentile and Giordano (2012, 2013) use cointegration and VECM/Granger causality tests to measure the existence and direction of contagion in European countries during the LBBC and ESDC, pointing out the occurrence of contagion phenomenon in both crises. Fourie and Botha (2015) using the same methodology provided by Gentile and Giordano (2012, 2013), but for sovereign ratings, proved contagion in European countries, during the two recent windows of crises: Lehman Crisis and European Union Sovereign Debt Crisis.

Andenmatten and Brill (2011) perform a bivariate test for contagion that is based on an approach proposed by Forbes and Rigobon (2002) to examine whether the co-movement of sovereign CDS premium increased significantly in emerging and industrialized countries during the Greek debt crisis of 2009. They conclude that contagion and interdependence occurred. Saghaian (2010) uses Granger causality to create contemporaneous contagion links between agriculture and energy markets within the commodity sector. Suleimann (2003) uses VAR to measure contagion in technology stock prices between Europe and the United States. Pontines and Siregar (2007) use Markov Switching and VAR to measure contagion in East Asian markets using stock exchange returns during periods of turbulence. Favero and Giavazzi (2000) use VAR to test contagion using money market spreads across European Monetary Union countries. Baig and Goldfajn (1999) use dummy variables in VAR and correlation models to prove contagion during the East Asian crisis.

³³ These models are closely related to the use of correlation coefficients to analyze contagion. Generally, they predict stock market returns or yield spreads while controlling for global factors and country-specific factors, as well as for the persistence of these factors through error-correction techniques. Contagion is then measured with an impulse-response function predicting the impact of an unanticipated shock to one country on others. These tests are less conservative than those based on correlation coefficients as they generally do not adjust for the heteroskedasticity in returns (and attempts to make this adjustment generate fragile results). Not surprisingly, papers using VARs generally find more evidence of contagion (Forbes, 2012).

3 Data & Methodology

3.1 Data

Our main objective is to test for contagion during the last two international financial crises³⁴, using an important financial market indicator: The *Stock Market Index* (SMI). Further on, we apply a tree-step econometric analysis³⁵ to test for contagion that will be discussed in detail later. We will analyze the different connections and co-movement between countries to identify any cross-market or cross-country connections that can explain and assess contagion phenomena in the BRICS stock markets³⁶.

Morgan Stanley Capital International (MSCI)³⁷ for large-caps is the main source used for stock price indices. The sample consists of five countries from the Emerging Markets known as BRICS: (Brazil (BRA), Russia (RUS), India (IND), China (CHI) and South Africa (SAF)) and one developed country, the United States (USA), using daily stock indices closing prices for each country. The daily frequency sample was considered, because interdependence phenomena can explode in a few days. So if we had considered weekly or monthly data (lower frequency data), we could have lost the measurement of interactions (innovations), which may last only a few days (Gentile & Giordano, 2012, 2013; Jin & An, 2016; Voronkova, 2004).

Table 1 Variables Explanation.

Variables	Explanation	Type
BRA	Log-level value of MSCI Brazil (large-caps) Stock Price Index	Exogenous/Endogenous
RUS	Log-level value of MSCI Russia (large-caps) Stock Price Index	Exogenous/Endogenous
IND	Log-level value of MSCI India (large-caps) Stock Price Index	Exogenous/Endogenous
CHI	Log-level value of MSCI China (large-caps) Stock Price Index	Exogenous/Endogenous
SAF	Log-level value of MSCI South Africa (large-caps) Stock Price Index	Exogenous/Endogenous
USA	Log-level value of MSCI United States (large-caps) Stock Price Index	Exogenous

Note: Regarding to national holidays, the index level was assumed to stay the same as that on the previous trading day. The USA variable is implicitly imputed in the data, because as it is stated in the literature that linkage patterns may be distorted when the influence of the US market is not taken into consideration³⁸.

The daily stock indices (in log-level) were presented also through graphical representation over the period of the study (see Figure 1). Visually, all indices were recovering jointly from 2003 until the beginning of the 2008

³⁴ The recent Lehman Brother bankruptcy Crisis (LBBC) and European Sovereign Debt Crisis (ESDC).

³⁵ *First*: A bivariate dynamic cointegration analysis; *Second*: Granger causality test and VECM/Gonzalo-Granger statistic; *Third*: we apply the Variance decomposition method following Baig and Goldfajn (1999), Beirne and Gieck (2012), Gentile and Giordano (2012, 2013), Fourie and Botha (2015) and Boubaker et al. (2016).

³⁶ The methodology that will be implemented is based on the definition of contagion as a significant increase of the total number of cross-market connections around the two crises following the definition of contagion suggested by Forbes and Rigobon (2002), Gentile and Giordano (2012, 2013) and World Bank (2016).

³⁷ For more detail see www.msci.com.

³⁸ For more details, see Khalid and Kawai (2003), Yang et al. (2003), Bekaert, Ehrmann, Fratzscher, and Mehl (2011), and Gentile and Giordano (2012, 2013).

as a period of economic growth that lasting until 2007. But subsequently most of the indices have shown swift positive and negative trend movements. Consequently, the USA subprime mortgage crisis, the confidence of banks in each other's solvability decreased sharply leading to the breakdown of the interbank lending market and turmoil on the financial market in the second half of 2007. Large downturns in stock prices followed and the interconnectedness of stock market indices rose again as all markets suffered from similarly intensive losses. Hence, after April 2008 until the insolvency of Lehman Brothers in September 2008, stock markets' tendencies started to move jointly, as we can see in Figure 1, first shade.

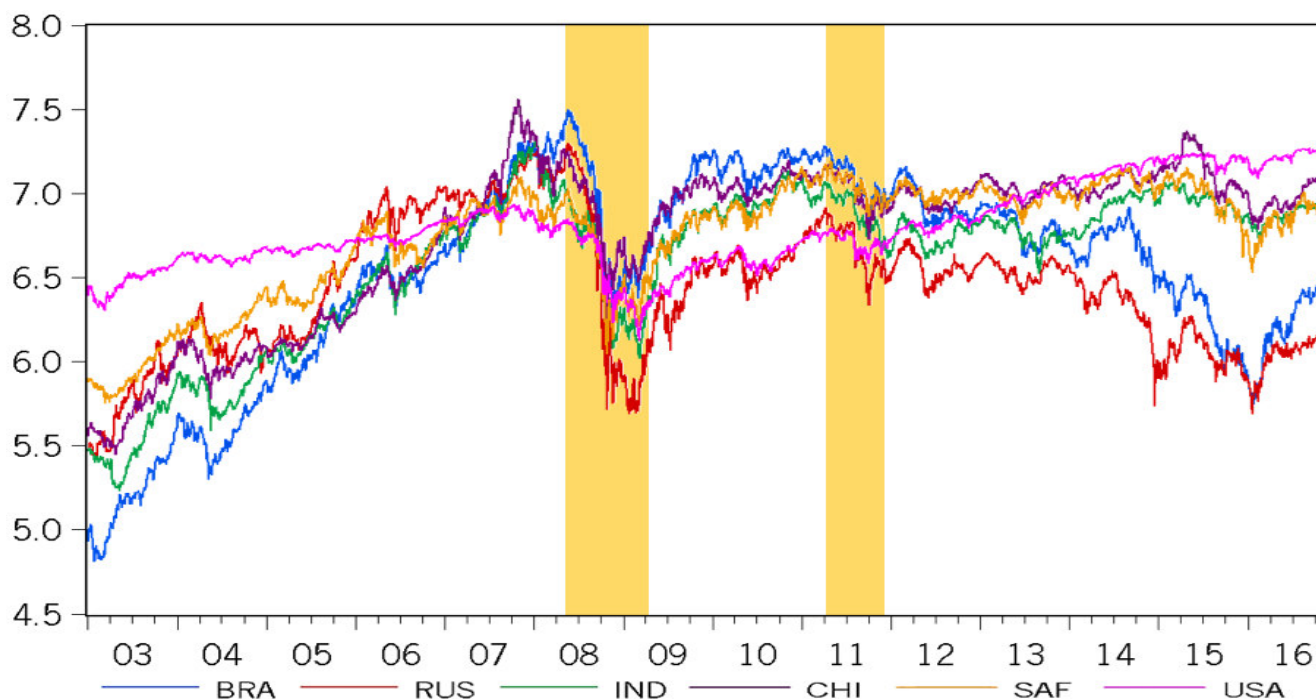


Figure 1: Source: Author's own. Using EVIEWS 9.0 program. Movement of BRICS and USA stock market Indices for full sample in daily log-level from January 1, 2003 to October 31, 2016 (13 years and 10 months, 3609 observations). The Highlighted first shadow refers to the period of the GFC 2007-2008 and the second shadow period refers to the European Sovereign Debt Crisis started in 2011 that will be studied in this research as a contagion window.

Daily stock prices were plotted to highlight the empirical regularities³⁹ of a crisis. Hence, according to Corsetti et al. (2001), when a crisis hits a stock market we would expect sharp falls in prices, increases in volatility and also increases in covariances (see Appendix A and B).

Regarding daily data, it is necessary to consider the differences in time zones and in trading hours of the exchanges when interpreting the results. Therefore, we considered a central time window around the two crises (LBBC and ESDC) as suggested by Jin and An (2016). A two day rolling average, as suggested by Forbes and Rigobon (2002) to account for time synchronization of different markets, which lay in different time zones has not been considered in this research due to severe autocorrelation problem as highlighted by Chiang, Jeon, and Li (2007) and Ahmad, Sehgal, and Bhanumurthy (2013).

³⁹ Crises are characterized by empirical regularities when: 1) Sharp falls in stock markets tend to concentrate in periods of international financial turmoil. 2) Volatility of stock prices increases during crisis periods. 3) Covariance between stock market returns increases during crisis periods. 4) Correlation between stock market returns is not necessarily larger during crisis periods than during tranquil periods.

3.1.1 Variable Transformation

We took natural logarithms of our data before proceeding to the analysis process (see table 1). The log form of stock indices were used in order to reduce the heteroskedasticity present in the data (Singh & Kaur, 2016), smoothing out the fluctuations (see appendix D and E), to make the data series linear and very helpful for the purpose of further analysis (Verma & Rani, 2016). Moreover, for evaluating the rate of daily returns needed for further analysis⁴⁰, the initially log-level variables were taken and calculated (Ahmad et al., 2013; Malliaris & Urrutia, 1992; Mensah & Alagidede, 2017; Pragidis & Chionis, 2014; Syriopoulos et al., 2015) on the following basis:

$$R_t = [\log(P_t) - \log(P_{t-1}) \times 100] = \left[\log\left(\frac{P_t}{P_{t-1}}\right) \times 100 \right] \quad (1)$$

Where, R_t is the percentage daily returns value at time t , P_t and P_{t-1} , are the percentage daily returns value at two successive days: t and $t - 1$, respectively.

After the transformation, the percentage daily stock return variables were defined as: SRBRA, SRRUS, SRIND, SRCHI, SRSFAF and SRUSA (see appendix C).

Daily closing prices of the BRICS stock markets were retrieved from *Thomson Reuters Datastream* database and are expressed in US dollars⁴¹, and the time range of the time series goes from January 1, 2003 to October 31, 2016⁴². Eviews 9.0 and *R programming* were used for arranging the data and implementation of econometric analyses.

3.1.2 Descriptive Statistics

For ascertaining preliminary know-how of behavioral characteristics of the data, Table 2 presents descriptive statistics of all the return indices.

In Table 2 we present descriptive statistics of BRICS and USA stock market indices from January 1, 2003 to October 31, 2016. As shown, stock returns changes demonstrate a slightly positive mean, which indicate that stock returns increases have been larger than its decreases in the sample period. On average, the highest returns are given by SRBRA (0.044%), SRCHI (0.041%) followed by SRIND (0.040%). Regarding to the stock return of SRRUS and SRBRA present the higher risk and volatility related to the other variables (Std. Dev.: 2.39% and 2.24%, respectively). Concerning skewness, which is a measure of asymmetry of the distribution of the series around its mean, has shown that the values are negatively skewed (excluding for SRCHI, which is positively skewed), indicating that there is a higher probability for investors to get negative rather positive returns from all the other variables.

⁴⁰ To deal with the unit root that we will see in further analysis.

⁴¹ Using US dollars: 1) it is possible to avoid volatility that is induced by monetary phenomena such as inflation rates; 2) Avoid the impact of exchange rates; 3) US dollars are especially relevant to international investors because of the interpretation problems in using stock indices denominated in the local currency (Bekaert & Harvey, 1995; Chen et al., 2002; Mollah, Zafirov, & Quoreshi, 2014; Roll, 1992; Singh & Kaur, 2016).

⁴² Data was set in the begin of 2003 to avoid contamination in the stock market from earlier bond crises in Russia and Latin America (Cronin, Flavin, & Sheenan, 2016, p. 6).

Kurtosis measures the peakedness or flatness of the distribution of the series. The sample distributions of SRBRA, SRRUS, SRIND, SRCHI, SRSFAF and SRUSA are skewed left and leptokurtic⁴³. Kurtosis is higher than ($K > 3$)⁴⁴ for these six variables, confirming significant non-normality (see Appendix E). In addition, the Jarque-Bera (JB) test (Jarque & Bera, 1980), is a test statistic for testing whether the series is normally distributed or not. JB test statistics clearly rejects the null hypothesis of normality for all the variables in the study, probability value is very small (p-value = 0,0000), rejecting the normality at 1% level. The Ljung-Box statistic test (Ljung & Box, 1978), detected significant autocorrelation in all cases, probability value is also very small (p-value = 0,0000), rejecting the null hypothesis of no serial correlation, as we can see in Table 2.

Table 2 Descriptive Statistics (log-level)

Variables	N	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
BRA	3609	6.5376	0.6074	-0.8550	2.9614	439.92*
RUS	3609	6.4310	0.3996	-0.0349	2.3848	57.639*
IND	3609	6.6023	0.4657	-1.1810	3.3801	860.64*
CHI	3609	6.7525	0.4680	-1.0687	2.9950	686.93*
SAF	3609	6.7473	0.3460	-1.1261	3.2410	771.53*
USA	3609	6.7967	0.2485	0.2497	2.3321	104.57*

Descriptive Statistics (percentage stock return)						
Variables	N	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Jarque-Bera
SRBRA	3609	0.0440	2.2425	-0.2206	10.143	7700.9*
SRRUS	3609	0.0169	2.3788	-0.4298	17.442	31473.*
SRIND	3609	0.0397	1.7098	-0.0369	12.280	12916.*
SRCHI	3609	0.0412	1.7646	0.0239	10.018	7406.6*
SRSFAF	3609	0.0288	1.9166	-0.2216	7.2509	2746.8*
SRUSA	3609	0.0233	1.1540	-0.3050	14.994	21689.*

Note: Source: Author's own based on Eviews 9.0 program. Representation of full sample of log-level and daily stock returns in percentage. (*) probability value (p-value) significant at 1% level. The Ljung-Box test for SRBRA (62.992*), SRRUS (106.43*), SRIND (85.003*), SRCHI (60.234*), SRSFAF (52.641*) and SRUSA (116.04*), respectively.

3.2 Methodology

3.2.1 Testing for Stationarity

Our financial time series are non-stationarity. The term stationary means that the series should have mean, variance, and covariance unchanged by the time change (Singh & Kaur, 2016). In order to test the stationarity, the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979, 1981) and Phillip-Perron (PP) test (Phillips & Perron, 1988), were used. A cointegration relationship requires the series to be non-stationary. Hence, it is necessary to conduct unit root tests⁴⁵ of all series included in the analysis to establish the order of integration of all variables. For that purpose, two different specifications of ADF tests and PP tests were applied. The first one includes

⁴³ Financial series are commonly leptokurtic, the kurtosis value is a largely positive. Meaning that, the statistical distribution is clustered, resulting in a higher peak, or higher kurtosis, than the curvature found in a normal distribution. This high peak and corresponding fat tails mean the distribution is more clustered around the mean than in a mesokurtic or platykurtic distribution and has a relatively smaller standard deviation.

⁴⁴ Regarding ($K < 3$), we can see, for example, the log-level variables – BRA, RUS, CHI and USA can be considered as a platykurtic distribution (see appendix D).

⁴⁵ Variables series that contains unit root is considered to be nonstationary. $I(n)$ denotes integration of order n ; $I(1)$ denotes unit root and $I(0)$ denotes stationarity.

the intercept term but excludes the trend term, and the second specification includes both the trend and the intercept term. Simultaneously, the selection of appropriate lag order is important. A unit root test is a statistical test for the proposition that the autoregressive parameter is one in an autoregressive statistical model of a time series. Therefore, the ADF test augments the lagged values of the dependent variable in the series based on the following equation⁴⁶:

$$\Delta y_t = \alpha_0 + \alpha_1 t + \delta y_{t-1} + \sum_{j=1}^k \gamma_j \Delta y_{t-j} + \varepsilon_t \quad (2)$$

Where, Δ is the difference operator, α_0 is a drift parameter, α_1 is the coefficient on time component t , δ is the testing coefficient of unit root, k is the lag order of first difference series, γ_j is the coefficient of lagged first difference series, y_t denotes index series at time t and ε_t is a stationary random error (white noise error term)⁴⁷. For an index series y_t , the ADF test consists in a regression on the first difference of the series against the series lagged k times. The null hypothesis is $\delta = 0$, where $\delta = (k - 1)$ and the alternate hypothesis is $\delta < 0$ (or $k < 1$). The acceptance of the null hypothesis proclaims the existence of a unit root in a series, making it nonstationary, whereas the alternate hypothesis states that the series is stationary.

In case of the ADF test, it is assumed that the errors are statistically independent and have a constant variance, while in the PP tests the error disturbances are allowed to have some correlation and heteroskedasticity:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 \left[t - \frac{N}{2} \right] + u_t \quad (3)$$

Where, y_t is an index series at time t ; t is the t statistics; N is the sample size and u_t is a random error at time t .

Time series data are generated by $y_t = y_{t-1} + u_t$ where $E(u_t) = 0$ for all t . The constant and the trend terms are retained only if they are significantly different from zero. The ADF test establishes optimal number of lags k , by using the Schwarz Information Criterion (SIC), and PP test establishes bandwidth by using Bartlett kernel. It is possible to transform nonstationary to stationary time series either by differencing or de-trending⁴⁸.

Our results in Table 3 indicate the presence of a unit root in the series in log-level but not in first difference. This is a strong indication that all series exhibit a unit root, qualifying them for inclusion in the cointegration

⁴⁶ The ADF test is conducted under the assumption that errors (residuals) may be serially correlated. The test is "augmented" by adding the lagged values of the dependent variable, Δy_t to eliminate the serial correlation.

⁴⁷ White noise process: $u_t \sim N(0, \sigma^2)$ such that it is *i. i. d* (independently and identically distributed) with $Cov(u_t, u_{t-s}) = 0$.

⁴⁸ Nonstationary data have means, variances and covariance's that change over time. Nonstationary behaviors can be trends, cycles, random walks or combinations of the three. As a rule, are unpredictable and cannot be modeled or forecasted. The results obtained by using nonstationary time series may be spurious (resulting in a non-reliable t-statistic) in that they may indicate a relationship between two variables where one does not exist. In order to receive consistent, reliable results, the nonstationary data (see Appendix A and B), needs to be transformed into stationary data (see Appendix C). In contrast to the nonstationary process that has a variable variance and a mean that does not remain near, or returns to a long-run mean over time, the stationary process reverts around a constant long-term mean and has a constant variance independent of time.

analysis⁴⁹. For analyzing the existence of long-run linkages among emerging stock market indices, it is desirable that the Johansen cointegration method be performed. But before that, it is essential to determine the order of integration of all variables. Both unit root tests, the ADF test, and the PP test are used to examine the stock indices' non-stationarity. These tests are applied after determining the appropriate lag structure and bandwidth, as indicated by SIC for the ADF test and Bartlett kernel for the PP test, respectively. The results of the ADF test and the PP test for unit root tests (see Table 3) show that all the variable series are nonstationary at level. However, the series are stationary at their first difference ($I(0)$), that is, all the series are integrated of Order one ($I(1)$). Thus, the stock index is an ($I(1)$) process and the series can be modeled by cointegration analysis, allowing one to perform the Johansen cointegration test (Boubaker et al., 2016; Chen, Firth, & Meng Rui, 2002; Li, Ho, & Yau, 2015; Singh & Kaur, 2016; Verma & Rani, 2016).

Table 3 Unit Root Tests

Variables	ADF(L) ^c	PP(L) ^c	ADF(FD) ^c	PP(FD) ^c	ADF(L) ^t	PP(L) ^t	ADF(FD) ^t	PP(FD) ^t
BRA	-2.6534 (0.0825)	-2.6829 (0.0771)	-56.695 (0.0001)*	-56.600 (0.0001)*	-1.9969 (0.6023)	-1.9562 (0.6244)	-56.751 (0.0000)*	-56.668 (0.0000)*
RUS	-2.5320 (0.1079)	-2.4318 (0.1330)	-55.641 (0.0001)*	-55.479 (0.0001)*	-2.5464 (0.3055)	-2.4412 (0.3579)	-55.664 (0.0000)*	-55.508 (0.0000)*
IND	-2.3170 (0.1666)	-2.3175 (0.1665)	-56.364 (0.0001)*	-56.327 (0.0001)*	-2.0186 (0.5904)	-1.9737 (0.6149)	-56.384 (0.0000)*	-56.341 (0.0000)*
CHI	-2.4839 (0.1195)	-2.4812 (0.1202)	-58.463 (0.0001)*	-58.463 (0.0001)*	-2.1142 (0.5371)	-2.1345 (0.5257)	-58.489 (0.0000)*	-58.484 (0.0000)*
SAF	-2.5689 (0.0996)	-2.4938 (0.1170)	-27.945 (0.0000)*	-58.732 (0.0001)*	-2.7248 (0.2264)	-2.4765 (0.3399)	-43.932 (0.0000)*	-58.805 (0.0000)*
USA	-1.0632 (0.7322)	-1.0582 (0.7341)	-47.315 (0.0001)*	-67.743 (0.0001)*	-1.7749 (0.7169)	-1.7783 (0.7153)	-47.309 (0.0000)*	-67.734 (0.0000)*

Note: Source: Author's own based on Eviews 9.0 program. **L** = log-level and **FD** = First Difference. The ADF and the PP Unit Root Test was performed on full sample ($N = 3609$); January 2003 to October 2016. Both tests are one-sided tests of the null hypothesis that the variable has a unit root. The index [**c**] indicates that the test allows for a constant, while [**T**] for a constant and a linear trend. The number of lags for the ADF was selected using the (SIC) with maximum value of 29 lags. The lag truncation for the PP test was selected using the Bartlett kernel method with the automatic Newey-West bandwidth. Both tests follow MacKinnon (1996) one-side p-values. P-values equal or below 0.05 indicate a rejection of the null of a unit root and a p-value greater than 0.05 indicate a failure to accept the null of a unit root. (*) denotes the p-values at significance of 1% confidence level.

3.2.2 Vector Autoregressive Model

Vector autoregressive models (VARs) were popularized in econometrics by Sims (1980) as a natural generalization of univariate autoregressive models⁵⁰, being a systems regression model, where there is more than one dependent variable (Brooks, 2008). VARs models has three different variations: Reduced form, Recursive and Structural (Stock, 2001).

⁴⁹ Although they exhibit a unit root based on the entire sample it is possible that there will be sub-periods where they do not. It has however been deemed to lie outside of the scope of this thesis to research the time-variability of the unit root of the series, setting the bar of inclusion in the study only to evidence of a unit root for the entire sample period. Any periodically deviations from the presence of a unit root will result in fewer significant vectors in the cointegration analysis as a unit root for at least two series is a pre-requisite for a cointegrating relation to exist.

⁵⁰ That being said, a VAR model is simply an extension of the AR (p) model where there is more than one dependent variable under study and thus more than one equation. In the model, each equation has as explanatory variables lagged values of all variables under study. A deterministic trend could also be included in the model. The model is used to find the evolution and interdependences between several time series, therefore, it is a theory free model because economic theory is simply limited to selecting the equations in the model, and we let the VAR find any relationship between the variables (Li et al., 2015).

We have chosen to use an unrestricted VAR model⁵¹ to study the interactions between the BRICS stock market returns. The main advantage of this model, introduced by Sims (1980), is its ability to capture the dynamic relationship among the variables of interest. A VAR model consists of a system of equations that expresses each variable in the system as a linear function of its own lagged value and the lagged value of all the other variables in the system (Park & Ratti, 2008). A VAR model of order p , where p denotes the number of lags, that includes k variables, can be expressed as:

$$Y_t = \phi_0 + \sum_{i=1}^p \phi_i Y_{t-1} + \theta Z_t + \varepsilon_t \quad (4)$$

Where, $Y_t = [Y_{1t} \dots Y_{kt}]'$ is a 5-variable vector containing the following equity market variables in order: Brazil, Russia, India, China and South Africa. Z_t represents the exogenous variable⁵² and the residual ε_t is a column of error terms that are assumed to be zero-mean independent white noise processes. Parameters ϕ_0 , ϕ_i and θ need to be estimated.

The advantage of using the VAR framework⁵³ in the mean equation is to account for the interdependence of returns between BRICS countries and the influence of the deterministic and/or exogenous variable Z_t (here we account for the influence of the USA-S&P 500 returns on BRICS equity returns). Another important feature of the VAR model is its flexibility and the ease of generalization. For example, the model could be extended to encompass moving average errors, which would be a multivariate version of an ARMA model, known as a VARMA. In addition, VAR models allow the compactness with which the notation can be expressed as we can see above. Furthermore, the model also can also be extended to the case where the model includes first difference terms and cointegrating relationships, as in a VECM (Brooks, 2008).

VARs are good at capturing co-movements of multiple time series. Granger-causality tests, impulse response functions and variance decompositions are well-accepted and widely used⁵⁴.

⁵¹ A *reduced-form VAR* expresses each variable as a linear function of its own past values and the past values of all other variables being considered and a serially uncorrelated error term. The error terms are viewed as “surprises”—movements in the variables after taking its past into account. If the different variables are correlated with each other, then the error terms will also be correlated across equations. A *recursive VAR* constructs the error terms in each regression to be uncorrelated with the error term in the preceding equation. This is done by adding carefully selected contemporaneous values as regressors. Estimation of each equation in the system by OLS produces residuals that are uncorrelated across equations. Moreover, OLS estimates are consistent and asymptotically efficient. Even though the errors are correlated across equations (Enders, 2010, p. 303). A *structural VAR* uses economic theory to sort out contemporaneous links among the variables. Structural VARs require “identifying assumptions” that establish causal links among variables.

⁵² For more detail about exogenous variable in VAR, see, for example, Brooks (2008, p. 298).

⁵³ For more detail about VAR models see, for example, Sims (1980), Sims, Stock, and Watson (1990), Brooks (2008) and Enders (2010).

⁵⁴ For example, Forbes (2012) indicates that the VAR framework generally predicts stock market returns or yield spreads while controlling for global factors and country-specific factors, as well as for the persistence of these factors through error-correction techniques. Forbes and Rigobon (1999) point out an advantage of the VAR approach, which is that it allows us to deal with the (potential) endogeneity problem that has affected many regression-based contagion studies. Rastogi (2013) states that VAR based model serves the purpose of taking all the nations markets at the same time. This systems or simultaneous equation model approach makes VAR an appropriate tool. Considering systems of equations approach and autoregressive method to take into consideration the lag effect. This unique feature of VAR based Johansen’s co-integration test is the main reason for using this test in this research.

3.2.3 Johansen Cointegration Approach

3.2.3.1 Trace Test

The Johansen method is used to determine the presence of cointegrating vectors in nonstationary time series; it can be applied in a bivariate or multivariate setting⁵⁵. The ADF has shown that the financial data (in log-levels) follows a nonstationary process, allowing to test for cointegration. To examine the existence of cointegration, the time series data should be integrated of the same order ($I(1)$)⁵⁶.

If a long run association has been observed between the variables, then we can further analyze any disequilibrium if it arises (Singh & Kaur, 2016). Cointegration implies the existence of common stochastic trends in the series (i.e., the regression will not be spurious) which, after a shock, move the considered time series back to a long-run equilibrium relationship⁵⁷(Ludwig, 2016). The inference of cointegration requires long sample periods. Due to their length, however, relationships between such series are likely to change in time (Ludwig, 2016). The present research employs the Johansen cointegration techniques^{58,59} proposed by Johansen (1988, 1991) to account for co-movement and the long term relationship between the Emerging Stock Market Indices.

The Johansen method is a maximum likelihood (ML) approach based on two likelihood tests: *Trace test* (λ_{trace}) and *Maximum Eigenvalue* test (λ_{max}) proposed by Johansen (1988, 1991, 1995). The method finds out the cointegrating vectors⁶⁰, which are further introduced in the VAR by imposing certain restrictions known as VECM. The VECM model analyzes the short-run as well as long-run equilibrium relationship among the variables. The existence of a cointegrating vector exhibits the presence of a long-run equilibrium relationship among the variables. The two test statistics are expressed as follows:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i) \quad (5)$$

$$\lambda_{max}(r, r + 1) = -T \ln(1 - \hat{\lambda}_{r+1}) \quad (6)$$

Where, r is the number of cointegrating vectors⁶¹, $(\hat{\lambda}_i)_{i=1,\dots,n}$ is the estimated eigenvalues in decreasing order from the $\alpha\beta'$ matrices (Π), (further discussed in the § 3.2.3.2). T is the number of usable observations and N is

⁵⁵ In the case of a multivariate setting, it has the advantage of finding and providing estimates for all the cointegrating vectors within a VAR (Li et al., 2015).

⁵⁶ Two nonstationary time series are cointegrated if there is a linear combination of them that is stationary.

⁵⁷ Two series will be cointegrated whether they have a long term, or equilibrium relationship between them. The global investors will stand to gain only if the co-movement among the countries is at a minimal level (Singh & Kaur, 2016).

⁵⁸ Johansen cointegration techniques have the advantage of considering the error structure of the underlying process. It can incorporate different short and long-run dynamics of a system of economic variables. It enables to estimate and test the equilibrium relationship among nonstationary series while abstracting from short-term deviations from equilibrium. Thus, it provides relatively powerful tests when the model is correctly specified (Chen et al., 2002, p. 1125).

⁵⁹ The cointegration framework is useful since we can distinguish between the nature of long-run and of short-run linkages among financial markets and also capture the interaction between them (Matos et al., 2015).

⁶⁰ The Johansen test of cointegration requires that the lag lengths should be appropriate and the present research employs (SIC) to ascertain the lag lengths. To check the lag lengths, firstly, a VAR model at level was employed, where in the stock market indices among which we try to capture co-movement are taken as endogenous variables.

⁶¹ For instance, BRICS main indices share a common stochastic trend, so the cointegrating vectors need to be identified. Since the series in the system is formed by five variables ($N = 5$), there may be at most ($r = 4 = N - 1$) linearly independent cointegrating vectors, which may be arranged in a matrix given by $(\alpha_{N \times r})$, whose range is said the cointegration space (Matos et al., 2015).

the number of variables. Under the Trace test, the null hypothesis is there is no cointegrating vector ($H_0: r = 0$), whereas the alternative hypothesis of cointegration is n cointegrating vectors ($H_1: r > 0$). The Maximum Eigenvalue test, tests the null hypothesis that the number of cointegrating vectors is equal to r , whereas the alternative hypothesis tests the number of cointegrating vectors as $r + 1$. Hence, for each value of r , for the given orders: ($r = 0, 1, 2, 3 \dots N - 1$), the test statistic is compared to the critical value to determine the number of cointegrating vectors. If the test statistic is greater than the critical value, then the null hypothesis of $r = 0$ cointegrating vector is rejected in favor of the alternative hypothesis $r = 1$. If the test statistic is lower than the critical value, however, the null hypothesis of no cointegrating vectors is not rejected. In this research, the λ_{trace} statistic is preferable to the λ_{max} statistic as it is more robust to deviations from the assumption of normally distributed errors (Cheung & Lai, 1993). Moreover, the research of Rahbek, Hansen, and Dennis (2002) shows that the trace statistic is robust so as to moderate the ARCH effect and, according to Juselius (2007), the choice of rank should take into account all relevant information given by different criteria (trace test statistics, root of the companion matrix) and especially the economic relevance of the results (Gentile & Giordano, 2012). Hence, we focus solely on the trace test in our research to test for cointegration, as we can see in the next section below.

3.2.3.2 Dynamic Bivariate Cointegration Analysis

According to Gentile and Giordano (2013), the financial literature has shown in recent years that during a crisis, new cointegration relationships among markets appear, which were not observed during tranquil periods of time. These new long-run links generally involve countries which have a relevant role in the spreading out of contagion (Arshanapalli, Doukas, & Lang, 1995; Click & Plummer, 2005; Jang & Sul, 2002; Ludwig, 2014; Malliaris & Urrutia, 1992; Sander & Kleimeier, 2003; Sheng & Tu, 2000; Yang, Kolari, & Min, 2003). Consequently, we use a bivariate dynamic cointegration analysis⁶² to test for the presence of new long-run equilibrium conditions among countries through the application of dynamic rolling cointegration analysis⁶³ for each pair of countries. Any increase of the percentage of cointegrated countries over the total number of possible pairs signals a shift of the shock transmission channels⁶⁴ and represents the first indicator of potential contagion. According to the results obtained in this step, it is possible to detect contagion windows by looking directly into the data, finding evidence which either

⁶² To individuate significant connections among pairs of markets, the bivariate Johansen cointegration test is applied to allow the identification of relations between pairs of markets which lead to slow price adjustment processes – long-run connections (Gentile & Giordano, 2012, 2013).

⁶³ To this end, most studies apply the rolling trace test. For recent contributions, see Mylonidis and Kollias (2010) and Peri and Baldi (2013). The rolling cointegration analysis can be considered more appropriate than the alternative recursive analysis, because when conducting rolling window tests the size of subsamples is kept constant, and both the first and the last observation in the subsamples roll through until the full sample is reached. That is, the test statistics are calculated for a rolling n observations time window by adding one observation to the end and removing the first observation and so on. Therefore, continuous plots of trace test statistics for a rolling, fixed length, window provides essential information about the time varying pattern of the number of cointegrating vectors (i.e., to estimate the cointegration rank in the VECM, rolling trace statistics enable the empirical researcher to graphically display the evolution of the cointegration rank (Ludwig, 2014). As in the case of recursive tests, the statistics obtained from the rolling cointegration tests are scaled by the adjusted critical values of the chosen significance level are plotted (Mylonidis & Kollias, 2010, p. 2060). The rolling window technique allows for the emergence of a clearer picture of the possible dynamic linkages among the stock markets as, although the sample size remains unchanged, the sample period moves ahead by one observation at a time. In other words, the rolling estimation with a fixed-length window can ensure that the effects of regime shifts are isolated and can be used to track possible structural breaks (Mylonidis & Kollias, 2010, p. 2060).

⁶⁴ We defined “*shift*” as a significant increase in cross-market co-movements after a shock, not related with fundamentals links (Gentile & Giordano, 2012).

confirms or rejects the assumption of the time periods during which the contagion process could have started to propagate during the two financial crises analyzed – LBBC and ESDC (Gentile & Giordano, 2012).

In the *first step*, following Gentile and Giordano (2012, 2013), we performed a pairwise countries rolling cointegration estimation for the BRICS stock returns in order to verify whether there has been contagion during the sample period by estimating at each point of time the number of markets long-run connections. A sharp increase in the number of cross-market connections signals a contagion phenomenon. According to the results obtained in this step, we detect the contagion window by looking directly to the data.

In order to determine the number of cointegrating equations, a VECM(κ) was applied according to Johansen (1988):

$$\begin{aligned}\Delta X_t &= \eta_X + \sum_{i=1}^{\kappa} \lambda_{X,i} \Delta X_{t-i} + \sum_{i=1}^{\kappa} \gamma_{X,i} \Delta Y_{t-i} + \alpha_1 \beta' \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \varepsilon_{X,t} \\ \Delta Y_t &= \varphi_Y + \sum_{i=1}^{\kappa} \lambda_{Y,i} \Delta Y_{t-i} + \sum_{i=1}^{\kappa} \gamma_{Y,i} \Delta X_{t-i} + \alpha_2 \beta' \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \varepsilon_{Y,t}\end{aligned}\quad (7)$$

Where, ΔX_t and ΔY_t are daily changes of stock returns referred to markets X and Y , X_t and Y_t are the correspondent log-price indices (in log-level). The long-run impact matrix can be expressed as $\Pi = \alpha\beta'$, where $\alpha' = [\alpha_1, \alpha_2]$, and $[\varepsilon_X, \varepsilon_Y]$ is a vector of white noise processes. The vector of coefficient β contains the parameters of the common stochastic trend, while α_1 and α_2 measure the speed of convergence. In particular, $\beta' \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix}$ represents a common stochastic trend towards which price dynamic slowly converges. Hence, the Johansen cointegration test mainly relies on the assumption that the rank of Π equals the number of cointegrating vectors. If the matrix Π has a rank r , there are r cointegrating relations. When $r = 0$, there is no long-run relation among international markets and the Equation 7 would be reduced to a VAR(k).

Now, for detecting possible periods of contagion, the above dynamic Johansen cointegration test is applied between all the possible pairs of countries⁶⁵ with a *rolling window of 1000-days*⁶⁶, by computing at each step t (t , represents each month) of the procedure the following **rolling indicator** of cross-country connections:

$$\text{Percentage of cross-country connections}_t = \frac{\text{Number of long – run relations}_t}{\text{Maximum number of long–run relations among all countries}} \times 100$$

(8)

⁶⁵ The sample in our research is formed by five ($n = 5$) Emerging countries, therefore we have 10 pair of combinations in total, that is given by the following formula: $\frac{n!}{r!(n-r)!} = \frac{5!}{2!(5-2)!} = 10$, see Gómez-Puig and Sosvilla-Rivero (2014, 2011, p. 13).

⁶⁶ The length of 1000 days-window (see Web Appendix 1 at https://sites.google.com/site/aguiarconraria/BRICS_WebAppendixes.pdf) is chosen in order to make the cointegration results more robust, allowing to explore the asymptotic properties of the Johansen test (Gentile & Giordano, 2012, 2013). Arce, Mayordomo, and Peña (2012), used a 1000 days-window to consider a higher number of price-discovery metrics per day. Further, in the presence of autocorrelation coefficients, the power of the trace test is as low as the nominal size for a window length of 250 days and becomes acceptable for windows of at least 1,000 days – four years (Ludwig, 2014, p. 19).

Using the rolling indicator in Equation 8, it is possible to discriminate as follows:

- Crisis periods are identified recording the *highest* values of *cross-country connections*.
- Tranquil periods are identified recording the *lowest* values of *cross-country connections*.

By comparing these highest and lowest percentage values, it may be possible to either confirm or reject the assumption made regarding the timing of the two crises episodes investigated: *Contagion occurs when cross-country co-movements (percentage of cointegrated countries – known as cross-country connections), increase during the crisis periods relative to cross-country connections during the tranquil periods.*

3.2.4 Granger Causality Approach

3.2.4.1 Shock Transmission Direction

The second step of our research is obtained through the Granger causality test and VECM/Gonzalo-Granger statistic (further discussed in §3.2.4.2), evaluating the significance of short-run connections between countries in addition to the long-run equilibrium detected in the previous step by the cointegration analysis (see § 3.2.3.2 and Web Appendix 4). Therefore, Granger causality methodology detects the versus⁶⁷ (short and long-run causality) of these connections, allowing to examine how shocks are transmitted through countries⁶⁸. An increase of Granger causality connections detected after a crisis period is a signal of contagion phenomenon. Hence, together with the short-run *versus* of the connections, the detection of the long-run *versus* of the countries connections is also very important and reached by implementing the Gonzalo-Granger statistic, allowing the identification of the direction of connections in the crisis episodes.

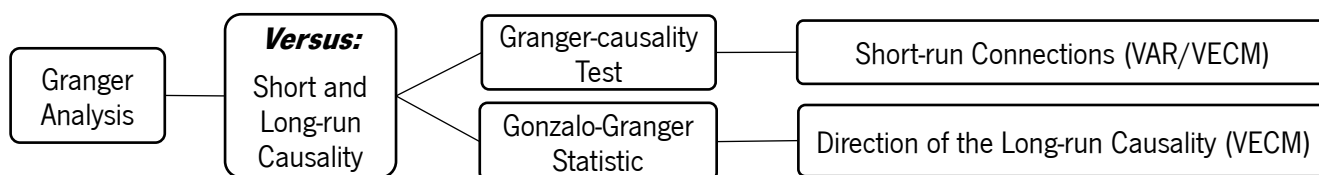


Figure 2: Source: Author’s own. Framework implementation of the Granger Causality Methodology.

In this section, following Gentile and Giordano (2012, 2013), we have implemented the Granger causality test because it allows one to investigate the short-run relationship among BRICS countries. The investigation resorted to the long/short-run econometric techniques (Cointegration and Granger causality test) that allow one to establish which country has a dominant role in the contagion process, being able to influence others

⁶⁷ The *versus* of the long-run (cointegrated analysis) is two types of causality: short-run connections obtained by the Granger causality test and the long-run causality, which is obtained in the context of the cointegration analysis based on the first step and it is applied in the Gonzalo-Granger statistic (see §3.2.4.2).

⁶⁸ The granger causality test detects whether past values of the stock indices can predict future values of other stock indices. The estimation is conducted for each sub-period (“contagion windows”) detected in the first step of the research according to Gentile and Giordano (2012, 2013).

(“leading country”) and it allows one to identify of the most fragile country, in other words, it is possible to identify the reaction of this country related to other countries’ price innovations (“follower country”). The method establishes how much of the current value of y can be explained by its past values and then to see whether adding values of x can improve the explanation.

In order to apply the Granger causality test, the following considerations were taken into account: first, the time series were tested for unit root (see Web Appendix 3)⁶⁹ in each sub-period established in the first step followed by the cointegration test among pairs of countries (see Web Appendix 4). Second, the results of unit root test applied earlier revealed that all the time series are nonstationary at log-level. However, the series are stationary at their first difference ($I(0)$), that is, all the series are integrated of Order one ($I(1)$). Based on these results, if the series are found to be ($I(1)$) and not cointegrated⁷⁰, the causality test proceeded according to the following equations:

$$\begin{aligned}\Delta X_t &= \alpha_X + \sum_{i=1}^k \beta_{X,i} \Delta X_{t-i} + \sum_{i=1}^k \gamma_{X,i} \Delta Y_{t-i} + \varepsilon_{X,t} \\ \Delta Y_t &= \alpha_Y + \sum_{i=1}^k \beta_{Y,i} \Delta Y_{t-i} + \sum_{i=1}^k \gamma_{Y,i} \Delta X_{t-i} + \varepsilon_{Y,t}\end{aligned}\quad (9)$$

However, if the series are found to be ($I(1)$) and cointegrated, causality test will be tested based on Equation 9. For cointegrated series, different approaches to causality testing have to be applied. Based on results of Sims et al. (1990), Demetriades and Hussein (1996) argue that test statistics derived from a level VAR framework are not valid unless the variables employed are either ($I(0)$) or ($I(1)$) and cointegrated. This assumption drives the causality test for Equation 9 if the series are not cointegrated. On the other hand, Engle and Granger (1987) and Granger (1988) argue that in the presence of cointegration, causality tests derived from the cointegration relationship, which ignore the ECT, are misspecified and suggest the re-parameterization of the model in the equivalent error correction model form (VECM). Therefore, the causality test in this case is conducted in the following equations:

$$\begin{aligned}\Delta X_t &= \alpha_X + \sum_{i=1}^k \beta_{X,i} \Delta X_{t-i} + \sum_{i=1}^k \gamma_{X,i} \Delta Y_{t-i} + \varphi_X ECT_{X,t-1} + \varepsilon_{X,t} \\ \Delta Y_t &= \alpha_Y + \sum_{i=1}^k \beta_{Y,i} \Delta Y_{t-i} + \sum_{i=1}^k \gamma_{Y,i} \Delta X_{t-i} + \varphi_Y ECT_{Y,t-1} + \varepsilon_{Y,t}\end{aligned}\quad (10)$$

The VECM-based test allows the differentiation between two types of causality: the short-run dynamics of the VAR and the disequilibrium adjustment of the error correction mechanism (ECM). Indeed, the F -test on the estimated

⁶⁹ All Web Appendixes are available at https://sites.google.com/site/aguiarconraria/BRICS_WebAppendixes.pdf

⁷⁰ The Equation 9 is only valid if the series are not cointegrated (MacDonald & Kearney, 1987).

coefficients γ_i provides evidence regarding a short-term adjustment dynamics. The *t-test* of the estimated coefficient φ provides evidence for the existence of an arbitrage type error correction mechanism that drives the variables back to their long-term equilibrium relationship that is embodied in the cointegration vector. In this step, the objective is to identify the creation of new short-run relations among countries as evidence of contagion (γ_i), conducting the Granger causality test separately for each contagion window (sub-periods defined in the first step) based on the stock returns of all countries. Regarding the lag length⁷¹ k , the criteria is chosen in order to generate a white noise error term ε_t .

3.2.4.2 Common Factors/Price-Discovery/Permanent-Transitory Decomposition

Besides the short-run connections discussed previously, it is possible to reveal the other part of causality: the long-run connections among the countries.

In order to detect the direction of the long-run causality among BRICS countries, we applied Gonzalo and Granger (1995) methodology⁷² to identify the direction through which adjustment is done (see Web Appendix 5). Hence, it is possible to estimate which country is the *leader* and which is the *follower* in the contagion transmission in the context of a bivariate cointegration analysis (Engle & Granger, 1987). Furthermore, we can measure the speed of convergence to the long-run equilibrium (α) of the two hypothesized countries, while (β) contains the parameters of the common stochastic trend (Gentile & Giordano, 2012, 2013).

Gonzalo and Granger's model⁷³ of price-discovery is based on the following VECM specification given by Arce et al. (2012), adapted to our context (with USA stock return as an exogenous variable)⁷⁴:

$$\begin{bmatrix} \Delta X_t^k \\ \Delta Y_t^j \end{bmatrix} = \alpha(X_{t-1}^k - \beta_2 Y_{t-1}^j - \beta_3 Z_{t-1}^{USA} - \beta_4) + \begin{bmatrix} \sum_{i=1}^p \lambda_{1,i} \Delta X_{t-i}^k \\ \sum_{i=1}^p \lambda_{2,i} \Delta X_{t-i}^k \end{bmatrix} + \begin{bmatrix} \sum_{i=1}^p \delta_{1,i} \Delta Y_{t-i}^j \\ \sum_{i=1}^p \delta_{2,i} \Delta Y_{t-i}^j \end{bmatrix} + \begin{bmatrix} \sum_{i=1}^p \vartheta_{1,i}^{USA} \Delta Z_{t-i}^{USA} \\ \sum_{i=1}^p \vartheta_{2,i}^{USA} \Delta Z_{t-i}^{USA} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix} \quad (11)$$

The above empirical model is a VAR system formed by two equations defined from the vector, which includes X_t^k and Y_t^j as the pair of BRICS stocks markets, $k, j = \text{Brazil, Russia, India, China, South Africa}$ ($k \neq j$); and an error correction term (ECT) defined by the expression $\alpha(X_{t-1}^k - \beta_2 Y_{t-1}^j - \beta_3 Z_{t-1}^{USA} - \beta_4)$, where β_2, β_3 and β_4

⁷¹ The criteria information is given by the Akaike information criterion (AIC), the Schwartz information criterion (SIC), the Hannan-Quinn criterion (HQ) and the Likelihood ratio statistic (LR). In this research, the SIC is preferable only when the serial correlation is not an issue. Otherwise, the preferable criterion will be the one that guarantees no serial correlation.

⁷² The method proposed by Gonzalo and Granger decomposes the time series X_t as: $X_t = \alpha(\beta' \alpha) \beta' X_t + \beta_1 (\alpha' \beta_1)^{-1} \alpha_1 X_t$; where $\alpha(\beta' \alpha) \beta' X_t$ is $I(0)$ and the transitory part, while $\beta_1 (\alpha' \beta_1)^{-1} \alpha_1 X_t$ is $I(1)$ and the permanent part (see Equation 11 in Gonzalo and Granger (1995)). The decomposition of the $[X_t, Y_t]$ into two components (transitory and permanent), allow the obtainment of different kind of information. For example, policymakers may be primarily interested in the trend (permanent component) behavior, but those concerned with business cycles are more interested in the cyclical component (transitory component). Moreover, singling out the common factors allow us to investigate how they are related to other variables (Gonzalo & Granger, 1995).

⁷³ The method is used to obtain the Matrix and Orthogonal Complement of α and β , extracting the Common Trends from a cointegration system according Gonzalo and Granger (1995), for a better understanding (see Web Appendix 5 and 6).

⁷⁴ As already mentioned, the variable USA is introduced in our model as an exogenous variable to account for the high influence that it has in the BRICS stock markets.

are estimated in an auxiliary cointegration regression and the parameter vector $\alpha' = (\alpha_1, \alpha_2)$ contains the error correction coefficients measuring each price's expected speed of adjustment. The estimation of the VECM equation is restricted to the existence of a cointegration relation between the stock market from both pair of countries. This cointegration relation appears in the ECT as $(X_{t-1}^k - \beta_2 Y_{t-1}^j - \beta_3 Z_{t-1}^{USA} - \beta_4)$. The parameters $\lambda_{1,i}$, $\lambda_{2,i}$, $\delta_{1,i}$, $\delta_{2,i}$, $\vartheta_{1,i}$, and $\vartheta_{2,i}$ for $i = 1, \dots, p$, with p indicating the total number of lags, contain the coefficients of the VAR system that measure the effect of the lagged⁷⁵ first difference in the pair of stocks from BRICS countries markets based on the first difference of such stocks at time t . Finally, u_t denotes a white noise vector $u_{i,t} \sim N(0,1)$.

The price-discovery for the pair of stocks from the BRICS markets, denoted by GG_{X^k} and GG_{Y^j} , respectively, can then be constructed from the elements of the vector α' , which contains the coefficients that determine each market's contribution to price-discovery:

$$GG_{X^k} = \frac{\alpha_2}{(\alpha_2 - \alpha_1)} \quad GG_{Y^j} = \frac{-\alpha_1}{(\alpha_2 - \alpha_1)} \quad (12)$$

Given that $[GG_{X^k} + GG_{Y^j} = 1]$, we would conclude that the $X^k(Y^j)$ market leads the price-discovery process whenever GG_{X^k} is **higher**(lower) than 0.5. The intuition for this is the faster the speed in eliminating the price difference from the long-term equilibrium attributable to a given stock market, the higher the corresponding α according Equation 11, and the higher the price discovery (Arce et al., 2012).

At this point, we adapted Equation 12 to the view of Gentile and Giordano (2012, 2013), for instance, assuming a pair of countries, as in the first step (see §3.2.3.2), the long-run coefficients matrix Π in Equation 7 can be expressed as $\Pi = \alpha\beta'$, where α measures the speed of convergence to the long-run equilibrium of the two hypothesized countries, while β contains the parameters of the common stochastic trend. Furthermore, following Equation 11, if the parameter of the speed adjustment of the first country (α_1) is statistically not significant, while the parameter of the speed adjustment of the second country (α_2) is positive and significant, it means that the adjustment process towards the long-term relationship is determined by changes to the variable of the second country in response to changes of the variable of the first country, indicating that the *leading role* in the contagion transmission is played by the first country. Otherwise, if (α_1) is negative and statistically significant, while (α_2) is not significant, this implies that the second country plays the *leading role*. However, when both countries are significant⁷⁶, both countries contribute to the contagion transmission process and the Gonzalo-Granger statistic (see Equation 12), defined as $\left[\frac{\alpha_2}{(\alpha_2 - \alpha_1)'} \right]$, allows one to determine which country makes the greatest contribution to the contagion transmission process. Hence, if the application of the ratio in Equation 12 for the first stock market

⁷⁵ Lag order selection based on the lag order selection criteria (LR, AIC, SC, HQ) obtained in the VAR, which guarantees a model free of serial correlation by applying the Autocorrelation LM test (See Web Appendix 6).

⁷⁶ In that case, there is a shift of signals (Gentile & Giordano, 2012, 2013).

exceeds 0.5 (50%), the price of the first country plays a more important role, while if it is lower than 0.5, the price of the second country plays a bigger role in the contagion transmission (Arce et al., 2012; Gentile & Giordano, 2012).

3.2.4.3 VECM: Unveiling Two Types of Causality

This section is adapted from Gentile and Giordano (2012, 2013) methodology in order to detect two types of causality by applying the VECM: the short-run dynamics of the VAR (identifying the short-term connections) and the disequilibrium adjustment of the error correction mechanism (ECM) (identifying the direction of the connections) for BRICS stock markets returns. Using the *F-test* on the estimated coefficients $\nu_{i,j}$ provides evidence of a short-term adjustment dynamics, while the *t-test* of the estimated coefficient $\alpha_k\beta'$ provides evidence for the existence of an arbitrage-type error correction mechanism that drives the variables back to their long-term equilibrium relationship that is incorporated in the cointegration vector. In addition, the creation of new short-run relations among countries reveals evidence of contagion ($\nu_{i,j}$).

The Granger causality test for the stock markets allows for the individualization of the short-term cross-market links and it is based on the estimation of the multivariate cointegration model in which the dependent variable is given by the stock return as follows⁷⁷:

$$R_t^k = \nu_0 + \sum_{i=1}^p \vartheta_i^{USA} R_{t-i}^{USA} + \sum_{j=i}^N \sum_{i=1}^p \nu_{i,j} R_{t-i}^j + \alpha_k \beta' \begin{bmatrix} \log(P_{t-1}^{USA}) \\ \log(P_{t-1}^{BRA}) \\ \log(P_{t-1}^{RUS}) \\ \log(P_{t-1}^{IND}) \\ \log(P_{t-1}^{CHI}) \\ \log(P_{t-1}^{S.AF}) \end{bmatrix} \quad (13)$$

Where, α_k is the coefficient which measures the speed of convergence to the long-run equilibrium; β is the vector which contains the parameters of the common stochastic trend; k and j represent country indices: $k, j =$ Brazil, Russia, India, China, South Africa ($k \neq j$) and N is the number of countries included in the sample ($N = 5$). When the time series are not cointegrated [$\alpha_k\beta' = 0$], the model becomes a VAR(p)⁷⁸. Otherwise, if the time series are found to be cointegrated [$\alpha_k\beta' \neq 0$], then the model becomes a VECM(p). At this point, the USA stock index returns⁷⁹ is included in the model to test for Granger causality⁸⁰. Regarding the synchronization issue, instead of

⁷⁷ The model represented in Equation 13 embody the representation of the VAR (Equation 9) and VECM (Equation10), which can be seen separately and in more detail in the (§ 3.2.4.1).

⁷⁸ The order p of the model is based on the application of Lag Order Selection Criteria. The priority is the elimination of the serial correlation. Hence, the chosen select criterion is the (SIC), just when the serial correlation is not an issue. Otherwise, the selection is based on another referred criterion (AIC, HQ or LR).

⁷⁹ Morgan Stanley Capital Index (MSCI) aggregate prices for USA based on the S&P 500 for Large Caps.

⁸⁰ The inclusion of the USA stock market is necessary because, more comprehensive information is provided by including the USA market, indeed, linkage patterns between the BRICS markets may be distorted when the influence of the USA market is not taken into consideration (Bekaert et al., 2011; Bonga-Bonga, 2015; Gentile & Giordano, 2012, 2013; Mensah & Alagidede, 2017; Yang et al., 2003).

introducing the USA stock indices in the econometric model with one day lag delay ($t - 2$) suggested by Malliaris and Urrutia (1992), or applying two day rolling moving average suggested by Forbes and Rigobon (2002), the chosen path to overcome the synchronization issue was to consider in the analysis a time window centered around the two crises (LBBC and ESDC) as suggested by Jin and An (2016), rather than a single one.

The application of the Granger causality test allows one to find relevant short-term connections among markets and to individuate the direction of these connections. For instance, if at least one $v_{i,j}$ for $i = 1, \dots, p$ is significantly different from zero, this means that R^j influences R^k . In addition, throughout this methodology we are able to find evidence of contagion, because this phenomenon amplifies the causality between markets following a shock (Granger, 1969; Sander & Kleimeier, 2003).

3.2.5 Variance Decomposition: Exposure to External Shocks

The *third step* used in this research is dedicated to the forecast-error variance decomposition (FEVD), the last contagion indicator, following Gentile and Giordano (2012, 2013). This methodology measures how much of the movements in one country can be explained by shocks in other countries (applied in the stock market scenario). Indicating that, as far as the proportion of the movements explained by other countries increases, the vulnerability of the system also increases and becomes more exposed to external shocks (more exposed to external markets). Following the conceptual framework discussed previously, at this point, our assumption is that *contagion occurs every time the degree of vulnerability of one country – measured as the fraction of its movements due to another country's shocks – increases after a crisis period*.

The FEVD, looking from the econometric point of view, measures the fraction of the forecast-error variance of an endogenous variable that can be attributed to orthogonalized shocks themselves or to another endogenous variable, giving the portion of the movements in the dependent variables that are due to their “own” shocks, versus shocks to the other variables⁸¹.

Initially, the FEVD indicator is given by the moving-average representation of the VECM as follows:

$$R_t = \sum_{s=0}^{\infty} C(s) u(t-s)$$

Where, the i, j -th component of $C(s)$ represents the impulse-response of the i -th country in s periods to a shock of one standard error in the j -th country, and u is the orthogonalized innovation in the sense that it has an identity

⁸¹ A shock to the i -th variable will directly affect that variable; however, it will also be transmitted to all other variables in the system through the dynamic structure of the VAR. Variance decompositions determine how much of the s -step-forward forecast error variance of a given variable is explained by innovations to each other explanatory variables for $s = 1, 2, 3, \dots, T$.

covariance matrix. Initiating from this mathematical representation of the stock return, the variance of the *n-step* forward forecast variance of the *i-th* return time series $[R_{i,t+n}]$ is given as follows:

$$\sigma_i(n)^2 = \sum_{j=1}^n C_{i,1}(j)^2 + \dots + \sum_{j=1}^n C_{i,N}(j)^2$$

Where, N is the number of countries included in the sample ($N = 5$)⁸². For each country stock market i the ratio:

$$W_i(k) = \frac{\sum_{j=1}^n C_{i,k}(j)^2}{\sigma_i(n)^2}$$

represents the portion of movements in country i due to shocks from country k , on the time horizon n . Therefore, for $[i = k]$ the ratio is as follows:

$$W_i(i) = \frac{\sum_{j=1}^n C_{i,i}(j)^2}{\sigma_i(n)^2}$$

indicating the portion of its forecast error variance which is explained by its own innovations. Consequently, its complement to one $[1 - W_i(i)]$ is the *rate of involvement indicator*, which measures the degree of vulnerability of country i , since it is the percentage of the variance of country i explained by innovations in other countries, being considered as a *measure of country exposure to external shocks*. In more detail, the *rate of involvement* – measures the degree of vulnerability of each country, as a *degree of exposure to the external shocks* – indicating how much “*domestic*” risk is explained by innovation in foreign countries.

⁸² Brazil, Russia, India, China and South Africa.

4 Results

4.1 Contagion Windows Definition

In our *first-step* results, we started by analyzing the connections among the BRICS markets through time. At each point of time ($t = \text{each month}$)⁸³, we estimated the linkages across markets. These linkages are able to influence and determine the stock returns between the BRICS stock markets. A sharp increase of cross-market connections signals a contagion phenomenon, as we can see in Figure 3 below.

Using a 1000-days⁸⁴ rolling window and the dynamic bivariate cointegration test, in the first of the three-step analysis, we detected the connections between markets (long-run relationships) that lead to slow price adjustment processes. Further, applying the *rolling indicator (Percentage of connections* in Fig. 3, see Eq. 8 §3.2.3.2), it is possible to detect the increasing or decreasing connections between markets that can confirm the assumption of tranquil or turbulent period of crisis. To identify these periods, the results of the rolling indicator are combined with the quartiles⁸⁵ to divide and set the precise timing of the contagion window by looking directly in the data in order to define when the contagion phenomenon started to spread between the two financial crises (LBBC and ESDC)⁸⁶. Supposing the rolling indicator exceeds the *III^o quartile* (Upper Bound - θ_{III} (75% percentile = 40%)), the percentage of relevant connections is considered significantly high and, therefore, the period is considered as *turbulent*. On the other hand, supposing the percentage of connections is high (but does not exceed the θ_{III}) and there are no significant changes in the number of connections, then we assume it as evidence of *interdependence* rather than *contagion phenomenon* (Gentile & Giordano, 2012, 2013). Therefore, the so called “tranquil” period is identified as equal or under the *III^o quartile* until the *I^o quartile*⁸⁷ (Lower Bound - θ_I (25% percentile = 10%)). Consequently, the “crisis” period is identified when the rolling indicator reveals a higher percentage of connections above the upper bound and the “tranquil” period is given when the rolling indicator reveals a lower percentage of connections equal to the *III^o quartile* (but without significant changes in the number of connections, indicating high interdependence) or below until the *I^o quartile* (lower bound).

⁸³ The results contemplate in total 121 months and consequently, 121 rolling window in total (see Web Appendix 1).

⁸⁴ In order to start (at the beginning of the month) and finish (at the end of the month), the rolling window was applied in an interval between [999;1002] days (see Web Appendix 1 and 2).

⁸⁵ The use of quantiles to identify significant increases (abnormal) of asset price co-movements, is justified by recent econometrics techniques (Caporin et al., 2013; Gentile & Giordano, 2012, 2013; Koenker, 2005; Koenker, Ng, & Portnoy, 1994; Mensi et al., 2014).

⁸⁶ Constâncio (2012, p. 110) and Caporin et al. (2013) maintain that a contagious event cannot occur in the absence of a shock, a large shock should occur. Enforcing the finds in this research in line with other studies. See for example, Fourie and Botha (2015) and Gentile and Giordano (2012, 2013).

⁸⁷ The median was taken in consideration to define the contagion window because most of the connections obtained from the rolling indicator is above the *I^o quartile*, which indicates evidence of high co-movements, suggesting interdependence between the markets rather than contagion phenomenon.

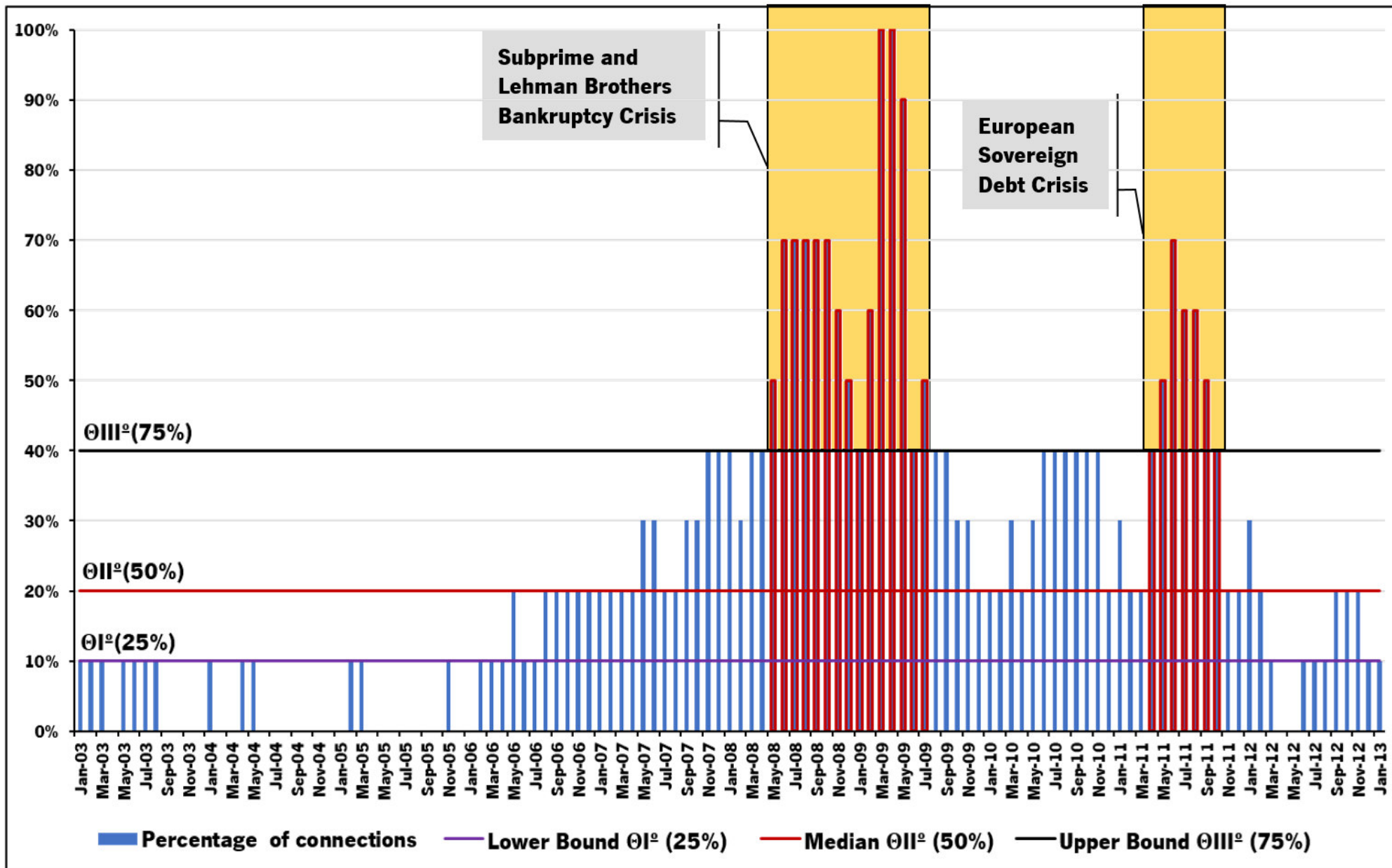


Figure 3: Graphical representation of the contagion window, using stock returns based on the results of the *rolling indicator* (see Web Appendix 2 for more details).

To detect and discriminate between crises periods and tranquil periods, we observed the increasing connections between the countries given by the *rolling indicator*. For instance, the date of the sharpest fall in the BRICS markets was May 2008⁸⁸ (see Figure 1, §3.1). The same month shows a sharp increase of cross-market connections, as demonstrated in Figure 3, signaling a contagion phenomenon (Gentile & Giordano, 2012). These findings strongly support the idea that contagion involves externalities and is distinct because it reflects market failure and dangerously amplified transmission of instability (González-Páramo, 2011). Moreover, the results support the view of Constâncio (2012, p. 110), that the spread of instability is abnormal and amplified, going beyond the bounds of normality.

Our results based on the rolling indicator, revealed two contagion windows. The *first contagion window* reveals the Lehman Brothers Crisis – from May 2008 to July 2009⁸⁹, lasting 15 months (covering approximately 327 days – when in 86,67% of the cases the indicator of connections is strictly above the upper bound), while the “tranquil” period goes from January 2003 to April 2008 (when the indicator is almost always below the III^o quartile going down until the I^o quartile). At the end of the “tranquil” period, the stock market started to show high signs of co-movements, which we considered as interdependence (Gentile & Giordano, 2012, 2013).

The *second contagion window* is related to the European Sovereign Debt Crisis – from April 2011⁹⁰ to October 2011, lasting 7 months (covering approximately 152 days – when in 71,43% of the cases the indicator is strictly above the III^o quartile). In this window, we considered the first and last month that did not pass the III^o quartile because the jump from the previous month was very high (20% higher), showing evidence of contagion (see Figure 3). Therefore, the “tranquil” period is defined from August 2009 to March 2011⁹¹, lasting 20 months (covering approximately 434 days). In this window, the indicator shows high co-movements in almost the whole period, but they do not grow significantly. Hence, any continued high level of market correlation suggests strong connections that exist in all states of the world, suggesting a situation of interdependence (Gentile & Giordano, 2012).

⁸⁸ May 2008 was also the month where the Dow Jones index reached the highest peak. The following months revealed that the crisis had become evident, spreading from the housing market to the global financial markets (Mollah, Zafirov, & Quoresh, 2014).

⁸⁹ The first window goes from May 2008 to July 2009. The data and the percentage indicator evidenced this period as a period of highly connections across the countries. The beginning of the contagion window shown in the graphical representation is coherent with the data from BRICS market (see Fig.1 and Fig.3), but is also coherent with the signs given by the international markets. The Dow Jones index peaked in May 2008, as already mentioned earlier, giving strong support to the contagion window chosen. Indeed, the subprime crisis had devastating effects, bursting the global asset bubble and quickly jumped to the stock market. By October 2008 it had already erased around US\$25 trillion from the value of stock markets. At the end of the first quarter of 2009, global market capitalization had already fallen 53% (Chittedi, 2014).

⁹⁰ The date of the sharp jump to the contagion refers to the announcement of the third country (Portugal) asking for a bailout of €78 billion (\$110 billion) from the EU and the IMF (Ray, 2015).

⁹¹ The “tranquil” period defined from August 2009 to March 2011 was a period where the world financial markets were in a very high level of tension. The problems of the Eurozone started to spread across the Union. The global financial markets started to react and the BRICS stock market was not an exception. In March 2010, the Greek Prime Minister (Papandreu) proposes a new financial package for Greece that includes additional public sector pay cuts and a 2% sales tax increase. On May 2010, IMF and Eurozone leaders agree to a €110 billion (\$143 billion) bailout package for Greece. Portugal starts to show vulnerabilities, the bond yields start to rise together with high volatility in the value of the euro (Ray, 2015). On June 2010, the Euro closes at its lowest rate of exchange against the US dollar since March 2006. In July 2010, the EU releases the results of “stress tests” conducted on 91 European financial institutions. The results were very bad, seven institutions did not maintain the minimum amount of capital required by examiners. In September 2010, it becomes known that the cost of bailing out Anglo Irish Bank could reach as much as €34.3 billion (\$46.6 billion). The results elevate Ireland’s budget deficit to 32% of GDP. In November 2010, Ireland’s government officially applies for bailout funds from the EU and the IMF. Embattled Irish Prime Minister Brian Cowen submits a harsh austerity budget and promises to call a general election in 2011. Within a week an €85 billion (\$113 billion) rescue package is approved by European leaders. In April 2010, Portugal’s Prime Minister (Socrates), requests a bailout relief from the EU and the IMF. The volatility in the markets exploded, and the contagion effect starts to spread. In June 2010, Standard & Poor’s downgrades Greece’s credit rating to CCC, turning Greece the world’s lowest-rated sovereign debt (Ray, 2015). The data from BRICS stock market showed that the contagion effect had reached the highest peak in the ESDC indicated by the second contagion window (see Fig.3).

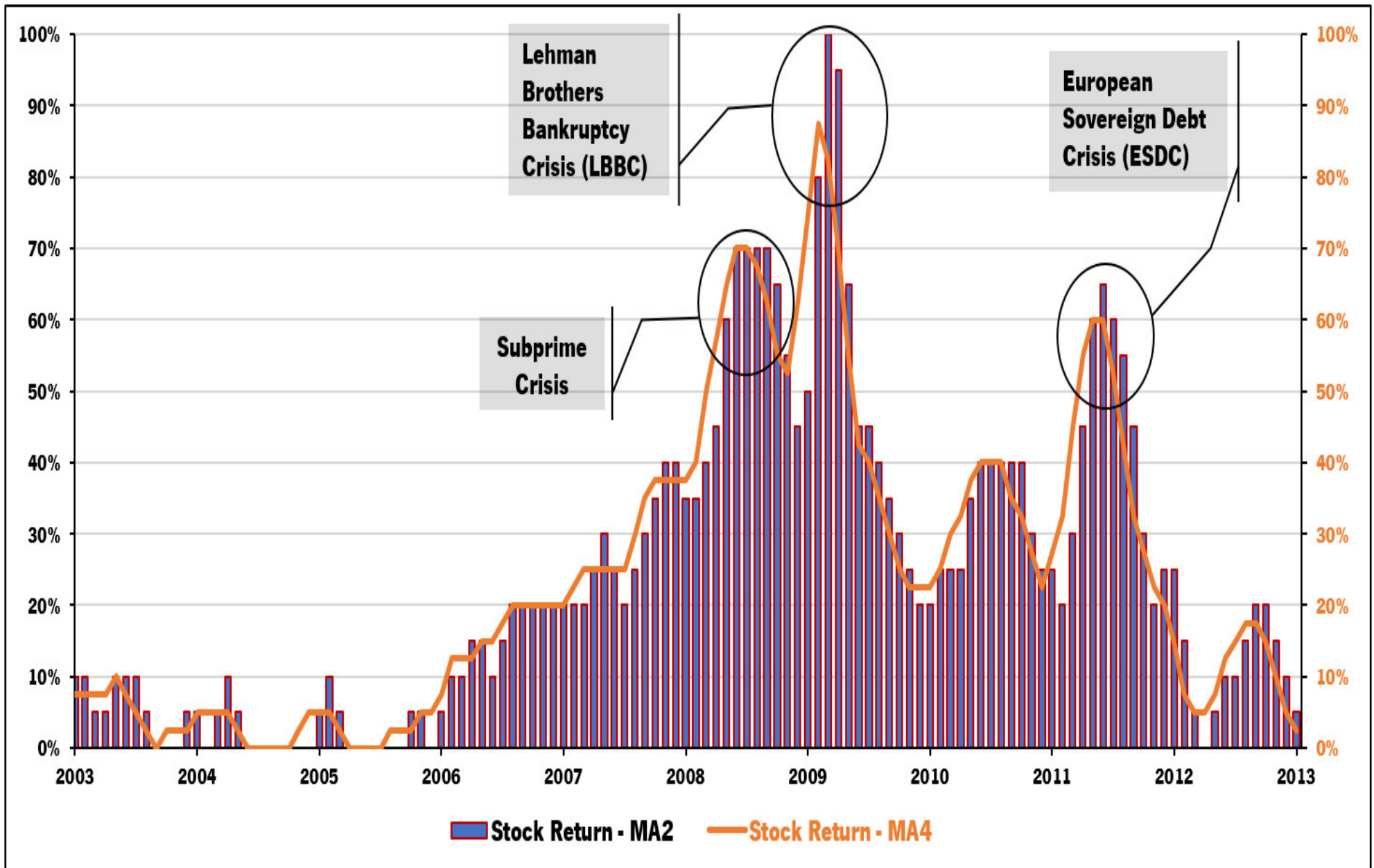


Figure 4: Graphical representation of the percentage of significant connections (*rolling indicator*), computed by applying a moving average of two months (MA2) and four months (MA4).

Connections between the stock returns are always above the median, but it is still reasonable to consider them the result of interdependence and not contagion.

In Figure 4 we present the total amount of possible relationships obtained from the rolling indicator for the BRICS stock returns. Figure 4 shows and highlights the differences in the pattern of crisis, making it possible to see the pattern of Subprime Crisis separately from the LBBC by applying the MA of two and four months.

The intensity of cross-market connections given by the rolling indicator shows a different pattern related to the stock market return, identifying two contagion episodes. The first one begins around May 2008 and ends around July 2009, including consequently, both the Subprime and Lehman Bankruptcy Crisis. The indicator shows that the peak is achieved in March and April 2009, reaching **100%** of cross-market linkages as significant⁹² (see Figure 3). The second contagion window pointing to the ESDC, from April to October 2009, reaches a peak of cross-market linkages of **70%**. However, the intensity of this crisis was much smaller and shorter in the BRICS economies than the first one related to the LBBC.

Table 4 Contagion Window Summary

Stock Market Returns	
<i>Lehman Brothers Bankruptcy Crisis</i>	<i>European Sovereign Debt Crisis</i>
Duration: 15 Months	Duration: 7 Months
01/05/2008 - 31/07/2009: Approximately 327 days. In 86,67% ⁹³ of the cases the rolling indicator is strictly above the upper bound III ^o Quartile ($\Theta_{III^o} \rightarrow 40\%$).	01/04/2011 - 31/10/2011: Approximately 152 days. In 71,43% of the cases the rolling indicator is strictly above the upper bound III ^o Quartile ($\Theta_{III^o} \rightarrow 40\%$).

In Table 4 the results of the contagion window are summarized. The results will be used in the next part of the research to analyze the contagion process inside the windows, comparing whether the number of cross-market connections in “crisis” period increases compared to the “tranquil” period. The first part of our research has considered until now just the long-run connections, implying just the slow price adjustment process given by the Johansen cointegration test. However, to verify the presence of a contagion effect, the total number of connections (long-run and short-run connections) is needed. For that purpose, the Granger causality test, the so called second step of our analysis will be applied, as we can see in the next section.

4.2 Revealing the Contagion Process

In our *second step* results, we analyze the results arising from the number of cross-market connections related with the “crisis” periods and compare them with the “tranquil” periods, by applying the cointegration test and the Granger causality test (see § 3.2.3.2 and §3.2.4.1). The bivariate cointegration test allows the identification

⁹² Revealing that the intensity of the crisis in BRICS countries was deeper than in previous times (Mollah, Zafirov, & Quoresh, 2014).

⁹³ Looking at Figure 3 §4.1, is possible to see 13 long-run connections out of 15 that are above the III^o Quartile (40%). Dividing 13 by 15 long-run connections, the result is 86,67% for the LBBC. The same is applied for the ESDC.

of connections between pairs of markets which lead to slow price adjustment process (long-run connections, see Web Appendix 4). But it is also possible to find the *versus* of each significant connection by applying the Gonzalo-Granger statistic (see § 3.2.4.2 and Web Appendix 5 and 6). Furthermore, the Granger causality test identifies connections which have a short-term influence on the price discovery process (short-run connections)⁹⁴, as demonstrated by Gentile and Giordano (2012, 2013). In Table 5 we can see the Gonzalo-Granger results.

Table 5 Results from Cointegration Test/Gonzalo-Granger Statistics.

January 2003 to April 2008 - Tranquil period				
Pair of Countries	Gonzalo-Granger Statistic	Speed of Adjustment [α]		Results
		α_1	α_2	Leading/Follower Countries
BRAZIL - INDIA	GGBRA	-0.001675		Leading country
	GGIND		0.011453***	Follower country
May 2008 to July 2009 - Turbulent period: Subprime and Lehman Brothers Crisis				
Pair of Countries	Gonzalo-Granger Statistic	Speed of Adjustment [α]		Results
		α_1	α_2	Leading/Follower Countries
BRAZIL - CHINA	GGBRA	-0.004429		Leading country
	GGCHI		0.044729***	Follower country
INDIA - CHINA	GGIND	-0.056525***		Follower country
	GGCHI		-0.002313	Leading country
INDIA - S. AFRICA	GGIND	-0.069595***		Follower country
	GGSAF		-0.002708	Leading country
CHINA - S. AFRICA	GGCHI	-0.146660***		Follower country
	GGSAF		0.061711	Leading country
August 2009 to March 2011 - Tranquil period				
Pair of Countries	Gonzalo-Granger Statistic	Speed of Adjustment [α]		Results
		α_1	α_2	Leading/Follower Countries
BRAZIL - CHINA	GGBRA	-0.042440**		Follower country
	GGCHI		0.018214	Leading country
April 2011 to October 2011 - Turbulent period: European Sovereign Debt Crisis				
Pair of Countries	Gonzalo-Granger Statistic	Speed of Adjustment [α]		Results
		α_1	α_2	Leading/Follower Countries
BRAZIL - INDIA	GGBRA	-0.024887		Leading country
	GGIND		0.117500***	Follower country
BRAZIL - CHINA	GGBRA	0.015320		Leading country
	GGCHI		0.157903***	Follower country
BRAZIL - S. AFRICA	GGBRA	0.258053***		Leading country
	GGSAF ←		0.237389***	Leading country
RUSSIA - S. AFRICA	GGRUS	0.081265		Leading country
	GGSAF		0.150673***	Follower country
INDIA - S. AFRICA	GGIND	-0.085531*		Follower country
	GGSAF		0.093486	Leading country
CHINA - S. AFRICA	GGCHI	0.023620		Leading country
	GGSAF		0.200972***	Follower country

Note: Source Author's on based on the imputes from EViews 9.0 Program. The results obtained from the VECM in the context of the Granger causality test (see Web Appendix 5 and 6) allow the obtainment of the speed of adjustment of the first country (α_1) and second country (α_2) respectively, in other words, the coefficients of error correction terms. [***] indicates the level of significance at 1% level; [**] at 5% level; [*] at 10% level. [←] represents the leading country that makes the greatest contribution to the contagion transmission process. Besides this, the line in bold indicates which country makes the greatest contribution to the contagion by applying the Gonzalo-Granger statistic $\left[\frac{\alpha_2}{(\alpha_2 - \alpha_1)r}\right]$. In this context, if the ratio for the first country exceeds 0.5, the first country plays a bigger role in the contagion transmission, while if the ratio is lower than 0.5 (the maximum is 1), the opposite is true (Gentile & Giordano, 2012).

⁹⁴ See (§3.2.4.3) for econometric details and Web Appendix 6.

The results from both techniques (the cointegration test/Gonzalo Granger statistic and the Granger causality test), allow the identification of significant cross-market connections and the directions of the relation. Subsequently, by applying the two tests it is possible to establish which countries have a dominant role in the contagion process, because they are able to influence other “*leading countries*”, and which countries are more vulnerable and reactive to other countries’ price innovations “*follower countries*”, as we can see in Table 5. The difference lies in the time horizon of the price adjustment process induced by the existence of cross-market connections, which is the long-run for the connections identified by the bivariate Johansen cointegration test, while the short-run is the connections detected with the Granger causality test.

To further comprehend the relationship among markets and equilibrium restoration, the VECM according Gonzalo and Granger (1995) is applied to obtain the coefficients of ECT of speed of adjustment parameters $[\alpha_1, \alpha_2]$ ⁹⁵ to restore the long-run relationship whenever a disequilibrium situation appears. Our results determined that in the first turmoil – LBBC, that Brazil, China, and South Africa (leading countries, see table 5 §4.2) are statistically not significant, which brings to light that these markets are weekly exogenous. However, they are the first to be affected by innovations (excluding Russia and India) and consequently, they are transmitting the shocks to the other markets (follower countries), being responsible for the contagion transmission process⁹⁶. Looking closely at the coefficients of ECT in Table 5, in the long term, a shock in the financial markets (LBBC), impacts the stocks in China⁹⁷(BRA-CHI(5%)) positively and negatively in India^{98,99}(for IND(6%)-CHI, IND(7%)-SAF) and China¹⁰⁰ (CHI(15%)-SAF). The information from the long term relationship indicates that under the LBBC, the stock market in China (BRA-CHI(5%)) provided some hedge against the contagion effect from LBBC, while India (IND(6%)-CHI, IND(7%)-SAF) and China (CHI(15%)-SAF) does not provide any hedge, see (e.g., Bianconi et al., 2013, p. 90).

In the second turmoil – ESDC, our analysis indicates that Brazil, Russia, China and South Africa (leading countries) are statistically not significant, and consequently, they are all hit by the ESDC in the first moment (excluding India). Furthermore, the innovations from the ESDC affect positively: India (BRA-IND(12%)), China (BRA-CHI(16%)) and South Africa (for RUS-SAF(15%), CHI-SAF(20%)), which means that these countries seem to have a higher level of resilience, providing some hedge against the ESDC. In contrast, India (IND(9%)-SAF) is affected negatively, and consequently, does not provide any kind of hedge.

⁹⁵ For example, in the case of (India-South Africa) for the LBBC, a positive shock in the pair of markets is capable of restoring the equilibrium level of the negative values of the ECT's, the VECM model is valid since the error correction term coefficient is, as expected, significantly negative. This suggests that the long-run linkages are confirmed by the short-run linkages and indicating the presence of contagion effects, since the error correction term coefficient records a rise in magnitude during the instability period, suggesting thus a shift in the adjustment speed for the equity markets of these countries. This insight reflects the effects of the LBBC on the linkages between the US stock market and the BRICS markets (Boubaker et al., 2016). Indeed, looking for India (IND-SAF) for instance, in the first day, (7%) adjustment is reached, while the rest is reached in the coming days for India stock market, see (e.g., Singh & Kaur, 2016). See Table 5 § 4.2 and Web Appendix 5.

⁹⁶ For more details, see Singh and Kaur (2016, p. 127).

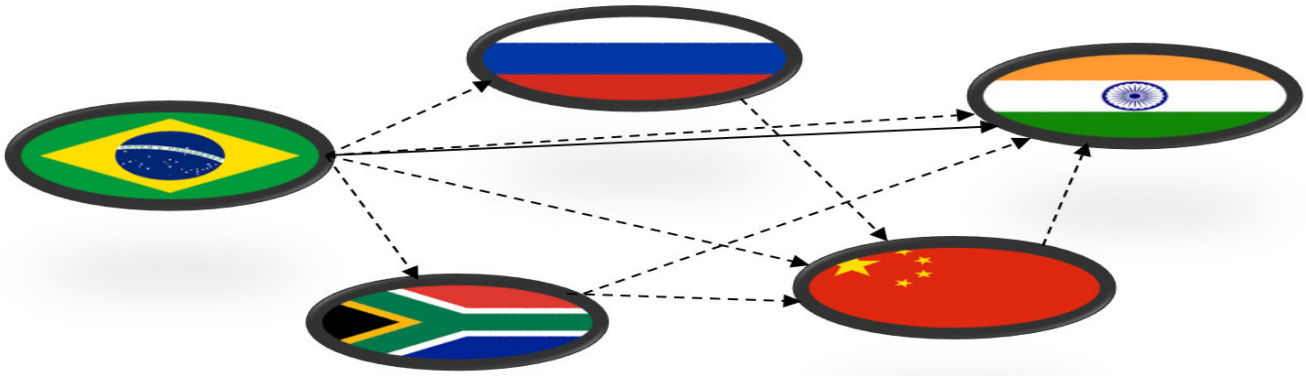
⁹⁷ In the case of Brazil-China pair of countries, just the coefficient of ECT from China (follower country) is statistically significant.

⁹⁸ In the case of India-China pair of countries, just the coefficient of ECT from India (follower country) is statistically significant.

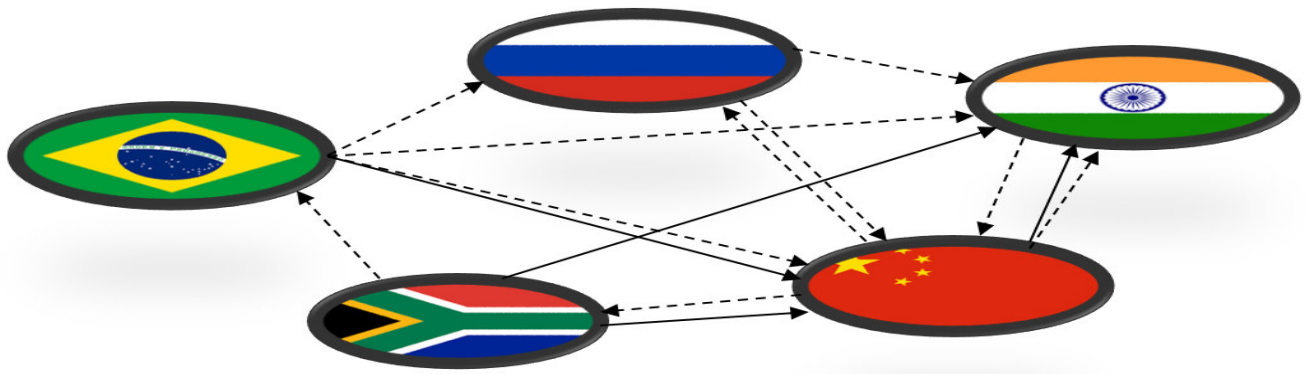
⁹⁹ In the case of India-South Africa pair of countries, just the coefficient of ECT from India (follower country) is statistically significant.

¹⁰⁰ In the case of China-South Africa pair of countries, just the coefficient of ECT from China (follower country) is statistically significant.

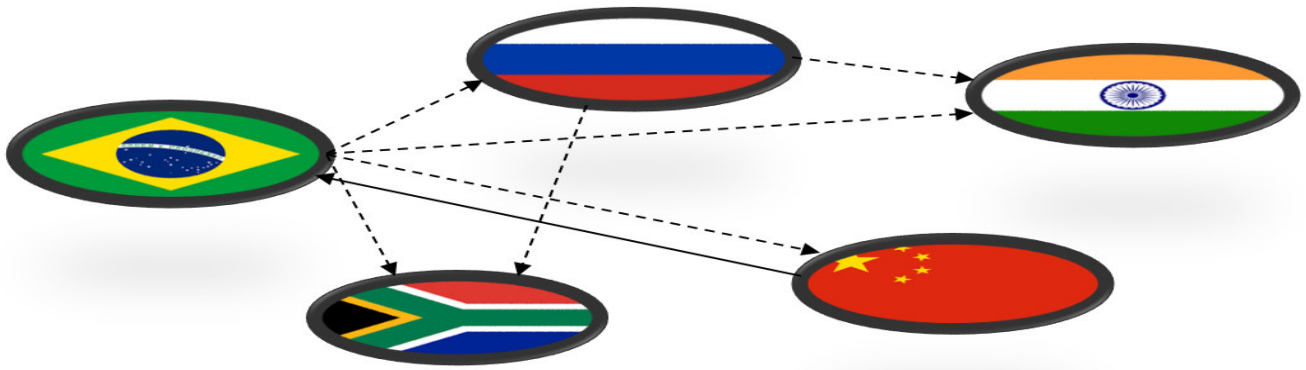
January 2003 to April 2008 TRANQUIL PERIOD	64 Months
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May 2008 to July 2009 SUBPRIME AND LEHMAN BROTHERS CRISIS	15 Months
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August 2009 to March 2011 TRANQUIL PERIOD	20 Months
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April 2011 to October 2011 EUROPEAN SOVEREIGN DEBT CRISIS	7 Months
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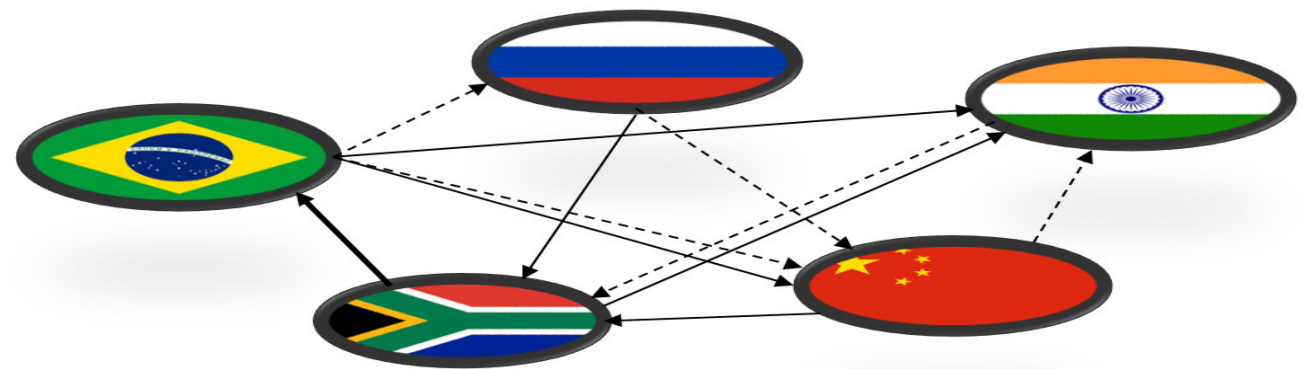


Figure 5: Stock return contagion test: short and long-run connections before and after the crises episodes. Dashed line represents the short-run connections, solid line is used to indicate the long-run connections and the thick solid line indicates that both countries contribute to the contagion transmission. Although one country plays a bigger role ("leading country").

Figure 5 shows the long and short-run relations among the stock returns markets and the direction of these connections (Figure 5 derived from Web Appendix 7), revealing the structure of the contagion propagation mechanism. Hence, when the connections are statistically relevant, the results from the test statistic are reported together with its significance level (see Web Appendix 7) by following Gentile and Giordano (2012, 2013).

Analyzing the results of long and short connections among the markets, it is possible to notice that Brazil, China and South Africa dominated the stock market during the LBBC as leading countries (May 2008 to July 2009) and the number of cross-markets connections increased sharply from 8 (January 2003 to April 2008) to 12 (May 2008 to July 2009). Thereafter, when the analysis is directed to the ESDC (April 2011 to October 2011), the number of cross-market connections increased from 7 (August 2009 to March 2011) to 10 (April 2011 to October 2011), wherein, China clearly lost the dominant role in the contagion transmission played in the Lehman Crisis. Regarding Brazil and South Africa, Brazil is the major leading country in the ESDC, playing a dominant role in the contagion transmission structure by influencing Russia, India, China (both short/long-run) and South Africa¹⁰¹ stock markets; it is followed by South Africa with much less intensity, playing a leading role in Brazil and India stock markets. Indeed, in 2008-09, Brazil was able to influence the stock returns of all other countries except for South Africa together with China. The latter was, in turn, able to influence all other countries excepted for Brazil.

A higher dominant role can be seen in the ESDC for the Brazil stock market (now influencing also South Africa, see Web Appendix 7, Table 5 and Figure 5), while for China, the dominant role of influencing other markets diminished clearly. In 2008-09, China had a dominant role in the contagion transmission by influencing Russia, India (both short/long-run) and South Africa, whereas in the ESDC it just leads the South Africa stock market, maintaining the connection only with the India stock market. Furthermore, South Africa, which during the LBBC had been able to influence Brazil, India and China stock markets, in the recent ESDC, it was only capable of influencing Brazil and India, losing the dominant role in transmitting contagion to China's stock market.

Regarding the LBBC, it is possible to analyze that Brazil and China were the greatest leading countries in the contagion transmission, followed by South Africa, whereas in the ESDC only Brazil stock market kept the strength, playing a dominant role in the contagion process. However, in the first crisis, there is evidence of high connections concentrated in the leading countries (Brazil, China and South Africa); while in the second crisis the evidence point towards for a dominant role in the contagion transmission mechanism coming strongly from Brazil, with much less intensity from South Africa and lastly, the contagion transmission running from China and Russia to South Africa market. In 2008-09 crisis, the number of relevant connections involving India and China is higher compared to what was observed in the latest crisis, where India and South Africa presented the same amount of connections. Indeed, in the Lehman Crisis, Russia and India absorbed shocks without being able to influence other countries (pure follower country), signaling a high degree of vulnerability. In the case of China, this market absorbed

¹⁰¹ The result in absolute value did not exceed 0.5 for Brazil (-11,48805). For South Africa, the value (12,488047) exceeded in absolute value 0.5. Therefore, the price of the second asset (South Africa (SAF)), plays a bigger role compared to the first asset (Brazil (BRA)), see Table 5 above.

shocks but also spread them, while in the case of Brazil, which is a major contributor to the contagion transmission (even in tranquil periods of times), was highly capable of spreading shocks to all other countries (in both crises) and was not influenced by any of them, excepting for South Africa in both crises. Despite being a pure follower country in the first crisis, Russia lost this role in the latest crisis, playing a leading role in South Africa. India continued to be a pure follower country, not being able to lead any country, but receiving shocks from all of them, revealing a high level of vulnerability in both crisis.

Our results also reveal the risk profile of India and China in the LBBC as sharply higher compared to the other countries based on the number of relevant connections. Therefore, the contagion process is mainly related to India and China stock markets. While in the ESDC, the risk profile of India and South Africa is the same but lower than the previous crisis, indicating that the process of contagion is mainly related with these two countries, with Brazil as a major source in spreading the contagion to all BRICS stock markets in both crises. One difference between the two crises considered (LBBC and ESDC) that clearly emerges, is related to the amount of short-run connections during LBBC (10 short-run connections over 14 total connections) compared to the ESDC (5 short-run connections over 11 total connections). Moreover, it seems that the LBBC is characterized by a strong increase in the number of short-run links, while the ESDC is characterized by a higher level of long-run connections (7 long-run links¹⁰² over 11 total connections). Overall, it seems that the LBBC was able to affect more intensively the BRICS markets than the ESDC. Although, the ESDC seems to be less severe but more dispersed between the BRICS countries, the contagion transmission seems to be more dangerous, due to the fact that all countries are transmitting/spreading the contagion to each other (with exception for India).

The most important result from this analysis is related to the confirmation of the existence of *contagion* as opposed to *interdependence or spillover*. The number of connections detected among countries (in both contagion windows), increased after the “crisis episodes” but did not remain at such a high level after the shock. Indeed, the number of connections increased intensively during “crisis periods” and then decreased drastically during “tranquil periods”. This movement is a critical test to distinguish between *contagion* and *interdependence*. As stated earlier in this research, *contagion* is a significant increase in the co-movement between assets during a period of crisis, compared with a tranquil period. Therefore, if there is a high level of market co-movement in all periods, that is the case of *interdependence*. As it is possible to see in this research (see Figure 3 and Figure 4, §4.1), a higher number of connections in the BRICS stock markets which do not hold steady after a shock, returning to the low values once the crisis is gone, is a signal of a temporary distortion of the transmission channels due to shocks – that is *contagion*, instead of a systematic change in the common economic structure, based on the real or financial links¹⁰³ (Gentile & Giordano, 2012, 2013).

¹⁰² The Brazil influence over South Africa, even though weaker, was considered at this point (see Table 5).

¹⁰³ These theories are usually based on standard transmission mechanisms, such as trade, monetary policy, and common shocks, for example, oil prices (Gentile & Giordano, 2012; Kishor & Singh, 2014; Nikkinen, Saleem, & Martikainen, 2013).

4.3 Measuring Countries Degree of Exposure to the Contagion Process

The *last step* is reached by applying the variance decomposition methodology, following Gentile and Giordano (2012, 2013). This methodology allows us to measure of each country's degree of exposure to the influence of foreign markets, indicating the rate of involvement in the contagion process (see §3.2.5). Furthermore, the results in Table 6 below reveal that South Africa is incredibly more significantly involved in the ESDC compared with its involvement in the LBBC. Indeed, all the BRICS countries exhibited a significant increase in the involvement of the contagion process in the second crisis ESDC. Regarding South Africa, for a time frame of 5 days (short term), the ratio of the forecast error variance (the rate of involvement indicator¹⁰⁴) explained by foreign markets increased from 2.82% (LBBC) to 31.32% (ESDC), making South Africa the most involved country in the contagion process with the highest degree of exposure to external shocks followed by India (from 11.27% to 27.30%), Russia (from 9.21% to 24%), China (from 21% to 31.36%) and Brazil (from 4.87% to 14.26%), with the lower degree of exposure to the contagion process¹⁰⁵.

Directing the analysis to the two crises considered, the variance decomposition methodology provides an insight about the contagion intensity for the countries in the sample. For instance, during the LBBC, the most involved country in the contagion process was China, the degree of exposure rose (from 12.92% to 21%)¹⁰⁶ after the crisis, much higher than the other countries. Still in the LBBC window, it is interesting to notice that South Africa represented the lowest level of vulnerability (from 9.23% to 2.82%), followed by India (from 11.82% to 11.27%), indicating that these two countries seem to have a strong degree of exogeneity to the system, not being affected essentially by the LBBC compared to the other countries¹⁰⁷. Concerning the ESDC, in the short-term, the most exposed country to external shocks and consequently more vulnerable and involved in the contagion process is South Africa (from 6.52% to 31.32%), followed by Russia (from 9.31% to 24%), India (from 14.52% to 27.30%), Brazil (from 2.08% to 14.26%) and lastly, China (from 24.24% to 31.36%)¹⁰⁸.

Summarizing, in the LBBC China was the most affected country in terms of degree of exposition to external markets (21% for the short period and 28.19% for the long period) and in terms of growth rate of vulnerability before and after the first crisis (from 12.92% to 21% for the short period and from 13.42% to 28.19% for the long period).

¹⁰⁴ The degree of vulnerability of each country (Gentile & Giordano, 2013).

¹⁰⁵ Reaching a growth rate of vulnerability of 28.50%(South Africa), followed by 16.03%(India), 14.79%(Russia), 10.36%(China) and 9.39%(Brazil). The percentage is calculated taking the difference between the last crisis (ESDC) minus the ratio of the first crisis (LBBC), as it is possible to see in Table 6 for 5 days forecast. In the long period, South Africa remains the most vulnerable country, reaching a growth rate of vulnerability of 55.54%, followed by 41.56% (Russia in the long period, overtakes India), 37.96%(India), 33.31%(Brazil) and lastly, 22.19%(China).

¹⁰⁶ Followed by Brazil (from 2.16% to 4.87%) and by Russia (from 7.72% to 9.21%).

¹⁰⁷ Looking at the long period, for South Africa (from 14.28% to 4.15%), Russia (from 12.17% to 9.44%) and Brazil (from 6.26% to 5.14%) was essentially unaffected in the LBBC, whereas for India (from 14.75% to 17.86%) there was an increase in the vulnerability to external shocks. As regards South Africa, the results indicate that it is even more unaffected compared to the short period.

¹⁰⁸ In the ESDC, all countries become sharply more exposed to external shocks. Therefore, South Africa records the most severe worsening of external fragility, reaching a growth rate of vulnerability of 24.80%, followed by Russia (14.69%), India and Brazil (with nearly the same rate of involvement, 12.78% and 12.18%) and China with (7.12%), the least fragile country. In the long period, South Africa remains the most fragile country, reaching a growth rate of vulnerability of 53.29%, but in the case of Russia (37.09%), Brazil (36.19%) and India (35.91%), the external fragility is almost the same, indicating that in the long period these countries are equally affected by external shocks, with the same rate of involvement in the Sovereign Debt Crisis. Lastly, China is the least fragile country with a growth rate of vulnerability of 17.78%.

Focusing the analysis on the ESDC, our results highlight that South Africa, Russia, India and Brazil are countries more exposed to financial contagion, mostly because of their higher degree of fragility (31.32%, 24%, 27.30% and 14.26%) in the short period, while for the long period the degree of fragility was (59.69%, 51%, 38.45% and 55.82%) for South Africa, Russia, Brazil and India, respectively. Furthermore, China records the worst performance in terms of rise of rate of involvement, mostly because of its high pre-Lehman vulnerability (from 24.24% to 31.36% for the short period; and from 32.60% to 50.38% for the long period). Comparing both crises in terms of growth rate of vulnerability, the results indicate that South Africa is the most exposed to the financial contagion (28.50% for the short period; and 55.54% for the long period), followed by India (16.03%) and Russia (14.79%) in the short period. In the long period, Russia (41.56%) overtakes India (37.96%), becoming more exposed to the financial contagion than India, followed by Brazil with a growth rate of vulnerability of (33.31%), indicating a large increase in the degree of exposition to external markets in contrast with the short period.

Table 6 Rate of Exposure to the Contagion Process based on the Stock Returns.

Countries	Forecast Horizon (Days)	Tranquil period Pre-Lehman Bankruptcy	Turbulent period Lehman Bankruptcy	Df_1	Tranquil period Pre-Sovereign Debt Crisis	Turbulent period EU Sovereign Debt Crisis	Df_2	Df_3
Brazil	5	2.16	4.87	2.71↑	2.08	14.26	12.18↑	9.39↑
	10	6.26	5.14	-1.12↓	2.26	38.45	36.19↑	33.31↑
Russia	5	7.72	9.21	1.49↑	9.31	24.00	14.69↑	14.79↑
	10	12.17	9.44	-2.73↓	13.91	51.00	37.09↑	41.56↑
India	5	11.82	11.27	-0.55↓	14.52	27.30	12.78↑	16.03↑
	10	14.75	17.86	3.11↑	19.91	55.82	35.91↑	37.96↑
China	5	12.92	21.00	8.08↑	24.24	31.36	7.12↑	10.36↑
	10	13.42	28.19	14.77↑	32.60	50.38	17.78↑	22.19↑
S. Africa	5	9.23	2.82	-6.41↓	6.52	31.32	24.80↑	28.50↑
	10	14.28	4.15	-10.13↓	6.40	59.69	53.29↑	55.54↑

Note: Source Author's on based on the imputes from EViews 9.0 Program. The results are presented in percentage. The variance decomposition was computed based on a 5 (short period) and 10 days (long period) forecast horizon. The Table 6 indicates the rate of involvement indicator $[1 - W_i(i)]$, measuring the degree of vulnerability of country i (each country's stock market) explained by innovations in all other countries, working as a measure of country's exposure to the external shocks (see §3.2.5). $[Df_1]$ represents the difference between tranquil and turbulent period in the Lehman Crisis. $[Df_2]$ represents the difference between tranquil and turbulent period in the Sovereign Debt Crisis and $[Df_3]$ represents the difference between both crises. For the results of each country's contribution to the contagion process individually (see Web Appendix 8).

4.4 Three-steps Results: Summary of the Major Findings

The main results obtained in sections: 4.1, 4.2 and 4.3 are summarized in Table 7 using stock market returns.

Equally noteworthy, is the fact that in our research, the results corroborate many more short-run linkages than long-run connections. The short connections are higher due to the nature of equity prices – shorter-term and

more responsive¹⁰⁹, responding more rapidly to shocks (Fourie & Botha, 2015). Therefore, in the short-run the domestic and global destabilizing factors cause varying levels of vulnerability in the BRICS stock market and price movements. These disturbances are temporary in nature since the variables revert to their equilibrating process to maintain the long-run co-movements. One adverse effect of such disparity is that it could possibly create arbitrage opportunities and short term speculative gains (Visalakshmi & Lakshmi, 2016). Another interesting feature regards Brazil. This country plays a major role in both crises as a leading country, serving as a channel of transmission and spreading the contagion effect to all other countries¹¹⁰. Even in tranquil periods, its links are strong among the other BRICS countries. Another surprising finding pertains to South Africa, the smaller country among BRICS, but the only one connected with and capable of influencing Brazil in both contagion windows¹¹¹.

Table 7 Summary Results from Three-step Methodology in both Crises.

2008 to 2009 - Subprime and Lehman Bankruptcy Crisis:	2011 - European Sovereign Debt Crisis:
<p>Contagion Evidence:</p> <p>The number of cross-market connections has largely increased between the tranquil and the turbulent period¹¹²: there is evidence of a contagion process.</p> <p>Direction of Contagion:</p> <p>Brazil, China and South Africa dominated the stock market, playing a leading role in the transmission mechanism. South Africa was able to lead two major countries, India and China. Nevertheless, China was connected and influenced by all other countries together with India, whereas Brazil was just connected with South Africa. India and Russia are considered pure follower countries¹¹³.</p> <p>Contagion Process: Degree of Vulnerability and Exposure to External Shocks:</p> <p>China was the most exposed country in the Lehman Crisis both in the short period and in the long period. In the case of South Africa, the results revealed that this country is strongly not exposed, neither in the short period nor in the long period, revealing a high degree of exogeneity to the system. India also presents a weak degree of exposure in the short period, but was affected in the long period. Brazil and Russia in contrast, show an increase in the degree of exposure in the short period but in the long period, they represent a lower rate of vulnerability.</p>	<p>Contagion Evidence:</p> <p>The number of cross-market connections has largely increased between the tranquil and the turbulent period: there is evidence of a contagion process.</p> <p>Direction of Contagion:</p> <p>Brazil plays a major role in the contagion transmission, being able to influence all other countries followed by far by South Africa, playing a leading role in the transmission mechanism. China has lost its leading role in the shock transmission mechanism. India (as a pure follower country) and South Africa were the most influenced by other countries.</p> <p>Contagion Process: Degree of Vulnerability and Exposure to External Shocks:</p> <p>All countries are highly involved, becoming more exposed to the financial contagion. South Africa is the most exposed country in this crisis with the highest degree of fragility. Brazil, Russia and India, show almost the same rise in the rate of involvement both in the short and long period, indicating a high degree of exposure to external markets and consequently, increasing domestic risk explained by innovations in foreign countries. Nevertheless, China seems to have the lower rate of vulnerability, comparing to the other BRICS countries.</p>

¹⁰⁹ The same occurs for bonds. However, in the case of sovereign credit ratings, for instance, more long-run relations exist per period. This is understandable since sovereign ratings are designed by rating agencies to capture a long-term state (Fourie & Botha, 2015).

¹¹⁰ In the second crisis, Brazil influenced South Africa. Therefore, South Africa played a bigger role based on the results from Gonzalo-Granger statistic (see §3.2.4.2, §4.2 and Web Appendix 7).

¹¹¹ As stated before, these findings corroborate to the fact that South Africa has the most developed and opened financial market among BRICS countries with rapid financial market development and sophistication, and is globally recognized as a source possessing sophisticated professional services and financial expertise (Liu et al., 2013; Zhang et al., 2013). This financial influence is capable of transmitting financial shocks in great degree and magnitude to the other BRICS countries (Bonga-Bonga, 2015).

¹¹² As already stated in this research earlier – contagion is a significant increase in the co-movement between assets during a period of crisis, compared with a tranquil period (Gentile & Giordano, 2012, 2013).

¹¹³ In the sense that these countries absorb shocks but are not able to influence (lead) other countries, indicating a higher level of vulnerability.

5 Conclusions

The contagion effect in the financial markets has been reinforcing the concerns in emerging and advanced economies, mostly after the large impact that started with the collapse of the USA mortgage market in 2007 (Subprime Crisis), triggering the financial turmoil in global markets materialized in a GFC¹¹⁴ after the Lehman Brothers Collapse, causing a massive devaluation in the global markets. To make matters worse, the GFC undermined the economies around the world, spreading and becoming more severe in some regions, revealing the weakness in economies around the globe, for instance in Europe, the GFC triggered the ESDC, another major crisis, that was capable of transmitting massive shocks throughout the financial markets.

Our research contributes to a better understanding of the contagion phenomenon¹¹⁵ by analyzing the changes in cross-market connections for the BRICS stock markets. The application of VECM cointegration and Granger causality methodology detected the contagion in order to measure shifts in the shocks transmission channels caused by the creation of new long-run equilibrium together with the raising of new short-run connections¹¹⁶, by analyzing changes in the long/short-run connections in both contagion windows (LBBC and ESDC).

Our results reveal that there was a contagion effect phenomenon in both crises¹¹⁷, given that the number of cross-market connections increased sharply after such crises events occurred and reduced afterwards¹¹⁸. A new long-run equilibrium relationship between BRICS markets was created, causing a deterioration of the diversification benefits in both crises compared to the tranquil times (i.e., the presence of a cointegrating vector indicates long-

¹¹⁴ However, the impact was in varying proportion depending on the internal strength of the economy of the individual BRICS countries. The crisis spread to the BRICS through all four channels: trade, finance, commodity and confidence channels. In Brazil, the local currency and stock market has seen huge fluctuation as foreign investment (see Appendix III) has gone down, demand for commodity export dried up and external credit decreased, the financial markets in Russian froze due to a rise in risk aversion and sudden change in exchange rate expectation which was triggered by the collapse of oil prices in September 2008 led the Russian banks and firms to seek to hedge their foreign currency exposure which led to pressure on the ruble. In the Indian economy, there was fall in GDP growth rate and external demand shock had a larger impact on output and employment. Impact of the financial crisis on China took the form of decrease in external demand which led to economic slowdown and rising unemployment. In case of South Africa, portfolio inflows had accounted for the bulk of financing of South Africa's large CAD (Current Account Deficit) which led to large net outflows, both export and import volumes fell which affected South Africa's main export commodities weakened. The global financial crisis inflicted significant loss in output in all the BRICS economies (Kishor & Singh, 2014, p. 415).

¹¹⁵ One of the main interest of contagion studies is concerned to the international portfolio diversification. Theoretically, diversification reduce portfolio risk, but when cross-country correlations increase during crises, this concept is undermined. Understanding financial contagion would clearly be beneficial for police makers in order to prevent future spreads of crises according to Gentile and Giordano (2012).

¹¹⁶ The significant rising in the short-run connections is evidence of contagion. This phenomenon amplifies the causality between markets followed by a shock (Boubaker et al., 2016).

¹¹⁷ Although BRIC (excluding South Africa) economies have heterogeneous profiles in terms of the cultural, political, social, demographic and macroeconomic contexts, or also observing human capital and labor market variables, the evidence corroborates with previous studies suggesting that their main stock market indices share short and long-run equilibrium relationships, thus indicating the evidence of the exist of high levels of integration and contagion. For more details, see Matos et al. (2015).

¹¹⁸ As stated in Gentile and Giordano (2012, 2013), contagion occurs when cross-country co-movements (represented by the percentage of cointegrated countries), increase during crisis periods and decrease in the tranquil periods. Hence cannot be explained by fundamentals, which involves just interdependence. In other words, how different the propagation of shocks is after a large negative realization has taken place (Edwards, 2000).

run relationship among the countries concerned during the crisis period. The co-movement reduces diversification benefits for the investors (Singh & Kaur, 2016, p. 126)). By applying the Granger causality¹¹⁹, our results point to changes in the short-run linkages between BRICS markets. These results confirm the transmission of shocks from the LBBC and ESDC to BRICS stock markets existed and was amplified during the crisis period¹²⁰. In fact, shocks from the LBBC and ESDC affected the BRICS stock markets in the short-run, implying that only trivial opportunities existed for diversifying risk of international investors. Furthermore, Brazil serve as a channel of contagion transmission, receiving shocks from both crises and spreading them to the rest of the BRICS. Additionally, movements from Brazil stock market, could serve as an indicator to predict behaviors in other BRICS markets.

The VECM/Gonzalo-Granger statistic¹²¹ revealed, that Brazil played a bigger role as a leading country in the transmission of the contagion to the other countries. It also Indicated also that India is the most vulnerable country in both crises (a pure following country). Moreover, innovations from LBBC hit Brazil, China and South Africa first, and consequently, they transmitted the contagion to the other countries. In this crisis, only China was able to provide some hedge against shocks from LBBC. On the other hand, in the ESDC, Brazil, Russia, China and South Africa were affected at same time, but in this crisis, the BRICS stock markets were able to be more resilient, providing a better degree of hedge against the innovations from ESDC.

Regarding the degree of vulnerability of BRICS markets to external shocks, the evidence corroborates that China was the most exposed country in the LBBC, whereas in the ESDC, all countries presented a higher degree of exposure and fragility, with South Africa being the most fragile country and more exposed to the financial contagion. These results bring great implications for the portfolio diversification in these markets. The effects of contagion in the BRICS markets can change investors' behavior, the financial stability can lead to high correlations in the markets, and phenomena like "*fight-to-quality*"¹²², "*heard behavior*" and "*bandwagon*" effects on the part of investors¹²³ may arise (Gentile & Giordano, 2012; Kazi & Wagan, 2014). However, it is interesting to notice an increasing integration between BRICS countries, through a much deeper relationship and bilateral trade agreements, which is opening their economies and financial sector. Their stock markets, however, are not fully cointegrated, making them still independent from the global financial system, benefiting, for instance, the global investors that intend to invest in the BRICS equity market indices to enjoy the diversification as well as international exposure benefits (Singh & Kaur, 2016).

¹¹⁹ Our model includes the USA stock market as an exogenous variable, which was able to influence/Granger cause all the BRICS countries in all time windows.

¹²⁰ Consequently, these findings suggest contagion effect and the sensitivity of the BRICS markets to news announcement from USA markets in the post-crisis period (Boubaker et al., 2016; Kishor & Singh, 2014). Indicating that investors can rely on lagged values of the USA equity prices as indicator to forecast the behavior of BRICS stock markets (Lakshmi et al., 2015, p. 317).

¹²¹ To a better understanding of these results (see table 5, §4.2).

¹²² As already mentioned, since the adopted definition of "*shift*" contagion relies on a significant increase in cross-market co-movements after a shock, which is not related with fundamentals linkages (financial, real, political). The only transmission that could explain contagion is the behavioral one (Gentile & Giordano, 2012).

¹²³ A form of group think, in which investor's probability of adopting any belief increases with the proportion who have already done so, hence investors do not discriminate among economic fundamentals across countries.

In the last decades, the BRICS countries underwent an important process of trade and financial liberalization to benefit from the advantages of market integration. Therefore, integrated financial markets allow, investors to allocate consumption risk more efficiently, decreasing the costs of capital faced by firms and stimulating investment and economic growth. However, the increased financial integration has intensified contagion effects across markets, causing severe welfare losses for large geographical regions. Consequently, integrating a national market with global financial markets may facilitate the transmission of international shocks to domestic stock markets, having important implications for the decisions of investors', risk managers, regulatory and monetary authorities and in particular, consequences for effective portfolio diversification (Zouhair et al., 2014).

Several important policy and economic implications can be drawn from the empirical results of this study. The evidence of the impact caused by both crises in the BRICS stock markets also provides meaningful insights pertinent to international asset pricing, risk management and the dynamic interactions in the global economy. For instance, gold's ability to act as a safe haven in the case of South Africa may have financial implications regarding the presence of diversification opportunities during extreme market conditions. With the "*financialization*" of the commodity markets, gold and oil can provide further protection against losses when the traditional assets (equities and bonds) experience large declines. Thus, including commodities in traditional portfolios that include BRICS markets, allow investors to avoid the downside risk in their investments. Gold can also provide protection against dollar devaluations (Mensi et al., 2014). This research is also particularly helpful for portfolio risk managers, energy traders, policymakers and international investors who should be cautious about making investments in simultaneous markets that exhibit *pure contagion*. Knowledge of dependencies of the BRICS is crucial for policymakers to help them discern the directions of the co-movements and to safe guard the BRICS stock markets from contagion during future crises or major events.

Understanding the reasons of financial contagion between BRICS and international stock markets can help policymakers to develop a prevailing financial system to make BRICS markets more immune to international shock transmission, limiting their exposure to the contagion effects by improving stock market liquidity, as the BRICS markets increasingly become more integrated with the international markets.

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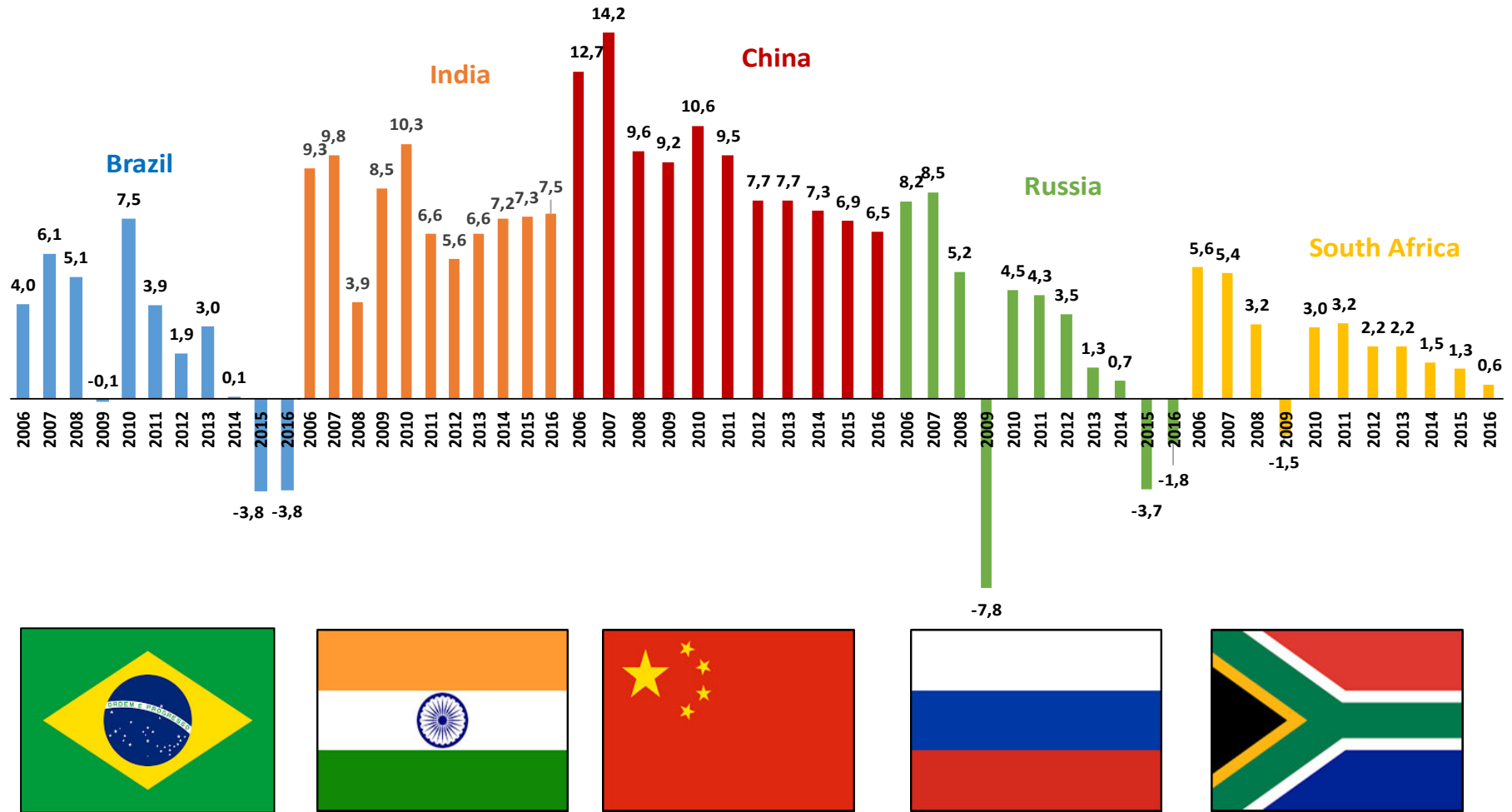
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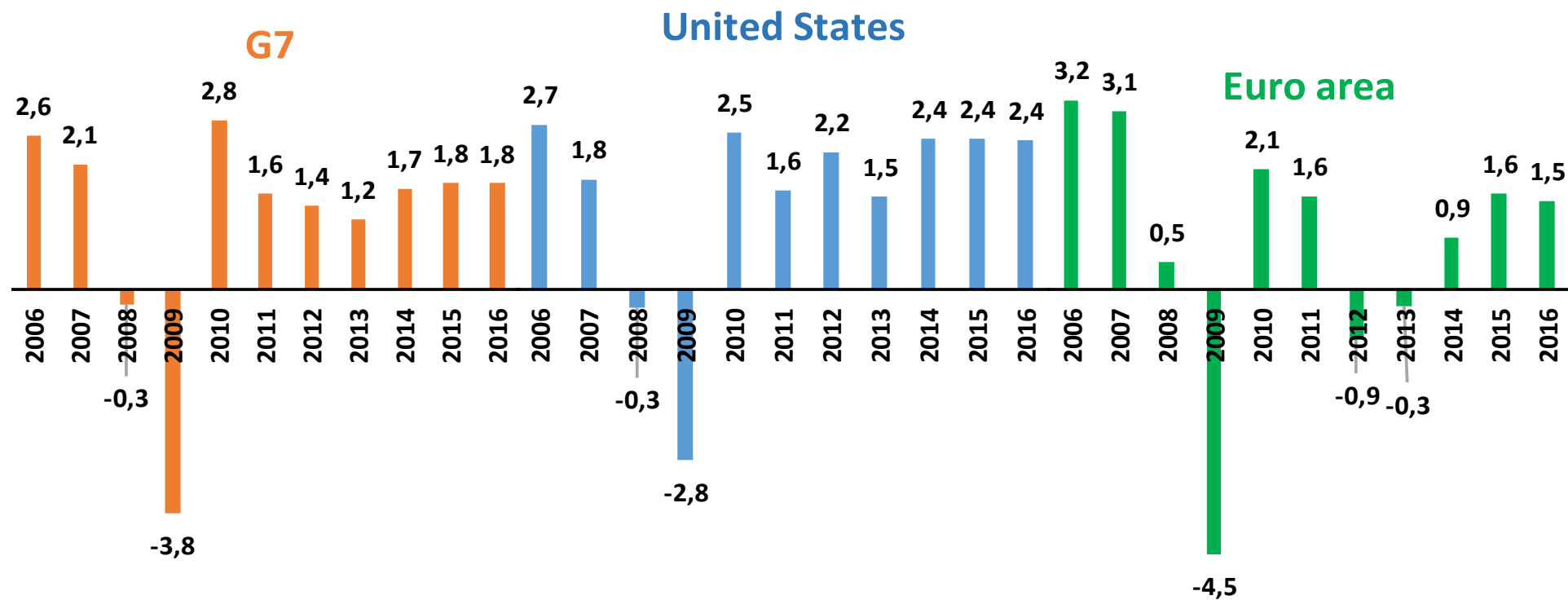
Appendixes

Appendix I: GDP Growth Rate for BRICS Emerging Markets.



Note: Source: Author's own based on data from IMF – World Economic Outlook Database, April 2016 (IMF, 2016).

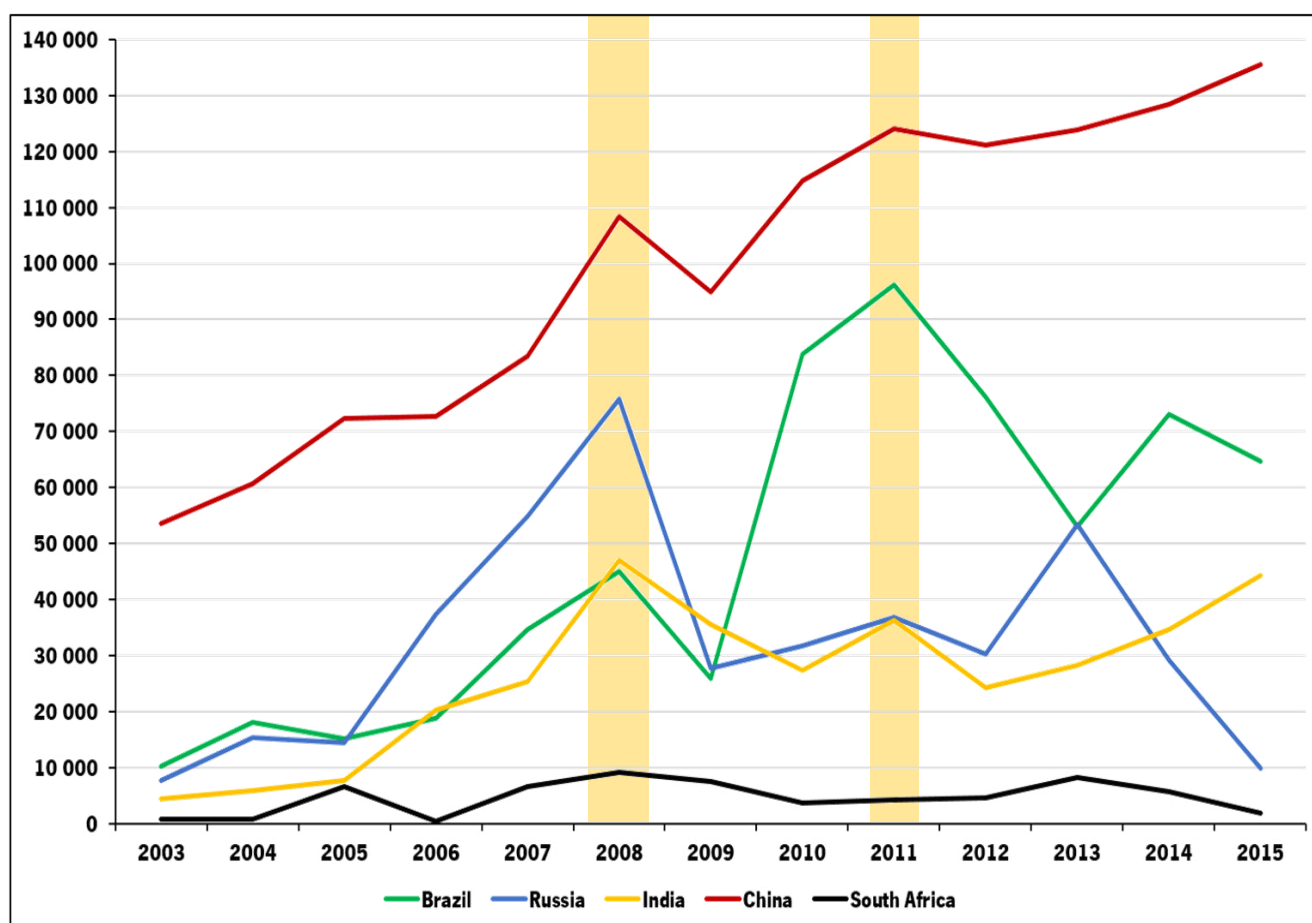
Appendix II: GDP Growth Rate for Developed Economies.



Note: Source: Author's own based on data from IMF – World Economic Outlook Database, April 2016 (IMF, 2016).

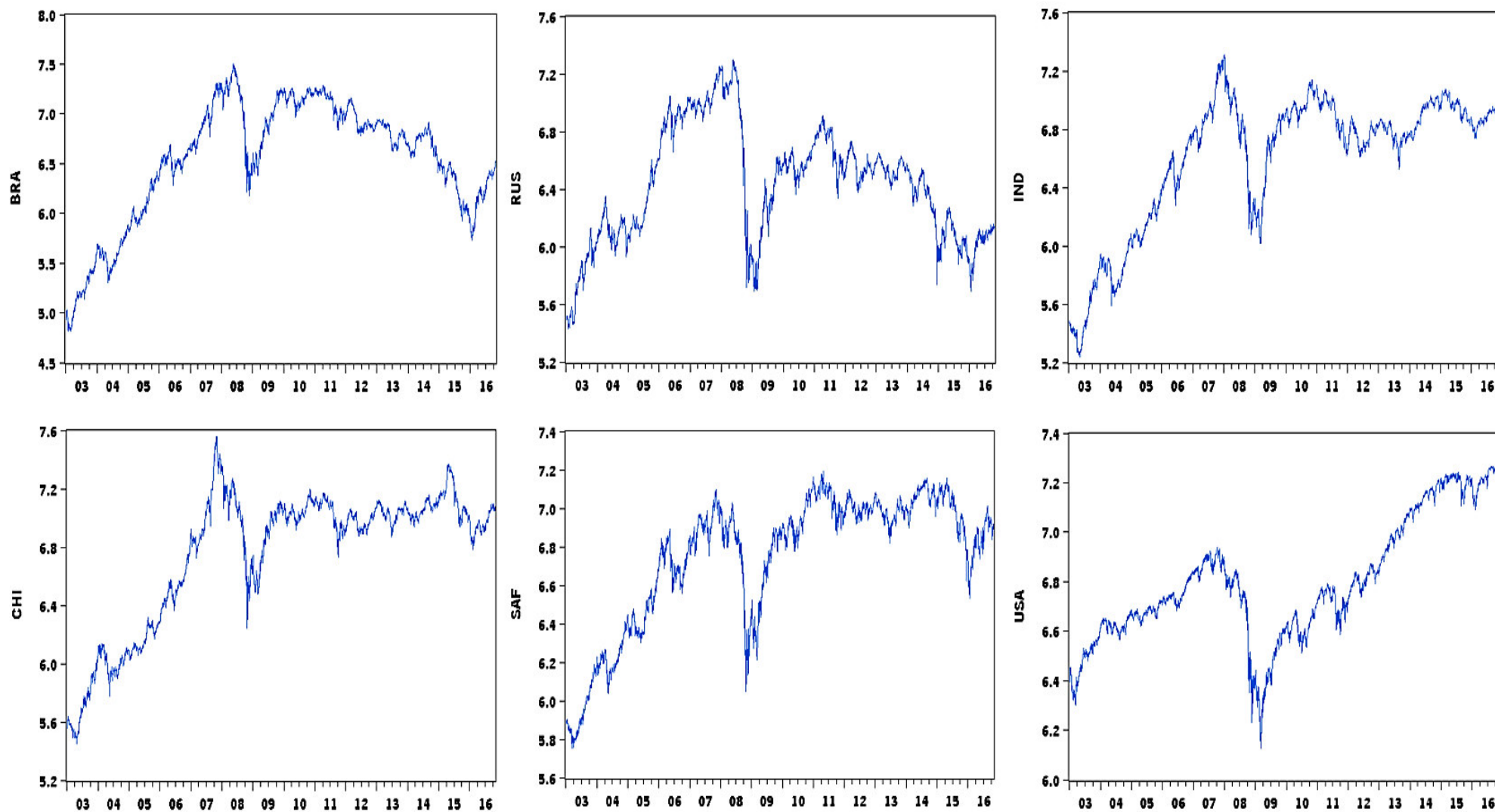
Appendix III: The Evolution of FDI Inflows in BRICS Countries.

Year	Brazil	Russia	India	China	South Africa
2003	10 143,52	7 754,76	4 321,08	53 504,70	733,67
2004	18 145,88	15 283,75	5 777,81	60 630,00	798,03
2005	15 066,29	14 375,05	7 621,77	72 406,00	6 646,93
2006	18 822,21	37 441,57	20 327,76	72 715,00	311,45
2007	34 584,90	54 921,85	25 349,89	83 521,00	6 538,06
2008	45 058,16	75 855,70	47 102,42	108 312,00	9 209,17
2009	25 948,58	27 752,26	35 633,94	95 000,00	7 502,06
2010	83 748,99	31 667,97	27 417,08	114 734,00	3 635,60
2011	96 152,37	36 867,77	36 190,46	123 985,00	4 242,87
2012	76 097,95	30 187,66	24 195,77	121 080,00	4 558,85
2013	53 059,74	53 397,14	28 199,45	123 911,00	8 300,10
2014	73 085,51	29 151,66	34 582,10	128 500,00	5 770,64
2015	64 647,88	9 824,93	44 208,02	135 610,00	1 772,41



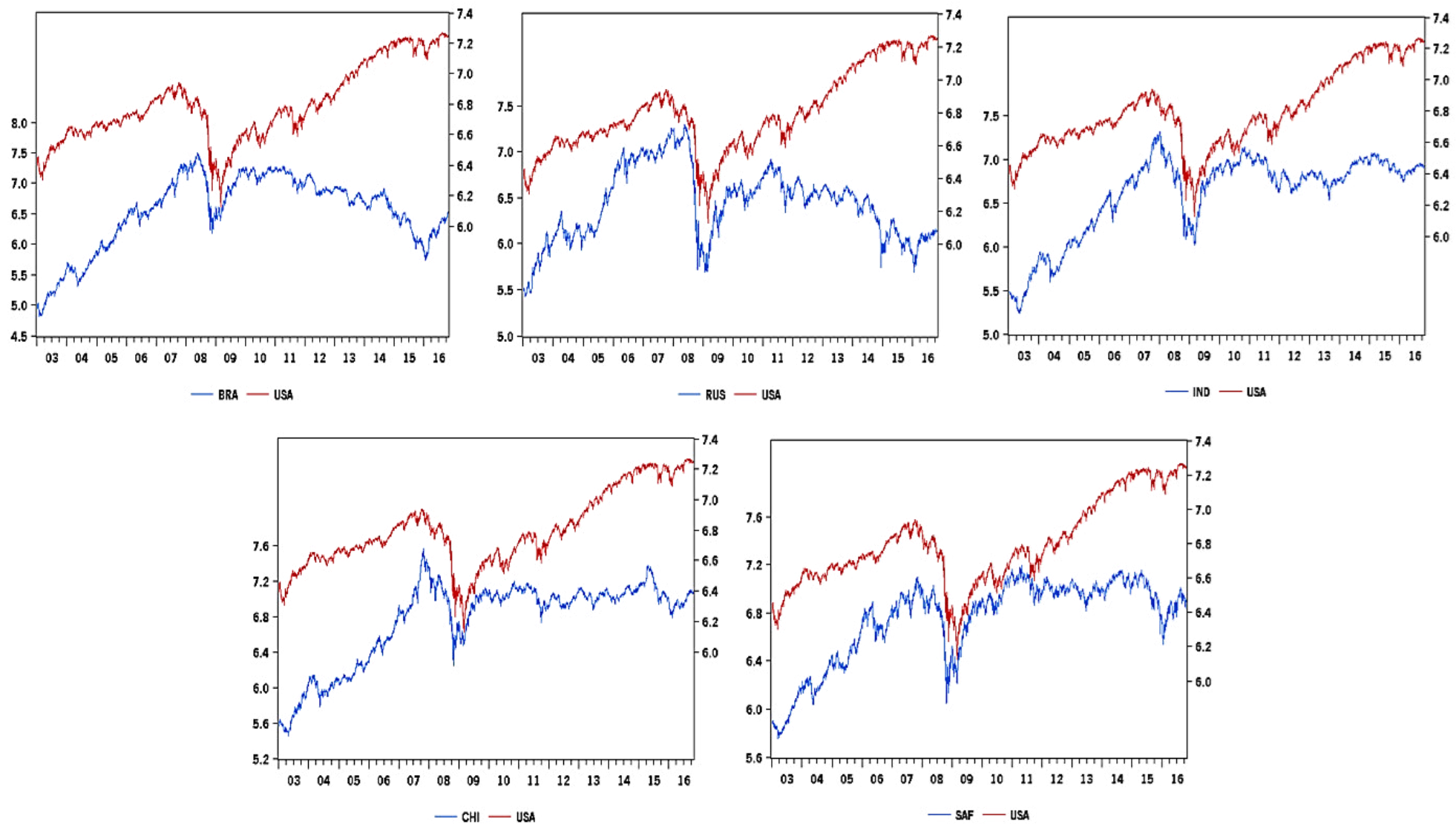
Note: Source: Author's own based on the data retrieved from United Nations Conference on Trade and Development (UNCTAD, 2017). The Foreign Direct Investment (FDI) inflows is presented in millions of dollars. The results present a major increase in the FDI inflows to the BRICS countries in the Subprime and Lehman Crisis and later in the European Sovereign Debt Crisis. The investor's behavior shifted to the Emerging Markets seeking to hedge their investments. It is possible to see also the inverse pattern (outflows) when the investors realized that even the BRICS countries were not capable of shielding their investments against the contagion effect in 2009 and 2012.

Appendix A: BRICS and USA Stock Markets – Individual Log-Level Representation.



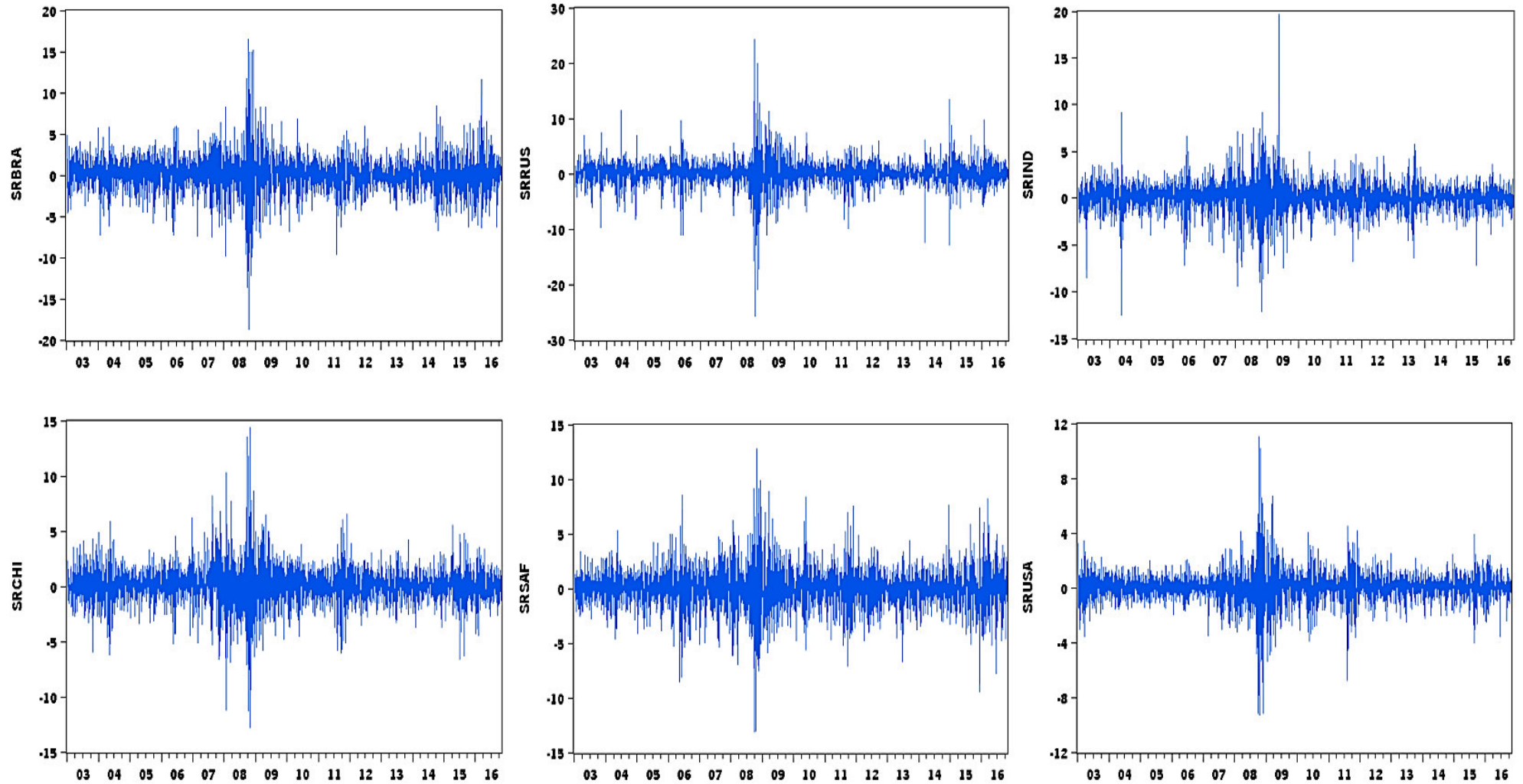
Note: Source: Author's own. Using EViews 9.0 program.

Appendix B: BRICS Vs USA Stock Markets - Log-Level Representation.



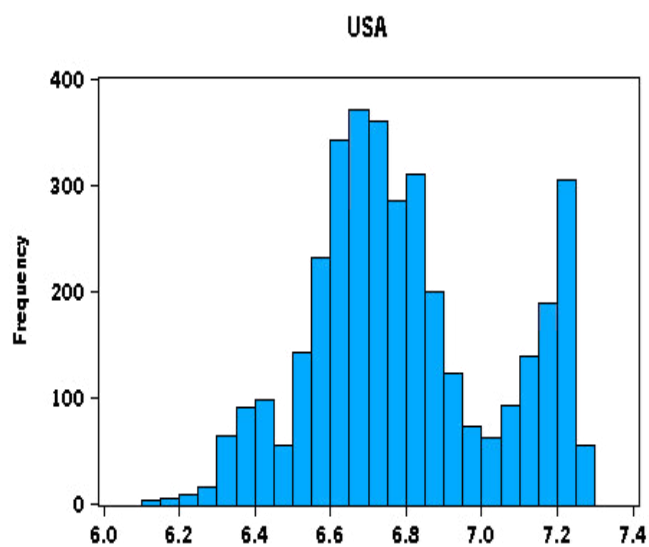
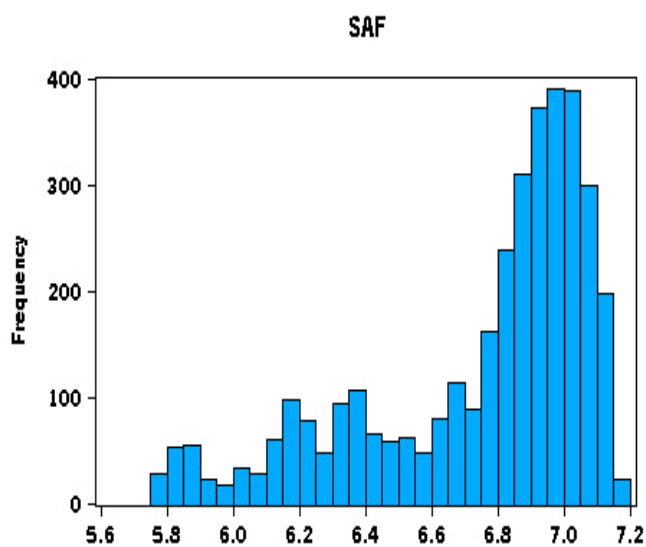
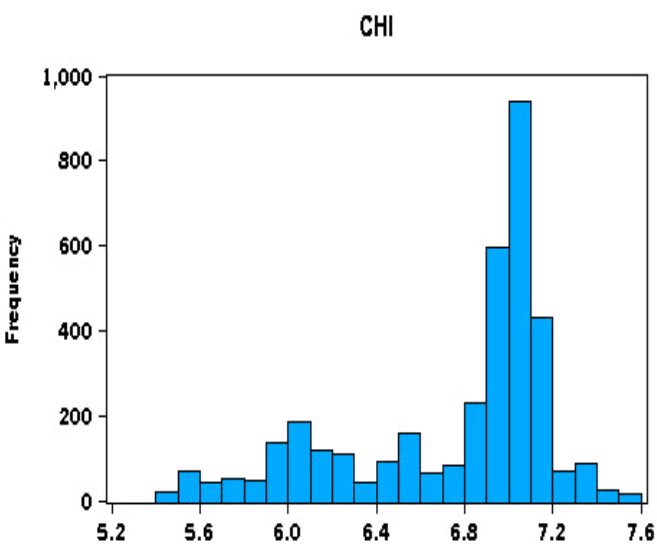
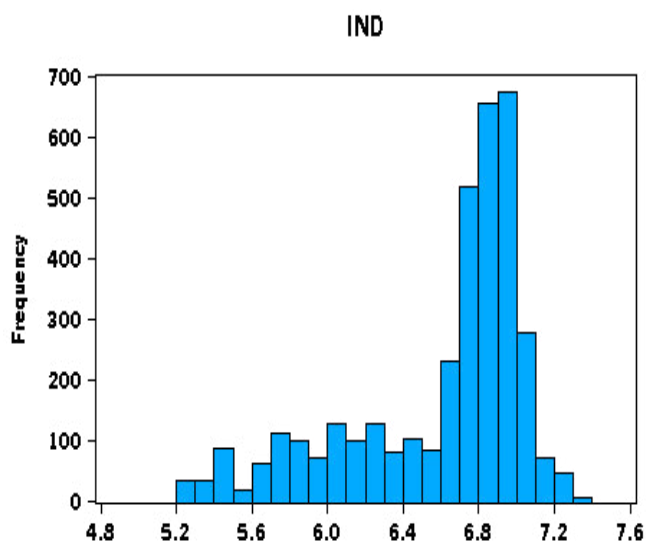
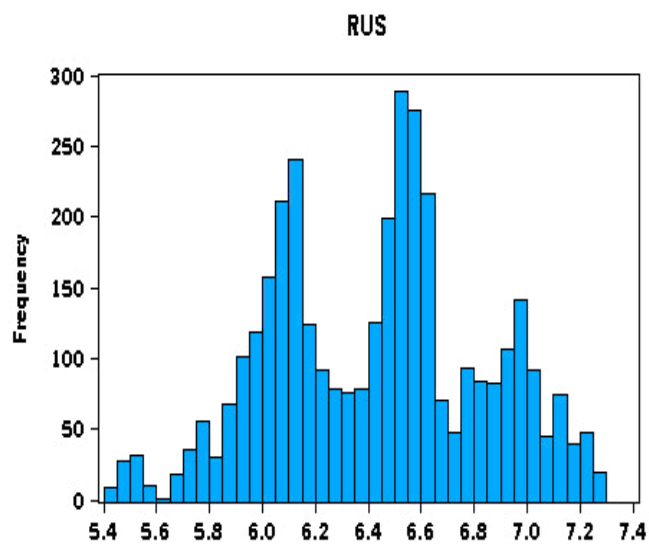
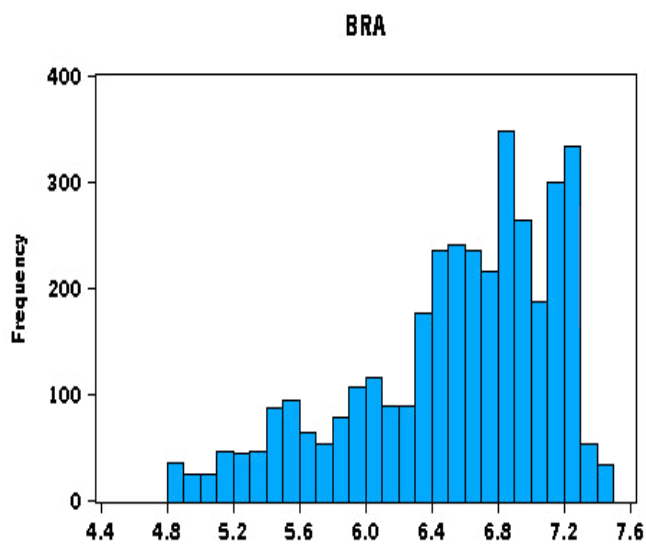
Note: Source: Author's own. Using EViews 9.0 program.

Appendix C: BRICS and USA Stock Markets - Percentage Daily Returns.



Note: Source: Author's own. Using EViews 9.0 program.

Appendix D: Raw Data from Thomson Reuters Datastream.

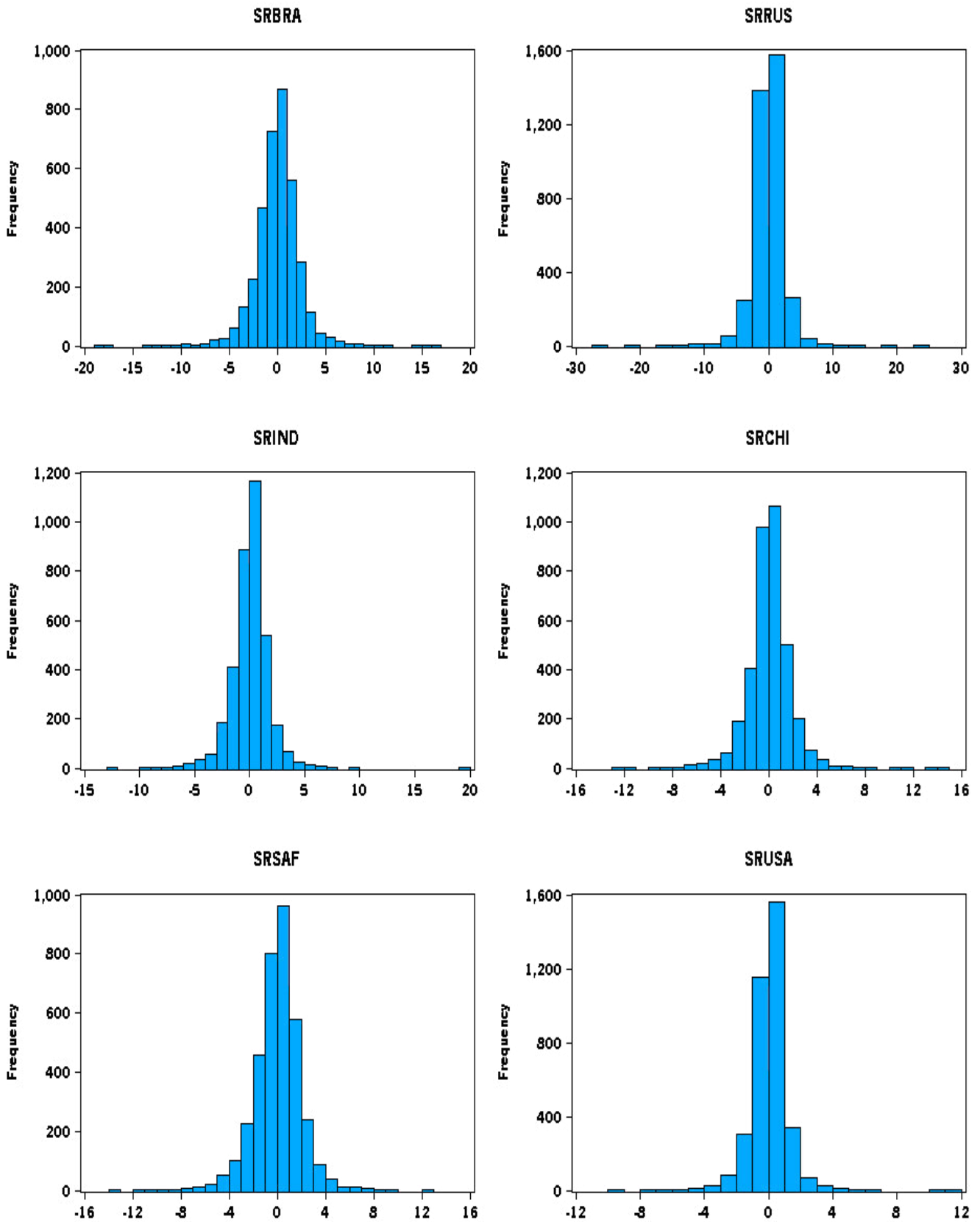


Note: Source: Author's own. Using EViews 9.0 program.

Appendix E: Data Transformation in Log-Level.

Eq. 1

$$\text{Formula: } R_t = [\log(P_t) - \log(P_{t-1}) \times 100] = \left[\log\left(\frac{P_t}{P_{t-1}}\right) \times 100 \right]$$



Note: Source: Author's own. Using EViews 9.0 program. Logged values are taking to reduce heteroskedasticity present in the data (Singh & Kaur, 2016).