VOLATILITY SPILLOVERS AND DETERMINANTS OF CONTAGION: A CASE OF BRICS EQUITY AND FOREIGN EXCHANGE MARKETS

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DEDICATION

To my late maternal grandmother, Mamoratuoa Nyopa, who recently passed on to glory. I am eternally grateful for your love, encouragement and prayers. You have been life's best gift to me.

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I would like to thank God for his immense grace and wisdom throughout the writing of this thesis. The words ‘never would have made it without you’ have never held more significance to me. My sincere gratitude also goes to my supervisor, Dr. Alwyn S Khumalo, for his guidance and support.

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ABSTRACT

This study investigates the relationship between the equity markets and foreign exchange markets in Brazil, Russia, India, China and South Africa (BRICS) using Diebold-Yilmaz spillover index. The study also identifies macroeconomic fundamentals that can enhance contagion in these markets using panel dynamic ordinary least squares regressions. The study spans the period from 1997 to 2018. We find that there are interdependencies between BRICS equity markets and foreign exchange markets, except for China, whose markets are relatively isolated from other BRICS markets. Brazil is the largest contributor of volatility spillovers to other BRICS markets. The spillover indexes also indicate significant increases in volatility spillovers associated with turmoil periods in domestic and global markets. This provides evidence for contagion during crises periods. We also find that fundamental indicators and trade linkages are major drivers of increased volatility spillovers (contagion) in BRICS; and global risk indicators, such as VIX and oil prices, explain volatility spillovers in BRICS. These results hold across both equities and foreign exchange markets.

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List of Acronyms

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
BIC	Swartz Bayesian Information Criterion
BRICS	Brazil, Russia, India, China and South Africa
BRL	Brazilian Real
CNY	Chinese Yuan
DOLS	Dynamic Ordinary Least Squares
DY	Diebold-Yilmaz
EDC	Eurozone Debt Crisis
EM	Emerging Market
EMDEs	Emerging Markets and Developing Economies
FEVD	Forecast Error Variance Decompositions
GFC	Global Financial Crisis
ICGR	International Country Risk Guide
IMF	International Monetary Fund
INR	Indian Rupee
NDB	New Development Bank
RUB	Russian Ruble
VAR	Vector Autoregression
ZAR	South African Rand
LLC	Levin, Liu & Chu
IPS	Im, Pesaran and Shin

CHAPTER 1
INTRODUCTION

1.1. INTRODUCTION AND BACKGROUND

The volatility spillover effect and co-movements among the financial markets are important issues in both economic and financial studies locally and globally. Volatility spillovers refer to how volatility in one asset transmits into the volatility of other assets. In their pioneering work on volatility spillovers, Engle, et al. (1990), investigate the "heat waves" and "meteor showers" hypotheses of volatility in well-integrated markets for major currencies. According to the *heat waves* hypothesis volatility in one market continues in the same market the next day while the *meteor showers* hypothesis allows volatility to be transmitted across markets. Studies into volatility co-movements tend to focus on the degree to which the volatility in one security may be related to the volatility of another security over a given period (Dedi & Yavas, 2016; Kavli & Kotze, 2014; Arshanapalli & Doukas, 1993; King, et al., 1994). These studies are important to financial market participants as an increase in co-movement between the markets over time would imply that there are fewer opportunities for diversification to hedge against risk in a portfolio.

An acceleration of international financial integration and liberalization has gradually increased the level of co-movements in various financial markets and thus increased volatility spillovers (Pramor & Tamirisa, 2006). Studies have shown that one of the benefits of financial integration is that it enhances financial stability through risk diversification (Mishkin, 2007; Levine, 1997; Obstfeld, 1994). However, some studies also show that a major threat of financial integration is the increased risk of financial instability (Agenor, 2003; Stiglitz, 2002; Obstfeld, 1998). In the aftermath of the Global Financial Crisis (GFC), which originated from the U.S and quickly spread to other international markets, is an increased interest in the risks associated with financial integration. Studies post the GFC show that shocks in financially integrated markets can easily spread and spillover to other markets (Glasserman & Young, 2015; Rejeb & Boughrara, 2015; Deveraux & Yu, 2014). Thus, increased financial integration can lead to contagion where shocks from one country (or a group of countries) intensify cross-market linkages and co-movement of asset price shocks to other countries (Biekpe & Motelle, 2018).

Since the early 1990s, there has been a surge of capital flows from foreign investors into developing economies' capital markets (Calvo, et al., 1996). This has been driven largely by their promising growth prospects as well as financial market and macroeconomic policy reforms. The increased participation of foreign investors in emerging stock markets, such as the BRICS bloc, points to the strengthening of the linkage between equity flows and foreign exchange rates. A priori expectations indicate that high levels of capital and portfolio inflows can lead to currency appreciation which can affect the competitiveness of an economy's exports in the international market leading to a potential trade deficit. The value of the domestic currency is important to BRICS economies as they are major exporters of commodities and manufactured goods (Centre for the Study of Governance Innovation, 2013).

The BRICS country grouping consists of the Federative Republic of Brazil, the Russian Federation, the Republic of India, the People's Republic of China and the Republic of South Africa. This bloc is not a regional bloc and their economies vary significantly. However, they are distinguished from other emerging market economies by their demographic characteristics and growth potential (O'Neill, 2013). Specifically, the five countries account for more than 40% of the world population and they cover more than 25% of the world's land area over four continents. Moreover, three of the BRICS economies are ranked among the 10 largest economies in the world by nominal GDP size, namely China (2), India (7) and Brazil (9). Russia is ranked 11th and South Africa is 34th (IMF, 2018). Wilson and Purushothaman (2003) project that by 2040 BRICs economies will be among the most dominant economies alongside the United States (US) and Japan surpassing other G6 countries. Furthermore, the BRICS economies share of global GDP (PPP based) has increased from 18% in 2000 to more than 31% in 2016, and China alone holds approximately 18% of total global GDP (IMF, 2017). Also, according to the New Development Bank (NDB) 2017 report, the combined economic weight of the BRICS countries in 2015 was about the same as that of the G-7 countries, signifying the increasing importance of BRICS in the global economic system.

Due to their size, development and growth prospects these economies attract significant portfolio flows and are also significant sources of cross-border flows into other emerging markets and developing economies (EMDEs) (NDB, 2017). However, like other emerging market economies, capital flows to BRICS are very volatile resulting in volatile exchange rates. This study focuses on the BRICS bloc because of their continually increasing role in the global economy. Furthermore, as a student from South Africa, I am interested in the degree of co-movement between South African financial markets and other BRICS countries, as in aggregation the BRICS countries are among South Africa's biggest trade partners. In particular, in 2018, 14.8% of South Africa's total exports were directed to BRIC countries and 24.6% of South Africa's total imports were from BRIC economies, with China – South Africa's largest trading partner – accounting for 9.2% of SA exports and 18.3% of SA imports (International Trade Center, 2018). As trade linkages increase among economies so does the likelihood of volatility spillovers and contagion effects among their financial markets.

1.2. PROBLEM STATEMENT

Excess volatility can cause uncertainty amongst investors, delaying investment decisions and adversely affecting growth and job creation. Caporale, et al. (2015) posit that exchange rate volatiliity increases the costs of international financial transactions and reduces the potential gains from international diversification. In recent years increased volatility in emerging market (EM) economies has led to a loss of investor confidence and as a result capital flight. This was evident during the height of the GFC when capital inflows to EMDEs turned negative. For instance, net portfolio inflows to India and Russia in 2007 were USD 35 billion and USD 19 billion respectively compared to portfolio outflows of USD 15 billion in both countries in 2008 (World Bank, 2008). The sudden withdrawal of funds from EMDEs led to a fall in stock prices and in turn pressure on their exchange rates which depreciated against the US dollar (Ferreiro & Serrano, 2011) and increased volatility in both equity and currency markets.

Given that emerging market returns tend to be more volatile compared to more developed markets (Bekaert & Harvey, 1997), volatility spillovers can be "a source of concern because they can propagate volatility shocks between the markets and increase the risk of a financial crisis" (Bonga-Bonga & Hoveni, 2013:261). Bae, et al. (2003) show that the high degree of risk inherent in emerging markets makes them more susceptible to financial crises and contagion. Moreover, King and Wadhani (1990) suggest that increased volatility leads to an increase in the size of contagion effects.

In the past 25 years, there have been several crises originating from both developed countries and emerging markets which have affected the global economy, such as the Mexican Peso Crisis, the Asian Financial Crisis (AFC), the Global Financial Crisis (GFC) and the Eurozone Debt Crisis (EDC). Furthermore, the recent commodity price crash of 2014-2016 affected Brazil, Russia and South Africa considerably because they are major net exporters of commodities. As BRICS economies have become increasingly integrated to the global economy through trade and investment linkages, they have also become more susceptible to economic and financial disturbances from other countries. Likewise, the increase in intra-BRICS trade and financial cooperation increases the likelihood of volatility spillovers and contagion effects among their financial markets. Thus understanding volatility co-movement and spillover effects between markets in BRICS is crucial to the management and prevention of financial crises in the bloc. Additionally, an understanding of the financial connectedness of BRICS equity and foreign exchange markets is important for international investors who wish to diversify their portfolios and also take advantage of the high growth rates in these markets.

1.3. OBJECTIVES AND RESEARCH QUESTIONS

The main aim of the study is to understand the relationship between the equity markets and foreign exchange markets in BRICS by investigating the spillover linkages amongst these markets and to identify macroeconomic fundamentals that can enhance contagion. The study also has the following secondary objectives:

- To determine the direction of volatility spillovers between equities and foreign exchange markets in BRICS
- To determine whether local or global factors drive volatility spillovers more

The following research questions are formulated:

- Are there market interdependencies (co-movements) among BRICS asset classes?
- Is there evidence of contagion in stocks and currencies among the BRICS countries during crises periods?
- If there is evidence of contagion, what are the determinants of fundamental contagion?

1.4. RESEARCH CONTRIBUTIONS

There is a growing body of literature on volatility spillover effects and co-movement among financial markets, however, most of the studies provide conflicting results. And most of the studies on volatility spillovers in BRICS countries focus on volatility transmission from developed countries (the U.S. and/or UK) to BRICS stock markets during the GFC (Mensi, et al., 2016; Sui & Sun, 2016; Chkili & Nguyen, 2014; Mishra, et al., 2007). Very few studies look at volatility transmission among BRICS markets on their own.

And of the studies that look at determinants of financial market spillovers, most of them are focused on advanced economies (Leung, et al., 2017; Balli, et al., 2015; Luchtenberg & Vu, 2015; Shinagawa, 2014). A few studies have also looked at contagion factors that impact BRICS equity markets (Mensi, et al., 2014; Hwang, et al., 2013; Aloui, et al., 2011). However, Aloui, et al. (2011) "do not explicitly search for the determinants of cross-market financial dependence" but consider economic structure as an important factor in explaining extreme financial dependencies of BRIC countries and the U.S.

This study aims to extend the previous studies by examining the financial connectedness in BRICS economies through volatility spillovers among both equity and foreign exchange markets. The study also extends the literature on the determinants of contagion by looking at other crises episodes throughout the period of the study. Being able to determine the exact nature of these relationships will assist investment analysts and portfolio managers seeking to manage their risk and diversify their investments in this country grouping. The study will also help economic policymakers to develop and implement policies that will mitigate the occurrence of contagion in BRICS economies during turmoil periods.

1.5. METHODOLOGICAL APPROACH

The study applies various econometric approaches to investigate the research questions. In particular, the EGARCH of Nelson (1991) is used to calculate volatilities in the returns series; the Diebold and Yilmaz (2009, 2012) spillover index approach (DY index) which is based on the Generalized Vector Autoregression (GVAR) model is used to calculate total and directional spillover indices for BRICS equity and foreign exchange markets; and panel cointegrating regressions (dynamic ordinary least squares (DOLS)) are used to examine determinants of spillovers in the BRICS equity and foreign exchange markets using directional spillover indices of the DY spillover index as dependent variables

The study spans from 2 January 1997 to 31 December 2018. This relatively long sample period is selected to cover crises periods of particular interest to our study, from the Asian Financial Crisis of 1997-1998 to the 2018 Turkish currency crisis. Eviews 10 is used to carry out the proposed empirical investigations.

1.6. THESIS STRUCTURE

The thesis is divided into six sections. In Chapter 2 provides a brief overview of the BRICS countries. In Chapter 3 we discuss the research that has been done on this topic. We review the theoretical and empirical literature regarding volatility spillovers effects between the exchange market and the stock market as well as contagion effects. Chapter 4 contains the data and methods used. Empirical results are reported and discussed in Chapter 5. Chapter 6 summarizes the findings, concludes the paper and gives policy recommendations.

CHAPTER 2

OVERVIEW OF BRICS

2.1. INTRODUCTION

This chapter provides a brief review of the BRICS countries. Section 2.2 provides a background on the evolution of the BRICS bloc. Section 2.3 focuses on financial liberalization and the globalization of BRICS into the world market. It discusses the development of BRICS equity markets and monetary policy and the evolution of exchange rate regimes in BRICS. Section 2.4 concludes the chapter.

2.2. BACKGROUND OF BRICS

The BRICS country grouping consists of the Federative Republic of Brazil, the Russian Federation, the Republic of India, the People's Republic of China and the Republic of South Africa. The BRIC acronym was initially formulated by Jim O'Neill, an economist at Goldman Sachs (O'Neill, 2001). At the time, these were the fastest-growing emerging market economies and the paper argued that they would outperform most of the richest countries in the world by the year 2040. In 2006 the four countries started regular informal diplomatic coordination, with annual meetings of Foreign Ministers. The success of these meetings was followed by the first BRIC summit in 2009. South Africa later joined the group in December 2010, forming BRICS.

The BRICS economies are quite different in terms of socio-economic development and political regimes. Of the five countries, only Brazil, India and South Africa are well-institutionalised democracies, China is a Marxist (socialist) people's republic, and Russia is a declared democracy with authoritarian characteristics (Aroul & Swanson, 2018). Furthermore, their sizes and standards of living are very diverse. For example, according to the World Bank (2018) data, China’s economy alone is more than that of the other BRICS countries combined and it is more than 37 times the size of the South African economy; and with a population of over 57.7 million, South Africa is much smaller than the other BRICS nations – Russia is the closest with a population two and a half times bigger. Likewise, India’s GDP per capita is only about 17% that of Russia.

Despite these differences, BRICS nations are distinguished from other emerging market economies by their demographic characteristics and growth potential. Table 2.1 below provides information on the profiles of the BRICS economies.

Table 2.1: Profile of the economy - BRICS

	Population	**Surface area**	**Gross national income**		**Purchasing power parity gross national income**		**Gross domestic product**	
			Atlas method	**per capita, Atlas method**		**per capita**		**per capita**
	millions	**sq. km thousands**	**$ billions**	**$**	**$ billions**	**$**	**% growth**	**% growth**
	2018	**2018**	**2018**	**2018**	**2018**	**2018**	**2018**	**2018**
Brazil	209.5	8,515.80	1,915.30	9,140	3,314.60	15,820	1.1	0.3
Russian Federation	144.5	17,098.30	1,501.70	10,230	3,949.80	26,470	2.3	2.3
India	1,352.60	3,287.30	2,733.50	2,020	10,391.80	7,680	7	5.9
China	1,392.70	9,562.90	13,184.10	9,470	25,266.10	18,140	6.6	6.1
South Africa	57.8	1,219.10	332.2	5,750	768.3	13,300	0.8	-0.6

Source: World Bank Development Indicators, 2019

Although the BRICS countries have achieved rapid economic growth, they have faced several challenges in the aftermath of the GFC. According to the IMF (2016) data, while China and India have maintained strong growth rates of 6.7% and 6.8% respectively, Brazil, Russia and South Africa's growth rates in 2016 were -3.6%, -0.2% and 0.3% respectively. These decline in growth rates were due to the Russian financial crisis in 2014-2015 following the plunge in global prices of crude oil and economic sanctions imposed on Russia for the invasion of Ukraine which led to the devaluation of the Russia ruble; the Brazilian economic crisis of 2014-2016 following the US Federal Reserve tapering which led to capital flight from many developing economies; and a fall in prices of commodities due to decreased demand from China and political instability. The South African economy also contracted as a result of the Fed tapering, the commodities crash and country-specific reasons.

Even with a reduction in growth levels, the BRICS economies remained one of the few major engines of global economic growth during and after the GFC. During the 2008-2017 period, their combined growth rate has been 5.4%. While this is lower than the 1998-2007 growth rate of 6.7%

it is still quite substantial compared to the average world growth rate of 1.7% in the same period (New Development Bank, 2017). As a result, the BRICS accounted, on average, for 56% of the growth of global GNP (at 2005 $PPP) during 2008-2017 (New Development Bank, 2017).

The BRICS states are some of the most resource-rich countries. In particular, China is one of the largest mineral producers in the world - it is the world's leading producer of coal, gold, most rare mineral products (PwC, 2012). Growth in infrastructure developments in China has also made it the leading consumer of most mining products, particularly commodities (PwC, 2012). The BRICS nations generally pursue an export-led growth strategy. Natural resources (fossil fuels, biofuels, minerals, etc.) constitute the bulk of BRICS exports especially in Russia, Brazil and South Africa. Due to lower labour costs in China and India, the majority of their exports consist of manufactured and processed goods and services (Maryam, et al., 2018).

The size, development and growth prospects of these economies attract substantial portfolio flows which are significant sources of cross-border flows (NDB, 2017). The bulk of foreign direct investment (FDI) inflows in China has focused on manufacturing, while a large part of FDI in India flows to the service sector. Most of the FDI in Brazil, Russia and South Africa has been focused on the exploitation of natural resources, particularly oil and mining (Centre for the Study of Governance Innovation, 2013). Table 2.2 below provides information on private financial flows to the BRICS economies.

Table 2.2: Global Private Capital Flows to BRICS

	Equity flows			**Debt flows**	
	FDI, net inflows	**FDI, net inflows**	**Portfolio equity**	**Bonds**	**Commercial bank and other lending**
	$ millions	**% of GDP**	**$ millions**	**$ millions**	**$ millions**
	2017	**2017**	**2017**	**2017**	**2017**
Brazil	70,258	3.4	5,674	-642	14,646
Russian Federation	28,557	1.8	-7,940	20,325	-55,648
India	39,966	1.5	5,928	33,602	5,109
China	166,084	1.4	36,209	82,088	4,127
South Africa	2,060	0.6	7,576	18,359	8,152

Source: World Bank Development Indicators, 2019

2.3. FINANCIAL LIBERALISATION AND GLOBALISATION OF BRICS

The increase in capital flows into BRICS's capital markets has been largely driven by economic reforms made by the countries in the 1980s and 1990s. These reforms included liberalization of the foreign exchange markets and the capital account, relaxation of import and export restrictions, and modernisation of stock markets. According to Bekaert, et al. (2003) as cited in Bhar and Nikolova (2007) the official equity liberalization of countries is defined as "the date of formal regulatory change after which foreign investors officially have the opportunity to invest in domestic equity securities and domestic investors have the right to transact in foreign equity securities abroad." Based on this definition, the official liberalization dates for the BRIC countries are May 1991 for Brazil, February 1992 for India, July 1993 for China, January 1994 for Russia and March 1995 for South Africa.

The economic reforms and trade liberalization efforts initiated by respective BRICS nations are considered as a primary reason for the gradual increment of the BRICS' share in the global trade. Currently, the BRICS nations account for more than 17% of world trade. And from 1998 to 2016, trade flows within BRICS have more than doubled. Intra-BRICS exports as a percentage of total BRICS exports increased from 3.4% to 6.9% and intra-BRICS imports as a percentage of total BRICS imports increased from 4.4% to 9.6% (NDB, 2017). The Fortaleza Declaration adopted at the Sixth BRICS Summit held in 2014, put forth trade and investment facilitation as one of the priority areas for intra-BRICS (BRICS, 2017), and as such, intra-BRICS trade is expected to increase even more. Studies show that trade linkages can transmit the effects of currency crises or more generally economic disturbances from one country to another (Bentivogli & Monti, 2001; Glick & Rose, 1999). Thus the increase in trade linkages within BRICS increases the likelihood of volatility spillovers among them.

2.3.1. BRICS STOCK MARKET DEVELOPMENT

Together the BRICS countries account for more than 16% of the world's stock market capitalization with USD 11.99 trillion (The World Federation of Exchanges, 2017). It is also estimated that by 2030, four of the BRICS countries (excluding South Africa) will account for 41% of the world's stock market capitalization (Hammoudeh, et al., 2013). According to the World Bank

(2018) data, China currently has the second-largest stock market in the world after the U.S. Stock market development in the BRICS economies has also deepened as measured by the market capitalisation to GDP ratio, also known as the Buffett ratio. In 2017 South Africa, India, China, Brazil and Russia's market capitalization to GDP ratios were 352.8%, 88.0%, 71.2%, 46.5% and 39.5% respectively; ranking 2nd, 17th, 23rd, 35th and 40th globally (World Bank, 2017).

However, a large stock market capitalization does not necessarily imply that the stock market is active or efficient thus it is important to also consider the liquidity of the market. This is especially so among BRICS nations where South Africa has the highest stock market to GDP ratio and thus the most developed stock market although it is not the most liquid market of the five economies. Foreign investors are more likely to avoid illiquid markets because prices in inefficient markets may not be particularly informative. Price discovery in illiquid markets may be delayed as new information is not rapidly incorporated into prices. In 2018 average turnover ratio of stocks traded, which measures liquidity in the market, was 206.7% in China, 83.9% in Brazil, 58.1% in India, 34.1% in South Africa and 25.5% in Russia (World Bank, 2018). Table 2.3 below provides information on BRICS stock markets.

Table 2.3: BRICS Stock Markets

	Market capitalization				**Market liquidity**		**Turnover ratio**		**Listed domestic companies**		**S&P/Global Equity Indices**	
					Value of shares traded		**Value of shares traded**					
	$ millions		**% of GDP**		**% of GDP**		**% of market capitalization**		**number**		**% change**	
	2010	**2018**	**2010**	**2018**	**2010**	**2018**	**2010**	**2018**	**2010**	**2018**	**2010**	**2018**
Brazil	1,545,566	916,824	70	49.1	41.1	41.2	58.8	83.9	373	334	6.5	-4.5
Russian Federation	951,296	576,116	62.4	34.8	33.2	8.9	53.3	25.5	556	221	21.7	-9.4
India	1,631,830	2,083,483	97.4	76.4	64.5	46.2	66.2	58.1	5,034	5,065	18.7	-11.4
China	4,027,840	6,324,880	66.2	46.5	135.7	96.1	205	206.7	2,063	3,584	6.9	-20.5
South Africa	925,007	865,328	246.4	235	73.9	80.1	30	34.1	352	289	32.1	-25.9

Source: World Bank Development Indicators, 2019

Some of the literature, explored in detail in the next chapter, show that BRICS stock markets are influenced by various domestic and global financial, macroeconomic, and political risk factors

(Aloui, et al., 2011; Hammoudeh, et al., 2013; Mensi, et al., 2014). This study explores the impact of some of these factors on BRICS equity and exchange rate markets and seeks to understand the financial interdependence of these markets over the period of study.

2.3.2. EXCHANGE RATE REGIMES AND MONETARY POLICY

According to the classification of IMF (2009), Brazil, India, and South Africa implement a free-floating exchange rate system, while China and Russia implement a system of managed floating exchange rates (Aroul & Swanson, 2018). India adopted a floating exchange rate system in March 1993 and South Africa adopted a single floating exchange rate in 1995. Russia, Brazil and China adopted managed floating rate regimes in August 1998, January 1999 and July 2005 respectively. At the height of the GFC, in July 2008, China readopted a crawling peg to the US dollar. This was again relaxed in 2010 until August 2015 when the People's Bank of China (PBC) decided to float the Renminbi (RMB) exchange rate (Yu, 2018). However, this did not work and led to a devaluation of the RMB and the PBC introduced a new central parity rate-setting mechanism calculated as the average of the previous' day's closing price and the current day's theoretical value of the RMB (Yu, 2018).

The currencies of the BRICS countries are among the 20 most traded currencies in the world (World Bank, 2018). In 2016, China, Russia, India, Brazil and South Africa had average daily turnovers of over-the-counter (OTC) foreign exchange instruments of USD 202 billion, USD 58 billion, USD 58 billion, USD 51 billion, and USD 49 billion respectively; ranking 8th, 17th, 18th, 19th and 20th respectively on a net-net basis (BIS, 2016).

The adoption of floating exchange rates regimes (both free-floating and managed floating exchange rates) by BRICS countries allows exchange rates to more accurately reflect prevailing market prices. And with the increased integration of the BRICS countries into the global economy, shocks to one market (country) are easily transmitted to another market (country) through trade and financial linkages. These shocks lead to fluctuations in the exchange rates which may have negative or positive effects on stock returns. These linkages between exchange rates and stock prices and returns warrant us to examine the financial interconnectedness of BRICS equity and exchange rate markets as they affect asset allocation, portfolio management and risk management decisions.

2.4. CONCLUSION

Despite a reduction in growth levels after the global financial crisis, the growth expectations of BRICS as the world's leading emerging market economies still hold (Bonga-Bonga, 2018; O'Neill, 2013). In particular, China and India have been among the fastest-growing economies over the past 15 years. The establishment of the New Development Bank (NDB) and the creation of the Contingent Reserve Arrangement (CRA) in July 2015 signified a major milestone in BRICS cooperation. The NDB was initially capitalized with USD 50 billion to finance infrastructure and sustainable development projects. The CRA was capitalized with $100 billion to support member states during financial difficulties (Wang, 2017). Furthermore, the influence of the BRICS bloc is increasing. According to Zhu (2014) BRICS have evolved into a vital multilateral cooperation mechanism across four continents. Hence research into their financial markets, which this study attempts to undertake is essential.

CHAPTER 3

LITERATURE REVIEW

3.1. INTRODUCTION

This chapter provides a review of the theoretical and empirical literature related to the topic. The purpose of this chapter is to articulate the theories underpinning the study and provide an assessment of the theories and existing empirical studies regarding volatility transmission in financial markets, in particular, the equity markets and foreign exchange markets, and theories on contagion during crises periods. This is important as it informs the methods to be used and macroeconomic variables to include in the econometric models.

This chapter is organised as follows: Section 3.2 explains the theoretical relationship between equity and foreign exchange markets and discusses the causes of contagion effects; Section 3.3 provides a review of the empirical literature on volatility spillovers in stock markets, foreign exchange markets, between the stock and foreign exchange markets and determinants of contagion in both of these markets; Section 3.4 concludes the chapter.

3.2. THEORIES IN LITERATURE

Several theories in the literature explain the behaviour of asset returns. These theories, which include the efficient market hypothesis (EMH), are the basis of most popular asset pricing theories. Interest-rate parity (IRP) conditions have also been used to explain the relationship between financial market returns. Such theories are important in forecasting expected returns on investments. According to Adjasi, et al. (2011:146) "the theoretical link between stock prices and the exchange rate is also derived within an efficient market environment". For brevity, this study will adopt the underpinning theories and be limited to discussions on theories that explicitly explain the link between equity and exchange rate returns and contagion as that is the focus of this thesis.

3.2.1. THE RELATIONSHIP BETWEEN STOCK RETURNS AND EXCHANGE RATE RETURNS

There are two main theoretical frameworks proposed in the literature to explain interdependence between equity and exchange rate markets: the flow-oriented model and the stock-oriented model. According to the flow-oriented model (also referred to as the goods market approach), the current account is an important factor in exchange rate determination. The model suggests that exchange rates will affect stock prices through their effect on the international competitiveness of a firm and the trade balance and thus influencing countries' outputs and real incomes. Because stock prices reflect the present value of expected income, fluctuations in the exchange rate affect stock prices (Dornbusch & Fischer, 1980). The flow-oriented model thus suggests that there is a positive relationship between exchange rates and stock prices with the direction of causality flowing from the foreign exchange market to the equity market. For instance, a depreciation of the domestic currency will make a country's exports more competitive in the international market; an increase in demand for domestic products will lead to an increase in incomes and domestic firms' stock prices. On the other hand, an appreciation of the domestic currency leads to a decrease in foreign demand for domestic goods, which in turn reduces exporting firms' profits and its stock price. If the flow-oriented model holds for this study, we expect to see directional spillovers received from BRICS exchange rate markets dominating BRICS stock markets, i.e. BRICS exchange markets will be net transmitters of volatility to their equity markets in our cross-market studies.

The stock-oriented models, on the other hand, emphasise the capital account as an important component in exchange rate determination. There are two types of stock-oriented models: the portfolio balance and monetary approach models (Branson, 1983; Frankel, 1983). According to the portfolio balance model, investors can allocate their wealth in different kinds of financial assets. Assuming a home bias and that domestic and foreign financial assets are not perfect substitutes, investors will rebalance their portfolio according to expected returns of the assets. Under a floating exchange rate regime, a decrease (increase) in domestic asset prices will lead to an increase (decrease) in the demand for domestic assets which will attract capital inflows (outflows) which affects the demand for money. This leads to changes in interest rates and subsequently appreciation (depreciation) of the domestic currency (Frankel, 1983). Thus in the portfolio balance model, there is an inverse relationship between the exchange rate and stock prices with changes in the equity market leading the foreign exchange market. If the theory holds in our study, we expect directional spillovers from the equity markets to dominate directional spillovers from exchange rate markets. In this case, BRICS equity markets will be net transmitters of volatility to foreign exchange markets.

In the monetary approach, persistent inflation (above foreign inflation) leads to an increase in the nominal interest rate. Expectations of higher domestic inflation cause the purchasing power of the foreign currency to increase relative to the purchasing power of the domestic currency, thereby making the domestic currency depreciate. In a market dominated by exporters (importers), depreciation (appreciation) of the domestic currency increases (decreases) the competitiveness of its firms which leads to an increase (decrease) in stock prices (Branson, 1983; Frankel, 1983).

These theories are of particular interest in this study because a lot of foreign capital flows from advanced economies to emerging and developing economies (EMDEs) are directed at BRICS countries, especially, China. Furthermore, the BRICS countries pursue export-oriented growth strategies and also import a lot of raw materials for production. Thus the value of the domestic currency and how it is determined are important to BRICS economies.

3.2.2. THEORIES ON CONTAGION

There is a lot of ambiguity about the definition of contagion in the literature. In very broad terms, contagion refers to the transmission of shocks from one region or market to others during financial crises (Bonga-Bonga, 2018). Although there is no consensus on the definition, several studies have suggested empirical tests to measure contagion and distinguish it from interdependence (Forbes & Rigobon, 2002; Boyer, et al., 1997). In these studies, an increase in cross-country co-movements during crises periods is not necessarily contagion but may be due to increase in the variance of a common factor, such as trade linkages, changes in US interest rates or third market competition-related spillovers, resulting in higher volatilities in several markets (Corsetti, et al., 2005). Because this study focuses on volatility spillovers, which can be defined as the variation in one asset that is attributed to, or caused by, shocks to another asset (Diebold and Yilmaz, 2009), we adopt the definition of contagion put forth by Dornbusch, et al. (2000) which describes contagion as a significant increase in cross-market linkages after a shock to an individual and group of countries. Understanding the determinants of contagion between BRICS countries is important because of the interactions between the countries.

Dornbusch, et al. (2000) classify the causes of contagion into two broad categories: fundamentals-based contagion and contagion due to investors' behaviour, some rational and some irrational. Fundamentals-based contagion results from the normal interdependencies among market economies such as real and financial linkages between the markets. And while these co-movements would not normally result in contagion, during periods of crises their effects are adverse (Dornbusch, et al., 2000). In the case of contagion due to investors' behaviour, a financial crisis is not linked to observable changes in macroeconomic fundamentals but is solely driven by other financial agents. This could be due to worries of liquidity problems or information asymmetries and coordination problems. For example, a negative shock in one market represents news events which directly affects investors' wealth and cash flows associated with securities in other markets. Also, investors who have suffered losses in one market may withdraw their asset holdings from another market perceived to be risky and invest in safe havens.

3.3. EMPIRICAL LITERATURE

3.3.1. VOLATILITY SPILLOVERS IN EQUITY MARKETS AND CONTAGION EFFECTS

3.3.1.1. Developed Countries around the 1987 stock market crash

There is a vast amount of literature on volatility spillovers and contagion. These literature have evolved over time. Early studies showed weak evidence of volatility transmission prior to the stock market crash of 1987. However, following the stock market crash in the US and the Exchange Rate Mechanism (ERM) crisis of the UK in 1992 the literature showed an increase in co-movements of equity returns although some provided conflicting results. For example, Hamao, et al. (1990) use the GARCH-in-mean (GARCH-M) model to examine the Tokyo, London and New York stock markets around the 1987 stock market crash. They find significant evidence of price volatility spillovers from New York to Tokyo, London to Tokyo and New York to London (Hamao, et al., 1990).

In a similar study, King and Wadhwani (1990), examine whether there has been a change in correlation coefficients between the Tokyo, London, and New York stock returns before and after the 1987 stock market crash. They find that correlation coefficients between the US and UK stock markets increased from around 0.2 before the crash to around 0.4 after the crash while correlation coefficients between the UK and Japan increase from around 0.2 to around 0.6 and correlations coefficients between Japan and the US increased from 0.2 to 0.49. These significant increases in correlation coefficients during turmoil periods indicate the presence of contagion.

Bae and Karolyi (1994) also studied returns and volatility dynamics in Tokyo and New York after the 1987 stock market crash. Based on the work of Glosten, et al. (1993) and the partially non-parametric GARCH model of Engle and Ng (1993), they extended the (G)ARCH framework of Engle (1982) and Bollerslev (1986) to account for asymmetric effects of good news and bad news. Their empirical results show evidence of leverage effects in volatility spillovers (Bae & Karolyi, 1994). In a similar study, Lin, et al. (1994) find significant evidence of price spillovers across the markets. However, in contrast to Hamao, et al. (1990) and King and Wadhwani (1990), they found evidence of bidirectional spillovers between the New York and Tokyo stock markets and evidence that the domestic market efficiently adjusts to foreign information. They postulate that returns and volatility of the two equity markets may be related due to close trade and investment linkages and growing financial market integration.

Conversely, King, et al. (1994) investigate volatility and linkages between 16 national stock markets from 1970 to 1988 and find that international equity markets go through certain periods of sustained co-movement, such as the 1987 stock market crash and other periods of low correlation between the markets (during tranquil periods). They conclude that despite periods of co-movement across the markets, there is no evidence for capital market integration.

Karolyi (1995) employs a bivariate GARCH model to examine stock returns and volatility transmission between the New York and Toronto stocks markets for the 1981-1989 period. These markets have synchronous trading hours and are therefore not affected by meteor showers. The study shows evidence of time-varying volatility in the Standard and Poor's 500 indexes (S&P 500) and the Toronto Stock Exchange index (TSE 300) returns suggesting that shocks originating from the US on Canadian stock returns decreased over time, that is, returns and volatility spillovers were lower.

3.3.1.2. Developing and Developed Countries around EM crises in the 1990s

Interest in emerging stock markets increased after the 1994-1995 Mexican Peso crisis and the 1997 AFC. Bekaert and Harvey (1997) used GARCH-type models to investigate the volatility of returns in emerging equity markets as well as common factors driving the volatility. They found that in segmented markets, local factors drive volatility more than global factors. Furthermore, they found that volatility decreased significantly after capital market liberalizations. Ng (2000) investigates the dynamics of volatility spillovers from Japan (regional) and the U.S. (global) to stock markets of six Pacific–Basin countries (Hong Kong, Korea, Malaysia, Singapore, Taiwan, and Thailand). Contrary to Bekaert and Harvey (1997), the empirical findings indicate that both regional and global factors are important in the Pacific-Basin region although global factors have more influence than regional factors. This study assumes that both local factors and global factors are significant drivers of volatility spillovers in BRICS markets. The section of determinants of volatility spillovers will explore these issues as our variables include both macroeconomic fundamentals and global risk factors and contribute to this discussion.

Edwards and Susmel (2001) study the volatility dynamics of a group of emerging Latin American economies. While they find strong evidence of volatility co-movement across the stock markets (especially among Mercosur countries), they find no evidence for contagion (Edwards & Susmel, 2001). Forbes and Rigobon (2002) test for contagion in international equity markets during the 1987 U.S. stock market crash, the Mexican peso crisis and the AFC. They argue that heteroskedasticity biases simple correlations tests in such a way that during crises periods market volatility increases substantially resulting in violation of the assumption of constant variance. Therefore, they test for co-movements in stock returns by calculating correlation coefficients from a reduced-form VAR model and then make adjustments for any bias that arises in the least-squares estimation of a single equation. They show that there are high levels of stock market co-movements during both crises periods and more stable periods – they call this market interdependence. Thus they argue that there is no contagion during crises periods, only interdependence (Forbes & Rigobon, 2002).

In more recent studies, however, there is evidence to support increased financial market interdependence and contagion effects. For instance, Baele (2005) studies the effects of globalization and regional integration in increasing equity market interdependence. The study investigates volatility spillovers from the aggregate European (EU) and U.S. markets to 13 local European equity markets and finds that volatility spillovers in both the EU and the US increased significantly over the 1980s and 1990s. The study also finds evidence for contagion from the U.S. to several local European equity markets during periods of high volatility in global markets. Bekaert, et al. (2005) use a two-factor asset pricing model with time-varying betas in three regions: Asia, Europe and Latin America, to examine contagion during the Mexican and Asian currency crises. Their results indicate that while there is increasing equity market interdependence during the Mexican peso crisis, there is no evidence of contagion effects. However, they find evidence of contagion during the AFC, especially among Asian countries.

3.3.1.3. Developing and Developed Countries around the GFC

Diebold and Yilmaz (2009) propose a spillover index constructed from the variance decomposition of VAR models of seven developed and 12 emerging stock markets. They find that spillovers in the volatility of equities are highly responsive to crises events, while returns spillovers show a steadily increasing trend but are not responsive to crises events. This implies that returns spillovers show no evidence for contagion but volatility spillovers indicate the presence of contagion. This could explain the varied results in studies that found no evidence of contagion effects as most early studies looked at returns rather than volatilities. Because our study employs the same method, we only consider contagion in volatility spillovers and not returns spillovers.

Furthermore, Kenourgios and Padhi (2012) use Asymmetric Generalized Dynamic Conditional Correlation (AG-DCC) GARCH models for both equity and bond markets of emerging economies. They find evidence of contagion effects during the 1998 Russian default and the US subprime crisis of 2007. However, they find no contagion effects for the other crises under investigation (the Mexican Peso crisis of 1994–1995, the 1997 AFC, the 1997-1998 Brazilian stock market crash, and the Argentine default crisis of 1999–2001). Using the same methods to analyze stock market co-movements from the UK to BRICS and Mexico, Indonesia, South Korea, and Turkey (MIST), Yarovaya and Lau (2016) also find evidence for contagion effects during the GFC. Their results also indicate that China is the most attractive option for the UK investor. And in another similar study, Ahmad, et al. (2013) examine the contagion effects between developed stock markets of the US, UK, Japan and Greece, Ireland, Portugal, Spain and Italy (GIPSI) on the emerging stock markets of Brazil, Russia, India, Indonesia, China, South Korea and South Africa (BRIICKS) during the Eurozone debt crisis (EDC). They find evidence of contagion in the BRICS countries while only market interconnectedness was evident in Indonesia and South Korea.

Recent studies that have also compared co-movements in emerging markets to co-movements in developed markets. Unfortunately, the also provide conflicting results. For instance, using dynamic factor model regressions on a panel consisting of 25 developed and 20 emerging stock markets, Duncan and Kabundi (2014) find that international volatility linkages are significantly stronger during crises periods. However, they find that EM co-movement is significantly lower than developed market co-movement during the AFC and GFC. This is unexpected as most studies show that EMs are more volatile than developed markets. In another study Bekaert, et al. (2014) use a factor model to analyze the transmission of the 2007-2009 global financial crisis across 55 equity markets and 10 sectors and find evidence of contagion effects. Moreover, they posit that there was particularly significant contagion from domestic markets to individual domestic portfolios, with the countries with the worst macroeconomic fundamentals affected the most.

3.3.1.4. Spillovers between Developed Countries and BRIC(S)

Studies that examine the spillover effect between the developed economies and BRIC(S) stock markets find evidence of significant shocks and volatility transmission between developed markets and BRIC(S) markets. These studies also indicate that geographical proximity amplifies co-movements of stock markets in the BRIC(S) bloc. For example, Bhar and Nikolova (2007) use the GARCH-M to investigate the dynamics of stock market returns and volatility spillovers emanating from regional and world indices to equity markets in the BRIC bloc. They find that regional trends have more influence on the BRIC stock markets than global trends. This implies that BRIC countries are more integrated into their respective regions than to world markets. They also find that world index returns have a significant influence on volatility spillovers across Brazil, Russia and India. However, there is a negative relationship between both regional and global index returns and the Chinese stock market, indicating that there are more opportunities for portfolio diversification in China for international investors. These findings are substantiated by Lehkonen and Heimonen (2014) who used wavelet analysis and DCC-GARCH methods to examine stock market correlations among BRICS and developed markets. Their study indicates that geographical proximity significantly affects co-movement of stock markets and purports that although diversification benefits across developed markets are low, the BRIC countries, especially China, still offer opportunities for portfolio diversification. Likewise, Aloui et al. (2011) employ multivariate GARCH models to examine the extent of the GFC and contagion effects it induced. They use copula functions and multivariate GARCH models to investigate the extreme financial interdependencies of BRIC stock markets with the US. Their empirical findings show strong evidence of time-varying dependence between each of the BRIC markets and the U.S. market, although the effect is less for China and India (Aloui, et al., 2011).

Chittedi (2014) uses the DCC and AD-DCC GARCH models to examine the effects of contagion from developed markets (U.S. and UK and Japan) to BRIC stock markets from 1996-2011. The empirical findings show evidence of contagion during the GFC and significantly higher correlation coefficients in the post-crisis period. Bonga-Bonga (2018) employs multivariate VAR-DCC-GARCH models to study the degree of financial shocks between South Africa and other BRICS stock markets during the period 1996-2012. The results provide evidence of contagion. Furthermore, the study finds that there is bidirectional transmission between Brazil and South African stock markets whereas crises originating from China, India and Russia affect South Africa more than these countries are affected by South African crises.

Syriopoulos, et al. (2015) employs a disaggregated VAR-GARCH model to assess the dynamic risk-return properties of the BRICS stock markets and model time-varying correlations and volatility spillover effects with the US stock market. Their findings confirm earlier evidence that the BRICS stock markets were severely affected by the GFC with China and India being the least affected markets (Bhar & Nikolova, 2007; Aloui, et al., 2011). These findings are also supported by Chkili & Nguyen (2014) and Fahami (2011). In contrast to this, An and Brown (2010) show that Brazil, Russia and India provide better diversification opportunities than China. Using unit root and cointegration tests to investigate the relationship between the US and BRIC stock markets, An and Brown (2010) find that only China is cointegrated with the US. They argue that this could be due to the strong trade linkages between the US and China. On the other hand, Singh and Singh (2015) show that while all BRIC stock markets have dynamic linkages in the short-run, there are no long-run dependencies between them. Furthermore, in the long run, China shows the lowest co-movement with other BRIC equity markets. Thus, they conclude that in the long run, all BRIC stock markets are favourable in the context of international portfolio diversification.

3.3.1.5. BRIC(S) Stock Markets and the Decoupling Hypothesis

Most of the literature on the transmission of volatility between emerging stock markets and the US during the GFC show support for the decoupling hypothesis in the pre-crisis period however after the fall of Lehman Brothers in October 2008 there is evidence of recoupling. For example, Dooley and Hutchison (2009) use AG-DCC GARCH and VAR methods to examine the transmission of the US subprime crisis in emerging countries. Their results show that emerging markets appeared to be insulated and decoupled from development in the US financial markets from 2007 to mid-2008, after which emerging markets responded very strongly to the crisis in the US markets.

Dimitriou, et al. (2013) as well as Mensi, et al. (2016) both use bivariate Dynamic Conditional Correlation Fractionally Integrated Power ARCH (DCC-FIAPARCH) models to examine the spillover effect between the U.S. and BRICS stock markets. They find no evidence of contagion in the early stages of the crisis indicating signs of decoupling. However, they find evidence of increased volatility centred on the Lehman Brothers collapse. Moreover, they find that for all BRICS (except for Russia in Mensi, et al. (2016)'s study) there is strong evidence recoupling after September 2008.

On the contrary, Bekiros (2014) examines contagion, decoupling and spillover effects of the US financial crisis on BRIC equity markets using multivariate GARCH models and VAR methods. The empirical findings provide evidence of contagion and suggest that BRIC markets have become more integrated to the US markets since the GFC. The results of the study do not show any evidence of decoupling. This is consistent with Jin and An (2016) who use a bivariate GARCH-

BEKK model and volatility impulse response function (VIRF) to examine the volatility spillovers and persistence of the volatility shocks between BRICS and US stock markets. Their results show significant contagion from the US to BRICS during the 2007-2009 GFC. Also, they find that stock market integration among the US and BRICS markets has increased significantly since the GFC (Jin & An, 2016).

3.3.1.6. General evaluation of literature on volatility spillovers in equity markets

This section has considered spillovers in equity markets and contagion effects from studies on advanced economies to emerging countries, particularly BRICS equity markets. Various methodological approaches have been used - from cross-market correlation coefficients, univariate and multivariate GARCH type models, cointegration, factor models and VAR-type models which include the DY spillover index which is of particular relevance to our research. While the studies provide conflicting results we can infer from the majority of them that with the increase in financial market integration, there is increasing evidence of co-movements across stock markets and evidence of contagion effects during turmoil periods. Moreover, since the GFC, stock markets seem to be more integrated especially regionally. And finally, most of the empirical studies on BRICS and US equity markets find evidence for contagion effects in most of the BRICS countries except China. The Chinese stock market appears to be independent of global shocks implying that China is a good investment destination for investors looking to diversify from advanced economies. We explore all the issues raised here in this study although our focus is limited to BRICS markets.

3.3.2. VOLATILITY SPILLOVERS IN FOREIGN EXCHANGE MARKETS

3.3.2.1. Developed Countries

The literature regarding volatility spillovers in foreign exchange markets is not as extensive. Engle, et al. (1990) investigate two types of volatility spillovers in the Japanese yen/U.S. dollar exchange rate. They find significant evidence for "meteor shower" type volatility spillover effects where volatility in the exchange rate during Tokyo trading hours spills over to other markets. Baillie and Bollerslev (1991) also find that over six months in 1986, hourly patterns in volatilities of four major exchange rates displayed abnormally similar patterns and exhibited some serial correlation. McMillan (2001) studied the common trend and volatility in the Deutsche mark and French franc per U.S. dollar exchange rates using a multivariate random walk stochastic volatility model and found a very high correlation between the volatility innovations suggesting that they are co-integrated.

Likewise, Andersen and Bollerslev (1998) studied intra-daily volatility models in the Deutsche mark and Japanese yen per U.S. dollar exchange rates and found evidence of significant spillovers in both the conditional first and second moments. And in a similar study, Melvin and Melvin (2003) examine volatility spillovers in the same currencies across regional markets and find significant evidence for spillovers both within the region and interregional. But contrary to Engle, et al. (1990) they find that volatility spillovers within the region are more significant indicating that *heat waves* are more important than *meteor showers*. Black and McMillan (2004) examine long-run trends and volatility dynamics in daily exchange rates of six developed market currencies – the Canadian dollar, Deutsche mark, French franc, Italian lira, British pound sterling, and the Japanese yen – relative to the US dollar for the period January 1974 to October 1998. They find significant volatility spillovers among the European economies signifying increased convergence among them.

In more recent studies, Wang and Yang (2009) use a heterogeneous autoregressive realized volatility model to examine the asymmetric volatilities of four currencies – the Australian dollar, Euro, British pound sterling and Japanese yen – relative to the U.S. dollar from 1996-2004. They find that a depreciation in the Australian dollar and British Pound against the US dollar leads to significantly greater volatility than an appreciation, whereas the opposite is true for Japanese yen. McMillan and Speight (2010) also use the realized volatility model and the DY spillover index to investigate return and volatility spillovers in three exchange rates – the US dollar, the British pound sterling and Japanese yen – relative to the Euro; they use high-frequency data (data is collected at five-minute intervals) for the period 2002 to 2006. Their results provide evidence for return and volatility spillovers in the exchange rates, in particular, they find that the euro-dollar exchange dominates spillovers to the other euro exchange rates while it is mostly independent (the euro-dollar is a net giver of volatility spillovers). Bubák, et al. (2010) use similar methods to investigate volatility transmissions among Central European currencies and euro-dollar exchange rates. They found strong evidence of spillovers and concluded that volatility spillovers tend to increase in periods characterized by market uncertainty such as the GFC. This is evidence of contagion.

Antonakakis (2012) uses dynamic conditional correlations (DCC) and the DY spillover index to investigate returns and volatility spillover effects among four currencies – the Deutsche mark (euro after 1999), British pound sterling, Japanese yen and Swiss franc against the US dollar before and after the introduction of the euro. The study finds evidence of bidirectional cross-market volatility spillovers among the markets - with the highest volatility spillovers occurring among the European markets, similar to Black and McMillan (2004). The findings also validate McMillan and Speight (2010) that the euro is the dominant currency (net giver of volatility spillovers) and the British pound sterling is a net receiver of volatility spillovers. Additionally, the results indicate that co-movement and volatility spillovers were significantly higher in the pre-euro period compared to the post-euro period and that return co-movements and volatility spillovers react strongly to extreme economic episodes (Antonakakis, 2012).

3.3.2.2. Emerging and Developing Countries

As with equities, the Mexican peso crisis and the AFC were very instrumental in changing the focus of the research in volatility spillovers. This was even more significant in exchange rate markets as the former was a currency crisis and started as currency crisis but turned into a full scale financial crisis as the shocks spread to other markets.

For example, Dungey and Martin (2004) propose a latent factor model of exchange rates to measure volatility transmission and contagion effects among four Asian currencies – the Thai baht, Malaysian ringgit, Indonesian rupiah and Korean won – relative to the US dollar during the AFC. Their results show significant evidence for contagion during the crisis with the largest proportions observed in the Korean won. Their results also confirm that Thailand acted as a trigger for the financial crisis with the direction of contagion running from Thailand to both Malaysia and South Korea and finally to Indonesia. Furthermore, they used a multifactor model to compare their results with those of Forbes and Rigobon's (2002) contagion test. Contrary to Forbes and Rigobon (2002), they found evidence of contagion not just interdependence from Thailand to the other countries, particularly Malaysia. They suggest that the results from Forbes and Rigobon (2002) may be biased due to misspecification errors from performing the analysis in a bivariate instead of the correct multivariate setting; or the bias may be from their selection of "crisis periods" and "non-crisis periods" (Dungey & Martin, 2004). These results are supported by Ito and Hashimoto (2005) who examine the co-movement of the exchange rates and the stock prices in terms of contagion between eight Asian countries during the crisis. They found evidence of statistically significant contagion among Asian countries through both the exchange rates and stock prices. In particular, the depreciation of the Indonesian rupiah had a significant effect on other currencies.

More recent studies conducted after the GFC show a significant increase in volatility spillovers from advanced countries to EM currencies especially during turmoil periods. For instance, Coudert, et al. (2011) use smooth transition regressions (STR) to examine the impact of volatility spillovers from advanced economies on 21 emerging market currencies. Their empirical findings show that exchange rate volatility increases more than proportionally with the global financial stress for most emerging countries. They also find evidence of regional contagion effects during tranquil periods whereas contagion across all markets increases in periods of turmoil. Kavli and Kotze (2014) also use the DY spillover index and the Liu-West particle filter to investigate the spillover effects of exchange rate returns and volatility for developed and emerging market currencies from 1997-2011. They find evidence that spillovers in exchange rate returns have increased steadily over time reacting moderately to economic events. Further, their empirical findings show that total volatility spillovers react more strongly to economic events, especially since the GFC.

3.3.2.3. Evidence from BRIC(S)

Looking at the BRIC(S) bloc, Aroul and Swanson (2018) examine foreign exchange dynamics between BRIC countries and the USA for the 2000-2013 period using cointegration tests and impulse response functions. They find that foreign exchange markets of China and India are heavily influenced by movements in the US dollar and that there are greater diversification benefits from Brazil and Russia as they are not cointegrated with the other markets. The results for the Chinese exchange rate markets are unexpected as the Chinese markets are known to be relatively isolated from other markets. However, these results show the importance of trade linkages in volatility transmission as China and India primarily export manufactured goods to the US market.

Caporale et al. (2017) employ the VAR-GARCH (1,1) model to examine the effects of newspaper headlines regarding both the US dollar and the Euro on the currencies of the BRICS from 2000 to 2013. While their results are different for each country, they still provide evidence of significant spillovers in some cases. These spillovers increased in magnitude during the GFC.

3.3.2.4. General evaluation of empirical literature on volatility spillovers in equity markets

In summary, the empirical studies on currency markets indicate that co-movements and volatility spillovers have been increasing over time signifying convergence among global currency markets. Using various empirical approaches, the studies provide significant evidence of volatility spillovers increasing more than proportionally during turmoil (crises) periods thus indicating the presence of contagion effects among currency markets. Interestingly, the results obtained in the studies focused BRIC(S) currency markets are quite different from the equity markets with currency markets in India and China offering fewer diversification opportunities than Brazil, Russia and South African markets. And as briefly discussed above, this may be due to the importance of trade linkages in explaining volatility. We investigate this later when we study the determinants of contagion.

3.3.3. VOLATILITY TRANSMISSION ACROSS EQUITY AND FOREIGN EXCHANGE MARKETS

3.3.3.1. Evidence from developed and emerging markets

Earlier research into the relationship between exchange rates and stock prices also primarily focused on industrialized countries (Aggarwal, 1981; Solnik, 1987; Ma & Kao, 1990; Bahmani-Oskooee & Sohrabian, 1992; Bondnar & Gentry, 1993; Chow, et al., 1997; Ajayi, et al., 1998) with mixed results.

However, as already stated, following the Mexican Peso crisis and the AFC interest in emerging stock and currency markets, especially in Asia-Pacific countries, increased. For instance, Abdalla and Murinde (1997) look at the relationship between exchange rates and stock prices in India, South Korea, Pakistan and the Philippines and find that exchange rates lead stock prices. This supports the flow-oriented model of exchange rate determination. On the other hand, Granger, et al. (2000) employed unit root and cointegration analysis to determine Granger causality between stock prices and exchange rates among nine Asian countries that were most affected by the AFC – Hong Kong, Indonesia, Japan, South Korea, Malaysia, the Philippines, Singapore, Thailand and Taiwan from 1986 to 1998. Their empirical findings showed mixed results although, for the majority of the countries considered, stock prices led exchange rates, in support of the stock-oriented models. Their results also show evidence of bidirectional causality for Malaysia, Singapore, Thailand and Taiwan (Granger, et al., 2000).

Applying the VAR methodology on daily data from 1995-1998, Baig and Godfajn (1999) test for contagion between the financial markets of Thailand, Malaysia, Indonesia, Korea and the Philippines during the AFC. Their results show a significant increase in cross-country correlations among currencies and sovereign debt but the results are mixed concerning equity markets. However, after controlling for own country good and bad news and other fundamentals they find evidence of cross-border contagion in both markets (Baig & Goldfajn, 1998). In another study, Mishra (2004) examined the dynamic linkages between the foreign exchange and stock markets for India for the period April 1992 to March 2002. In contrast to Baig and Godfajn (1999), their empirical results suggest that there is no Granger causality between stock return and exchange rate return. These results are consistent with Bahmani-Oskooee and Sohrabian (1992) who used Granger causality tests and cointegration techniques and found that in the short run, there is evidence of bidirectional causality between stock prices measured by S&P 500 index and the effective exchange rate of the dollar for the period July 1973 to December 1988. But no long term relationship exists between the two markets.

Dungey and Martin (2007) employ a multifactor model with GARCH conditional variances (to account for the time-varying nature of volatility of financial returns) to investigate linkages between stock and foreign exchange markets of Australia, Indonesia, Malaysia, South Korea, Thailand, and the US during the AFC. They find that spillovers and contagion effects are statistically significant across markets, although spillover effects were greater than contagion effects. Their results also show that volatility is greater in developing markets than developed markets with Malaysia experiencing the most increase in volatility in equity returns and Thailand the least among the developing markets. Volatility in Australia, the US and South Korea is found to be due to interdependence.

Using cointegration methodology and multivariate Granger causality tests to a group of five Pacific Basin countries (Hong Kong, Malaysia, Singapore, Thailand and the Philippines), Phylaktis and Ravazzolo (2005) examine the dynamic relationship between stock prices and exchange rates. They find evidence of bidirectional spillovers between the foreign exchange rate and stock market returns. In a similar study looking at six Asian countries (Indonesia, Malaysia, the Philippines, South Korea, Thailand and Taiwan), Doong, et al. (2005) also find evidence of bidirectional causality between exchange rates and equity prices in Indonesia, Korea, Malaysia and Thailand. However, their results show that financial variables are not cointegrated.

Conversely, some empirical studies find evidence of a unidirectional relationships between the equity and the foreign exchange markets. In studies from advanced markets, Kanas (2000) employs an extension of a bivariate EGARCH model to study the volatility spillovers between the exchange rate and the stock price in six industrial countries: Canada, Japan, United Kingdom, German, France, and United States. He finds that except for Germany, there is strong evidence of volatility spillover from the stock market to the exchange market in support of stock-oriented models; however, spillovers from exchange rate returns to stock returns were not significant across all the countries. He also finds that volatility spillovers are symmetrical around the release of bad news and good news (Kanas, 2000).

In a similar research, Yang and Doong (2004) investigate the nature of the mean and volatility transmission mechanisms in the two markets but expand the sample size to G-7 countries. They also find a unidirectional volatility spillover from the stock market to the foreign exchange market, however, they find that volatility spillover effects are asymmetric.

In the context of developing markets, Bonga-Bonga and Hoveni (2013) use multi-step GARCH models to investigate volatility spillovers between equity and foreign exchange markets in South Africa and show that there is a unidirectional relationship in terms of volatility spillovers from the equity market to the foreign exchange market. These results are supported by several studies from both developing and emerging markets that show that the foreign exchange market is largely a receiver of volatility from the equity market and other asset classes (Ajayi, et al., 1998; Aloui, 2007; Choi, et al., 2009; Diebold & Yilmaz, 2012; Duncan & Kabundi, 2011).

3.3.3.2. Evidence from BRICS

In the aftermath of the GFC, there has been increasing interest in co-movements and spillovers of volatility in the BRIC(S) bloc. For example, Chkili and Nguyen (2014) use Markov-switching (MS)-VAR models, to show that there is a unilateral impact from stock markets to exchange rates (in support of the stock-oriented models) for all BRICS except South Africa especially during periods of high volatility. They also find that the Chinese Yuan is mostly insensitive to movements of the U.S. dollar value.

Sui and Sun (2016) use VAR and vector error correction models (VECM) to investigate spillover effects between exchange rates and stock returns from BRICS during the GFC and spillover effects between U.S. and BRICS stock markets. Contrary to Chkili and Nguyen (2014), they find unidirectional spillover effects from the exchange rates to stock returns in the short-run; these effects are stronger during the 2007-2009 financial crisis providing possible evidence of contagion. Their findings support the flow-oriented model and imply that trade flows between the US economy and BRICS could affect stock markets. Also, they find that shocks to the U.S. S&P 500 significantly influence stock markets in Brazil, China and South Africa (Sui & Sun, 2016).

Using other econometric techniques gives contrasting results. For instance, Dahir, et al. (2018) use wavelet analysis and find that exchange rates lead stock returns in Brazil and Russia while stock returns lead exchange rates in India; South Africa seems to have a more bidirectional causality; however they find no correlation in Chinese exchange rates and stock returns.

3.3.3.3. General evaluation of empirical literature on volatility spillovers between equity markets and foreign exchange markets

In summary, empirical studies into the nature of the relationship between foreign exchange rates and stock market returns have also produced varying results. The differences are sometimes due to the frequency of the data used (intra-day, daily, weekly, monthly or quarterly), the length of the period chosen and the methods and techniques employed. Nonetheless, the majority of the studies under consideration support the stock-oriented models (in particular the portfolio approach) of exchange rate determination. A few studies find evidence for the flow-oriented model and others find bidirectional spillover effects. Another noteworthy issue is that in the short-run, most of the studies find evidence of increased spillover effects and contagion during crises periods but in the long run, stock returns and exchange rate returns are not cointegrated.

3.3.4. DETERMINANTS OF FINANCIAL MARKET SPILLOVERS AND/OR CONTAGION

3.3.4.1. Empirical evidence in Developed Countries, Asia Pacific and MENA

Due to the lack of consensus in the literature on what constitutes financial contagion, our review of the literature is not limited to any one definition. Instead, we also consider studies that look at the determinants of financial market spillovers. Most of the research is focused on the determinants of stock market contagion.

Shinagawa (2014) uses the Arellano-Bond estimator – General Method of Moments (GMM) to investigate determinants of financial market spillovers across Eurozone countries, other advanced economies (non-euro), and emerging market economies. The author finds that the amount of bilateral portfolio exposure in another country, as well as the degree of home bias, are the main factors that determine financial market spillover. The results also show that advanced countries tend to show greater financial connectedness compared to emerging countries as they attract a larger share of capital inflows due to their deeper and more developed equity markets.

Similarly, Forbes (2012) uses extreme value analysis to identify contagion in 48 countries across the Eurozone, other advanced economies (outside the Eurozone) and emerging markets from 1980 to 2012. The empirical findings of the study indicate that contagion is spread through trade (bilateral trade and competition in third-party markets), banks and other financial institutions, portfolio investments and fundamentals reassessment (wake-up calls). Additionally, the study finds that more financial integration does not necessarily imply more contagion. Instead, countries with greater international exposure through portfolio assets can reduce their vulnerability to contagion as they have better risk diversification opportunities and can easily sell off their foreign holdings after negative shocks. However, countries with greater reliance on debt tend to be more vulnerable to contagion. These findings are supported by other studies such as Tong and Wei (2010); Hau and Lai (2011) and Bekaert and Harvey (2014).

Balli et al. (2015) investigate the return spillovers and volatility spillovers from developed markets of Europe, the US and Japan, into the stock markets of selected emerging countries in Asia and the Middle East and North Africa (MENA) region over the period 2000-2013. Their empirical findings show mixed volatility spillovers effects from advanced economies to emerging stock markets. They also find that the size of the shocks varies across countries. Moreover, they find that factors such as bilateral trade volume, foreign portfolio investment, domestic market capitalization, past colonial ties and distance are significant in explaining the spillover effects from advanced economies to emerging stock markets.

Luchtenberg and Vu (2015) apply logistic regression analysis to identify the existence of contagion and find its determinants in stock markets across North America, Europe and the Asia Pacific regions. They find evidence of a significant increase in cross-market linkages across many financial markets even after controlling for crisis-related volatility. They also find that after the 2008 financial crisis, the US and other mature financial markets were not only transmitters of contagion but that there was a bidirectional transmission between advanced and emerging stock markets. Furthermore, they find that macroeconomic fundamentals such as changes in the relative level of exports, bilateral trade dependence, relative inflation, industrial production, and relative interest rates, and changes in investors risk aversion are significantly related to the level of contagion. They also note that these results are consistent with the Kenourgios (2014) finding of increased investor risk aversion at the beginning of the GFC.

Leung, et al. (2017) analyze the volatility spillover effect between equity markets and foreign exchange markets in New York, London and Tokyo and find an increase in spillover between equity and exchange rate markets during crises periods. Furthermore, they find that pure contagion and fundamental contagion explain the increase in spillovers between London and Tokyo stock markets to the New York stock market during the GFC and from the foreign exchange markets to the New York stock market during the EDC.

3.3.4.2. Empirical evidence in BRICS markets

Concerning BRICS markets, Mensi, et al. (2014) use a quantile regression approach to study dependence between BRICS stock markets and influential global factors which include the global stock market (represented by the US S&P 500 index), oil prices, gold prices, VIX, and the US economic policy uncertainty index, over the period 1997 to 2013. They find evidence of a constant asymmetric dependence structure between the BRICS stock markets and global stock markets, however, the Chinese stock markets do not show significant co-movement with the S&P 500 stock index in times of stress and turmoil. With regard to the commodity markets, they find that oil prices display symmetric independence with BRICS countries (except South Africa) although there has been a significant increase in co-movements since the GFC; but gold prices show constant co-movement with BRICS stock markets (except for Brazil and Russia whose stock markets showed extreme tail end movement). Furthermore, they find that stock market uncertainty, as measured by the VIX, is an important factor for explaining financial dependence of all BRICS countries during a bear market but it is insignificant in a bull market (except for Brazil and India). Lastly, they found that US economic policy uncertainty is not a significant factor (Mensi, et al., 2014).

Rao and Padhi (2018) use a panel probit model with random effects to examine common determinants of currency crises in BRICS for the period 1996-2015. Their study indicates that macroeconomic variables such as base money to broad money, broad money growth, current account balance, exports, imports, inflation, real interest rate and the real effective exchange rate

(REER) work as leading indicators of crises events and major contributing factors in a country's vulnerability to crises.

3.3.4.3. General evaluation of empirical literature on volatility spillovers between equity markets and foreign exchange markets

Most of the literature reviewed above focuses on the determinants of contagion among advanced economies and contagion from advanced economies to emerging markets. In the past, this was justified as most capital flows to emerging markets originated from advanced countries and so it would stand to reason that international foreign investors could easily reduce their vulnerability to contagion emanating from EMDEs by selling off their foreign holdings after negative shocks whereas EMDEs, with greater reliance on capital inflows and debt are more vulnerable to contagion. However, with developments in stock markets of some emerging countries and their increased participation in global trade, more recent studies show that advanced economies are no longer just givers of contagion but also receive contagion effects from emerging markets. Moreover, the studies show that macroeconomic factors (fundamentals), global risk factors and investor sentiments and perception of risk drive contagion effects.

3.4. CONCLUSION

From the literature reviewed, we have seen evidence of increasing spillovers as financial markets have become more integrated. During turmoil periods, the literature shows very strong evidence of contagion effects, especially since the global financial crises. There are conflicting results on the direction of volatility transmission between equity and exchange rate markets and as we have seen some of it has to do with the choice of research methodology and the frequency of the data used. We have observed that with the vast amount of literature reviewed, very few studies have look at volatility spillover effects among emerging markets only. Of those that have looked at BRICS markets, because of the late addition of South Africa to the bloc, a lot of the research reviewed has primarily concentrated on the original BRIC markets. And even then, the main area of study has been on BRICS equity markets. There is very limited research on cross-market spillovers within BRICS equity and foreign exchange markets. There are even fewer studies on determinants of contagion in BRICS equity and exchange rate markets. This study aims to add to this research gap.

This study will be similar to Leung, et al. (2017) with the following key differences: we use daily closing data of stock indices and exchange rates instead of hourly data; and instead of the GARCH (1, 1) model, this study employs the EGARCH (*p, q*) model and DY spillover index. Also, to examine determinants of contagion we apply panel dynamic OLS regressions instead of individual OLS regressions. Lastly, the study will limit itself to fundamentals-based contagion with the focus on the emerging countries that form the BRICS bloc instead of advanced countries.

CHAPTER 4

METHODOLOGY AND DATA ANALYSIS

4.1. INTRODUCTION

This chapter discusses the underlying philosophical assumptions as well as the methodological approach used in this study. Section 4.2 discusses the research paradigm and Section 4.3 looks at the research design which also specifies the methodology and the theoretical framework, defines the data and provides estimation techniques and diagnostics tests used in this study. Section 4.4 concludes the chapter.

4.2. RESEARCH PARADIGM

The term “research paradigm” was first used by Thomas Kuhn in 1962 to refer to a conceptual framework for conducting research that has been adopted by a community of researchers to provide them with relevant models to investigate problems and find solutions. Kuhn (1996) defines research paradigm as “universally recognized scientific achievements, that for a time, provide model problems and solutions for a community of researchers”. A research paradigm thus refers to a “collection of logical, connected concepts and proposition that provide theoretical perspectives frequently guiding the research approach to a topic” (Ulin, et al., 2002).

There are three main approaches to research in the social sciences: interpretivism, positivism or critical postmodernism (Gephart, 1999). On the other hand, Guba & Lincoln (1994) classify research paradigms into four main approaches: positivism, postpositivism, critical theory (and its variants) and constructivism.

Positivism examines the cause and effect relationship between objects and applies experimental or manipulative methodology which focuses on verification of a hypothesis. The positivist approach applies technical knowledge about measurement, design and quantitative methods with less but substantial emphasis on theories (Guba & Lincoln, 1994). This study follows the positivist paradigm.

To answer the research questions posed in Chapter 1, the study tests for the following hypotheses:

a. H_0: there is a significant increase in volatility spillovers in equity returns and exchange rates in BRICS countries during crises periods

   H_1: there is no significant increase in volatility spillovers in equity returns and exchange rates in BRICS countries during crises periods

b. H_0: fundamentals-based contagion determines volatility spillovers in equities and exchange rate

   H_1: fundamentals-based contagion does not determine volatility spillovers in equities and exchange rate

4.3. RESEARCH DESIGN

A research design is an overall plan that describes all the components of the research to be undertaken: the sample and data used, sources of data and the methods used for analysing the data (Oskamp, 1965). It shows how the data will be collected to answer the research questions and objectives.

Three approaches can be used in undertaking research: qualitative, quantitative and mixed approach (Marshall, 1996). Marshall (1996) explains the differences between them as follows: qualitative research aim to understand complex psychosocial issues and are most useful for answering humanistic 'why?' and 'how?' questions whereas quantitative research aim to draw a representative population sample so that inferences on the population can be made from the sample results. Conversely, quantitative studies test pre-determined hypotheses and produce generalizable results and are most useful for answering 'what?' questions. A mixed approach uses a combination of both qualitative and quantitative approaches.

The research design informs the methodology that will be employed to compile data and analyse it (Zikmund, 2003). This study employs a quantitative research design. Financial econometrics techniques and statistical models used are adequate to answer the research questions posed. Nonetheless, Mouton (2001) posits that statistical models are not free from limitations. The quality of the data and the complexity of the phenomena may not always allow for a complete specification of the model. In terms of the quality of the data used in this study, the research uses secondary data obtained from Thomson Reuters Datastream, the World Bank and the Federal Reserve Bank of St. Louis – these sources are reliable and widely used. The Eviews 10 statistical package is employed to analyse the data.

4.3.1. MODEL SPECIFICATION AND THEORETICAL FRAMEWORK

This study adopts econometric data analysis methods and uses the Diebold-Yilmaz (2009, 2012) (DY) spillover index to calculate volatility spillovers between equity and exchange rate markets in BRICS. We also use cointegrating regressions to examine the determinants of contagion. This section provides a detailed outline of the models employed in this study.

4.3.1.1. Volatilities of Return Series

To construct the volatility spillover indexes we first need an estimate of volatility in each of the BRICS stock indexes and currencies. Diebold and Yilmaz (2009, 2012) used Garman-Klass (GK) volatility estimators for equities and other assets. These estimates are based on the difference between weekly high, low, opening and closing prices obtained from the underlying daily high, low, opening and closing data.

GK estimators require high-frequency data which we do not have access to. Duncan and Kabundi (2011) and Kavli and Kotze (2014) encounter the same challenge and use squared returns/yields to measure volatility instead. However, this volatility measure fails to consider the asymmetry of returns. Our study seeks to address this limitation by employing the GARCH framework. We use the EGARCH model to generate daily conditional volatilities. The EGARCH model captures asymmetric effects in financial data.

GARCH models

The Generalized ARCH (GARCH) (p,q) model was proposed by Bollerslev (1986) as an extension of Engel (1982)'s original work. Bollerslev (1986) developed a technique that allows the conditional variance to be an autoregressive moving average (ARMA) process. A key feature of the GARCH models is that the conditional variance of the disturbances of the y_t sequence acts like an ARMA process (Enders, 2015). The model is specified as follows:

Given that asset return follow an ARMA (p,q) model, returns can be modelled as

$$r_t = \mu_t + \varepsilon_t \quad (1)$$

Where μ_t denotes average asset returns, and

- ε_t denotes the residual returns (error terms) which are used to construct the variance equation for the conditional variance and is defined as

$$\varepsilon_t = v_t\sqrt{h_t}$$

Where v_t is a white-noise process with zero mean and $\sigma_v^2 = 1$, and $h_t = \sigma_t^2$,

The conditional volatility is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 \quad (2)$$

Where α_0 and α_1 are constants such that $\alpha_0 > 0$ and $0 \leq \alpha_1 \leq 1$.

Bollerslev (1986) proposed the AR(q) process to take the following form:

$$h_t = \alpha_0 + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i h_{t-i} \quad (3)$$

Where $\alpha_0 > 0$, $\alpha_i \geq 0$ and $\beta_i \geq 0$, $\alpha_i + \beta_i < 1$,

- α_i denotes the effect of new information (size effect),
- β_i represents the persistence of conditional volatility
- ε_{t-i}^2 represents the lagged or previous interval squared residual returns from the mean
  equation representing past information about volatility, i.e. the ARCH term; and
- h_{t-i} represents the lagged historic interval variance (volatility), i.e. the GARCH term

EGARCH model

Like most GARCH-type models, the bivariate EGARCH model developed by Nelson (1991) captures the stylized facts of financial time series such as volatility clustering, volatility persistence, leptokurtic tails and leverage effects. Other asymmetric GARCH models such as the Glosten, Jagannathan and Runkle (GJR) model impose parameter restrictions to ensure the non-negativity of conditional variances. However, by specifying the logarithm of the variance $ln(\sigma_t^2)$, the EGARCH model allows the coefficient of the asymmetric term to be negative thereby reflecting the true direction of the shocks. This is important for this study as we examine determinants of contagion using directional volatility spillovers.

Nelson (1991) proposed the following model for the conditional variance:

$$ln(\sigma_t^2) = \omega + \beta ln\sigma_{t-1}^2 + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \quad (4)$$

Where ω is the time invariable mean reversion value

- β measures the persistence of conditional volatility
- α is the effect of new information (size effect),
- γ measures the asymmetric effects of the shocks to volatility (sign effect)

4.3.1.2. Volatility Spillovers

After calculating volatilities, we now turn to investigate our first two research questions. We apply the DY spillover index which is based on the recursive VAR model of Sims (1980). The VAR model is often used to capture linear relationships among multiple macroeconomic variables. The main advantages of using VAR models is they are easy to estimate and have good forecasting capabilities. Furthermore, they do not require the researcher to specify which variables are endogenous or exogenous unlike structural models with simultaneous equations (Sims, 1980). All variables in the model are endogenous.

VAR models

The VAR model is specified as follows:

First, consider a covariance stationary VAR model matrix of order *p* specification and N variables. The moving average (MA) representation of the VAR is given by

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \quad (5)$$

Where x_t is an Nx1 vector containing each of the N variables included in the VAR

- ε_t is an Nx1 vector of independently and identically distributed (i.i.d) disturbances,

- A_i is the N x N coefficient matrix, such that, $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, with
- A_0 being an N x N identity matrix, $A_0 = I_m$, and $A_i = 0$ for $i < 0$
- x_t is expressed as the sum of past and current error vectors, ε_t, such that, $x_t = \sum_{k=1}^{p} \Phi x_{t-i} + \varepsilon_t$

The MA representation can then be used to forecast the future *H*-steps-ahead vector of independent variables.

Using variance decompositions (VD) allows splitting the forecast error variance of each variable into parts attributable to the various system shocks – in particular, it allows answering the questions: "what fraction of the one-step-ahead error variance in forecasting x_1 is due to shocks to x_1? Shocks to x_2?" (Diebold and Yilmaz, 2009). However, the VAR model has limitations. It uses Cholesky decompositions to orthogonalize the innovations. Forecast error variance decompositions (FEVDs) based on Cholesky factorisation are highly sensitive to the ordering of the variables to ensure that there is no correlation between the forecast errors. This can lead to erroneous and unrealistic results (Dekker, et al., 2001).

The DY spillover index (2009) has the same limitations as it uses Cholesky factorisation. To address these constraints, Diebold and Yilmaz (2012) extended the DY spillover index (2009) using the generalized VAR (GVAR) and generalized FEVD (GFEVD) models, proposed by Koop, et al. (1996) and Pesaran and Shin (1998). In contrast to the traditional VAR model, the GVAR does not require orthogonalisation of shocks but allows for correlated shocks. Furthermore, the generalised impulse response functions (GIRFs) produce FEVDs that are not dependent on the ordering of variables. The following section outlines the econometric methodology of Diebold and Yilmaz (2009, 2012).

Diebold-Yilmaz Spillover Index

Variance Shares

Diebold and Yilmaz (2009) define *own variance shares* as fractions of forecast error variances in forecasting x_i caused by shocks to x_i, for $i = 1, 2, \ldots,$ N and *cross-variance shares*, or *spillovers*, as fractions of the H-step-ahead forecast error variances in forecasting x_i due to shocks to another variable, x_j, for i, j = 1, 2,..., N, such that $i \neq j$. The H-step-ahead forecast error variance decompositions is given by

$$\theta_{i,j}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \qquad (6)$$

where Σ is the variance matrix for the error vector ε,

- σ_{jj} is the standard deviation of the error term for the jth equation and,
- e_i is the selection vector with one as the ith element and zeros otherwise.

The sum of the elements of each row in forecast error variances decompositions derived from orthogonalised VARs sum up to unity. However, in the GFEVD above, they do not. That is, $\sum_{j=1}^{N} \theta_{i,j}^{g}(H) \neq 1$. As a result, we cannot think of $\theta_{i,j}^{g}(H)$ as a share of total variance in i. To allow for such an interpretation, Diebold and Yilmaz (2012) suggest normalizing each entry of the VD matrix by the sum of the elements of each row as follows:

$$\theta'^{g}_{i,j} = \frac{\theta_{i,j}^{g}(H)}{\sum_{j=1}^{N} \theta_{i,j}^{g}(H)} \qquad (7)$$

where, $\sum_{j=1}^{N} \theta'^{g}_{i,j}(H) = 1$ and $\sum_{i,j=1}^{N} \theta'^{g}_{i,j}(H) = N$.

Total and Directional Spillovers

The total spillover index, which measures the contribution of spillovers of shocks across N variables to the total forecast error variance, is then defined as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \theta'^{g}_{i,j}(H)}{\sum_{i,j=1}^{N} \theta'^{g}_{i,j}(H)} * 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \theta'^{g}_{i,j}(H)}{N} * 100 \qquad (8)$$

The directional volatility spillovers transmitted from market i to all other markets j are calculated as:

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \theta'^{g}_{j,i}(H)}{\sum_{i,j=1}^{N} \theta'^{g}_{i,j}(H)} * 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \theta'^{g}_{j,i}(H)}{N} * 100 \qquad (9)$$

In the same way, directional volatility spillovers received by market i from all other markets j are given by

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \theta'^{g}_{i,j}(H)}{\sum_{i,j=1}^{N} \theta'^{g}_{i,j}(H)} * 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \theta'^{g}_{i,j}(H)}{N} * 100 \qquad (10)$$

Thus the directional volatility spillovers separate the total spillovers into those coming from (or to) a particular source.

The net volatility spillovers from market i to all other markets j is calculated as the difference between gross volatility shocks transmitted to (7) and gross volatility shocks received from all other markets (8), such that

$$S_i^g(H) = S_{.i}^g(H) - S_{i.}^g(H) \tag{11}$$

If $S_i^g(H) > 0$, we conclude that market i is a net transmitter of volatility. Conversely, if $S_i^g(H) < 0$ then market i is a net receiver of volatility from other markets.

Diebold and Yilmaz (2012) also measure net pairwise volatility spillovers defined as the difference between the gross volatility shocks transmitted from one market, i, to another market, j, and those transmitted from j to i. This study does not consider pairwise spillovers as there were no a priori expectations regarding directional spillover between any two specific markets. The analysis of net pairwise volatility spillovers across all BRICS stocks and currency markets is tedious and will make the analysis unmanageable, therefore net pairwise spillovers are excluded in this study.

Lag Specification

Because the DY spillover indices are derived from the variance decompositions of a VAR (p) estimation, the lag length is important. Thus, the Akaike Information Criterion (AIC) and the Swartz Bayesian Criterion (BIC) are used to determine the optimal lag length.

Time-varying Volatility Spillovers

To allow for possible time-variation in the spillovers, we use rolling window estimations. Following Diebold and Yilmaz (2009, 2012) and Duncan and Kabundi (2011), we use a rolling 200 day period. Kavli and Kotze (2014) posit that using large rolling window estimates gives a smooth dynamic index series and more accurate estimates but it also implies that the true index does not change during the period. In preliminary testing, both smaller (100 days) and larger rolling windows (780 days) are considered and the results support Kavli and Kotze (2014). The shorter period is too volatile and does not allow for any trend to develop which makes forecasts more unreliable. In contrast, the 780-day rolling period index results are too smooth and fail to capture fluctuations in the index over the three years. We, therefore, restrict this study to 200 rolling window estimates.

4.3.1.3. Volatility spillover effects in financial crises (contagion)

To evaluate our third research question, panel cointegrating regressions are estimated to examine determinants of spillovers in the BRICS equity and foreign exchange markets using the calculated directional volatility spillover indices as dependent variables. We follow Leung, et al. (2017) and apply linear regression methods instead of threshold or regime-switching models as they argue from various studies, such as Dacco and Satchell (1999), that regime-switching and threshold models generate inaccurate and poor out-of-sample forecasts because of the difficulty in forecasting the regime that the series will be in. However, instead of using individual linear regressions, this study will apply panel regressions as they have more power. Because the number of our cross-sections (five) is less than the number of explanatory variables we cannot apply traditional methods of estimating pooled models such as Random Effects model or Arellano-Bond GMM estimators. We, therefore, choose to apply panel dynamic OLS methods.

Kao and Chiang (1999), Mark and Sul (1999) and Pedroni (2001) propose panel Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS) methodologies to estimate the long-run cointegrating vector for non-stationary panel datasets. The DOLS and FMOLS correct for serial correlation and endogeneity of regressors. Furthemore, Kao and Chiang (1999) show that the DOLS estimator outperforms standard OLS and Fully Modified OLS (FMOLS) models in panel datasets with finite time dimension. The standard OLS and FMOLS models exhibit small sample bias. Therefore, this study applies the DOLS methodology.

The panel DOLS method is a panel extension of Saikkonen (1992) and Stock and Watson (1993) DOLS methods which involve adding lags and leads of the differenced regressors in the cointegrating regression so that the stochastic error term is independent of all past innovations in stochastic regressors. Stock and Watson (1993) DOLS estimator allows variables to be integrated of different orders. The panel DOLS model is specified as follows:

First, consider a panel structure for the n+1-dimensional vector with the cointegrating equation:

$$y_{i,t} = \beta_i{}'x_{i,t} + \gamma_{1i}{}'D_{1i,t} + \varepsilon_{i,t} \tag{12}$$

Where $x_{i,t}$ is an n-dimensional vector of independent variables, such that, $x_{i,t} = x_{i,t-1} + \epsilon_{i,t}$

- i denotes the cross-sections
- t represents the time-periods,
- β is the cointegrating vector, and
- $D_{1i,t}$ are deterministic regressors

The panel DOLS estimator is given by

$$y_{i,t} = \beta_i{}'x_{i,t} + \sum_{j=-p}^{q} \zeta_{ij}\Delta x_{i,t+j} + \gamma_{1i}{}'D_{1i} + \varepsilon_{i,t} \tag{13}$$

Where q denotes the number of leads, and

- p is the number of lags

Definition of variables and model specification

The indicators used in the regression analysis are defined as follows:

Dependent variables

EQUITIES_SPILL$_{G(R)}$: Directional spillovers to (and from) other BRICS equity markets. Derived from the DY spillover index. A significant increase in them represents contagion.

FXSPILL$_{G(R)}$: Directional spillovers to (and from) other BRICS foreign exchange markets. Derived from the DY spillover index. A significant increase in them represents contagion

Independent Variables – measured quarterly

Country-specific variables – Macroeconomic fundamentals

GDP: It captures the change in national income. Increases in GDP are supposed to reduce the occurrence of contagion effects. Thus we expect a negative relationship with directional spillovers (Aka, 2006; Comelli, 2014).

TRADE_BALANCE: It is the difference between a country's exports and imports of goods and services. It is a proxy for international trade linkages. A high trade balance is supposed to reduce the occurrence of contagion effects in the country. But a low trade balance in a major trading partner can increase the occurrence of contagion in the trading partner which could lead to a fall in asset prices in the economy and increasing volatility (Leung, et al., 2017). Thus we expect a negative relationship with directional spillovers given to and a positive relationship with directional spillovers received from other markets.

OPEN*:* Trade openness. The sum of a country's exports and imports of goods and services (total trade) as a percentage of GDP. It is also a measure of international trade linkages. The more open an economy is, the higher the economic growth rate, and therefore, the more resilient it is to crises (Comelli, 2014; Rao & Padhi, 2018). However, the more open economy is, especially in an emerging market context, the more susceptible it is to external shocks and contagion (Kamiri & Voia, 2019; Komulainen & Lukkarila, 2003; Leelahaphan, et al., 2015). Rao and Padhi (2018) also explain this twofold effect. As a result, we expect a negative relationship in the directional spillover given (to) side but a positive relationship on the directional spillover received (from) side.

CPI: Consumer Price Index - the rate at which the average price level of a basket of goods and services in an economy increases over time. A measure of inflation. Rising inflation is associated with macroeconomic instability. In an inflation-targeting environment, an increase in inflation leads to contractionary monetary policy by Central Banks. This raises interest rates leading to a decline in borrowing and in turn a fall in investments. Which can lead to a crises event (Komulainen & Lukkarila, 2003; Kamiri & Voia, 2019; Rao & Padhi, 2018; Tamgac, 2011). Thus we expect a positive relationship between CPI and directional spillovers.

INTEREST: Yields on each country's 10-year benchmark bond. High interest rates reflect higher risk premiums and fears about currency devaluation (Kaminsky & Reinhart, 1999). And as explained above, rising interest rates may also result in a decline in investments which can result in a crises event. So we would expect a positive relationship. On the other hand, lower interest rates could signal expansionary monetary policy during a crisis (Kaminsky & Reinhart, 1999). In this case, we would expect a negative correlation between interest rates and directional spillovers. Thus a positive relationship would imply that interest rates are leading factors while a negative relationship would suggest that interest rates are lagging indicators of crises.

RES: A change in foreign currency reserves held by each country's central bank as a percentage of GDP. It is a proxy for financial risk. An increase in foreign reserves as a percentage of GDP signals financial stability. Thus an increase in a country's holding of foreign reserves leads to a decrease in the spillovers it transmits to and receives from other markets. We, therefore, expect a negative relationship (Comelli, 2014).

TED: The difference between the London Interbank Offered Rate (LIBOR) and each country's short term interest rate. It is also a proxy for financial risk. Higher interest rate differentials usually signal increases in global uncertainty, which lead to capital flight from EMs. Thus, we expect a positive relationship.

PRI: International Country Risk Guide (ICGR) Political Risk Index. An overall measure of a country's risk calculated by PRS using 17 risk components including turmoil, financial transfer, foreign direct investment, and exports markets. It is a proxy of political risk. The higher the ICRG political risk index, the more stable the country is and thus, the more resilient it is to crises. We expect a negative relationship between PRI and directional spillovers to and from other markets.

Global Risk Control Variables:

VIX: Index of US market volatility as calculated by the Chicago Board Options Exchange (CBOE). It is a proxy for global risk (Mensi, et al., 2014; Leelahaphan, et al., 2015). The higher the VIX, the greater the risk aversion, which leads to capital flight from EMs. Thus, we expect a positive relationship.

OIL: West Texas Intermediate (WTI) crude oil is used as a benchmark in global oil pricing. It is a proxy for global risk (Mensi, et al., 2014; Leelahaphan, et al., 2015). Higher oil prices lead to uncertainty in global markets which increases the likelihood of capital flight from emerging markets and in turn a crises event. Higher oil prices also have an inflationary effect which causes instability in domestic markets (Miller & Ratti, 2009). We would, therefore, expect a positive correlation between oil prices and directional spillovers. Yet, most BRICS economies are oil-exporting countries (Centre for the Study of Governance Innovation, 2013), so higher oil prices for them raise stock returns and thus reduces the likelihood of a crises event. In this case, the relationship would be negative.

GOLD: Gold fixing price in the London Bullion Market. It is a proxy of global risk (Mensi, et al., 2014; Leelahaphan, et al., 2015). Gold is usually used as a hedge and safe haven against volatilities in other financial markets. Thus during periods of increased volatility in stock and exchange rate markets, we would expect investors to divest from them to gold, which would raise gold prices. Therefore we expect a positive relationship between gold prices and directional spillovers.

Based on the above, the DOLS models take the form:

Model 1:

$$\begin{aligned} &EQUITIES\_SPILL \\ &\quad = \beta_1 LNGDP_{i,t} + \beta_2 TRADEBAL_{i,t} + \beta_3 OPEN_{i,t} + \beta_4 CPI_{i,t} + \beta_5 VIX_t \\ &\quad + \beta_6 LNOIL_t + \beta_7 LNGOLD_t + \beta_8 RES_{i,t} + \beta_9 INTEREST_{i,t} + \beta_{10} TED_{i,t} \\ &\quad + \beta_{11} PRI_{i,t} \end{aligned} \tag{14.1}$$

$$\begin{aligned} &FXRATE\_SPILL \\ &\quad = \beta_1 LNGDP_{i,t} + \beta_2 TRADEBAL_{i,t} + \beta_3 OPEN_{i,t} + \beta_4 CPI_{i,t} + \beta_5 VIX_t \\ &\quad + \beta_6 LNOIL_t + \beta_7 LNGOLD_t + \beta_8 \Delta RES_{i,t} + \beta_9 INTEREST_{i,t} + \beta_{10} TED_{i,t} \\ &\quad + \beta_{11} PRI_{i,t} \end{aligned} \tag{14.2}$$

Model 2:

$$\begin{aligned} EQUITIES_{SPILL} = {} & \beta_1 LNGDP_{i,t} + \beta_2 TRADEBAL_{i,t} + \beta_3 OPEN_{i,t} + \beta_4 CPI_{i,t} + \beta_5 VIX_t + \\ & \beta_6 LNOIL_t + \beta_7 LNGOLD_t + \beta_8 RES_{i,t} + \beta_9 INTEREST_{i,t} + \beta_{10} TED_{i,t} + \\ & \beta_{11} PRI_{i,t} + \varphi_1 D\_ONE_{2006Q2} + \varphi_2 D\_TWO_{2012Q2} \end{aligned} \tag{15.1}$$

$$\begin{aligned} FXRATE_{SPILL} = {} & \beta_1 LNGDP_{i,t} + \beta_2 TRADEBAL_{i,t} + \beta_3 OPEN_{i,t} + \beta_4 CPI_{i,t} + \beta_5 VIX_t \\ & + \beta_6 LNOIL_t + \beta_7 LNGOLD_t + \beta_8 \Delta RES_{i,t} + \beta_9 INTEREST_{i,t} + \beta_{10} TED_{i,t} \\ & + \beta_{11} PRI_{i,t} + \varphi_1 D\_ONE_{2011Q2} \end{aligned} \tag{15.2}$$

Where φ_1 and φ_2 represent the coefficients of the break dummies.

4.3.2. DATA

4.3.2.1. Equity and foreign exchange markets

The data used to estimate volatilities are daily closing exchange rates and stock market indexes for the BRICS countries. The stock indexes for the BRICS countries are the Bovespa Equity Index for Brazil (IBOV); the Russian Trading System Index (RTSI), the National Stock Exchange (NSE) NIFTY 50 index for India; the Shanghai Composite Index (SSEC) for China and FTSE/JSE All Share Index (JALSH) for South Africa. The exchange rates, namely, the Brazilian Real (BRL), Russian Ruble (RUB), Indian Rupee (INR), Chinese Yuan (CNY), and South African Rand (ZAR) are expressed in the local currency against the U.S. dollar.

Data Transformation

We calculate the returns of the exchange rates and stock indices as the difference between the logarithms of the closing prices between two subsequent days. Thus the formula for the returns is given by

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100 \qquad (16)$$

Where R_t denotes asset returns,

- P is the price index, and
- t and $t-1$ indicate time

The trading hours of the BRICS equities and exchange markets are not synchronous. To avoid the "meteor showers" effects that were demonstrated by Engle, et al. (1990) we must address this problem of non-overlapping trading hours. Various solutions to the problem of non-overlapping and partially overlapping trading hours have been suggested in the literature (Bae, et al., 2003; Hamao, et al., 1990; Melvin & Melvin, 2003). We follow Forbes and Rigobon (2002) approach of using two-day rolling window average returns.

No data for weekends is used as the markets are closed on weekends. Missing observations due to trading holidays across the five countries are replaced with the previous days' returns before calculating volatilities.

Definition of Sample

The study will span from 2 January 1997 to 31 December 2018. This relatively long sample period is selected to cover crises periods of particular interest to our study, such as the Asian Financial Crisis of 1997-1998, the 1998 Russian bond default, the Brazilian Crisis of 1999, the 2000 dotcom bubble crisis, the Rand Crisis of 2001, and more recently the Global Financial Crisis of 2007-2009, the Eurozone debt crisis of 2009-2012 and the 2018 Turkish currency and debt crisis which spread to many emerging market economies.

During the study period, only two countries, South Africa and India, had freely floating exchange rate regimes throughout. Russia, Brazil and China had fixed exchange rate systems and only adopted managed floating rate regimes in August 1998, January 1999 and July 2005 respectively. The fixed rates, particularly in the case of China, give rise to the problem of multicollinearity among the regressors in the VAR model on which the DY spillover index is based. To correct for this, and in effect weaken exchange regime impacts, the periods in which the countries had adopted fixed exchange regimes are excluded. Table 4.1 provides more details regarding sample selection.

Table 3.1: Sample Selection

	COUNTRY	**SAMPLE PERIOD**
Cross-market, in-country volatility spillovers	Brazil	01/13/1999-12/21/2018
	Russian Federation	08/11/1998-12/31/2018
	India	01/02/1997-12/31/2018
	China	07/21/2005-12/31/2018
	South Africa	01/02/1997-12/31/2018
Cross-market, in-country volatility spillovers	ALL	07/21/2005-12/31/2018
Volatility spillovers between equity markets	ALL	01/02/1997-12/31/2018
Volatility spillovers between foreign exchange markets	ALL	01/02/1997-12/31/2018

4.3.2.2. Macroeconomic indicators

This section provides a summary of the sources and availability of the data and macroeconomic variables used in the study. As mentioned, the study follows the existing literature. In particular, we follow Leelahaphan, et al. (2015) who examine determinants of spillovers in equity markets of selected countries. They apply measures of international trade linkages, financial risk, and global risk factors to represent volatility spillover channels. And following Leung, et al. (2017), we extend the regression model to include the following crisis indicators as proxies for fundamental contagion: trade balance, which also measures trade linkages, inflation, and long-term interest rates. We also include a country's GDP to proxies of fundamental contagion.

The global risk indicators, VIX, gold prices and crude oil prices are used as control variables as studies have shown that changes in volatility spillovers can be explained by major global events (Diebold & Yilmaz, 2009; Mensi, et al., 2014).

Table 4.2 provides the definitions of the variables and information on the data sources and availability.

Table 4.2: Summary of data measurements, sources and availability

Variable	Source	Availability
GDP	Source: Thomson Reuters Datastream	ALL
TED	Federal Reserve Bank of St. Louis, Economic Research Division (for LIBOR) and Thomson Reuters Datastream (for countries' 3-month interest rates)	2001Q1
RES	Thomson Reuters Datastream	2001Q1
VIX	Federal Reserve Bank of St. Louis, Economic Research Division	ALL
OPEN	Thomson Reuters Datastream	ALL
OIL	Federal Reserve Bank of St. Louis, Economic Research Division	ALL
CPI	Thomson Reuters Datastream	ALL
INTEREST	Thomson Reuters Datastream	2003Q1
GOLD	Federal Reserve Bank of St. Louis, Economic Research Division	ALL
PRI	World Bank from Political Risk Services (PRS), International Country Risk Guide (ICGR)	2002Q1

Because of the availability of data, the regressions for determinants of directional volatility spillovers in equities are estimated from 2003Q1. For exchange rates, the sample period is estimated from 2007Q4.

Data Transformation

To test for determinants of fundamental contagion, the daily exchange rate and stock market spillover indices are first transformed to quarterly compounded to have the same sampling frequencies as the macroeconomic variables. All other variables that are not quarterly are also transformed into quarterly using Eviews 10.

Most macroeconomic time series exhibit seasonality. The standard technique for dealing with seasonality in the data is to use the Hodrick-Prescott (HP) filter to detrend the time series. The HP (1981, 1987) decomposes a variable into its trend and cycle components. However, other studies show that it has a lot of drawbacks (Harvey & Jaeger, 1993; King & Rebelo, 1993; Canova, 1994; Schuler, 2018).

In more recent studies, Hamilton (2018) theorizes that the HP filter produces spurious cycles that have no basis in the underlying data-generating process and suffers from end-of-sample bias. Also, the value of the smoothing parameter, λ, is at odds with common practice. He proposes an alternative regression filter. Nonetheless, Schuler (2018) suggests that the Hamilton filter also has its drawbacks: when applied to a random walk process, the regression filter cancels certain frequency cycles and amplifies others. We, therefore, decide to follow standard practice and apply the HP filter as Ravn and Uhlig (2002) state that "the HP filter has stood the test of time and the fire of discussion remarkably well".

4.3.3. ESTIMATION TECHNIQUES

4.3.3.1. EGARCH Model

Properties of the Returns series

To determine the properties of the returns series, a histogram, which gives measures of skewness and kurtosis of the series, and Jarque-Bera statistics were used to test for normality. The Augmented Dickey-Fuller (ADF) test was used to test for stationarity of the returns series. The main advantage of ADF tests is that they can handle large and complex time series models however the disadvantage is that they are weak if the root is close to the non-stationary border. We therefore also employ Phillip-Perron (PP) tests. If the data are not stationary, they are converted into stationary by differencing

Box-Jenkins Model Selection – ARMA

Having confirmed that the returns series are stationary, an ARMA model is estimated using the Box-Jenkins model selection approach. In the identification stage, the correlograms of the series are plotted and looking at the autocorrelation functions (ACF) and the partial autocorrelation functions (PACF) several plausible models are suggested. In the estimation stage, each of the plausible models is fit and the coefficients are examined (Enders, 2015). To ensure that we select the most parsimonious model both the Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC) are used. We select the model with the smallest AIC and SBC. We also use the Eviews ARIMA Forecasting to verify our model selection. The last stage of the Box-Jenkins approach which involves diagnostic checking is done by plotting the residual series and examining them for structural defects. If the residuals are independent and identically distributed (i.i.d), it is a 'white noise' process and there will be mean reversion even if there are shocks in the market.

Autoregressive Conditional Heteroskedasticity (ARCH) Model

We then test for heteroskedasticity using the ARCH LM test. If the returns series show evidence of arch effects, then estimating generalized autoregressive conditional heteroskedasticity (GARCH) type models is justified.

4.3.3.2. DY index

Because the DY index is based on the VAR framework, the first step is to test all variables for stationarity using the ADF tests. Since the variables used in this step will have already been transformed before estimating the EGARCH model, we assume that they are already stationary and continue to estimate the VAR model and determine the optimal lag length.

4.3.3.3. Panel regression

Breakpoint Tests

The Bai-Perron (1998) multiple break test is used to determine whether there are breaks in the data and the exact breakpoints. The test allows for a maximum of five break points in a series Due to the difference in sampling periods, we apply a smaller trimming percentage (5%) to the BRICS foreign exchange rate spillover index (whose data begins in 2006Q2), to allow capturing of breaks associated with the GFC. For the equities spillover index, we apply the standard 15% trimming percentage.

Cross-Section Dependence Tests

Panel data models are likely to exhibit cross-sectional dependencies in the residuals. Cross-sectional dependencies may arise due to common shocks and idiosyncratic elements resulting in strong comovements among the economic variables (Pesaran, 2004; Baltagi, 2005). The presence of cross-sectional dependency distorts the size of the panel unit root, therefore it is important to test for it before conducting unit root tests. The Breusch-Pagan LM (1980), Pesaran scaled LM (2004) and Pesaran Cross-Sectional Dependency (CD) (2004) tests were applied to test for cross-dependencies. Pesaran CD is considered the most general as it is suitable for both stationary and non-stationary panel data.

Unit Root Tests

The variables are then tested for unit root. We apply panel-based unit root tests as they have more power than unit root tests for individual series. Eviews 10 computes five tests: Levin, Lin and Chu (2002), Breitung (2000), Im, Pesaran and Shin (2003), Fisher-type ADF and PP tests (Maddala and Wu (1999) and Choi (2001). These tests are referred to as the first generation of panel unit root tests. They assume that all cross-sections are independent (Hurlin, 2010). However, the Im, Pesaran and Shin (IPS) W-statistic relaxes the restrictive assumptions of panel homogeneity and no serial correlation by using lags and specification of the deterministic component of each cross-section ADF equation. Therefore, where the results are ambiguous, we consider the IPS W-statistic. If the series are not unit root stationary, we conduct cointegration tests for panel data.

Panel Cointegration Tests

Because our panel data has several orders of integration, we test for panel cointegration using Johansen-Fisher Panel Cointegration tests.

Panel DOLS Model

If the data is non-unit root stationary and the variables are cointegrated, we can proceed to estimate cointegrating DOLS regressions. We use directional spillovers computed from the DY rolling estimations for both equity and exchange rate markets as dependent variables.

Because all the variables used in the regression model have been detrended, the equations are estimated without a deterministic trend. The Akaike Information Criterion (AIC) is used to select the optimal lag and lead lengths. We apply the Newey-West (1987, 1994) heteroskedasticity-and-autocorrelation consistent (HAC) estimators of the variance-covariance matrix to correct for autocorrelation and heteroskedasticity in our standard errors. We also allow for heterogeneous variances in our coefficient covariance matrix.

4.3.4. DIAGNOSTIC TESTS

4.3.4.1. EGARCH Model

As a final check on the adequacy of the selected models, the residuals of the EGARCH models are examined. The following diagnostic tests were performed:

a. The standardized residuals were plotted to determine their distribution.
b. The standardized residuals were checked to see whether they exhibited autocorrelation using correlograms.
c. ARCH LM tests were conducted on the squares of the standardized residuals to determine if there were any remaining ARCH effects

4.3.4.2. Panel regression

Granger and Newbold (1974) and Phillips (1986) showed that when non-stationary variables are regressed on other non-stationary variables, the results may lead to a spurious regression. In a spurious regression, the OLS estimates converge to a random variable – they are not consistent and the t-statistic diverges (Barbieri, 2008). As a result, a spurious regression tends to produce significant relationships between variables even if they are independent. As a final check on the adequacy of the selected models, the residuals of the DOLS model are tested for unit roots to determine whether they are spurious regressions.

4.4. CONCLUSION

This chapter discussed the research methodology that will be used in this study. We follow a positivist paradigm since this is a quantitative study. The study uses secondary data from Thomson Reuters Datastream, World Bank, and the Federal Reserve Bank of St. Louis, Economic Research Division. To calculate volatilities in BRICS equity and foreign exchange markets, daily closing data of the relevant stock indexes and currencies is used. To determine fundamental factors that explain volatility spillovers, and/or contagion, quarterly data of selected macroeconomic variables are used.

We employ the EGARCH model for calculating volatilities; the DY spillover index to derive spillovers between equity and foreign exchange markets in BRICS, and finally, we use panel DOLS regressions to assess determinants of contagion. We discuss all diagnostic tests required to run the selected models and also test for the validity of the models.

The following chapter discusses the results and empirical finding of this study.

CHAPTER 5

DATA ANALYSIS, EMPIRICAL RESULTS AND DISCUSSION

5.1. INTRODUCTION

This chapter presents the main results of the study. It includes a review of the descriptive statistics. It also discusses the diagnostic tests performed, the regression results and the findings from the hypothesis testing which form the basis upon which conclusions and recommendations of the study are drawn from.

5.2. DESCRIPTIVE STATISTICS

Table 5.1 and Table 5.2 present descriptive statistics of the log-transformed index returns on equities and currencies respectively as well as preliminary results of the data sample. Appendix A presents the graphs of the data series.

Table 5.1: Descriptive Statistics - Equities

Statistic	*IBOV*	*RTSI*	*NIFTY*	*SSEC*	*JALSH*
Observations	5738	5738	5738	5738	5738
Mean	0,71%	0,46%	0,69%	0,28%	0,61%
Median	1,32%	0,51%	1,28%	0,00%	1,03%
Maximum	187,43%	325,78%	154,33%	132,68%	94,42%
Minimum	-166,89%	-341,83%	-169,22%	-135,85%	-151,41%
Std, Dev,	16,05%	38,89%	17,13%	17,73%	14,06%
Skewness	-21,05%	-45,90%	-46,20%	-27,95%	-48,62%
Kurtosis	14,723	12,062	10,459	7,736	8,829
Jarque-Bera	32897,23	19836,20	13506,46	5437,50	8348,89

From Table 5.1 we observe that average daily returns in BRICS equities are below 1% over the period of January 2007 to December 2018. IBOV has the highest average returns of 0.71%, followed by NIFTY, JALSH and RTSI indexes with a sample mean of 0.69%, 0.61% and 0.46% respectively while SSEC returns are much lower at 0.28%. RTSI is the most volatile stock index with a standard deviation of 38.59% while the JALSH has the lowest volatility (14.06%) over the sample period. All five equity market returns are negatively skewed and leptokurtic indicating non-normality. In addition, the Jarque-Bera statistics for all the indices are far greater than the critical value of approximately 6 (chi-squared at the 5% with 2 degrees of freedom) with p-values of 0.000. We therefore reject the null hypothesis of normality at the 1% level of significance and conclude that the returns are not normally distributed.

Table 5.2: Descriptive Statistics - Exchange Rates

Statistic	*REAL*	*RUB*	*INR*	*CNY*	*ZAR*
Observations	5738	5738	5738	5738	5738
Mean	0.37%	0.71%	0.19%	-0.05%	0.31%
Median	0.27%	0.04%	0.00%	0.00%	0.00%
Maximum	141.58%	385.03%	54.75%	22.37%	137.33%
Minimum	-139.93%	-404.66%	-37.36%	-16.36%	-103.16%
Std. Dev.	11.95%	18.16%	4.51%	1.36%	12.23%
Skewness	49.93%	233.03%	37.92%	12.47%	56.20%
Kurtosis	1772.25%	21659.78%	1429.61%	3626.95%	1096.57%
Jarque-Bera	52060.2	10913139	30645.04	264646.2	15472.5

Table 5.2 shows that average returns of all four of the BRICS currencies are positive except for the Chinese Yuan. There is a lot there is variation among the currencies. The Russian Ruble has the highest returns (0.71%) followed by the Brazilian real (0.37%), the South African Rand (0.31%) and the Indian rupee (0.19%). The Chinese Yuan exhibits negative returns (-0.05%) over the sample period. The Ruble is also the most volatile currency (18.16%) followed by the Rand and the Real at 12.23% and 11.95% respectively. The Chinese Yuan is the least volatile currency (1.36%) and the Rupee has a relatively low returns volatility (4.51%).

The exchange rate returns also show signs of non-normality. They are highly leptokurtic but in contrast to the equity market returns, all five currency returns are positively skewed. The deviations from the Gaussian distribution are also confirmed by the Jarque-Bera test. We therefore reject the null hypothesis of normality at the 1% level of significance and conclude that the returns are not normally distributed. This conclusion is reasonable as it is common phenomenon in emerging stock markets.

Table 5.1 and Table 5.2 show that on average stock returns are higher than exchange rate returns for all BRICS countries except Russian. From the standard deviation measures, it is evident that equity returns are also more volatile than currency returns. These results are consistent with Chkili and Nguyen (2014) and provide evidence of linear and non-linear dependencies which justify estimating the ARMA model.

5.3. RESULTS OF ESTIMATION TECHNIQUES

5.3.1. EGARCH MODEL

5.3.1.1. Data Analysis

Unit Root Tests

In order to test for stationarity we conduct Augmented Dickey Fuller (ADF) and Phillip-Perron tests in the five stock indices. The results from the test are shown in Table 5.3 below.

Table 5.3: Unit Root Tests

	ADF	Probability	Phillips-Perron	Probability
Equities				
IBOV	-12.67093	0.0000	-27.74297	0.0000
RTSI	-67.28900	0.0001	-67.28900	0.0001
NIFTY	-16.34180	0.0000	-40.01526	0.0000
SSEC	-14.20396	0.0000	-42.25297	0.0000
JALSH	-13.79356	0.0000	-37.69803	0.0000
Currencies				
BRL	-14.30627	0.0000	-41.56024	0.0000
RUB	-65.27005	0.0001	-65.21491	0.0001
INR	-12.28436	0.0000	-44.93594	0.0000
CNY	-8.631653	0.0000	-34.63684	0.0000
ZAR	-13.79214	0.0000	-37.70919	0.0000

Both the absolute ADF and PP test statistics are statistically greater than all absolute t-critical values. Looking at the corresponding p-values, we reject the null hypothesis of unit root and conclude that at a 1% level of significance, the returns series are stationary. They were made stationary through differencing, therefore the order of integration is I (1).

5.3.1.2. Model Selection and Model specification

The Box-Jenkins approach and ARIMA forecasting in Eviews are used to determine the ARMA models. Results of selected Q-statistics are shown in Appendix B.

5.3.1.3. Diagnostic Checking

Residual Analysis

Figure C1 in Appendix C plots of the residual series of the ten indices. All plots show spikes and clustering which point towards the possibility of autocorrelation in the returns. The variances of the residuals are also not constant.

Autocorrelation

Tables C2.1 and C2.2 in Appendix C shows the Q-statistics of the squared residuals. The null and alternative hypotheses of the test are:

H_O: No Autocorrelation

H_1: Autocorrelation

The results confirm the presence of autocorrelation. The Q-statistics along with their corresponding p-values show there is dependence in the daily returns of all indices. We proceed to test whether ARCH effects are indeed present using the ARCH LM test.

Heteroscedasticity

Table C3 in Appendix C shows the results of the ARCH LM test. The null and alternative hypotheses of the ARCH LM test are:

H_O: No ARCH effects

H_1: Arch effects

Looking at the values of Obs*R-squared and their corresponding p-values of 0.0000, we reject the null hypotheses of no ARCH effects and conclude that at the 1% level of significance, there is evidence of arch effects for all ten indices. Therefore the need to estimate GARCH type models is justified.

5.3.1.4. Model Estimation Results

The results of the EGARCH models shown in Appendix D indicate that negative shocks (bad news) have large impacts on the volatility y of both the stock and exchange rate returns of BRICS countries than positive shocks (good news). Furthermore, the β parameters, which capture the persistence of conditional volatility are large on all indices, these imply that volatility on the BRICS stock and foreign exchange markets takes a long time to die out following a crisis in the market.

5.3.1.5. Model Diagnostics

Normality

From the results in Tables E1.1 and E1.2 of Appendix E, we notice that the kurtosis of all indices still exceed the normal distribution threshold of three but not by a large margin (except for INR and CNY), indicating that although our returns are still fat-tailed, they are less so. In addition, the Jarque-Bera statistics for all the indices have reduced significantly. Despite this, they are still far greater than the critical value of approximately 6 (chi-squared at the 5% with 2 degrees of freedom). The corresponding p-values are also highly significant. We therefore reject the null hypothesis of normality at the 1% level of significance and conclude that the returns are not normally distributed.

Remaining ARCH effects

Table E2 in Appendix E shows the results of the ARCH LM test. The null and alternative hypotheses of the test are:

H_O: No ARCH effects

H_1: Arch effects

Looking at the values of Obs*R-squared and their corresponding p-values, we fail to reject the null hypotheses of no ARCH effects and conclude that there are no remaining GARCH errors. The

Durbin-Watson statistics are also approximately equal to two which means that there is no serial correlation in the samples. To confirm this we look at the correlogram of the squared standardized residuals.

Autocorrelation

Tables E3.1 and E3.2 in Appendix E shows selected Q-statistics of the squared residuals. The null and alternative hypotheses of the test are:

H_O: No Autocorrelation

H_1: Autocorrelation

The Q-statistics up to the 15th order autocorrelation are insignificant suggesting that the null hypothesis of no autocorrelation in daily returns cannot be rejected. We therefore conclude that the daily returns are now independent.

5.3.1.6. Volatilities

We proceed to generate a GARCH series from the conditional variance. The graphs in Figure 5.1 below show volatility time series using the EGARCH model for the five BRICS equity markets

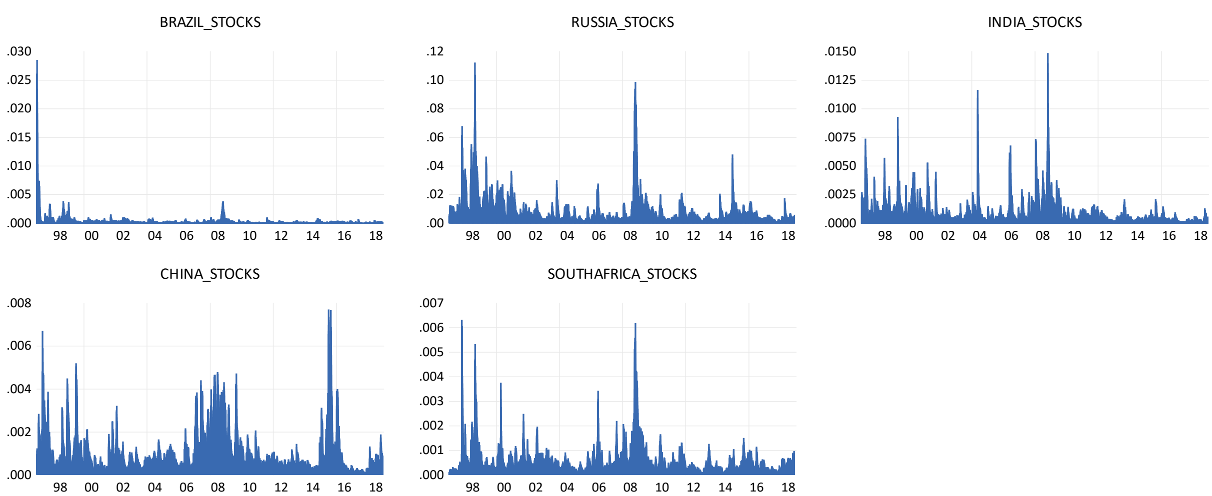

Figure 5.1: Volatility of BRICS stock markets

Figure 5.2 shows volatility time series using the EGARCH model for the BRICS exchange rate markets.

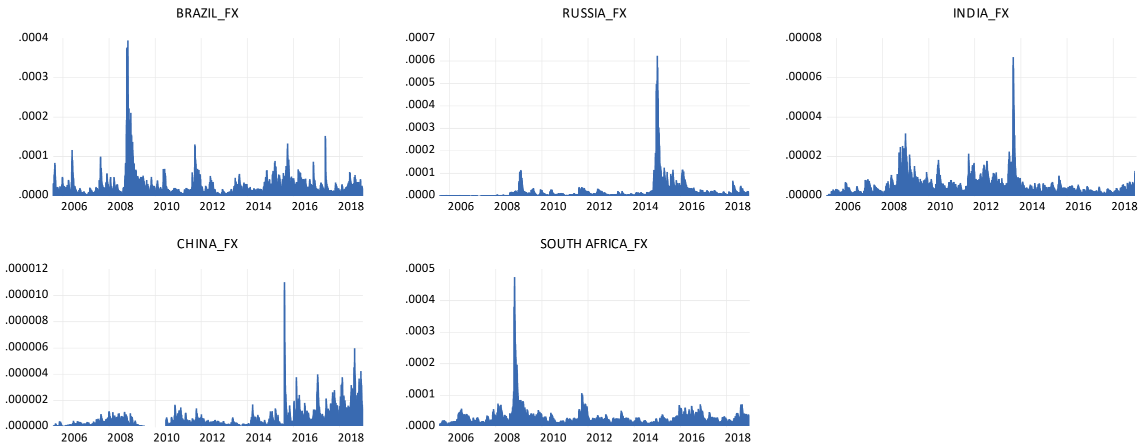

Figure 5.2: Volatility of BRICS exchange rate markets

5.3.2. DIEBOLD-YILMAZ (DY) SPILLOVER INDEX

The results in this section are presented in four subsections. We first estimate the DY spillover indices based on the VDs from our samples in order to analyse market interdependencies (co-movements) among BRICS asset classes. Subsequently, we consider the time variation in the volatility spillovers using rolling window estimations. Next, we focus on directional spillovers and lastly, we look at net directional spillovers for each of the BRICS markets.

5.3.2.1. Full sample analysis

BRICS Equity Markets

Table 5.4 presents the results of volatility spillover among BRICS stock markets. The results are based on a VAR of order 5 selected using the Schwartz Bayesian Criterion (BIC) and a forecast horizon of 10 days. The AIC suggested a lag order greater than 20 while the SBC suggested the volatility to also be best modelled by a VAR (5) model. Hence for parsimony, the VAR (5) model was chosen to estimate stock returns.

The table presents the estimated contribution to the 10-day forecast error variance of market i coming from shocks to market j. The diagonal elements ($i = j$) represent own market shocks. The off-diagonal elements in the table estimate pairwise directional spillover. The "Contribution to others” row measures the spillover effect transmitted by a particular market to all others while the “From others” column represents the total spillovers received by a particular market from all other markets. The total spillover index is given by summing either the “contribution to others” row or the “From others” column. The net total directional spillover is obtained by calculating the difference between the sum of the “Contribution to others” row and the “From others” column (excluding own variance shares). This is shown in more detail (cell by cell) in Table 5.5 below. A positive value of the “Net” indicates that the market is a net transmitter of volatility to other markets whereas a negative value shows that the market is a net receiver of volatility from other markets.

Table 5.4: Static Spillover (Connectedness) Index

	IBOV	RTSI	NIFTY	SSEC	JALSH	From Others
IBOV	87.0	3.9	1.4	0.4	7.3	13.0
RTSI	6.3	65.2	3.8	0.6	24.1	34.8
NIFTY	3.1	4.9	79.9	0.4	11.7	20.1
SSEC	0.2	1.5	1.4	94.9	2.0	5.1
JALSH	7.8	18.6	6.3	0.6	66.7	33.3
Contribution to others	17.4	28.8	13.0	2.0	45.0	106.2
Contribution including own	104.4	94.0	92.9	96.9	111.8	21.2%
Net	4.4	-6.0	-7.1	-3.1	11.7	

The results presented in Table 5.4 indicate that the total spillover among BRICS equity markets is 21.2% whereas 79.8% of the forecast error variance is explained by own market shocks. China has the highest own connectedness (94.9%) followed by Brazil (87%) and India (79.9%). South Africa and Russia have relatively lower own connectedness, 66.7% and 65.2% respectively, indicating that they are more integrated to other BRICS stock markets.

The South Africa equity market index (JALSH) has the highest effect followed by the stock market indices of Russia and Brazil. In particular, the equity market of South Africa contributes 24.1% and 11.7% to the stock markets of Russia and India, respectively while it only contributes 2% to the Chinese stock market. Russia contributes 18.6% of the forecast volatility to South Africa and only 1.5% to China. China has the lowest contribution to the forecast volatility contributing only

2% of the volatility to the other markets. However, it also has the lowest risk of volatility transmission - only 5.1% of the forecast volatility it receives is from other markets. This implies that the connectedness of China to other markets in BRICS is low. This result is consistent with Bekiros (2014), Wang, et al. (2016) and Lee & Lee (2019). Conversely, the stock markets of Russia, South Africa and India have higher risk of volatility transmission from other markets – 34.8%, 33.3% and 20.1% respectively. Brazil receives 13% of volatility from other markets most of which is from South Africa (7.3%). Interestingly, it also transmits about the same level of volatility to the market of South Africa (7.8%). This is consistent with Bonga-Bonga (2018) who reports evidence of bidirectional transmission between Brazil and South African stock markets.

Table 5.5: Net Directional Spillovers - Equities

	IBOV	RTSI	NIFTY	SSEC	JALSH	NET	Conclusions
IBOV	0	-2.4	-1.7	0.2	-0.5	4.4	Net transmitter
RTSI	2.4	0	-1.1	-0.9	5.5	-5.9	Net receiver
NIFTY	1.7	1.1	0	-1	5.4	-7.2	Net receiver
SSEC	-0.2	0.9	1	0	1.4	-3.1	Net receiver
JALSH	0.5	-5.5	-5.4	-1.4	0	11.8	Net transmitter

The net directional spillovers presented in Table 5.5 indicate who the main recipients and transmitters of volatility spillovers are. From the table, it is shown that South Africa and Brazil equity market indices are net transmitters of volatility spillovers to other BRICS equity markets while the stock markets of India, Russia and China are net recipients of volatility.

BRICS Foreign Exchange Markets

Table 5.6 presents the results of volatility spillovers among BRICS currency markets. The results are based on a VAR of order 11 selected using the Schwartz Bayesian Criterion (BIC) and a forecast horizon of 10 days.

Table 5.6: Static Spillover (Connectedness) - Currencies

Spillover (Connectedness) Table

	BRL	RUB	INR	CNY	ZAR	From Others
BRL	82.1	0.2	1.5	0.2	16.0	17.9
RUB	0.3	99.5	0.1	0.1	0.1	0.5
INR	3.5	0.5	94.9	0.1	1.0	5.1
CNY	0.0	0.4	0.1	99.5	0.0	0.5
ZAR	25.6	0.1	0.5	0.0	73.8	26.2
Contribution to others	29.4	1.2	2.1	0.3	17.1	50.1
Contribution including own	111.5	100.7	97.1	99.8	90.9	10.0%
Net	11.5	0.7	3	-0.2	-9.1	

The results presented in Table 5.6 indicate that 90% of the forecast error variance among BRICS exchange rate markets is explained by own market shocks. The total spillover is only 10%, most of which is explained by spillovers between the Brazilian Real (BRL) and the South African Rand (ZAR). China and Russia have the highest own connectedness (99.5%) followed by India (94.5%). Brazil and South Africa currency indexes have relatively lower own connectedness, 82.1% and 73.8% respectively, indicating that they are relatively more integrated to other BRICS stock markets.

The Brazilian Real has the highest effect followed by the South Africa Rand. In particular, the exchange rate of Brazil contributes 25.6% to the exchange rate of South Africa, while it only contributes 3.5%, 0.3% to the exchange rates of India and Russia respectively. South Africa contributes 16% of volatility to the Brazilian Real and only 1% and 0.1% to the volatility of the Indian Rupee and the Russian Ruble. Brazil and South Africa's currency markets are highly integrated to each other, however, they do not transmit any volatility to the Chinese Yuan. Among the BRICS states, volatility in the Russian Ruble contributes the most to the Chinese Yuan (0.4%) followed by the Indian Rupee (0.1%). China has the lowest contribution to the forecast volatility, contributing only 0.3% of the volatility to the other markets. The Rand has the highest risk of volatility transmission – it receives 26.2% of the forecast volatility from other markets, while China and Russia both have the lowest risk of volatility transmission –receiving only 0.5% of the forecast volatility from other markets. This is particularly interesting as we noted earlier that the

Ruble is the most volatile currency in BRICS and yet it transmits very little of that volatility to other BRICS markets. This further confirms that the connectedness of China to other markets in BRICS is low.

The net column in Table 5.6 shows who the main recipients and transmitters of volatility spillovers are. From the table, it is shown that the South African Rand and Chinese Yuan are net recipients of volatility spillovers from other BRICS foreign exchange markets, with net volatility spillover of 9% and 0.2% respectively. Brazil, India, and Russia are net transmitters of volatility to other BRICS currency markets.

BRICS cross-market, in-country analysis

To look at the relationship between different markets (equities and exchange rate markets) in the same country, we estimate time-aggregated volatility spillovers among them. Tables 5.7 summarizes the estimation results for the 10 financial markets in BRICS. Each asset class is calculated as the sum of the cross-market spillover measures in each of the five BRICS countries.

Table 5.7: BRICS cross-market spillovers

Cross-market Spillover (Connectedness) Table

	FX(5)	Stocks(5)	From Others
FX (5)	476.1	23.9	23.9
Stocks (5)	28.6	471.4	28.6
Contribution to others	28.6	23.9	52.5
Contribution including own	504.7	495.3	5.28%
NET	4.7	-4.7	

Table 5.7 shows that in aggregate foreign exchange markets in BRICS are net transmitters of volatility shocks to BRICS equity markets, while stocks are net recipients of volatility from the exchange markets. Because this findings are in contrast with some of the literature whose results support the stock-oriented models, for example, Chkili and Nguyen (2014), we consider the individual country’s volatility spillovers between the two markets. The results are reported in Appendix F.

We note that Brazil, India and South Africa's exchange rate markets are net transmitters of volatility to the stock markets. Only Russia's exchange rate market is a net recipient of volatility from its stock market. The net transmission to China is zero. These findings are in line with Sui and Sun (2016) who posit that stock-oriented models are not prevalent since most emerging countries still strongly intervene in the foreign exchange market and restrict capital flows across their borders. However this argument does not hold for some of the BRICS countries whose exchange rates are freely floating, such as South Africa and India. We suggest that the foreign exchange markets in most BRICS countries might be more susceptible to global shocks than country-specific shocks. We investigate this in the last section of this chapter where we look at determinants of contagion.

BRICS cross-market, cross-country analysis

In this subsection, we explore the relationship between equities and exchange rate markets across all BRICS countries. Table 5.8 presents the results on how volatility shocks in one BRICS market spill over to all other BRICS markets.

Table 5.8: BRICS Cross-country, cross-market Spillovers

Spillover (Connectedness) Table

	IBOV	BRL	RTSI	RUB	NIFTY	INR	SSEC	CNY	JALSH	ZAR	FROM OTHERS
IBOV	95.5	1.2	0.7	0.2	0.9	0	0	0	0.6	0.8	4.5
BRL	20.9	70	3.5	0.4	1.2	0.1	0.3	0	1.7	2.2	30.4
RTSI	31.7	1.3	65	0.2	0.4	0.2	0.2	0.1	0.5	0.9	35.4
RUB	0.6	0.1	4.9	92	0.3	0.1	0.1	0	1.3	0.2	7.6
NIFTY	21.4	2.7	1.6	0.1	69.7	0	0.3	0.2	1	3	30.3
INR	2.1	1.5	1.6	0.1	0.3	94	0.1	0	0.2	0.3	6.2
SSEC	4	0.1	0.5	0	2.2	0.1	92.6	0.2	0.2	0.1	7.4
CNY	0	0.1	0.1	0.1	0.4	0.2	0.3	99	0	0.1	1.1
JALSH	30.9	0.7	7.5	0.1	4.5	0.2	0.1	0.3	55	0.9	45
ZAR	14.8	11	2.2	0.6	0.3	0.1	0.1	0.2	0.8	70	29.7
Contribution to others	126	18	23	1.8	10.5	0.9	1.5	1	6.3	8.5	197.8
Contribution including own	222	88	87	94	80.1	95	94.1	100	61.3	79	19.80%
NET	122	-12	-13	-5.8	-20	-5.3	-5.9	-0.1	-39	-21	

China has the highest own financial connectedness, in particular, the Chinese Yuan has the highest own connectedness (99%) and only 1% is from shocks from other markets. As shown in the cross market, in-country table, Chinese markets (equities and exchange rates) also have the lowest connectedness among themselves. This is consistent with findings from other studies such as (Lee & Lee, 2019) and (Wang, et al., 2016) On the other hand, South African markets have the lowest own financial connectedness, and the highest risk of volatility transmission. In particular the JSE All Share Index only has 55% own connectedness 45% of the shocks in the JALSH index are from shocks from other BRICS markets. The Russian and Indian stock markets are also highly connected to other BRICS stock and exchange rate markets. 35.4% and 30.3% of volatility in these markets are from other BRICS markets. The Brazilian Real and South African Rand have the highest risk of volatility transmission among the BRICS currencies receiving 30.4% and 29.7% of volatility respectively. Most of this volatility is received from the Bovespa Index. The Bovespa index is the most contagious market, transmitting a net of 122% of shocks to other BRICS markets, although it gives no volatility to the Chinese Yuan. On the other hand, the JALSH index has the lowest net connectedness measure of -39% followed by the South African Rand and the Nifty 50 with -21% and -20% respectively. Moreover, IBOV transmits the most shocks to RTSI (31.7%) and JALSH (30.9%). The financial connectedness between the Real and the Rand is the highest among BRICS currency pairs – transmissions from the Real to the Rand are 11% and from the Rand to the Real are 2.2%. Interestingly, the Chinese Yuan only receives shocks from the South African Rand, and none from all other BRICS currencies. Total financial connectedness is 19.80%.

While there is evidence of bidirectional volatility spillovers between stocks and currency markets in BRICS, except for India which shows unidirectional volatility spillovers, most of the shocks flow from the equity market to the foreign exchange markets for the four BRIC economies. South African markets show the opposite, with most of the volatility spilling from the Rand to the JALSH index. With the exception of South Africa and Russia, the findings from the cross-market, cross-country analysis of BRICS financial markets contradict the results obtained from the cross-market, in-country analysis. The results in this section provide more support for stock-oriented models except for South African markets.

5.3.2.2. Rolling sub-sample analysis

The full sample analysis assumes that volatility remains unchanged throughout the sample period and only provides the average of volatility spillovers over time. Thus it ignores increases in price and volatility that are consistent with major financial and currency crises. In order to take into account these major economic and financial events, we employ a time-varying volatility spillover index. We follow Diebold and Yilmaz (2009, 2012) and calculate volatility spillover over time using a 200 day rolling sample window and a forecast horizon of 10 days.

Dynamic volatility in BRICS Stocks

Figure 5.3 below plots the time-varying volatility spillover for BRICS equity markets. As expected the figure shows that spillover indices are not constant over the sample period. Furthermore, major economic and financial events are associated with increases in the volatility spillover in the equity markets. This is consistent with Diebold and Yilmaz (2009) who investigate volatility spillovers between 19 equity markets and find that the spillover index displays clear peaks during crises events. During crises periods, it can be observed that volatility spillovers move higher than the average range of 20%-40%. In particular, volatility spillovers rise from around 30% to 46% during the Asian Financial Crisis (1997-1998). Spillovers then drop briefly and rise again during the 1998 Brazilian currency crisis. After that spillovers fall and range between approximately 9% and 40% until 2006. Although spillovers were lower between 1998 and 2006, the spillover index shows some peaks – that are also associated with BRICS currency crises and other major global events. Specifically, peaks in volatility spillovers are observed during the 1999 Russian debt crisis, the tech stocks bubble burst in 2000, the September 11, 2001 attacks and the subsequent Gulf War in 2003. Also evident is the increase in volatility spillovers above 30% in 2001 to 2002 – a period associated with the South African currency crisis and increased volatility in global markets due to the events in the US.

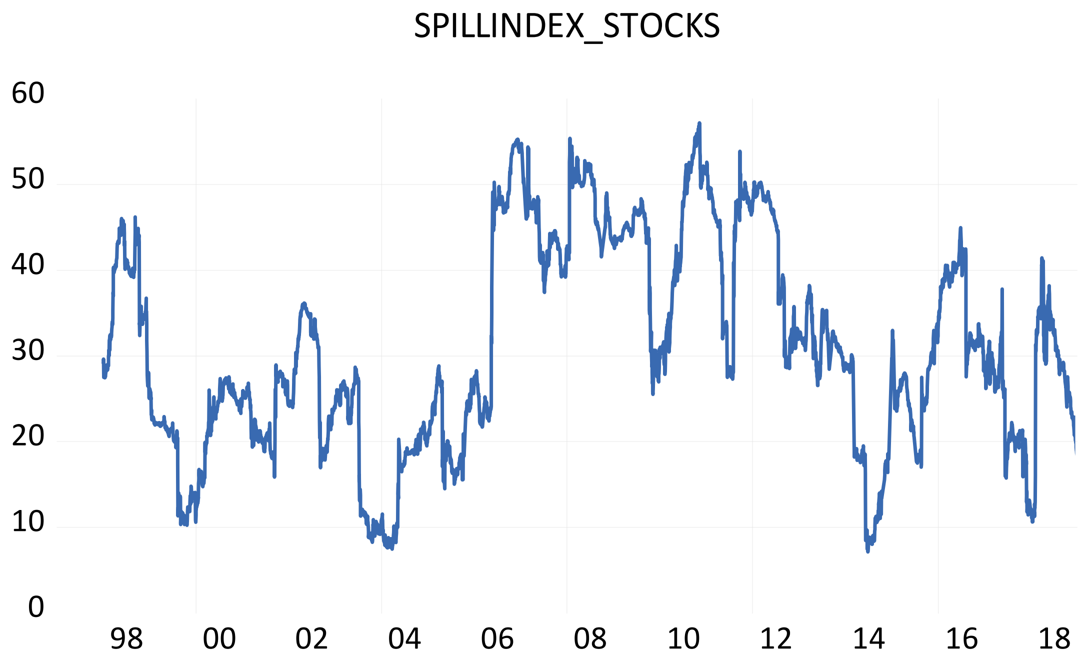

Figure 5.3: Time-varying spillover index for BRICS Stocks

From mid-2006 to the end of 2009, volatility spillovers increase significantly, ranging around 40% to 55%. The spike in volatility in 2006 is associated with the oil crisis which resulted in the US Federal Reserve Bank's decision to implement contractionary monetary policy and the subsequent rise in US interest rates to 5.25% in June (Diebold & Yilmaz, 2009) and Yilmaz (2010). This precipitated the flight of capital from many emerging stock markets, and is evident in the decline in BRICS stock market returns shown in Appendix A. The significant increase in volatility levels in the pre-crisis period of the GFC and during the crises may provide some evidence against the decoupling hypothesis, as contagion is seen even in the pre-crises period in contrast to Dimitrou, et al. (2013) and Mensi, et al. (2016). However the results are consistent with Jin and An (2016). Nonetheless, because our study does not actually test spillovers between the US and BRICS stock markets, we cannot make a definitive conclusion on this as we do not know whether the relationship is unidirectional or bidirectional. The spillover index falls to around 25% after the GFC but subsequently peak again throughout the Eurozone debt crisis.

The next significant increases in volatility spillovers are in 2014 to 2016. This period is associated with a series of several crises in emerging markets, the commodities market crash (which affected several emerging markets that are major exporters of commodities, such as Brazil and Russia), the Brazilian economic crisis, the Russian currency crisis and the Chinese stock market crash. It also coincided with the Taper tantrum crisis following the US Federal Reserve's suspension of Quantitative Easing (tapering program) and the 2016 United Kingdom European Union membership referendum (Brexit) which led to increased uncertainty in global stock markets, and volatility in currency markets – especially those of emerging and developing economies due to capital flight. A final spike in spillovers is observed in 2018 which may be associated to the US-China trade war and/or the Turkish Lira crisis.

Dynamic volatility in BRICS Currencies

Figure 5.4 below plots the time-varying volatility spillover for BRICS foreign exchange markets.

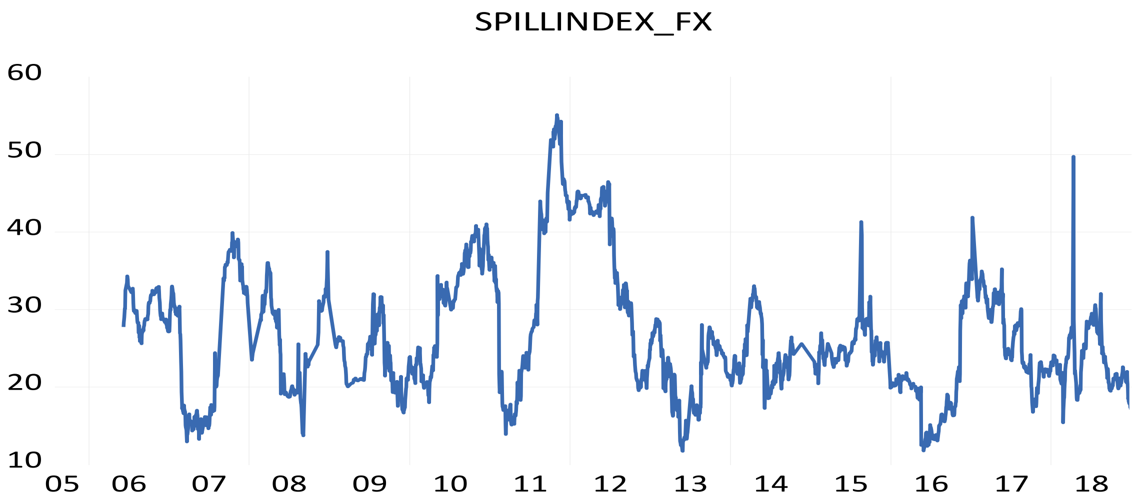

Figure 5.4: Time-varying spillover index for BRICS exchange rates

As expected, the volatility spillover index increases during turmoil periods. This is in line with Coudert, et al. (2011) who show that major crises events can trigger a surge in the exchange rate volatility in emerging markets. During crises periods, it can be observed that volatility spillovers move higher than the average range of 15% - 35%. A significant increase in volatility spillovers from around 15% to 40% can be observed in 2007. Spillovers remain around 30% throughout the GFC and decline towards the end of 2009 but increase again during the Eurozone debt crisis in early 2010. In 2011-2012 when the crisis dramatically worsened, spillovers in exchange rates peaked from 20% to 55%, the highest they were throughout the sample period.

In 2015, the volatility spillover index shows another spike. This may be associated with the Brazilian crisis and the Russian currency crisis triggered by sanctions against it for invading Ukraine. This is expected as we have seen that the Real and the Ruble are net transmitters of volatility to other BRICS currency markets. Another peak in volatility is seen at the end of 2016 and a larger one, up to 50%, in 2018. These are also associated with turmoil episodes (Brexit and the Turkish Lira crisis which affected many emerging market currencies, especially ZAR).

Cross-market, in-country rolling window analysis

Figure 5.5 shows volatility spillovers between equities and foreign exchange markets of BRICS. Brazil and Russia show the highest spillover measures, above 40%, followed by South Africa and India. China has the lowest spillovers – its highest index measure is 14% reported in 2018 due to the US-China trade war. This may provide evidence for the trade flow-oriented model as suggested by Sui and Sun (2016) who argue that trade flows between the US economy and BRICS significantly affect firms' performance and as a result stock markets.

We note that spillovers between equities and foreign exchange markets are higher during country-specific events. Other common periods of high volatility coincide with the 2006 oil crisis and announcement of increased interest rates by the US Federal Reserve, the 2010-2012 Eurozone debt crisis, the Chinese stock market crash, in which the SSEC index fell 43% in just over two months from June to August 2015 (Riley & Yan, 2015; Lee, 2015), and the emerging markets currency crisis and US-China trade war.

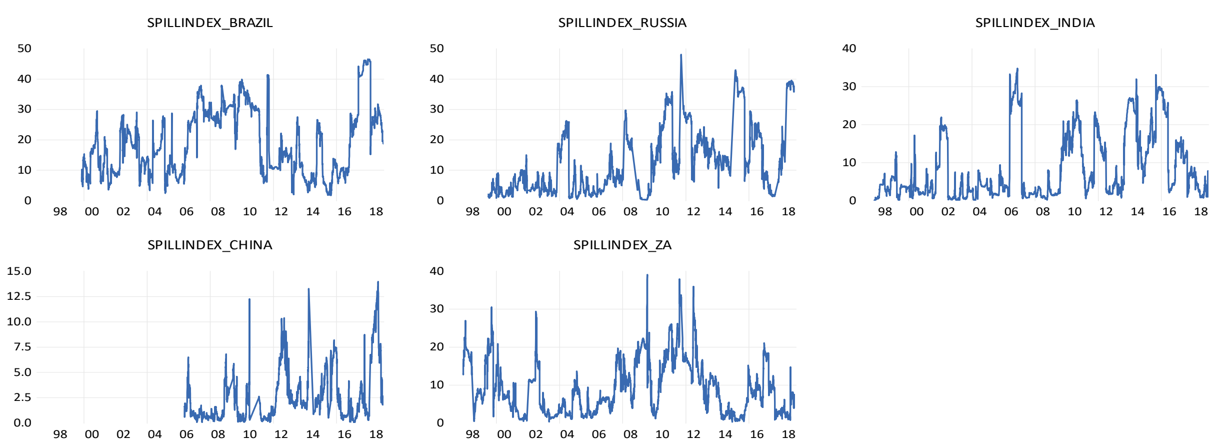

Figure 5.5: Time-varying spillover indexes - BRICS cross-market, cross-country analysis

Only Brazil showed significant increase in volatility spillovers between its equity and foreign exchange market throughout the period of the GFC. Volatility spillovers increased in other BRICS countries after Lehman Brothers collapsed until the end of the crisis except for India whose volatilities were relatively low throughout the crisis period with the exception of the small peak after September 2008. China's volatility spillovers were also relatively low which was expected because China instituted a hard peg against the US dollar during the period. Volatility spillovers increased significantly for the BRICS markets during the EDC. This is expected under the trade-oriented flow model as EU is the largest single export destination for all BRICS countries except China (the US is China's biggest export destination, followed by the EU).

Cross-market, cross-country rolling window analysis

Figure 5.6: BRICS cross-country, cross-market spillover index

Figure 5.6 shows that over the sample period, BRICS cross market spillover measures have generally been high. When looking at both equities and foreign exchange markets in aggregate, we see more evidence of contagion during turmoil periods than looking at individual markets. While they never go over 100%, we see clear spikes in volatility spillovers associated with turmoil periods that have already been discussed. Of note is the spiked from around 35% to over 55% in 2006, the fall in volatilities at the end of 2006 followed by the sharp increase 40% to around 59% in the first quarter of 2007 and another spike to over 60% in the third quarter of 2007. Volatility spillovers remained over 40% throughout the GFC period and increased to over 60% during the EDC, even reaching 70% after the first pan-European stress test results of the banking sector were published. Another noteworthy spike is the increase of the volatility spillover index to over 60% at the beginning of 2015, possibly associated with the Brazilian crisis. This is expected as we have seen that the Bovespa index is the largest transmitter of volatilities to other BRICS markets – it makes sense that shocks originating from the Brazilian stock market will reverberate to other BRICS markets so sharply. Another increase in 2015 is associated with the Chinese stock market crash, although it is not as large (50%). This is interesting because one would expect the bigger Chinese market that is also the largest in terms of intra-BRICS trade, to dominate volatility transmissions to other BRICS economies more than Brazil. However, this is not the case. As we have seen, the Chinese equity and exchange rate markets are not very integrated to other BRICS markets.

Directional Spillovers

This section focuses on directional spillovers for each of the BRICS equity and foreign exchange markets.

Equity markets

The graphs in Appendix G show the volatility transmitted or given to other markets and the volatility received from other markets respectively. We note that all BRICS countries have volatile spillovers as expected of markets from emerging economies. We also observe that all BRICS stock markets transmit more volatility to others during crisis periods. Similarly, they receive more volatility from other markets during crisis periods. The directional spillovers given increase to around 60% and more during volatile periods. Directional spillovers received from other markets demonstrate even more variation – from relatively low levels during tranquil periods to very high levels during volatile periods. For example, China and Brazil receive on average 10% and 30% of shocks from other BRICS markets respectively during tranquil times but spillovers spike up to 160% during crisis periods. This is evidence of contagion. China has the lowest volatility transmitted to other markets, particularly before the GFC. In addition, it has the lowest volatility received from other markets supporting the position that the Chinese stock market is still not as integrated to other BRICS markets.

The net directional spillovers shown in Figure 5.7 below are given by the difference between volatility transmitted to other markets and volatility received from other markets confirm that Brazil and South Africa are net transmitters of volatility. In addition, they indicate that IBOV dominates other BRICS stock markets followed by JALSH index.

We also note that South Africa is a net receiver of volatility during country-specific crises. This is in contrast to other BRICS markets that are net emitters of volatility during country-specific crises. For example, during the Brazilian crises, the Russian crises and the Chinese stock market crash, these three countries are net emitters of volatility to others. This could be due to their market size relative to other BRICS markets.

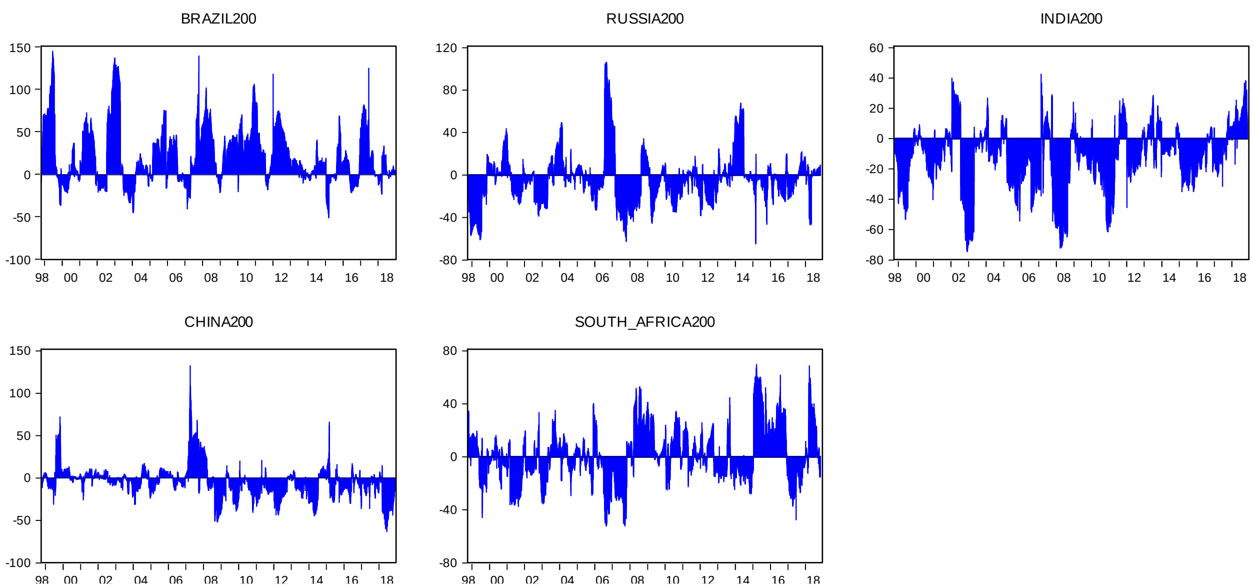

Figure 5.7: Net Directional Spillovers - BRICS Equity Markets

Foreign exchange markets

BRICS currencies are not as integrated as their stock markets. With the exception of the Brazilian Real and the South African Rand, the other exchange rates volatility spillovers are generally low throughout the sample period. The exchange rates are all volatile, showing a lot of variation between tranquil periods and volatile (crises) periods. This provides further evidence for contagion.

Figure 5.8 demonstrates that the Brazilian real dominates the other markets – transferring the most volatility to them, especially during crisis periods. Volatility spillovers from the Real to other markets spiked to over 200% during the EDC. As expected the Chinese Yuan is the most stable of the BRICS currencies transferring very low shocks to other markets until the Yuan was allowed to float freely in 2015. Our results show a very significant peak in volatilities transmitted then – from around 40% to close to 120%.

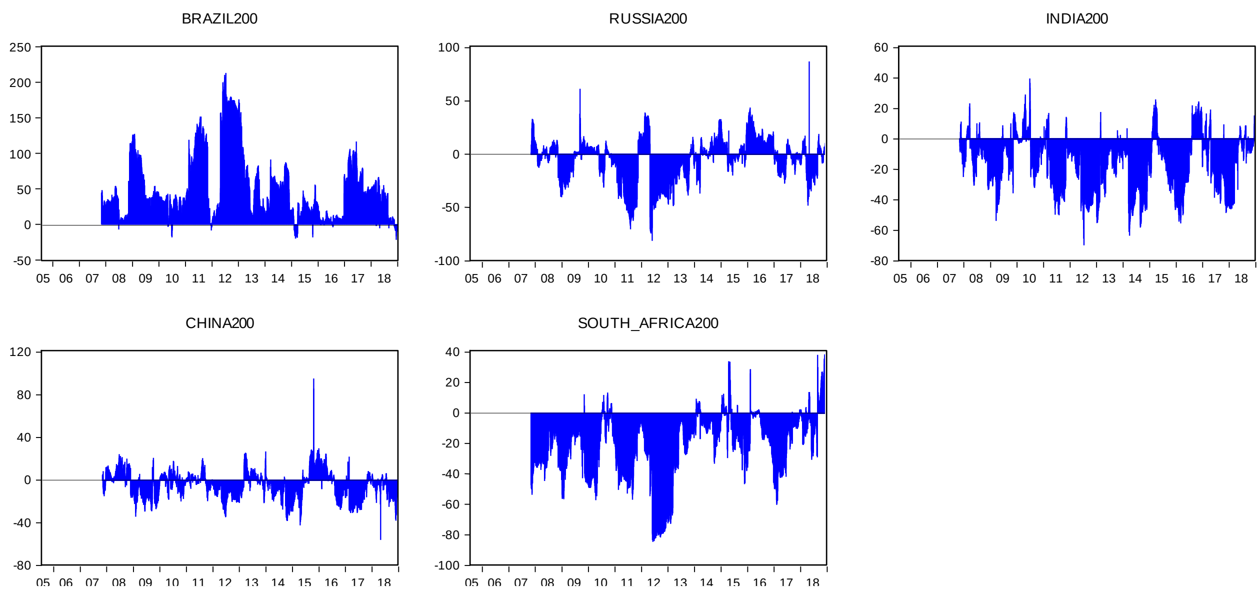

Figure 5.8: Net Directional Spillovers - BRICS Exchange Rate Markets

In addition, we find that Brazil is the lowest recipient of volatilities from other exchange rates whereas South Africa, India and Russia receive most of the shocks from other BRICS currencies. This is also expected as the Russian Ruble and the South African Rand are known to be among the most volatile currencies in the world. The high variations in exchange rates may be due to prices of imports and exports, especially the prices of oil and other commodities, which have an inflationary effect. China receives a lot more volatility than it gives – this may also be due to volatility in global prices. Because China and India are major exporters of manufactured goods, foreign demand, which can be very depressed during recessionary periods, significantly affects their exchange rates. We examine these further in the section on determinants of contagion.

Equity & Foreign Exchange Markets

The net directional spillover reported in Appendix G confirm that IBOV is the largest net transmitter of volatilities to other BRICS markets. In terms of currencies, the Brazilian Real also dominates other BRICS currencies. And as expected, South Africa and India's equity and exchange rate markets are large net receivers of volatility from other BRICS markets. RTSI also transmits a lot of shocks to other BRICS markets on average while the Chinese markets are stable, transmitting and receiving very little shocks from other BRICS markets. Although we observe very high peaks in the Chinese Yuan in 2010 (around 140%) and 2015(>200%). These movements coincide with changes in the Yuan exchange rate regime, to a managed float at the end of the GFC and when it was allowed to float freely in 2015.

5.3.3. PANEL DYNAMIC OLS REGRESSION

The results in this section are presented in three subsections. We first analyse the properties of our panel data by conducting breakpoint tests for both equities and exchange rate spillovers. We then test for cross-dependencies in the panel dataset and conduct panel unit root tests. Next we test for cointegration between the data series. Subsequently we estimate the Panel DOLS regressions and lastly we check whether the regressions are spurious or whether our model is adequate.

5.3.3.1. Analysis of Panel Data

Multiple Breakpoint Test

The results of the Bai-Perron multiple breakpoint test for the equities and exchange rate spillover indices are shown in Appendix H. Both data series have five breakpoints throughout the sample period. All estimated break dates are associated with known crises periods discussed in Section 5.5.

Cross–section dependency Tests

The results of the cross section dependency tests are reported in Appendix H. The null and alternative hypotheses for the three test are:

H_O: No cross-section dependence (correlation) in residuals

H_1: Some cross-section dependence

The test-statistics are significant for all three tests at a 1% significance level. We therefore reject the null hypothesis and conclude that for all sample periods the residuals from the standard panel regression will be contemporaneously correlated and this should be corrected for.

Panel Unit Root Tests

The null and alternative hypotheses for the tests are:

H_O: Unit root

H_1: Some cross-sections without Unit Root

Specifically, the null hypothesis of the Levin, Lin and Chu (2002) and Breitung (2000) tests are "Panel contains common unit root" while the null hypothesis for the Im, Pesaran and Shin (2003), Fisher-type ADF and PP tests are "Panel contains individual unit root".

The test results are presented in Appendix H. They indicate that most of our variables are stationary at levels, whereas others (CPI, VIX, TED and Interest rates) are made stationary by differencing. Our panel data sets also have different orders of integration. Because some of our data are unit root non-stationary, we cannot conduct static OLS as some of the estimates will be biased downwards and it can result in spurious regressions.

The limitations of our tests are that Eviews 10 does not have second generation unit root tests for panel data. Since our data has cross-section dependencies, it would have been more accurate to use second generation test instead of first generation tests. However, as already stated, the IPS test does take into account possible serial correlation and panel heterogeneity.

Cointegration Tests

The null and alternative hypothesis for both tests are:

H_O: No cointegration

H_1: Some variables are co-integrated

The results of the tests are reported in Appendix H. For both samples, the Fisher statistics from trace tests and maximum-eigenvalue tests, are significant for all variables. Thus, we reject the null hypotheses and conclude that our variables are co-integrated.

5.3.3.2. Results of the Panel DOLS Regression

Because the number of observations in between breakpoints is too short to allow for subsample estimations with lags and leads, regressions are estimated on only one full sample for both equity and exchange rate spillovers. The sample period for BRICS equity markets covers 2003Q3 to 2018Q4, this coincides with the first structural break in the series. The sample period for determinants of exchange rate spillovers starts from 2007Q4.

Model 1 Results

Tables 5.9 and Table 5.10 present the results of Model 1 and Model 2 of the panel regression of directional volatilities in BRICS equities and foreign exchange markets, respectively. The regression tests whether macroeconomic variables explain changes in volatility spillovers.

Determinants of Directional Spillovers in BRICS Equity Markets

To analyse the results of the panel DOLS regression we first consider trade linkages variables. The results suggest that trade balance and the degree of openness of BRICS economies are both insignificant at a 5% level in explaining volatility transmission to other equity markets. However, both variables can explain volatility spillovers received from other BRICS equity markets. The trade balance coefficient is negative on the “to/give” side but positive on the “from/receive” side. This is consistent with our a priori expectations. In economic theory, a higher trade balance is associated with macroeconomic stability, as such we expect countries with a higher trade balance to be less susceptible to crises. However, if shocks originate from an importing trade partner, the deterioration in the importing country's fundamentals would lead to a reduction in corporate profits and increased volatility in that economy which can spill over into the exporting country (Leung, et al., 2017). This would explain the negative relationship between a country's trade balance and volatility spillovers given to other markets on the "to/give" side. This argument would also explain the positive relationship shown on the "from/receive" side. Countries with lower trade balance are more prone to shocks in their stock markets, and as such, and would receive more volatility from other BRICS markets

Table 5.9: Model 1 - Panel DOLS Results

Variables	*Equities Spillover*		*Exchange Rate Spillover*	
	TO (GIVEN)	FROM (RECEIVED)	TO (GIVEN)	FROM (RECEIVED)
GDP	-299.8388 (0.3337)	-521.2007*** (0.0034)	2776.591*** (0.0000)	-2825.786*** (0.0011)
TRADE_BALANCE	-1.03E-09 (0.9545)	2.44E-08** (0.0211)	1.41E-07*** (0.0001)	-2.87E-07*** (0.0000)
OPEN	250.4555 (0.0176)	-407.2519*** (0.0082)	528.3599*** (0.0012)	-3329.804*** (0.0000)
RES	-241634.5*** (0.0000)	-87774.91*** (0.0000)	-94163.04** (0.0339)	-378368.6*** (0.0000)
VIX	-270.0337*** (0.0000)	-59.16472*** (0.0000)	68.77965 (0.2073)	-594.7470** (0.0000)
GOLD	1982.566*** (0.0000)	169.9906 (0.4811)	-4537.386*** (0.0000)	13891.61*** (0.0000)
OIL	-2027.770*** (0.0000)	-279.7774 (0.2636)	3315.728*** (0.0007)	-5004.463*** (0.0031)
CPI	-204.9182*** (0.0000)	164.7190*** (0.0000)	-183.2060** (0.0180)	264.3154* (0.0513)
INTEREST	241.8582* (0.0709)	-383.9088*** (0.0016)	1062.946*** (0.0000)	-826.3181*** (0.0000)
TED	13045.27*** (0.0073)	-10395.02*** (0.0001)	-24105.84*** (0.0000)	-36306.25*** (0.0002)
PRI	-4609.229 (0.1033)	-3593.018 (0.0570)	179.7966 (0.0000)	-28599.54*** (0.0023)
R-Squared	0.925690	0.929874	0.985543	0.969580
Adjusted R	0.802975	0.814069	0.877113	0.672687
Observations	290	290	205	205

Notes: ***, ** and * represent significance at 1%, 5% and 10%, respectively.

The numbers in parenthesis are p-values

In constrast to the trade balance, the trade openness coefficient is positive but insignificant on the "to/give" side but negative and highly significant on the "from/received". This suggests that the more open an economy the less volatility it receives from other BRICS stock markets. The negative relationship is expected as the more open an economy, the more it can expand which makes it more resilient to economic crises. This result is consistent with Comelli (2014). Another interesting observation, is the size of the trade balance coefficient which is infinitesimal (<0.0001) in comparison to the size of the openness coefficient indicating that openness of BRICS economies has greater impact in volatility transmission than their trade balance.

Secondly, we consider financial and political risk indicators. The TED spread coefficient is highly significant in both directions but the correlation is positive on the "to/given" direction and negative on the "from/received" direction. The positive relationship in short term interest rate differentials is to be expected as increases in global uncertainty (during crises periods) often lead to capital flight from emerging market economies to safe havens and investors require a higher premium for holding emerging market assets. The rise in EM interest rates implies a higher TED spread. The converse is also true; during tranquil periods, TED spreads are lower and so are volatility spillovers. This results are consistent with Leelahaphan, et al. (2015). The negative relationship implies that countries with lower (higher) TED spreads receive more (less) volatility spillovers from other BRICS markets. This is contradictory to our a priori expectations. We suggest that the reason for this could be countries with higher interest rate differentials being more volatile during turmoil periods, as just discussed. If contagion is present, such countries will transmit that volatility to countries with lower TED spreads. Thus the TED spread variable in our regression is not a leading indicator for crises but rather a response to that shocks outside being transmitted to the economy.

A change in a country's foreign reserves as a percentage of GDP is significant and negatively related to volatility spillovers to and from other BRICS markets. An increase (decrease) in foreign reserves as a percentage of GDP signals financial stability (instability). Countries that are more stable relative to others tend to attract more investments and portfolio flows which raises corporate incomes, and reduces the likelihood of volatility in the stock markets. Thus an increase in a country's holding of foreign reserves leads to a decrease in the volatility it transmits to and receives from other markets. This findings are consistent with the results of Comelli (2014) who suggests that growth in foreign exchange reserves is negatively related to crises incidence.

The political risk measure, PRI, has a negative correlation that is mildly significant on the directional spillovers received from other markets. We observe the same negative relationship on the “to/given” side but it is not significant. The negative correlation is consistent with a priori expectations that the more (less) stable a country is politically, the more (less) resilient it is to negative shocks from other markets. This negative relationship is also substantiated by Bekaert, et al. (2014) who find that countries with lower economic and political risk (a high PRI) reduced the vulnerability of their economies and mitigated contagion.

Next we turn to our macroeconomic fundamental indicators, growth in GDP, inflation rates and long term interest rates. Growth in GDP has a negative relationship with volatility transmission to other BRICS stock markets and a positive correlation with volatility transmissions from other BRICS markets. The coefficient is not significant on the “to/given” direction but it is significant on the “from/received” direction. This implies that countries with higher GDP growth rates receive more volatility from other markets. This is inconsistent with a priori expectations. We put forth the same explanation we applied for TED spreads that countries with weaker fundamentals are more volatile during turmoil periods, and markets tend to overreact to bad news, and would therefore amplify volatility in those markets. If contagion is present, such countries will transmit that volatility to countries with better fundamentals (higher GDP growth, in this instance).

We observe a similar correlation between inflation rates and directional spillovers to and from other markets. However, with CPI, the coefficients are highly significant in both direction. The positive relationship observed on the “from/received” direction is consistent with a priori expectations and is substantiated by several studies (Komulainen & Lukkarila, 2003; Kamiri & Voia, 2019; Rao & Padhi, 2018; Tamgac, 2011) .The negative relationship between inflation rates and stock market contagion was not expected. Nonetheless, it is validated by Leung, et al. (2017). Our explanation for this is that while inflation is linked to macroeconomic instability, rising price levels are also associated with economic booms and in turn, increases in stock market returns. During turmoil periods, when volatility spillovers are high, output growth tends to decline (as seen above), which can lead to a reduction in demand and decrease price levels. A reduction in price levels (falling inflation) associated with lower growth results in a fall in stock price returns. The fall in returns can lead to investors moving their assets from that country, and if there is contagion, this would spill over to other emerging BRICS markets with better fundamentals.

Long-term interest rates show a positive but mildly significant relationship to directional spillovers transmitted to other equity markets but they are highly significant and negatively related to directional spillovers from other markets. The negative relationship is also consistent with Leung, et al. (2015). It suggests that when interest rates increase (decrease) it leads to a decrease (increase) in volatility transmission from other markets. This seems counterintuitive as we expect interest rates to rise for most emerging market economies during crises periods because they are perceived to be risky, which is what we observe in the positive relationship with volatility transmission to other markets. Prasad, et al. (2018) explain that during crises periods (when volatility spillovers are higher) investors adjust their portfolios from stock markets to bond markets which would raise interest rates. To explain the negative relationship, we apply the same arguments for lower inflation rates during crises that during turmoil periods, when volatility spillovers are higher, Reserve Banks tend to take an expansionary monetary policy and lower interest rates in order to avoid economies going into recession or experiencing prolonged recessions (Kaminsky & Reinhart, 1999). As a result, interest rates will be very low during periods of contagion (high volatility spillovers) but higher during non-crises periods and leading up to them. Market participants have also come to expect lower interest rates during turbulent stock market periods in order to attract or keep investments.

Lastly, we consider the results obtained for our three control variables for global risk, US volatility index (VIX), gold prices and oil prices. All are significant in explaining directional spillovers to other markets but only VIX is significant on the “from/received” direction. The positive relationship between US VIX and directional spillovers received from other BRICS markets is consistent with Hwang, et al. (2013) and Leelahaphan (2015) who find a positive relationship between VIX in both given and received directional spillovers of equities. The negative relationship observed between US VIX and spillovers on the “to/give” direction can be explained by Mensi, et al. (2014) who find that BRICS stock markets tend to co-move with global markets when are bullish but they are independent when global markets are bearish, except for Brazil. Bekaert, et al. (2014) also find that the effect of VIX on EM stock markets decreased significantly during the GFC. Together with our results, this could provide evidence of decoupling of BRICS stock markets from US stock markets. It could also explain why emerging stock markets were not as affected by the GFC which originated from the US.

With regard to commodities, gold prices have a significant positive relationship with directional volatilities to BRICS stock markets. This is in line with our expectations as gold is considered a safe haven investment and its price would also be expected to rise in times of increased volatility as demand for it increased. These findings are consistent with the results of Leelahaphan, et al. (2015) who theorize that during crises periods, investors diversify their portfolios from equities to commodities and Kang, et al. (2017) who find that volatility in commodity markets increase during crises. Oil prices however, indicate a negative relationship with directional spillovers to other markets. This makes sense as all BRICS countries (except South Africa) are major oil producers thus an increase in oil prices raises stock index returns, attracting more investment into the markets and therefore reducing the likelihood of a crises event. Thus their markets will be relatively stable which would lead to lower volatility transmissions. Oil and gold prices do not explain volatility transmission from other markets. This suggests that country-specific factors are more important drivers of volatility spillovers than global factors in BRICS stock markets.

Determinants of Directional Spillovers in BRICS Exchange Rate Markets

To analyse the results of the panel DOLS regression on directional volatility spillovers in BRICS foreign exchange markets we first consider trade linkages variables. The results suggest that trade balance and the degree of openness of BRICS economies are highly significant in explaining volatility transmission to and from other foreign exchange markets. Their coefficients are both positive on the “to/given” direction but negative on the “from/received” direction which suggests that markets with higher (lower) trade balance, that are more (less) open transmit more (less) volatility to other BRICS exchange rate markets. The converse is also true; markets with higher (lower) trade balance, that are more (less) open receive less (more) volatility from other markets.

Intuitively, the positive relationship between trade balance and openness with spillovers makes sense. This is also in agreement with previous studies that show that the probability of a currency crises in emerging markets increases with trade openness and trade linkages (Komulainen & Lukkarila, 2003; Kamiri & Voia, 2019). However, other studies show the opposite (Comelli, 2014; Rao and Padhi, 2018). Their studies indicate that trade balance is negatively related to crises incidence. These can explain the negative relationship on the "from/received" direction. The more open an economy is, and the higher its trade balance, the less susceptible it will be to shocks from other markets, and vice versa. Rao and Padhi (2018) also explain the twofold effect of openness to trade. They argue that a more open economy has greater chances of expansion than a closed economy, which makes it more resilient to crises. However, an open economy is also more exposed to external shocks and contagion. This argument can explain why more open economies transmit more shocks to others while they receive less shocks from others.

Secondly, we consider financial and political risk indicators: TED spread, percentage change in foreign reserves and political risk index. The TED spread and percentage change in foreign reserves are significant and negatively related to volatility transmission in both directions. One of the stylized facts on currency crises is increasing interest differentials (Fontaine, 2005). Thus the negative relationship with TED spreads in both directions is inconsistent with our a priori expectations. It suggests that higher (lower) interest differentials are associated with lower (higher) volatility transmission among BRICS currencies. We again theorize that this could be the effect of loose monetary policy during turmoil periods that results in lower interest rates globally. With short-term interest rates in advanced economies reaching the zero lower bound (ZLB) (as seen during the GFC), interest differentials may narrow as EMs also cut their interest rates. This could result with TED spreads being higher during stable periods but lower during more volatile periods when directional spillovers are high.

With regard to percentage change in foreign reserves, the negative relationship observed is consistent with a priori expectations. The increase (decrease) in foreign reserves as a percentage of GDP signals financial stability (instability). Thus an increase in a country's holding of foreign reserves leads to a decrease in the volatility it transmits to and receives from other markets. Furthermore, countries with higher reserves are less likely to experience speculative attacks on their currencies and therefore less likely to experience currency crises. This findings are consistent with the results of Comelli (2014) and Berg and Pattillo (1999) who suggests that growth in foreign exchange reserves is negatively related to currency crises incidence.

Turning to political risk, we observe a positive but insignificant relationship on the "to/given" side and a negative but significant relationship on the "from/received" direction. We apply the same argument we made for equities spillovers that the more stable a country is politically (the higher the PRI), the less vulnerable it is to shocks from other markets.

Next we consider to our macroeconomic fundamental indicators, growth in GDP, inflation rates and long term interest rates. The coefficient of GDP growth is significant and positive in the "to/give" direction but negative in the "from/received" direction. This implies that economies with lower GDP growth rates transmit less volatility to others while they receive more volatility from other markets. This is consistent with Aka (2006) findings that low GDP growth rates are likely to increase the probability of currency crises.

We observe similar results to those in equities spillovers when we look at inflation rates: significant coefficients that are negative on the "to/given" direction but positive on the "from/received" direction. We apply the same explanation for the negative relationship that while inflation is linked to macroeconomic instability, rising price levels are also associated with economic booms and in turn, increases in stock market returns. During turmoil periods, when volatility spillovers are high, output growth tends to decline (as seen above), which can lead to a reduction in demand and decrease price levels. A reduction in price levels (falling inflation) associated with lower growth results in a fall in stock price returns. This can leads to investors rebalancing their portfolios and disinvesting in the country and result in increased volatility in exchange rate markets. If there is contagion, this would spill over to other emerging BRICS markets with better fundamentals. The positive relationship is consistent with expectations as rising inflation is associated with macroeconomic instability. In an inflation-targeting environment, an increase in inflation leads to contractionary monetary policy by Central Banks. This raises interest rates leading to a decline in borrowing and in turn a fall in investments. Which can lead to a crises event. These findings are consistent with other studies (Tamgac, 2011; Komulainen & Lukkarila, 2003; Rao & Padhi, 2018; Kamiri & Voia, 2019).

Long term interest rates are highly significant and positively correlated with directional spillovers to other BRICS exchange rate markets, however, they are negatively correlated with directional spillovers from other currency markets. These results are the same relationship as those found when we looked at determinants of equity spillovers and we apply the same reasoning. During crises periods interest rates will rise for most emerging market economies that are perceived to be risky. Higher interest rates reflect a higher risk premium and fears about currency devaluation (Kaminsky & Reinhart, 1999). This increases volatility in the markets and as a result spillovers increase. This results are supported by Rao and Padhi (2018). On the other hand, lower interest rates signal loose monetary policy during turmoil periods (when spillovers are high). This explains the negative correlation with volatility spillovers received from other markets.

Our global risk factors, measured by VIX, gold prices and crude oil prices are found to be highly significant in determining exchange rate market volatility across BRICS exchange rate markets in both directions except for VIX, which is insignificant in the “to/given” direction.

VIX has a negative relationship to foreign exchange spillovers received from other markets. This implies that when VIX levels are high, BRICS markets receive less volatility from others. These results are compatible with the findings of Mensi, et al. (2014) that BRICS markets tend to co-move with global markets when are bullish (shown by lower levels of VIX) but they are independent when global markets are bearish (high levels of VIX). This independence with uncertainty in the US market could provide evidence for the decoupling hypothesis.

Our results suggest that gold and oil prices have opposing effects on volatility transmission in the foreign exchange markets. During periods of high volatility spillovers when gold prices are high, volatility transmitted to other markets reduces and volatility shocks received from other markets increase. But when oil prices are high, volatility transmitted to other markets increases and shocks received from other markets decrease.

Increased volatility in global equity and foreign exchange markets leads to investors disinvesting in them and investing in commodities, such as gold to hedge their portfolios. This propagates volatility increases in the markets which results in increased spillovers between the markets. It therefore, explains the positive relationship between gold prices and directional spillovers from other markets. These results are in line with a priori expectations. On the other hand, four of the BRICS countries, China, Russian Federation, South Africa and Brazil are among the world's largest gold producers (Els, 2019). Increases in gold prices during periods of heightened global volatility have positive effects on their currencies. This explains the negative relationship between gold prices and directional spillovers to other BRICS currency markets.

Oil prices have an opposite effect. Higher oil prices lead to uncertainty in global markets which increases the likelihood of capital flight from emerging markets and as a result volatility in the foreign exchange markets. Hence the positive relationship between oil prices and directional spillovers to other currency markets. Another explanation put forth by Diebold and Yilmaz (2012) is that during some crises episodes (2002-2003, 2004-2005, and the first half of 2008 and during 2009) volatilities in oil prices rose and spilled over to other markets - stocks, bonds but mostly to the foreign exchange market. We explain the negative relationship between oil prices and spillovers received from other currency markets by applying our previous analysis for equity spillovers that since all BRICS countries (except South Africa) are major oil producers, an increase in oil prices raises stock index returns. This would in turn have a positive effect on BRICS currencies. Thus their markets will be relatively stable which would make them more resilient to volatility transmissions from other markets.

Model 2 Results

In Model 1, the DOLS regression models did not include any dummy variables as the models had controlled for structural breaks using the global risk factors (VIX, gold and oil prices) as transition variables in the model. However, due to their unexpected negative coefficients and the variables being found insignificant in some of the estimated models, and as we have noted that global factors may have less effect on BRICS stock markets than country-specific factors, we run another model which includes dummy variables for some of the breaks identified. We cannot add dummies for all the breaks because they create multicollinearity problems in the models. We employ a maximum of two break dummies to the equities spillover model and one break dummy for the exchange rate spillover model. The results of Model 2 are reported in Table 5.10.

Table 5.10: Model 2 - Panel DOLS Results

Variables/Dependent Variable	*Equities Spillover*		*Exchange Rate Spillover*	
	TO	FROM	TO	FROM
GDP	-633.5003* (-1.851071)	152.2964 (-2.621672)	8494.005*** (6.953722)	-18418.20*** (-24.33717)
TRADE_BALANCE	-3.98E-08** (-2.135630)	-5.73E-08*** (-4.527249)	5.76E-07*** (12.28811)	-6.24E-07*** (-23.33582)
OPEN	860.5341*** (3.314900)	-1268.932*** (-6.899304)	6283.390*** (15.68896)	-2535.363*** (-8.673304)
RES	-168164.8*** (-7.160153)	17606.60 (1.307047)	-3847912*** (-23.23141)	-2605928*** (-37.93593)
CPI	-425.9961*** (-10.63162)	60.64389** (2.270748)	1359.352*** (5.359442)	2566.692*** (19.53245)
INTEREST	-5915.064*** (-5.466224)	-5304.582*** (-4.371595)	728.0741 (1.441201)	-4116.003*** (-18.49051)
TED	23597.22*** (4.996757)	-11089.29*** (-3.874914)	-39878.24** (-3.118467)	-52309.14*** (-9.060511)
PRI	5415.981** (2.033958)	-2564.362 (-1.399072)	-187906.3*** (-17.06644)	-182002.3*** (-22.18820)
VIX	-225.1187*** (-10.02348)	64.61647*** (3.853860)	1457.769*** (10.29155)	101.0892 (1.079816)
GOLD	1829.684*** (4.508705)	954.4026*** (3.676175)	-38434.22*** (-15.30753)	32816.46*** (27.60244)
OIL	-359.3861 (-0.934161)	-0.629352 (-0.002482)	-29266.23*** (-10.95164)	-58918.04*** (-28.36172)
D_ONE2006Q2	-31.80886*** (-3.822373)	-21.95955*** (-4.048855)		
D_TWO2012Q2	-8.657114 (-0.1420)	13.85657 (3.581891)		
D_ONE2011Q3			-182.9963*** (-15.14148)	-5.827149 (-1.048601)
R-Squared	0.954613	0.949558	0.993770	0.990117
Adjusted R	0.829652	0.810679	0.841130	0.774889
Observations	290	290	206	206

Notes: ***, ** and * represent significance at 1%, 5% and 10%, respectively.

The numbers in parenthesis are t-statistics

The inclusion of break dummy variables increases the coefficient of determination (R-squared) and the adjusted R-squared slightly implying that the model with the dummy variables has slightly more explanatory power than Model 1. Comparing the models with dummies and our original models without dummy variables indicates significant differences in the signs of the coefficients and the significance of some variables.

In the "to/given" direction, Model 1 suggests that four of the independent variables, GDP, trade balance, and openness to trade, are not able to explain directional spillovers in BRICS equity markets. However, Model 2, shows that only the political risk index and oil prices are insignificant. These results are more consistent with to most of the studies we have already discussed above.

Further, we observe different signs of the coefficients of interest rates and the political risk index. In Model 2, interest rates are negatively related to directional spillovers to other BRICS countries. As we have already seen, lower interest rates during turmoil periods signal expansionary monetary policy to prevent a recession or, where one is already in progress, to shorten one (Kaminsky & Reinhart, 1999).

The coefficient of the political risk indicator is both positive and significant. The positive correlation deviates from a priori expectations. It suggests that a(n) decrease (increase) in PRI leads to an decrease (increase) in the amount of shocks a country transmits to others. We know that when political risk increases, investors disinvest in a country due to the increased uncertainty. This leads to a fall in stock prices and an increase in volatility in the stock markets of the country. However, our results suggest that these shocks are only country-specific (own country shocks) and are not transmitted to other markets.

In the "from/received" direction, the adjusted R-squared is slightly smaller in Model 2 and we observe a lot more difference between Model 1 and Model 2 in terms of the nature of the relationship between the explanatory variables and directional spillovers. In terms of significance of the variables, we see difference in GDP, gold prices and percentage change in foreign reserves held. In Model 2 gold prices are highly significant whereas Model 1 indicates that gold prices do not explain directional spillovers from other markets. On the other hand, percentage change in foreign reserves held are insignificant in Model 2 but significant in Model 1. These results are consistent with those obtained by Leelahaphan, et al. (2015). Likewise, positive and insignificant in Model 2 whereas it is negative and significant in Model 1. These results are contrary to a priori expectations however they are in line with Rao and Padhi (2018).

Although they are significant in both models, the signs of the coefficients of trade balance and VIX are different in the two models. Trade balance shows a negative correlation while VIX indicates a positive correlation. These results are consistent with a priori expectations as already explained that markets with a higher trade balance a less susceptible to contagion from other markets; and further the higher the VIX, the greater the risk aversion, the more volatility there is in emerging stock markets. If contagion is present, the increased volatility in the markets is transmitted to other markets.

To determine which model is a better fit, we conduct Wald-Chi squared tests in both models and we find that the coefficients of GDP, trade balance and openness to trade are actually significant. Thus, we conclude that for equity market spillovers, Model 1 is misspecified and the model with the break dummy is a better fit. Based on the above discussion, we suggest that the inclusion of the dummy variables captures the effects of the structural breaks during crises periods more effectively than the global risk indicators on their own.

Determinants of Directional Spillovers in BRICS Exchange Rate Markets

With regard directional spillovers given (to), the addition of the break dummy seems to increase the explanatory power of the model as shown by both the R-squared and the adjusted R-squared. Furthermore, all independent variables (except interest rates) are found to be significant in the model with the dummy variables whereas Model 1 suggests that VIX and PRI are insignificant. Further three variables, oil prices, inflation and PRI have opposing signs. As in equities spillovers, oil prices and PRI show a negative correlation to our dependent variable. Inflation rates however show a positive correlation. The signs of the coefficients of PRI and inflation are consistent with expectations. As explained in the previous section, a high PRI signifies low political risk, and thus the more stable the country and its financial markets. Therefore, the currency market will be more resilient to a crisis event. Whereas a higher CPI indicates macroeconomic instability. A rise in inflation rates, leads to contractionary monetary policy and as a result increased volatility in currency markets (Komulainen & Lukkarila, 2003; Kamiri & Voia, 2019). We expect the shocks to be transmitted to other markets in the presence of contagion.

In the "from/receive" direction, we find only two differences between models 1 and 2 although the addition of the dummy variable significantly increases the explanatory power of the model (as shown by the adjusted R-squared). In Model 1 all variables were found to be significant, although CPI was only mildly significant. In Model 2 all variables, with the exception of VIX are found to be highly significant. Once again we apply the results of Mensi, et al. (2014) that BRICS markets are independent when global markets are bearish (high levels of VIX). We also note that in model 2, the VIX is positively correlated to directional spillovers from other markets are expected but as it is not significant, we do not concern ourselves with it.

5.3.3.3. Diagnostic Tests

Appendix I reports the results of the panel unit root test after estimating the regressions. The null and alternative hypothesis for the tests are:

H_O: Unit root

H_1: Some cross-sections without Unit Root (Stationary)

For both Model 1 and 2, the test-statistics are significant for all four tests at a 1% significance level. We therefore reject the null hypothesis and conclude that for all sample periods the residuals from the standard panel regression are stationary and therefore the cointegrating regressions are not spurious regressions.

CHAPTER 6
FINDINGS, CONCLUSION AND RECOMMENDATIONS

6.1. INTRODUCTION

This chapter summarizes the econometric results of this study. Recommendations arising from the study are also discussed.

6.2. KEY FINDINGS OF THE STUDY AND CONCLUSION

Our results indicate strong interdependencies among BRICS equity and foreign exchange markets, except for China, which is relatively isolated from other BRICS markets. These results support the findings of Bekiros (2014), Wang, et al. (2016) and Lee and Lee (2019). Brazil, in particular its stock market, is the largest contributor of volatility spillovers to other BRICS markets. South Africa and India are large net receiver of the volatilities from other BRICS. In accordance with Bonga-Bonga (2018), our results provide strong evidence of cross-transmission and interdependence between Brazil and South African markets relative to other BRICS markets. Roughly 20% of static spillover is due to cross-country, cross-market spillovers. Furthermore, our results indicate that spillovers in these markets vary over time.

Moreover, we find that significant increases in volatility spillovers in both markets coincide with domestic and global crises periods such as the GFC, EDC, Brazilian crisis, Russian crisis and the Chinese stock market crash. This is consistent with Coudert, et al. (2011). We also notice significant spillovers linked to the US/China trade war and the Turkish Lira crisis. Volatility spillovers have sometimes spiked sharply from around 12% to 55%. This provides evidence for contagion effects in BRICS markets. We also find more evidence of contagion when looking at interactions between equity and foreign exchange markets in aggregate than looking at individual markets.

Looking at BRICS cross-country, cross-market static analysis, we find evidence of bidirectional volatility transmission between equity and foreign exchange markets of BRICS countries, except for India, which shows unidirectional volatility spillovers from its stock market to the exchange rate market. In aggregate, for all BRICS, except South Africa, shocks from the equity markets dominate the foreign exchange markets. This finding, which supports stock-oriented models, is consistent with several studies from both developing and emerging markets (Ajayi, et al., 1998; Aloui, et al., 2011; Choi, et al., 2009; Diebold & Yilmaz, 2012; Duncan & Kabundi, 2011; Bonga-Bonga & Hoveni, 2013; Chkili & Nguyen, 2014). The Chinese markets have the lowest connectedness among themselves. However, when looking at individual countries, Brazil India and South African foreign exchange markets dominate their equity markets, in support of flow-oriented models. Sui and Sun (2016) report similar findings and posit that stock-oriented models are not prevalent in most emerging countries. There are no interdependencies in the Chinese markets. These conflicting results, in terms of transmissions between individual countries and across all BRICS, explain the lack of consensus in the literature about direction of spillovers among BRICS economies.

We also investigate the determinants of contagion using directional spillovers (to and from) in BRICS equity and exchange rate markets. The results of our dynamic panel regressions suggest that all fundamental indicators considered and trade linkages measures such as GDP, inflation, interest rates, trade balance, and trade openness are major drivers of increased volatility spillovers (contagion) to other BRICS equity markets, while inflation, interest rates, trade balance, and trade openness are drivers of contagion from other markets. Furthermore we find that volatility transmission to and from other markets can be explained by global risk factors such as gold prices and VIX. However, in contrast to Mensi, et al. (2014), Model 1 indicates that oil and gold prices were insignificant in explaining directional spillovers from other markets. We posit that country-specific factors have more impact on BRICS volatility spillovers than global factors. Also, the VIX coefficient is negative, which suggest that BRICS equity markets were decoupled from global markets. However, when we account for structural change, we find no evidence for the decoupling hypothesis, in constrast to Dimitrou, et al. (2016) and Mensi, et al. (2016). Nonetheless, these findings are supported by Jin and An (2016) and are also consistent with the results of the BRIC stocks rolling sample analysis which showed significant increase in volatility levels both in the pre-crisis period of the GFC and during the crises. But as explained in the previous chapter, since our study does not explicitly test spillovers between the US and BRICS stock markets, we cannot make a definitive conclusion on this as we do not know whether the relationship is unidirectional or bidirectional. In the second model, oil prices, still fail to explain volatility transmission between BRICS stock markets. Our financial and political risk indicators suggest that changes in percentage foreign reserves, TED spread and PRI explain directional spillovers to other BRICS equity markets but only the TED spread explains directional spillovers received from other markets. Thus the TED spread is a better measure of financial risk in BRICS stock markets.

To explain contagion in BRICS exchange rate markets, we find that all fundamental indicators and trade linkages measures (except interest rates), explain volatility spillovers to and from other currency markets. Interest rates only explain volatility transmission from other currency markets. Additionally, all financial and political risk indicators can explain directional spillovers to and from other BRICS exchange rate markets. Lastly, we find that increases in volatility spillovers in the foreign exchange market can be explained by global risk factors such as commodity prices (gold and oil) and VIX, although VIX only explains spillovers received from other markets.

6.3. RECOMMENDATIONS

The observations presented in this paper may suggest important implications for policymakers and investors in BRICS equity and foreign exchange markets. From the investors' perspective, our results provide useful insight into portfolio diversification and risk management in BRICS. BRICS foreign exchange markets provide better diversification opportunities than equity markets as they are still less integrated. The Chinese equity and foreign exchange markets remain attractive for hedging and risk management. From policymakers' perspective, it is important to monitor movements in the Brazilian markets as they dominate spillovers to other BRICS markets. Any shocks originating from Brazil will affect Russia, India and especially South Africa. Another lesson for policymakers is that they should improve their country's fundamentals to mitigate risks of spillovers to their markets. In particular, policymakers should focus on the trade balance, opening their economies, managing inflation and maintaining lower interest rates to reduce the risk of contagion from other BRICS equity and foreign exchange markets. High levels of GDP and percentage change in reserves are also important in managing contagion in exchange rate markets.

6.4. LIMITATIONS OF THE STUDY

The main limitations of this study are the use of daily data instead of high-frequency data such as intra-daily data to calculate volatilities which would be more accurate. Additionally, fixed exchange rate regimes affect the volatility of returns. To minimise the impact of government interventions in the exchange rate market, the study excludes data for periods of fixed exchange rates. This effectively excludes important crises periods, such as the Asian financial crisis, for some of the BRICS economies, and therefore results in challenges when interpreting results.

6.5. AREAS FOR FURTHER RESEARCH

While this thesis found a lot of interesting results regarding volatility spillovers among BRICS equity and foreign exchange markets, it is important to include other financial markets in BRICS, especially since BRICS countries are very involved in the commodities markets and this study has shown that commodity prices influence volatility transmission in BRICS stock and exchange rate markets. It would be useful for future research to investigate volatility spillovers across all financial markets in BRICS. It would also be interesting to consider volatilities generated from more high-frequency data in future. Lastly, this study looked at country-specific fundamentals in examining determinants of contagion. It would be constructive to also include country fundamentals relative to other BRICS markets, such as trade intensity index between all BRICS country-pairs and stock market capitalization relative to others, in future research.

6.6. CONCLUSION

This paper tests for market interdependencies (co-movements) among BRICS equity and foreign exchange markets and examines contagion effects in both markets during crises periods. We use the EGARCH framework to calculate daily volatilities in BRICS stocks and currency indices between January 1997 and December 2018. We apply Diebold and Yilmaz (2012) spillover index to calculate total and directional spillover indices for BRICS equity and foreign exchange markets. We also apply panel ordinary least squares regressions to find macroeconomic variables that are determinants of contagion in BRICS equity and exchange rate markets. The theories discussed in the literature suggest that interdependencies exist between equity and currency markets. While there is a lack of consensus regarding contagion, some theories put forth suggest that during financial crises the normal interdependencies among market economies which are transmitted through fundamentals are heightened and have adverse effects. This paper adds to these discussions. The results provide additional understanding to investors and policymakers on the behaviour of volatility in BRICS equity and foreign exchange markets and also provide insight on factors that drive contagion in these markets.

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APPENDICES

APPENDIX A: Returns Series

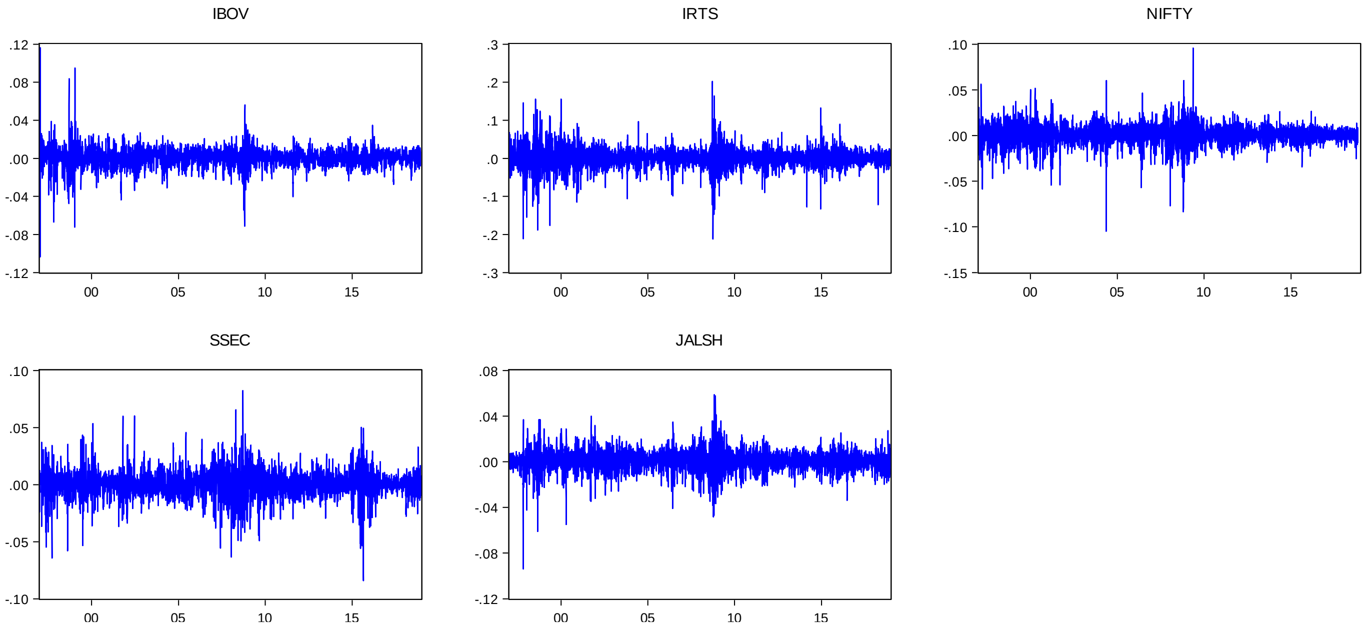


Figure A1: BRICS Stock Returns

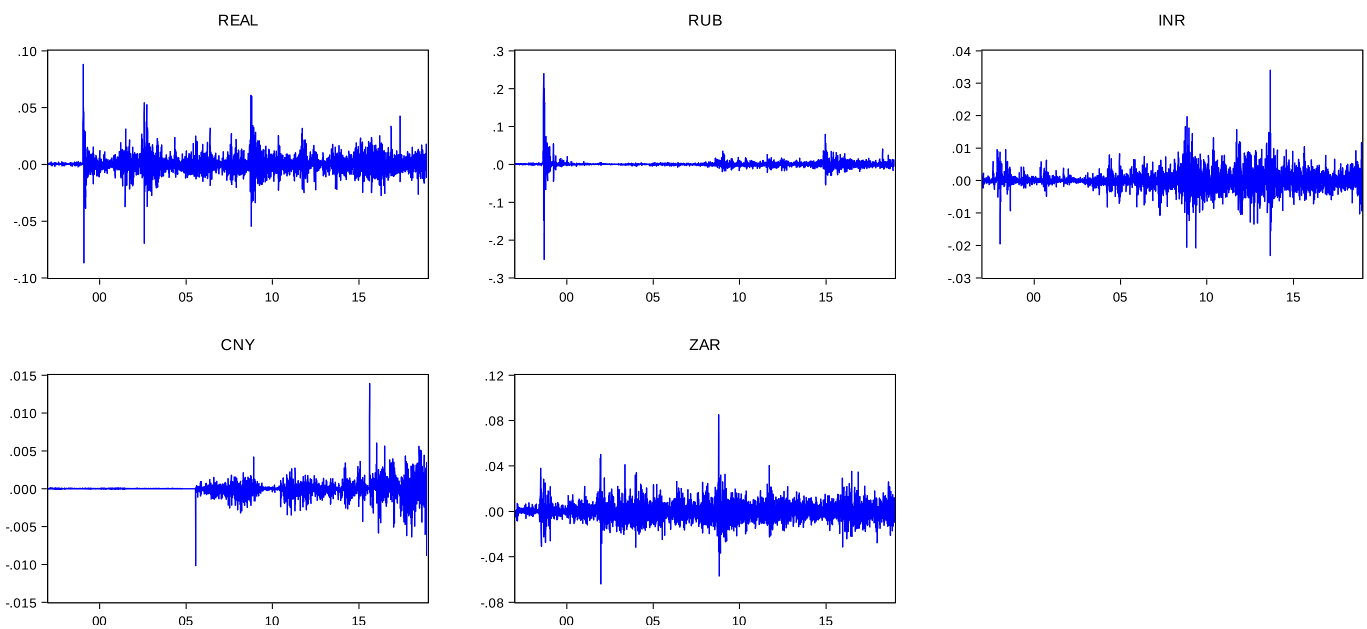


Figure A2: BRICS Exchange Rate Returns

APPENDIX B: Correlograms

Correlogram of IBOV

Date: 11/04/19 Time: 12:47
Sample: 1/13/1999 12/31/2018
Included observations: 5209

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.731	0.731	2786.9	0.000
		2	0.446	-0.191	3822.6	0.000
		3	0.173	-0.169	3978.1	0.000
		4	-0.082	-0.191	4012.7	0.000
		5	-0.063	0.371	4033.1	0.000
		6	-0.037	-0.112	4040.1	0.000
		7	-0.013	-0.075	4041.0	0.000
		8	0.008	-0.085	4041.3	0.000
		9	0.021	0.245	4043.6	0.000
		10	0.037	-0.057	4050.6	0.000
		11	0.038	-0.066	4058.0	0.000
		12	0.038	-0.042	4065.6	0.000
		13	0.047	0.203	4077.0	0.000
		14	0.060	-0.010	4095.7	0.000
		15	0.066	-0.077	4118.4	0.000
		16	0.061	-0.049	4137.6	0.000
		17	0.044	0.142	4147.9	0.000
		18	0.012	-0.044	4148.6	0.000
		19	0.007	-0.011	4148.9	0.000
		20	0.011	-0.038	4149.5	0.000

Correlogram of RTSI

Date: 11/04/19 Time: 12:54
Sample: 8/11/1998 12/31/2018
Included observations: 5320

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.112	0.112	66.768	0.000
		2	-0.000	-0.013	66.768	0.000
		3	-0.010	-0.009	67.298	0.000
		4	0.021	0.023	69.636	0.000
		5	0.006	0.001	69.831	0.000
		6	0.005	0.004	69.941	0.000
		7	0.013	0.013	70.829	0.000
		8	-0.031	-0.035	75.903	0.000
		9	0.009	0.017	76.341	0.000
		10	0.018	0.015	78.075	0.000
		11	-0.019	-0.025	80.052	0.000
		12	0.015	0.022	81.196	0.000
		13	0.030	0.026	85.844	0.000
		14	0.047	0.041	97.875	0.000
		15	0.034	0.027	104.18	0.000
		16	-0.000	-0.009	104.18	0.000
		17	0.005	0.006	104.29	0.000
		18	-0.056	-0.058	120.96	0.000
		19	-0.006	0.003	121.14	0.000
		20	-0.024	-0.024	124.11	0.000

Correlogram of NIFTY

Date: 11/04/19 Time: 12:58
Sample: 1/02/1997 12/31/2018
Included observations: 5738

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.512	0.512	1502.5	0.000
		2	-0.002	-0.358	1502.5	0.000
		3	-0.009	0.274	1502.9	0.000
		4	0.016	-0.199	1504.4	0.000
		5	-0.019	0.114	1506.4	0.000
		6	-0.062	-0.157	1528.4	0.000
		7	-0.038	0.129	1536.8	0.000
		8	0.024	-0.063	1540.1	0.000
		9	0.076	0.146	1573.8	0.000
		10	0.054	-0.118	1590.5	0.000
		11	-0.020	0.054	1592.8	0.000
		12	-0.014	-0.028	1594.0	0.000
		13	0.042	0.078	1604.0	0.000
		14	0.049	-0.032	1618.0	0.000
		15	0.016	0.039	1619.5	0.000
		16	-0.006	-0.041	1619.8	0.000
		17	-0.006	0.025	1619.9	0.000
		18	-0.008	-0.043	1620.3	0.000
		19	-0.014	0.031	1621.4	0.000
		20	-0.029	-0.060	1626.3	0.000

Correlogram of SSEC

Date: 11/04/19 Time: 13:00
Sample: 7/22/2005 12/31/2018
Included observations: 3507

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.499	0.499	874.07	0.000
		2	0.006	-0.323	874.21	0.000
		3	0.055	0.315	884.76	0.000
		4	0.087	-0.179	911.30	0.000
		5	0.017	0.115	912.37	0.000
		6	-0.039	-0.137	917.74	0.000
		7	0.008	0.157	917.99	0.000
		8	0.047	-0.103	925.74	0.000
		9	0.022	0.102	927.47	0.000
		10	-0.001	-0.093	927.47	0.000
		11	0.000	0.079	927.47	0.000
		12	0.030	-0.028	930.74	0.000
		13	0.045	0.065	937.90	0.000
		14	0.016	-0.061	938.75	0.000
		15	0.027	0.107	941.25	0.000
		16	0.045	-0.077	948.24	0.000
		17	0.030	0.093	951.49	0.000
		18	0.000	-0.110	951.49	0.000
		19	-0.014	0.095	952.22	0.000
		20	0.037	-0.025	957.02	0.000

Correlogram of JALSH

Date: 11/04/19 Time: 13:01
Sample: 1/02/1997 12/31/2018
Included observations: 5737

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.531	0.531	1621.1	0.000
		2	0.019	-0.367	1623.1	0.000
		3	-0.039	0.230	1631.7	0.000
		4	-0.047	-0.218	1644.6	0.000
		5	-0.046	0.139	1657.0	0.000
		6	-0.029	-0.127	1661.9	0.000
		7	0.009	0.136	1662.4	0.000
		8	0.028	-0.100	1666.8	0.000
		9	0.016	0.089	1668.3	0.000
		10	-0.011	-0.107	1668.9	0.000
		11	-0.028	0.072	1673.4	0.000
		12	-0.012	-0.055	1674.2	0.000
		13	0.023	0.092	1677.4	0.000
		14	0.043	-0.047	1687.8	0.000
		15	0.038	0.069	1696.0	0.000
		16	0.015	-0.069	1697.4	0.000
		17	-0.015	0.040	1698.6	0.000
		18	-0.032	-0.064	1704.4	0.000
		19	-0.025	0.055	1708.0	0.000
		20	-0.008	-0.050	1708.3	0.000

Correlogram of BRL

Date: 11/04/19 Time: 13:02
Sample: 1/13/1999 12/31/2018
Included observations: 5209

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.467	0.467	1136.4	0.000
		2	-0.038	-0.327	1143.8	0.000
		3	0.021	0.282	1146.0	0.000
		4	0.020	-0.225	1148.2	0.000
		5	-0.015	0.169	1149.4	0.000
		6	0.000	-0.129	1149.4	0.000
		7	0.026	0.141	1153.1	0.000
		8	0.022	-0.109	1155.6	0.000
		9	0.019	0.122	1157.4	0.000
		10	0.030	-0.079	1162.2	0.000
		11	0.029	0.097	1166.7	0.000
		12	0.025	-0.061	1170.0	0.000
		13	0.015	0.060	1171.1	0.000
		14	0.015	-0.032	1172.3	0.000
		15	0.051	0.101	1186.0	0.000
		16	0.063	-0.042	1206.6	0.000
		17	0.023	0.042	1209.3	0.000
		18	-0.010	-0.059	1209.9	0.000
		19	-0.001	0.063	1209.9	0.000
		20	0.021	-0.035	1212.3	0.000

Correlogram of RUB

Date: 11/04/19 Time: 13:04
Sample: 8/11/1998 12/31/2018
Included observations: 5320

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.645	0.645	2217.3	0.000
		2	0.118	-0.511	2291.5	0.000
		3	-0.183	0.073	2470.5	0.000
		4	-0.343	-0.317	3096.6	0.000
		5	-0.302	0.181	3584.0	0.000
		6	-0.128	-0.120	3671.3	0.000
		7	0.050	0.149	3684.6	0.000
		8	0.158	-0.084	3818.0	0.000
		9	0.178	0.116	3986.0	0.000
		10	0.111	-0.108	4051.2	0.000
		11	-0.021	0.000	4053.7	0.000
		12	-0.106	0.005	4113.8	0.000
		13	-0.074	0.097	4142.8	0.000
		14	0.008	-0.004	4143.1	0.000
		15	0.091	0.091	4187.3	0.000
		16	0.122	-0.071	4266.3	0.000
		17	0.068	0.030	4290.7	0.000
		18	-0.007	-0.026	4290.9	0.000
		19	-0.029	0.116	4295.3	0.000
		20	0.013	0.040	4296.2	0.000

Correlogram of INR

Date: 11/04/19 Time: 13:05
Sample: 1/02/1997 12/31/2018
Included observations: 5738

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.478	0.478	1314.3	0.000
		2	-0.053	-0.366	1330.6	0.000
		3	-0.008	0.302	1331.0	0.000
		4	0.082	-0.142	1369.5	0.000
		5	0.084	0.171	1409.6	0.000
		6	0.019	-0.145	1411.8	0.000
		7	0.009	0.156	1412.2	0.000
		8	0.028	-0.119	1416.8	0.000
		9	0.022	0.116	1419.7	0.000
		10	0.022	-0.079	1422.4	0.000
		11	0.015	0.075	1423.6	0.000
		12	0.009	-0.059	1424.1	0.000
		13	0.025	0.085	1427.7	0.000
		14	0.033	-0.052	1433.9	0.000
		15	0.017	0.051	1435.5	0.000
		16	-0.003	-0.054	1435.6	0.000
		17	-0.008	0.038	1436.0	0.000
		18	-0.003	-0.042	1436.0	0.000
		19	0.031	0.092	1441.4	0.000
		20	0.042	-0.062	1451.6	0.000

Correlogram of CNY

Date: 11/04/19 Time: 13:06
Sample: 7/22/2005 12/31/2018
Included observations: 3507

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.476	0.476	795.70	0.000
		2	-0.003	-0.296	795.72	0.000
		3	0.046	0.268	803.23	0.000
		4	0.079	-0.125	825.15	0.000
		5	0.063	0.139	838.99	0.000
		6	0.041	-0.075	844.95	0.000
		7	0.046	0.102	852.42	0.000
		8	0.075	-0.003	872.17	0.000
		9	0.076	0.056	892.61	0.000
		10	0.026	-0.051	895.01	0.000
		11	0.007	0.045	895.20	0.000
		12	0.025	-0.021	897.38	0.000
		13	0.023	0.020	899.25	0.000
		14	0.018	-0.005	900.40	0.000
		15	0.036	0.041	904.96	0.000
		16	0.060	0.023	917.78	0.000
		17	0.046	0.000	925.14	0.000
		18	0.045	0.048	932.13	0.000
		19	0.091	0.062	961.31	0.000
		20	0.079	-0.011	983.58	0.000

Correlogram of ZAR

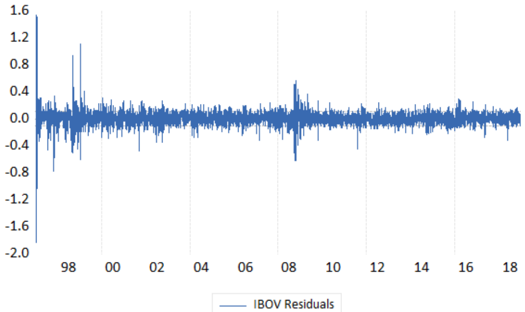
Date: 11/04/19 Time: 13:07
Sample: 1/02/1997 12/31/2018
Included observations: 5737

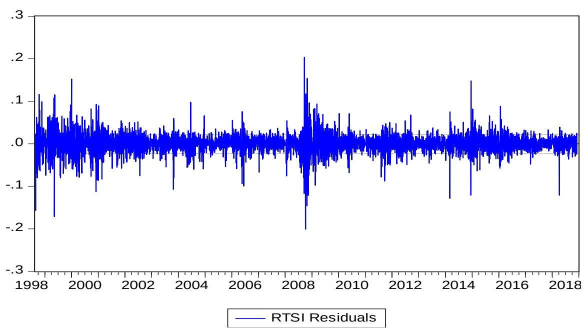
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.469	0.469	1265.2	0.000
		2	-0.058	-0.358	1284.8	0.000
		3	-0.042	0.240	1294.8	0.000
		4	-0.012	-0.194	1295.6	0.000
		5	-0.009	0.143	1296.1	0.000
		6	-0.022	-0.147	1298.8	0.000
		7	-0.002	0.142	1298.9	0.000
		8	0.024	-0.100	1302.2	0.000
		9	0.003	0.073	1302.3	0.000
		10	-0.005	-0.057	1302.4	0.000
		11	0.015	0.073	1303.8	0.000
		12	-0.009	-0.101	1304.3	0.000
		13	-0.018	0.092	1306.1	0.000
		14	0.004	-0.077	1306.2	0.000
		15	-0.009	0.045	1306.7	0.000
		16	-0.016	-0.050	1308.1	0.000
		17	-0.004	0.045	1308.2	0.000
		18	-0.003	-0.049	1308.2	0.000
		19	0.017	0.079	1310.0	0.000
		20	0.033	-0.041	1316.4	0.000

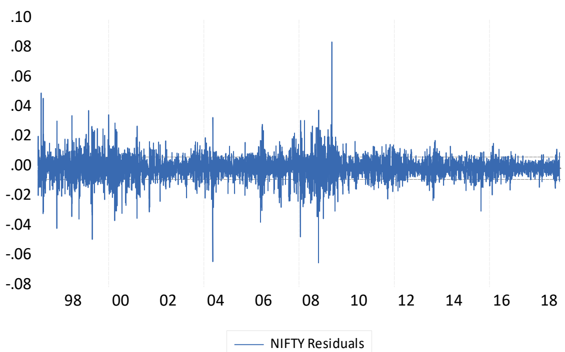
APPENDIX C: Diagnostic Checking

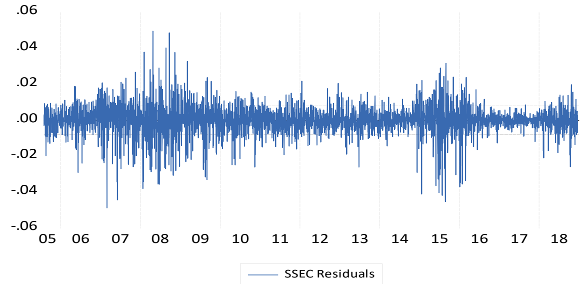
C1. Residual Plots

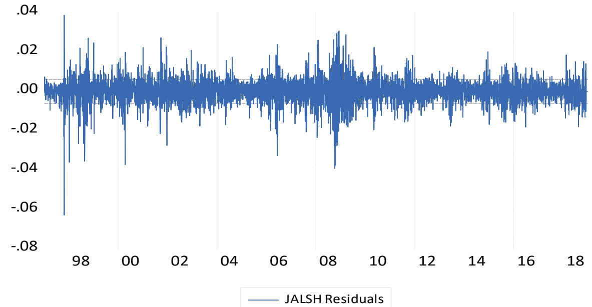
Figure C1. Residual Plots

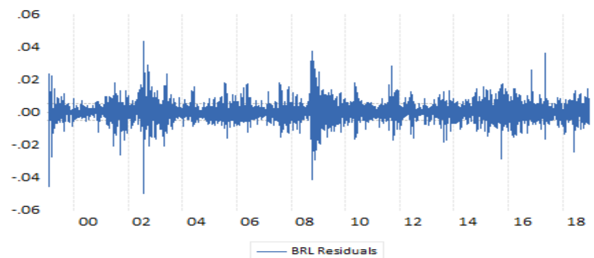


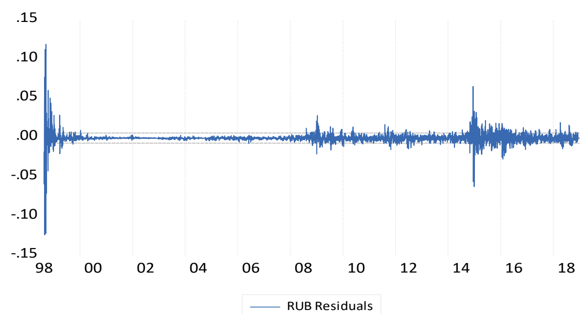


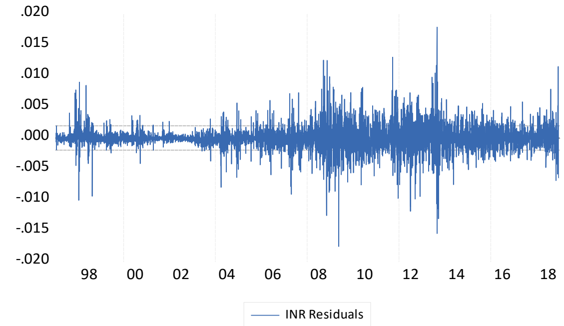


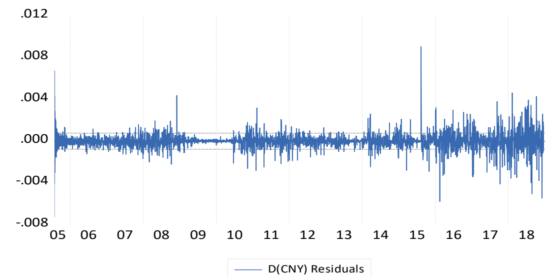


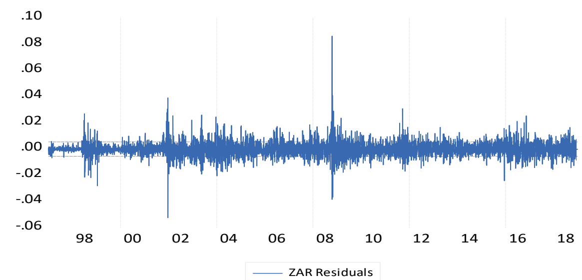












C2. Autocorrelation Tests

Table C2.1: Autocorrelation Test_ Equities

	IBOV	RTSI	NIFTY	SSEC	JALSH
Q(5)	4065.4	81.270	1506.4	1423.0	1656.6
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	4176.1	96.268	1590.5	1430.9	1668.6
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(15)	4208.1	133.91	1619.5	1454.5	1695.7
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	4232.1	150.03	1626.3	1468.4	1707.9
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table C2.2: Autocorrelation Test_ Exchange Rates

	BRL	RUB	INR	CNY	ZAR
Q(5)	1265.6	3862.6	1409.6	1449.4	1296.4
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	1279.6	4366.0	1422.4	1538.7	1302.8
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(15)	1305.7	4512.6	1435.5	1555.0	1307.0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	1334.5	4629.8	1451.6	1676.8	1316.8
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

C3. Heteroscedasticity Tests

Table C3: Heteroscedasticity Test - ARCH LM

	F-statistic	*Prob. F*	*Obs*R-squared*	*Prob. Chi-Square*
Equities				
IBOV	3353.527	0.0000	21116.865	0.0000
RTSI	247.1255	0.0000	236.2287	0.0000
NIFTY	289.6837	0.0000	275.8373	0.0000
SSEC	126.9502	0.0000	122.5743	0.0000
JALSH	553.4384	0.0000	504.8606	0.0000
Exchange Rates				
BRL	490.3103	0.0000	448.2420	0.0000
RUB	1275.001	0.0000	1028.558	0.0000
INR	534.9855	0.0000	489.5086	0.0000
D(CNY)	527.1863	0.0000	458.4870	0.0000
ZAR	287.7138	0.0000	274.0626	0.0000

APPENDIX D: EGARCH MODEL

Table D1: Variance Equations

	ω	α	γ	β	*Log-likelihood*	*Durbin-Watson*
Equities						
IBOV	-0.264442***	0.134699***	-0.117378***	0.967916***	27795.30	2.012563
	(-13.86374)	(13.61731)	(-16.48571)	(322.6095)		
RTSI	-0.264368***	0.143224***	-0.046725***	0.980125***	13577.51	1.969519
	(-15.92980)	(22.38568)	(-12.10397)	(600.3417)		
NIFTY	-0.390686***	0.210067***	-0.089121***	0.976946***	20874.18	2.112146
	(-16.59229)	(24.43162)	(-14.99592)	(472.2291)		
SSEC	-0.277484***	0.164013***	-0.022939***	0.986253***	25229.67	2.000331
	(-14.66893)	(24.6425)	(-5.787758)	(668.9326)		
JALSH	-0.334891***	0.155934***	-0.081416***	0.979450***	22013.22	2.001601
	(-14.34632)	(26.15771)	(-19.32019)	(463.2035)		
Exchange Rates						
BRL	-0.470723***	0.204222***	0.062775***	0.970852***	13947.99	2.019742
	(-11.07957)	(13.99712)	(7.334752)	(291.9858)		
RUB	-0.207204***	0.151240***	0.069032***	0.992039***	15316.21	2.150147
	(-11.19648)	(13.19540)	(10.31195)	(774.1352)		
INR	-0.377997***	0.241603***	0.039722***	0.984255***	29503.34	1.975367
	(-19.91427)	(34.51101)	(8.894606)	(713.9043)		
D(CNY)	-0.519858***	0.221430***	-0.029328***	0.974613***	20934.99	1.956331
	(-21.40369)	(18.81428)	(-3.739925)	(706.2000)		
ZAR	-0.225800***	0.114877***	0.052013***	0.986971***	13527.59	2.041067
	(-6.458078)	(10.05235)	(8.101339)	(349.5504)		

Notes: ***, ** and * represent significance at 1%, 5% and 10%, respectively.

The numbers in parenthesis are t-statistics

APPENDIX E: MODEL TESTING

E1. Normality Tests

Table E1.1: Normality Tests _ Equities

	IBOV	RTSI	NIFTY	SSEC	JALSH
Skewness	-0.221262	-0.351290	-0.087453	-0.460896	-0.268197
Kurtosis	4.128732	6.915322	5.793919	5.243583	4.547688
Jarque-Bera	350.6238	3504.216	1871.635	858.2356	640.8031

Table E1.2: Normality Tests_ Exchange Rates

	BRL	RUB	INR	CNY	ZAR
Skewness	0.315312	0.318924	0.444394	1.768939	0.429192
Kurtosis	5.708789	6.410591	10.29878	55.36795	4.953740
Jarque-Bera	1677.254	2665.632	12914.09	401759.0	1087.439

E2. Heteroscedasticity Tests

Table E2: ARCH LM Test

	F-statistic	*Prob. F*	*Obs*R-squared*	*Prob. Chi-Square*
Equities				
IBOV	0.613389	0.4335	0.613537	0.4335
RTSI	0.919143	0.3377	0.919330	0.3377
NIFTY	0.046776	0.8288	0.046792	0.8287
SSEC	0.009187	0.9236	0.009192	0.9236
JALSH	0.028749	0.8654	0.028759	0.8653
Exchange Rates				
BRL	1.746659	0.1864	1.746744	0.1863
RUB	2.657165	0.1031	2.656836	0.1031
INR	3.031766	0.0817	3.031766	0.0817
D(CNY)	2.176769	0.1402	2.176659	0.1401
ZAR	3.148678	0.0760	3.148047	0.0760

E3. Autocorrelation Tests

Table E3.1: Autocorrelation Tests _ Equities squared residuals

	IBOV	RTSI	NIFTY	SSEC	JALSH
Q(5)	12.955	18.172	3.5453	6.8631	2.8317
	(0.584)	(0.111)	(0.548)	(0.231)	(0.243)
Q(10)	25.805	18.921	8.3510	14.764	7.4929
	(0.712)	(0.217)	(0.595)	(0.141)	(0.379)
Q(15)	29.071	22.589	15.238	16.329	12.078
	(0.481)	(0.207)	(0.434)	(0.294)	(0.439)

Table E3.2: Autoorrelation Tests _ Exchange Rates squared residuals

	BRL	RUB	INR	CNY	ZAR
Q(5)	4.9758	4.3861	6.7722	1.768939	5.3548
	(0.419)	(0.495)	(0.238)	(0.811)	(0.374)
Q(10)	6.4515	16.715	9.7214	2.4227	10.497
	(0.775)	(0.081)	(0.465)	(0.992)	(0.398)
Q(15)	8.6463	22.555	13.955	2.5819	11.923
	(0.895)	(0.277)	(0.529)	(1.000)	(0.685)

APPENDIX F: Cross-markets, In-country Spillovers

Brazil

Spillover (Connectedness) Table

	brl_vol	ibov_vol	From Others
brl_vol	86.0	14.0	14.0
ibov_vol	19.8	80.2	19.8
Contribution to others	19.8	14.0	33.8
Contribution including own	105.9	94.1	16.9%

Russia

Spillover (Connectedness) Table

	rtsi_vol	rub_vol	From Others
rtsi_vol	99.7	0.3	0.3
rub_vol	2.9	97.1	2.9
Contribution to others	2.9	0.3	3.2
Contribution including own	102.6	97.4	1.6%

India

Spillover (Connectedness) Table

	inr_vol	nifty_vol	From Others
inr_vol	99.9	0.1	0.1
nifty_vol	1.4	98.6	1.4
Contribution to others	1.4	0.1	1.5
Contribution including own	101.4	98.6	0.7%

China

Spillover (Connectedness) Table

	cny_vol	ssec_vol	From Others
cny_vol	99.9	0.1	0.1
ssec_vol	0.1	99.9	0.1
Contribution to others	0.1	0.1	0.2
Contribution including own	100.0	100.0	0.1%

South Africa

Spillover (Connectedness) Table

	jalsh_vol	zar_vol	From Others
jalsh_vol	93.0	7.0	7.0
zar_vol	6.8	93.2	6.8
Contribution to others	6.8	7.0	13.8
Contribution including own	99.8	100.2	6.9%

APPENDIX H: ANALYSIS OF PANEL DATA

H1. Cross-Section Dependence Test

Table H1: Cross-section dependence tests

TEST/DEPENDENT VARIABLE	*EQUITIES_SPILLOVER*	*FXRATE_SPILLOVER*
Breusch-Pagan LM	55.29652 (0.0000)	67.48546 (0.0000)
Pesaran scaled LM	10.12861 (0.0000)	12.85414 (0.0000)
Pesaran CD	-5.983501 (0.0000)	12.85414 (0.0000)

H2. Breakpoint Tests

Table H2: Multiple Breakpoint Test

NO. OF BREAKS	EQUITIES_SPILLOVER	FXRATE_SPILLOVER
1	2006Q2	2012Q4
2	2006Q2, 2012Q3	2011Q4, 2012Q3

3	2003Q2, 2006Q2, 2012Q3	2010Q3, 2011Q4, 2012Q3
4	2003Q2, 2006Q2, 2009Q3, 2012Q3	2010Q3, 2011Q1, 2011Q3, 2012Q4
5	2003Q2, 2006Q2, 2009Q3, 2012Q3, 2015Q4	2007Q1, 2010Q3, 2011Q1, 2011Q3, 2012Q4

H3. Panel Unit Root Tests

Table H3.1: Panel Unit Root Tests _ Equities Spillover

Variable		LLC t*	IPS W-stat	ADF – Fisher	PP - Fisher
EQUITIES_SPILL	Level	-13.8676	-11.6243	121.951	52.2238
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
GDP	Level	-2.54582	0.44062	9.68272	7.00732
		(0.0055)	(0.6703)	(0.4688)	(0.7248)
	1st difference	2.83947	-3.37534	35.4913	218.454
		(0.9977)	(0.0004)	(0.0001)	(0.0000)
TRADE_BALANCE	Level	-3.41357	-2.56135	22.8529	14.5296
		(0.0003)	(0.0052)	(0.0113)	(0.1502)
OPEN	Level	-1.97820	-1.94864	21.3050	24.7286
		(0.0240)	(0.0257)	(0.0191)	(0.0059)
VIX	Level	9.09498	7.75586	0.00631	1.94051
		(1.0000)	(1.0000)	(1.0000)	(0.9968)
	1st difference	4.02619	-0.18238	7.03623	8.76668
		(1.0000)	(0.4276)	(0.7220)	(0.5544)
	2nd difference	-3.07003	-3.84008	32.4232	7.05617
		(0.0011)	(0.0001)	(0.0003)	(0.7201)
GOLD	Level	-6.93195	-7.04422	68.0906	62.6316
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
OIL	Level	-1.76139	-2.88867	24.0086	16.3537
		(0.0391)	(0.0019)	(0.0076)	(0.0899)
CPI	Level	0.26489	-0.83489	10.5620	14.5336
		(0.6045)	(0.2019)	(0.3926)	(0.1500)
	1st difference	-0.13132	-3.42836	31.3995	18.8961
		(0.4478)	(0.0003)	(0.0005)	(0.0416)
RESG	Level	1.22221	0.41286	6.94178	8.66776
		(0.8892)	(0.6601)	(0.7309)	(0.5639)
	1st difference	-5.22360	-3.93465	43.3724	8.75951
		(0.0000)	(0.0000)	(0.0000)	(0.5551)
INTEREST	Level	1.90528	2.17651	4.70151	12.1842
		(0.9716)	(0.9852)	(0.9102)	(0.2729)
	1st difference	1.78442	1.28777	6.75314	10.8993
		(0.9628)	(0.9011)	(0.7485)	(0.3654)
	2nd difference	0.31145	-2.31079	20.1484	10.7915
		(0.6223)	(0.0104)	(0.0279)	(0.3740)
PRI	Level	0.40815	-1.04534	17.2087	4.54750
		(0.1479)	(0.1479)	(0.0699)	(0.9193)
	1st difference	-6.12640	-5.12695	47.5459	11.0637
		(0.0000)	(0.0000)	(0.0000)	(0.3526)
TED	Level	3.24705	1.35561	16.0856	3.95879
		(0.9994)	(0.9124)	(0.0972)	(0.9492)
	1st difference	4.20606	2.69642	1.67570	3.94750
		(1.0000)	(0.9965)	(0.9983)	(0.9497)
	2nd difference	-1.57686	-2.33175	20.9836	7.35785
		(0.0574)	(0.0099)	(0.0212)	(0.6913)

Notes: The numbers in parenthesis are p-values

Table H3.2: Panel Unit Root Tests _ Exchange Rate Spillovers

Variable		*LLC t**	*IPS W-stat*	*ADF – Fisher*	*PP - Fisher*
FXRATE_SPILL	Level	-4.65500	-5.24832	50.0613	43.8103
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
GDPG	Level	-3.93406	-2.17132	19.7337	18.2866
		(0.0000)	(0.0150)	(0.0319)	(0.0503)
TRADE_BALANCE	Level	-4.90387	-4.47713	44.4089	6.89953
		(0.0000)	(0.0000)	(0.0000)	(0.7349)
OPEN	Level	-3.46513	-2.97526	29.2464	21.6792
		(0.0003)	(0.0015)	(0.0011)	(0.0168)
VIX	Level	-12.0443	-11.7989	125.195	0.98233
		(0.0000)	(0.0000)	(0.0000)	(0.9998)
GOLD	Level	0.02538	-7.25334	69.0077	62.2239
		(0.5101)	(0.0000)	(0.0000)	(0.0000)
OIL	Level	-18.2350	-14.9455	161.523	0.05815
		(0.0000)	(0.0000)	(0.0000)	(1.0000)
CPI	Level	8.67391	4.38719	8.22690	0.46070
		(1.0000)	(1.0000)	(0.6067)	(1.0000)
	1st difference	-2.28811	-1.57044	25.9096	7.77947
		(0.0111)	(0.0582)	(0.0039)	(0.6504)
RESG	Level	-3.76012	-2.17751	25.2270	7.20374
		(0.0001)	(0.0147)	(0.0049)	(0.7061)
INTEREST	Level	0.91005	0.25247	26.1118	2.58818
		(0.8186)	(0.5997)	(0.0036)	(0.9895)
	1st difference	2.16525	1.46731	6.03491	3.61121
		(0.9848)	(0.9289)	(0.8123)	(0.9632)
	2nd difference	-3.29857	-3.86809	39.2038	10.3494
		(0.0005)	(0.0001)	(0.0000)	(0.4104)
PRI	Level	-36.3579	-5.91494	60.4281	8.29454
		(0.0000)	(0.0000)	(0.0000)	(0.6001)
TED	Level	-44.3257	-1.90715	31.1402	6.17892
		(0.0000)	(0.0283)	(0.0006)	(0.8000)

Notes: The numbers in parenthesis are p-values

H4. Cointegration Tests

Table H4.1: Johansen Fisher Panel Cointegration Test _ Equities Spillover

Hypothesized No. of CE(s)	*Fisher Stat. (from trace test)*	*Prob*	*Fisher Stat. (from max-eigen test)*	*Prob*
None	1317.	0.0000	204.1	0.0000
At most 1	1317.	0.0000	214.5	0.0000
At most 2	494.0	0.0000	191.2	0.0000
At most 3	212.1	0.0000	554.0	0.0000
At most 4	828.9	0.0000	209.5	0.0000
At most 5	307.3	0.0000	325.6	0.0000
At most 6	311.9	0.0000	152.4	0.0000
At most 7	264.2	0.0000	130.9	0.0000
At most 8	231.0	0.0000	130.1	0.0000
At most 9	159.3	0.0000	112.1	0.0000
At most 10	99.23	0.0000	74.65	0.0000
At most 11	11.6151	0.0741	11.6151	0.0741

Table H4.2: Johansen Fisher Panel Cointegration Test _ Exchange Rate Spillover

Hypothesized No. of CE(s)	*Fisher Stat. (from trace test)*	*Prob*	*Fisher Stat. (from max-eigen test)*	*Prob*
None	1317.	0.0000	204.1	0.0000
At most 1	1317.	0.0000	214.5	0.0000
At most 2	494.0	0.0000	191.2	0.0000
At most 3	212.1	0.0000	500.2	0.0000
At most 4	821.7	0.0000	209.5	0.0000
At most 5	307.3	0.0000	284.1	0.0000
At most 6	312.2	0.0000	154.0	0.0000
At most 7	267.0	0.0000	161.1	0.0000
At most 8	232.7	0.0000	130.1	0.0000
At most 9	165.8	0.0000	113.6	0.0000
At most 10	98.72	0.0000	102.6	0.0000
At most 11	7.606	0.6673	7.606	0.6673

APPENDIX G: Directional Spillovers

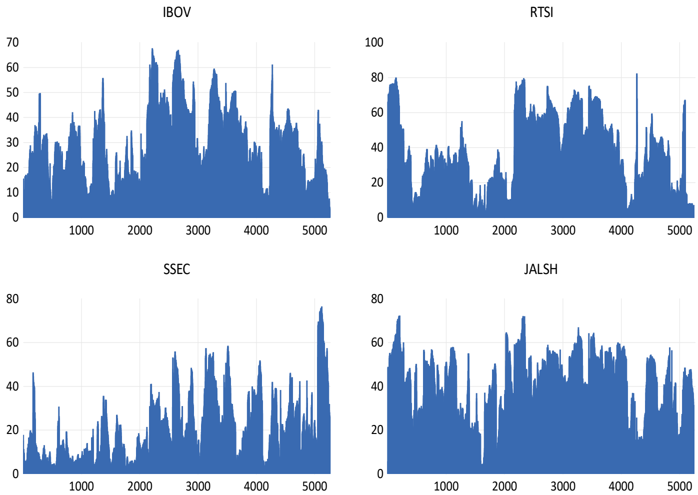


Figure G1: Directional Spillovers GIVEN_ Equities

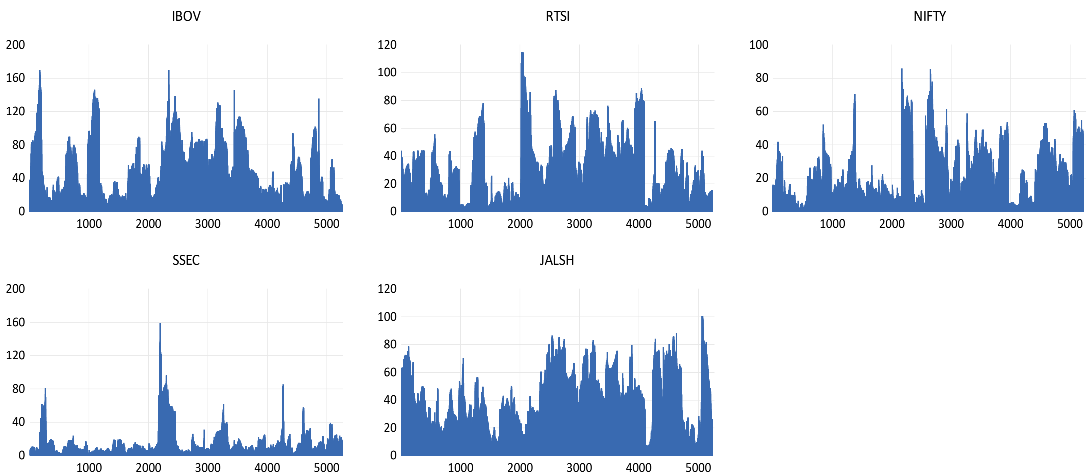


Figure G2: Directional Spillovers RECEIVED_ Equities

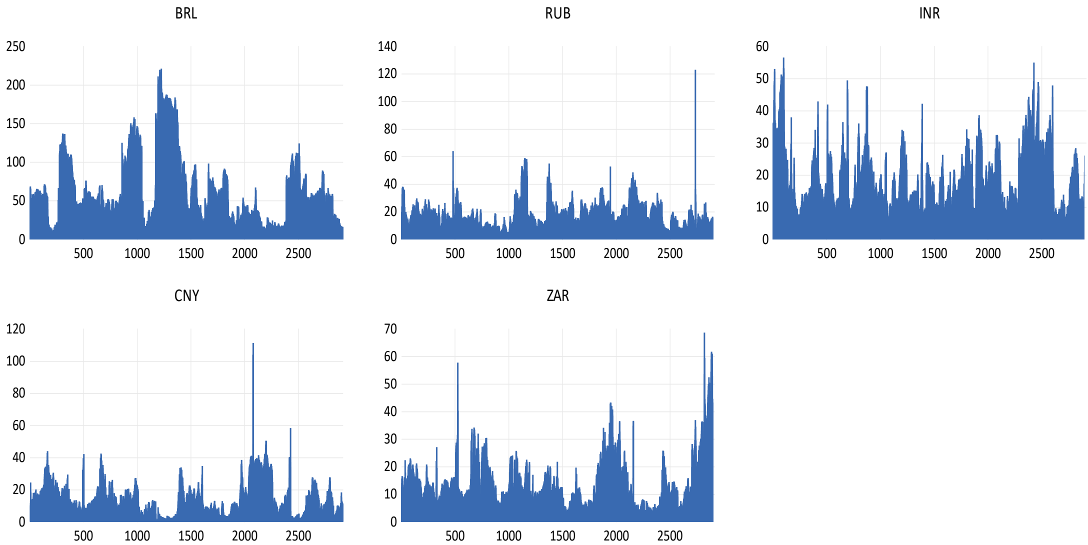


Figure G3: Directional Spillover GIVEN _ Exchange Rates

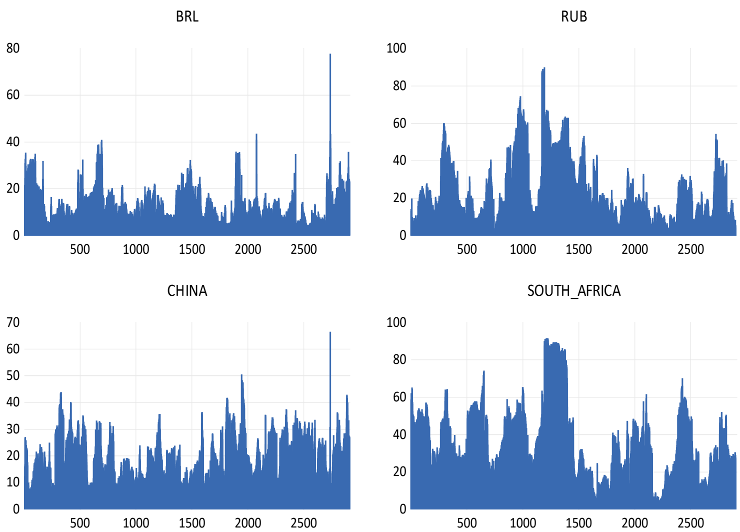


Figure G4: Directional Spillover RECEIVED _ Exchange Rates

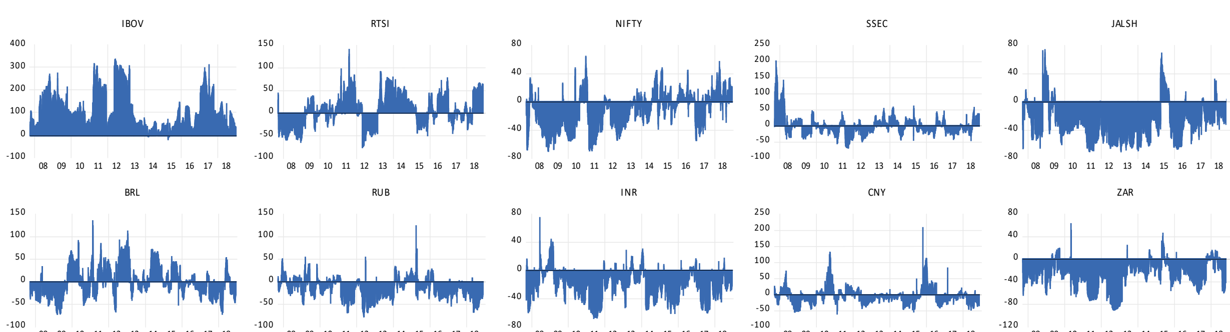


Figure G5: Net Directional Spillovers _cross-country, cross-market

APPENDIX I: RESIDUAL DIAGNOSTICS

Table I1: Model 1 Residual Diagnostics _ Panel Unit Root Tests

Dependent Variable/ Test		*LLC t**	*IPS W-stat*	*ADF – Fisher*	*PP - Fisher*
Equities_Spillover					
Directional TO	Level	-11.7326	-12.4340	138.680	196.078
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Directional FROM	Level	-12.5495	-19.7730	182.365	92.1034
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fxrate_Spillover					
Directional TO	Level	-12.4305	-19.7730	182.365	92.1034
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Directional FROM	Level	-17.0392	-18.9873	174.174	92.1034
		(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: The numbers in parenthesis are p-values

Table I2: Model 2 Residual Diagnostics_Panel Unit Root Tests

Dependent Variable/ Test		*LLC t**	*IPS W-stat*	*ADF – Fisher*	*PP - Fisher*
Equities_Spillover					
Directional TO	Level	-14.5454	-17.4621	189.927	221.986
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Directional FROM	Level	-15.8596	-16.3302	186.809	158.592
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fxrate_Spillover					
Directional TO	Level	-19.6544	-23.6814	200.576	116.359
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Directional FROM	Level	-14.3405	-20.3319	192.004	107.397
		(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: The numbers in parenthesis are p-values