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FINANCIAL CONTAGION IN EMERGING MARKETS: EVIDENCE FROM BRICS COUNTRIES

By

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DECLARATION

I, **Olivier Niyitegeka,** declare that:

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"Trust in the LORD with all thine heart; and lean not unto thine own understanding"

(Proverbs 3:5, King James Version).

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DEDICATION

This thesis is affectionately dedicated to my wife, Rika Sonia and my two daughters Joy Munyana and Audrey Uwamahoro, without whom this thesis would not have been completed.

ABSTRACT

The present study examines the pure form of contagions in the BRICS countries, namely Brazil, Russia, India, China, and South Africa. The pure form of contagion refers to the propagations of shocks due to reasons that are not related macroeconomic fundamentals, and are solely the result of irrational phenomena, such as panics, herd behaviour, loss of confidence and risk aversion. The choice of BRICS was motivated by the fact that these emerging countries have stronger partnerships through the BRICS association. Additionally, these countries come from various continents across the world. This allowed the study to have a worldwide overview of how contagions are transmitted, not only in one region but across regions.

The main objective of this study was to examine co-movement and volatility spillover in BRICS countries from 'source' markets of the U.S. and Eurozone region. Specifically, the study sought to accomplish the following objectives: (i) To examine the salient characteristics of equity markets in BRICS countries, (ii) To investigate the nature of stock market returns' volatility for BRICS countries during periods of financial turmoil, (iii)To examine the presence of time-varying conditional correlations in BRICS' equity market returns, in the wake of the financial crises that took place in the U.S. and Eurozone countries, and (iv) To investigate the presence of time-frequency correlations in BRICS stock markets, following the financial crises that took place in the U.S. and Eurozone countries.

The following four econometric models were formulated and utilised by the study: (i) GARCH (1, 1) and its extensions; (ii) the diagonal VECH GARCH (1, 1); (iii) the Dynamic Conditional Correlation GARCH ; (iv) and Wavelet analysis.

The study found that stock markets within BRICS countries are heterogeneous as they differ in their structural characteristics, economic policies, and geopolitical importance. The Chinese and Russian markets are still in the maturing process as they only reopened recently after decades of communist regimes that prohibited security markets. The Brazilian, Russian and South African stock markets are dominated by natural resource-based stocks and they are well-known commodity exporters. Among the BRICS stock markets, China's market has experienced the most rapid growth in the past 20 years.

The results of Univariate GARCH modelling revealed the persistence of volatility in the BRICS returns, with China (SSE) having the highest volatility persistence, followed by India (SENSEX) and Russia (RTSI). Using GARCH (1,1) variants, the study also found evidence of leverage effect in all BRICS stock markets except China.

Bivariate GARCH models were used to examine the dynamic cross-correlation between individual BRICS stock markets as target markets and the U.S. and Eurozone as ground zero (source) markets. The study showed that the cross-conditional volatility coefficient is high in magnitude during periods of financial upheaval compared to a tranquil period, hence the conclusion that there was financial contagion in BRICS stock markets (with the exception of the Chinese stock market) during the U.S. sub-prime and the Eurozone sovereign debt crises.

The wavelet cross-correlations analysis showed evidence of positive cross-correlation between the U.S. and individual BRICS stock markets, and the cross-correlation was identified in both short and coarse scales, with the U.S. leading BRICS countries. The cross-correlation between the U.S. and Chinese equity market could not be established.

Regarding the Eurozone sovereign debt crisis, the wavelet cross-correlation analysis shows evidence of co-movement and volatility spillover in the short scales, with the DAX leading the BRICS market indices. Evidence of financial contagion emanating from Eurozone stock markets could only be identified in the South African and Russian stock markets. For the Brazilian, Indian and Chinese markets, no correlation was identified in the short scale period, hence the conclusion that no financial contagion took place in these three stock markets following the Eurozone sovereign debt crisis.

The study recommends that since volatility spillover between individual BRICS equity markets and the U.S. market is unidirectional policymakers, investors and regulatory authorities should focus more on monitoring the volatility of the U.S. equity market, as efforts by authorities in BRICS countries to stabilise BRICS stock markets is futile as shocks are exogenous.

The current study also recommends that regulatory authorities should come up with initiatives that enable investors to reduce significant risk exposure by formulating sound risk management policies and macroprudential regulations.

Given the fact that the current study could not identify financial contagion in Brazilian, Chinese and Indian stock markets emanating from Eurozone countries, the study recommends that policymakers policy makers need to pay due attention to idiosyncratic shock channels in responding to volatility spillover.

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ABBREVIATIONS, ACRONYMS AND DEFINITION OF TERMS

ACF	Auto Correlation Function
ADF	Augmented Dickey Fuller
AIC	Akaike information criterion
AR	Autoregressive (process)
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive moving average (process)
B3 S.A	Brasil Bolsa Balcão Sociedade Anónima
BBF	Bolsa Brasileira de Futuros
BM&F	Bolsa de Valores, Mercadorias
BMSP	Bolsa de Mercadorias de São Paulo
BOLT	Bombay Online Trading
BOVESPA	Bolsa de Valores de Sao Paulo
BRICS	Brazil, Russia, India, China and South Africa
BRIICKS	Brazil, Russia, India, Indonesia, China, South Korea and South Africa
BSE	Bombay Stock Exchange
BVRJ	Bolsa de Valores do Rio de Janeiro
CBLC	Companhia Brasileira de Liquidacao e Custodia
CCP	Clearinghouse and Central Counterparty
CPP	Capital Purchase Program
CSD	Central Securities Depository
CSRC	China Securities Regulatory Commission
CTE	Central Trading Engine
CVM	Commissão de Valores Mobiliários
DAX	Deutscher Aktien Index
DCC-GARCH	Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity

DF	Dickey Fuller
DWT	Discrete Wavelet Transform
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
ESM	European Stability Mechanism
EU	European Union
EZDC	EuroZone Sovereign Debt Crisis
FCSM	Federal Commission on Securities Market
FEBRABAN	Federação Brasileira das Associações de Bancos
FIIs	Foreign Institutional Investors
FTSE/JSE	Financial Times Stock Exchange /Johannesburg Stock Exchance
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GJR GARCH	Glosten, Jagannathan and Runkle Generalized Autoregressive Conditional Heteroskedasticity
GKO	Gosudarstvennoye Kratkosrochnoye Obyazatyelstvo
HKS	Hong Kong Stock
HQC	Hanna-Quinn (criterion)
IMF	International Monetary Fund
IPO	Initial Public Offering
KPSS	Kwiatowski-Phillips-Schmidt-Shin
LM	Lagrange Multiplier
LTCM	Long Term Capital Management
MICEX	Moscow Interbank Currency Exchange
MODWT	Maximum Overlap Discrete Wavelet Transform
NASDAQ	National Association of Securities Dealers Automated Quotations
NEAT	National Exchange for Automated Trade

NSE	National Stock Exchange
NSSA	Share and Stockbrokers Association
NYSE	New York Stock Exchange
OLS	Ordinary least squares
OTC	Over The Counter
OTCEI	Over the Counter Exchange of India
PP	Phillips–Perron
PRC	People's Republic of China
QFII	Qualified Foreign Institutional Investor
RFCSE	Russian Federation Commission on Securities and Exchanges
RQFII	Renminbi Qualified Foreign Institutional Investor
RTS	Russian Trading System
S&P 500	Standard & Poor's 500
SBIC	Schwarz-Bayesian information criterion
SEBI	Securities and Exchange Board of India
SENSEX	Sensitive Index
SOE	State Owned Enterprise
SPCEX SC	Stock Company Saint-Petersburg Currency Exchange
SSE	Shenzhen Stock Exchange
SZSE	The Shenzhen Stock Exchange
TAF	Term Auction Facility
TARP	Troubled Asset Relief Program
TCP	Transmission Control Protocol
TR	Trade Repository
U.S.	United States of America
UDP	User Datagram Protocol
UK	United Kingdom
UMDF	United Market Data Feed
VAR	Vector autoregressive
VEC	Vector error correction

VECH GARCH	Vector-Half Generalized Autoregressive Conditional Heteroskedasticity
VECM	Vector error correction model
WT	Wavelet Transformation
WTC	Wavelet Coherence

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND AND PROBLEM STATEMENT

The 1990s will go down in history as a period of systemic financial crisis for emerging economies. Latin American countries were first to be hit, following the 1994 Mexican peso crisis and its impact on other emerging markets (Herman and Klemm, 2019). This was followed by other crises that reverberated across emerging economies in Western Europe, East Asia and South Asia (Lam, 2002).

In the beginning, blame was directed toward poor domestic policies, and little attention was given to the propagation aspect of these crises. It was only in the late 1990s, after more severe crises such as the 1997 Asian flu, the 1998 Russian cold, and the 1999 Brazilian fever, that economics and finance scholars began documenting the propagations of the crises from one country to another (Kaminsky and Reinhart, 2000). These propagations — if they cannot be explained by economic fundamentals alone —are referred to as financial contagions (hereafter referred to as contagions).

The term contagion has primarily been defined in the context of the banking industry. In this context, imperfect information about the quality of a bank's portfolio — from depositors' point of view — induces bank runs which spread to other banks (Valdés, 2000). The expression was devised to indicate shock transmission that cannot be explained by fundamentals or co-movements that are viewed as excessive (Bekaert, Ehrmann and Fratzscher, 2014). Over the years, the term contagion has gone through a gradual refinement and measurement process. Even though contagions have been documented in various papers, there is no consensus in the literature on the exact definition of what constitutes contagion and how it is measured. The definition of Forbes and Rigobon (2002:3) of contagion as "a significant increase in cross-market linkage after a shock to one country or group of countries", has been the most popular. However, it is regarded by some academics as a narrow definition and is not universally accepted (Ranta, 2013). Gallegati (2012) emphasised the need to differentiate between what he called ''fundamentals-based'' and ''pure'' contagion. He stated that an increase in cross-market linkages from the pre-crisis period to the crisis period might take the form of interdependence or contagion. Interdependence means that shocks can be transmitted across countries due to their financial linkages. Pure contagion refers to the propagations that are not related to shocks in macroeconomic fundamentals. The propagations are solely the result of irrational phenomena, such as panics, herd behaviour, loss of confidence and risk aversion.

The World Bank (2013) reviewed the literature on contagion and observed three layers of definitions for contagion, namely, (i) the broad, (ii) the restrictive and (iii) the very restrictive. The broad definition defines contagion as the cross-country transmission of shocks or the general cross-country spillover effects. This definition holds the view that contagion can take place during both tranquil and crisis periods. The restrictive definition considers contagion as a result of the propagation of shocks to other countries, or the cross-country correlation, beyond any fundamental link among the countries and common shocks. This definition is commonly referred to as excess co-movement and can be explained by investors' herd behaviour. Finally, the very restrictive definition of contagion refers to the increase in cross-country correlations during crisis periods, relative to correlations during tranquil periods.

Emerging economies have been the most affected by contagions. Kaminsk, Reinhar and Végh (2003) identified three key elements, which they dubbed the "unholy trinity", that make emerging markets prone to contagions; they are, (i) an abrupt reversal in capital inflow, (ii) a surprise announcement, and (iii) a leveraged common creditor. Regarding the reversal in capital inflow Kaminsk, Reinhar and Végh (2003) noted that before financial contagions, crisis-prone markets experience a surge in international capital inflow, but after the initial shock has taken place, the affected economies experience an abrupt halt in capital inflow. Regarding surprise announcements, they explained that an unexpected announcement triggers a chain reaction that always comes as a surprise to the financial market. Regarding a common creditor, Kaminsk, Reinhar and Végh (2003) stressed that in most cases a leveraged common creditor is involved, as is the case for American banks in Latin American crises or Japanese banks in Asian crises.

In the aftermath of the 2008-2009 Global Financial Crisis (GFC) from the U.S. and the 2009-2012 EuroZone Sovereign Debt Crisis (EZDC), an extensive body of literature on financial contagion has been developed. The literature includes, among others, Naoui, Khemiri and Liouane (2010) who examined financial contagion using the Dynamic Conditional Correlation

Generalised AutoRegressive Conditional Heteroscedasticity (DCC- GARCH) model. They found evidence of significant conditional correlations between emerging market returns (Argentina, Brazil, South Korea, Hong Kong, Indonesia, Malaysia, Mexico, Shanghai, Singapore and Taiwan) and the American market during the sub-prime crisis except for the Shanghai market (China). Kenourgios and Dimitriou (2015), who surveyed the contagion effects of the GFC of 2008 and 2009 in ten sectors within six developed and emerging regions during different phases of the crisis, found that the global financial crisis of 2008 -2009 could be characterised by contagion effects across regional stock markets and regional financial and non-financial sectors. However, they noted that the developed Pacific region and some sectors (in particular consumer goods, healthcare and technology) across all regions were less affected by the crisis. The authors also found that the most vulnerable sectors were observed in the emerging Asian and European regions. Ahmad, Sehgal and Bhanumurthy (2013) investigated the contagion effects of the Greece, Ireland, Portugal, Spain, Italy, the U.S., UK and Japan markets on BRIICKS (Brazil, Russia, India, Indonesia, China, South Korea and South Africa) stock markets during the Euro-zone crisis period, and their empirical results indicated that among Eurozone countries, Ireland, Italy and Spain appeared to be most contagious for BRIICKS markets compared to Greece. The study also indicated that Brazil, India, Russia, China and South Africa were strongly hit by the contagion shock during the Eurozone crisis. However, Ahmad, Sehgal and Bhanumurthy (2013) found that Indonesia and South Korea experienced only interdependence and not contagion. Hemche, Jawadi, Maliki and Cheffou (2016) studied the contagion hypothesis for ten developed and emerging stock markets (namely France, Italy, UK, Japan, China, Argentina, Mexico, Tunisia, Morocco and Egypt) with reference to the U.S. market in the context of GFC. Their findings indicated that there was an increase in dynamic correlations following the sub-prime crisis for most markets under consideration.

It is against this background that the current study posed the following key research questions:

1. What are the salient characteristics of equity markets in BRICS countries that make the market prone to financial contagion?
2. What is the nature of volatility in the equity market return series in BRICS countries?
3. Is there evidence of co-movement and volatility spillover in BRICS equity markets in the wake of financial crises that took place in U.S. and Eurozone countries?

4. Taking into consideration various time scales, what is the dynamic structure of the relationship between BRICS equity markets returns, as potential target markets, and the U.S. as well as Eurozone equity market returns, as potential source market?

1.2 RESEARCH OBJECTIVES

The main objective of this study was to examine contagions within the BRICS countries. Specifically, the study sought to accomplish the following objectives:

1. To examine the salient characteristics of equity markets in BRICS countries.
2. To investigate the nature of the volatility of stock market returns in BRICS countries during periods of financial turmoil.
3. To examine the presence of time-varying conditional correlations in BRICS equity market returns, in the wake of the financial crises that took place in the U.S. and Eurozone countries.
4. To investigate the presence of time-frequency correlations in BRICS stock markets, following the financial crises that took place in the U.S. and Eurozone countries.

1.3 NEED FOR THE STUDY

For the past two decades, emerging economies have been characterised by financial instability caused by financial contagions. For some reasons that are not always apparent, certain financial events like the devaluation or default on sovereign debt[1] triggered an adverse chain of reactions among emerging economies (Kaminsk, Reinhart and Vegh, 2003). The economic impact of these shocks on emerging economies was disastrous in most instances. It included declines in equity prices, spikes in the cost of borrowing, scarcity in the availability of international capital, declines in the value of currencies, and falls in economic output (Kaminsk, Reinhart and Vegh, 2003). The present study examined contagions within the BRICS countries, namely Brazil, Russia, India, China and South Africa. The choice of these emerging countries was motivated by the fact that they have stronger partnerships through the BRICS association. Additionally, these countries come from various continents across the world. This allowed the researcher to have a worldwide overview of how the contagions are transmitted, not only in one region but across regions.

[1] A sovereign debt refers to the amount of money that a country's government has borrowed, typically issued as bonds denominated in a reserve currency.

Various reasons underpin the need for this study. Firstly, there is an increasing need among researchers and policymakers to investigate the nature and effects of contagion, bearing in mind that there is no clear-cut definition of contagion since the term is used ambiguously in the literature. As a result, there has been no agreement on the econometric methodology to be used when it comes to measuring contagion (Gómez-Puig and Sosvilla-Rivero, 2014). The disparities and inconsistencies among studies using different methodological approaches and different definitions of the channel of transmission of crises made it challenging to compare results, hence the inability to draw meaningful conclusions (Dungey, Fry, González-Hermosillo and Vance, 2005). The current study intended to bring more insights into the cause and nature of contagions.

Finally, the study also sought to provide new perspectives to investors and policymakers in BRICS economies on how to formulate portfolio investment and crisis management strategies during periods of financial turmoil.

1.4 SCHEMATIC FRAMEWORK

The present study examined the contagion of financial crises among BRICS economies, namely those of Brazil, Russia, India, China and South Africa. This was achieved by investigating shock spillovers empirically from one market to another. The current study only focused on the propagation of financial crises that cannot be explained by economic fundamentals, commonly known as pure contagion or shift-contagion. The study, as written up in this thesis, first discusses theories on financial crises contagions in the fields of economics and finance. This is followed by a descriptive analysis of the BRICS stock markets and the theoretical expectations of the study. After that, econometric and statistical techniques are used to test cross-market correlation during recent financial crises. Conclusions are then drawn from the results of the empirical analysis and recommendations made. Figure 1-1 provides a schematic representation of the conceptual framework.

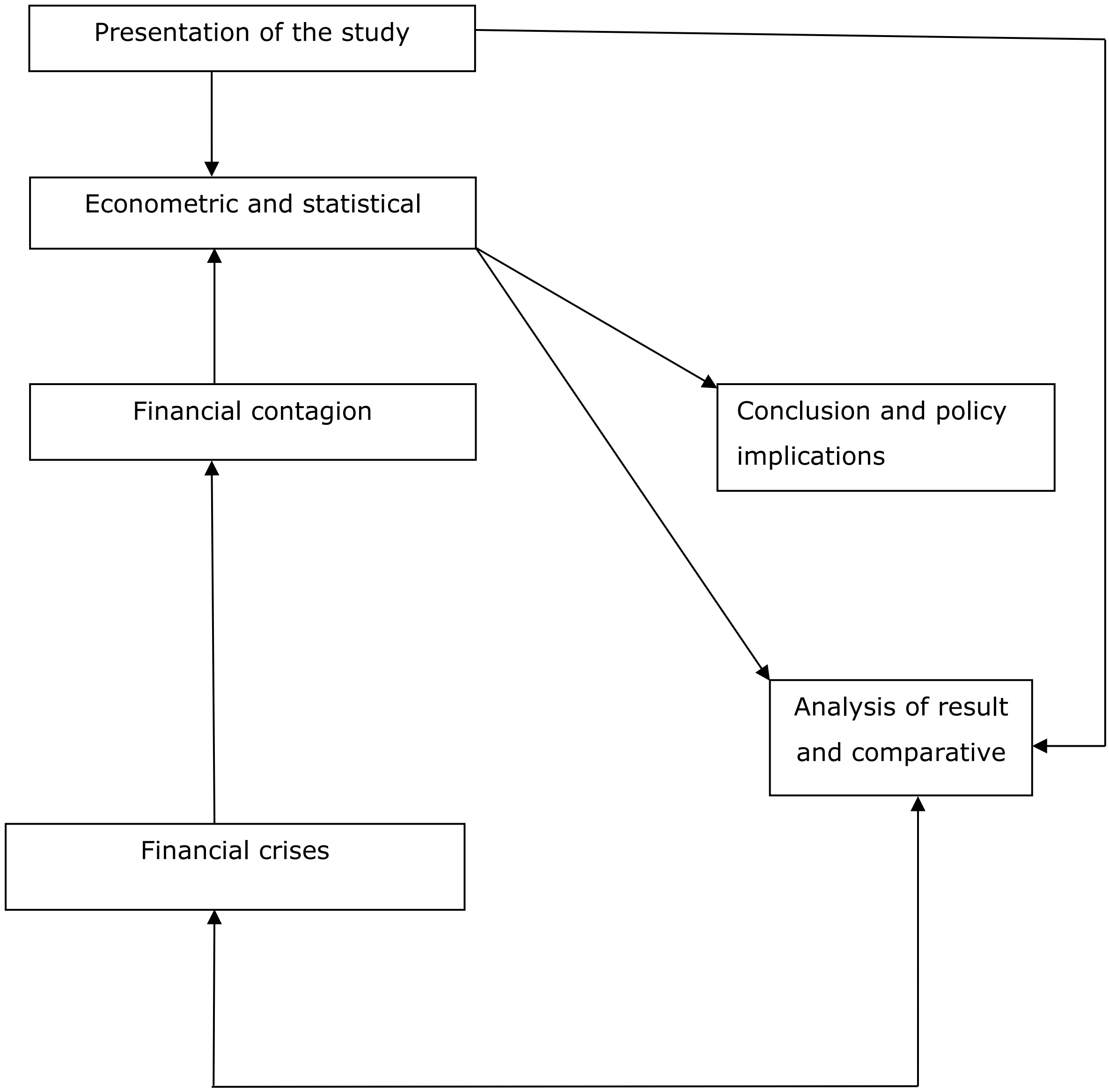

Figure 1-1: A Schematic Diagram of the Conceptual Framework

1.5 RESEARCH STRUCTURE AND LAYOUT

The chapters of the thesis are organised as follows. An analysis of financial crises literature and an in-depth review of both theoretical and empirical academic literature on financial contagion is provided in Chapter Two. Statistical data and exploratory techniques are discussed and analysed in Chapter Three. Objective one (*To examine the salient characteristics of equity markets in BRICS countries*) is addressed in Chapter Four. Objective two (*To investigate the nature of volatility of stock market returns in BRICS countries during financial turmoil*) is achieved in Chapter Five. Objective three (*To examine the presence of time-varying conditional correlations in BRICS equity market returns, in the wake of the financial crises that took place in the U.S. and Eurozone countries*) is accomplished in chapter Six. Chapter Seven addresses objective four (*To investigate the presence of time-frequency correlations in BRICS stock markets, following the financial crises that took place in the U.S. and Eurozone countries*). The summary, findings, conclusions and policy recommendations are presented in Chapter Eight.

CHAPTER TWO

LITERATURE REVIEW

This chapter discusses both theoretical and empirical literature on financial contagions. The chapter starts by highlighting various types of financial crisis, with the intention of giving the reader a deeper understanding of the occurrence of crises and how they are transmitted in the form of financial contagion. The chapter is organised into four sections. Section one focuses on the three main types of financial crises, namely currency, banking and stock market crises. A general review of financial contagion is presented in section two. The discussion on empirical literature on financial contagion is presented in section three. The chapter concludes with a brief summary of the review in section four.

2.1 THEORETICAL LITERATURE ON FINANCIAL CRISES

For the last three decades, financial markets around the world have been hit — sometimes without interruption — by financial turmoil on an unprecedented scale. For example, over the period 1975-1997, on a sample of 50 developed and developing countries, the International Monetary Fund (IMF) estimated at 158 the number of currency crises and 54 the number of banking crises (Boyer, Dehove and Plihon, 2004). The crises were particularly frequent and profound in emerging countries that had been recently integrated into the international financial market (Rejeb and Boughrara, 2015).

The Mexican crisis in late 1994 and early 1995 opened the cycle of crises in the 1990s. It was followed two years later, in July 1997, by the Thai crisis, which, spreading over a large part of Asia in 1997 and 1998, hit Korea, Malaysia, Indonesia and the Philippines. In August 1998 it was followed by the Russian crisis that destabilised the Brazilian economy significantly towards the end of 1998 and early 1999. Turkey sank into crisis in late 2000, and then a crisis hit Argentina and Brazil in 2001 and again in 2002. Major industrial countries were not spared from these crises. For instance, the bankruptcy of a large investment fund, the Long Term Capital Management (hereafter referred to as LTCM), put in jeopardy the financial stability of the U.S. markets in 1998. The crisis sent a shockwave through all major industrial countries in one of the biggest stock market meltdowns in their histories (Dungey, Fry, González-Hermosillo and Vance, 2006). Towards the end of the 2000s, world economies suffered yet another severe financial crisis. The crisis started in the U.S. sub-prime sector and spread throughout the world, triggering an unparalleled global crisis in the real economy. Most recently, the Eurozone crisis that erupted in the wake of the sub-prime crisis has affected several Eurozone countries. The crisis is the result of the inability of some Eurozone countries to repay their government debt or to bailout their over-indebted banks (Chittedi, 2014).

Depending on the nature of contagion, Pericoli and Sbracia (2003) identified three main types of financial crisis: (i) stock market crisis, (ii) currency crisis and (iii) banking crisis. It should, however, be drawn to the reader’s attention that there is a wide variety of financial crises, including crises that have played critical roles in financial histories, such as housing market crises, sovereign debt crises and industrial crises. These crises can be easily linked to the above three main crises. For example, the housing crisis can be attributed to banking crises; the sovereign debt crises can easily be combined with the currency crises, while banking crises and industrial crises can be linked to stock market crises.

2.1.1 CURRENCY CRISES

A currency crisis is a situation in which investors flee from a currency *en masse* out of fear that it might be devalued (Kaminsky, 2016). Glick, Guo and Hutchison (2006) concur and posit that a currency crisis is often speculative attacks on the foreign exchange value of a currency. The authors point out that such a speculative attack could result in a sharp depreciation or force the authorities to defend the currency by selling foreign reserves or raising domestic interest rates. For an economy with a fixed exchange rate regime, a currency crisis usually implies a situation in which the economy is under pressure to give up the current exchange rate peg or regime. Table 2-1 lists some currency crises that have occurred during the past 30 years, together with their causes and the countries that were affected.

Table 2-1: Selected Currency Crises in the World during the Past 30 Years

Date and origin	Origin of the shock	Countries affected
September 8, 1992, Finland	The Finnish markka is floated and the Exchange Rate Mechanism (ERM) crisis unfolds.	All the countries in the European Monetary System except Germany
December 20, 1994, Mexico	Mexico announces a 15 per cent devaluation of the peso. It sparked a crisis of confidence and by March 1995, the peso's value had declined by almost 100 per cent.	Argentina suffered the most, losing about 20 per cent of deposits in early 1995. Brazil was next, while losses in other countries in the region were limited to declines in equity prices.
July 2, 1997, Thailand	Thailand announces that the baht will be allowed to float. By January 1998 the baht had depreciated by 113 per cent	Indonesia, Korea, Malaysia and the Philippines were hit hardest. Financial markets in Singapore and Hong Kong experienced some turbulence.
January 13, 1999, Brazil	Brazil devalues the real and eventually floats the currency on February 1. Between early January and the end of February, the real depreciated by 70 per cent.	Significant and protracted effect on Argentina, as Brazil is Argentina's largest trading partner.
February 22, 2001, Turkey	Turkey devalues and floats the lira.	There has been some conjecture that the Turkish crisis may have exacerbated the withdrawal of investors from Argentina. However, given the weakness in Argentina's fundamentals at the time, it is questionable to suggest developments were caused by contagion.
2016 Venezuela	Venezuelan President announces government plans to withdraw the largest banknote of 100 bolivar from circulation to stop "mafias" hoarding the currency. The 100 bolivar note accounts for 77 per cent of all currency in circulation.	The decision caused widespread panic and confusion in Venezuela, as well as long queues at banks, ATMs, and stores.

Source: Author's Compilation, Based on Information Obtained from Kaminsk, Reinhart and Vegh (2003), Claessens and Kose (2013) and Sornette (2017).

Currency crises have been intensively documented in academic literature. Krugman (1996) identified three generations of models, with each model having been developed in the wake of significant currency crises that characterised the period of the 1980s and the 1990s. These generations are discussed below.

2.1.1.1 First-Generation Models

The first-generation models were conceived following the currency crises that devastated emerging economies throughout Latin America. These models were dubbed by Alves, Ferrari, and De Paula (1999) as “canonical” crisis models. The first-generation models assume that currency crises are a result of fundamental inconsistency between domestic policies and the attempt to maintain a fixed exchange rate. Fritz, Dullien, and Mühlich (2015) stress that first-generation models describe attacks on fixed currency exchange regimes, through rational expectations[2]. The attacks are triggered by inconsistent government policies or flight out of public bonds which make public debt unsustainable.

Studies on the first-generation models include that of Krugman (1979), who described how inconsistencies between domestic economic conditions and exchange rate commitment lead to the collapse of pegged currencies. He stressed that excessively expansionary stances of domestic policies bring about the situation where absorption surpasses production. The difference between domestic absorption and production then spills over into the balance-of-payments, resulting in a deficit. To finance the deficit in the balance-of-payments, the central bank expands its reserves. This causes reserves to fall below a critical level, at which point a speculative attack is launched. Flood and Garber (1983) studied the collapse of a fixed exchange rate regime, using a pair of linear examples. The first example assumes a “perfect-foresight continuous-time model” and the second presupposes “a discrete-time stochastic model” that yields endogenous probability distribution over the collapse time and produces a forward discount of the exchange rate. Regarding the perfect-foresight continuous-time model, Flood and Garber (1983) showed that the fixed exchange rate regime is subject to the same type of dynamic instability problem as a floating currency regime. As for the second example,

[2] The rational expectations theory is an economic idea that the people in an economy make choices based on their rational outlook, available information and past experiences.

they illustrated that the model produced a forward discount during the fixed-rate currency regime.

The first-generation model is informative and straightforward, but Ickes (2014) warns that it has one significant flaw, i.e., it assumes that while agents are rational in the model, the policymakers in the government are believed to be irrational and act like "dumb robots losing reserves each period" (Ickes, 2014:7).

2.1.1.2 Second-Generation Models

After the realisation that conventional theories were unable to provide consistent answers for the East Asian crises of the early 1990s, the second-generation of models was developed. The second-generation models were more sophisticated than the first-generation models, and the government policy in these models was less mechanical. Second-generation models assume that the governments (in countries affected by crises) can choose between defending or not defending a pegged exchange rate. The choice involves making a trade-off between short-run macroeconomic flexibility and long-term credibility. The models presuppose that "a fixed exchange rate will be costly to defend because people, in the past, anticipated that it would be depreciated at any time or because economic agents now anticipate it will be depreciated in the future" (Alves, Ferrari and De Paula, 1999:5). Glick and Hutchison (2013) concurred and posited that in the second-generation models the government weighs the costs and benefits of defending the currency and it is willing to give up an exchange rate target if the costs of defending the currency exceed the benefits. Alves, Ferrari and De Paula (1999) also recognise the need for a trade-off. The authors argue that higher interest rates trigger crises when the market feels that currency security is not going to succeed. In this instance, the country has to make a trade-off between the cost of maintaining the parity and the cost of abandoning the fixed exchange rate. If there are concerns that the country is likely to devalue its currency in the future, it would be wise to seek to dispose of the currency (before the devaluation take place), even in the absence of a speculative attack. In doing so, however, they would worsen the government's trade-off, most likely leading to an earlier devaluation. The result can be a crisis that ends the fixed exchange rate regime before the fundamentals appear to make devaluation necessary.

Among the studies documenting second-generation models, one conducted by Obstfeld (1988) found that first-generation models could not explain the currency crises that took place in

Europe in the 1990s. He stressed that several factors, such as the effects of high-interest rate and the growing unemployment rate, come into play in determining government responses to currency crises. He explained that a fixed-rate regime will be costly to defend if speculators expected in the past that it would be depreciated now. For example, debt holders might have demanded a high rate of interest in anticipation of depreciation, making the current debt burden so substantial that it is hard to manage without depreciation. Alternatively, unions, expecting depreciation, might have set wages at levels that leave the country's industry uncompetitive at the current exchange rate. Sachs, Tornell and Velasco (1996) conducted a study on the Mexican peso crisis to uncover new lessons about the nature of financial crises. In their model, they assumed that the level of a state varies to determine the pay-offs at the disposition of the government at each point in time. They concluded that multiple equilibria and self-fulfilling runs are possible, but only at certain levels of debt. Sachs, Tornell and Velasco (1996) found that a surprise devaluation could either increase or decrease future expected devaluation relative to a no-devaluation situation. Jeanne (1997) analysed the 1992-1993 crisis of the French franc, using a model that views self-fulfilling speculation as a phenomenon resulting from a bifurcation in the fundamental economic variable. He found some evidence that self-fulfilling speculation was at play. Frankel (1999) posited that the choice of the exchange rate depends on the particular circumstances faced by the country in question. Combes, Kinda and Plane (2012) refuted the assumption that intermediate regimes are more vulnerable to crises, compared to the hard peg and the fully floating regimes.

Other studies focused on the geographic location of currency crises. These studies hypothesised that currency crises are regional and tend to affect countries in close geographic proximity. The implication is that patterns of international trade are essential in understanding how currency crises are spread (Glick and Rose, 1999). In their study, Glick and Rose (1999) were able to support the ideas mentioned above. Using data for five different currency crises in 1971, 1973, 1992, 1994 and 1997 they showed that currency crises affect clusters of countries tied together by international trade. They also established that macroeconomic and financial influences are not closely associated with the cross-country correlations in exchange market pressure during a crisis episode.

However, the second-generation models were criticised for their lack of realism and robustness; for instance, Krugman (1996) questioned the theoretical robustness of the self-fulfilling view by presenting an escape clause model that does not give rise to multiple equilibria.

2.1.1.3 Third-Generation Models

Although the literature on contagious currency crises has helped to explain the spread of devaluations and their magnitudes, the first two generations of models on currency crises failed to provide a policy recommendation for central banks in the face of a crisis. Even though the two models had a considerable significance in the crises that occurred before the 1990s, they could not explain significant crises that occurred in Asian countries. Interestingly, before the Asian currency crisis, governments in the affected countries instituted sound fiscal policies, and economic growth showed signs of excess capacity. The affected economies had not faced the kind of trade-off between employment and exchange rate stability.

The third-generation currency crisis models were first suggested by Krugman (1999) and Aghion, Bacchetta and Banerjee (2000, 2001) who examined the effects of monetary policy in currency crises. More specifically, they gave more emphasis to two factors that had been omitted from the previous two models, namely: (i) the role of companies' balance sheets in determining their ability to invest, and (ii) the role of capital flows in affecting the real exchange rate. These models reason that fragility in the banking and financial sector reduces the amount of credit available to firms and increases the likelihood of a crisis. Third-generation models have suggested that a currency crisis is driven by a combination of high debt, low foreign reserves, falling government revenues, rising expectations of devaluation, and domestic borrowing constraints.

In seeking to explain currency crises in the spirit of third-generation models, Radelet and Sachs (1998) provided an analysis of the financial crisis in Asia by focusing on the empirical record in the build-up to the crisis. Their study highlighted the role of financial panic as an essential element of the Asian crisis. The study showed that although there were underlying problems, and weak fundamentals that troubled Asian economies — on both macroeconomic and microeconomic levels — the imbalances were not sufficiently severe to justify a financial crisis of the magnitude felt in Asian countries. Radelet and Sachs (1998) asserted that a mixture of panic on the part of international investors, bad government policies and ill-planned international rescue programmes ended up turning the simple withdrawal of foreign capital into a fully-fledged financial panic and deepened the crisis more than was necessary. Kaminsky and Reinhart (1998) examined the role of international bank lending, the potential for cross-market hedging, and bilateral and third-party trade in the propagation of crises. They concluded that, rather than a causal relationship from banking to balance-of-payments crises, the macroeconomic “stylised facts” that characterise these episodes seem to have common causes. Two years later Kaminsky and Reinhart (2000) also analysed the link between banking and the balance-of-payments crises during the Exchange Rate Mechanism (ERM) and the Mexican currency crises. They pointed out that the fact of knowing there are banking problems allows market players to predict a balance-of-payments crisis, but the opposite was not true. They also found that financial liberalisation usually presages banking crises and helps predict them.

2.1.2 BANKING CRISES

A banking crisis can be defined as a period during which the financial sector experiences bank runs. These crises are usually accompanied by an abrupt rise in default rates, followed by significant losses in capital, resulting in government intervention and bankruptcy (Boissay, Collard and Smets, 2013). Laeven and Valencia (2013) defined a systemic banking crisis as one associated with recessions. They stipulated two conditions that need to be met for a banking crises to qualify as systemic: (i) substantial signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system and bank liquidations), and (ii) considerable banking policy intervention measures in response to substantial losses in the banking system.

Calomiris (2009) surveyed the history of banking crises. He traced the banking crises to what he called “risk-inviting microeconomic rules” of the banking game, created by governments. These risk-inviting rules take the form of visible subsidies for risk-taking and the expansion of government-sponsored deposit insurance and other bank safety net programmes. The U.S. government subsidisation of sub-prime mortgage risk that resulted in the 2007-2008 crisis is a typical example. Calomiris (2009) listed the government-imposed structural constraints on banks, such as entry restrictions that constrain competition, prevent diversification of risk, and limit the ability to deal with shocks. Bordo, Eichengreen, Klingebiel and Martinez-Peria (2001) noted that the incidence of bank crises and even “twin crises,” that is, combined banking and currency crises, increased significantly during the period between 1973 and 1997 compared with the period before the Bretton Woods era. Laeven and Valencia (2013) concurred and maintained that bank crises had become a more common occurrence in the post-Bretton Woods era, particularly in emerging markets. Husain, Mody, and Rogoff (2005) presented evidence that demonstrated that emerging markets experience more banking and twin crises than do upper-income or developing economies. They highlighted the fact that emerging economies are more exposed to capital flows than developing economies, but their financial sectors are more fragile compared with developed economies.

The concept of twin crises was also documented by Eichengreen and Arteta (2002). Their statistical analysis of twin crises suggested that banking crises are more likely to precede currency crises. Nakatani (2016) constructed a twin banking and currency crisis model by introducing the banking sector into the currency crisis model. He examined the case in which the exchange rate risk is located in the banking system. Nakatani (2016) demonstrated that an unanticipated shock caused by the shift of investors' expectations and a negative productivity shock could trigger a twin banking and currency crisis.

A small number of studies have documented poor management as a leading cause of banking crises. For instance, Fahlenbrach, Prilmeier, and Stulz (2012) analysed stock return performance of banks during the 1998 crisis. Their study showed that the risk culture and aspects of the business model of a bank could make its performance sensitive to crises. Beltratti and Stulz (2012) investigated a sample of banks across the world and illustrated that banks with more fragile financing and with better governance performed worse during crises. Table 2-2 displays various banking crises that have occurred in the past 40 years.

Table 2-2: Selected Banking Crises in the World during the Past 40 Years

Date and origin	Origin of the shock	Countries affected
1981–1982 Emerging markets	Between 1979 and 1982, real commodity prices fall by about 40 per cent. U.S. real interest rates hit about 6 per cent — their highest readings since 1933. The beginning of the decade-long debt crisis in emerging markets.	Emerging markets: Argentina, Chile, Colombia, Congo, Ecuador, Egypt, Ghana, Mexico, the Philippines, Turkey and Uruguay.
1987–1988 African countries	The tail-end of a nearly decade-long debt crisis.	Many small, mostly low-income countries; Sub-Saharan Africa particularly hard hit.
1991–1992 Nordic countries and Japan	Real estate and equity price bubbles in the Nordic countries and Japan burst; many transition economies cope with liberalisation and stabilisation.	Advanced countries such as the Czech Republic, Finland, Greece, Japan, and Sweden. Others: Algeria, Brazil, Egypt, Georgia, Hungary, Poland, Romania and Slovakia.
2007 US	The U.S. sub-prime real estate bubble — and other real estate bubbles in advanced economies.	Germany, Hungary, Iceland, Ireland, Japan, Spain, UK and US.
2008 Ireland	The post-2008 Irish banking crisis was the situation whereby, due to the Great Recession, several Irish financial institutions faced almost imminent collapse due to insolvency. In response, the Irish government instigated a €64 billion-euro bank bailout.	Greece, Ireland, Portugal, Italy, France and Germany.
2008 Spain	Referred to as the Great Spanish Depression, it started in 2008 during the world financial crisis of 2007–08. In 2012 it made Spain a late participant in the European sovereign debt crisis when the country was unable to bail out its financial sector and had to apply for a €100 billion rescue package provided by the European Stability Mechanism (ESM).	Eurozone countries.

Source: Author's Compilation Based on Information Obtained from Kaminsk, Reinhart ,Vegh (2003) Claessens and Kose (2013) and Sornette (2017).

2.1.3 TWIN CRISES OF BANKING AND CURRENCY

Although currency crises have become a rare occurrence in developed countries, they have increased in intensity for recently integrated economies (Kaminsky, 2016). In some instances, the joint occurrence of banking and currency crises has given rise to a new type of financial crisis referred to as twin crises (Kaminsky, 2016). Twin crises are a result of an intense speculative attack on domestic currency combined with a series of bank failures. To explain the joint occurrence Boyer, Dehove and Plihon (2004) highlighted the fact that foreign assets liabilities constitute a significant component of commercial banks' balance sheets in emerging economies. They also contended that the causality between bank and currency crises might run in either direction. Figure 2-1 is a graphic representation of the set of events associated with twin crises.

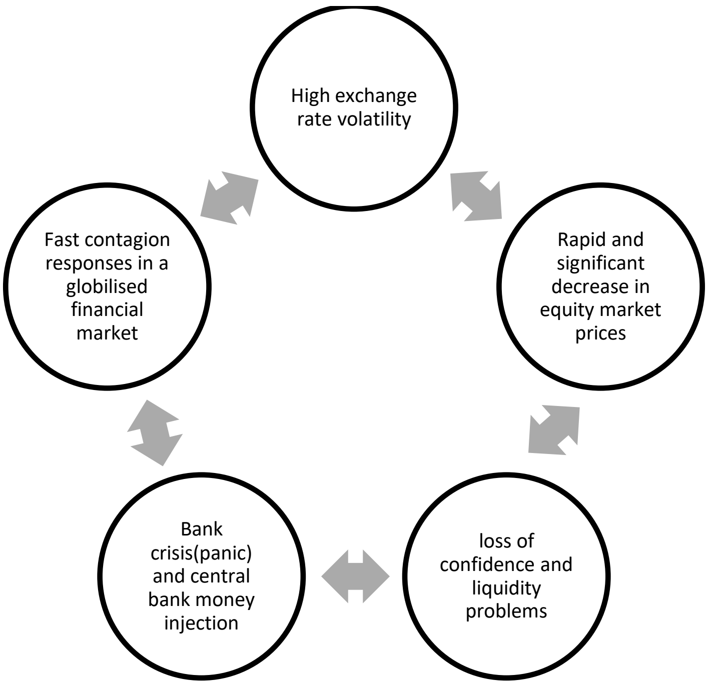

Figure 2-1: A Set of Events Associated with Twin Crises of Banking and Currency

One set of events suggested by Stoker (1996), begins with balance-of-payments problems and leads to a banking crisis. In his chain of events external shocks, such as an increase in foreign interest rates, combined with a commitment to a fixed parity will lead to loss of reserves. If not sterilised, this will result in a credit crunch, increased bankruptcies, and financial crisis. Another set of events proposed by Mishkin (1996) posits that, if devaluation occurs, the position of banks is weakened further given the fact that a large share of their liabilities is denominated in a foreign currency. Other models point in a different direction where financial sector turmoil leads to the currency collapse. In these models, the attempts to bail out troubled financial institutions by the central banks (by printing money) lead to currency crash prompted by excessive money creation (Hale and Arteta, 2009).

2.1.4 STOCK MARKET CRISES

A stock market crisis (or stock market crash) is a sudden decline of stock prices across a significant cross-section of a stock market, resulting in a substantial loss of wealth. Crashes are driven as much by panics as by underlying economic factors. They often follow speculative stock market bubbles. There is little research on international stock market crises, with only restricted literature on foreign currency and the U.S stock market (Sandeep and Sarkar, 1998). Table 2-2 lists some of the significant stock market crises that have occurred in the past 30 years.

Boyer, Dehove and Plihon (2004) pointed out that the term financial market crisis has two different meanings that are not mutually exclusive. The first refers to bursting of speculative bubbles[3]. The second relates to a swift and severe (fast and furious) decline in stock prices.

Concerning the first meaning, there has been an increasing number of theoretical and empirical papers that studied speculative bubbles. On theoretical grounds, it has been shown that asset price paths reflect the irrational behaviour of economic agents (Tirole, 1982; Diba and Grossman, 1988). Various studies on rational and behavioural theories have attempted to explain why bubbles occur. Hamilton and Whiteman (1985) documented the occurrence of speculative bubbles and concluded that it is not easy to differentiate speculative bubbles from unobservable movements in economic fundamentals.

[3] Speculative bubbles are an instance whereby there is a large and persistent deviation of security prices relative to their fundamental values.

Table 2-3: Selected Stock Market Crises in the World during the Past 30 Years

Name date and origin	Origin of the shock	Countries most affected
19th October 1989 Black Monday	Programme trading, overvaluation, illiquidity and market psychology.	Hong Kong, European Union countries, the US, Australia and New Zealand
March 2000 Dot-com bubble U.S.	The collapse of a technology bubble, world economic effects arising from the September 11 attacks and the stock market downturn of 2002.	All industrialised countries
September 2008 U.S.	Failures of large financial institutions in the United States, due primarily to exposure of securities of packaged sub-prime loans and credit default swaps issued to insure these loans and their issuers, rapidly devolved into a global crisis, resulting in several bank failures in Europe and sharp reductions in the value of equities (stock) and commodities worldwide.	All industrialised countries
April 2010 European sovereign debt crisis	Standard and Poor's downgrades Greece's sovereign credit rating to junk four days after the activation of a €45-billion EU–IMF bailout triggering the decline of stock markets worldwide and the Euro's value, furthering a European sovereign debt crisis.	Greece, Portugal, Ireland, Spain, Cyprus
June 2015 China	Enthusiastic individual investors inflated the stock market bubble through massive amounts of investments in stocks, often using borrowed money, exceeding the rate of economic growth and profits of the companies they were investing in.	Australia, New Zealand and Asian countries, but the fall in the value of energy and commodity prices had a wider impact on Canada, South Africa, Latin America.

Source: Author's Compilation Based on Information Obtained from Kaminsk, Reinhart and Vegh (2003) and Claessens and Kose (2013)

Thus, as Hamilton and Whiteman (1985) maintained, without complete information on economic fundamentals, the existence of a bubble cannot be verified. Gürkaynak (2008) surveyed the econometric tests for rational price bubbles. He found that the empirical results are mixed: for each paper that finds evidence of bubbles, others fit the data equally well without allowing for a bubble. Other researchers turned to behavioural finance paradigms to explain the occurrence of bubbles. Shiller (2003), for instance, asserted that “price-to-price” feedback theories could explain the occurrence of speculative bubbles.

Concerning the second meaning of fast and furious decline in stock prices, Mishkin and White (2002) have shown that, irrespective of the origin of the crash, whether due to a decline in the fundamentals or a bubble burst, a significant decline in stock prices has an adverse effect on the economic stability of the countries concerned. The shock is transmitted through the effect that a considerable loss in wealth has on consumer spending. The shock is spread by way of the impact it has on the cost of capital and investment, both of which are standard channels in the monetary transmission mechanism (Mishkin and White, 2002).

2.2 THEORETICAL LITERATURE ON FINANCIAL CONTAGION

Contagion can be defined as a significant increase in cross-market linkages after a shock. According to Claessens and Forbes (2004), the term contagion started to gain popularity in financial and international economics literature in the aftermath of the “Asian Flu”, the currency crisis that engulfed Thailand in 1997. The crisis quickly spread through East Asia and later Russia and Brazil. Before this crisis, the term “contagion” usually referred to the spread of a medical disease. Although drawing analogies between the propagation of the financial crisis and the propagation of medical disease might seem fanciful, Claessens and Forbes (2004) pointed out that the comparison is useful on several levels. Both refer to the transmission of a malady through direct or indirect contact. Even earlier figurative (non-medical) definitions of contagions are highly applicable to contagion in financial markets.

According to Cheung, Tam and Szeto (2009), a metaphorical definition of contagion, as “the spreading of a harmful idea or theory”, is also applicable to the spread of a financial crisis. They pointed out that some financial contagions, like the Russia virus that occurred in 1998, were based on changes in investor “psychology,” “attitude,” and “behaviour”, for various reasons. For instance, less-informed investors might opt to discard their information and instead decide to follow the “leader” blindly, causing markets to move together. Despite the surge of interest in contagion after the series of crises in the 1990s, many of the critical questions remain unanswered on the correct definition of contagion. There have been disagreements as to whether the term contagion should apply between two countries that have similar macroeconomic fundamentals and are closely linked. The U.S. and Canada, for example, are in the same geographic area and have many similarities in terms of market structure and history. Furthermore, the two countries have strong direct linkages through trade and finance. The U.S. and Canada are always linked during stable and crisis periods. The propagation of a significant scare during a period of crisis is just a continuation of the interdependence that exists during tranquil periods. Academics would agree that the transmission of a shock from U.S. stock market crashes to the Canadian market does not constitute contagion.

Nevertheless, there are mixed views concerning whether the propagation of a crisis that occurred between Brazil and Argentina at the beginning of 1999 was a contagion. On 13 January 1999, the Brazilian stock market fell by 13 per cent, and the Argentine stock market declined by 9 per cent. This propagation was an example of contagion. The following day the Brazilian market recovered by 23 per cent and the Argentine market rose by 11 per cent. However, during that period of crisis Argentina had relatively stable fiscal and current account balances and the spillover onto Argentina’s economy was unwarranted, given Argentina’s strong economic fundamentals (Forbes and Rigobon, 2002). Most academics agree that when two economies are located in a separate geographic area and have weak macroeconomic fundamentals, nor have direct linkages (such as financial trade) the propagation of crisis from one country to another is undoubtedly contagion. This is also the case of the contagion that occurred between Russia and Brazil towards the end of 1998.

Claessens and Forbes (2004) propose a more inclusive definition of contagion. It captures the vulnerability of one country to events happening in other countries. The vulnerability exists regardless of the cause, or whether or not there are links between the countries concerned. However, as the authors argue, it is useful to distinguish between a broader definition of contagion and shift contagion to allow policymakers and government officials to assess the effectiveness of the intervention and financial assistance packages needed during the financial crisis.

An extensive literature on financial contagion has developed in the aftermath of the global financial crisis of 2008-2009 and the Eurozone crisis of 2009-2012. These include, among others Kenourgios and Dimitriou (2015) who examined the contagion effects of the global financial crisis of 2008 and 2009 in ten sectors within six developed and emerging regions during different phases of the crisis. Their findings indicated that the global financial crisis of 2008-2009 can be characterised by contagion effects across regional stock markets and regional financial and non-financial sectors. However, they noted that developed countries in the Pacific region, and some sectors (in particular consumer goods, healthcare and technology) across all regions, were less affected by the crisis, while the most vulnerable sectors were observed in the emerging Asian and European regions. Ahmad, Sehgal and Bhanumurthy (2013) investigated the contagion effects of Greece, Ireland, Portugal, Spain, Italy, USA, UK and Japan markets on BRIICKS (Brazil, Russia, India, Indonesia, China, South Korea and South Africa) stock markets, during the Euro-zone crisis period, and their empirical results indicated that among Eurozone countries, Ireland, Italy and Spain appeared to be most contagious for BRIICKS markets compared to Greece. The study also indicated that the contagious shock strongly hit Brazil, India, Russia, China and South Africa during the Eurozone crisis. However, Ahmad, Sehgal and Bhanumurthy (2013) found that Indonesia and South Korea experienced only interdependence and not contagion. Hemche, Jawadi, Maliki and Cheffou (2016) studied the contagion hypothesis for ten developed and emerging stock markets (namely France, Italy, UK, Japan, China, Argentina, Mexico, Tunisia, Morocco and Egypt) concerning the U.S. market in the context of the sub-prime crisis. Their findings indicated that there was an increase in dynamic correlations following the sub-prime crisis for most markets under consideration with respect to the U.S. market.

2.2.1 FINANCIAL LIBERALISATION AND FINANCIAL CONTAGION

Stock market liberalisation refers to the reduction or removal of market-based regulatory policies. The liberalisation of the stock market causes a paradigm shift from an administrative system to a market-based system. The operation of forces of supply and demand serves as the framework for deciding stock prices in a liberalised stock market. Given the fact that prices are determined by market forces, stock prices appear to be more volatile (Adeyeye, Aluko, Fapetu, and Migiro, 2017). Furthermore, financial liberalisation generally attracts short-term investors to an economy, and this leads to asset price bubbles and financial system instability (Singh, 2003).

Since its adoption by developed countries, the primary goal of financial liberalisation has been to improve financial integration to reap its benefits (risk diversification, reduction of capital costs, data efficiency). The achievement of these goal depends almost entirely on the economic conditions of each nation at the opening of its market. Implementing such a policy in emerging markets has several ramifications. For example, several previous studies have shown that financial liberalisation appears to decrease volatility and improve knowledge efficiency in emerging markets (Rejeb and Boughara, 2015). Financial liberalisation also plays a crucial role in efforts to improve the financial situation, and thus improves economic growth of emerging markets.

Nonetheless, despite its many benefits, studies have shown that financial liberalisation in the short term is often followed by a surge of financial crises, most of which have taken on a global scale and have struck the recently liberalised markets, emerging markets in particular. The promotion of financial integration as the primary objective of financial liberalisation was achieved by slowly eliminating the most important obstacles to foreign investment and increasing capital mobility restrictions.

2.2.2 INVESTORS' BEHAVIOUR AND FINANCIAL CONTAGION

A limited number of studies have attempted to use behavioural finance theories to explain financial contagion. These studies illustrate how financial contagion could arise from psychological propensities of investors who fail to update their beliefs correctly. For instance, research in experimental psychology has proven that market agents tend to overreact to unexpected and dramatic news or events in violation of Bayes' rule[4] (DeBondt and Thaler, 1985). Even if they updated beliefs correctly, market agents sometimes make choices that are not normatively acceptable. A survey of the literature by the researcher revealed two main behavioural finance hypotheses to explain how contagion can arise from market agents behaviours. They are the overreaction and the herding contagion hypotheses.

[4] Bayes rule is a theorem that provides a way to revise existing predictions or theories given new or additional evidence.

2.2.2.1 Overreaction Hypothesis

Overreaction is a hypothesis of behavioural finance, asserting that market agents react disproportionately to new security information. Overreaction causes the security's price to change dramatically immediately following the event and the price no longer reflects the security's real value (DeBondt and Thaler, 1985). Studies have shown that overreaction to social learning channels can contribute to infectious panics, because market agents put too much weight on the actions they observe in a foreign country, thus reinforcing the channels of social learning (Trevino, 2004). The pioneering study by DeBondt and Thaler (1985) probed the relationship between market behaviour and individual decision-makers' psychology. The study showed that the stock market overreacts to information in past earnings or security prices, at the expense of longer-run trends. Using the New York Stock Exchange (NYSE) monthly return data for the period 1926-1982, DeBondt and Thaler (1985) constructed two portfolios, Winner and Loser. The Winner portfolio comprised extreme high return securities while the Loser portfolio consisted of extremely low return securities. Their empirical results showed that, on an average, the Loser portfolio outperformed the market by 19.6%, and the Winner underperformed the market by 5%. DeBondt and Thaler (1985) explained that the overreaction occurs because stock prices systematically overshoot and that their reversal is predictable. They posited that subsequent price movements would follow two hypotheses on investor overreaction: (i) Extreme movements in stock prices in the opposite direction, (ii) The more extreme the initial price movement, the higher the subsequent adjustment.

Following DeBondt and Thaler's (1985) study, the overreaction hypothesis generated much interest in subsequent years. Other studies that have documented the overreaction hypothesis include Brown and Harlow (1988) who extended the study of DeBondt and Thaler (1985) by investigating the relationship between the magnitudes of the reaction and the amount of time of initial price change. They formulated three propositions, namely (i) Directional effect, which states that movements will follow extreme movements in stock prices in the opposite direction. (ii) Magnitude effect, which explains that the more extreme the initial price change, the more extreme the offsetting reaction. (iii) Intensity effect, which hypothesises that the shorter the duration of the initial price change, the more extreme the subsequent response. Fama and French (1988) and Poterba and Summers (1988) also found results consistent with the predictability of stock returns, supporting the DeBondt and Thaler (1985) study. Howe (1986) demonstrated that, based on a substantial price decline over a week, the Winners displayed unusual negative returns up to one year after portfolio creation. Broner and Rigobon (2006) revealed that markets with regular overreaction activities, such as emerging markets, display excess volatility. Leijonhufvud (2007) concurred and stressed that the concentration of risk in emerging markets and the resultant formation of bubbles in asset prices can be attributed to organisational form and the compensation system. Agosin and Huaita (2012) studied the overreaction of capital flow in an emerging market. They found that capital boom (a surge in capital flows) can predict future sharp contractions or sudden stops in capital flows. By using an extensive list of possible economic fundamentals as control variables, they illustrated that the best predictor of a sudden stop is a preceding capital boom.

2.2.2.2 Herding Contagion Hypothesis

The term herding contagion was coined by Calvo and Reinhart (1996) who noted that contagion could arise from factors independent of fundamentals. They stressed that this category of contagion exists when common shocks or all channels of interdependence between affected markets are not present or are controlled. In this instance, investors follow other investors in a way that cannot be justified by their expectations about the market (Trevino, 2014).

Herd behaviour has been extensively documented in behavioural finance theories. According to Scharfstein and Stein (1991), herd behaviour is a phenomenon that takes place when investors "...mimic the investment decision of others..., ignoring substantive private information". Daniel, Hirshleifer and Teoh (2002) define herding as "mutual imitation, leading to a convergence of actions". Bikhchandani and Sharma (2001) assert that herd behaviour occurs when an investor decides not to invest for the simple reason that others decided not to invest, but would have invested should he/she not have known other investors' decision; conversely, he/she would change his/her decision not to invest after finding out that other investors did so.

Literature on herd behaviour can be traced as far back as the 1930s when Keynes, the renowned economist, questioned the ability of long-term investors to make sound investment decisions (Scharfstein and Stein, 1991). He pointed out that investors may be unwilling to trade using their private information out of fear that contrarian behaviours of others will spoil their reputations as credible decision-makers; as he explained further, investors "follow the herd" simply because they are worried that others will negatively assess their ability to make sound investment decisions. Nevertheless, it was during the 1990s that herd behaviour started to attract the attention of a considerable number of academic researchers in the field of behavioural finance. For instance, Sharfeistein and Stein (1991) developed a model with two kinds of managers, “smart ones” who receive correct, useful information about the value of an investment and “dumb ones” who receive merely noisy information. They concluded that herd behaviour could arise from various circumstances as a result of a rational attempt by managers to boost their reputations. Banerjee (1992) proposed a model based on sequential decisions where decision-makers observe the actions of their predecessors. He concluded that their behaviour is rational as their predecessors might have important information that they do not have.

Bikhchandani and Sharma (2000) proposed a sequential model based on what they called “informational cascades” to explain not only conformity to the actions of others but also to explain quick and short-lived phenomena such as trends, fashions, and crashes. Devenow and Welch (1996) argued that herd behaviour is irrational at an individual level when one bears in mind that investors ignore their earlier beliefs and follow the crowd blindly. Cont and Bouchaud (2000: 6) criticised the idea of a sequential model proposed by Banerjee (1992) and Bikhchandani and Sharma (2000) as unrealistic since traders submit their orders simultaneously. They note that “orders from various market participants enter the market simultaneously, and it is the interplay between different orders that determines the aggregate market variables”. As a result, the authors adopted a model that avoids a sequential decision process; instead, they based their model on a random communication process with groups of agents making independent decisions. They argued that these random interactions between agents give rise to a heterogeneous market structure. Bikhchandani and Sharma (2001) stressed that one must differentiate between “intentional” and “spurious” herding; the latter occurs when a group of decision-makers faced with the same problems and information set arrive at the same conclusions about their investment decisions. An example of spurious herding would be an increase in interest rates that induces investors to reduce their stock holdings *en masse*. Alemanni and Ornelas (2006) noted that even though herd behaviour might be rational at the individual investor level, it is still irrational at the group level since it can lead to mispricing, and the resulting equilibrium is inefficient.

2.3 EMPIRICAL LITERATURE REVIEW ON FINANCIAL CONTAGION[5]

There is a plethora of empirical literature testing how crises are propagated. Most of this literature uses the narrow (or pure) definition of contagion that describes it as a significant increase in cross-market linkages after a shock to one country or group of countries. This definition stresses that it is only contagion if cross-market co-movement increases significantly after a shock. If the co-movement does not intensify considerably, then any persistent high level of market correlation suggests only strong linkages between the two markets or economies, commonly referred to as interdependence. Although the narrow definition of contagion is restrictive, it has two main advantages. Firstly, it provides a straightforward framework of testing contagion by simply comparing linkages between two markets during a relatively stable period with linkages immediately after a shock. Secondly, it provides a straight-forward method of distinguishing between alternative explanations of how crises are transmitted across markets (Forbes and Rigobon, 2001).

Cheung, Tam and Szeto (2009) reviewed empirical studies on contagion and classified empirical literature on contagion in two categories: (i) ones that have no identified linkages and (ii) ones that have identified linkages. These categories are displayed in Figure 2-2 below and are discussed in the next sections.

[5] This section relies heavily on Cheung, Tam and Szeto (2009).

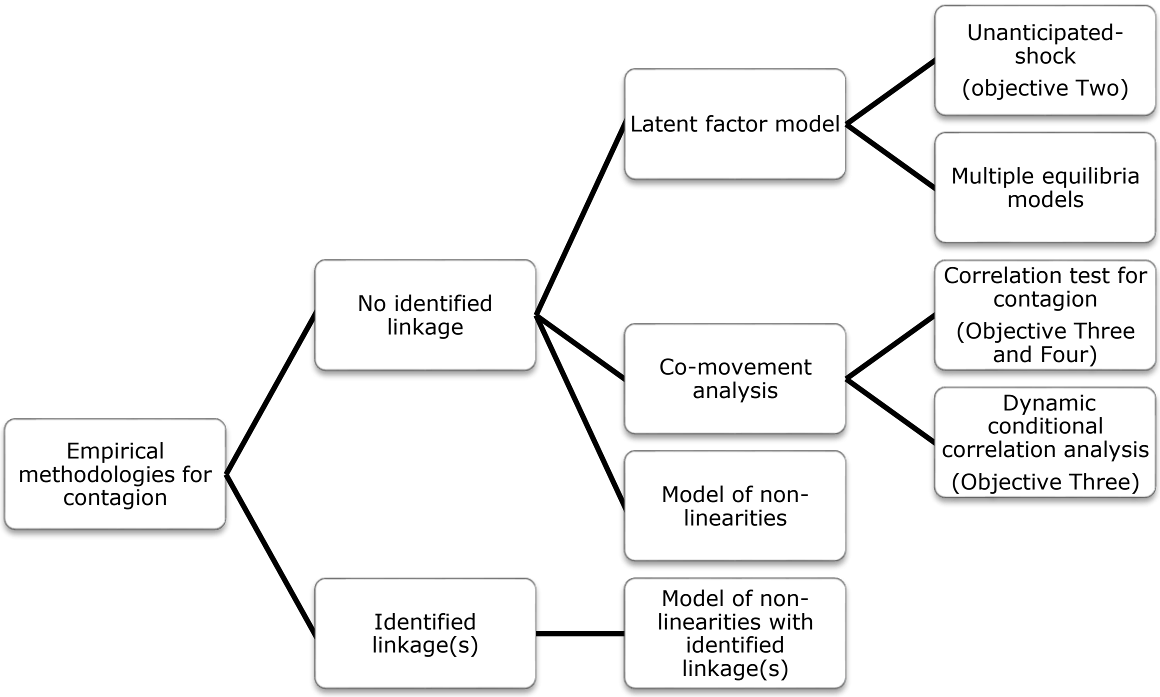

Figure 2-2: An Overview of Various Empirical Methodologies Used to Model Financial Contagion

The present study uses unanticipated-shock models factor model in the form of univariate GARCH (1,1) to address objective two (*To investigate the nature of volatility of stock market returns in BRICS countries during financial turmoil*).In order to accomplish objective three (*To examine the presence of time-varying conditional correlations in BRICS equity market returns, in the wake of the financial crises that took place in the U.S. and Eurozone countries*) and objective four (*To investigate the presence of time-frequency correlations in BRICS stock markets, following the financial crises that took place in the U.S. and Eurozone countries*), the current study uses the non-identified linkages models. For instance co-movement analyses are conducted to test correlation using the VECH GARCH model, and multiscale analysis of correlation utilising wavelet correlation. The dynamic conditional correlations methodologies are used in the form of a DCC GARCH model and wavelet analyses.

2.3.1 MODELS WITH NO IDENTIFIED CHANNEL OF TRANSMISSION

Three major types of models have been identified in the literature: (i) latent factor models, (ii) co-movement models, and (iii) models of asymmetries and nonlinearities.

2.3.1.1 Latent Factor Models

In these models, the term contagion is described as the effect of shocks across asset markets during a period of crisis. The shock can occur as an unanticipated shock in a simple asset return model or be triggered by the change in beliefs or expectations of investors in a regime-switching model (Gómez-Puig and Sosvilla-Rivero, 2014). Cheung, Tam and Szeto (2009) identified two latent factor models: (i) the unanticipatedshock and (ii) the multiple equilibria models.

The unanticipated-shock models are based on the following bivariate factor models and are formulated as follows:

$$y_{1,normal,t} = \lambda_1 w_t + \delta_1 u_{1,t} \qquad \ldots\ldots 2.1$$

$$y_{2,normal,t} = \lambda_2 w_t + \delta_2 u_{2,t} \qquad \ldots\ldots 2.2$$

$$y_{1,crisis,t} = \lambda_1 w_t + \delta_1 u_{1,t} \qquad \ldots\ldots 2.3$$

$$y_{2,crisis,t} = \lambda_2 w_t + \delta_2 u_{2,t} + \gamma_{2,1} u_{1,t} \qquad \ldots\ldots 2.4$$

where $y_{1,normal,t}$ and $y_{1,crisis,t}$ are asset returns in economy 1 during the pre-identified normal and crisis periods, respectively; $w_t$represents common shocks that impact upon all asset returns in the system (of both economies), with loading λ_i; the terms $u_{i,t}$ are idiosyncratic latent factors of the asset market in economy 1 at time *t* with loading δ_i.

The expressions in (2.1) and (2.2) imply that the asset return in economy 2 is also being affected by the idiosyncratic shocks of other economies with loading during the crisis period, reflecting that there is contagion from economy 1 to economy 2, if $\gamma_{2,1}$ is significant. Under a set of standard assumptions on the properties of $w_t$and $u_{i,t}$, the test of contagion can be done by focusing on the changes in the volatility of pairs of asset returns between the normal and the crisis periods. From equations (2.1) and (2.2), the respective covariances between the asset returns of economies 1 and 2 in each of the two states are:

$$Normal: E(\gamma_{1,normal,t}\gamma_{2,normal,t}) = \lambda_1\lambda_2 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 2.5$$

$$Crisis: E(\gamma_{1,crisis,t}\gamma_{2,crisis,t}) = \lambda_1\lambda_2 + \gamma_{2,1}\delta_1 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.6$$

Comparing (2.5) and (2.6) shows that the change in the covariance between two states is $\gamma_{2,1}\delta_1$. Therefore, the significance of change can be examined by testing the statistical significance of $\gamma_{2,1}$. As the literature review done by the researcher revealed, this approach was adopted by Dungey *et al.* (2006), to test financial contagion in the aftermath of the collapse of the LTCM. Their results showed that there were substantial international contagion effects resulting from the LTCM crisis.

Multiple equilibria models consider latent shocks under a multimodal framework. The rationale behind these models is that changes in investors' expectations, beliefs, and thus behaviours, during the crisis period are common explanations for contagion (Dornbusch, Park, and Claessens, 2000). Such changes imply that the underlying distribution of asset returns should be multimodal in general, i.e., the underlying model has two or more stable equilibria. In an N-equilibria case, these properties can be captured by a mixture of distributions:

$$f(y_{i,t}) = \sum_{j=1}^{N} \varphi_j f_j(y_{i,t}) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.7$$

where $f(y_{i,t})$is the probability density of asset return $y_{i,t}$; φ_i are weights of individual densities $f_j(y_{i,t})$in the mixture such that $\sum_{j=1}^{N} \varphi_j = 1$.

It is, however rather difficult to formulate a model of contagion related to these changes, as they are generally not observable.

Studies of multiple equilibria models include those of Fratzscher (2003) and Jeanne and Masson (2002) who used the Hamilton Markovian switching model and found that contagion effects were the most critical factors of currency crises in 24 emerging economies during the period 1986- 1998.

2.3.2 CO-MOVEMENT MODELS

The rationale behind these models is that when an exogenous shock transmits from the first economy to the others, the financial markets of the subsequent economies are likely to respond in a similar way to the first one, causing co-movements. Such co-movements of financial market variables (for example asset return and volatility) are valuable hints of contagion. In practice, analysing the correlation coefficient is the most straightforward way to investigate such co-movements, while principal component analysis is an alternative way to identify common factors in the movement of the financial market variables. Two co-movement models were identified by Cheung, Tam and Szeto (2009), namely the correlation test for contagion, and dynamic conditional correlation analysis.

2.3.2.1 Correlation Test for Contagion

Among all the empirical methods adopted in the study of contagion, correlation and covariance analysis is the most straightforward approach. These models consist of testing the significance of the increase in cross-market correlation during the pre-identified crisis period when compared to the tranquil period. For example, Baig and Goldfajn (1998) used correlation analysis to test for contagion in the equity, currency and money markets in emerging economies during the Asian financial crisis in the late 1990s. They found that correlations in currency and sovereign spreads increased significantly during the crisis period, whereas equity market correlations offered mixed evidence. The major drawback of this model is a problem of heteroskedasticity in the estimation of the correlation coefficients. The estimated correlation coefficients during the crisis period are, in general, upwardly biased and, hence, a test based on the biased correlation would imply spurious contagion.

To tackle the problem of heteroskedasticity, Forbes and Rigobon (2002) proposed an adjustment for the correlation coefficient during the turmoil period. The model is formulated as follows: Considering a test for the existence of contagion between economy 1 and economy 2, in which economy 1 is the origin of the crisis, the standard deviations of asset market return in economy 1 during the normal period and those during the turmoil period are $\sigma_{1,normal}$and $\sigma_{1,turmoil}$ respectively. It is common to see $\sigma_{1,normal} > \sigma_{1,turmoil}$. If, besides, there is no change to the fundamental relationship between the asset returns in the two markets, then the correlation of asset returns during the turmoil period will be more significant than that during normal times, i.e. $\sigma_{1,turmoil} > \sigma_{1,normal}$. According to Forbes and Rigobon (2002), the adjusted correlation is given by:

$$\tilde{\rho}_{turmoil} = \frac{\rho_{turmoil}}{\sqrt{1 + \left(\frac{\sigma^2_{1,turmoil}}{\sigma^2_{1,normal}}\right)(1 - \rho^2_{turmoil})}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.8$$

This is a non-linear scaling function, which decreases in line with the change in variance of equity return in economy 1. To examine the existence of contagion between equity markets in 1 and 2, the null hypothesis is: $H_0: \tilde{\rho}_{normal} = \rho_{normal}$. The simple t-test can be used for comparing the size of two correlation coefficients used in this study. The test statistic is then given by:

$$T = \frac{F(\tilde{\rho}_{turmoil}) - F(\rho_{normal})}{\sqrt{\frac{1}{N_{turmoil} - 3} + \frac{1}{N_{normal} - 3}}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.9$$

where $N_{turmoil}$and $N_{normal}$are the numbers of observation of the specified periods respectively, and *F*(.) is the operator of Fisher's transformation

$$F(x) = \frac{1}{2}\ln\left(\frac{1+x}{1-x}\right) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.10$$

Using this adjustment method, Forbes and Rigobon (2002) show that there was little evidence of contagion during the 1987 U.S. market crash, the 1994 Mexican devaluation and the 1997 Asian financial crisis.

2.3.2.2 Dynamic Conditional Correlation Analysis

The correlations between two markets can show the period where an increase occurs in co-movements. One possibility is to look at the time-varying conditional correlations between market returns using the Dynamic Conditional Correlation (DCC) model (Engel, 2002). The advantage of the DCC model is that it captures the time-varying nature of correlation. By looking at the correlations during the crisis period one can estimate whether the correlations increased during that period. The GARCH framework model has been used extensively to estimate the variance-covariance transmission mechanisms between markets. The DCC GARCH model has a two-step procedure for estimating conditional variances and correlations. An assumption is that the returns of the individual country index are normally distributed with zero mean conditional on the information available at t-1.

$$E_{t-1}(r_t) \sim N(0, H_t) \qquad \ldots\ldots 2.11$$

In the first step, the following univariate GARCH model is used to estimate the variance σ_u^2using the following GARCH(1,1) specification:

$$\sigma_{\mathrm{it}}^2 = \gamma_1 + \alpha_1 r_{\mathrm{it}}^2 + \beta_i \sigma_{\mathrm{it\text{-}1}}^2 \qquad \ldots\ldots 2.12$$

The conditional return of each of the markets is standardised by dividing it by its standard deviation obtained in the previous step. This gives the following standardised vector of returns:

$$E_{\mathrm{t\text{-}1}}(\varepsilon_t) \sim N(0, R_t) \qquad \ldots\ldots 2.13$$

Correlation between any two markets *i* and *j* can be written as:

$$\rho_{\mathrm{ij,t}} = \frac{E_{\mathrm{t\text{-}1}}\left(\varepsilon_{\mathrm{i,t}}\varepsilon_{\mathrm{j,t}}\right)}{\sqrt{E_{\mathrm{t\text{-}1}}\left(\varepsilon_{\mathrm{i,t}}^2\right)E_{\mathrm{t\text{-}1}}\left(\varepsilon_{\mathrm{j,t}}^2\right)}} = E_{\mathrm{t\text{-}1}}\left(\varepsilon_{\mathrm{i,t}}\varepsilon_{\mathrm{j,t}}\right) \qquad \ldots\ldots 2.14$$

By using a GARCH(1,1) specification, the covariance between the random variables can be written as:

$$q_{\mathrm{ij,t}} = \overline{\rho}_{\mathrm{ij}} + \alpha\left(\varepsilon_{\mathrm{i,t\text{-}1}}\varepsilon_{\mathrm{j,t\text{-}1}} - \overline{\rho}_{\mathrm{ij}}\right) + \beta\left(q_{\mathrm{ij,t\text{-}1}} - \overline{\rho}_{\mathrm{ij}}\right) \qquad \ldots\ldots 2.15$$

The unconditional expectation of the cross product is $\overline{\rho}_{\mathrm{ij}}$, while for the variances it is $\overline{\rho}_{\mathrm{ij}} = 1$. The correlation estimator is:

$$\rho_{\mathrm{ij,t}} = \frac{q_{\mathrm{ij,t}}}{\sqrt{q_{\mathrm{ii,t}}q_{\mathrm{jj,t}}}} \qquad \ldots\ldots 2.16$$

This model will be mean reverting if $+\beta < 1$. The matrix version of this model can then be written as:

$$Q_t = S(1\text{-}\alpha - \beta) + \alpha(\varepsilon_{t-1}\varepsilon_{t-1}) + \beta \mathrm{Q}_{\mathrm{t\text{-}1}} \qquad \ldots\ldots 2.17$$

where S is the unconditional correlation matrix of the disturbance terms and $Q_t = |q_{i,j,t}|$ .The log-likelihood for this estimator can be written as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(\text{nlog}(2\pi) + 2\text{log}|D_t| + \text{log}|R_t| + \varepsilon_t R_t^{-1}\varepsilon_t\right) \qquad \text{……………………2.18}$$

In the second stage of the estimation, the likelihood estimator is used in estimating the parameters of Equation 2.17.

Once the correlations between the two markets are estimated, the time-series properties of the correlations can be tested for structural breaks and to identify specific periods with increased correlations. If the structural break occurs around the time of the crisis it can be an indication that the crisis in one market has changed the relationship between the returns of these markets.

Hamoa, Masulis, and Ng (1990) used GARCH models to analyse the market in the wake of the 1987 U.S market crisis. They found evidence of a considerable price-volatility spillover from New York to London and Tokyo, and from London to Tokyo. Edwards (2000) analysed the co-movement between bond markets following the Mexican peso crisis. He established that there were significant spillovers from Mexico to Argentina, but they failed to establish the presence of a spillover from Mexico to Chile. It is worth noting that studies that are based on ARCH and GARCH models show that market volatility is transmitted after the relevant shock or crisis. Therefore, while these papers provide important evidence that volatility is transmitted across markets, most do not explicitly test contagion as understood in its narrow definition.

2.3.3 MODEL OF ASYMMETRIES AND NONLINEARITIES

The linearity assumption on the relationship between asset returns and foreign shock is sometimes considered to be too strong in examining extreme episodes. To this end, vector autoregressive (VAR) models are used to estimate cross-market linkages utilising probing cross-market linkages tests for changes in the cointegrating vector between markets over a long period. These models are estimated as follows:

$$z_t = \Phi z_{t-1} + v_t \qquad \text{……………………………………2.19}$$

the N-variate first-order VAR model, where z_t is the pooled asset returns across the two states (normal and turmoil) in the sample, where Φ contains the coefficient, and v_t is the reduced-form disturbance with zero mean and constant covariance matrix, with the variance given by $E(v_t^2) = \sigma_1^2$, i = 1,...,N. The dummy variables which capture the outliers are defined as:

$$d_{\mathrm{i,k,t}} = \begin{cases} 1: |v_{i,t}| > 3\sigma_t^2 \\ 0: \text{otherwise} \end{cases} \qquad \text{……………………………………2.20}$$

where the dummy variable is assigned the value of one for each observation that is an outlier. These dummy variables are then included in a structural model of asset returns. To illustrate, let us consider a model with two asset return series. If only one outlier is identified in each series, then the structural model is given as follows:

$$z_{1,\mathrm{t}} = \alpha_{1,2} + \theta_1 z_{1,t-1} + \gamma_{1,1} d_{1,1,\mathrm{t}} + \gamma_{1,2} d_{2,1,\mathrm{t}} + \eta_{1,t} \qquad \text{…………………………………2.21}$$

$$z_{2,\mathrm{t}} = \alpha_{2,1} + \theta_2 z_{2,t-1} + \gamma_{2,1} d_{1,1,\mathrm{t}} + \gamma_{2,2} d_{2,1,\mathrm{t}} + \eta_{2,t} \qquad \text{…………………………………2.22}$$

Hence, the application of both the joint test for the existence of contagion between the economies by testing the null hypothesis of $H_0: \gamma_{1,2} = \gamma_{2,1} = 0$ and an individual test of contagion from either country to another with the null hypothesis of $H_0: \gamma_{i,j} = 0$, for $\mathrm{i} \neq j$.

Favero and Giavazzi (2002) used a vector autoregressive (VAR) model to control interdependence among asset returns within the system, and then used the heteroskedasticity and non-normalities of the residuals from that VAR to identify unexpected shocks that may be transmitted across countries, and which are being considered as evidence of contagion. Their results showed that there were non-linearities in the propagation of devaluation expectation (i.e. contagion) among the members of the Exchange Rate Mechanism in the European Monetary System during the previous few decades.

2.3.4 MODELS WITH IDENTIFIED CHANNELS OF TRANSMISSION

The importance of transmission channels or fundamental linkages is usually suppressed in the studies mentioned above, which focus on the investigation of the significance of the latent factor. On the other hand, there are some other studies which focus on the examination of the importance and/or relative importance of the identified transmission channels of shocks, such as bilateral trade, financial flows and economic similarities. Instead of focusing on the existence of contagion, most of these studies concentrate on the investigation of the importance of different transmission channels of contagion risks. To this end, the probability model is the common instrument for this branch of studies, in which the importance of various channels is measured by their contribution to the probability of the occurrence of the crisis. The general model is as follows:

$$\mathrm{Crisis}_{\mathrm{i,t}} = A(\mathrm{channel}_{0,\mathrm{i,t}}) + BX_t \qquad \text{...23}$$

where $\mathrm{Crisis}_{\mathrm{i,t}}$ is a dummy variable equal to one during the crisis period in economy *i* and zero otherwise; $X_t$is a set of other possible explanatory variables and B is the corresponding coefficient matrix; $\mathrm{channel}_{0,\mathrm{i,t}}$ is a variable (or a set of variables) which measures the intensity of the transmission channel in question between the identified "ground zero" economy and economy *I*, with its corresponding coefficient matrix being A. The significance of the coefficient thus indicates the significance of the transmission channels.

2.4 CHAPTER SUMMARY

This chapter reviewed the relevant literature relating to the various objectives of the study. Both theoretical and empirical literature were discussed. The theoretical literature focused on financial crises and financial contagion. Regarding financial crises, three types of crisis were highlighted, namely the currency crisis, the stock market crisis, and the banking crisis. Theories on financial contagion focus on defining this market anomaly. Two types of contagion definitions were identified, namely, ''fundamentals-based'' and ''pure'' contagion. The empirical literature review focused on various models used to detect financial contagion. Two broad categories of the model were highlighted, namely, models with identified linkages, and models with no identified linkages.

CHAPTER THREE

EXPLORATORY ANALYSIS AND DATA PREPARATION

This Chapter describes the statistical data used for empirical analysis in the present study. The Chapter is organised as follows: the first section discusses exploratory techniques used for the initial analysis of data, consisting of unit root tests and the estimation of correlations between variables using a correlation matrix; section two describes the data used for empirical analysis; results of exploratory analysis of statistical data are presented in the third section. Conclusions are provided in the fourth section.

3.1 EXPLORATORY ANALYSIS

Estimating empirical models using time series data requires that the variables are stationary; this means that unit root tests should be done before carrying out other analysis. The correlation matrix of statistical data is also presented as a way to summarise data and as an input into a more advanced analysis on conditional correlation.

3.1.1 STATIONARITY

An empirical analysis of time series data, like the one used in the current study, requires that the underlying series are stationary; in other words, the series must be integrated of order I[0] (Gujarati 2004: 807). A stationary stochastic process is the one that contains constant mean (E (Y_t) = μ) and variance (E (Y_t - μ)^2 = $\sigma^2 < \infty$) over time and a covariance that is not serially correlated (γ_k = E [(Y_t - μ) (Y_{t+k}- μ)) (Gujarati 2010: 807). The stationarity of series has paramount importance for two reasons. Firstly, if the series is stationary, it is possible to make forecasts. Secondly, stationarity minimises the possibility of spurious regressions (Fapohunda and Eragbhe, 2017).

The condition of stationarity is achieved through testing for the presence of a unit root in a time series. The unit root is tested either by checking the significance of autocorrelation function coefficients or by examining the correlogram plots to determine whether the correlogram is decaying or not (Brooks, 2002: 377). However, Brooks (2002: 377) warns that by analysing the decay of a correlogram, one can sometimes reach the wrong conclusion about the existence of stationarity within a time series. Thus, only formal stationarity hypothesis testing is presented.

Three concepts of stationarity are discussed: (i) the conventional Dickey-Fuller stationarity test (hereafter referred to as DF) and its extension, the Augmented Dickey-Fuller (hereafter referred to as ADF), (ii) the Phillips–Perron unit root test (hereafter referred to as PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root test. The PP test is used for purposes of robustness and completeness as it tackles the problem of uncorrelated error terms differently compared to the ADF.

3.1.1.1 Dickey-Fuller Stationarity Test (DF) and Augmented Dickey-Fuller Unit Root Test (ADF)

Given the following three random walk processes with no drift (3.1), with drift (3.2), or with both deterministic and stochastic trend:

$\Delta Y_t = \delta\ Y_{t-1} + \mu_t\ ,\ \delta < 1$ ……………………………………………….…….(3.1)

$\Delta Y_t = \delta\ Y_{t-1} + \beta_1 + \mu_t,\ \delta < 1$ ……………………………………...………… (3.2)

$\Delta Y_t = \delta\ Y_{t-1} + \beta_1 + \beta_2\ t + \mu_t,\ \delta < 1$ …………………………………………….…(3.3)

where $\Delta Y_t = Y_t - Y_{t-1,}$ with Y_t the value of a time series Y for any given period of study, and Y_{t-1} the value of a time series is the value of Y seen in the previous time period t-1 and μ_t is with the noise error term. The Dickey-Fuller test consists of testing the null hypothesis of $\delta = 0$, i.e. the time series is stationary, against the alternative hypothesis of $\delta < 1$, meaning that is the time series is not stationary (Gujarati, 2010: 815). It should be noted that the critical values of the DF test are different for each of the specifications mentioned above, and that using the wrong estimate for a given specification will result in a specification error. Unfortunately, there is no clear- cut way to identify the correct specification other than trial and error and data mining (Gujarati, 2010: 816). The critical values for DF tests are given in Fuller (1976: 373), Brooks (2002: 675), and Gujarati (2010: 975) and can be obtained by simulation.

The DF test assumes that the error term in Equations 3.1, 3.2 and 3.3 are independent and identically distributed. In other words, the error terms are uncorrelated. For cases where the error terms are correlated, Dickey and Fuller (1979) developed a test commonly known as the Augmented Dickey-Fuller (ADF). The ADF test consists of augmenting the initial DF regressions by the lagged dependent variables (ΔY_{t-1}). In this way, the autocorrelation is removed. To be specific, given Equations 3.1, 3.2 and 3.3, the ADF test consists of estimating the following regressions:

$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^{m} \alpha \Delta y_{t-1} + \varepsilon_t$ ………………………………..……………………….. (3.4)

$\Delta Y_t = \beta_1 + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha \Delta y_{t-1} + \varepsilon_t$ …………………………………………………… (3.5)

$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha \Delta y_{t-1} + \varepsilon_t$ ……………………………….…………… (3.6)

where ε_t is pure with a noise error term, and $\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$ and $\Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$ etc. the number of lagged difference terms to include must be determined imperially by including enough terms so that the error term in the above equations is serially uncorrelated (Gujarati 2010:817). As in the DF test, the ADF tests the null hypothesis of $\delta = 0$, and it follows the same asymptotic distribution as the DF test.

3.1.1.2 Phillips–Perron Unit Root Test (PP)

As mentioned above, the DF test assumes that error terms are uncorrelated. To solve the problem of possible serial autocorrelation in the error terms, ADF includes the lagged difference term of the dependent variable. The Phillips–Perron (PP) test tackles this problem differentlyby using a non-parametric statistical method to deal with serial correlation in the error term without adding a lagged difference term (Gujarati, 2010).

The test regression for the PP tests is therefore specified as follows:

$\Delta Y_t = \delta Y_{t-1} + u_t$ .... (3.7)

where $\Delta Y_t = Y_t - Y_{t-1}$, with Y_t the value of a time series Y for any given period of study, and Y_{t-1} the value of a time series is the value of Y seen in the previous period t-1 and μ_t is the noise error term. The error term u_t is I(0) and may be heteroskedastic. The PP test corrects for any serial correlation and heteroskedasticity in the errors u_t, by directly modifying the DF test statistics. The PP's Z_t and Z_π statistics are calculated as follows:

$$z_t = \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{1/2} \cdot t_{\pi=0} - \frac{1}{2}\left(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}\right) \cdot \left(\frac{T \cdot SE(\hat{\pi})}{\hat{\sigma}^2}\right)$$

$Z_\pi = T_{\hat{\pi}} - \frac{1}{2}\frac{T^2 \cdot SE(\hat{\pi})}{\hat{\sigma}^2}\left(\hat{\lambda}^2 - \hat{\sigma}^2\right)$ …………………………………………………………...(3.8)

The terms $\hat{\sigma}^2$ and $\hat{\lambda}^2$ are consistent estimates of the variance parameters

$\sigma^2 = \lim_{T \to \infty} T^{-1} \sum_{t=1}^{T} E\left[u_t^2\right]$ ....(3.9) and

$\lambda^2 = \sum_{t=1}^{T} E[T^{-1}S_T^2]$ ……………………………………………………………(3.10)

Respectively, where $S_T = \sum_{t=1}^{T} = \mu_t$is the sample variance of the least-squares residual, $\widehat{\mu_t}$ is a consistent estimate of σ^2 and the Newey-West long-run variance estimate of μ_t using $\widehat{\mu_t}$ is a consistent estimate of λ^2.Under the null hypothesis that δ = 0, the PP Z_t and Z_π statistics have the same asymptotic distributions as the ADF t-statistic and normalised bias statistics. One advantage of the PP test over the ADF test is that it is robust to general forms of heteroskedasticity in the error termμ_t. Another advantage is that the user does not have to specify a lag length for the test regression (Zivot and Wang, 2006).

3.1.1.3 Kwiatkowski-Phillips-Schmidt-Shin Test (KPSS)

Kwiatkowski,Phillips,Schmidt and Shin (1992) developed a model (KPSS) that helps to get around the problem of committing type II or type I errors -that is, of failing to reject the null hypothesis of unit root or failing to accept the null hypothesis when it is true - while running DF or ADF tests (Maddala and Kim,1998: 126-128). The KPSS test was developed for a series appearing stationary by default in those cases where there is little information within the sample of data (Kwiatkowski *et al*., 1992). For empirical tests, it is suggested that KPSS should be run as a conformity analysis to compare the results obtained from the DF/ADF to see if the same conclusions are achieved (Nsabimana, 2010). One should note that the null and alternative hypotheses under each test are not the same and are as follows:

DF/ADF	**KPSS**
$H_0 : y_t \sim I(1)$	$H_1: y_t \sim I(0)$ …………………………………………………..…(3.11)
$H_1: y_t \sim I(0)$	$H_0 : y_t \sim I(1)$ …………………………………………………..…(3.12)

Nsabimana (2010) remarks that in comparing the results from AD/ADF and KPSS tests, the four following outcomes can take place:

(i) Reject 0 *H* in ADF/PP test and do not reject 0 *H* in KPSS test

(ii) Do not reject 0 *H* in ADF/PP test and reject 0 *H* in KPSS test

(iii) Reject 0 *H* in ADF/PP test and reject 0 *H* in KPSS test

(iv) Do not reject 0 *H* in ADF/PP test and do not reject 0 *H* in KPSS test

If the results from testing stationarity in the empirical research fall under the outcomes (i) and (ii), we can unambiguously conclude the presence of stationarity. Conflicts arise if outcomes (iii) or (iv) occur. In this case, it will be challenging to make a decision, and the only way to avoid this difficulty is to obtain more information.

3.1.2 UNCONDITIONAL CORRELATION

The Pearson correlation coefficient has been widely used to measure the degree of financial contagion (Mighri and Mansouri, 2013). Nevertheless, the correlation coefficient between stock market returns is found to be time-varying; therefore, modelling the time-varying characteristics of the correlation matrix is recommended to avoid the drawback for a simple correlation matrix. The Pearson correlation coefficient is formulated as follows:

Given that the covariance of two random variables X and Y is defined as

$$\mathrm{Cov}(X, Y) = E[(X - E(\bar{X}))(Y - E(\bar{Y}))] = E(XY) - E(\bar{X})E(\bar{Y}) \tag{3.13}$$

the covariance is standardised (by dividing it by the standard deviation of each variable involved) to give the coefficient called Pearson's correlation formulated as follows:

$$r = \frac{\sum\left(X-\bar{X}\right)\left(Y-\bar{Y}\right)}{\sqrt{\sum\left(X-\bar{X}\right)^2\left(Y-\bar{Y}\right)^2}} \tag{3.14}$$

where $\bar{X}$ and $\bar{Y}$ are the averages of X respectively Y variable. Pearson's correlation coefficient is a measure of linear dependence between two variables X and Y. The coefficient ρ has a range between $-1 \le \rho \le +1$ for the true population. A perfect positive or negative linear coefficient equals to ±1, which corresponds to data sample points lying precisely on a line.

3.2 DATA PREPARATION

Various methodologies were used to achieve the desired objectives as outlined in Chapter One. They are summarised in Table 3-1. In order to accomplish the first objective yearly data on market capitalisation and the number of listed companies in BRICS markets were used; the data were sourced from the World Bank's world development indicators. To achieve the second, third and fourth Objectives, this chapter examines data consisting of a total of 10 pairs of source-targets composite indices. For the source markets, daily data for the S&P 500 composite from the U.S. and the German DAX 30 were used. The S&P500 index is a proxy of the U.S. stock market, while the DAX index is a proxy for the Eurozone (continental Europe) stock market. For the target markets, daily stock prices for indices from BRICS countries were used. The composite indices are the BOVESPA, RTS, SENSEX, the SSE and the FTSE/JSE for Brazil, Russia, China, India and South Africa, respectively. The data were sourced from Thomson Reuters Datastream.

Table 3-1: The study objectives with Related Methodology and Data

No	Objectives	Methodology	Data
1	To examine the salient characteristics of equity markets in BRICS countries	Numerical figures and charts	• Annual market capitalisation of total number of listed companies in the Brazilian, Chinese, Indian, Russian and South African security markets. • Daily data BOVESPA, RTS, Sensex, the SSE, the FTSE/JSE, DAX and S&P 500 composite indices.
2	To investigate the nature of volatility of stock market returns in BRICS countries during financial turmoil.	(Vanilla) GARCH, EGARCH, GJR GARCH,	• Daily data for BOVESPA, RTS, Sensex, the SSE, the FTSE/JSE, and S&P 500 composite indices.
3	To examine the presence of time-varying conditional correlations in BRICS equity market returns, in the wake of the financial crises that took place in the U.S. and Eurozone countries.	Diagonal VECH GARCH(1,1) and DCC GARCH (1,1)	• Daily data BOVESPA, RTS, Sensex, the SSE, the FTSE/JSE and DAX composite indices.
4	To investigate the time-frequency dynamics in correlations in BRICS stock markets and source markets, following the financial crises that took place in the U.S. and Eurozone countries.	Wavelet analysis	• Daily data BOVESPA, RTS, Sensex, the SSE, the FTSE/JSE, DAX and S&P 500. .

Source: Author's Compilation

The data sample used runs from the period between 11th of January, 2005 and 26th of December, 2017. This period was chosen because it is during this period that the world experienced two major financial crises, namely the GFC and the EZDC.

In instances where market data were not available for an index due to market closure, the observation (date) in question was eliminated for all indices. Eliminating the dates in this way does not impact the results as all of the available market information is reflected in the price, as stated by the efficient market hypothesis (Srnic, 2014).

It is important to highlight that the choice of DAX as a proxy of the Eurozone countries (continental Europe) was motivated by the fact that the development in the DAX is often viewed as an indicator for the development of the German economy. As a result, the DAX can be seen as a proxy for continental Europe economic health since the German economy accounts for almost one-third of the total value of the Eurozone economy.

For detrending and in order to achieve more stationary time series data, the daily composite price indices were transformed into natural logarithmic returns expressed as follows:

$$R_t = [ln(P_t) - ln(P_{t-1})]\times 100$$

where P_t is the closing price index recorded for period t, and P_{t-1} is the closing price index recorded for period t-1. The reason for multiplying the expression $ln(P_t) - ln(P_{t-1})$ by 100 is due to numerical problems in the estimation part. This did not affect the structure of the model since it is just a linear scaling.

3.3 RESULTS OF EXPLORATORY ANALYSIS

This section presents results for exploratory data analysis consisting of the unit root test, and unconditional correlation for the log-return of composite indices used in the present study.

3.3.1 UNIT ROOT TEST

Table 3-2 shows the results from the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests. In performing the Augmented Dickey-

Fuller (ADF) test, the number of lags of each variable was determined through considering the minimum values of Schwarz-Bayesian Information Criterion (SBIC) statistics (the lags are provided in brackets). The SBIC was chosen because it penalises strongly any term added to the regressors to investigate the presence of unit roots within time series data (Brooks, 2002: 427).

The results for the unit root test are presented in Table 3-2; the results indicate that all variables are stationary. It can be seen that the null hypothesis of unit root is rejected at the 1% level of significance for ADF and PP test. The stationarity of the log return series is confirmed with the KPSS, and this test operates with the null hypothesis that the series is stationary (i.e. there is no presence of unit root). It can be seen in Table 3-2 that the KPSS test does not reject the null hypothesis of stationarity.

Experiments with more lags in the augmented regression yielded the same conclusion. It should also be drawn to the reader's attention that when the variables are differenced the results become more significant, hence confirming the stationarity of the series,

Table 3-2: Unit Root Test on Market Return Indices

Variable	ADF		PP		KPSS	
	Z(t)	5% crit. Value	Z(t)	5% crit. Value	Z(t)	5% crit. Value
S&P500	-7.301686***[16]	-2.863672	-59.13932***	-2.862405	0.121491	0.463000
Δ S&P500	-9.510465***[26]	-2.866195	-374.8628****	-2.862445	0.020117	0.463000
DAX	-11.87209***[17]	-2.862552	-54.44152***	-2.862339	0.063877	0.463000
Δ DAX	-16.03637***[26]	-2.862725	-527.6982**	-2.862350	0.112488	0.463000
BOVESPA	-4.341675***[25]	-2.866091	-52.31418***	-2.862435	0.147160	0.463000
Δ BOVESPA	-8.012553***[26]	-2.866805	-253.7464**	-2.862485	0.072026	0.463000
FTSE/JSE	-16.19319***[8]	-2.862700	-51.25948***	-2.862399	0.223617	0.463000
Δ FTSE/JSE	-11.48140***[25]	-2.863972	-244.8472***	-2.862434	0.037069	0.463000
RTS	-7.810455***[28]	-2.862309	-49.51719***	-2.862301	0.223071	0.463000
Δ RTS	-19.89440***[1]	-2.862309	-645.8037***	-2.862301	0.025802	0.463000
SENSEX	-7.647694***[21]	-2.864364	-50.17779***	-2.862459	0.168615	0.463000
Δ SENSEX	-9.061033***[26]	-2.865093	-404.9063***	-2.862517	0.055367	0.463000
SSE	-14.21251***[9]	-2.862640	-51.48340***	-2.862403	0.152435	0.463000
Δ SSE	-13.99533***[23]	-2.863246	-278.5603**	-2.862426	0.554594	0.463000

Source: Estimation

3.3.2 UNCONDITIONAL CORRELATION

In the next step, the unconditional correlation among variables is examined. Table 3-3 shows pairwise unconditional correlations between stock markets. Table 3-3 shows the correlation coefficient between the composite return indices used in the present study. The highest correlation is found between the U.S. and the Brazilian stock markets (0.664002), followed by the correlation between South Africa and Russia (0.641089), whereas the lowest correlation coefficient is observed between the U.S. and Chinese markets (0.064352).

From the point of view of the U.S. stock market as a source market for the transmission of shocks, it can be seen in Table 3-3 that the U.S. stock market is highly correlated with the Brazilian stock market. The high correlation can be a sign of a significant regional transmission due to geographic proximity between the two countries and high interdependence between the two markets.
As for the Eurozone as the source market, Table 3-3 shows that the FTSE/JSE (South Africa) has the highest correlation with the DAX, while SSE (China) has the lowest correlation.

It is worth noting that, in general, the Chinese stock market has the lowest correlation with any stock market under consideration. This can be explained by the fact that the Chinese equity market is still primarily driven by local retail investors, who hold close to 50% of the market's total free-float market capitalisation and account for 80% of total trading volume (Lu,2019). This is also because, for an extended period, Chinese authorities barred foreigners from investing in A-shares.

Table 3-3: Unconditional Correlation Matrix of Market Returns

	BOVESPA	DAX	JSE	RTS	S&P500	SENSEX	SSE
BOVESPA	1	0.512471	0.463959	0.469762	0.664002	0.290545	0.146914
DAX	0.512471	1	0.625136	0.563563	0.644323	0.408316	0.109419
JSE	0.463959	0.625136	1	0.641089	0.411096	0.443092	0.164732
RTS	0.469762	0.563563	0.641089	1	0.388643	0.432924	0.192757
S&P500	0.664002	0.644323	0.411096	0.388643	1	0.254042	0.064352
SENSEX	0.290545	0.408316	0.443092	0.432924	0.254042	1	0.222381
SSE	0.146914	0.109419	0.164732	0.192757	0.064352	0.222381	1

Source: Estimation

3.4 CHAPTER SUMMARY

This chapter described the exploratory techniques for initial data analysis; they consist of the unit root test and the unconditional correlation matrix. The results for ADF, PP and KPSS revealed that the log-returns of all composite indices used in the current study are stationary. The unconditional correlation was computed using the Pearson correlation coefficient. The highest correlation is recorded between the U.S. and the Brazilian stock markets, while the lowest correlation is found between the U.S. and the Chinese stock markets.

CHAPTER FOUR

CHARACTERISTICS OF STOCK MARKETS IN BRICS ECONOMIES

The acronym BRICS was coined by O'Neil (2001), in a World Bank publication titled "Building Better Global Economic BRICs". BRIC pertained to the original four countries – Brazil, Russia, India, and China. Because of their large size, population, desire to become the world's leading economies, and motivated by their extraordinary rise, BRIC countries were the rising stars of emerging markets. South Africa joined the group as a full member at the 2011 Sanya Summit, in China. The group was therefore renamed BRICS, in order to reflect the expanded membership of the group.

Two decades after O'Neil's publication, the aspirations of the BRICS countries as the world's leading emerging-market economies remain today and for the future as the global economy's development engines (Bonga-Bonga, 2018). Wilson and Purushothaman (2003) projected that the BRIC (without South Africa) economies would become a much stronger force in the global economy within the next 50 years. They foresaw the total nominal Gross Domestic Product (GDP) to hit US$128 trillion by 2050 for the four BRIC countries, compared with US$66 trillion for the G7 countries at the time.

Chapter four provides an overview of the BRICS stock markets. The major thrust of the chapter is to present the economic environment of the stock markets in which this study was conducted. The chapter thus accomplishes the first objective (*To analyse the salient characteristics of equity markets in BRICS countries*). The chapter gives special attention to changes that are believed to have impacted the efficiency of trading for each stock market.

The chapter is divided into six sections; the first five sections discuss each BRICS' stock market, namely the Brazilian, Chinese, Indian, South African and Russian stock markets. Each market is discussed in terms of the significant features of the market, how trading and settlement are conducted, and how information is disseminated among market players. Special attention is given to changes that are believed to have impacted the efficiency of trading for each stock market. Concluding remarks are provided in the sixth section.

4.1 THE BRAZILIAN STOCK MARKET

At about US$938 billion of market capitalisation, the Brazilian stock market is among the twenty largest stock markets in the world. The market capitalisation of the Brazilian equity market equals about half of the country's GDP. The history of the stock market in Brazil dates back to as early as 1817 when the first Brazilian stock exchange was inaugurated. The Rio de Janeiro Stock Exchange opened in 1820, and the Sao Paulo Stock Exchange opened in 1890.

4.1.1 OVERVIEW OF THE BRAZILIAN STOCK MARKET

The Brazilian stock market enjoyed significant developments, especially during the 1990s and the late 2000s. Today, Brazil has several stock markets, which gradually acquired one another or emerged over the years to form one big stock exchange, the B3. The various bourses that constitute the Brazilian stock market are discussed below.

4.1.1.1 The São Paulo Stock Exchange/Bolsa de Valores de São Paulo

This bourse was inaugurated August 1890, and at its inception the Bolsa de Valores de São Paulo (Bovespa) was a state-owned institution. It was only in 2007 that it was privatised and became a for-profit company. During self-regulation, Bovespa conducted its activities under the supervision of the Securities and Exchange Commission of Brazil/Commissão de Valores Mobiliários (CVM), a government agency responsible for protecting investors, maintaining fair and orderly functioning of securities markets and facilitating capital formation (Nyasha and Odhiambo,2013). Since the 1960s Bovespa has initiated changes in its operations with the help of technologies such as computer-based systems. For instance, in the 1970s, the bourse became the first Brazilian stock exchange to introduce an automated system for dissemination of information online and in real-time. Furthermore, in 1997, an electronic trading system called Mega Bolsa was introduced, which increased the potential information processing capacity, allowing the bourse to boost its overall volume of activities (Nyasha and Odhiambo,2013). In 2008, Bovespa merged with BM&F to form a bigger entity known as BM&FBOVESPA.

4.1.1.2 The Rio de Janeiro Stock Exchange/Bolsa de Valores do Rio de Janeiro

Established in 1820, Bolsa de Valores do Rio de Janeiro (BVRJ) is the second largest bourse in Brazil after Bovespa and the oldest of the Brazilian Stock Exchanges in operation. It was inaugurated on 14 July 1820, three years after the inauguration of the 1st Brazilian stock exchange (the now-defunct Salvador Exchange), and before the start of the Brazilian independence movement. It was the most important Brazilian Exchange from its inception up until the early 1970s. After the crash of the markets in 1971, it slowly lost ground to Bovespa. After the crash of the national stock markets in 1989, the BVRJ definitively lost its position as the country's leading stock exchange in Latin America. It was ultimately sold in 2002 to the Brazilian Mercantile and Futures Exchange/Bolsa de Valores, Mercadorias (BM&F).

4.1.1.3 The São Paulo Commodities Exchange/ Bolsa de Mercadorias de São Paulo

Bolsa de Mercadorias de São Paulo (BMSP) was established in October 1917 by exporters, businesspeople and commodity producers. It became the first institution in Brazil to offer forward trading. BMSP has a rich tradition in the trade of commodities such as, coffee, live cattle and cotton.

4.1.1.4 Mercantile and Futures Exchange/ The Bolsa de Mercadorias & Futuros

Bolsa de Mercadorias & Futuros (BM&F) was created in 1991, and over the years established itself as a respectable world futures exchange market, offering derivatives on various financial assets. In May 1991 MSP and BM&F joined forces to become a new entity but retained the name of BM&F. The merger brought together a long tradition of trading in commodities and the dynamism of BM&F.

In June 1997, an agreement with Brazilian Futures Exchange (BBF) of Rio de Janeiro (which was founded in 1983) saw the strengthening of the domestic commodity market and significant improvement in BM&F's position as a key derivative trading centre.

In April 2002 BM&F initiated Foreign exchange clearing activities and was granted in the same month the rights to manage and operate a clearinghouse for government bonds, fixed income securities and other securities issued by the Brazilian Clearing and Depository Corporation (CBLC). In November 2002, BM&F entered into an agreement with the Brazilian Federation of Banks (FEBRABAN), and with the Central Clearing and Settlement S.A., in an attempt to discontinue all of the S.A.'s activities related to registration, clearing and settlement of trades involving public and private fixed-income securities, consequently centralising all of these activities at BM&F.

In 2002, BM&F also opened the Brazilian Commodities Exchange, which amalgamated the commodity exchanges from various states in Brazil, thereby transforming these exchanges into regional operating centres. BM&F became the clearing and settlement service for this new exchange. This resulted in the creation of an integrated domestic market for agricultural commodities with new price-discovery mechanisms and an organised marketing structure. The Brazilian Commodities Exchange opened for trading on 22 October 2002.

4.1.1.5 BM&FBOVESPA

In May 2005, BM&F and BOVESPA merged and became BM&FBOVESPA. By then, the bourse was the worlds' third largest. The upward trend continued until December 2010 when it reached a market capitalisation of US$1.5 trillion, making it the eighth largest market in market capitalisation at the time.

4.1.1.6 Brasil, Bolsa, Balcão – B3 S.A.

In March 2017 the securities, commodities and futures exchange activities of BM&FBOVESPA were combined with the activities of Cetip, a provider of financial services for the regulated OTC market to become what is known as B3. This combination strengthened further the Company's position as a financial market and enabled it to extend the range of services and products offered to customers while creating efficiencies for the Company and the market. B3 has its headquarters in São Paulo and has units in Rio de Janeiro and Alphaville. It also has representative offices in London (UK) and Shanghai (China) to support local market participants in activities with foreign customers and relations with regulators, and to disseminate its products and governance practices to potential investors. B3 is a public company traded under ticker symbol B3 SA on the Novo Mercado premium listing segment for companies committed to the highest standards of corporate governance. Its stock is tracked by the Ibovespa, IBrX-50, IBrX and Itag indices.

4.1.2 CHARACTERISTICS OF THE BRAZILIAN STOCK MARKET

The equity market plays a crucial role in a country's economic development because it constitutes an efficient mechanism for allocating resources. Unfortunately, Brazil was not able to take advantage of this until recent years. The Brazilian business environment traditionally has been dominated by closely held "family" companies and by foreign multinational corporations. Neither of these groups has made significant use of the Brazilian equity securities market to raise investment capital. The establishment of an effective, broad-based securities market has been determined by Brazilian policymakers to be a necessary prerequisite for further economic development. A variety of incentives exist for companies to go "open," that is, allow their equity shares to be traded on an organised stock exchange. Several incentives exist for individuals to invest in equity. For example, one of the most significant components of the securities market is the so-called "157 Funds." These are special mutual funds administered by investment banks to which individuals may apply a portion of their income tax payable rather than paying the tax to the government.

Over the years, a number of stock market reforms have been implemented in Brazil. Among these have been the restructuring of the financial market, the replacement of the traditional trading systems by full electronic trading systems, and the enactment of new laws such the Brazilian Law No. 4.728, dated 14 April 1965 culminating in the first Capital Market Act. This law enhanced order in the Brazilian stock market (Nyasha and Odhiambo, 2013). The formation of a regulatory body known as the CVM in 1976 also assisted in the creation of an environment conducive for the growth and development of the stock market. Since the implementation of these reforms, the Brazilian stock market has developed significantly in terms of market capitalisation, the total value of stocks traded, and turnover ratio.

Brazil initiated a modernisation strategy in the 1990s that, motivated by the Washington consensus, replaced import-substitution subsidies with international competition, and inaugurated a comprehensive privatisation process. The reduction in the barriers to foreign capital enabled a significant inflow of foreign investment into the country. As a result, the São Paulo Stock Exchange saw a record increase in its market capitalisation compared to that of previous periods (Gilson, Hansmann and Pargendler, 2010). In July, August, and September 2011, foreign investors were responsible for 33%, 34%, and 36% of the Bovespa's trading volume, respectively (BM&FBovespa, 2011). Although foreign investments bring many benefits to the country, they also cause adverse effects, including causing an imbalance in the country and the inability of the government to prevent fight of capital in the presence of financial crisis (Clemente, Taffarel and Espejo, 2012).

Another characteristic of the Brazilian stock market is that it is highly concentrated in terms of its small number of companies in comparison to developed countries. In the Brazilian bourse, just eight sectors represent 85.0% of the share trading volume, and the major 24 companies account for 72.3% of that volume. Not only is there a high concentration in the stock market, but there is also a concentration in equity. On average, the three largest shareholders control Brazilian companies (Cavalhal da Silva and Leal, 2005).

4.1.3 NUMBER OF REGISTERED COMPANIES, MARKET CAPITALISATION AND THE BROAD STOCK VALUE INDEX

Figure 4-1 illustrates the total number of domestic listed companies[6] together with the market capitalisation[7] (in the current US$100 million) in the Brazilian stock market. It can be seen that there is a decline in the total number of listed companies from 497 companies in 2000 to 335 companies in 2017. A sharp decrease started in the year 1997, which corresponds to the period of financial instability due, in large part, to government-sponsored reform to the Corporations Law in 1997 (Gilson *et al*., 2010). The new law removed statutory protection, then available to minority shareholders. The enactment of the new law aimed at maximising the proceeds of the federal government from privatisation (Gilson *et al*., 2010). Political instabilities compounded the problem due to a major presidential election that took place in Brazil in 2012. The presidential elections created an impasse given the fact that Fernando Henrique Cardoso, who since 1995 had contributed to modernising the Brazilian government and economy, was unable to run for re-election.

From the year 2004 there has been an impressive improvement; seven companies performed IPOs (Initial Public Offerings) amounting to US$1.57 billion while for 2005, eight companies performed IPOs amounting US$2.4 billion. In 2006, a sharp rise was observed in the number of companies accessing the equities market – when approximately US$14.04 billion was tapped using this type of instrument.

[6] Listed domestic companies, including foreign companies which are exclusively listed, are those which have shares listed on an exchange at the end of the year. Investment funds, unit trusts, and companies whose only business goal is to hold shares of other listed companies, such as holding companies and investment companies, regardless of their legal status, are excluded. A company with several classes of shares is counted once. Only companies admitted to listing on the exchange are included.

[7] Market capitalisation (also known as market value) is the share price times the number of shares outstanding (including their several classes) for listed domestic companies. Investment funds, unit trusts, and companies whose only business goal is to hold shares of other listed companies are excluded. Data are end of year values.

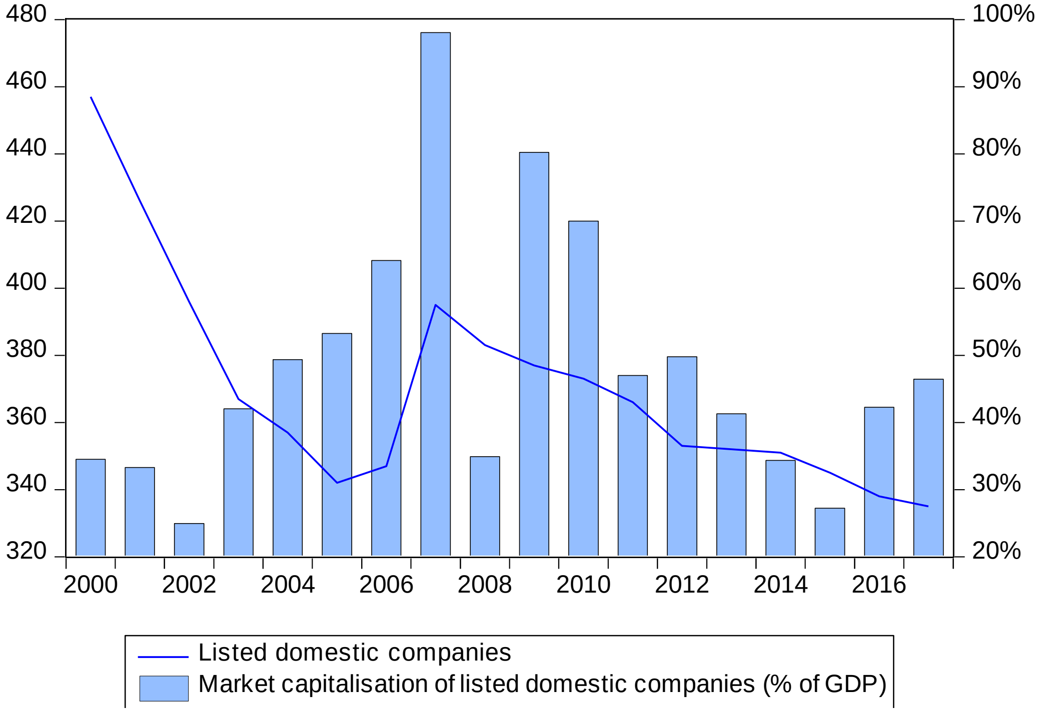

Figure 4-1: Total Number of Listed Domestic Companies and Market Capitalisation in Brazil.
Source: Constructed based on data obtained from the World Bank (2018).

The growth of the stock market in Brazil can also be explained by using the stock-market capitalisation of listed companies. Figure 4-1 shows that the year 2007 registered a peak in market capitalisation of US$1.37 trillion, which represents 98.04% of Brazilian GDP. However, after the year 2008 the stock market suffered a severe slump, as the market capitalisation fell below US$600 billion (34.91% of GDP). This was due to the global financial crisis that started in 2008. Despite the economic meltdown, the Brazilian stock market showed a quick recovery and registered a market capitalisation of more than US$1.33 trillion from US$590 billion (70% of GDP in 2009, from 35.7% in 2008); the market went on to register the highest peak ever recorded of US$1.55 trillion in domestic market capitalisation. Another decrease in market capitalisation was recorded in the year 2015, when Brazil experienced a severe economic crisis that was triggered by a decrease of the external demand in commodities, particularly from China, and a fall in the prices of commodities. As in the previous crisis, the economic crisis was coupled with political uncertainty that resulted in the impeachment of President Dilma Rousseff and widespread dissatisfaction with the political system.

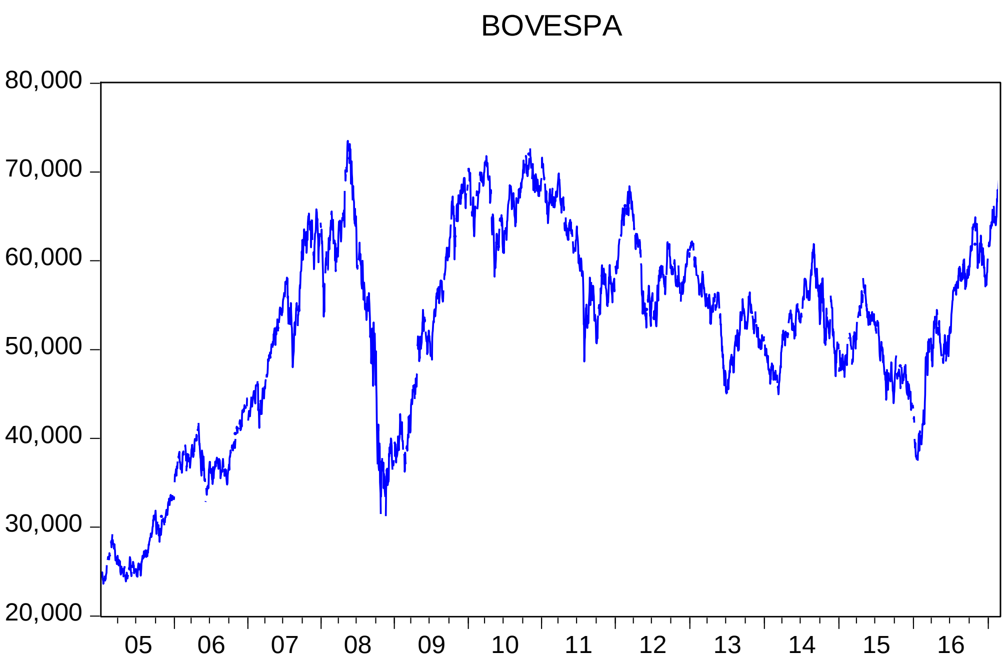

Figure 4-2: Brazilian Broad Market Index.

Source: Constructed based on data obtained from Thomson Reuters Datastream (2017).

Figure 4-2 displays time series for the BOVESPA index, commonly referred to as Ibovespa, the benchmark index of about 60 stocks that are traded on the B3. Ibovespa represents 70 per cent of all the stock value traded within 12 months. The data ranges from January 2005 to January 2017. Figure 4-2 illustrates that the Ibovespa increased by a mere 7.62 per cent, as it moved from 25,772.01 in 2005 to 66,662.10 in 2017.

4.1.4 TRADING IN THE BRAZILIAN STOCK MARKET

The Brazilian stock market is ruled by the CVM, a government agency that serves as the primary regulator of the securities trade. It attempts to ensure that all trades are fair and that no price manipulation or insider trading occurs. CVM was established in 1976 to regulate and discipline the operation of the Brazilian capital market. By offering institutional guarantees to investors and the desired operational flexibility, CVM fosters companies' capitalisation and economic growth using a better allocation of resources. In order to achieve its objectives CVM ensures the efficiency, and regulates the functioning of, the securities and stimulates its expansion through various activities. These activities include, (i) the protecting of investors and securities holders by avoiding or preventing irregularities, frauds and manipulative practices, and (ii) guaranteeing ample and fair disclosure of relevant information concerning securities traded and issuer companies (Securities and Exchange Commission, 2018).

The B3's main activity is share trading and it follows specific rules. There are three trading channels in the B3: (i) mega bolsa, (ii) open-outcry sessions, and (iii) after-market trading sessions. Irrespective of the channel used, only authorised brokers operate share trading. Primary equities are issued through the Bovespa. Private and public sector corporations that meet the registration requirements of the Brazilian Securities Commission (CVM) become eligible to issue equity shares through the Bovespa. Such corporations can count on the market expertise and financial leverage of underwriters to launch stocks on the market. An underwriter may guarantee that the issuer will receive a specific price on the stocks sold. In 1999 a home broker system was put in place to allow investors to communicate with the brokerage firm by using the Internet, and its use has been growing ever since.

To execute trades in various asset classes, as well as to manage risks, B3 S.A uses a feature-rich electric platform know as PUMA. B3 offers developers many tools to help connect to the platform. Some of the principal architects of the PUMA platform include the following: (i) EntryPoint, which is multi-asset order entry messaging that provides a unified message specification allowing seamless access to multiple market segments, such as equities, fixed income, derivatives, and foreign exchange, (ii)United Market Data Feed (UMDF), which is a service that offers low latency access to market data and allows client systems to access the full set of exchange-traded instruments in different asset classes such as derivatives and BM&FBOVESPA's indexes, and finally, (iii) the UMDF PUMA conflated platform which is a service that uses the TCP (Transmission Control Protocol), unlike UMDF which uses the UDP (User Datagram Protocol). The TCP platform costs less to implement and maintain.

4.2 THE CHINESE STOCK MARKET

China's equity market is relatively young compared to other developed countries. While the Shanghai Stock Exchange (SSE) was inaugurated in the 1860s, it only reopened in 1990 after being closed in 1949 when the communists took power. The Shenzhen Stock Exchange (SZSE) also opened that same year. While the Hong Kong Stock Exchange was founded in 1891 (and Hong Kong operates as a politically autonomous region from mainland China), it first began listing the most significant Chinese state-owned enterprises only in the mid-1990s. The Chinese stock market is home to two of the top 16 stock exchanges commonly known as the "$1 Trillion Club". The two stock markets are the SSE, which is ranked 4th in the word with a market capitalisation of US$4.02 trillion, and Hong Kong Stock Exchange (HKS), which is ranked fifth and has US$3.93 trillion market capitalisation.

In contrast with the other developed stock markets, China's stock market is not also an indicator of the health of the country's economy. The total value of every stock traded on its exchange markets represents only a third of its economic output, as measured by GDP. That compares to 100 per cent for most developed countries.

4.2.1 OVERVIEW OF THE CHINESE STOCK MARKET

The first security market in China was established in China in 1891 with the creation of the Shanghai Share Brokers' Association. However, the communist revolution interrupted its activities. It was only in 1990 that Deng Xiaoping, the Chinese leader at the time, initiated the Shanghai and Shenzhen stock exchange and transformed China's weak and centrally planned economy into an export-oriented economy. The economy remains one of the world's largest economies (Vanassche and Petitjean, 2016). In parallel, the Hong Kong stock market has its own characteristics because of the differences in term of jurisdiction; hence it cannot be transplanted entirely or directly to Mainland China. However, the HKS contributes significantly to the Chinese economy (Vanassche and Petitjean, 2016).

4.2.2 CHARACTERISTICS OF THE CHINESE STOCK MARKET

The chinese stock market has some distinguishing characteristics that set it apart from other emerging markets, as discussed by Vanassche and Petitjean, (2016). They are (i) abnormal returns, (ii) share classes, (iii) government ownership and control, (iv) substantial volatility and (v) dependence on external growth. These are discussed below.

4.2.2.1 Abnormal Returns

Since its creation in 1990 the Chinese stock market has been characterised by remarkable growth. Vanassche and Petitjean (2016:20) showed that between 1994 and 2001 the Down Jones China Index recorded a staggering cumulative return of 79.82%. The author identified three trends — which they referred to as "oddities" — that fostered this extraordinary growth, namely, (i) the "1996 Oddity", (ii) the "Single-day Oddity" and (iii) the "Segment Oddity". Concerning the 1996 Oddity, Vanassche and Petitjean (2016) noted that the outperformance in the stock market registered in 1996 could be imputed to a significant increase of 125% on the DJ Shanghai Index[8]. Regarding the Single-day Oddity, before the implementation of the 10% day limit threshold towards the end of 1996, Chinese stock market growth relied heavily on single-day trading sessions with some day's percentage gain exceeding 20%. Lastly, the Segment Oddity refers to the fact that growth in China is not equal in its various market segments; for instance, the Dow Jones China Offshore Index fell and performed poorly in the 1994-2001 period.

4.2.2.2 Share Classes

The Chinese security market has various share classes, described by Delfed (2007) as "a hot and sour alphabet soup" comprising A, B, H, N, L, S and G shares. Share classes A, B, and H are the major share classes. A and B share are traded in the Shanghai and Shenzhen stock exchange, while the H share classes are traded in Hong Kong.

[8] The DJ Shanghai index is an international equity index created by the Dow Jones to provide data on the Chinese market.

The A shares are mainly available to residents of the People's Republic of China (PRC) or under the Qualified Foreign Institutional Investor (QFII), the Renminbi Qualified Foreign Institutional Investor (RQFII) rules, or via the Stock Connect programs[9]. Since 2002 a limited number of foreign investors who attain the QFII quota can also trade these shares. The minimum required for a company to make an Initial IPO through tradable A-shares is 25% of the total outstanding shares.

The A-share consists typically of state-owned shares (owned by either the central government or the local government), legal-person (LP) shares (owned by state-owned institutions) or negotiable-shares owned by individual domestic investors (Vanassche and Petitjean, 2016).

B-shares are intended for non-residents the PRC investors and are mainly denominated in US dollars. Since the inception of the QFII program, B-shares seem less attractive. Furthermore, B shares represent a tiny part of the outstanding shares. They can also be traded by residents of the PRC with appropriate foreign currency dealing accounts.

H Shares are securities of companies that have their main activities in the PRC and trade on the Hong Kong Stock Exchange. This share class is traded in Hong Kong dollars. Similar to other securities trading on the Hong Kong Stock Exchange, there are no restrictions on who can trade H Shares.

It is essential to highlight that some stocks are dual-listed on China A and China H. China A's constituency — whether government-owned (Red Chips) or not (P Chips) — is overall much more domestic- driven. China A offers relatively fewer financial stocks, the specific sectors that benefit most from the Chinese domestic growth story are consumers (both discretionary and staples), information technology and health care. .

N, L, and S-share classes represent shares of Chinese companies that have their primary business operation in China but trade in a foreign stock exchange. N share classes represent shares of

[9] A stock connect program is a cross-boundary investment channel that connects the Shanghai Stock Exchange and the Hong Kong Stock Exchange.

companies listed on the New York Stock Exchange and the National Association of Securities Dealers Automated Quotations (NASDAQ), while the L-shares denote companies listed on the London stock exchange but also incorporated companies in the Cayman Islands, Bermuda, British Virgin Islands, and Jersey. S Chips are shares of companies owned by Mainland Chinese or by individuals. These shares must be incorporated outside the PRC and traded on the Singapore Stock Exchange with most of its revenue or assets derived from Mainland China.

Finally, G share class shares are mostly the same as Ashares as they relate to shares of companies that are transacted in the stock exchanges of mainland China and that have achieved stock right division reforms and have resumed business on the market. Delfeled (2007) noted that the segmentation brought about lop-sidedness in values between shares traded in Shanghai and those traded in the Hong Kong stock market. For instance, companies actively traded in both the H-share and A-share markets are trading at a premium in Shanghai and Shenzhen compared to those traded in Hong Kong. Furthermore, as Delfeled (2007) posited, these “balkanised” share structures also eliminate arbitrage opportunities for investors willing to trade between different markets.

Table 4-1 helps us to understand various share classes found in the Chinese capital market. It can be seen that Chinese companies incorporated and listed in the PRC can issue different classes of share depending on which bourse they are listed with and which investors are allowed to own them. These classes are A, B, and H, which are all renminbi-denominated shares but traded in different currencies, depending on where they are listed. Chinese companies incorporated and listed outside PRC are generally referred to as ‘Red Chips’, ‘P Chips’, ‘S Chips’ or ‘N Shares’ depending on their ownership structure, revenue source, and listing location. It is worth drawing to the reader’s attention that the types of shares may have different definitions among index providers or exchanges; Table 4-1 uses FTSE Russell’s definitions.

Tables 4-1: Share Classes in the People's Republic of China

	A share	B share	H share	Red chip	P chip	S chip	N share	L share	G share
Description	The onshore domestic market providing a full representation of all stocks and sectors traded	A subset of the full large-cap market traded in foreign currency in China	A subset of the full market traded in Hong Kong (HK)	A subset of directly or indirectly controlled government stocks traded in HK	A subset of the full small to mid-cap market traded in HK	A subset of the full small to mid-cap market traded in Singapore dollar (SGD) in Singapore	A subset of the full market trading on the exchange in the US	A subset of the full small-cap market traded in Pound sterling (GBP) in London	The onshore domestic market providing a full representation of all stocks and sectors traded and that have achieved reform.
Country of incorporation	PRC	PRC	PRC	Non-PRC	Non-PRC	Non-PRC	Non- PRC	Non-PRC	PRC
Country of Listing	China	China	Hong Kong	Hong Kong	Hong Kong	Singapore	United States	United Kingdom	China
Availability to Mainland China investors	Yes	Yes (if they have approved currency accounts)	Yes (if QDII approved or under stock connected programs)	Yes (if QDII approved or under stock connected programs)	Yes (if they have approved currency accounts)	Yes (if QDII approved)	Yes (if QDII approved)	Yes (if QDII approved)	Yes (if they have undertaken right reforms)
Available to other investors	Yes (under/QFII/RQFII/ Stock connect programs)	yes	yes	yes	yes	yes	yes	yes	yes

Source: Author's compilation adapted from FTSE Russell (2019).

Figure 4-3 illustrates the five categories that were traded in the Chinese stock market in 2017; they are (i) Tradable A-shares, (ii) State Shares, (iii) Employee Shares, (iv) Legal person Shares and (v) Foreign Shares (H-Shares and B-Shares). It can be seen from Figure 4-3 that tradable A-shares are the most owned with 76% of the total shares, while State shares and Legal person shares all represent 5% each, Employee shares stood at 4%, and foreign shares represented 10% of total shares.

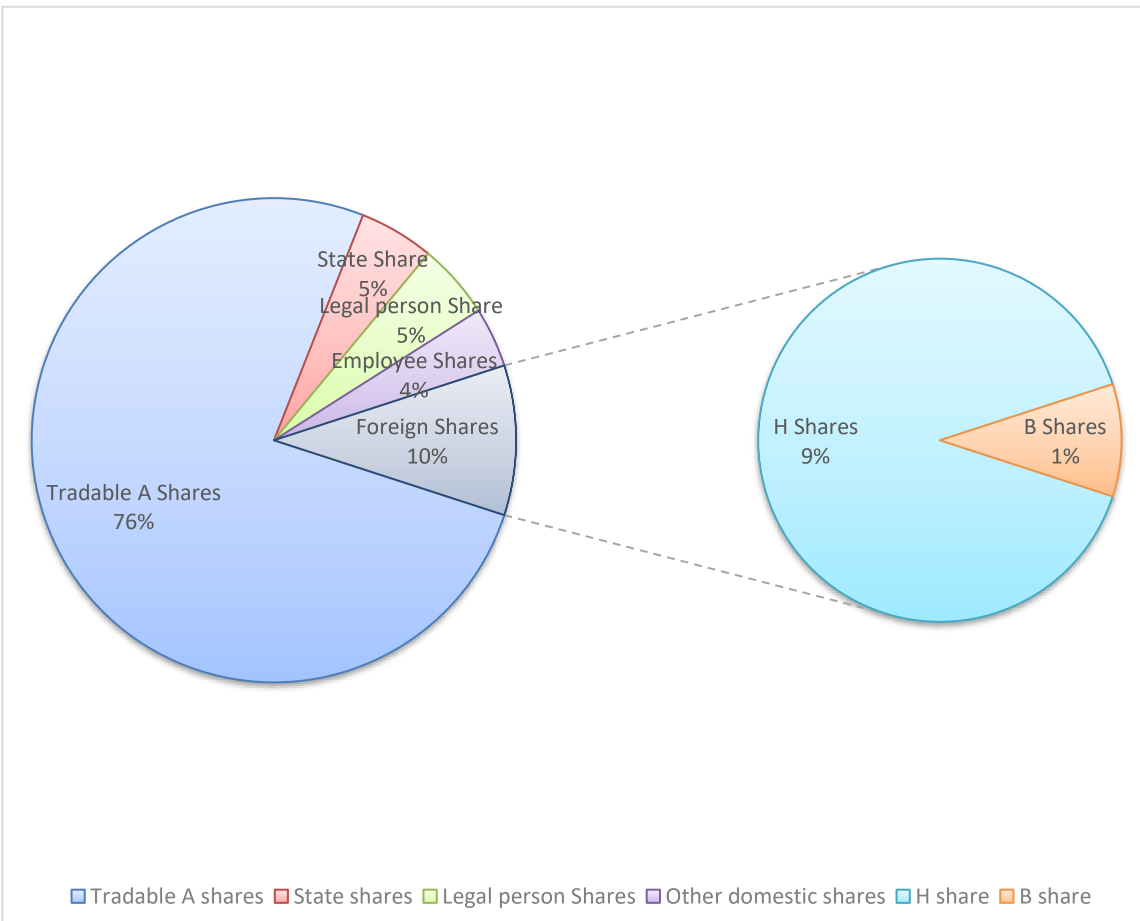

Figure 4-3: Categories of Shares Traded in the Chinese Stock Market.
Source: Rathnayake, Kassi, Louembé, Sun, and Ding (2019).

4.2.2.3 Government Control

In developed economies around the world, government interventions in the financial market, especially during a crisis, come in various forms. For instance, during the 2008 crisis, the U.S. government took a variety of measures to restore the market, including short-selling bans, the Term Auction Facility (TAF), the Capital Purchase Program (CPP) and the Troubled Asset Relief Program (TARP) (Troccon-Herbuté, 2016). Unlike its Western peers, the Chinese state influences its economy by enacting laws and rules to monitor and control economic agents (Troccon-Herbuté, 2016). The Chinese government controls its stock market by shaping market trends through the intermediary of the state-owned market insider; hence why the Chinese stock market is described as a policy-driven market (Vanassche and Petitjean, 2016).

As discussed above, China's stock markets have been divided and fragmented since their inception to prevent (i) foreign institutions from taking control over Chinese companies and (ii) to protect China's market against the fluctuations of the world's markets. Many of the shares issued on the Chinese stock markets are non-tradable shares as they are the possession of either the government or the business itself. However, since February 2014, the Chinese authorities have decided to relax the registration rules in an attempt to support growth, thus, in 2014, 3.65 million new private companies were entered in the commercial register, representing a 46% increase from 2013 (Troccon-Herbuté, 2016). However, this does not necessarily imply a complete withdrawal of the government. The government continues to play an essential role since it traces the market limits and supports State Owned Enterprises (SOEs).

4.2.2.4 Substantial Volatility

The Chinese stock market is still immature and has a tremendous amount of volatility. For this reason, the Chinese security market has often been referred to as a "casino" characterised by a significant amount of speculation (Vanassche and Petitjean, 2016). The leading causes of market volatility are the following: (i) the Chinese authority firmly controls the Chinese stock markets and the markets are, at most, partially privatised ones in which the state maintains state shares in varying amounts (Chui and Kwok, 1998; Yang, 2003, Vanassche and Petitjean, 2016); (ii)The presence of market segmentation gives rise to mispricing, information asymmetry, and makes the market imperfect and incomplete, thus leading to its volatility (Vanassche and Petitjean, 2016); (iii) The Chinese stock market is thinly traded, with only 7 per cent of China's population owning stocks. Given that participation is so low, a few wealthy investors own 80 per cent of tradable shares.

4.2.3 NUMBER OF REGISTERED COMPANIES, MARKET CAPITALISATION AND THE BROAD STOCK VALUE INDEX

Figure 4-4 illustrates the total number of listed companies together with a market capitalisation of listed companies (as the percentage of the GDP) of listed companies on the Chinese stock market on the mainland between the year 2003 and 2017. It can be seen that, unlike other emerging stock markets, there is a sustained increase in the total number of listed companies from 1285 in 2003 to 3485 in 2017. Domestic market capitalisation started an upward trend in 2005. Market capitalisation of domestic companies stood at US$4.02 trillion (representing 17.58 % of the GDP), in the wake of reform relating to non-tradable shares that began in May 2005. This process of remodelling China's stock market saw 98% of the companies in Shanghai and Shenzhen markets completing, or having access to, share reform programs. The 2005 reforms ushered in an era of vigorous development in the Chinese equity market, where capital market financing and resource allocation functions were improved significantly. The Chinese market reached ita all- time high in 2007, with market capitalisation representing 126.15% of the GDP. The upswing, however, was short-lived, as it was interrupted by the global financial crisis in 2008, when the percentage of domestic market capitalisation to GDP decreased significantly to 38.72%.

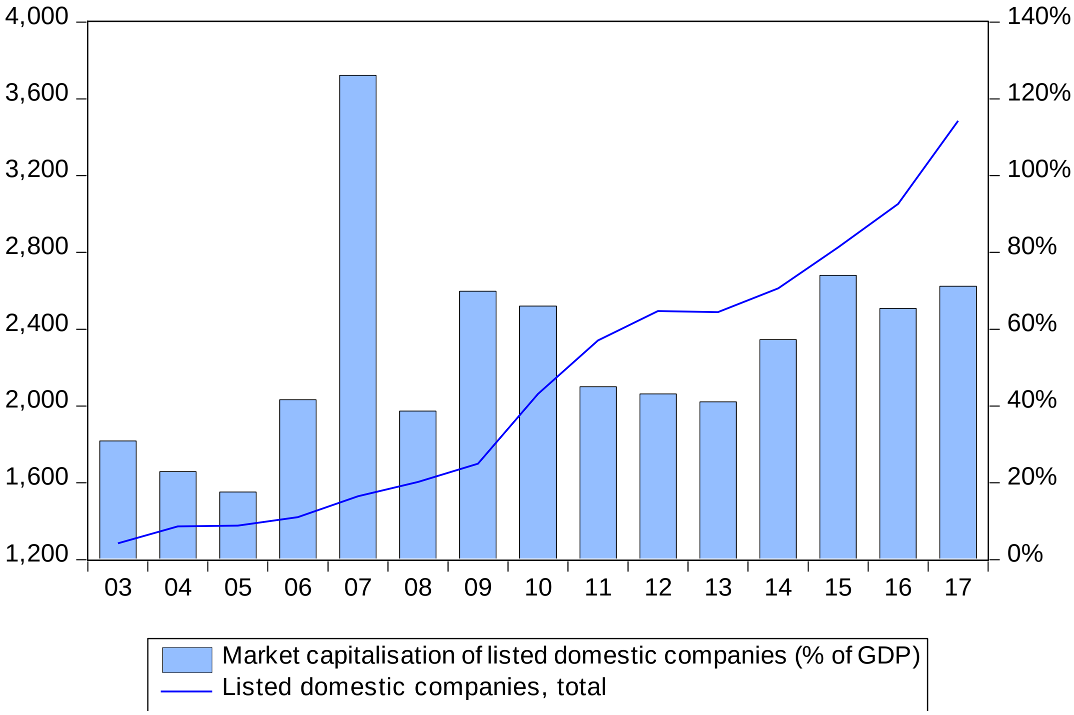

Figure 4-4: Total Number of Listed Domestic Companies and Market Capitalisation in the People's Republic of China. Source: Constructed based on data obtained from the World Bank (2018).

Table 4-2 summarises the various stock classes available in the Chinese stock market. From Table 4-2 it can be seen that there was a sustained increase in the number of domestic listed companies for the period between 2000 and 2017.

Table 4-2: Listed Companies in the People's Republic of ChinaYear

	Shares A & B on the Mainland (Total)	Shares A & B on the Mainland (Shanghai Stock Exchange)	Shares A & B on the Mainland (Shenzhen Stock Exchange)	Shares A only on the Mainland	Shares B (foreign fund) on the Mainland	Shares A + H on the Mainland (cross-listed)	Shares A & B on the Mainland
2000	1,088	572	516	1,060	114	19	86
2001	1,160	646	514	1,140	112	23	92
2002	1,224	715	509	1,213	111	28	100
2003	1,287	780	507	1,277	111	30	101
2004	1,377	837	540	1,363	110	31	96
2005	1,381	834	547	1,358	109	32	86
2006	1,434	842	592	1,411	109	38	86
2007	1,550	860	690	1,527	109	52	86
2008	1,625	864	761	1,602	109	57	86
2009	1,718	870	848	1,696	108	61	86
2010	2,063	894	1,169	2,041	108	65	86
2011	2,342	931	1,411	2,320	108	72	86
2012	2,494	954	1,540	2,472	107	—	85
2013	2,489	953	1,536	2,468	106	—	85
2014	2,613	995	1,618	2,592	104	—	83
2015	2,827	1,081	1,746	2,808	101	—	82
2016	3,052	1,182	1,870	3,034	100	—	82
2017	3,485	1,396	2,089	3,467	100	—	82

Source: National Bureau of Statistics of China (2018).

Figure 4-5: Chinese broad market index.

Source: Constructed based on data obtained from the Thomson Reuters Datastream (2017).

Figure 4-5 displays daily time series data for the Shanghai Stock Exchange (SSE) composite index from January 2005 to January 2017. The index is made up of all stocks – both A-shares and B-shares – that trade on the Shanghai Stock Exchange (SSE). It gives a broad overview of the performance of companies operating in the Chinese market. The most notable market fall was experienced in 2008 during the global financial crisis that occurred in that period. The Chinese market fell just under 2,000. It should also be noted that between June 2014 and June 2015, the Chinese market went through another boom and bust cycle. The SSE Composite index rose about 150 per cent, reaching a high of 5 166 in June. Then, in less than a month, it fell to 3 507, which represents a 32 per cent decline. Speculative activities of inexperienced retail investors caused China's Stock Market Crash in 2015 following the lifting of the ban on margin trading practices[10] (Zeng, Huang, and Hueng, 2016).

4.2.4 TRADING IN THE CHINESE STOCK MARKET

Trading services in the Chinese security market are classified into two categories, depending on the carrier of service. The two categories are (i) the trading system-based service and (ii)

[10] The Chinese government lifted the prohibition, changing policy to strictly regulate the practice of margin trading.

the non-trading system-based service. Trading system-based service can be further divided into two types based on the service model employed, namely: (i) centralised trading service and (ii) trading-related service. Non-trading system-based service includes negotiated transfer, warrant creation, and cancellation. Centralised trading refers to the change of securities ownership effected through an exchange trading system using price inquiry, quotation, and auction. Trading-related service refers to the offering, entitlement, trading relations and other related forms of service that are closely related to centralised securities trading and provided by stock exchanges through a trading system. Compared with similar services offered through the over-the-counter market, trading system-based service has the following major differences: (i) service is provided through the trading system; (ii) special securities codes are assigned, and (iii) trading is conducted through a broker.

In November 2014 the Chinese government linked the Shanghai and the Shenzhen exchanges with the Hong Kong exchange through the Stock Connect program. The program allows international and Mainland Chinese investors to trade securities in each other's markets through the trading and clearing facilities of their home exchange. Chinese citizens are allowed to trade up to US$1.7 billion a day. Before the program, only Chinese citizens and a few foreign fund managers could trade in Mainland China. The program also encourages Chinese savers to buy stocks and earn higher.

The supervision is done by the China Securities Regulatory Commission (CSRC) which monitors, supervises and regulates the market by setting quotas for a new listing each year and selecting qualified companies.

4.3 THE INDIAN STOCK MARKET

The Indian stock market ranks second after the United States in terms of the number of listed companies. Its two main stock exchange markets are (i) the Bombay Stock Exchange (BSE) and (ii) The National Stock Exchange of India Limited (NSE). The BSE has a market capitalisation estimated at US$2.06 trillion and is ranked 10th in market value. The bourse is also ranked third in the world in the number of equity transactions. NSE has a market value of US$2.03 trillion and is ranked 11th. The two stock exchanges, therefore, belong to the US$ 1 trillion club.

4.3.1 OVERVIEW OF THE INDIAN STOCK MARKET

The origins of the Indian stock market can be traced back to the eighteenth century when a group of brokers formed the Native Share and Stockbrokers Association (NSSA), the precursor of the BSE. The NSSA was created out of the necessity to have legitimate means of investment rather than widespread unorganised speculation in securities that prevailed at the time. The BSE is, therefore, the oldest stock exchange in Asia. Today, the BSE is managed under the overall direction of the board of directors, which formulates broader policy issues and exercises overall control. The board comprises eminent professionals, representatives of trading members and the managing director of the BSE.

There are a total of 24 recognised stock exchanges in India, operating at a national or regional level. However other main exchanges – the National Stock Exchange (NSE) and the Over the Counter Exchange of India Limited (OTCEI) – which operate at a national level. The BSE and NSE have established themselves as the two leading exchanges and account for about 80 per cent of the equity volume traded in India. The BSE was established in 1875. The NSE, on the other hand, was founded in 1992 and started trading in 1994. Both exchanges follow the same trading mechanism, trading hours and settlement process. The number of listed companies was reported to be over 5000 by 2018 for the BSE, whereas the rival NSE had about 1 600. Out of all the listed firms on the BSE, only about 500 firms constitute more than 90% of its market capitalisation; the rest consists of highly illiquid shares. Today, there are a total of 24 recognised stock exchanges in India, operating at a national or regional level.

4.3.2 CHARACTERISTICS OF THE INDIAN STOCK MARKET

The Indian stock market played a pivotal role in the industrialisation of India in the late nineteenth and early twentieth century. As Rawal (2015) posits, early textile mills and steel plants were funded in the stock market. Over the years the Indian stock market has experienced significant structural transformation. The main objective of these transformation exercises was to improve market efficiency to make stock market transaction more transparent, curb unfair trade practices and bring the Indian security markets up to international standards (Rawal, 2015).

The India stock market is one of the best in terms of technology. Advances in computer and communication technologies have played a significant role in shattering geographic boundaries and have helped enlarge investor base (Rawal, 2015). The exchanges are now crossing national boundaries to extend their service areas, and this has led to cross-border integration. The Indian stock market is the world's third-largest stock market based on the investor base and has a collective pool of about 20 million investors.

The activities of the Indian stock market are regulated and controlled by the Securities and Exchange Board of India (SEBI). The SEBI is responsible for regulating and supervising the stock market, and it has consistently laid down market rules in line with best market practices. The SEBI also enjoys significant power to impose penalties on market participants who contravene the rules.

In the Indian stock market, the term Foreign Institutional Investors (FIIs) refers to those established or incorporated outside India that are investing in the financial markets of India by registering themselves with the SEBI. The FIIs played a significant role in the process of capital formation in the Indian bourse. For instance, in the financial year shortly after the new FIIs regulations in 1992-93, the FIIs in India were only Rs.13.4 crores[11]. Subsequently, there was a dramatic increase that saw the financial year 2010-11 increase to Rs.1 434.4 crores.

According to Labroo (2013), the Indian stock markets are mainly affected by two E's, namely (i) Earnings/Price Ratio, which is an essential factor affecting the stock price of a company, in the sense that it gives a fair indication of the company's share price when it is compared to its

[11] A crore or koti (prevalent in Bengal/ eastern India) denotes ten million (10,000,000 or 10^7 in scientific notation)

earnings. (The stock becomes undervalued if the price of the share is much lower than the earnings of a company. Nevertheless, if this is the case, it has the potential to rise in the near future. The stock becomes overvalued if the price is much higher than the actual earning of the company) (ii) Emotions / Sentiments, which are a significant part of investing. Emotions play a big part in both the rise and fall of the SENSEX, the benchmark index of the BSE. For instance, when the market gets positive news about a company, it increases the buying interest in the market. On the other hand, when there is a negative press release, it diminishes the prospect of a stock to increase in value.

Another notable aspect of the Indian stock market, especially during the post-economic liberalisation of 1990, is the incidence of regular scams that shook the Indian stock market at cyclical regularity to the extent that, as Pathak (2011:105) pointed out, "they may lead to someone believing that scams and liberalisation are correlated phenomena". The most prominent scam was the infamous Securities Scam of 1992 that led to an estimated loss of Rs4 000 in value. The repercussions of this scam were so severe that it led the BSE to remain closed for one month. Harshad Mehta, the mastermind behind the scam, was a well-known stockbroker who engaged in a massive stock manipulation scheme financed by worthless bank receipts. The scandal exposed the loopholes in the Indian banking system, the BSE transaction system, so SEBI introduced new rules to cover those loopholes (Pathak, 2011). Other scandals that occurred in the India stock market post-1990 are listed in Table 4-3 below[12].

[12]A survey of the literature by the author could not identify any major scam that occurred in the past 6 years, this can be attributed to the fact that SEBI has continuously passed bye-laws and security measures to ensure that same mistake is not repeated in the market

Table 4-3: Major Scams in Indian Stock Markets in the Past 30 Years

Year	Mastermind	Estimated value (in crore)	Modus operandi
1991	Chain Roop Bhansali	Rs 1 200	Raised public funds, from fixed deposits, mutual funds and debentures using non-existent firms and invested them in stocks for personal benefit.
1992	Harshad Mehta	Rs 4 000	Used money from banks to make personal gains via investment in shares.
2001	Ketan Parekh	Rs 800	Manipulated prices of specifically chosen securities, using large sums of money borrowed from banks.
2009	Ramalinga Raju	Rs 7 000	Manipulated accounting figures of an IT services company of which he was the chairman.
2010	Subrata Roy	Rs 24 029	Flouted SEBI regulations by issuing bonds from conglomerate he was the chairman of, to scamming an estimated of 29.6 million investors.
2013	Ram Sumiran Pal	Rs 2 200	Asked investors to subscribe to an e-magazine, after which they qualify to answer surveys and get paid for each survey.
2013	Jignesh shah	Rs 5 600	Wooed investors by offering fixed returns on paired contracts with agricultural and industrial commodities. Stocks were missing, and so-called borrowers allegedly siphoned money.

Source: Author's Compilation Based on Information Obtained Mishra (2018).

4.3.3 NUMBER OF REGISTERED COMPANIES MARKET CAPITALISATION AND THE BROAD STOCK VALUE INDEX

Figure 4-6 presents the market domestic market capitalisation of domestic listed companies (as a percentage of GDP) and the total number of listed companies in the Indian stock market between the years 2003 and 2017. It can be seen that in 2007 the Indian stock market had a total of 5615 companies, making India the country with the highest number of listed companies, even beating the US. Then it can be seen that during this period the number of listed companies consistently remained within the band of 5000 with an average of 5209 while the lowest number of 4725 was recorded in 2004.

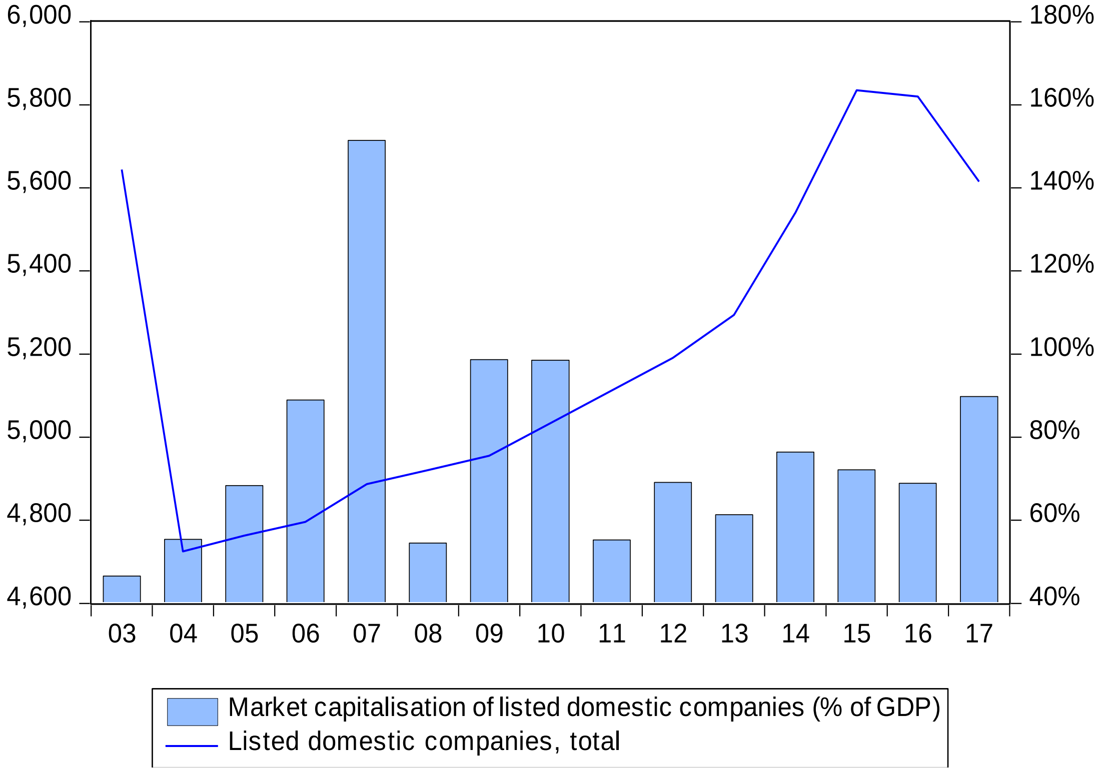

Figure 4-6: Total Number of Listed Domestic Companies and Market Capitalisation in India.
Source: Constructed based on data obtained from the World Bank (2018).

Regarding domestic market capitalisation Figure 4-6 also shows that from the year 2003 to the year 2017 their market capitalisation soared from US$200 billion to US$2.3 trillion, an increase as percentage of GDP from 45.93% to 87.90%. Rawal (2015) highlighted that this upward trend started in the 1990s when the government embarked on significant reform initiatives aimed at opening up the economy. The stock market growth was interrupted by a sharp decline in 2004. The decline in domestic market capitalisation was largely caused by selling pressures from foreign institutional investors (FIIs), which resulted the in SENSEX index declining from about the 5 900 in April to around 4 500 in May. On 17th May, the SENSEX registered a record 800-point decline, which is the steepest fall in the 130-year-old history of the stock exchange. However the index recovered to close 564 points lower (Chittedi, 2008).

Another minor decline was experienced in the global financial crisis of 2008 and the Eurozone debt crisis in 2011. The declines were due to the fact that the Indian equity market is relatively integrated with and open to the global economy. These crises saw FIIs pulling out a record US$13 billion in 2008, the most massive outflows since India opened its doors to FIIs 15 years prior to 2008 (Mishra,2012).

Figure 4-7 presents daily time-series data from January 2008 to January 2017 for SENSEX index, as the benchmark broad market index. Sensex comprises 30 of the largest and most actively traded stocks on the BSE, providing an accurate measure of the stock market in India. It can be seen that after a decline associated with the 2008 global crisis, where the Sensex fell below 10 000, the index managed to recover its losses and was on an upward trend from its recovery in 2009.

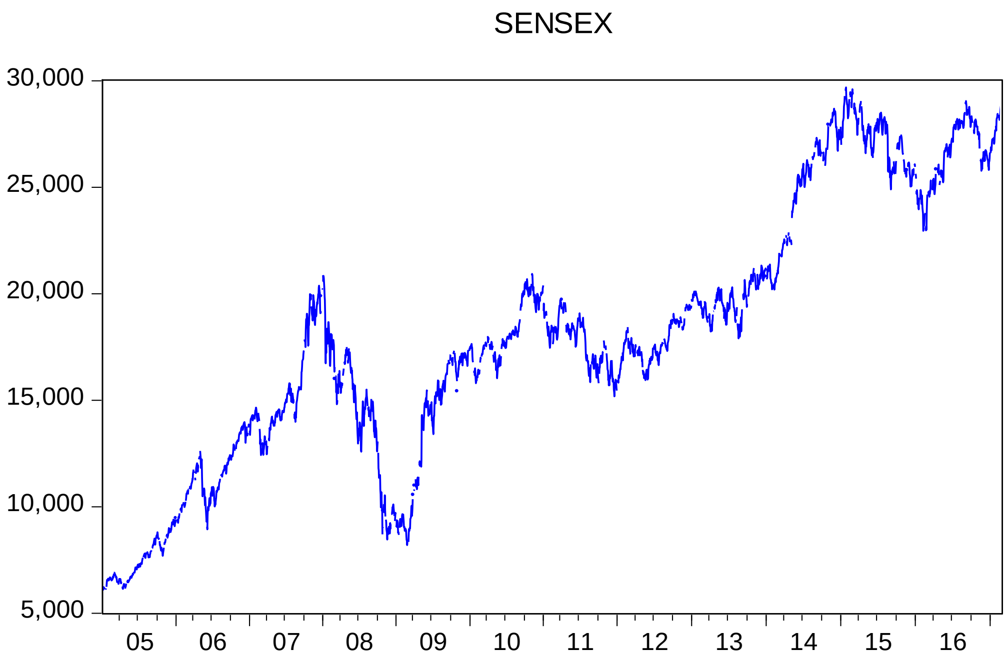

Figure 4-7: Indian Broad Market Index

Source: Constructed based on data obtained from the Thomson Reuters Datastream (2017).

4.3.4 TRADING ON THE INDIAN STOCK MARKET

Historically trading used open outcry as a method of communication between professionals at the Indian stock exchanges. There was no use of information technology for immediate matching or recording of the transactions, hence trading on Indian bourses was time-consuming and inefficient (Ryakala, 2013). In 1993 the NSE became the first bourse in the world to introduce a fully automated screen-based electronic trading system, commonly known as the National Exchange for Automated Trade (NEAT). With NEAT members can enter the quantities of securities and prices at which they wish to transact, and the transactions are executed as soon as they find a matching sale for the buy or sell order counterpart. Ryakala (2013) highlighted the following advantages of the NEAT system: (i) it increases operational efficiency as it electronically matches orders on a strict price/time priority and hence reduces time, cost and risk of error, (ii) it improves informational efficiency as it facilitates faster incorporation of price-sensitive information into prevailing prices, (iii) it provides equal access to everybody since it improves flexibility significantly for the users in terms of the kind of orders that can be placed on the system, (iv) it improves velocity and liquidity of the market since it allows market participants to view the full market in real-time, thereby making it transparent, and it also allows a large number of participants, regardless of their geographical location, to trade with one another simultaneously, and (v) it provides a perfect audit trail that helps to resolve disputes by logging in trade execution process in its entirety.

The BSE stock market exchange has a trading system commonly known as BSE's Online Trading (BOLT). The BSE launched the system in 1995. The system has a two-tier architecture; they are (i) the trader workstation that is linked directly to the backend server, which acts as a communication server, and (ii) a Central Trading Engine (CTE). BOLT also provides other services such as index computation, information dissemination, and position monitoring. For more efficiency and transparency BOLT has an interface with various information vendors like Bloomberg, Bridge and Reuters (Ryakala, 2013).

4.4 THE RUSSIAN STOCK MARKET

The Russian stock market has become a major emerging market following its explosive 700 per cent growth between 2001 and 2006. Driven by vast crude oil reserves and moves towards free-market initiatives, the country became a popular destination for many investors. The country's military intervention in Ukraine and a downturn in commodity prices have hurt its prospects from 2014 and beyond, but investors still keep an eye on this market that has a market capitalisation of US$ 623 billion.

4.4.1 OVERVIEW OF THE RUSSIAN STOCK MARKET

The Moscow Exchange is the largest stock exchange in Russia in terms of volume. It was established in 2011 through the merger of the Moscow Interbank Currency Exchange (MICEX) and the Russian Trading System (RTS), the two biggest Russian exchanges at the time. The development of the Russian equity market can be traced back to before the First World War, due to fast industrial growth and mass construction of railways. Nonetheless, only a small number of the population participated in stock investments. The low participation was due to various reasons including a negative attitude to the stock market which was considered as a very risky institution, and lower wages that made it unaffordable for the majority (Podgorny, 2016).

From 1917 to 1990 the security market in Russia was prohibited. During this period, money, and material resources were distributed by the government and there were no securities except government bonds (Podgorny, 2016). From 1990 the Russian stock market experienced development, but this was interrupted by the 1998 crisis. The significant macroeconomic events that determined the development of the Russian securities market can be divided into three periods, (i) the pre-crisis period, (ii)the crisis period and (iii) the post-crisis period. They are discussed below.

4.4.1.1 Pre-Crisis Period

According to Kovaleva (2015), the pre-crisis stock market development in Russia occurred in three stages. The first stage, spanning the middle of 1990 till 1991, started in the wake of adoption by the Russian Council of Ministers of a resolution regarding the provision on joint-stock companies. This stage was characterised by “the securities market boom” (Kovaleva, 2015:114) that produced approximately 800 securities exchanges. As Harwood (2012) explained, during this stage, the securities exchanges ended up being the first component of the Russian market structure.

The second stage coincided with the system of privatisation legislation in 1992-1994 and the establishment and development of an organised government securities market in 1993. Voucher (Cheque) privatisation technology became a crucial factor for the development of securities market infrastructure. The voucher had three major distinctive characteristics, namely (i) bearer’s nature of such securities, (ii) issue of the mentioned securities for cash purposes, and (iii) the redeemability of such securities being limited to only instruments of payment in privatisation deals (Vasiliev, 2001). During this period the Russian Federation Commission on Securities and Exchanges (RFCSE) was instituted in 2004.

The third stage of equity market development spans from 1996 to 1997. It was characterised by three key features, namely: (i) the introduction of Joint 5 Stock Company Law and Securities Market Law in 1996, which constituted development of the legislative basis for the equity market, (ii) infrastructure development characterised by an increase in the number of professional market participants, the emergence of licensed registrars and depositories, and the establishment and development of the Russian Trading System, (iii) generally positive macroeconomic trends and significant potential for growth of market liquidity and capitalisation, and (iv) increased market stability. At the same time, weak corporate governance made Russian securities somewhat risky investments.

4.4.1.2 Crisis Period

The financial crisis in Russia, commonly known as the Russian cold (or Russian flu), started in 1998. The crisis was triggered by the Asian crisis of 1997 and a significant decrease in world prices for primary goods (Zubarevich and Fedorov, 2016). However, as Vasiliev (2001) stressed, the unfavourable external financial condition cannot be solely blamed for the financial market woes in Russia. Other internal adverse factors such as the restructuring of Government short-term debt securities (GKOs) that turned out to be a pyramid-type financial scheme, the overvalued ruble rate, and inadequate regulation and supervision of the banking sector also contributed significantly to the stock market downfall. The situation was later aggravated by loss in foreign investors' confidence mainly caused by the inability of the Russian government to service its debt security.

The financial crisis of 1998 became a severe challenge to professional market participants holding assets in government securities, which incurred substantial losses. These losses affected the overall market intermediaries' business. The number of professional market participants (brokerage, dealing, fiduciary securities management) decreased significantly, especially in brokerage services related to the termination of the "vacuum cleaner" era[13] of the market's functioning. At the same time in 1998 the dealer market for foreign investors also experienced a crisis, whereas traditional exchanges turned out to be the most viable in crisis conditions (Vasiliev, 2001).

4.4.1.3 Post-crisis Period

The post-crisis Russian security market ushered in a period of development prospects for the Russian securities market. This was due to the following factors: (i) an increase in interest of foreign investors in the Russian market in general and industries not associated with the

[13] The vacuum cleaner era refers to the period when smaller regional brokers were buying out shares for Moscow brokers, who, in turn, were selling them further to non-residents.

extraction and processing of hydrocarbons in particular, (ii) Russian investors also being interested in the stock market. In 2008 the post-market rally was first interrupted by the global financial crisis and growing tensions in international relations that took place, causing a massive withdrawal of investors from the Russian market and a slump in the Russian stock market.

As mentioned above, in 2011 the Moscow Exchange was established through the merger of the Moscow MICEX and RTS. The capitalisation of the combined company was valued at US$4.5 billion ahead of the merger. The specific goals of the merger included the optimisation of the Russian stock market, the reduction of the number of organisations with overlapping functions, the creation of a single platform for issuers, traders and investors, the reduction of transaction costs, and easier trading.

The Russian stock market took another hit in 2014 and well into 2015 when foreign investors ditched Russian assets following economic and financial sanctions that the West imposed on Russia over its role in the Ukraine crisis (Reuters, 2019). In 2016 the Russian equity market proved again that it belongs in the league of highly volatile markets which can either perform poorly or offer best rates, depending on a particular year. In this year the RTS Index, which reflects the price of shares in U.S. dollar terms, gained 52.3%, and the Index MICEX (which reflects the price of shares in rouble terms) increased by 26.8%, becoming an absolute leader in terms of rate of return among all the other stock markets. The bull rally of the Russian security market continues on the back of favourable sentiments among foreign investors and the buoyant oil prices.

4.4.2 CHARACTERISTICS OF THE RUSSIAN STOCK MARKET

At present, the Russian financial market is one of the most dynamic stock markets in the world. The excellent performance of the Russian stock market can be attributed not only to fundamental economic reasons, such as the rebounding price of crude oil and a resilient ruble. The good performance is also reflected investors' growing confidence that no economic sanctions will be taken against Russia in the near future (Abramov, 2017). The Russian stock market currently has over 30% of investors in the domestic market who are non-residents.

The main distinguishing feature of the Russian stock market is the over-concentration of ownership; in most cases, the majority owners are the state or super-rich individuals, commonly known as the Oligarchs[14]. The majority of companies have 2 to 4 stakeholders[15]control 70 to 80% of the equity capital and are not interested in its dilution. Furthermore, the transactions in the orderly share market[16] are concentrated in the top 10 issuers' securities and represent 98% of all transaction in countries with a well-developed stock market this percentage does not exceed 20-30% (Guriev and Rachinsky, 2005).

Rubtsov and Annenskaya (2018) noted that foreign portfolio investors constitute the driving force in the Russian stock market. This is a direct consequence of the fact that domestic funds available for investment in the Russian stock market are minimal. As the authors explained, the paucity of domestic funds could be attributed to low household savings in Russia, as a direct consequence of the low income of the vast majority of the population. Furthermore, with the centrally planned economy that was in place in Russia till the early 1990s, there was no need (and no funds) to save for retirement or the loss of health or employment. The state guaranteed a certain minimum level of pensions and medical care while wages were kept at a low level.

Another distinguishing characteristic of the Russian equity market is that Russian stock prices depend mainly on the crude oil price. This can be seen in Figure 4-8 where RTS, as a proxy for Russian stock markets, move in lockstep with oil prices. Since the start of the 21st century, the Russian economy has relied heavily on oil sales, with some evidence of the so-called "Dutch disease[17]", whereby the export of oil crowds out other products and export items (Burton, 2015).

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[14] Russian oligarchs are wealthy business leaders with a great deal of political influence. The term highlights the nature of Russia's largest private companies, especially their ownership structure. Oligarchs normally have tight relations with the State (or more exactly with some high-ranking officials), and stable oligopolistic positions in the modern Russian economy.

[15]Here Russia's ownership structure is comparable to German and Japanese "stakeholder" economies.

[16] An orderly market is any market in which the supply and demand are reasonably equal. The orderly market would thus be said to be in a state of equilibrium.

[17] Dutch disease is a term which was coined by The Economist magazine in 1977 following a study on the financial crisis that occurred in The Netherlands after the discovery of vast natural gas deposits in the North Sea in 1959 Majbouri.

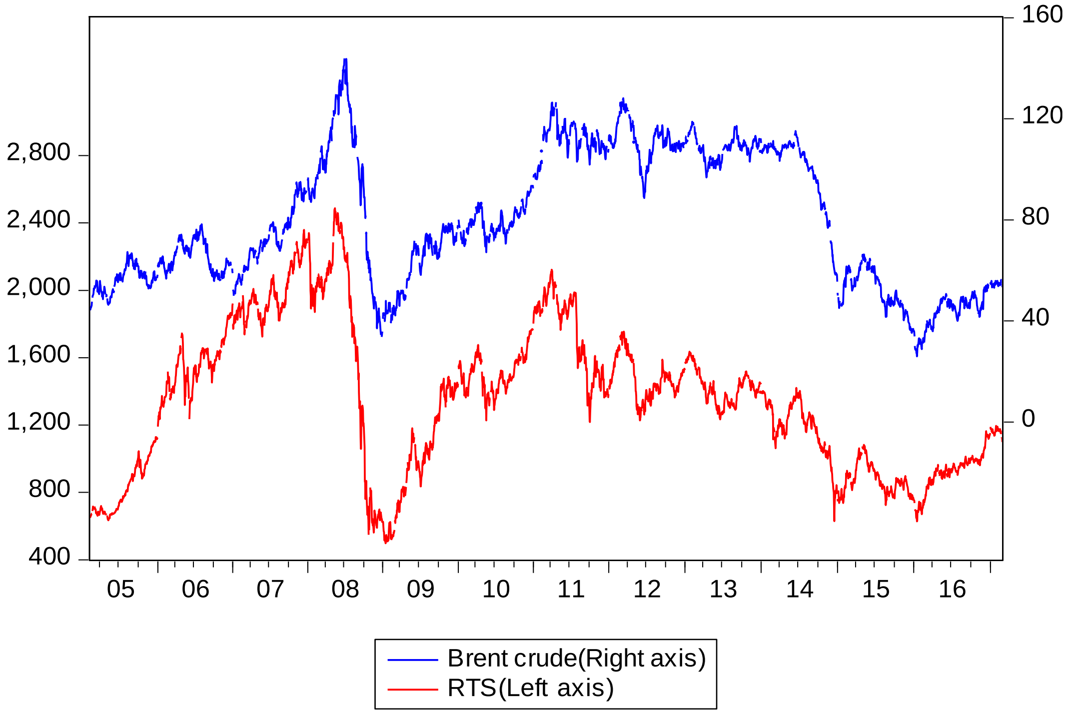

Figure 4-8: Russian Market Performance versus the Closing Price of Brent Crude Oil

Source: Constructed based on data obtained from Thomson Reuters Datastream (2017).

4.4.3 NUMBER OF REGISTERED COMPANIES MARKET CAPITALISATION AND THE BROAD STOCK VALUE INDEX

The total market capitalisation of domestic listed companies stood at US$623 billion at the end of 2017, and this represented 39.49% of the Russian GDP. As can be seen in Figure 4-9, the domestic market capitalisation fell significantly from US$ 771 billion in 2011 to US$386 billion at the end of 2014 (from 38.19% to 18.73% as a percentage to GDP). This was a result of the financial turmoil that affected the Russian stock market due to economic and financial sanctions imposed on the country. While the overall size of the market is comparable to its BRICS country peers, the number of listed companies is smaller. Figure 4-9 shows that the number of listed companies has been shrinking every year since 2011, falling to just 230 at the end of 2017. Bagchi, Dandapat, and Chatterjee (2016) explained that the difference between these two measures of the market size (i.e. market capitalisation and the number of listed companies) could be explained by the fact that a large proportion of market capitalisation comes from a few firms. In Russia, 62.1%of market capitalisation comes from the most significant ten companies. Most companies in the Russian stock market are in the extractive industries and have a high degree of state involvement.

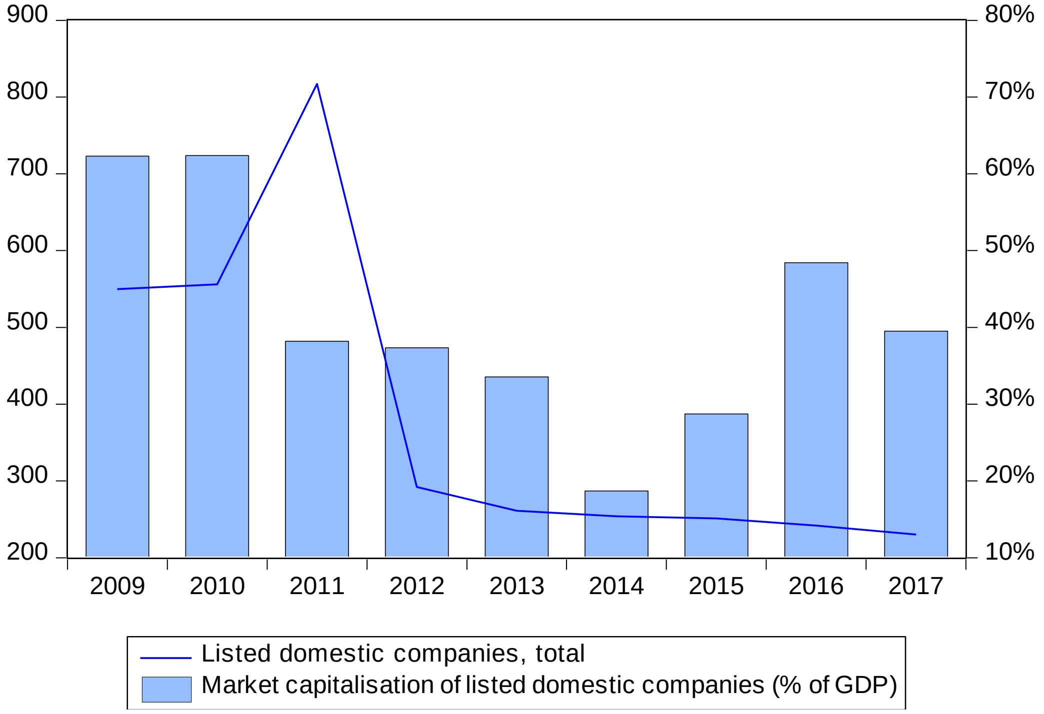

Figure 4-9: Total Number of Listed Domestic Companies and Market Capitalisation in Russia

Source: Constructed based on data obtained from the World Bank (2018).

Figure 4-10 displays time series for the RTS index (base value 100). RTS is a market index computed on prices of the 50 most liquid Russian stocks of the largest and dynamically developing Russian issuers presented on the Moscow Exchange. As mentioned above, the RTS index is calculated in real time and denominated by the Moscow Exchange in U.S. dollars, which is an adjustment of MICEX index values by the current exchange rate. The market capitalisation was US$159 billion by the end of 2019 (Moscow Exchange, 2019).

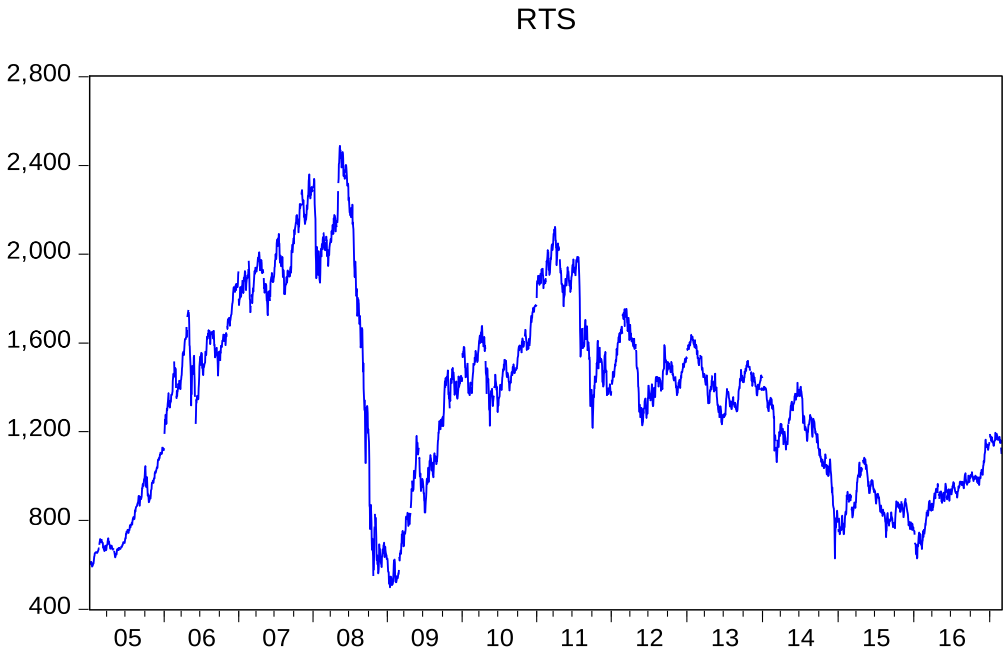

Figure 4-10: Russian Broad Market Index

Source: Constructed based on data obtained from the Thomson Reuters Datastream (2017).

It can be seen from Figure 4-10 that the Russian stock market had drastically improved from its 2008 level when the Russian stock market plunged fivefold. In 2014-2015 there was a new interruption caused by the secession of Crimea, war in Donbas and the sanctions imposed on Russia. The signs of a weak recovery emerged in 2016 (Rubtsov and Annenskaya, 2018).

4.4.4 TRADING ON THE RUSSIAN STOCK MARKET

The Moscow Exchange (MOEX) and the Stock Exchange Saint-Petersburg (SPBEX) are the two largest exchanges operating on the Russian stock market. Apart from stocks, they also offer bonds, currencies, and futures. The largest Russian stock exchange by far is MOEX, headquartered in Moscow, Russia’s capital and leading economic centre.

In the Russian stock market trading, settlement and clearing are done with infrastructures that were built in the mid-90s during the GKO and post-privatisation stock market (Guriev and Rachinsky, 2005). The system was designed for non-resident investors who were investing in Russia through offshore companies without actually bringing funds into Russia in order to minimise Russian jurisdiction, and operational and custodial risks. This means that brokers instead of investors are the ones who carry the risks, as mentioned above.

The National Settlement Depository (NSD), which acts as a central securities depository and a trade repository, is part of the Moscow Exchange Group and performs the functions of a central securities depository (CSD), settlement depository systemically important payment system (PS), and trade repository (TR). The NCC is a fully owned subsidiary of the Moscow Exchange and functions as the clearinghouse and central counterparty (CCP) for various financial markets. The Moscow Exchange Group's share of the total value of local exchange securities and derivatives trading is almost total 99.9%. Other organisations licensed as professional securities market participants authorised to carry out activities for the organisation of trading in securities on the stock exchange are (i) Stock Company Saint-Petersburg Currency Exchange (SPCEX SC), and (ii) Saint Petersburg's Exchange (PJSC). These stock exchanges' share of the total value of securities and derivatives trading is about 0.1% (National Settlement Depository, 2018).

The Federal Commission on Securities Market (FCSM) of Russia oversees the Russian securities market. Its main functions are to regulate the securities market by ensuring that investors are protected and have the freedom to participate in the market. The main concern of the FCSM is to foster corporate governance of Russian companies, by promoting their transition to international financial reporting standards, and development of the institution of collective investment, particularly mutual funds, tax optimisation, investors and market participants (Rubtsov and Annenskaya, 2018).

4.5 THE SOUTH AFRICAN STOCK MARKET

The South Africa stock market has mature capital markets that serve the domestic economy and the wider continent. It is one of the world's 20 largest exchanges by its market capitalisation of just over US$898.99 billion and is the largest exchange in Africa.

4.5.1 OVERVIEW OF THE SOUTH AFRICAN STOCK MARKET

The Johannesburg Stock Exchange (JSE) is the only stock exchange currently in operation in South Africa, although there is a statutory provision in the Securities Services Act of 2004 to allow the operation of more than one stock exchange. The JSE is the largest and oldest bourse in Africa, started initially to support the gold rush in 1887 (Marais, 2008). The JSE is licensed as a stock exchange under the South African Securities Services Act of 2004. The JSE constitutes an essential pillar of the South African economy. This is because listed equities play a relatively dominant role in the South African economy in terms of capital allocation (Marais, 2008).

4.5.2 CHARACTERISTICS OF THE SOUTH AFRICAN STOCK MARKET

One of the distinctive characteristics of the JSE is that it is mostly resource-based. This is because the biggest listed companies in the South African stock market are mining conglomerates. As a result, movements of the main index follow movements in resource prices, especially of gold and platinum (Muroyiwa, 2011). The JSE possesses some of the attributes that characterise an emerging stock market. These include low correlation to the world market, high non-normally distributed returns and volatility, weak market efficiency and higher costs of capital (Marais, 2008).

The JSE has undergone significant changes over the past decade in terms of foreign participation, legislation reform and modernisation of the trading environment. The changes led to the rapid growth of the JSE, as reflected in the increase in the number of listed companies, the increase in market capitalisation and the rise in the value of the broad stock index. These indicators are discussed below.

4.5.3 NUMBER OF REGISTERED COMPANIES MARKET CAPITALISATION AND THE BROAD STOCK VALUE INDEX

Figure 4-11 shows the total number of listed companies and total domestic market capitalisation. It can be seen that there was a decline in the total number of listed companies from 604 companies in 2000 to 294 companies in 2013. The decline in the total number of listed companies can be attributed to various reasons. These include: (i) an increase in mergers and acquisitions among South African companies as a result of stringent laws that encouraged South African companies to take over other firms while, at the same time, discouraging exporting capital (Yartey, 2008; Muzindutsi, 2011), (ii) the development of private equity funds in South Africa (Yartey, 2008), and (iii) the introduction of new listing requirements that forced a number of smaller firms to de-list, as they failed to meet the new listing requirements (Mbendi, 2008). It should be drawn to the attention of the reader that even though the numbers of listed companies have declined the number of foreign listed companies significantly increased over the same period. Indeed, the number of foreign listings increased from 22 to 49; this increase is an indication of the confidence in South African markets among foreign investors.

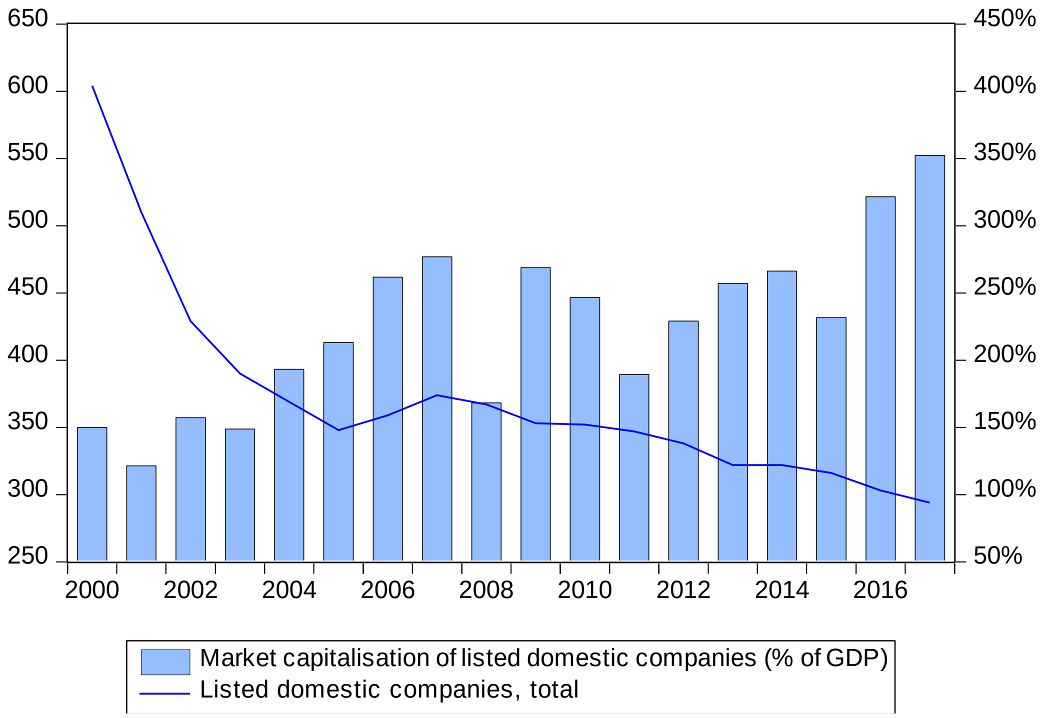

Figure 4-11: Total Number of Listed Domestic Companies and Market Capitalisation in South Africa

Source: Constructed based on data obtained from the World Bank (2018).

Figure 4-11 also presents domestic market capitalisation as a percentage of GDP for South Africa. It reveals that domestic market capitalisation was on an upward trend for ten years, except for a sharp decline between November 2007 and February 2009[18]. The increase in market capitalisation can be associated with a high level of GDP growth experienced by South Africa in the period under consideration (Muzindutsi, 2011). The highest domestic market capitalisation of US$533 billion was achieved in January 2013, representing 257.15% of the South African GDP, while the lowest domestic market capitalisation for this period was in April 2003, at US$84.3 billion (148.78%).

[18] This decrease can be associated with the financial crisis that occurred in 2007 and 2008.

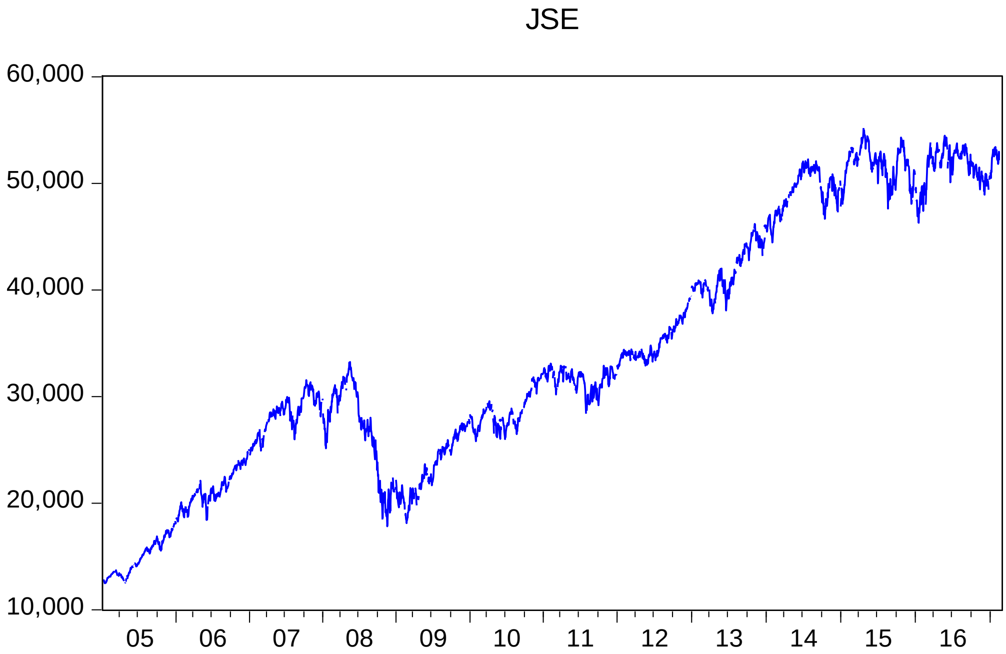

Figure 4-12: South African Broad Value Index

Source: Constructed based on data obtained from the Thomson Reuters Datastream (2017).

The excellent performance of the JSE is also illustrated by an upward trend in the broad stock index. The value of the broad index serves as a benchmark for measuring the performance of the stocks or portfolios such as mutual fund investments; the index is generally market capitalisation-weighted. It includes a large sample of listed domestic companies as the all-share or composite indices (World Federation of Exchanges, 2013). Figure 4-12 shows that the JSE ALSI index increased by 78.88 per cent, as it moved from 28,640.42 in 2003 to 51,146.05 in 2013.

4.5.4 TRADING AND SETTLEMENT AT THE JSE

Trading and settlement at the JSE are done using the latest technologies, to keep in line with global developments. For instance, in June 1996 a centralised and automated trading system, known as the Johannesburg Equities Trading (JET) system, was introduced. This marked the end of the open outcry-trading floor that had been in use. In May 2002 the JET system was replaced by the Stock Exchange Trading Systems (SETS), which are also used on the London Stock Exchange (LSE). The TradElect system in 2012, in turn, replaced the JSE SETS system (the system is operated under the license from the LSE). TradElect delivers high levels of performance and scalability, with reduced latency and increased capacity. The system has been designed to be resilient to hardware failures, with a significant reduction in fail-over times (JSE, 2012).

Clearing and settlement are done electronically through STRATE (Share TRAnsactions Totally Electronic), a system introduced in November 1999. STRATE Ltd is the licensed Central Securities Depository (CSD) for the electronic settlement of financial instruments in South Africa. It provides an electronic settlement for securities, including equity, bond and derivative products, such as warrants, Exchange Traded Funds (ETFs), retail notes, and tracker funds for the JSE (Mkhize and Mswell-Mbanga, 2006).

In order to make informed decisions, investors use the information on companies in particular, and on the economy, in general. This information is conveyed to the market through various channels, which include company announcements, as well as the government's announcements on its fiscal and monetary policies (Mabhunu, 2004). Before 1997 there were no clear guidelines as to when a company should make their announcements and what exactly should be included in these announcements (Mlambo and Biekpe, 2007). In this regard, the JSE issued *The Guidelines on the Dissemination of Price Sensitive Information* and subsequently introduced the Stock Exchange News Service (SENS) in August 1997.

The primary purpose of the SENS guidelines is to improve the dissemination of price-sensitive information, to help companies to manage price-sensitive information, and to give the media, company advisors, institutional shareholders and analysts a greater understanding of the framework within which companies should disseminate such information (Mabhunu, 2004). In terms of the SENS framework, price-sensitive information is any "unpublished information, which, if it were to be published, would reasonably affect a company's share price" (Mabhunu, 2004: 17). However, as long as the information remains confidential, possession of price-sensitive information does not necessarily compel the company to disclose it. If it is reasonably believed that confidentiality cannot be maintained, or that the information has leaked, a company has to make cautionary announcements as soon as possible (Mabhunu, 2004).

The JSE, also through SENS, provides comprehensive guidelines to ensure that shareholders receive equal treatment when it comes to information dissemination. For instance, companies should avoid consulting on price-sensitive issues with material shareholders before other shareholders. The listing requirements at the JSE stipulate that:

> companies may not release price-sensitive information to any third party during JSE trading hours until the information has been published through SENS; and outside JSE trading hours, unless arrangements have been made for such information to be published through SENS, before the next opening of [the] JSE (Johannesburg Stock Exchange, 2011).

Even after a cautionary announcement has been made public, further cautionary announcements must be issued every six weeks, until a full announcement, or an announcement withdrawing the previous cautionary announcements, has been published (Mabhunu, 2004). The guideline stipulates that, regardless of analysts' constructive role in assisting the market in their understanding and evaluation of companies, companies should decline to answer analysts' questions where the answers, on their own or when combined with others, might reveal, or at least expose, price-sensitive information. Therefore, draft reports from analysts sent to comment on inaccurate figures or assumptions should not even be corrected unless the contents of the report cannot be regarded as price-sensitive. In the same vein, companies should not feel compelled to make a formal announcement correcting forecasts by analysts unless it is clear that the market is being materially misled (Mabhunu, 2004). Should there be concerns of being misinterpreted, or mistakenly accused of providing price-sensitive information, companies should initiate internal procedures to reduce that risk. Bearing in mind the contributions of the media to a well-informed market, companies are required to exercise extreme caution when dealing with the media, especially when price-sensitive, or potentially price-sensitive, information is involved. Companies should be ready to give a 'no comment' response when journalists are pressing for unpublished price-sensitive information.

In instances where there is the likelihood that sufficient price-sensitive information has been gathered for a story to be 'broadly' accurate, a company should ensure that an announcement is made through SENS and in the press to guarantee that the correct information is widely available. If it appears to be premature to publish the full information, a cautionary announcement, through SENS and the press, should be made.

According to Mabhunu (2004), five minutes prior to the release of any announcements through SENS, a neutral warning of an impending announcement is sent through the JSE SETS system. This allows traders to retract their orders from the system if they so wish. Announcements received by SENS that have been authenticated and approved are transmitted electronically to the primary wire services, where customers of these services will then have access to the full announcements. The onus is on the company to establish a clear communication policy, and the company is still required to publish announcements in the press once the announcements have been issued through SENS.

In May 2002 the JSE introduced another live information dissemination system known as InfoWiz (Mabhunu, 2004). InfoWiz is an innovation in information dissemination. It is an innovation for its live public data delivery system. InfoWiz transmits live data to subscribed information vendors, JSE members, and financial institutions. Data broadcast by InfoWiz include: best bid and offer; mid-price; number and volume at best price; uncrossing price and volume; official closing price; trade report volume and price; the start of day reference data; full market depth and indices values. SENS publications are also broadcast through InfoWiz.

4.6 SIMILARITY AND DISSIMILARITY OF BRICS EQUITY MARKETS

There are no standard criteria for qualifying to be described an emerging country. However, the most common characteristics of the stock markets in BRICS economies are the following: (i) Significant economic growth that averages 5% for the long run, (ii) strong demographic indicators characterised by a young and educated population, combined with notable demographic growth (studies have shown that having 100 million inhabitants is a minimum in order to constitute a sizeable domestic market), (iii) a diversified economy that does not relying only on the export of raw materials, meaning that sectors such as industry and services are well developed, and finally, (iv) political stability where political institutions are stable enough to allow the implementation of long-term policies.

Table 4-4 presents the economic condition in which BRICS stock markets operate. The table also presents the world ranking for each BRICS equity market together with the turnover ratio for domestic share. Turnover ratio is the value of domestic shares traded divided by their market capitalisation. The value is annualised by multiplying the monthly average by 12. Share turnover is a measure of stock market liquidity on an economy-wide basis; it indicates how easy, or difficult, it is to sell shares of a particular stock on the market.

Table 4-4: Economic Condition of BRICS Countries

	World ranking	Turnover ratio	Current economic condition
Brazil	15th	83.90%	Brazil's economic growth has been impressive, but from 2010 and beyond, problems accumulated as investors questioned the country's economic future. Most of the concerns stemmed from the instability of the previous Brazilian government, dissolved in 2016 after the arrest of former President Dilma Roussef. However, on January 1, 2019, Jair Bolsonaro took office. Although controversial, his economic policies of freezing expenses and reducing taxes have been well received by the financial markets. Moreover, the Brazilian real has gained 10% against the U.S. dollar since his inauguration. Despite the prevailing optimism, the debacle of 2018 undermined growth forecasts for Brazil, with the IMF announcing only 2.4% in 2019.
China	2nd	206.65%	Although China is the world's second-largest economy, it has been considered an emerging market for more than 25 years. While China enjoyed very significant growth from the 1990s to the 2000s, it has experienced a slowdown over the last decade, due to the development of the public sector and increased financial risks. In 2017, China's growth rate rose for the first time since 2010 to 6.9%, but, in 2018 we saw a further decline in growth because of Beijing's policy of deleveraging and the intensification of the trade war with the United States. While fear of tension has negatively impacted market sentiment around Chinese equities and the yuan, the country is still forecasting growth of 6.2% for 2019.
India	9th	58.07%	India is the third-largest emerging economy and the seventh-largest world economy. The country's economic development began in the 1990s as the government introduced a policy of increasing competition, the standard of living and per capita income. In 2015, the Indian economy grew by 7.2%, a figure higher than any other emerging market. Moreover, this growth should even intensify in 2019, with forecasts at 7.4%.
Russia	18th	25.55%	Russia ranks 12th in the world economy, according to its GDP, but its growth rate was negative during most of the 1990s because of the post-Soviet sanctions. However, following the failure to pay debts of the post-Soviet era, in 1998 the Russian economy saw the first signs of growth. At the end of 2014 concerns were raised about Russia's dependence on oil exports, particularly in the face of international sanctions following the military intervention in Ukraine. After considerable efforts to ensure financial stability, the IMF revised its Russian GDP growth forecasts upwards to 1.7% or even 1.8% despite the decrease in its forecasts worldwide.
South Africa	13th	34.09%	South Africa is an emerging middle-income country, and although its economy experienced a steady increase in growth between 1997 and 2007, it has slowed since then. This is due to the country's broad dependence on natural resources, which implies that when commodity prices are low, South Africa's economy is doing worse than its peers. In the first half of 2018, South Africa fell into its first recession since mid-2009. The South African rand fell against the dollar from US$0.085 in February to a low of US$0.065 in September. This created additional pressure on the emerging market currency and caused the MSCI EM index to fall to 0.7% in September. The South African economy still benefits from positive forecasts for 2019, though reduced to 0.9% growth.

Source: Author's compilation.

It can be seen in Table 4-4 that the Chinese stock market has the highest turnover ratio while Russia has the lowest ratio. It is also worth noting that the South African stock market is lagging in most aspects used to describe emerging economies as it has the lowest economic growth. The country also has a population that is less than 100 million. However, the South African stock market remains a leading equity market.

4.7 CHAPTER SUMMARY

The BRICS stock markets are among the most developed stock markets, and BRICS countries all have at least one stock exchange that is ranked among the world's top 20 bourses (by domestic market capitalisation), with China and India as world powerhouses in the global market.

Stock markets in BRICS countries are heterogenous as they differ in their structural characteristics, economic policies, and geopolitical importance. Chinese and Russian markets are still in the maturing process as they only reopened recently after decades of Communist regimes that prohibited security markets. Brazilian, Russian and South African stock markets are dominated by natural resource-based stocks and are well-known commodity exporters. These countries are characterised by high growth rates relative to those observed in industrialised countries. Among the BRICS stock markets, China's market has experienced the most rapid growth in the past 20 years.

India and Brazil are relatively more domestic demand-driven markets. This can be explained by the fact that both experienced a more rapid economic recovery from the 2008 financial crisis than advanced and other emerging market economies.

Trading and settlement in BRICS bourses are done using the latest technologies, to keep in line with global developments, with the Indian stock market leading the way in this regard.

CHAPTER FIVE

NATURE OF VOLATILITIES OF STOCK MARKET RETURNS IN BRICS COUNTRIES

This chapter responds to objective two of the study (*To investigate the nature of stock market returns' volatility in BRICS countries during periods of financial turmoil*). The chapter concerns itself with analysing time series properties and return distribution for BRICS stock markets. It is grouped into four sections for ease of presentation of the information. A contextual background on market volatility is provided in the first section, where the emphasis is on stylised facts of financial time series. The methodology used in the analysis of volatility in BRICS market return series is detailed in the second section, where an in-depth discussion on univariate GARCH models and their extensions is conducted. The data used to analyse the nature of volatility in BRICS equity market returns is presented in the third section. Empirical results, as well as the key findings obtained from the analysis, are presented and discussed in the fourth section. The chapter concludes with a summary in the fifth section.

5.1 CONTEXTUAL BACKGROUND

Uncertainty plays a crucial role in financial theories. Many models in finance use variance (or standard deviation) as a measure of uncertainty. In most of these models, the variance is assumed to be homoscedastic, meaning that it is constant through time (Brooks, 2002). However, empirical evidence on financial time series data has disproved this assumption. It has been established that the volatility of financial time series exhibits stylised empirical facts such as non-Gaussian distributions (characterised by excess kurtosis), fat-tailed distributions (characterised by the law of decay in the tail of the distribution), high-frequency persistence (characterised by super-diffusive behaviour at short time scales), volatility clustering (characterised by non-stationarity in price changes), and leverage effect(where negative returns tend to increase the volatility by more significant amounts than positive returns of the same magnitude).

This chapter reports on the most widely discussed stylised facts namely, volatility clustering effect (or volatility-volatility correlation) and the leverage effect (or the volatility-return correlation). The interest in these two stylised facts among economists, stock market analysts, government regulators and policymakers stems from their implications for market efficiency and the analysis of financial contagion (Mekoya, 2013). Modelling these two stylised facts therefore improves the usefulness of measuring the intrinsic value of securities and provides insight for a better way to design appropriate policies (Mekoya, 2013).

This chapter details an empirical analysis on equity returns volatility using the univariate Generalised AutoRegressive Conditional Heteroscedasticity (GARCH) model. GARCH-type is widely modelled for detecting distributional patterns, volatility and predictability of stock returns. Their popularity stems from their healing power for heteroskedasticity in regression models and their ability to model nonlinear dynamics (Hourvouliades, 2007).

5.2 METHODOLOGY

This section discusses univariate volatility modelling for BRICS market returns, using the GARCH(p,q) model and its extensions.

5.2.1 UNIVARIATE GENERALISED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY (GARCH) MODEL

The Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model by Bollerslev (1986) is the simplest and most basic form of modelling volatility. The fundamental concept behind GARCH models is the conditional variance, that is, the variance conditional on the past information. In other words, the conditional variance can be expressed as a linear function of the squared past time series innovations.

Given a log return series r_t, and assuming that the mean equation of the process can be adequately described by an AutoRegressive Moving Average (ARMA) model, and by letting $a_t = r_t - \mu_t$,,the mean-corrected log return follows a GARCH (p,q) model if:

$$a_t = \sigma_t \varepsilon_t,$$

$$a_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-j}^2, \ldots\ldots(5.1)$$

where ε_t is a sequence of an independent identically distributed (iid) random variable with mean 0 and variance 1.0. where α_i and β_i are nonnegative constants, α_0 is a strictly positive constant and $\sum_{i=1}^{max(p,q)} \alpha_i + \beta_i < 1$. The constraint $\alpha_i + \beta_i$ implies that the unconditional variance a_t is finite, whereas its conditional variance σ_t^2 evolves. $\varepsilon_t$is often assumed to be a standard normal or standardised student‘s t-distribution. Equation 5.1 reduces to a pure ARCH(p) model if q = 0.

To understand the properties of GARCH models, it useful let $\eta_t = a_t^2 - \sigma_t^2$ so that $\sigma_t^2 = a_t^2 - \eta_t$. By plugging $\sigma_{t-i}^2 = a_{t-i}^2 - \eta_{t-1}$ (i = 0,....,p) into Equation 5.1 we can rewrite the GARCH model as:

$$a_t^2 = \alpha_0 + \sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_i) a_{t-i}^2 + \eta_t - \sum_{j=1}^{q} \beta_j \eta_{t-j} \quad \text{...(5.2)}$$

Equation 5.2 is an ARMA representation of a GARCH(p,q) model for the squared innovations $a_t^2 . \eta_t$. It can easily be shown to be a martingale difference sequence satisfying $E[\eta_t] = 0$ and $cov(\eta_t, \eta_{t-j}) = 0$ for $j \geq 1$

The present study utilises first order GARCH models, GARCH(1,1). Generally, GARCH models with p, q ≤ 2 are used. The first order GARCH (1,1) models are adopted following the literature which shows that such models are parsimonious even though higher-order models do exist (Hansen and Lunde 2005; Ijumba,2013; Mpovu, 2015). The first order GARCH(1,1) models are so often empirically adequate to test volatility clustering and leverage effects that they have achieved something of a canonical status (Diebold, 2012). The main feature of GARCH (1,1) models is that they allow only one lagged value term of variance and one lagged error term to be used in estimation. Brooks (2014) explained why the models are widely used. Firstly, it because the model specification is enough to capture the entire volatility clustering of series without the need for additional lags. Secondly, many researchers find it difficult to determine the most suitable length of lags and focus on first order GARCH models for simplicity. Furthermore, GARCH models rely on autoregressive properties within the data set. Even though the additional lags result in the reduction of the residual sum of squares, it will require extra coefficients to be estimated and this will reduce the degrees of freedom.

5.2.1.1 GARCH(1,1)

Working under the assumption that volatility depends on the last period's conditional volatility, the GARCH (1,1) model is expressed as:

$$r_t = \mu_t + \varepsilon_t \qquad \text{...(5.3)}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad \text{...(5.4)}$$

where Equation 5.3 is the mean equation and Equation 5.4 is the conditional variance equation, α_0 is a constant term, σ_t^2 is the volatility at time t, ε_{t-1}^2 is the previous period's squared error term and σ_{t-1}^2 is the previous period's volatility. Statistically significant positive parameter estimates α_1 and β (with the constraint $\alpha_1 + \beta < 1$) would indicate the presence of clustering, with the rate of persistence expressed by how much closer $\alpha_1 + \beta$ is to unity. The constraint $\alpha_1 + \beta < 1$ allows the process to remain stationary, with the upper limit of $\alpha_1 + \beta = 1$, which represents an integrated process.

A key feature for an appropriate mean equation (Equation 5.3) is that it should be 'white noise', meaning that its error terms should be serially uncorrelated. In this regard the mean equation must be tested for autocorrelation (or ARCH effects), using the Durbin Watson (DW) test and/or the Lagrange Multiplier (LM) autocorrelation test. Should there be evidence of autocorrelation, lagged values of the dependent variable should be added to the right-hand side of Equation 5.4 until serial correlation is eliminated. The appropriate mean equation must also be tested for autoregressive conditional heteroscedastic (ARCH) effect[19]to confirm that it is necessary to proceed to estimate GARCH models (Chinzara and Aziakpon, 2009).

5.2.2 ASYMMETRIC GARCH MODELS

One of the major drawbacks of GARCH models is that they enforce symmetric response of volatility to positive and negative shocks. The conditional variance in equations such as in Equation 5.4 is a function of the magnitudes of the lagged residuals and not their signs; this implies that by squaring the lagged error in Equation 5.4, the sign is lost. However, studies have shown that, due to leverage effects or volatility feedback, volatility seems to be affected

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[19] The ARCH (AutoRegressive Conditional Heteroskedasticity) effect takes place when the variance of the current error term is related to the size of the previous period's error term.

asymmetrically by positive and negative news. In other words, a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude (Brooks,2014). To remedy the problem of asymmetric effect, the study estimated GJR GARCH and EGARCH models.

5.2.2.1 Glosten, Jagannathan And Runkle GARCH (GJR GARCH) (1,1,1)

The GJR GARCH (1,1,1) model (also known as the Threshold GARCH or TGARCH) is a simple extension of GARCH(p,q) with an additional term added to account for possible asymmetries. The conditional variance is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.5)$$

where I_{t-1} is equal to 1 if ε_{t-1}^2 < 0 and I_{t-1} is equal to 0 otherwise. I is the asymmetry component, and γ is the asymmetry coefficient. The presence of asymmetric effects is indicated by a significantly positive γ. The idea behind this is that good news (ε_t> 0) and bad news (ε_t< 0) will have different impacts on conditional variance. Good news will have an impact on $\alpha_1$and bad news will have an impact on α_1+ γ. As a result, if γ is significantly different from zero, the impact of good news is different from the impact of bad news on current volatility (Arguile, 2012). The condition for non-negativity will be $\alpha_0 \geq 0,\ \alpha_1 \geq \beta \geq 0$, and $\alpha_1 + \gamma \geq 0$, that is, the model is still acceptable, even if γ is negative provided that $\alpha_1 + \gamma \geq 0$.

5.2.2.2 Exponential GARCH (EGARCH) (1,1,1)

Another GARCH model that accounts for asymmetric effects is the Exponential GARCH (1,1,1). It is expressed as follows:

$$ln(\sigma_t^2) = \alpha_0 + \alpha_1 \left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - E\left[\frac{|\varepsilon_{t-1}|}{\sigma_t} \right] \right) + \beta\, ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(5.6)$$

whereα_1 and β are still interpreted as they are in the GARCH (1, 1) model, i.e. as the coefficient of lagged residuals and the coefficient of the lagged conditional variance respectively, and γ is the asymmetry coefficient. For $\varepsilon_t \sim N(0, \sigma_t^2)$ the standardised variable $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ follows a standard normal distribution, hence $E\left[\frac{|\varepsilon_{t-1}|}{\sigma_t}\right] = \sqrt{\frac{2}{\pi}}$ (Schmitt, 1996). The inclusion of the standardised residual $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ allows the EGARCH model to be asymmetric for $\gamma \neq 0$. The asymmetry is captured by the ARCH effect, represented by $(\alpha_1 + \gamma) \cdot \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ for positive residuals $\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} > 0\right)$ or good news and by $(\alpha_1 - \gamma) \cdot \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ for negative residual $\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} < 0\right)$or bad news. If γ = 0, $ln(\sigma_t^2)$responds symmetrically to $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ (Schmitt, 1996). Besides accounting for asymmetric effects, another advantage of EGARCH (1,1,1) is the fact that when ln(σ_{t-1}^2) is modelled, σ_t^2 will remain positive, even in instances where the parameters are negative. There is thus no need to artificially impose no-negativity constraints on the model parameter (Brooks, 2014).

5.2.3 EXPLORATORY TECHNIQUES FOR GARCH (p, q) MODEL[20]

The appropriateness of GARCH models is assessed by checking the significance of the parameter estimates and measuring how good they model the volatility process. The present study conducted the following primary tests: (i) the Jarque-Bera to test for normality in the data; (ii) the LM-ARCH test to investigate for ARCH effects; and (iii) the Ljung-Box test to examine autocorrelation in the data.

5.2.3.1 Testing for Normality

A GARCH model may assume several kinds of distributions depending on the nature of the time series data under consideration. The most common distribution is the normal distribution; however, most financial time series data are not always consistent with this kind of distribution (Danielsson, 2011), so it is crucial to determine an appropriate distribution for the data. The present value uses the Jarque-Bera (JB), a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The JB test is used to test the following hypothesis:

H_0: the innovations (ε_t) are normally distributed

versus

Ha: the innovations are not normally distributed.

[20] This Section Relies heavily on Ijumba (2013).

The test statistic is given as follows: $S_N = N\left(\frac{\hat{\tau}^2}{6}+\frac{\left(\hat{k}-3\right)^2}{24}\right)$,

where $\hat{\tau} = \frac{\frac{1}{N}\sum_{t=1}^{N}\left(\varepsilon_t - \bar{\varepsilon}\right)^3}{\left(\frac{1}{N}\sum_{t=1}^{N}\left(\varepsilon_t - \bar{\varepsilon}\right)^2\right)^{\frac{3}{2}}}$, $\hat{k} = \frac{\frac{1}{N}\sum_{t=1}^{N}\left(\varepsilon_t - \bar{\varepsilon}\right)^4}{\left(\frac{1}{N}\sum_{t=1}^{N}\left(\varepsilon_t - \bar{\varepsilon}\right)^2\right)^2}$, $\bar{\varepsilon} = \frac{1}{N}\sum_{t=1}^{N}\varepsilon_t$ …………..(5.7)

N is the sample size, $\hat{\tau}$ and $\hat{k}$ are the estimators of skewness τ and kurtosis k respectively. Skewness is the measure of the asymmetry of a probability distribution, whereas kurtosis is the measure of the degree of peakedness of distribution relative to the tails.

5.2.3.2 Testing ARCH for Effects

A time series exhibiting conditional heteroscedasticity — or autocorrelation in the squared series — is said to have *autoregressive conditional heteroscedastic* (ARCH) effects. The current study employs the Lagrange multiplier (LM) ARCH test to test the significance of ARCH effects. Consider the regression that gives an ARCH(p) given as follows:

$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + ... + \alpha_p\varepsilon_{t-p}^2$ ……………………………………………………….(5.8)

Since $\mathrm{E}\left(\varepsilon_t\right) = 0$ and $\mathrm{E}_{t\text{-}1}\left(\varepsilon_t^2\right) = \sigma_t^2$, Equation 5.8 becomes

$\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + ... + \alpha_p\varepsilon_{t-p}^2 + u_t$
…………………………………………….………….(5.9)

where $u_t = \varepsilon_t^2 - E_{t-1}(\varepsilon_t^2)$ is a zero-mean white noise process. Equation 5.9 represents an Autoregressive (AR) process for ε_t^2.given that an ARCH model denotes an AR model for the squared innovations ε_t^2 then, a simple LM test for ARCH errors can be used based on the auxiliary Equation 5.9. $\alpha_1 = \alpha_2 = \ldots = \alpha_p = 0$ is the null hypothesis under which there are no ARCH effects, and the alternative hypothesis is the presence of ARCH effects. The ARCH-LM test statistic is given as:

LM = N.R^2 ,

where N is the sample size and R^2 is the squared multiple correlation coefficient calculated from the auxiliary regression Equation 5.9 using estimated innovations. The test statistic has an asymptotic chi-square distribution with *p* degrees of freedom.

5.2.3.3 Testing for Autocorrelation

As mentioned previously, one of the stylised facts of financial time series is clustering in time series returns in the form of autocorrelation in squared and absolute returns. The importance of these autocorrelations can be tested using the Ljung-Box Q-statistic by Ljung and Box (1978). The test is formulated at follows:

$$Q(p) = N(N+2)\sum_{k=1}^{p}\frac{\rho_k^2}{N-k} \quad \text{……………………………………………………..(5.10)}$$

where ρ_k is the k-lag sample autocorrelation of the squared or absolute return and N is the sample size. The Ljung-Box tests the null hypothesis that the data are independently distributed against the alternative that they are not. If the data are white noise, then the *Q(p)* statistic will have an asymptotic chi-square distribution with p degrees of freedom. An insignificant Q statistic value with a *p*-value greater than 0.05 provides evidence of absence of any significant autocorrelations in the fitted residuals and vice versa.

5.2.4 DIAGNOSTIC TECHNIQUES FOR THE GARCH (p, q) MODEL

After fitting GARCH models it is imperative to assess the adequacy of the fitted model by using several graphical and statistical diagnostics. The goodness of fit of a GARCH model is assessed by checking the significance of the parameter estimates and measuring how good it models the volatility process.

For an adequately specified GARCH model the standardised residuals are given by:

$$\tilde{\varepsilon}_t = \frac{\hat{\varepsilon}_t}{\hat{\sigma}_t} \quad \text{………………………………………………………………………………(5.11)}$$

from a sequence of independent and identical distributed random variables. The study explores the goodness of fit of the model by examining the series of estimated standardised residuals. If the GARCH model is correctly specified, the residuals should portray no serial correlation, conditional heteroscedasticity or any nonlinear dependence.

Further, the distribution of the standardised residuals should match the specified error distribution used in the estimation. To detect the ARCH effects, the Auto Correlation Function (ACF) of the squared standardised residuals was plotted. Statistically, the modified Box-Ljung statistics can be used to test the null hypothesis of no autocorrelation up to a specified lag, and the LM ARCH model can be employed to test the ARCH effect. If it is assumed that errors are normally distributed, then a Quantile-Quantile(Q-Q) plot should look roughly linear, and the Jarque-Bera statistic should not be too much larger than six (Zivot, 2009).

5.3 DATA DESCRIPTION

The data comprise daily closing stock price of indices from BRICS, Germany and the United States. The data spans a period between 11th of January, 2005 and 26th of December, 2017 (providing 2443 daily observations for each market). The 'target' stock market indices examined are those in the Brazilian BOVESPA (São Paulo Stock Exchange/Bolsa de Valores de São Paulo index), the Chinese SSE (Shanghai Stock Exchange index,), the Indian SENSEX (Bombay Stock exchange index), the Russian RTS (Moscow Exchange index) and the South African FTSE/JSE All share (Johannesburg Stock Exchange index, hereafter referred as FTSE/JSE). For 'source' markets the daily stock price index of the United States, the S&P 500, and the German, DAX Composite index is used as the proxy for the Eurozone (continental Europe) stock market.

The study used daily data to get meaningful statistical generalisation and obtain a clearer picture of the movement of market returns. A potential drawback is the effectiveness of daily data due to trading hour differences, but, as Forbes and Rigobon (2002) stressed, this represents a relative problem as attempts to circumvent the problem by using the average returns failed to find a meaningful difference in their results.

Figures 5-1 displays the time series plot of indices used in the current study. The time series is non-stationary due to the non-constant mean.

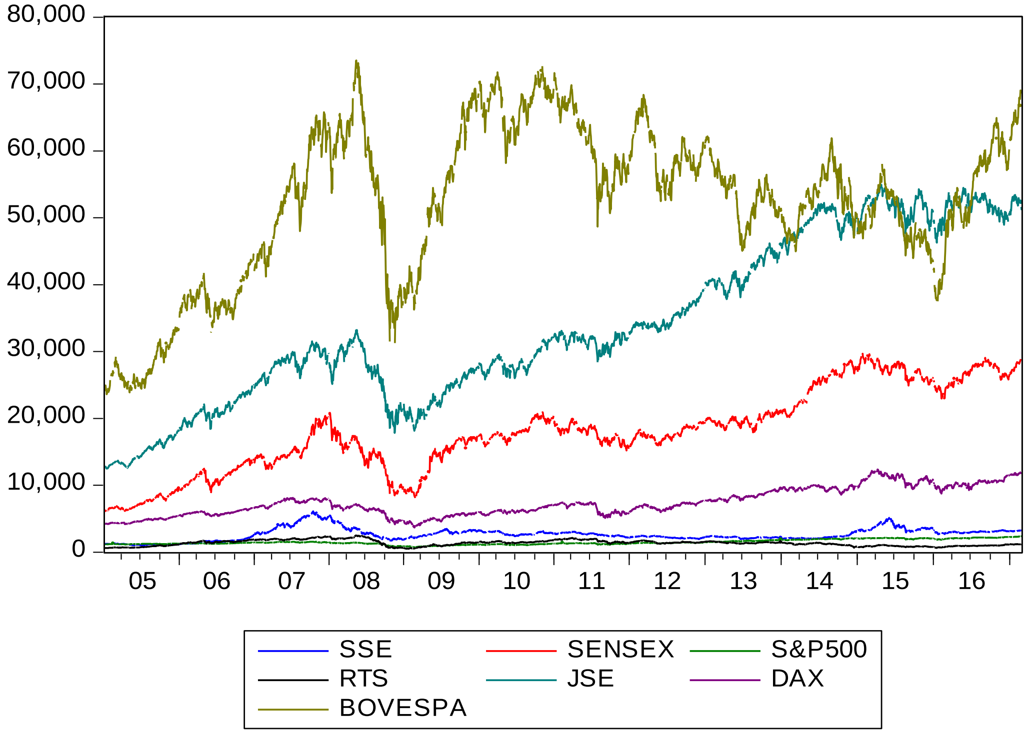

Figure 5-1: Daily Stock Market Indices of BRICS Countries, Germany and the U.S.

For detrending, and in order to achieve more stationary time series data, the daily price indices were transformed into natural logarithmic returns expressed as follows:

$$R_t = [ln(P_t) - ln(P_{t-1})] \times 100$$

where P_t is the closing price index recorded for period t, and P_{t-1} is the closing price index recorded for period t-1.The reason for multiplying the expression $ln(P_t) - ln(P_{t-1})$ by 100 is due to numerical problems in the estimation part. This will not affect the structure of the model since it is just a linear scaling.

Figures 5-2 to 5-7 illustrate the daily log returns series for price indices used in the present study. It can be seen that returns series display periods of volatility clustering, i.e. periods of high volatility are followed by periods of high volatility, and periods of low volatility are also followed by periods with the same features. The presence of volatility clustering justifies the use of GARCH models. GARCH family models have proved to be capable of capturing conditional volatility effectively (Bashir, 2018).

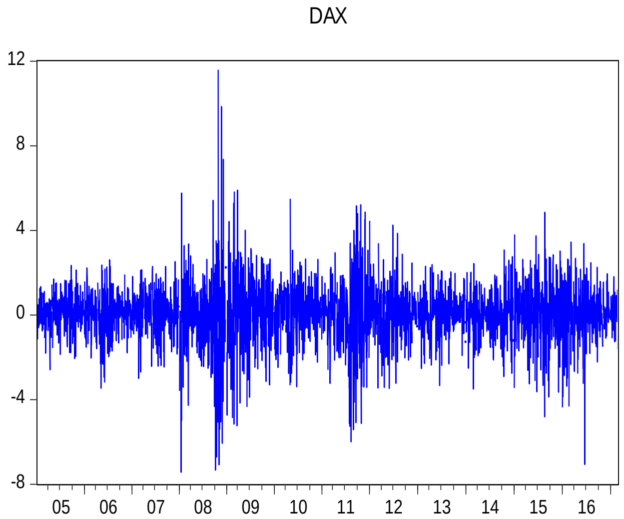

Figure 5-2: Daily Return Series for DAX (Europe)

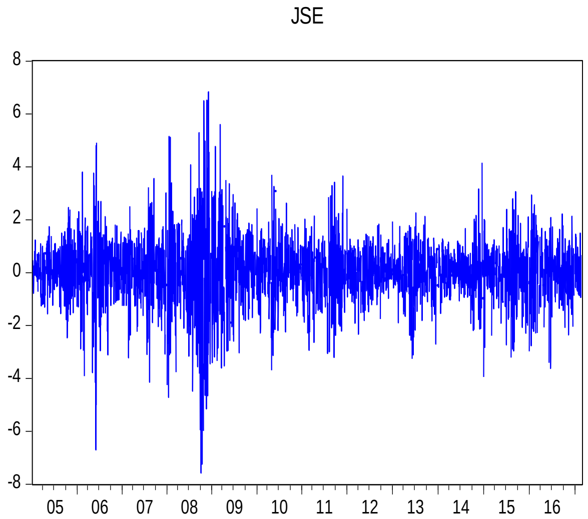

Figure 5-3: Daily Return Series for the FTSE/JSE All share Index (South Africa)

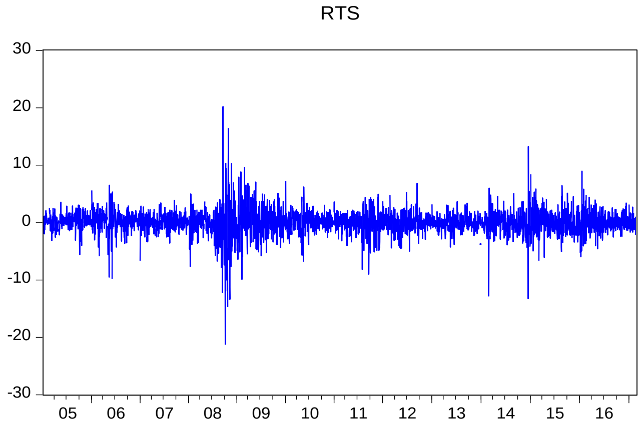

Figure 5-4: Daily Return Series for RTS (Russia)

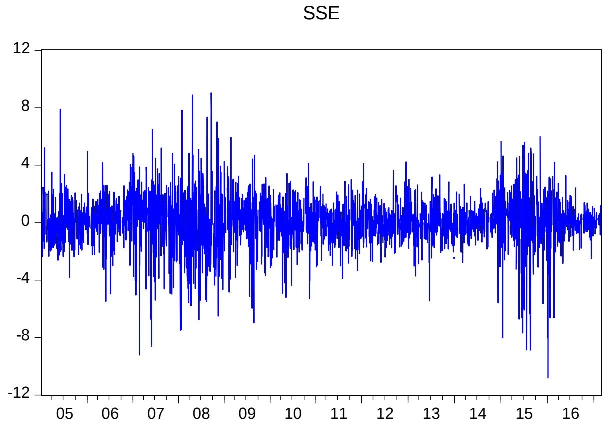

Figure 5-5: Daily Return Series for SSE (China)

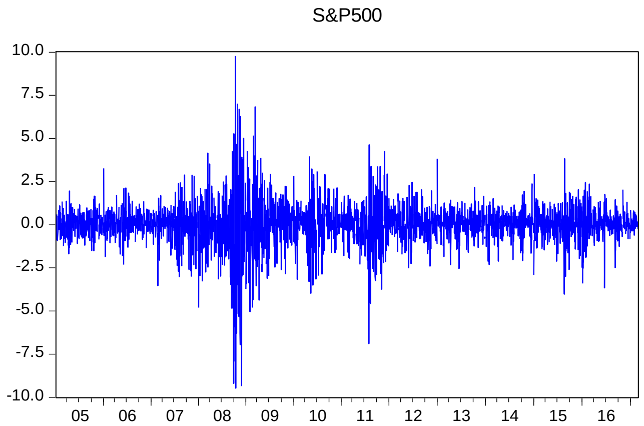

Figure 5-6: Daily Return Series for S&P500 (U.S.)

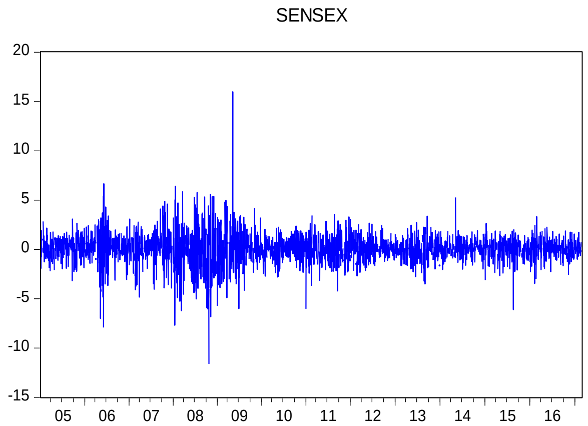

Figure 5-7: Daily Return Series for SENSEX(India)

Tables 5-1 presents estimates of the various summary statistics such as minimum, maximum, mean, median, kurtosis, standard deviation, coefficient of variation and skewness of the data (time series) used for empirical analysis. The maximum and minimum estimates measure the degree of variations in the variables. The arithmetic mean, which measures the central tendency of the variables, is of good.

Table 5-1 Summary Statistics for Market Index Returns for the Entire Period

	S&P500	DAX	BOVESPA	FTSE/JSE	RTS	SENSEX	SSE
	The entire period: January 2005 to December 2017						
Mean	0.015842	0.030027	0.039265	0.042375	0.031931	0.042848	0.07468
Median	0.073345	0.10761	0.0553	0.084598	0.103205	0.074755	0.069071
Maximum	7.017758	11.58819	9.136653	6.833971	20.20392	15.98998	9.034458
Minimum	-9.469514	-7.082808	-12.09607	-7.242465	-14.71659	-11.60444	-10.83238
Std. Dev.	1.211795	1.429626	1.751772	1.260403	2.176709	1.489052	1.768013
Skewness	-0.745188	-0.0428	-0.240382	-0.117774	-0.122831	0.063367	-0.492949
Kurtosis	10.79904	8.693878	6.725473	6.540896	11.19235	13.21902	7.529022

Source: Estimation

The arithmetic mean of the series indicates that the source markets in this study underperformed compared to target markets. During the period under investigation all individual emerging markets, except for the Russian stock market, outperformed the S&P 500 index in the United States, while the DAX index of Germany only outperformed the Chinese and the Russian markets. Saleem (2008) explained that high returns in emerging economies could be associated with a high risk (standard deviation). As for the low return on the Russian and Chinese stock markets, this can be explained by the fact that in the period of studies, the two stock markets are still in their initial stage of development, having reopened only in the 1990s after decades with no stock market activity under a command socialist economy that prevailed in the two countries. Generally, volatility, as measured by the standard deviation in Table 5-1, appears very high in all the BRICS stock markets. Russia recorded the highest volatility with a standard deviation of 2.177. This position is further strengthened by Russian recording the minimum return (-14.717) that is far lower than its counterparts. Conversely, the RTS has the highest maximum return (20.203). Higher returns are required as compensation for investing in more volatile or risky assets. This feature is consistent with financial theory relating to the risk-return trade-off.

From Table 5-1 it is clear that all return series, without exception, exhibit strong skewness to the left and have leptokurtic properties that are shared in most financial data (James, Marchant, Gerlach, and Cripps, 2019). For all the variables, the kurtosis is more than three, meaning that the distributions are slim and long-tailed.

5.4 RESULTS OF EMPIRICAL MODELS AND DISCUSSION

This section utilises GARCH (1,1) EGARCH(1,1) and GRJ(1,1) models to examine the volatility of individual equity markets used in the current study. Generally, GARCH models with p, q ≤ 2 are used. First-order GARCH models are adopted following the literature, which shows that such models are parsimonious even though higher-order models do exist (Hansen and Lunde 2005; Ijumba,2013; Mpovu, 2015).

5.4.1 RESULTS OF EXPLORATORY ANALYSIS OF GARCH (1,1)

Table 5-2 presents results for exploratory analysis, as discussed in Table 5-1. The data exhibit strong skewness to the left, and have leptokurtic properties. This is confirmed by the Jarque-Bera test statistic (with the p-value reported) in Table 5-2 which indicates that the assumption of normality is rejected decisively for all BRICS market return series.

The present study also estimated the Ljung-Box portmanteau (or Q statistic) and the adjusted Q statistic with 24 lags to test for serial correlation in the data. The null hypothesis of no serial correlation is rejected in all index return series except the SENSEX(India). The results of the statistically significant LM ARCH test statistics confirm the existence of autoregressive conditional heteroskedasticity (ARCH) in all the market return and squared return series, hence justifying the use of GARCH models.

Table 5-2: Results of Exploratory Data Analysis.[21]

	S&P500	DAX	BOVESPA	FTSE/JSE	RTS	SENSEX	SSE
	Period: January 2005 to December 2017						
Jarque-Bera	**5464.004**	**2810.389**	**4327,397**	**1091.43**	**5821.833**	**9051.846**	**1861.95**
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
LM ARCH(5)	**0.275114**	**0.197555**	**0.226985**	**0.167639**	**0.072713**	**0.070655**	**0.061158**
p-value	0.0000	0.0000	0.0000	0.0000	0.0001	0.0033	0.0020
Q(24)	**114.04**	**71.498**	**61.705**	**52.760**	**58.957**	33.216	**42.838**
p-value	0.0000	0.0000	0.0000	0.001	0.0000	0.100	0.010
Qs(24)	**4727.8**	**2011.1**	**2828.4**	**3652.0**	**3577.0**	**571.92**	**838.47**
p-value	0.0000	0.0000	0.0000	0.0000	0.000	0.0000	0.0000

Source: Estimation.

A GARCH (1,1) model may assume several conditional distributions, depending on the nature of the time series data. The most familiar conditional distribution is the Gaussian normal distribution; therefore, each of the market indices returns is fitted under this assumption and a Q-Q plot for each market returns is plotted as shown in Figures 5-8 to 5-14. For a standard normal Gaussian distribution a theoretical Q-Q plot takes the shape of the line y = x. Therefore, empirical data is assumed to have its points lying around the normal prediction line. Any deviations of the points away from this line indicate deviations from normality.

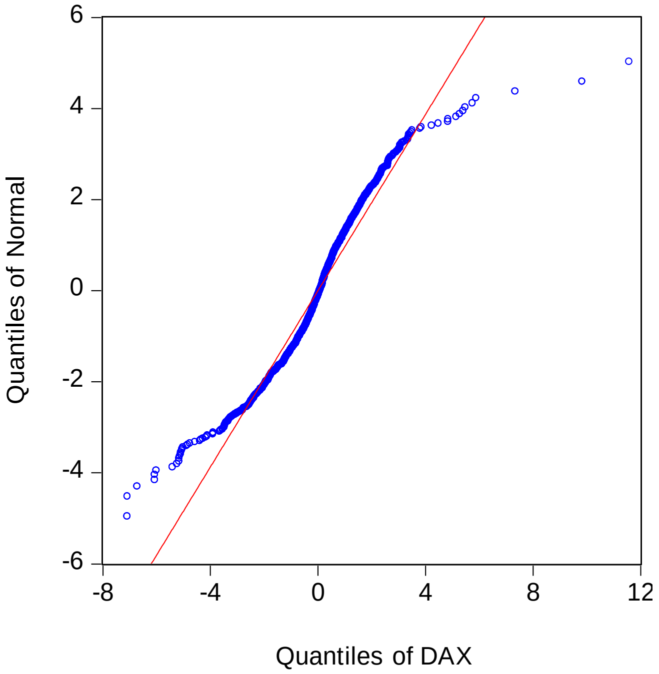

Figure 5- 8 Q-Q Plots of DAX Composite Index Return under the Gaussian Normal Distribution Assumption

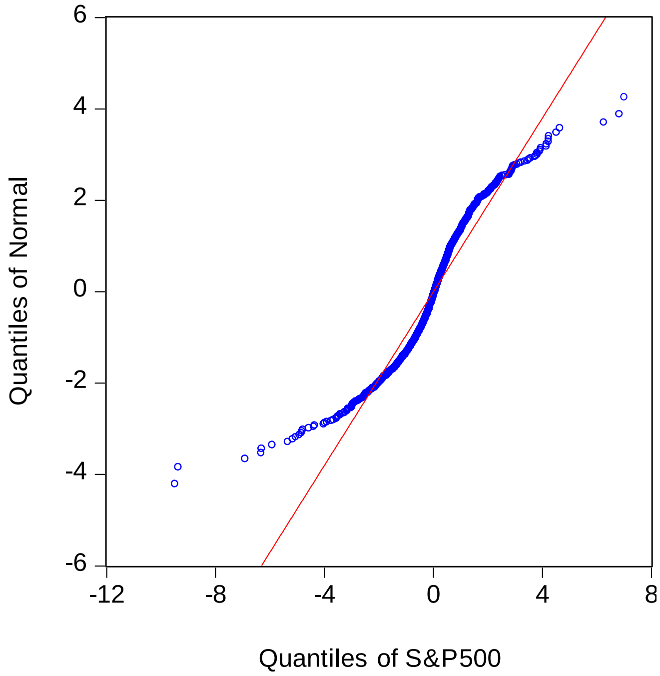

Figure 5- 9 Q-Q Plots of S&P500 Composite Index Return under the Gaussian Normal Distribution Assumption

[21] For all parameter estimates in the current study the statistical significance in the tables is not indicated by asterisks, but rather by the p-values. Statistically significant parameters < 10% are highlighted in bold.

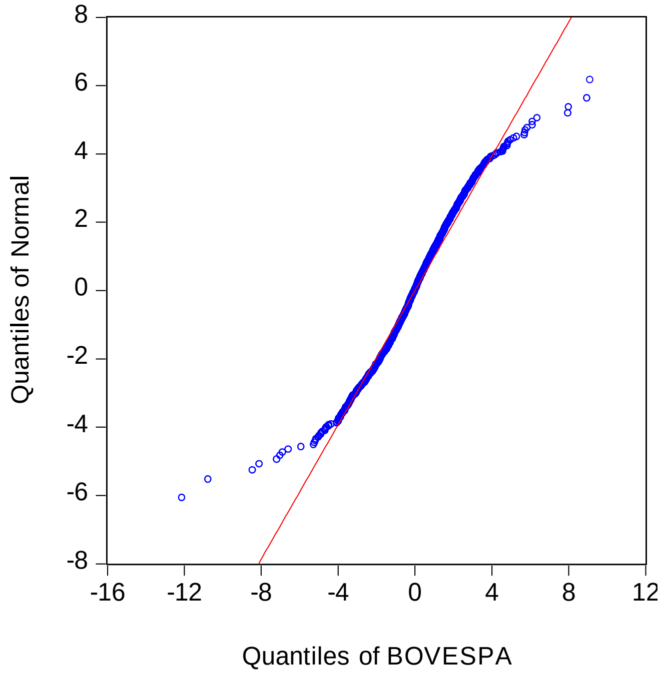

Figure 5- 10 Q-Q plots of BOVESPA Composite Index Return under the Gaussian Normal Distribution Assumption

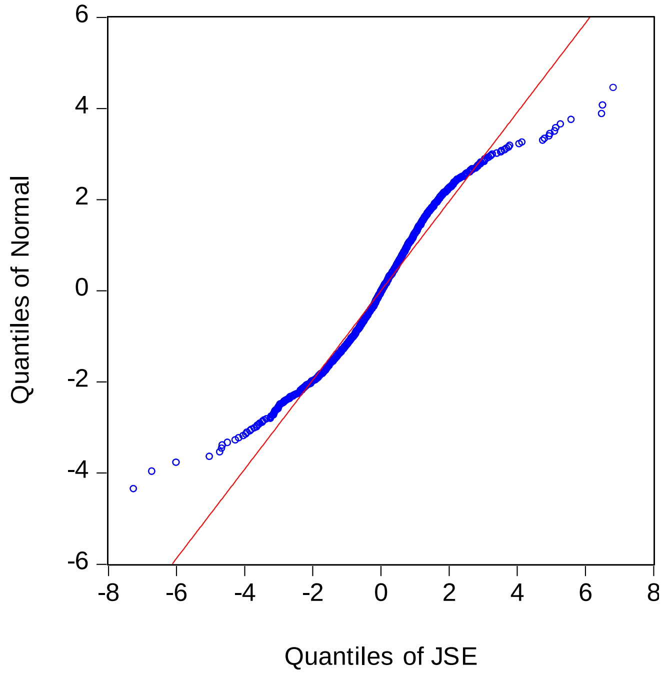

Figure 5- 11 Q-Q plots of FTSE/JSE Composite Index Return under the Gaussian Normal Distribution Assumption

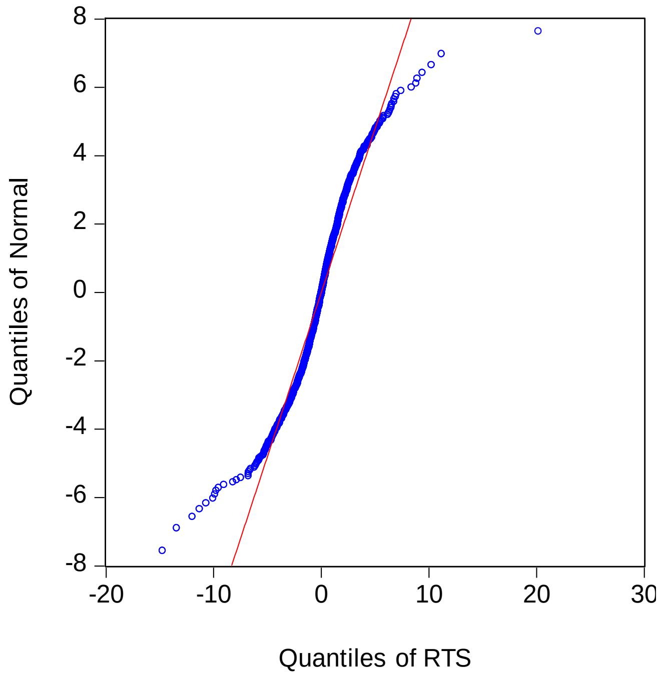

Figure 5- 12 Q-Q plots of RTS Composite Index Return under the Gaussian Normal Distribution Assumption

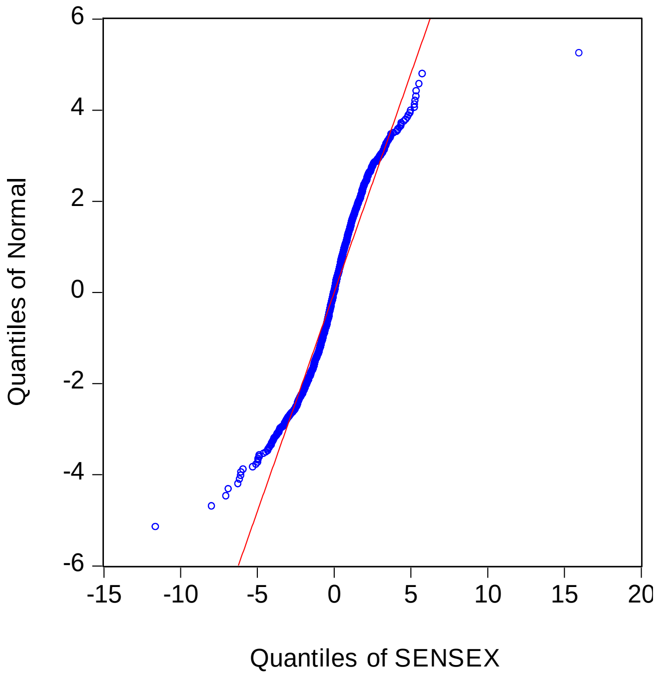

Figure 5- 13 Q-Q Plots of SENSEX Composite Index Return under the Gaussian Normal Distribution Assumption

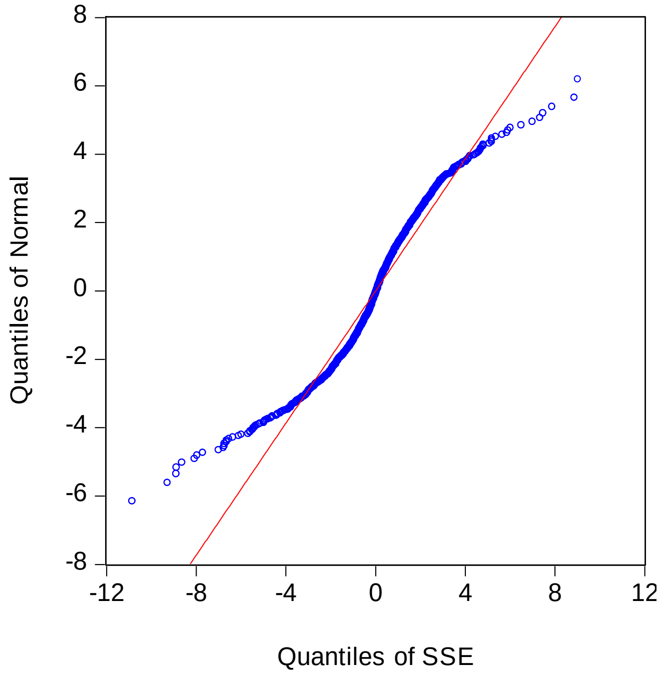

Figure 5- 14 Q-Q Plots of SSE Composite Index Return under the Gaussian Normal Distribution Assumption

From Figures 5-8 to 5-14 it is evident that most of the points lie on the normal line. Nevertheless, towards the lower ends of the plots, the points of each return series appear to move relative to the normal line, indicating the presence of heavy left tails. In practice, the right and left tail distributions of returns are in most cases different. It is therefore good practice to allow the conditional distribution to be a skewed one.

The deviation from normality suggests the use of other distribution. In this regard, the present study uses the Student's t-distribution, as a substitute for the normal distribution. As Pesaran and Pesaran (2007) pointed out, market yields tend to follow a student's t-distribution (Ijumba, 2013).

5.4.2 RESULTS FOR GARCH (1,1) MODEL

After determining the distribution of the return series, the present study estimated parameters for GARCH (1,1). The summary table of the GARCH (1,1) model parameter estimates for each of the BRICS equity market returns is presented in Table 5-3.

It can be seen in Table 5-3 that the sum of estimates $\hat{\alpha}_1$and β_1 is less than one for all of the market return series, implying that the unconditional volatility for each of the market return series is finite. Furthermore, the Chinese equity market (SSE) is seen to have the highest volatility persistence with a rate of persistence of $\hat{\alpha}_1 + \hat{\beta}_1 = 0.998$, followed by DAX with a volatility persistence of $\hat{\alpha}_1 + \hat{\beta}_1 = 0.988$ whereas, BOVESPA appears to have the lowest volatility persistence of $\hat{\alpha}_1 + \hat{\beta}_1 = 0.965$. These results are similar to the studies by Kasman (2009) and Ijumba (2013), who found that China (SSE) had the highest volatility persistence among the BRIC equity markets. However, Kasman (2009) warns that ignoring structural breaks in a return series could lead to overestimation of volatility persistence.

Table 5-3: GARCH (1, 1) Parameter Estimates Using Student's t-distribution

Returns	Parameter	Estimate	SE	p-value
S&P500	μ	**0.081990**	0.019392	0.0000
	α_0	**0.029765**	0.007957	0.0002
	α_1	**0.158841**	0.023630	0.0000
	β_1	**0.833318**	0.020499	0.0000
	$\alpha_1 + \beta_1$	0.992159	—	—
DAX	μ	**0.108006**	0.022598	0.0000
	α_0	**0.034770**	0.010833	0.0013
	α_1	**0.114536**	0.017603	0.0000
	β_1	**0.875560**	0.017126	0.0000
	$\alpha_1 + \beta_1$	0.990096	—	—
BOVESPA	μ	**0.078346**	0.032127	0.0147
	α_0	**0.105261**	0.028727	0.002
	α_1	**0.091301**	0.014764	0.0000
	β_1	**0.872946**	0.019849	0.0000
	$\alpha_1 + \beta_1$	0.964247	—	—
JSE	μ	**0.079807**	0.021234	0.0002
	α_0	**0.036498**	0.009949	0.0002
	α_1	**0.036498**	0.014919	0.0000
	β_1	**0.855250**	0.020234	0.0000
	$\alpha_1 + \beta_1$	0.891748	—	—
RTS	μ	**0.110371**	0.034431	0.0013
	α_0	**0.082106**	0.023924	0.0006
	α_1	**0.091335**	0.014086	0.0000
	β_1	**0.889344**	0.016226	0.0000
	$\alpha_1 + \beta_1$	0.980679	—	—
SENSEX	μ	**0.084224**	0.023066	0.0003
	α_0	**0.037294**	0.011357	0.0010
	α_1	**0.096474**	0.015409	0.0000
	β_1	**0.886752**	0.016345	0.0000
	$\alpha_1 + \beta_1$	0.983226	—	—

SSE	μ	**0.043825**	0.026296	0.0956
	α_0	**0.024677**	0.009740	0.0113
	α_1	**0.075343**	0.012477	0.0000
	β_1	**0.922608**	0.011221	0.0000
	$\alpha_1 + \beta_1$	0.997951	—	—

Source: Estimation.

Figures 5-15 to 5-21 plot the estimated volatility of return indices used in the current study. Based on the volatility scale on the plots, RTS (Russia) appears to have the highest volatility, followed by SENSEX (India). It is clear from Figures 5-15 to 5-21 that all of the BRICS returns exhibit high volatility during the global financial crisis between the years 2008 and 2009, and smaller volatility during the Eurozone sovereign debt crisis between 2009 and 2012.

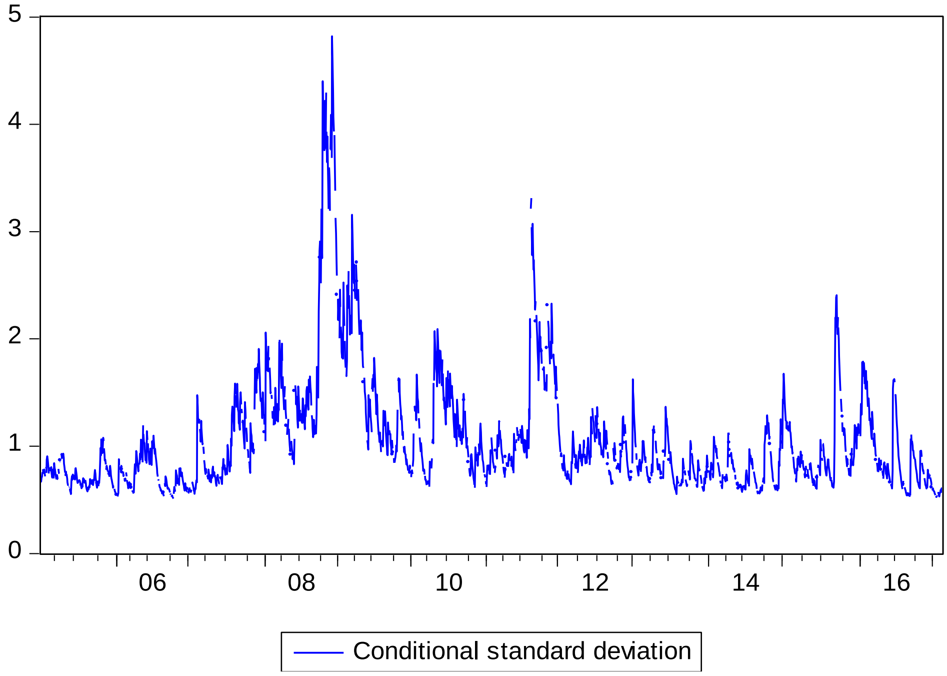

Figure 5-15: Plots of the Estimated Volatility of S&P500 Composite Index.

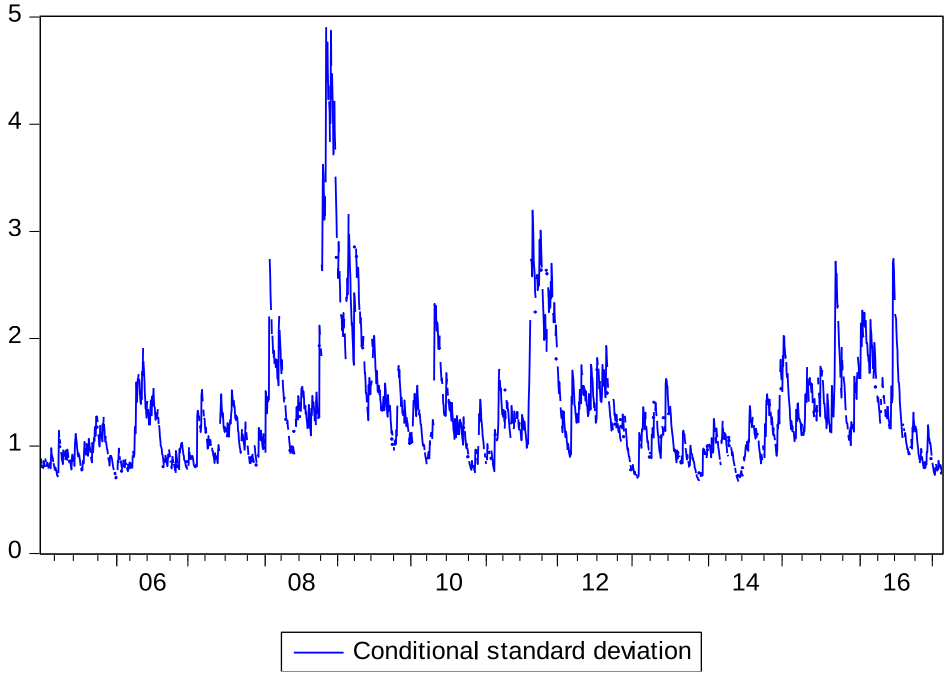

Figure 5-16: Plots of the Estimated Volatility of DAX Composite Index.

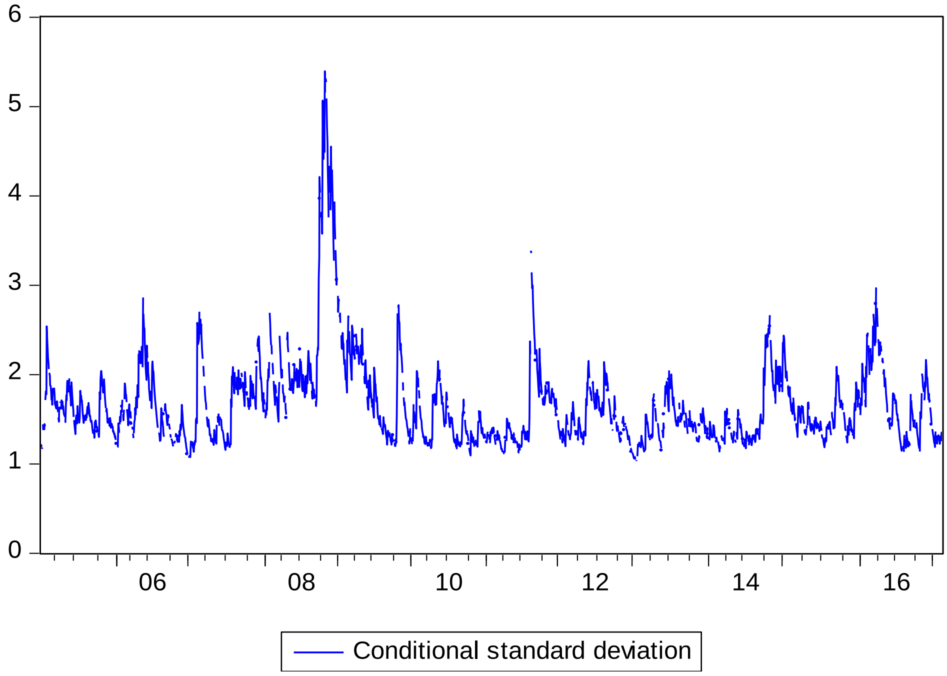

Figure 5-17: Plots of the Estimated Volatility of BOVESPA Composite Index.

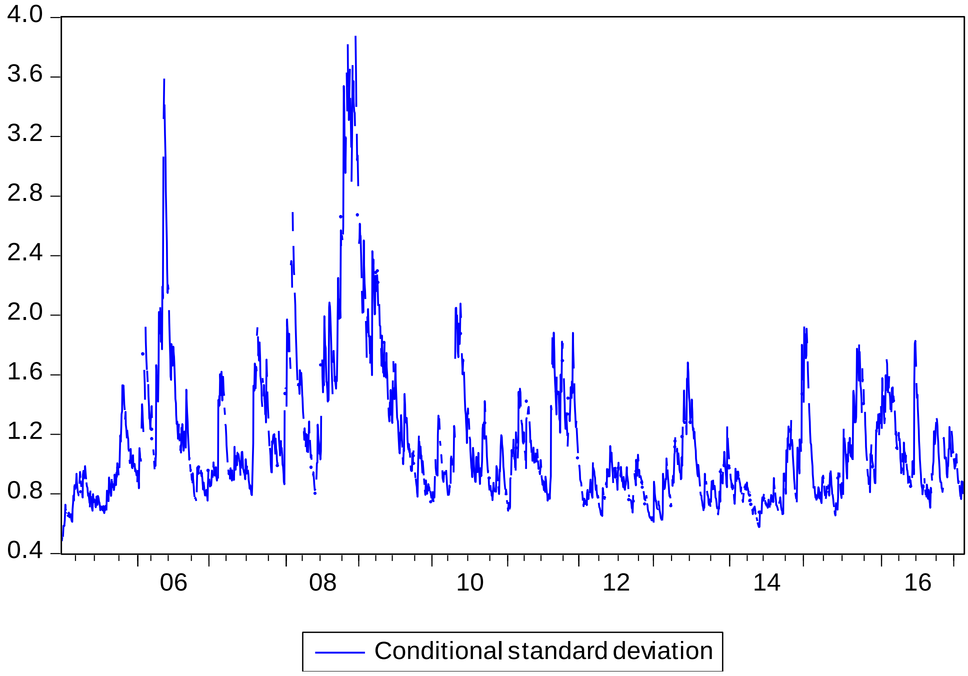

Figure 5-18: Plots of the Estimated Volatility of FTSE/JSE Composite Index.

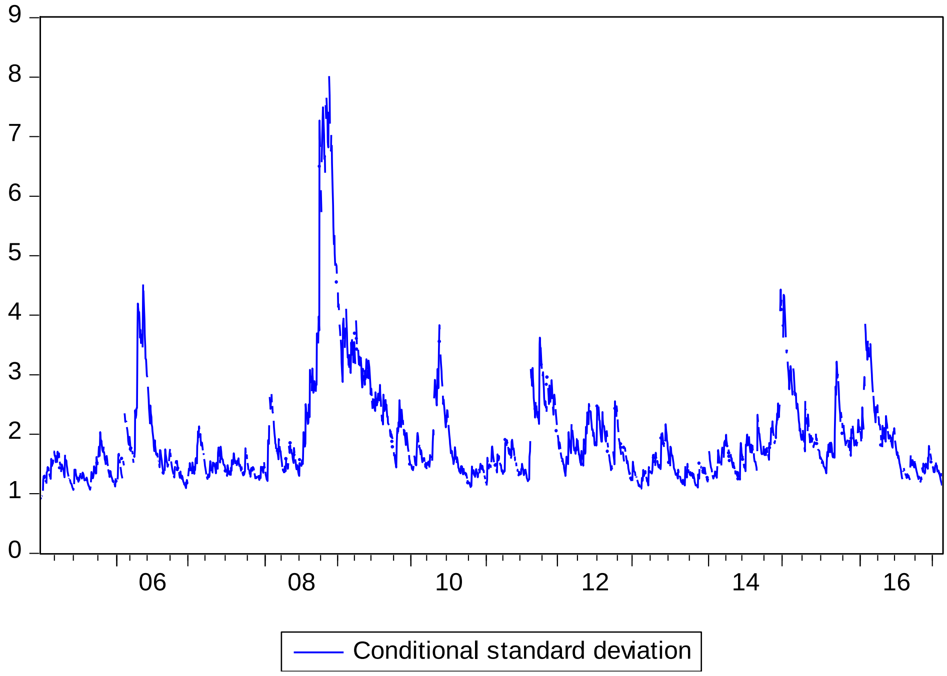

Figure 5-19: Plots of the Estimated Volatility of RTS Index Composite Index.

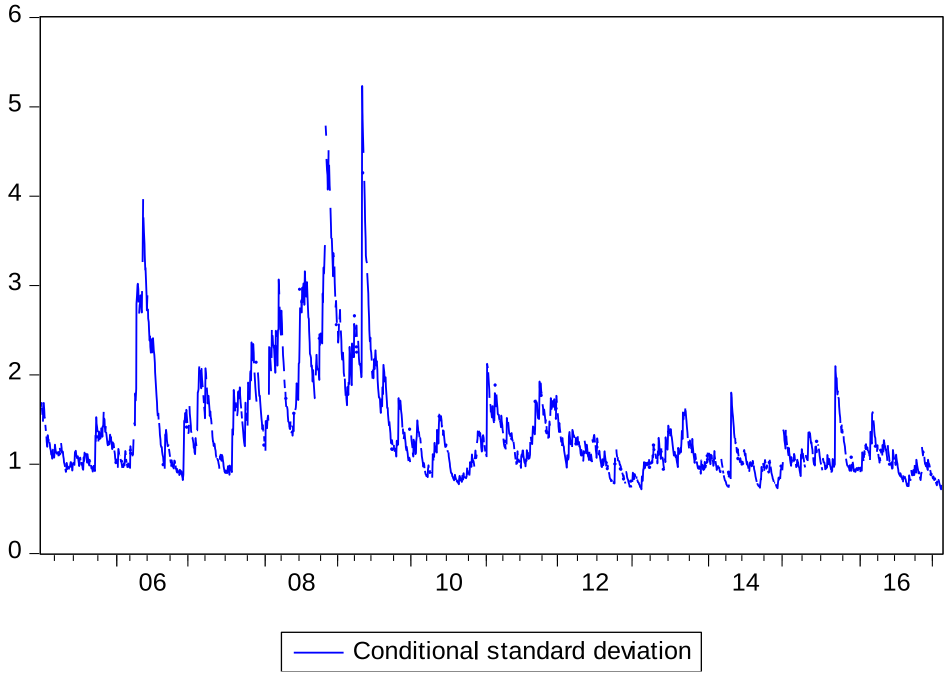

Figure 5-20: Plots of the Estimated Volatility of SENSEX Composite Index.

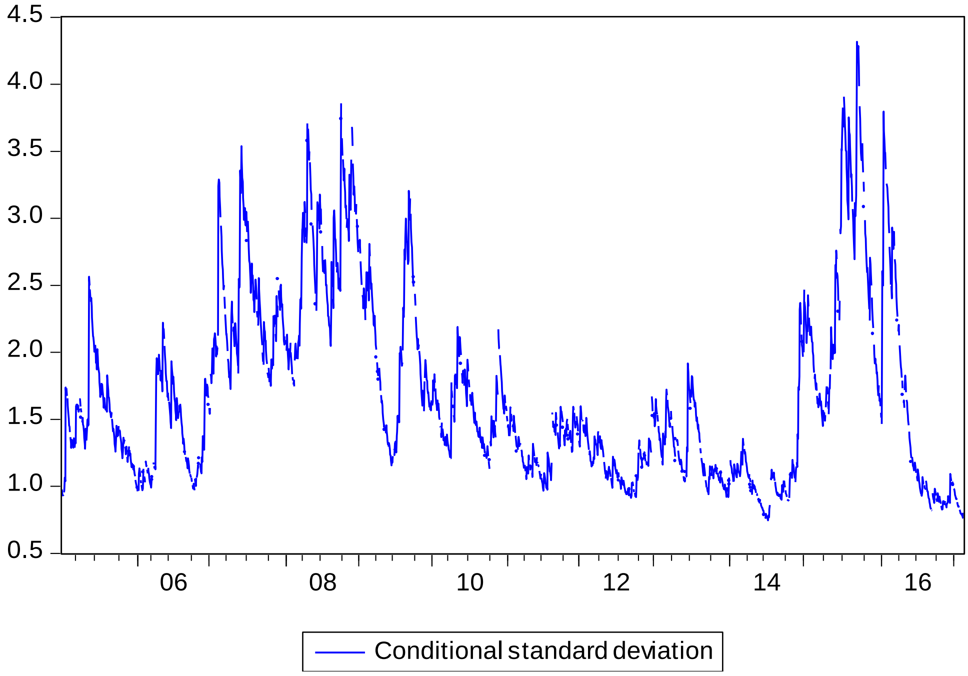

Figure 5-21: Plots of the Estimated Volatility of SSE Composite Index.

5.4.2.1 Diagnostic Tests for GARCH (1, 1)

For any model to be deemed adequate it must be submitted to several diagnostic assessments after being fitted. Several diagnostic tests were carried out on the fitted GARCH(1,1) model including (i) the JB test, (ii) Ljung-Box test and (iii) the ARCH-LM test. The JB test checks for the normality of fitted residuals, the Ljung-Box test checks for serial correlation of the fitted residuals, and the ARCH-LM test checks for the presence of ARCH errors in the fitted residuals. The Ljung-Box test was carried out on both residuals of returns and squared returns for each of the market returns stock market. A summary of the diagnostic test results is displayed in Table 5- 4.

It is apparent from Table 5-4 that except for the JSE and SSE no heteroscedasticity is left in the fitted models. The LM ARCH test statistic is not significant, indicating the absence of autoregressive conditional heteroskedasticity (ARCH) in the fitted residual. To corroborate this conclusion the Box-Ljung test for standardised residuals is used. The values of the Box-Ljung test statistic Q (24)and Qs(24) are not statistically significant for all market returns (with the exception of SEE and RTS); this is evidence of little or no serial correlation in the fitted residuals.

Table 5-4: Diagnostic Test Results for the GARCH (1,1) Model

Returns	Diagnostic test	Statistics	P-value
S&P500	Jarque-Bera	**495.7750**	0.000
	ARCH(5)	0.070630	0.9437
	Q(24)	31.923	0.129
	Qs(24)	19.952	0.700
DAX	Jarque-Bera	**180.9883**	0.000
	ARCH(5)	0.847525	0.3968
	Q(24)	25.692	0.369
	Qs(24)	28.802	0.228
BOVESPA	Jarque-Bera	**71.84995**	0.000
	ARCH(5)	-0.514556	0.6069
	Q(24)	25.004	0.406
	Qs(24)	**34.218**	0.081
FTSE/JSE	Jarque-Bera	**70.54053**	0.0000
	ARCH(5)	**2.156823**	0.0311
	Q(24)	23.454	0.524
	Qs(24)	23.454	0.493
RTS	Jarque-Bera	**194.3864**	0.000
	ARCH(5)	1.180272	0.2380
	Q(24)	**50.700**	0.001
	Qs(24)	25.811	0.363

SENSEX	Jarque-Bera	**1391.720**	0.000
	ARCH(5)	0.001789	0.9351
	Q(24)	22.275	0.563
	Qs(24)	15.005	0.921
SSE	Jarque-Bera	**598.1983**	0.000
	ARCH(5)	-0.000895	0.9675
	Q(24)	**35.286**	0.064
	Qs(24)	14.324	0.939

Source: Estimation.

It is worth drawing to the reader's attention that before applying the GARCH (1,1) model to the data, both the LM ARCH test and Box-Ljung test illustrated rejection of their respective null hypothesis, showing overwhelming evidence in support of ARCH effects and serial correlation. In the post-estimation applying standardised residuals based on the estimated GARCH (1,1) model, the corresponding test results are an affirmation of their respective null hypothesis. The results confirm the effectiveness of the GARCH (1,1) model.

The results of The JB test, on the other hand, reject the property of normality on the fitted residuals of all the market returns. Ijumba (2013) posited that the application of the JB test on conditional heteroscedastic models is weak. Therefore, a graphical assessment on normality was carried out on each of the fitted residuals of the market return series using a normal Q-Q plot as shown in Figures 5-22 to 5-28.

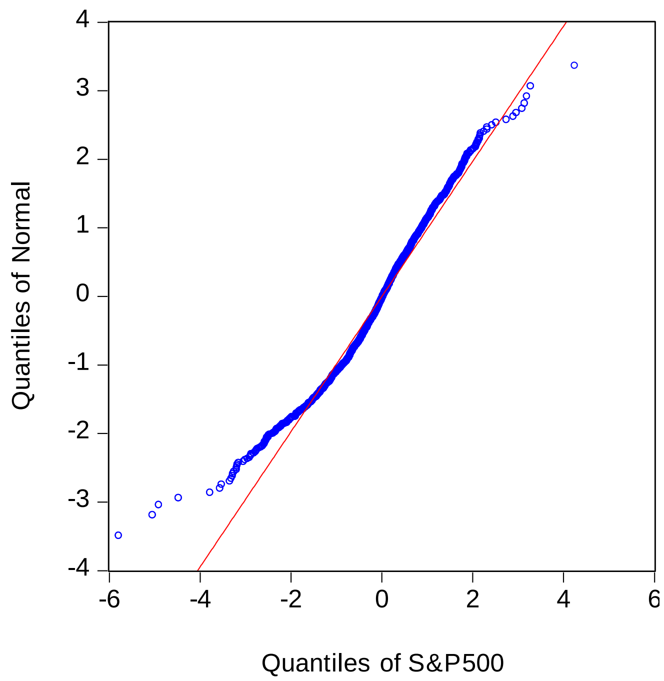

Figure 5-22: Q-Q Plots of the GARCH(1,1) Fitted Residuals for S&P500 Composite Index

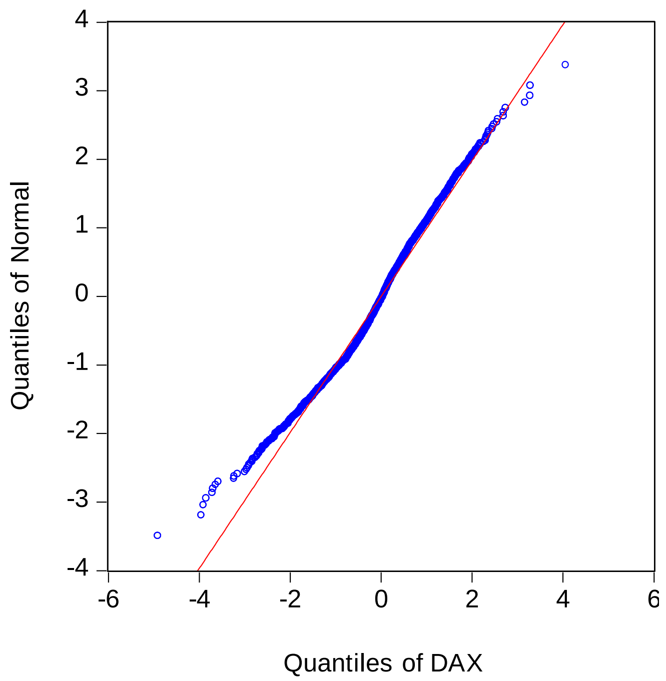

Figure 5-23: Q-Q Plots of the GARCH(1,1) Fitted Residuals for DAX Composite Index

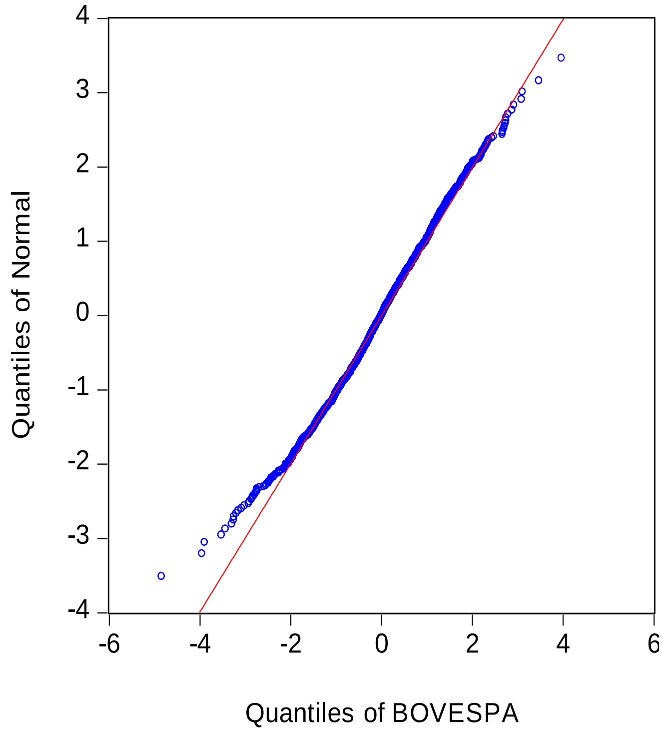

Figure 5-24: Q-Q Plots of the GARCH(1,1) Fitted Residuals for BOVESPA Composite Index

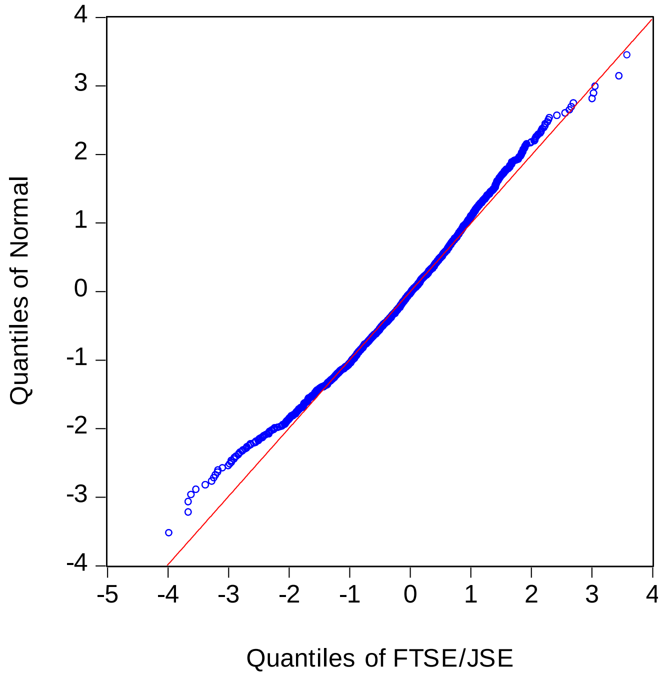

Figure 5-25: Q-Q Plots of the GARCH(1,1) Fitted Residuals for JSE Composite index

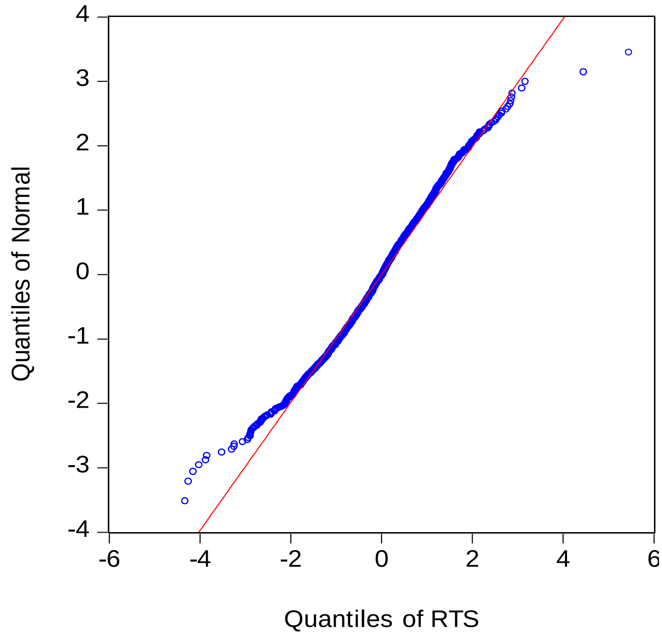

Figure 5-26: Q-Q Plots of the GARCH(1,1) Fitted Residuals for RTS composite index

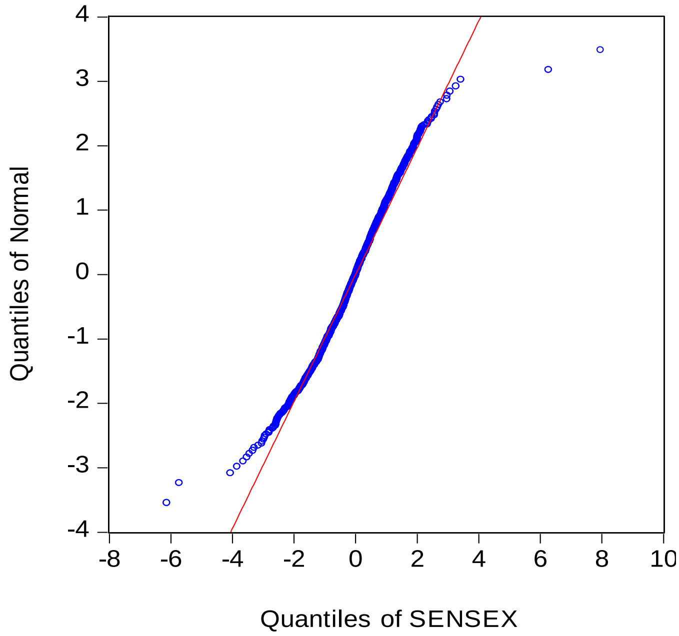

Figure 5-27: Q-Q Plots of the GARCH(1,1) Fitted Residuals for SENSEX Composite index

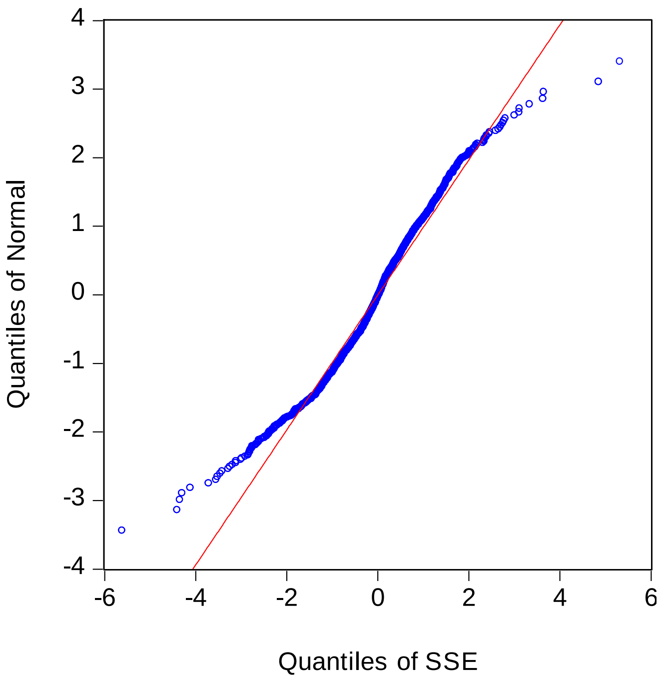

Figure 5-28: Q-Q Plots of the GARCH (1,1) Fitted Residuals for SSE Composite Index

The Q-Q plots in Figures 5-22 to 5-28 appear to support normally distributed residuals with a few outliers, given that the majority of the points lie on the normal line or very close to it. Thus, the GARCH (1, 1) model under the skew student's t-distribution appears to be an adequate model for each of the market returns.

5.4.3 ESTIMATIONS OF THE GARCH (1,1) EXTENSIONS

The GARCH (1,1) model assumes that good and bad news have a symmetrical effect on volatility, but this is not always the case in various financial time-series. A stylised fact of financial volatility is that bad news (negative residuals) tends to have a larger influence on the volatility than good news (positive residuals) of the same magnitude (Black, 1976). The asymmetric impact on volatility is generally referred to as the leverage effect. In this regard, the present study estimates EGARCH and GJR GARCH models using student's t-distribution. The results for EGARCH (1,1) and GJR GARCH (1, 1,1) for all market returns are displayed in Table 5-5 below:

Table 5-5: Parameter Estimates for EGARCH(1,1) and GJR GARCH(1,1,1)

Returns	Parameters	EGARCH(1,1,1)			GJR GARCH(1,1,1)		
		Estimate	SE	p-value	Estimate	SE	p-value
S&P500	α_0	**-0.097673**	0.018316	0.0000	**0.110815**	0.026815	0.0000
	α_1	**0.171241**	0.024611	0.0000	**0.033554**	0.016213	0.00385
	β	**0.962851**	0.008509	0.0000	**0.872492**	0.019154	0.0000
	γ	**-0.087315**	0.016971	0.0000	**0.110900**	0.025884	0.0000
	$\alpha_1 + \beta$	1.134092	—	—	0.983307	—	—
	AIC	3.772566	—	—	3.767675	—	—
	BIC	3.778528	—	—	3.783945	—	—
DAX	α_0	**-0.119397**	0.018530	0.000	**0.047811**	0.010446	0.0000
	α_1	**0.172775**	0.025845	0.000	0.004719	0.016422	0.7738
	β	**0.964287**	0.006697	0.000	**0.872045**	0.016528	0.0000
	γ	**-0.1535512**	0.019952	0.000	**0.192311**	0.032096	0.0000
	$\alpha_1 + \beta$	1.14262	—	—	0.876759	—	—
	AIC	3.196286	—	—	3.202063	—	—
	BIC	3.212556	—	—	3.21833	—	—
BOVESPA	α_0	**-0.097673**	0.018316	0.0000	**0.110815**	0.026815	0.0000
	α_1	**0.171241**	0.024611	0.0000	**0.033554**	2.069617	0.0385
	β	**0.962851**	0.008509	0.0000	**0.872492**	0.019154	0.0000
	γ	**-0.087315**	0.016971	0.0000	**0.110900**	0.025884	0.0000
	$\alpha_1 + \beta$	1.134092	—	—	0.906046	—	—
	AIC	3.772566	—	—	3.767675	—	—
	BIC	3.788835	—	—	3.783945	—	—
FTSE/JSE	α_0	**-0.14384**	0.019787	0.0000	**0.033918**	0.008089	0.0000
	α_1	**0.187495**	0.025895	0.0000	**0.029453**	0.017357	0.0897
	β	**0.971782**	0.006066	0.0000	**0.874177**	0.01739	0.0000
	γ	**-0.107869**	0.016562	0.0000	**0.142109**	0.027005	0.0000
	$\alpha_1 + \beta$	1.11527	—	—	0.90636	—	—
	AIC	2.979400	—	—	2.98003	—	—
	BIC	2.985362	—	—	2.985995	—	—
RTS	α_0	**-0.106116**	0.017475	0.0000	**0.084455**	0.020316	0.0000
	α_1	**0.173711**	0.024525	0.0000	**0.037787**	0.014944	0.0115
	β	**0.977951**	0.005501	0.0000	**0.895878**	0.01772	0.0000
	γ	**-0.061047**	0.012695	0.0000	**0.085601**	0.019410	0.0000
	$\alpha_1 + \beta$	1.1155061	—	—	0.980235	—	—
	AIC	3.989398	—	—	3.984761	—	—
	BIC	4.005668	—	—	4.001030	—	—
SENSEX	α_0	**-0.13833**	0.018297	0.0000	**0.048471**	0.012339	0.0001
	α_1	**0.196216**	0.025282	0.0000	**0.032934**	0.014196	0.0203
	β	**0.974875**	0.006486	0.0000	**0.872213**	0.017318	0.0000
	γ	**-0.093506**	0.016476	0.0000	**0.144141**	0.027254	0.000
	$\alpha_1 + \beta$	1.171091	—	—	0.905147	—	—
	AIC	3.244509	—	—	3.246914	—	—
	BIC	3.260778	—	—	3.263184	—	—

SSE	α_0	**-0.104958**	0.014859	0.0000	**0.023739**	0.009559	0.0130
	α_1	**0.158635**	0.021976	0.0000	**0.078472**	0.016954	0.0000
	β	**0.989939**	0.004028	0.0000	**0.923801**	0.011217	0.0000
	γ	-0.006285	0.012378	0.6117	-0.007515	0.018147	0.6788
	$\alpha_1 + \beta$	1.148574	—	—	1.002273	—	—
	AIC	3.636972	—	—	3.639671	—	—
	BIC	3.626665	—	—	3.639671	—	—

Source: Estimation.

Table 5-5 shows that even though all parameter estimates for EGARCH are significant at conventional levels, the stationarity condition ($\alpha + \beta < 1$) is violated. For this reason, the study concludes that EGARCH cannot be used to test the leverage effect.

As for the GJR model, the asymmetry coefficient γ is positive and statistically significant at the 5% level of significance in all markets except the Chinese market. It can be seen in Table 5-5 that the GJR GARCH model is explosive as the stationarity condition as expressed by the sum $\alpha + \beta$ is violated as it is greater than unity. Furthermore, the parameter estimate of the asymmetric coefficient γ is negative in the case of China.

With the above GJR GARCH estimates, the study concludes that asymmetric effects of news on conditional volatility are prevalent in all markets except China. The absence of a leverage effect in the Chinese market has been documented in previous studies. For instance, Li and Zhang (2008) explained that the existence of "adverse leverage effect" in the Chinese stock market is due to the fact that Chinese investors are risk-lovers. As the authors explain, when a stock market rises, Chinese investors tend to be panicked into purchasing stocks, in the expectation that the stock prices will rise further. However, when the stock market turns bearish, they are less panicked into selling stocks, in the hope that market downturns will not last for long. Steinhardt (2012) attributes the lack of leverage effect in the Chinese stock market to the high level of trust in China, which reduces the spread of asymmetric information.

It is also worth noting that the current study uses the most common selection criterion namely Akaike information criterion (AIC) and the Schwartz Bayesian information criterion (BIC). From Table 5-5 it can be seen that in all instances, except for China, GJR GARCH (1,1) model has the smallest AIC and BIC compared to the EGARCH model, hence confirming the appropriateness of the GJR GARCH model.

5.5 CHAPTER SUMMARY

This chapter analysed the nature of volatility for BRICS equity markets returns. The study ran an exploratory test which consists of testing for normality, autocorrelation and ARCH effect. Upon the detection of autocorrelation and ARCH effect in Equity market returns the present study proceeded with modelling the volatility of each of the BRICS markets using a univariate GARCH model.

Estimates from the univariate GARCH model revealed the persistence of volatility in the BRICS returns, with China (SSE) having the highest volatility persistence, followed by India (SENSEX) and Russia (RTSI). Using GARCH (1,1) variants, the chapter also investigated the presence of leverage effect, which was found to be statistically significant in all BRICS stock markets except China.

CHAPTER SIX

BIVARIATE CONDITIONAL HETEROSCEDASTICITY MODELS WITH DYNAMIC CORRELATIONS FOR TESTING CONTAGION IN BRICS COUNTRIES

This chapter accomplishes objective three (*To examine the presence of time-varying conditional correlations in BRICS equity market returns, in the wake of the financial crises that took place in the U.S. and Eurozone countries*). The chapter deals with bivariate conditional heteroscedasticity models in order to test financial contagion in BRICS equity markets. The chapter is divided into five sections. It begins with a contextual background on volatility spillover. The main empirical models used and the estimation methodology employed are presented in section two. The time series data used in this chapter is analysed and discussed in section three, which also covers the descriptive statistics and preliminary data analysis. The discussion on key findings and statistical estimates of bivariate GARCH models are presented in section four. The chapter concludes with a summary in section five.

6.1 CONTEXTUAL BACKGROUND

The uncertainty in market returns has become a natural outcome. These uncertainties — commonly referred to as volatility — may persist over a while (that is, high returns follow high volatility and low returns follow low volatility), giving rise to the volatility clustering that was discussed in Chapter Five. The volatility may also spread from one market to another, resulting in what is termed volatility spillover (Patnaik, 2013). With globalisation and liberalisation, countries have become more prone to volatility spillovers. This is evident from capital markets behaviour during recent financial crises (Singh, Singh, 2017). The crises that began in the U.S.and the Eurozone markets spread to other financial sectors, thus also impacting the other economies.

BRICS economies were no exception to this volatility spillover phenomenon. Due to the availability of a broad range of opportunities and attractive macroeconomic climate in BRIC nations global portfolio managers consider these markets as a pivotal part of their portfolio (Singh, Singh, 2017).

This chapter investigates volatility spillover and time-varying correlations in BRICS stock markets in the wake of the U.S. sub-prime and Eurozone sovereign debt crises. It uses a Bivariate Autoregressive Conditional Heteroskedasticity (MGARCH) model as a measure of the spillover of volatility.

It is generally recognised that financial volatility can move across assets and markets together over time. Identifying these feature byways of multivariate modelling results in more insightful analysis than operating with separate univariate models. From a financial perspective, it paves the way to better decision-making tools in different fields, such as asset pricing, portfolio selection, option pricing, hedging, and risk management.

6.2 METHODOLOGY

Following pioneering work by Engle (1982) and Bollerslev (1986), comprehensive literature on conditional volatility modelling was developed. The initial models were quickly extended into multivariate versions. This section discusses the multivariate GARCH models that will be used to examine volatility spillover in BRICS stock markets following the financial crises that took place in the U.S. and Eurozone countries.

6.2.1 MULTIVARIATE GARCH MODELS

Multivariate GARCH models are normally used to examine how equity markets are inter-related, as volatilities of financial series are known to move synchronously across different markets or be slightly delayed. Multivariate GARCH models are in essence very similar to their univariate counterparts, except that they also specify equations for how the covariances move over time. Several different multivariate GARCH formulations have been proposed in the literature, and this section focuses on giving a general description of two multivariate GARCH models used in the present study, namely, the Diagonal VECH[22] and the dynamic conditional correlation (DCC) GARCH models.

[22]The vech (or vector-half) operator takes a symmetric d×d matrix and stacks the lower triangular half into a single vector of length d(d+1)/2.

6.2.1.1 The VECH Model

A common specification VECH model proposed initially by Bollerslev, Engle and Wooldridge (1988) is as follows:

$$VECH\left(H_t\right) = C + AVECH\left(u_t u_{t-1}'\right) + BVECH\left(H_{t-1}\right) \qquad \ldots\ldots (6.1)$$

With $u_t|\psi_{t-1} \sim N(O, H_t)$ ……………………………………………………..…. (6.2)

where H_t is a 2 x 2 conditional variance-covariance matrix, u_t is a 2 x 1 disturbance vector, ψ_{t-1} represents the information set at time *t*-1, C is a 3 x 1 parameter vector, A and B are 3 x3 parameter matrices, and VECH(.) denotes the column-stacking operator applied to the upper portion of the symmetric matrix. The model requires the estimation of 21 parameters. The elements of the VECH are as follows:

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix}, u_t = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}, C = \begin{bmatrix} c_{11} \\ c_{21} \\ c_{31} \end{bmatrix} \qquad \ldots\ldots (6.3)$$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \qquad \ldots\ldots (6.4)$$

The *VECH* operator takes the 'upper triangular' portion of a matrix, and stacks each element into a vector with a single column. For example, in the case of *VECH* (*Ht*), this becomes

$$VECH(H_t) = \begin{bmatrix} h_{11t} \\ h_{22t} \\ h_{12t} \end{bmatrix} \qquad \ldots\ldots (6.5)$$

with h_{iit} representing the conditional variances at time *t* of the two return series (*i* = 1, 2) used in the model, and h_{ijt} $(i \neq j)$ representing the conditional covariances between the asset returns. In the case of $VECH\left(u_t u_t'\right)$ this can be expressed as

$$VECH(u_t u_t') = VECH\left(\begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \begin{bmatrix} u_{1t} & u_{2t} \end{bmatrix}\right)$$

$$= VECH\begin{pmatrix} u_{1t}^2 & u_{1t}u_{2t} \\ u_{1t}u_{2t} & u_{2t}^2 \end{pmatrix}$$

$$= \begin{bmatrix} u_{1t}^2 \\ u_{2t}^2 \\ u_{1t}u_t \end{bmatrix} \qquad \ldots\ldots (6.6)$$

The *VECH* model in full is given by:

$h_{11t} = c_{11} + a_{11}u_{2t-1}^2 + a_{12}u_{2t-1}^2 + a_{13}u_{2t-1} + b_{11}h_{11t-1} + b_{12}h_{22t-1} + b_{13}h_{12t-1}$…….(6.7)

$h_{22t} = c_{21} + a_{21}u_{2t-1}^2 + a_{22}u_{2t-1}^2 + a_{23}u_{2t-1} + b_{21}h_{11t-1} + b_{22}h_{22t-1} + b_{23}h_{12t-1}$……(6.8)

$h_{12t} = c_{31} + a_{31}u_{1t-1}^2 + a_{32}u_{2t-1}^2 + a_{33}u_{2t-1} + b_{31}h_{11t-1} + b_{32}h_{22t-1} + b_{33}h_{12t-1}$…….(6.9)

In this way, it is evident that the conditional variances and conditional covariances depend on the lagged values of all of the conditional variances of, and conditional covariances between, all of the asset returns in the series, as well as the lagged squared errors and the error cross-products.

6.2.1.2 The Diagonal VECH Model

As discussed in Section 6.2.1.1 above, the simple two series, the conditional variance, and covariance equations for the unrestricted *VECH* model contain 21 parameters. As the number of series used in the model increases, the estimation of the *VECH* model can quickly become cumbersome and even infeasible. Hence the *VECH* model's conditional variance-covariance matrix has been restricted to the form developed by Bollerslev, Engle, and Wooldridge (1988), in which *A* and *B* in Equation 6.1 are assumed to be diagonal. This reduces the number of parameters to be estimated to 9, with *A* and *B* each having 3 elements. The model, known as a diagonal *VECH*, is now characterised by:

$h_{ij,t} = c_{ij} + \alpha_{ij}u_{i,t-1}u_{j,t-1} + \beta_{ij}h_{ij,t-1}$ ……………………………………..………...(6.10)

for *i,j =1,2,*

where ω_{ij}, α_{ij} and β_{ij} are parameters. The diagonal VECH multivariate GARCH model could also be expressed as a geometrically declining average of past cross products of unexpected returns, with recent observations carrying higher weights. An alternative solution to the dimensionality problem would be to use orthogonal GARCH or factor GARCH models.

The diagonal VECH multivariate GARCH (1,1) in full is thus given by:

$h_{11t} = c_1 + \alpha_{11}u_{1,t-1}^2 + \beta_{11}h_{11,t-1}$ …………………………………....(6.11)

$h_{22t} = c_2 + \alpha_{22}u_{2,t-1}^2 + \beta_{22}h_{22,t-1}$ ………………………..……….....(6.12)

$h_{12t} = c_3 + \alpha_{33}u_{1,t-1}u_{2,t-1} + \beta_{33}h_{12,t-1}$ ………………………...………....(6.13)

The diagonal VECH multivariate GARCH estimation uses maximum likelihood to jointly estimate the parameters of the mean and the variance equations. Assuming multivariate normality, the log-likelihood contributions for GARCH models are given by:

and $l_t = -\frac{1}{2}\text{mlog}(2\pi) - \frac{1}{2}log|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1}\varepsilon_t$ ………………. (6.14)

where m is the number of mean equation residual. For student's t-distribution, the contributions are in the form:

$$l_t = \log\left\{\frac{\Gamma\left(\frac{v+m}{2}\right)v^{\frac{m}{2}}}{(v\pi)^{\frac{m}{2}}\Gamma\left(\frac{v}{2}\right)(v-2)^{\frac{m}{2}}}\right\} - \frac{1}{2}\log(|H_t|) - \frac{1}{2}(v+m)\log\left[1+\frac{\varepsilon_t' H_t^{-1}\varepsilon_t}{v-2}\right] \quad \text{……….……..(6.15)}$$

where v is the estimated degree of freedom.

Brooks (2014) highlights the disadvantage of the *VECH* model. They include among other things the fact that there is no guarantee of a positive semi-definite covariance matrix. A variance-covariance or correlation matrix must always be 'positive semi-definite', and in the case where all the returns in a particular series are all the same so that their variance is zero is disregarded, then the matrix will be positive definite. Among other things, this means that the variance-covariance matrix will have all positive numbers on the leading diagonal, and will be symmetrical about this leading diagonal. These properties are intuitively appealing as well as important from a mathematical point of view, for variances can never be negative, and the covariance between two series is the same irrespective of which of the two series is taken first, and positive definiteness ensures that this is the case. A positive definite correlation matrix is also important for many applications in finance; for example, from a risk management point of view. It is this property which ensures that, whatever the weight of each series in the asset portfolio, an estimated value-at-risk is always positive. Fortunately, this desirable property is automatically a feature of time-invariant correlation matrices which are computed directly using actual data. An anomaly arises when either the correlation matrix is estimated using a non-linear optimisation procedure (as multivariate GARCH models are), or when the risk manager uses modified values for some of the correlations. The resulting modified correlation matrix may or may not be positive definite, depending on the values of the correlations that are put in, and the values of the remaining correlations. If, by chance, the matrix is not positive definite, the upshot is that for some weightings of the individual assets in the portfolio, the estimated portfolio variance could be negative.

6.2.1.3 Dynamic Conditional Correlation GARCH[23]

The Dynamic Conditional Correlation (DCC)-GARCH model was introduced by Engle (2002) to capture the dynamic time-varying of conditional covariance. The DCC-GARCH model is a dynamic model with time-varying mean, variance and covariance of return series r_t with the following equation:

$$r_t = u_t + \varepsilon_t \qquad \text{...(6.16)}$$

$$\varepsilon_t|\Omega_{t-1} \rightarrow N(0,\mathrm{H}_t)$$

From the residuals of the mean equation, the conditional variance of each return is derived using equation (6.17) given below.

$$h_{i,t}^2 = \alpha_0 + \sum_{j=1}^{p_i} \alpha_j\, \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_j\, \sigma_{i,t-j}^2 \qquad \text{... (6.17)}$$

where $\sum_{j=1}^{p_i} \alpha_j + \sum_{j=1}^{q_i} \beta_j < 1$.

Then the multivariate conditional variance H_t is estimated as follows:

$$H_t = D_t R_t D_t \qquad \text{... (6.18)}$$

where H_t is the Conditional Covariance matrix of r_t, D_t represents a (k × k) diagonal matrix of time-varying standard deviations obtained from the univariate GARCH specifications given in Equation (6.17), R_t is the (k x k) time-varying correlations matrix derived by first standardising the residuals of the mean Equation 6.16 of the univariate GARCH model with their conditional standard deviations derived from Equation 6.17, to obtain $\eta_{it} = \frac{\varepsilon_{it}}{\sqrt{h_{it}{}^2}}$.

The standardised residuals are then used to estimate the parameters of conditional correlation as given in equation
6.20 and 6.21 below.

$$R_t = \left(\mathrm{diag}(Q_t)\right)^{\frac{-1}{2}} Q_t \left(\mathrm{diag}(Q_t)^{\frac{-1}{2}}\right) \qquad \text{... (6.20)}$$

and

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \eta_{t-1} \eta'_{t-1} + \theta_2 Q_{t-1} \qquad \text{...(6.21)}$$

[23] This section relies heavily on Chittedi (2015).

where $\bar{Q}$ is the unconditional covariance of the standardised residuals. The Q_t does not generally have ones on the diagonal, so it is scaled as in Equation 6.20 above to derive R_t, which is a positive definite matrix. In this model, the conditional correlations are thus dynamic, or time-varying. θ_1 and θ_2 from Equation 6.21 are assumed to be positive scalars with $\theta_1+\theta_2<1$.

Finally, the conditional correlation coefficient, ρ_{ij}, between two market returns, i and j, is expressed by the following equation:

$$\rho_{ij} = \frac{q_{ij,\mathrm{t}}}{\sqrt{q_{ij,\mathrm{t}}, q_{jj,\mathrm{t}}}}, \text{ i,j=1,2,.......,n, and } i \neq j \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6.22)$$

can be expressed in typical correlation form by putting $Q_t = q_{ij,\mathrm{t}}$ as follows:

$$\rho_{ij} = \frac{(1-\theta_1-\theta_2)\overline{q}_{12} + \theta_1\eta_{1,\mathrm{t-1}}\eta_{2,\mathrm{t-1}} + \theta_2 q_{12,t-1}}{\sqrt{\left[(1-\theta_1-\theta_2)\overline{q}_{11} + \theta_1\eta_{1,t-1}^2 + \theta_2 q_{11,\mathrm{t-1}}\right]}\sqrt{\left[(1-\theta_1-\theta_2)\overline{q}_{22} + \theta_1\eta_{2,t-1}^2 + \theta_2 q_{22,\mathrm{t-1}}\right]}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6.23)$$

The parameters of the DCC model are estimated using the likelihood for this estimator and can be written as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\,log(2\pi) + 2\,log|D_t| + log|R_t| + \eta'_t R_t^{-1}\eta_t) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(6.24)$$

Where $D_t = diag\left\{\sqrt{h_{i,t}}\right\}$ and R_t is the time-varying correlation matrix.

As mentioned in Chapter Five, one of the stylised facts of financial time series data is that they deviate in two respects from the usual white noise generated from a Gaussian stochastic process. Firstly, the unconditional distribution is severely leptokurtic. In other words, it is more peaked in the centre and displays fat tails, with more unusually large and small observations than would be implied from the Gaussian law. Secondly, they exhibit volatility clustering, where calm and volatile episodes are observed, such that at least the variance appears to be predictable (Chinzara and Azakpioko, 2009). Consequently, Gaussian assumptions in the DCC-GARCH procedure can be violated. To circumvent this problem, the t-DCC-GARCH procedure is used in which the DCC model is applied with an assumption that market yields follow a multivariate t-distribution as suggested by Pesaran and Pesaran (2007).

To achieve this, Pesaran and Pesaran (2007) introduced the use of devolatilised returns which are approximately Gaussian, instead of standardised returns. The devolatilised returns $\bar{r}_{it}$ are computed by allowing returns to be normalised by realised volatility rather than by conditional volatilities in the GARCH-type models (Barassi, Dickinson, and Le, 2011).

$$\bar{r}_{it} = \frac{r_{it}}{\sigma_{it}^{realised}} \quad \tilde{\sigma}_{it}^{2}(d) = \frac{\sum_{s=0}^{d-1} r_{1,t-s}^{2}}{d} \qquad \text{……………. (6.25)}$$

The devolatilised returns, $\bar{r}_{it}$ are used in Equation (6.17) to calculate the conditional correlations.

It is worth noting that the current study uses univariate GARCH (1,1) process is used hence the equation becomes

$$h_{i,t}^{2} = b_0 + b_1\varepsilon_{1t}^{2} + b_2 h_{1,t-1}^{2} \qquad \text{……………………(6.26)}$$

6.2.1.4 Diagnostic Test for Multivariate GARCH Models

Once the model has been fitted, it is essential to assess the adequacy of the specification of the model. In order to check the adequacy of the fitted multivariate GARCH models, the current study uses Box-Ljung statistics on the standardised squared residuals for univariate GARCH models as well as the multivariate version of Box-Ljung.

The Ljung-Box test for univariate GARCH models is similar to the one described in section 5.2.2.3. It consists of estimating the diagonal elements of the matrix Dt, and running the diagnostic tests of residuals to check whether or not they are all insignificant.

As for the Multivariate Ljung-Box portmanteau (or Q) statistic, it is given by

$$LB(s) = T(T+2)\sum_{j=1}^{s}\frac{1}{T-j}tr\left[\hat{C}_{0j}\hat{C}_{00}^{-1}\hat{C}_{0j}^{'}\hat{C}_{00}^{-1}\right] \qquad \text{……………………(6.27)}$$

where *tr* denotes the trace of a matrix.

Yt = *vech* $(y_t y_t^{'})$ and C_{Yt} (j) is the sample autocovariance matrix of order j. Under the null hypothesis, Q_m (k) is distributed asymptotically as $\chi^2(p^2k)$.

6.3 DATA

In order to examine spillover volatility in BRICS equity markets following the sub-prime crisis, the present study uses two sub-periods, namely, the (i)'pre-crisis'(Panel A) sub-period that ranges from 11th February 2005 to 1st February 2007 and (ii) the 'crisis' (Panel B) sub-period that extends from 2nd February 2007, the explosion of the real estate bubble in the U.S., to 10th July 2009. The study considers the S&P 500 index as the "ground zero" host market and the volatility from the S&P500 is construed as an exogenous shock to volatility in BRICS markets.

The summary statistics for index returns used to analyse cross volatility spillover among BRICS markets following the sub-prime crisis is presented in Table 6-1. From Table 6-1 it can be seen that all individual equity markets recorded a lower return in the crisis period compared to the pre-crisis period. In all equity markets, with the exception of the Brazilian market, individual stock markets during the 'crisis' period have negative mean returns, whereas the return for the 'post-crisis' period is positive. It can also be seen in Table 6-1 that the standard deviation as a measure of volatility is high during the period of financial upheaval in the U.S. vis-à-vis the stable period. The highest volatility is recorded in the Russian equity market (3.241) during the 'crisis' period while on the other hand, the lowest volatility is recorded in the South African market during the 'pre-crisis' period (1.15498).

In order to analyse volatility spillover in BRICS equity markets emanating from the Eurozone, the current study uses two sub-periods: they are (i) the 'crisis' (Panel C) sub-period which spans from 12th August 2009 (following the Greek government defaulting on its debt) to 31st December 2012, and (ii) the 'post-crisis' (Panel D) sub-period that starts on 1st January 2013 and ends on 28th February 2017 in the aftermath of the Eurozone sovereign debt crisis. The present study uses the German DAX composite index as the proxy of the Eurozone (continental Europe) stock market. In other words, the DAX index is used as the "ground zero" host market. Volatility from the DAX index is construed as an exogenous shock to volatility in BRICS markets.

Table 6-1: Summary Statistics on Market Returns During the Sub-prime Crisis

	S&P500	BOVESPA	FTSE/JSE	RTS	SENSEX	SSE
	Panel A: Pre-crisis period 11th of January, 2005 and 1st of February, 2007					
Mean	0.047466	0.101208	0.142098	0.223401	0.173346	0.152884
Median	0.079993	0.159023	0.223531	0.272200	0.266820	0.118121
Maximum	0.262727	6.149911	4.917269	6.531325	6.667006	7.890427
Minimum	-2.311098	-6.559909	-6.700281	-9.840338	-7.928759	-5.482561
Std. Dev.	0.195236	1.574503	1.15498	1.710889	1.420336	1.47509
Skewness	0.195236	-0.171090	-0.623249	-1.043792	-0.718948	0.293580
Kurtosis	4.597620	3.981284	7.687449	8.540531	7.931015	5.839484
Jarque-Bera	**53.53365**	**20.74508**	**468.5582**	**743.4686**	**507.8622**	**164.9958**
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ARCH(2)	**1.931402**	0.673702	**10.79647**	**5.309437**	**8.161299**	1.350170
p-value	0.0541	0.50093	0.0000	0.000	0.000	0.1776
Q(24)	**34.065**	29.940	**38.554**	**39.414**	**42.093**	**34.990**
p-value	0.084	0.187	0.030	0.025	0.013	0.069
Qs(24)	**34.925**	**54.792**	**319.31**	**221.92**	**525.77**	**44.396**
p-value	0.070	0.0000	0.0000	0.0000	0.0000	0.007
	S&P500	BOVESPA	FTSE/JSE	RTS	SENSEX	SSE
	Panel B: Crisis (turmoil) period: 2nd February 2007 to 10th July 2009					
Mean	-0.084850	0.026352	-0.038225	-0.136935	-0.664302	0.023890
Median	0.065779	0.128736	0.005928	0.107645	0.074755	0.256313
Maximum	9.774300	9.630997	6.833971	20.20392	15.98998	9.034458
Minimum	-9.469515	-12.09607	-7.580684	-21.19942	-11.60444	-9.256085
Std. Dev.	2.024399	2.515630	1.893789	3.241326	2.362209	2.439303
Skewness	-0.340646	-0.280379	-0.13682	-0.224565	0.218631	-0.190784
Kurtosis	7.329106	6.043696	4.560280	11.45696	7.766668	4.424224
Jarque-Bera	**446.5236**	**218.3108**	**36.34445**	**1787.071**	**513.6179**	**50.09278**
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ARCH(3)	**6.754902**	**4.836744**	**3.29318**	**8.159222**	**1.133635**	**1.879478**
p-value	0.0000	0.000	0.0013	0.000	0.2576	0.0608
Q(24)	**65.681**	**34.014**	**54.606**	**39. 414**	18.998	22.961
p-value	0.000	0.084	0.000	0.025	0.752	0.522
Qs(24)	**756.31**	**576.19**	**849.23**	**221.92**	19.134	**28.471**
p-value	0.0000	0.0000	0.0000	0.0000	0.745	0.0.241

Source: Estimation.

It is also worth drawing to the reader's attention that exploratory analysis similar to the one conducted for the univariate GARCH model in Chapter Five confirms that the data are not normally distributed as the JB test statistic (with the p-value reported) is significant at all levels, hence the rejection of the null hypothesis of normal distribution.

The present study also estimated the Q-statistic (and adjusted the Q-statistic) with 24 lags to test for serial correlation. The results in Table 6-1 show that the null hypothesis of no serial correlation and no ARCH effect is rejected. Similarly, the LM ARCH test statistics confirms the existence of autoregressive conditional heteroskedasticity (ARCH) in all the market return and squared return series, hence justifying the use of GARCH models.

The summary statistics for index returns used to examine cross volatility spillover among BRICS in the stock market, in the aftermath of the Eurozone sovereign debt crisis are presented in Table 6-2. The Table 6-2 results seem to be different from the ones obtained during the sub-prime crisis in the US, although individual equity markets recorded lower return in the ‘crisis’ period compared to the ‘pre-crisis’ period. In some countries, such as South Africa and Russia, the average market returns in the ‘crisis’ period seem to be higher compared to the ‘post-crisis’. The lowest market returns are recorded in the ‘crisis ‘period, with the lowest recorded in China (-0.055) and the highest found in South Africa. The standard deviation as a measure of volatility seems to be relatively high in the ‘crisis’ period. The highest volatility is recorded in the Russian equity market (1.943) during the ‘post-crisis’ period. The results in Table 6-3 seem to indicate that the BRICS stock markets were not affected by volatility spillover from Eurozone countries following the Eurozone sovereign debt crisis.

Table 6-2: Summary Statistics on Market Returns During the Eurozone Financial Sovereign Debt Crisis

	DAX	BOVESPA	FTSE/JSE	RTS	SENSEX	SSE
	Panel C: Crisis (turmoil) period: 12 July 2009 to 31 December 2012					
Mean	0.044468	-0.002750	0.062721	0.046224	0.023748	-0.054964
Median	0.086221	0.041047	0.107650	0.139754	0.045007	0.007514
Maximum	5.491476	5.746151	3.698099	7.23877	4.188628	4.678913
Minimum	-5.994658	-8.430565	-3.693919	-9.005220	-6.027934	-6.982861
Std. Dev.	1.442582	1.454346	1.021702	1.841829	1.155453	1.374026
Skewness	-0.142047	-0.316009	-0.147496	-0.356262	-0.143395	-0.4671189
Kurtosis	4.916528	5.149921	4.015299	5.034243	4.439856	5.27817
Jarque-Bera	**128.5673**	**160.4822**	**36.65624**	**163.3786**	**68.52482**	**196.2949**
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ARCH(3)	**5.221497**	**3.212430**	**4.012326**	**2.704509**	**2.728926**	**5.332627**
p-value	0.000	0.0014	0.0001	0.0070	0.0065	0.000
Q(24)	**41.396**	25.714	**34.275**	26.168	29.728	26.088
p-value	0.015	0.368	0.080	0.345	0.194	0.349
Qs(24)	**534.73**	**110.28**	**221.88**	**131.45**	**43.015**	**134.88**
p-value	0.0000	0.0000	0.0000	0.0000	0.010	0.0000
	DAX	BOVESPA	FTSE/JSE	RTS	SENSEX	SSE
	Panel D: Post Crisis (stable) period: 1 January 2013 to 28 February 2017					
Mean	0.038720	0.003587	0.012503	-0.031554	0.032846	0.033344
Median	0.109823	0.00487	0.048937	-0.088446	0.044765	0.093064
Maximum	4.852051	6.387348	-3.944842	13.24619	5.260866	6.02245
Minimum	-7.067271	-5.108744	0.983533	-13.25455	-6.11712	-10.83238
Std. Dev.	1.224634	1.511756	0.983533	1.943683	0.967398	1.666913
Skewness	-0.462112	0.028707	-0.329059	-0.105178	-0.262231	-1.256825
Kurtosis	5.111047	3.749273	4.31097	10.20044	6.042261	10.26192
Jarque-Bera	**223.0498**	**22.61181**	**87.27542**	**2250.754**	**370.4948**	**2344.930**
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ARCH(2)	**2.751931**	**5.206350**	**6.130116**	1.497399	1.581475	**5.42411**
p-value	0.0060	0.000	0.000	0.1346	0.1142	0.000
Q(24)	**51.434**	24.318	25.239	30.309	23.564	**58.798**
p-value	0.000	0.444	0.358	0.175	0.487	0.000
Qs(24)	**206.23**	**202.56**	**196.13**	**389.45**	**35.994**	**414.76**
	0.0000	0.0000	0.0000	0.0000	0.055	0.0000

Source: Estimation.

Exploratory analysis revealed the presence of serial correlation and confirmed the existence of autoregressive conditional heteroskedasticity (ARCH) in all the market return and squared return series.

6.4 RESULTS OF EMPIRICAL MODELS AND DISCUSSION

This section uses bivariate GARCH models to examine volatility spillover in BRICS, as 'target' market[24], from 'source' markets, namely U.S. and Eurozone stock markets.

6.4.1 ESTIMATIONS OF DIAGONAL VECH GARCH MODEL

Given the fact that the returns series distribution is not normal; the present study uses the student's t-distribution. The results for VECH models following the sub-prime crisis and the Eurozone sovereign debt crises are discussed below.

6.4.1.1 VECH GARCH Estimations for Financial Contagion in BRICS Countries Following the Sub-prime Crisis

In order to analyse volatility spillover from the U.S. to BRICS equity markets in the wake of the sub-prime financial crisis the current study divide the data into two sub-periods namely the (i) 'pre-crisis'(stable) sub-period that ranges between 11th February 2005 and 1st February 2007 and (ii) the 'crisis' sub-period that extends from 2nd February 2007, the explosion of the real estate bubble in the U.S., to 10th July 2009. The main thrust is to examine the change in correlation between the two sub-periods.

Tables 6-3 and 6-4 present estimated coefficients for mean equation (μ_1 and μ_2) and the diagonal (bivariate) VECH GARCH model (c_{11}, c_{22}, c_{12}, α_{11}, α_{22}, α_{12}, β_{11}, β_{22}, β_{12}) for pairwise correlations between individual BRICS equity markets vis-à-vis the U.S. market.

[24] It is worth drawing to the reader's attention that, unlike previous studies such as Karunanayake, Valadkhani and O'Brien (2009) and Islam, Islam and Chowdhury (2013) that analysed multivariate conditional correlation for all series combined, the present study analysed pairwise correlations.

Table 6-3: Parameter Estimation for Bivariate Diagonal VECH (1, 1) Equation for Conditional Correlation with Pairs of the U.S. (as the source) and Individual BRCS Market (as target markets) in Pre-Crisis Period.

Parameter		μ_{11}	μ_{22}	c_{11}	c_{22}	c_{12}	α_{11}	α_{22}	α_{12}	β_{11}	β_{22}	β_{12}	Student - t	L. Likelihood
S&P500/BOVEPA	Estimate	**0.065977**	**0.182911**	0.022961	**0.150919**	**0.03225**	**0.067169**	**0.061355**	**0.064196**	**0.876943**	**0.877516**	**0.876943**	**12.39378**	-88.0936
	SE	0.031557	0.07611	0.022961	0.0.097019	0.017328	0.029174	0.028621	0.023502	0.056921	0.059266	0.042555	5.296585	
	p-value	0.0366	0.0163	0.1273	0.0274	0.0274	0.0213	0.0321	0.0063	0.0000	0.0000	0.0000	0.0193	
S&P500/JSE	Estimate	**0.056436**	**0.195231**	**0.027723**	**0.030855**	**0.007283**	0.039209	**0.101989**	**0.063237**	**0.890691**	**0.876758**	**0.883697**	**14.46338**	-821.521
	SE	0.032730	0.045942	0.028836	0.017892	0.006020	0.027415	0.033363	0.024454	0.090686	0.047946	0.038126	6.257852	
	p-value	0.0847	0.0000	0.3363	0.0846	0.2263	0.1527	0.0022	0.0097	0.0000	0.0000	0.0000	0.0354	
S&P500/RTS	Estimate	**0.062228**	**0.332400**	0.029401	**0.178181**	0.005314	0.031105	**0.090144**	**0.052952**	**0.897556**	**0.829531**	**0.862873**	**7.384825**	-952.501
	SE	0.031763	0.070371	0.037632	0.082355	0.008297	0.028365	0.033363	0.026551	0.110214	0.055199	0.059178	2.049712	
	p-value	0.0501	0.0000	0.4346	0.0305	0.5219	0.2728	0.0000	0.0461	0.0000	0.0000	0.0000	0.0003	
S&P500/SENSEX	Estimate	**0.05524**	**0.205546**	0.035021	**0.133117**	0.002839	**0.052327**	**0.124597**	**-0.08745**	**0.858947**	**0.792042**	**0.824816**	**10.38937**	-898.185
	SE	0.031893	0.062903	0.002839	0.057439	0.008007	0.035038	0.040253	0.028791	0.103665	0.065065	0.057448	3.519367	
	p-value	0.0873	0.0011	0.2648	0.0205	0.7229	0.0050	0.0020	0.0000	0.0000	0.0000	0.0000	0.0075	
S&P500/SSE	Estimate	0.049334	0.046256	0.037131	0.156484	0.004082	0.072345	0.029033	0.045830	**0.845061**	**0.891872**	0.868151	**6.512676**	-934.581
	SE	0.031140	0.069261	0.033491	0.136291	0.007997	0.049153	0.023676	0.023676	0.110397	0.083183	0.0.069960	1.565822	
	p-value	0.1131	0.5042	0.2676	0.2509	0.6097	0.1411	0.2201	**0.0558**	**0.0000**	**0.0000**	**0.083183**	**0.0000**	

Subscript i=j=1 indicates parameter estimate for the U.S. stock markets, whereas i=j=2 indicates estimates for individual BRICS stock markets.

Source: Estimation.

Table 6-4: Parameter Estimation for Bivariate Diagonal VECH (1, 1) Equation for Conditional Correlation with the U.S. in Crisis Period'.

Parameter		μ_{11}	μ_{22}	c_{11}	c_{22}	c_{12}	α_{11}	α_{22}	α_{12}	β_{11}	β_{22}	β_{12}	Student -t	L. Likelihood
S&P500/BOVEPA	Estimate	0.057029	**0.221806**	**0.033439**	**0.130154**	**0.057950**	**0.087774**	**0.0920223**	**0.090223**	**0.915337**	**0.902884**	**0.909089**	**4.801781**	-1478.155
	SE	0.055964	0.090318	0.013775	0.067152	0.026408	0.021543	0.026762	0.022738	0.015750	0.02608	0.018160	0.976208	
	p-value	0.3082	0.0141	0.0152	0.0526	0.0282	0.0282	0.0005	0.0001	0.0000	0.0000	0.0000	0.0000	
S&P500/JSE	Estimate	0.028255	0.079651	**0.040825**	**0.086742**	**0.022177**	**0.081182**	**0.094857**	**0.086742**	**0.910400**	**0.887640**	**0.898948**	**8.653345**	-1545.178
	SE	0.063976	0.071340	0.016402	0.050130	0.014187	0.022332	0.032943	0.020785	0.016402	0.034921	0.021719	2.603757	
	p-value	0.6587	0.2642	0.0128	0.0836	0.1180	0.0003	0.0040	0.0000	0.0000	0.0000	0.000	0.0009	
S&P500/RTS	Estimate	0.044705	**0.145865**	**0.038036**	**0.075881**	0.014577	**0.088144**	**0.079179**	**0.083542**	**0.909614**	**0.917062**	**0.913331**	**6.532378**	-1685.720
	SE	0.063238	0.086891	0.016748	0.039633	0.013244	0.024404	0.021307	0.017849	0.020703	0.020730	0.020730	1.532409	
	p-value	0.4796	0.0932	0.0231	0.0555	0.2711	0.0003	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	
S&P500/SENSEX	Estimate	0.04071	**0.205004**	**0.040865**	**0.246729**	0.022921	**0.084203**	**0.156754**	**0.114887**	**0.913350**	**0.817735**	**0.864221**	**5.974179**	-1660.335
	SE	0.061399	0.088194	0.017241	0.116975	0.022763	0.024710	0.04786	0.026668	0.021271	0.048063	0.028340	1.143466	
	p-value	0.5098	0.0201	0.0178	0.0349	0.3140	0.0007	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000	
S&P500/SSE	Estimate	0.031901	**0.292355**	**0.032017**	0.110912	0.003083	**0.085880**	**0.061381**	**0.072604**	**0.915179**	**0.922704**	**0.915179**	**6.060515**	-1711.522
	SE	0.061046	0.101503	0.016189	0.127293	0.015944	0.025401	0.023592	0.018398	0.021124	0.033477	0.020008	1.384365	
	p-value	0.6013	0.0040	0.0480	0.3836	0.8467	0.0007	0.0093	0.0001	0.0000	0.0000	0.0000	0.0000	

Subscript i=j=1 indicates parameter estimate for the U.S. stock markets, whereas i=j=2 indicates estimates for individual BRICS stock markets.

Source: Estimation.

From Table 6-3 it can be seen that during the ‘pre-crisis’ period the own-mean spillover coefficients (μ_{22}), in BRICS stock markets are significant at the 1% level except for China. The own-mean spillovers vary between the largest 0.332400 (Russia) and the smallest 0.046256 (China). The coefficient estimate (μ_{11}), indicating mean spillovers from the U.S. market, is not statistically significant in the ‘pre-crisis’ period and is hence inconclusive.

Parameter estimates α_{22} indicating own innovation (ARCH effect) spillover in individual BRICS stock markets are significant except for China and fluctuate from 0.124597(India) to 0.029033(China). This points towards the presence of ARCH effects, where the precedent shocks occurring from the one market will have the strongest impact on its future market volatility compared to the shocks stemming from the U.S. market. Parameter estimates α_{12} indicate cross-innovation spillover between the U.S. and individual BRICS stock markets. It can be seen in Table 6-3 that all cross-innovation spillover coefficients are significant at the 5% level and their magnitude is lower compared to own innovation spillover coefficients α_{22} (except BOVESPA). The strongest α_{12} coefficient is found in Brazil (0.064196), while the weakest is recorded in India (-0.083010). Based on the magnitudes of the estimated cross-volatility coefficients, innovation in all of the BRICS stock indices is influenced by the instability from the U.S. stock market, but the own-volatility shocks are relatively bigger than the cross-volatility shocks. Put another way, past volatility shocks in individual markets have a larger effect on their own future unpredictability than past volatility shocks occurring from the US. Hence the conclusion that lagged country-specific shocks (ARCH influence) do add to the BRICS stock market volatility of any given country in a recursive way.

During the ‘pre-crisis’ period, the coefficient for own conditional volatility (GARCH effect) (β_{22}) is significant at all levels. The largest value is 0.891872 (China), while the lowest is 0.792042 (India). This indicates the persistence of volatility in all BRICS stock market returns. Similarly, the cross- conditional volatility coefficients (β_{12}) are significant and are slightly higher in magnitude compared to the β_{22} coefficient. The highest β_{12} is found in South Africa (0.883697), while the lowest is in India (0.862873). High β_{12} estimates compared to β_{22} implies that precedent shocks occurring from the U.S. markets have a greater impact on BRICS stock markets than own lagged market volatility.

In Table 6-4 results for the ‘crisis’ period are similar to the ones obtained in the ‘pre-crisis’ period, for instance, the ARCH effects as expressed by coefficient estimate α_{22} are significant at the 1% level and seem to be higher in magnitude compared to the cross volatility coefficient α_{12}. The highest ARCH effect recorded is 0.156754 (India) and the lowest is 0.061381(China), whereas the cross-innovation spillover volatility coefficient α_{12} ranges between 0.090223 (Brazil) and 0.072604 (China). Similarly, the GARCH effect as expressed by the β_{22} coefficients is lower compared to cross-conditional volatility coefficient β_{12}, suggesting that precedent shocks occurring from the U.S. markets have a greater impact on BRICS stock markets than own lagged market volatility.

It is also worth noting that its own conditional correlation and cross-correlation (covariance) are significantly stronger during the 'crisis' period compared to the 'pre-crisis' period. Figures 6-1 to 6-6 present conditional variance and covariance plots from by diagonal VECH GARCH for both the 'pre-crisis' period and the 'crisis' period. The plots show a significant increase in conditional covariance during the 'crisis' period, with the exception of the Chinese stock market.

It can also be seen in Figures 6-1 to 6-6 that for all stock markets, with the exception of the Chinese market, the conditional covariance reached the highest in the 4^{th} quarter of 2008. Similar results are obtained with the conditional correlation plots from Figure 6-7 to 6-10 where the conditional correlation in the 'crisis' period is higher in magnitude compared to the 'pre-crisis' period.

In Tables 6-3 and 6-4 the student's t-distribution and Log-likelihood are also presented. This Student's t-test has a coefficient estimated for the degrees of freedom of the distribution. The coefficients student's t-distribution is statistically significant at 1% and are between 6 and 14.

It needs to be noted that, in order to have a defined variance the degrees of freedom have to be greater than 2, hence the conclusion that with the diagonal VECH model the variance is well defined. Additionally, as we know, the student's t-distribution tends towards the normal distribution when we consider infinite degrees of freedom. Having such small figures (still well defined as mentioned before) leads us to believe, and confirm, that our data follow, most likely, a heavy-tailed distribution.

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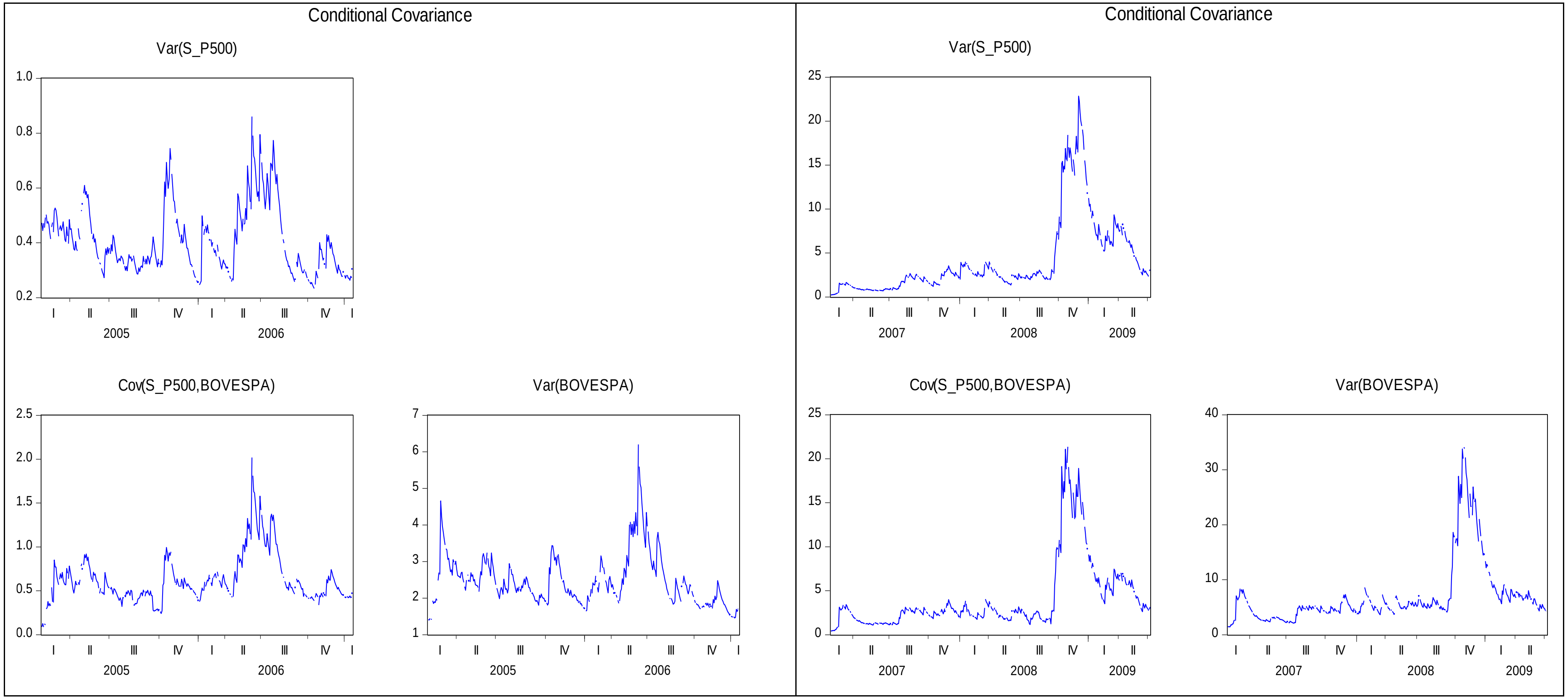


Figure 6-1: Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and BOVESPA represents the Brazilian Stock Market.

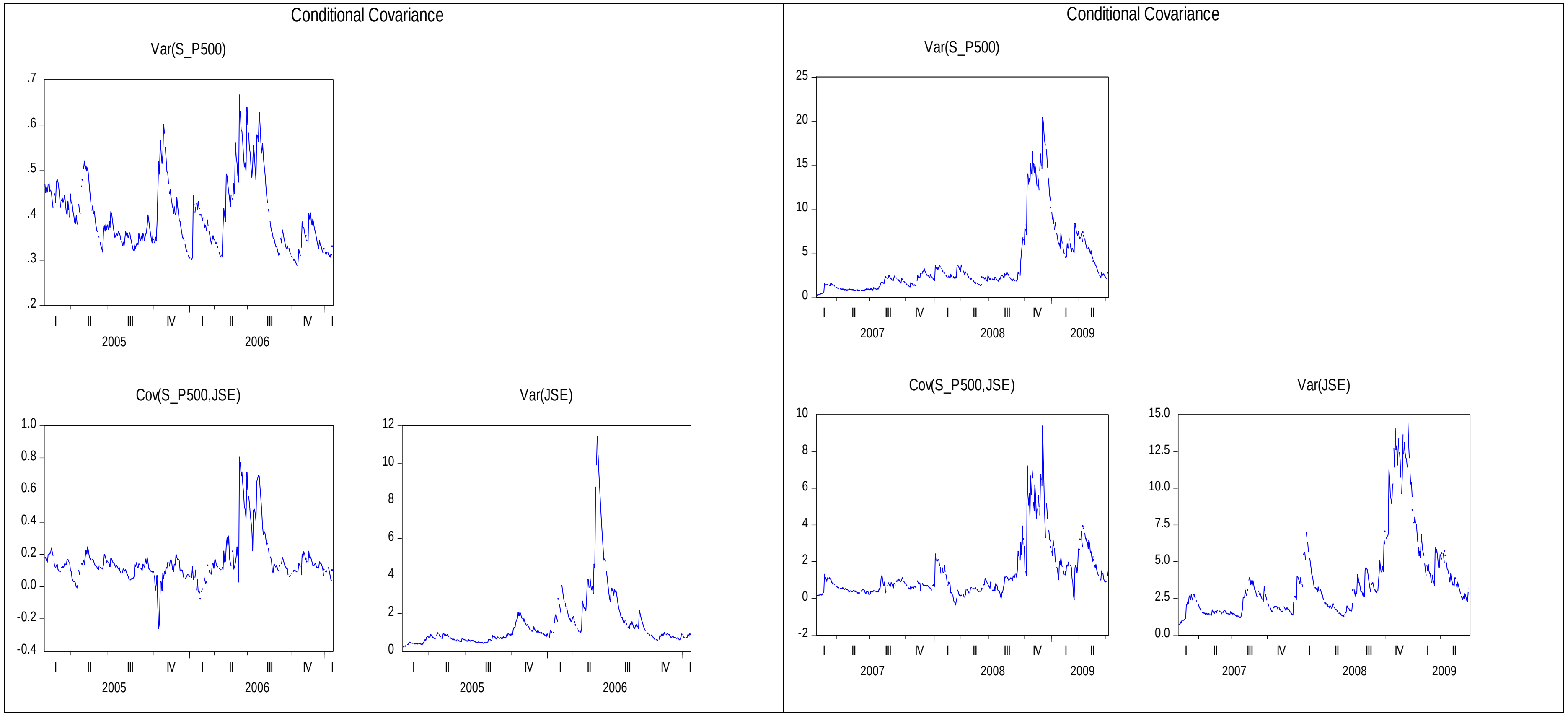


Figure 6-2: Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and FTSE/JSE represents the South African Stock Market.

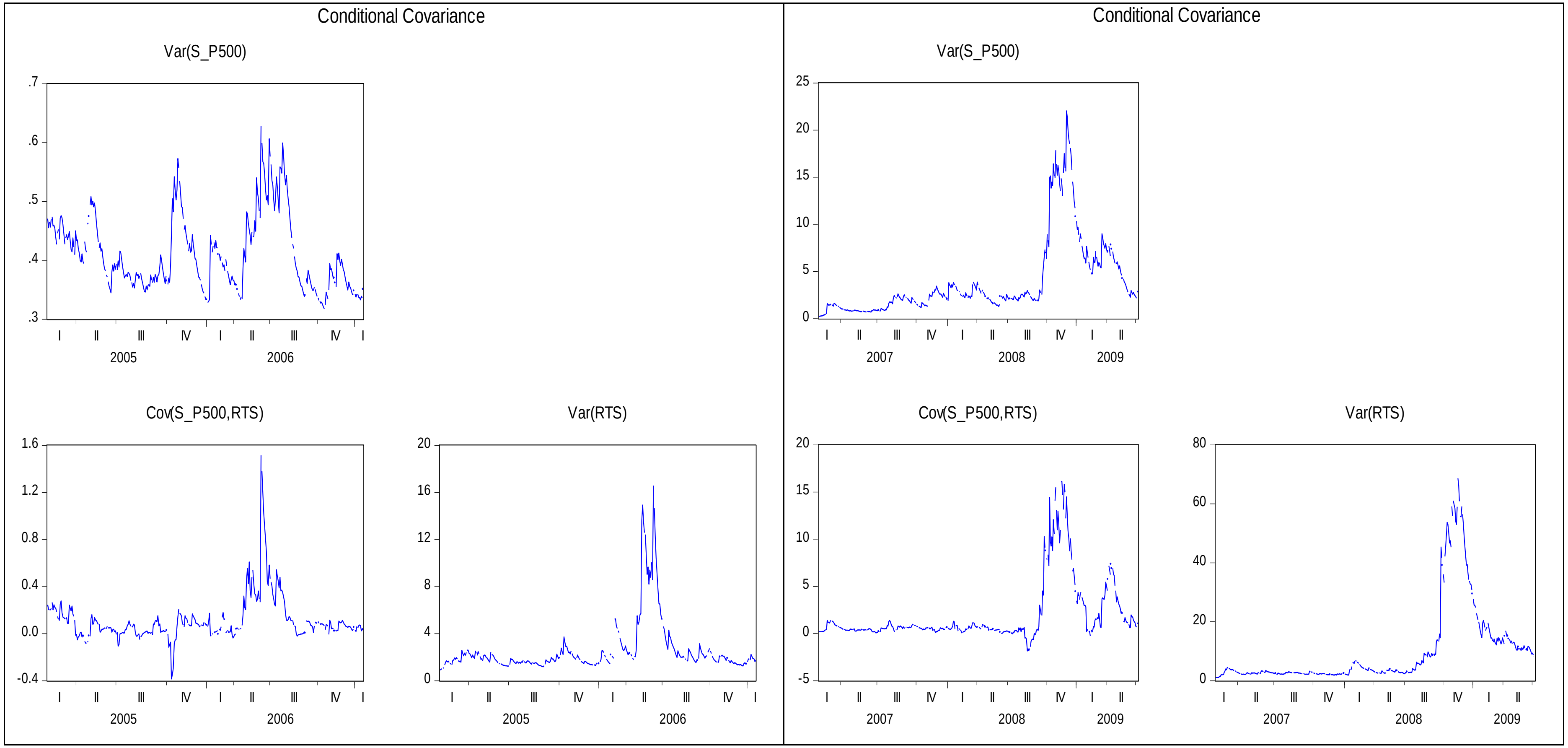


Figure 6-3: Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and RTS represents the Russian Stock Market.

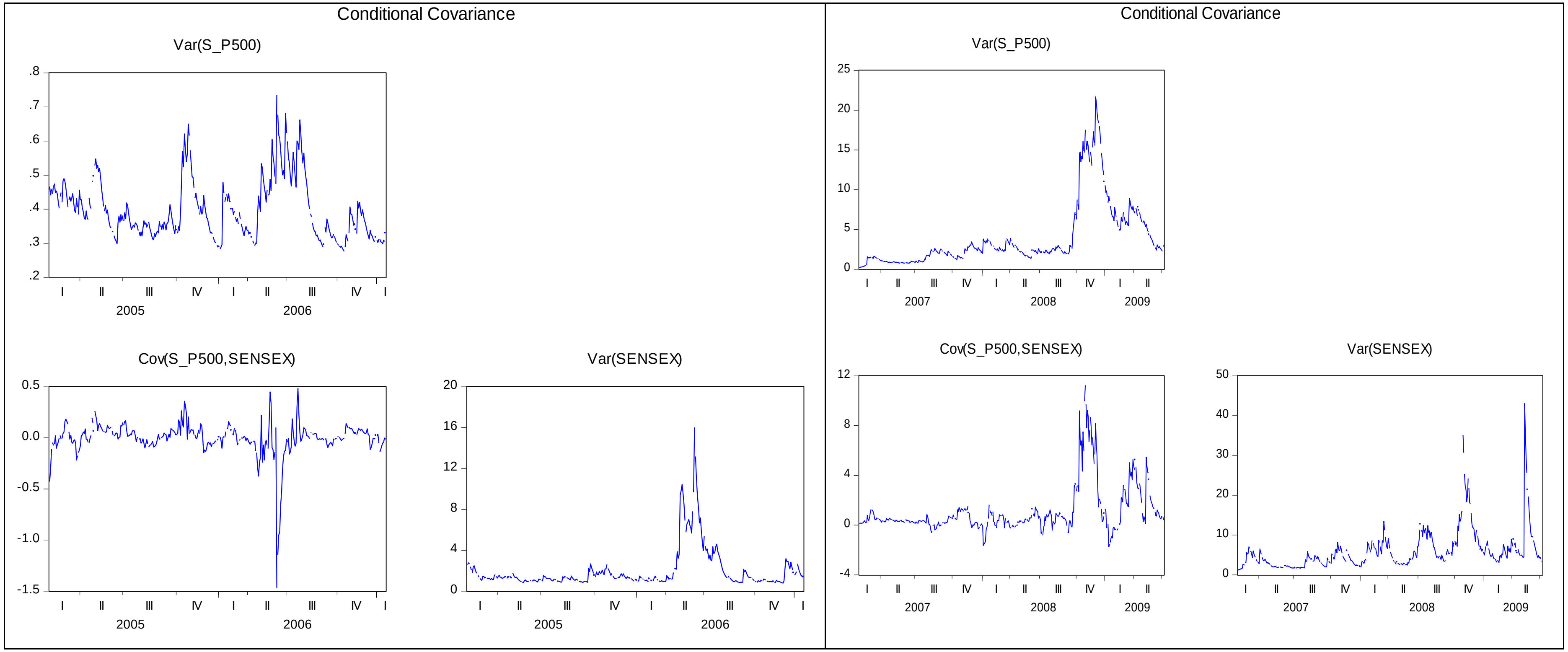


Figure 6-4: Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and SENSEX represents the Indian Stock Market.

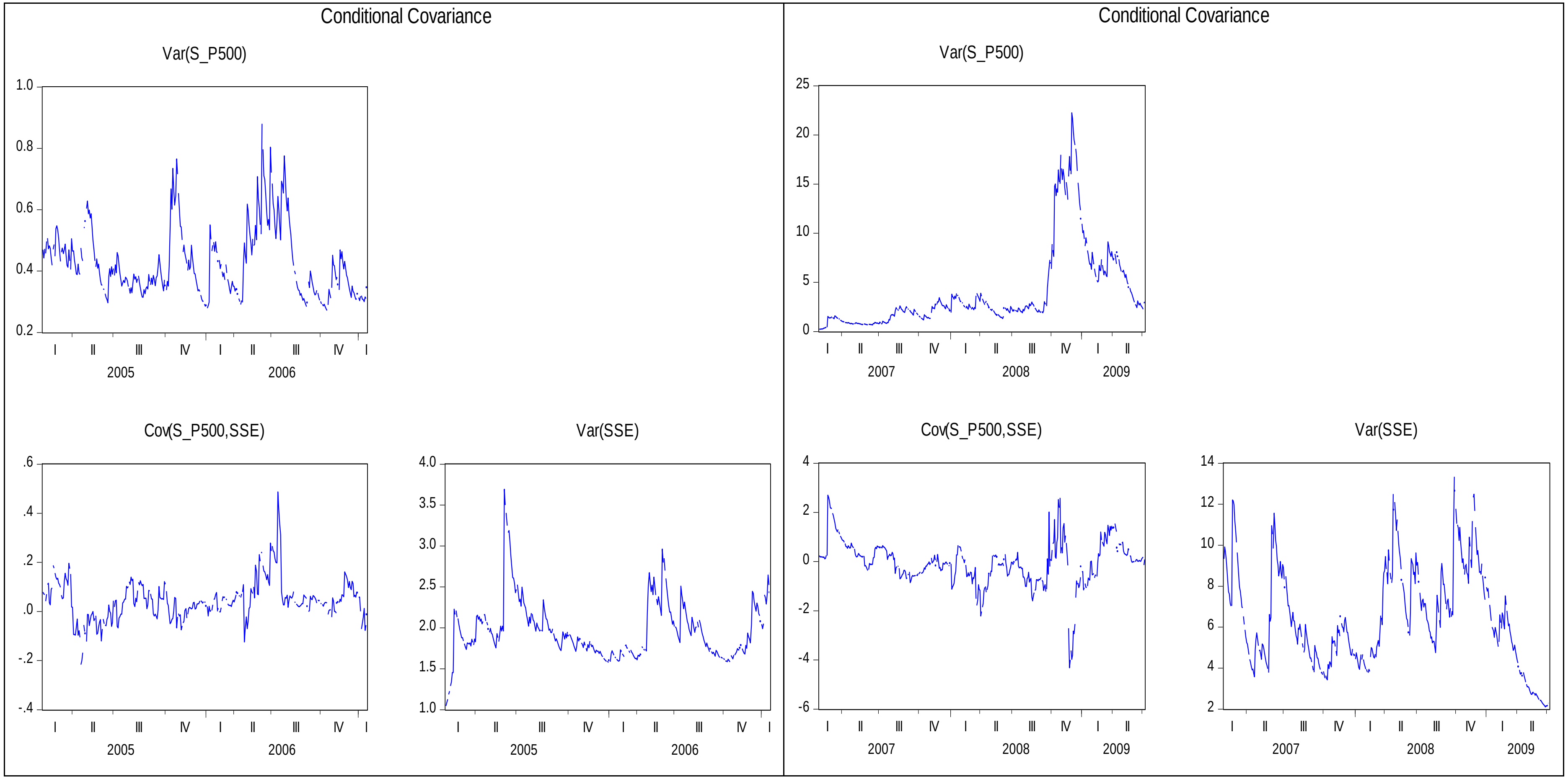


Figure 6-5: Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and SSE represents the Chinese Stock Market.

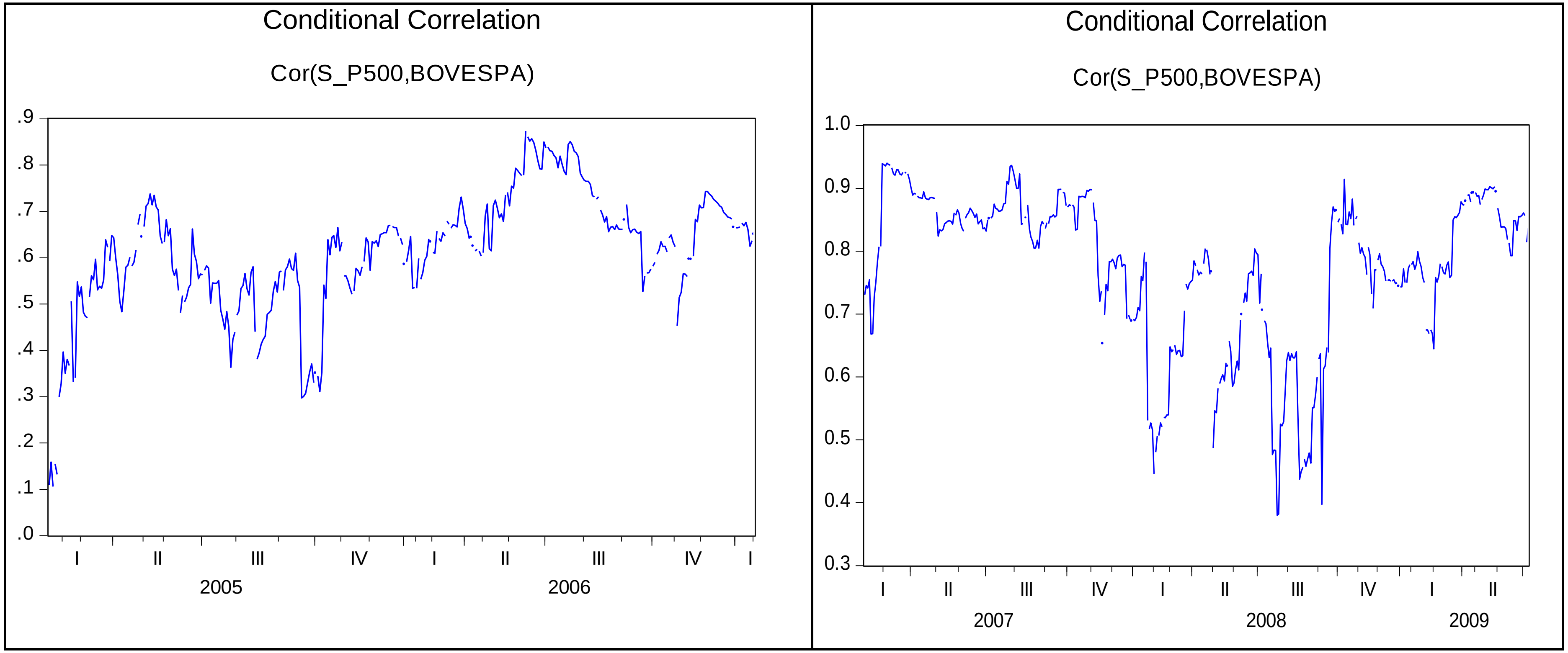


Figure 6-6: Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and BOVESPA represents the Brazilian Stock Market.

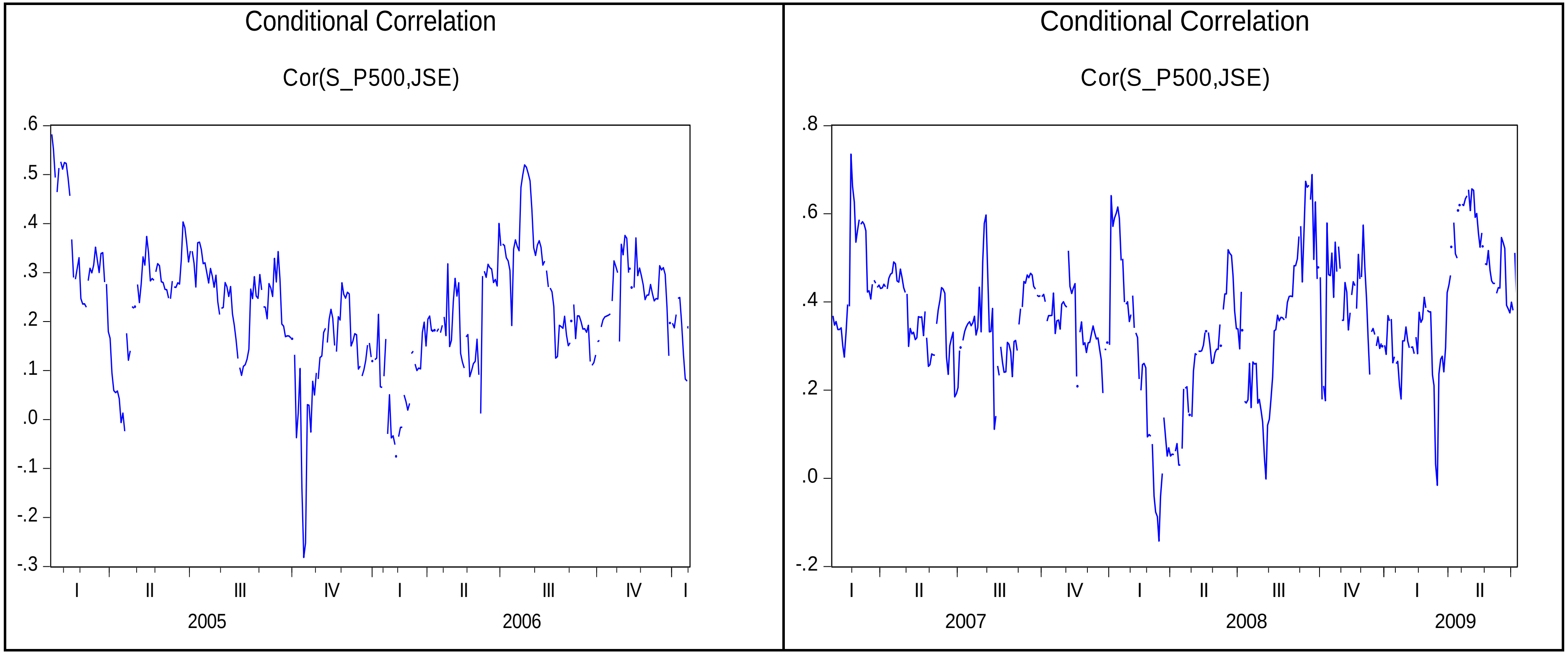


Figure 6-7: Conditional Correlation using Diagonal VECH GARCH under Student's t- distribution, for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and FTSE/JSE represents the South African Stock Market.

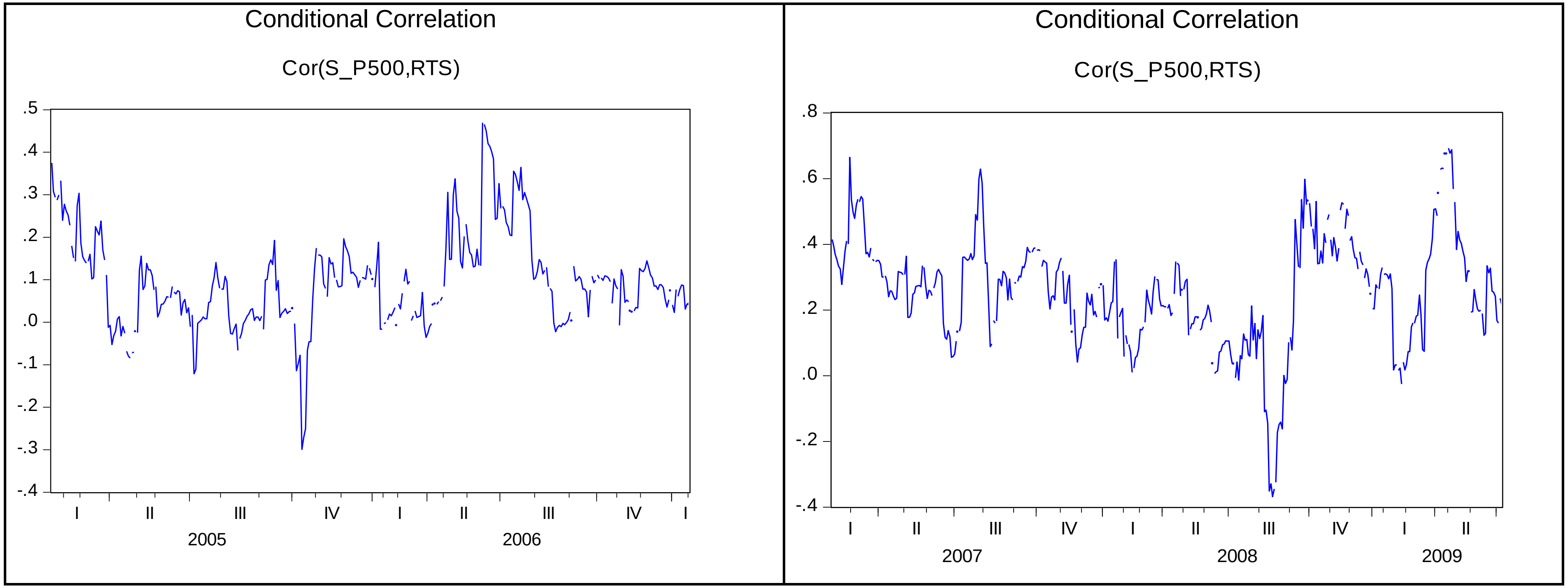
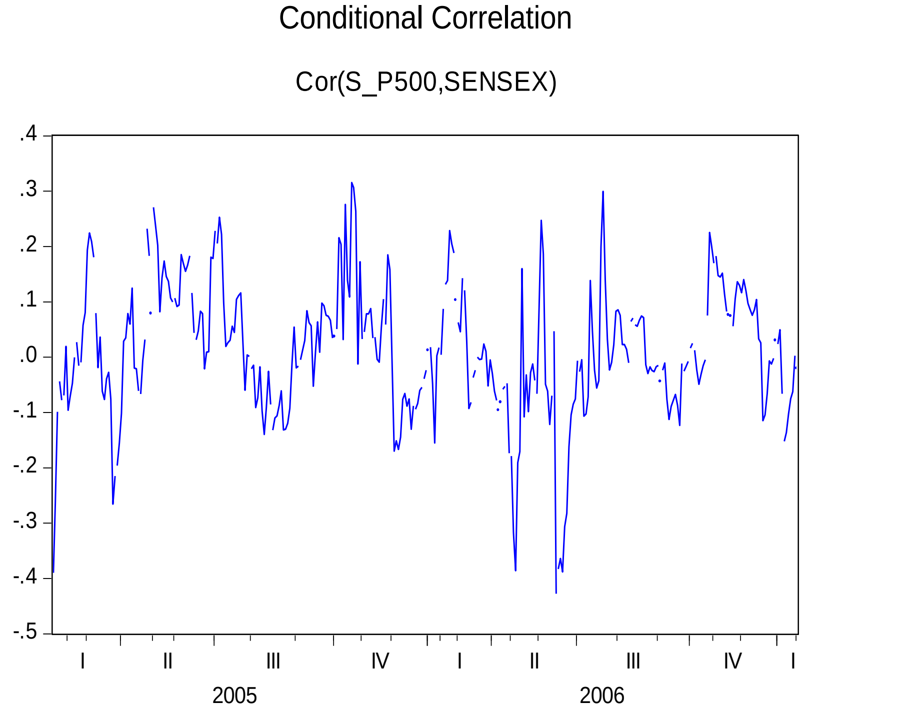


Figure 6-8: Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution, for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and RTS represents the Russian Stock Market.



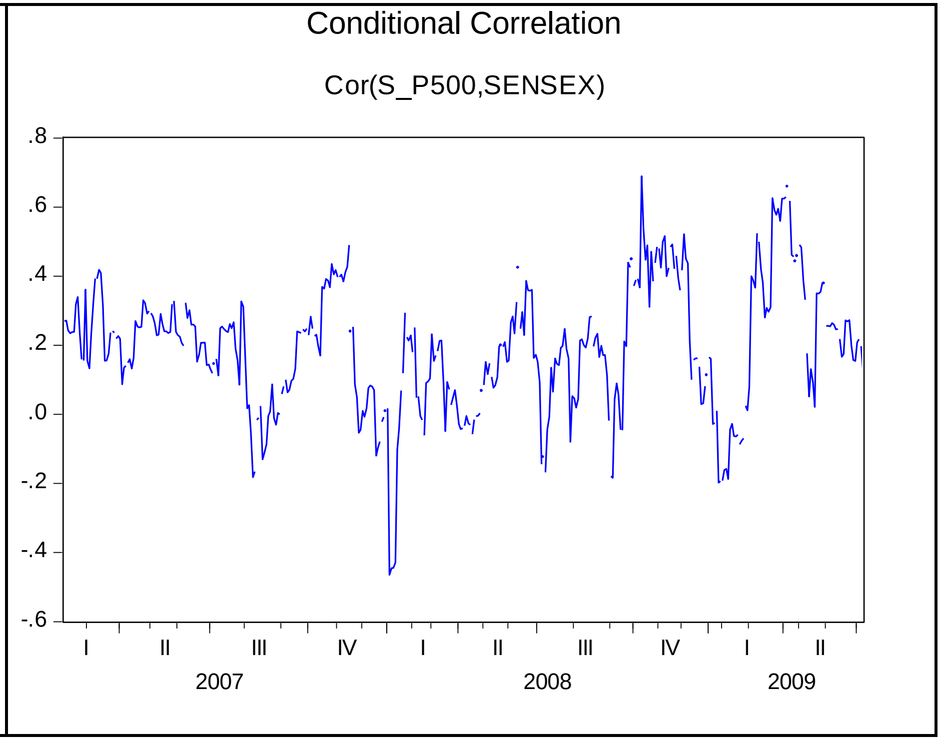


Figure 6-9: Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution, for 'pre-crisis' Period (left) and 'crisis' Period (right) where S&P500 represents the U.S. Stock Market, and SENSEX represents the Indian Stock Market.

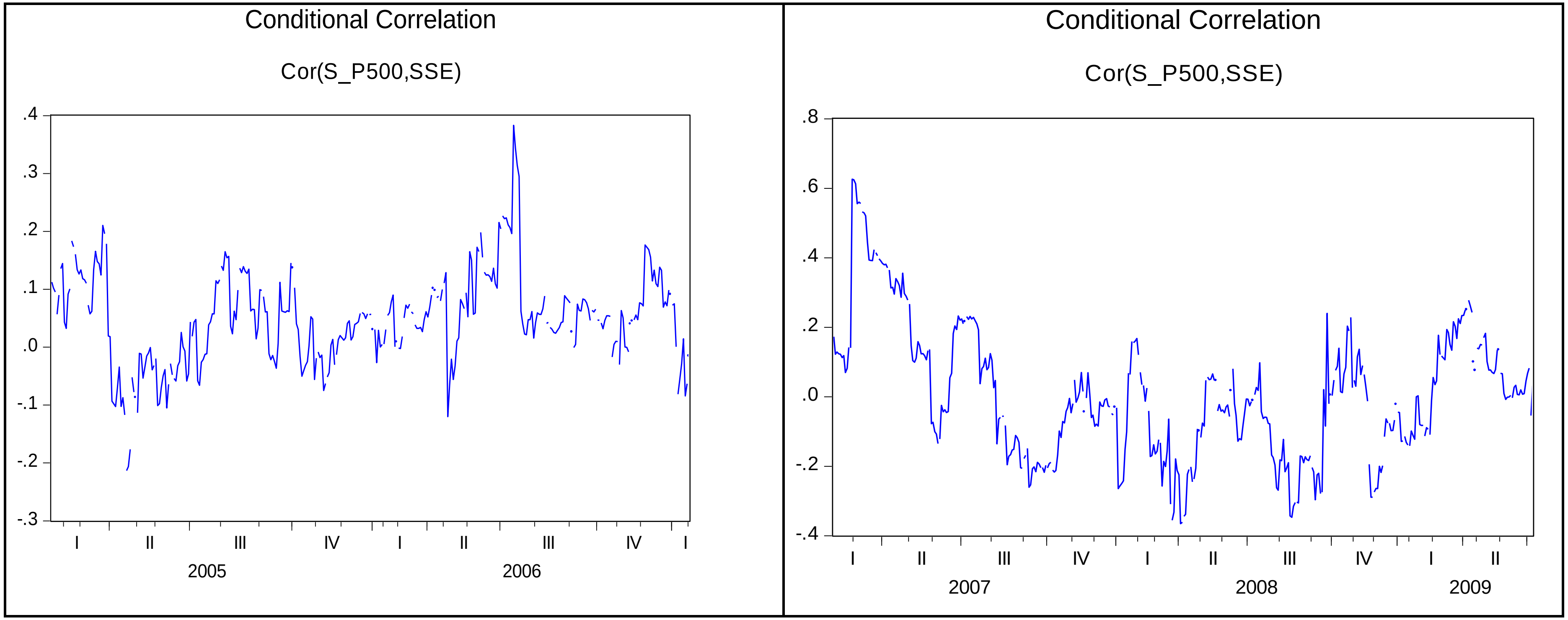


Figure 6-10: Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution, for 'Pre-crisis' Period (left) and 'Crisis' Period (right) where S&P500 represents the U.S. Stock Market, and SSE represents the Chinese Stock Market.

6.4.1.3 Diagonal VECH GARCH Estimation for Financial Contagion following the Eurozone Crisis

In order to analyse volatility spillover in BRICS equity markets emanating from the Eurozone, the current study uses two sub-periods, namely: (i) the 'crisis' (turmoil) sub-period which spans from 12th August 2009 to 31st December 2012 and (ii) 'the post-crisis' (stable) sub-period that starts on 1st January 2013 and ends on 28th February 2017 in the aftermath of the Eurozone sovereign debt crisis. The present study estimates coefficients for mean equation (μ_{11} and μ_{22}) and the diagonal (bivariate) VECH GARCH model (c_{11}, c_{22}, c_{12}, α_{11}, α_{22}, α_{12}, β_{11}, β_{22}, β_{12}). The results are presented in Tables 6-5 and 6-6 for the present the 'crisis' and 'post-crisis' periods, respectively.

Table 6-5: Parameter Estimation for Bivariate Diagonal VECH (1, 1) Equation for Conditional Correlation with the Eurozone Stock Market in Crisis Period

Parameter		μ_{11}	μ_{22}	c_{11}	c_{22}	c_{12}	α_{11}	α_{22}	α_{12}	β_{11}	β_{22}	β_{12}	Student -t	L. Likelihood
DAX/BOVEPA	Estimate	0.066810	0.052544	0.097419	0.253479	0.095947	0.076157	0.054777	0.064589	0.871354	0.821413	0.846015	8.218655	-1953.333
	SE	0.050830	0.054954	0.041500	0.110876	0.037263	0.022737	0.01552	0.01754	0.038173	0.064149	0.041297	2.087305	
	p-value	0.1887	0.3390	0.0189	0.0008	0.0100	0.0008	0.0051	0.0003	0.0000	0.0000	0.0000	0.0001	
DAX /JSE	Estimate	0.063361	0.081137	0.057972	0.076777	0.048240	0.111699	0.096834	0.104002	0.880954	0.889182	0.885058	8.883959	-1459.055
	SE	0.063256	0.071215	0.022156	0.036770	0.019360	0.027016	0.029102	0.024373	0.024463	0.029311	0.022567	2.262781	
	p-value	0.3165	0.2546	0.0089	0.0368	0.0127	0.0000	0.0009	0.0000	0.0000	0.0000	0.0000	0.0001	
DAX /RTS	Estimate	0.081338	0.102485	0.065919	0.155161	0.071201	0.069977	0.049633	0.058934	0.898794	0.903493	0.901140	6.268179	-2029.674
	SE	0.049496	0.067109	0.030254	0.074546	0.029206	0.019620	0.015118	0.015264	0.026556	0.031346	0.024678	1.152527	
	p-value	0.1003	0.1267	0.0293	0.0374	0.0148	0.0004	0.0010	0.0001	0.0000	0.0000	0.0000	0.0000	
DAX /SENSEX	Estimate	0.078270	0.039535	0.097106	0.043656	0.02287	0.114136	0.037585	0.065496	0.812331	0.929702	0.869037	7.540683	-1807.477
	SE	0.04699	0.043267	0.036982	0.023862	0.010639	0.032177	0.015393	0.016499	0.047358	0.025252	0.027730	1.592480	
	p-value	0.0545	0.3609	0.0086	0.0673	0.0316	0.0004	0.0146	0.0001	0.0000	0.0000	0.0000	0.0000	
DAX /SSE	Estimate	0.085838	-0.046787	0.088465	0.017919	0.011198	0.128175	0.017568	0.047453	0.809145	0.971172	0.886465	7.446793	-1917.283
	SE	0.040298	0.049926	0.036232	0.013046	0.008470	0.037237	0.007137	0.011938	0.049582	0.012098	0.027671	0.049582	
	p-value	0.0332	0.3487	0.0146	0.1696	0.1862	0.0006	0.0138	0.0001	0.0000	0.0000	0.0000	0.0000	

Source: Estimation.

Table 6-6: Parameter Estimation for Bivariate Diagonal VECH (1, 1) Equation for Conditional Correlation with the Eurozone in Post-crisis period

Parameter		μ_{11}	μ_{22}	c_{11}	c_{22}	c_{12}	α_{11}	α_{22}	α_{12}	β_{11}	β_{22}	β_{12}	Student -t	L. Likelihood
DAX/BOVEPA	Estimate	**0.109272**	0.043049	**0.047988**	**0.094356**	**0.024293**	**0.106259**	**0.044362**	**0.068658**	**0.865167**	**0.918073**	**0.891228**	**9.268349**	-2358.328
	SE	0.037919	0.051922	0.017786	0.042670	0.010068	0.023055	0.015076	0.014647	0.026251	0.027705	0.020426	2.325470	
	p-value	0.0040	0.4070	0.00070	0.0270	0.0158	0.0000	0.0033	0.0000	0.0000	0.0000	0.0000	0.0001	
DAX /JSE	Estimate	**0.100010**	**0.059076**	**0.037181**	**0.062585**	**0.027318**	**0.064988**	**0.087331**	**0.075336**	**0.908764**	**0.847838**	**0.877772**	**8.201100**	-1920.380
	SE	0.037409	0.032258	0.012287	0.026229	0.011174	0.015252	0.023097	0.015679	0.018607	0.041757	0.025547	1.749412	
	p-value	0.0075	0.0670	0.0025	0.0170	0.0145	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	
DAX /RTS	Estimate	**0.104892**	-0.040603	**0.038201**	**0.055345**	**0.021443**	**0.073532**	**0.078011**	**0.075738**	**0.903534**	**0.911427**	**0.907472**	**6.983685**	-2390.427
	SE	0.037887	0.055814	0.014419	0.030046	0.010536	0.018818	0.017446	0.014440	0.021212	0.020576	0.020576	1.446665	
	p-value	0.0056	0.4669	0.0081	0.0655	0.0418	0.0001	0.0000	0.0000	0.00000	0.0000	0.0000	0.0000	
DAX /SENSEX	Estimate	**0.108081**	**0.066879**	**0.05097**	0.02768	**0.015027**	**0.095838**	**0.026721**	**0.050605**	**0.873209**	**0.873209**	**0.909502**	**6.149525**	-2001.283
	SE	0.036270	0.032699	0.019487	0.022457	0.007093	0.025053	0.011575	0.014352	0.028834	0.028834	0.022518	0.969268	
	p-value	0.0029	0.0408	0.0089	0.2701	0.0341	0.0004	0.0210	0.0004	0.0000	0.0000	0.0000	0.0000	
DAX /SSE	Estimate	**0.115362**	0.048582	**0.033010**	**0.032539**	0.000459	**0.057169**	**0.077573**	**0.066594**	**0.929769**	**0.908598**	**0.919123**	**4.510778**	-2287.868
	SE	0.036446	0.036974	0.16333	0.013573	0.004902	0.019068	0.018124	0.014658	0.020778	0.017077	0.013969	0.623279	
	p-value	0.0015	0.1889	0.0433	0.0165	0.9254	0.0027	0.0000	0.00000	0.0000	0.00000	0.0000	0.0000	

Source: Estimation.

From Table 6-5, it can be seen that during the ‘crisis’ period, the own-mean spillover coefficients in all BRICS markets (μ_{22}) and the U.S. stock market (μ_{11}) are not significant and hence inconclusive.

For the ‘crisis’ period parameter estimates α_{22} and $\alpha_{11,}$ indicating ARCH effects, are all significant and have a p-value < 0.05. This indicates the presence of ARCH effects in BRICS and Eurozone stock markets. Parameter estimates α_{12} indicate cross-innovation spillover between the Eurozone and individual BRICS stock markets. Table 6-5 shows that during the Eurozone sovereign debt crisis, all cross-innovation spillover coefficients were significant with a p-value <0.01 and their magnitudes are higher compared to own innovation spillover coefficients α_{22}. The strongest α_{12} coefficient is found in South Africa (0.104002), while the weakest is recorded in China (0.047453). Based on the magnitudes of the estimated cross-volatility coefficients, innovation in all of the BRICS stock indices is influenced by the instability of the European stock market, with the cross-volatility shocks being relatively bigger than the own-volatility shocks.

During the ‘crisis’ period, the coefficient for own conditional volatility (GARCH effect) (β_{22}) is significant at all levels. The largest value is 0.971172 (China), while the lowest is 0.824143 (India). This indicates the persistence of volatility in all BRICS stock market returns.
The cross- conditional volatility coefficients (β_{12}) for the ‘crisis’ period are significant and are slightly lower in magnitude compared to the β_{22} coefficients. The highest β_{12} is found in Russia (0.901140) while the lowest is in India (0.846015). Low β_{12} estimates compared to β_{22} implies that precedent shocks occurring from the Eurozone markets have less impact on BRICS stock markets than own lagged market volatility.

Table 6-6 presents results from the ‘post-crisis’ period. It can be seen that ARCH effects as expressed by coefficient estimate α_{22} are significant at the 1% level and seem to be slightly lower in magnitude compared to the cross volatility coefficient α_{12} (except for Brazil and India). The highest ARCH effects are recorded for South Africa (0.08733) and the lowest for China (0.026721). The cross-innovation spill over volatility coefficient for the ‘post-crisis’ period α_{12} ranges between 0.050605 (India) and 0.075738 (Russia). Similarly, the GARCH effect as expressed by β_{22} coefficients is lower compared to cross- conditional volatility coefficient β_{12} in the case of South Africa, India and China, suggesting that precedent shocks occurring from the Eurozone market have a greater impact on BRICS stock markets than own lagged market volatility.

Figures 6-11 to 6-20 present conditional variances and covariance plots by diagonal VECH GARCH for both the 'crisis' and the 'post-crisis' periods, following the Eurozone sovereign debt crisis. The conditional covariance plots do not show major differences in conditional variance and covariance for the 'crisis' period compared to the 'post-crisis', except for the Chinese stock market. Hence the conclusion that during the Eurozone sovereign debt crisis financial contagion did not take place in the BRICS stock markets. The above results are in line with the Aizenman, Jinjarak, Park and Lee (2012) study, which noted that the effects of Eurozone crisis shocks on emerging countries was mixed and limited during the period 2005 to 2011. However, they cautioned that it would be a mistake for one to assume that there was a decoupling of emerging countries from the Eurozone crisis. The authors posited that, unlike the massive financial contraction triggered by the collapse of Lehman Brothers, the Eurozone crisis had evolved at a slower pace, and thus making it harder to identify the ultimate adverse effects of a deep Eurozone crisis on emerging countries at times of heightened financial instability.

Note that in Figures 6-11 to 6-20 for all stock markets, with the exception of the Chinese market, the conditional covariance reached the highest in the 2^{nd} quarter of 2011 - a period that coincided with the deepening of the Eurozone crisis with the bailout of Portugal, a second bailout for Greece and adoption of austerity measures for Italy.

In Tables 6-11 and 6-20, the student's t-distribution and Log-likelihood are also presented. This Student-t test has a coefficient estimated for the degrees of freedom of the distribution. The coefficients of student's t-distribution are statistically significant at 1% and are between 6 and 14. One should also note that for having a defined variance, the degrees of freedom have to be greater than 2, hence the conclusion that with the diagonal VECH model, the variance is well defined. Additionally, as we know, the Student's t distribution tends towards the normal distribution when we consider infinite degrees of freedom. Having such small figures (although still well defined, as mentioned before) leads us to reason, and confirm, that our data follows a heavy-tailed distribution.

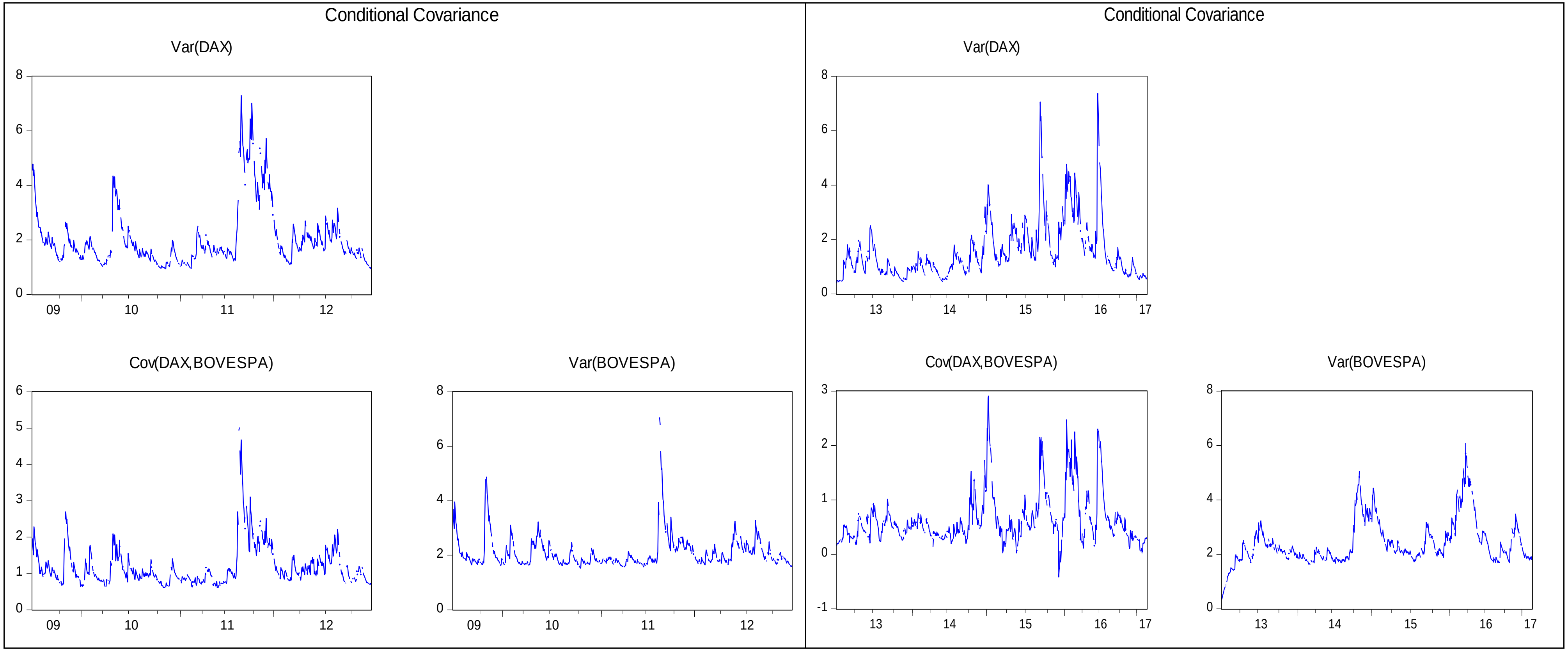


Figure 6-11: Estimated Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis' Period (left) and 'Post-crisis' Period (right) where DAX represents the Eurozone Stock Market, and BOVESPA represents the Chinese Stock Market.

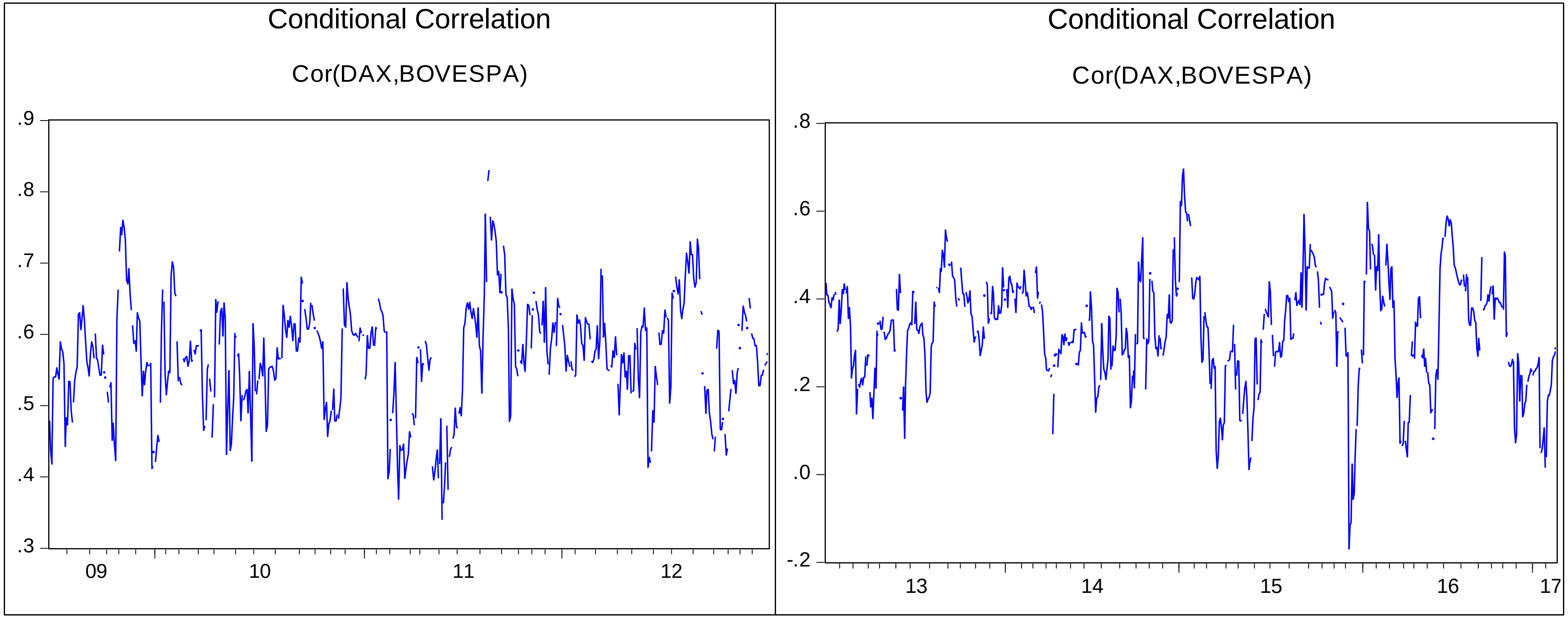


Figure 6-12: Estimated Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis' Period (left) and 'Post-crisis' Period (right) where DAX represents the Eurozone Stock Market, and BOVESPA represents the Brazilian Stock Market.

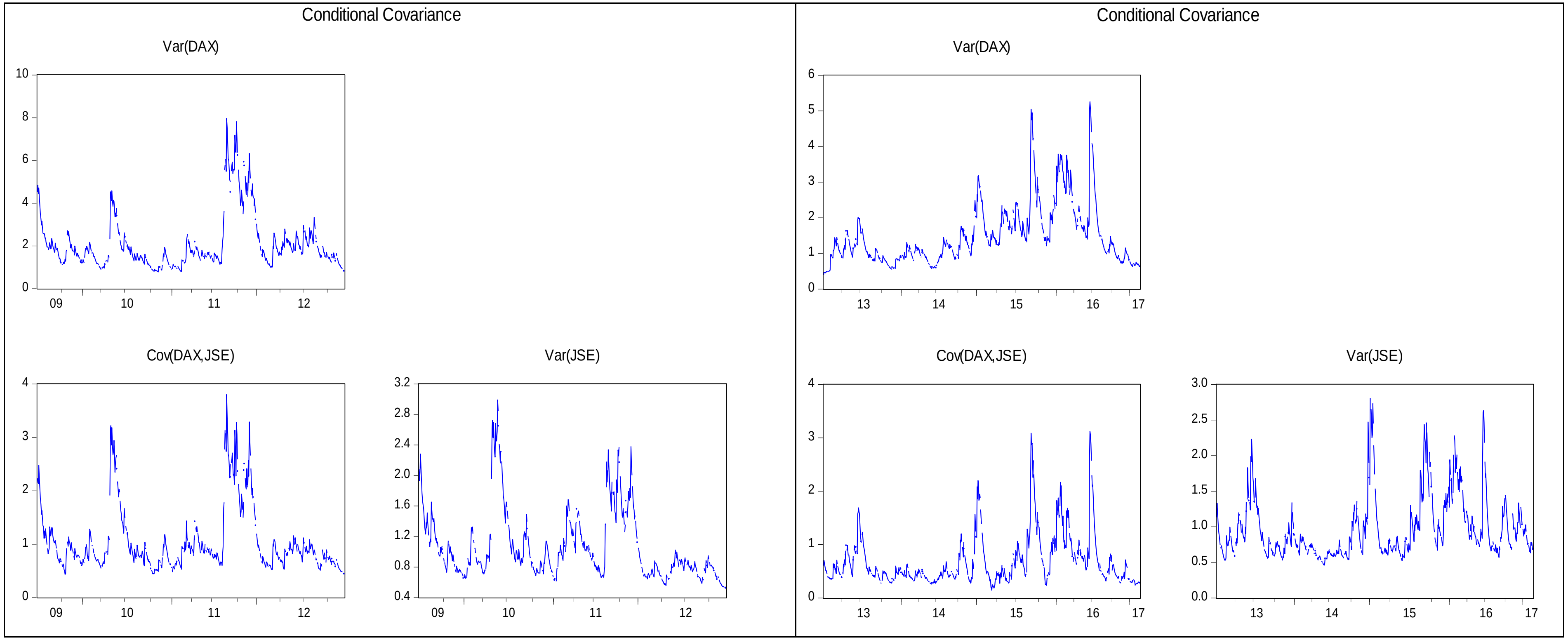


Figure 6-13: Estimated Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis' Period (left) and 'Post-crisis' Period (right) where DAX represents the Eurozone Stock Market, and JSE represents the South African Stock Market.

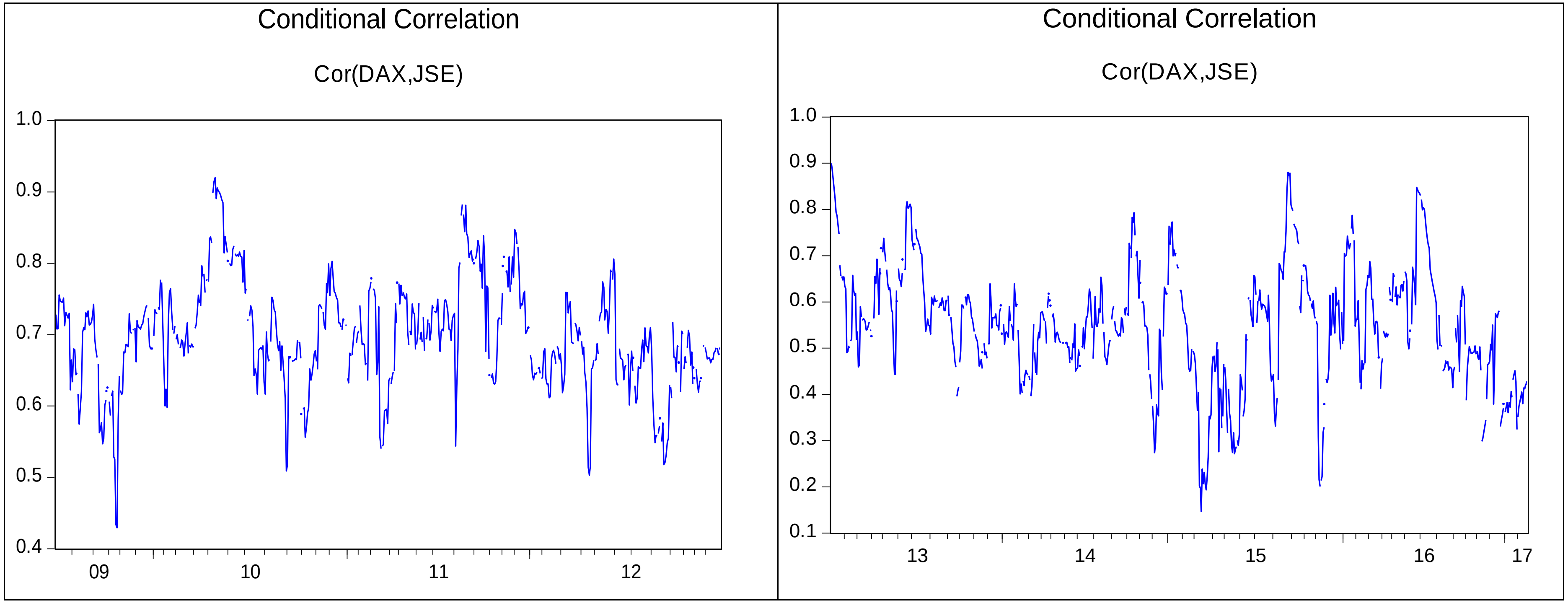


Figure 6-14: Estimated Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution, for 'crisis' Period (left) and 'post-crisis' Period (right) where DAX represents the Eurozone stock market, and JSE represents the South African Stock Market.

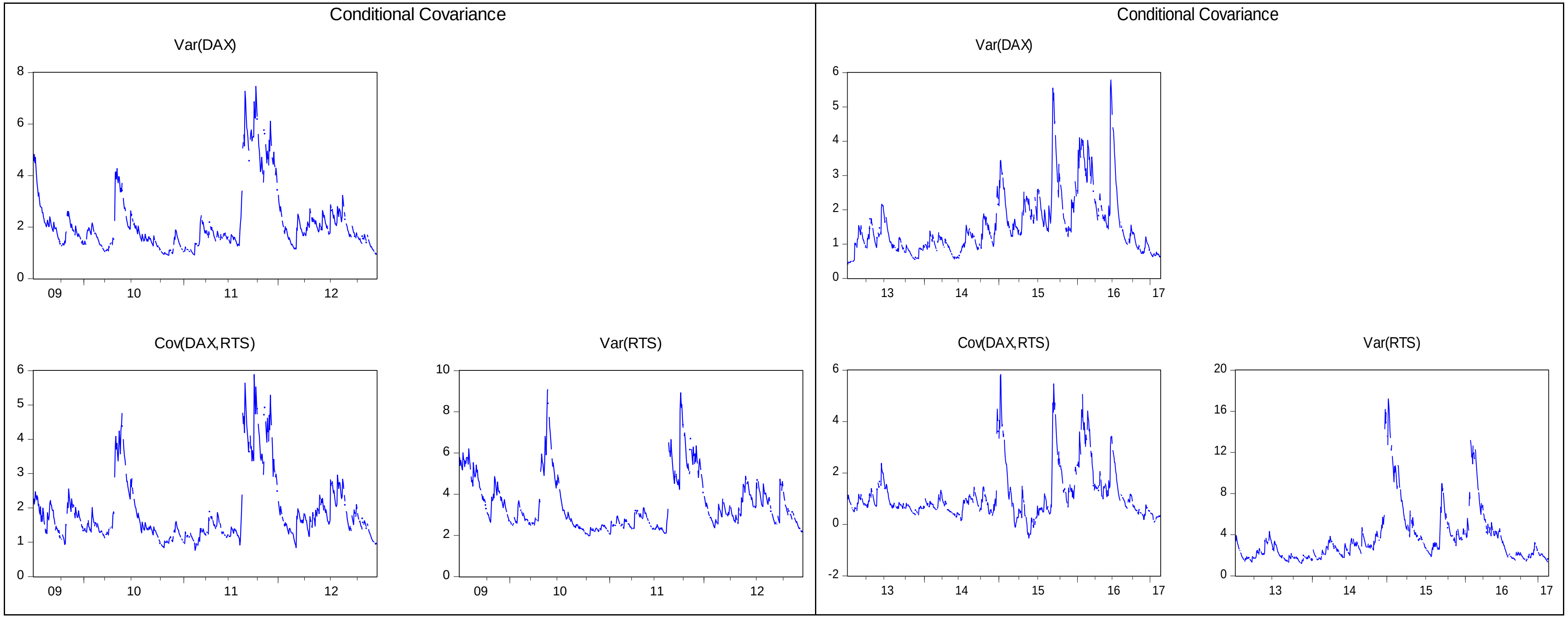


Figure 6-15: Estimated Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis' Period (left) and 'Post-crisis' Period (right). Where DAX represents the Eurozone Stock Market, and RTS represents the Russian Stock Market.

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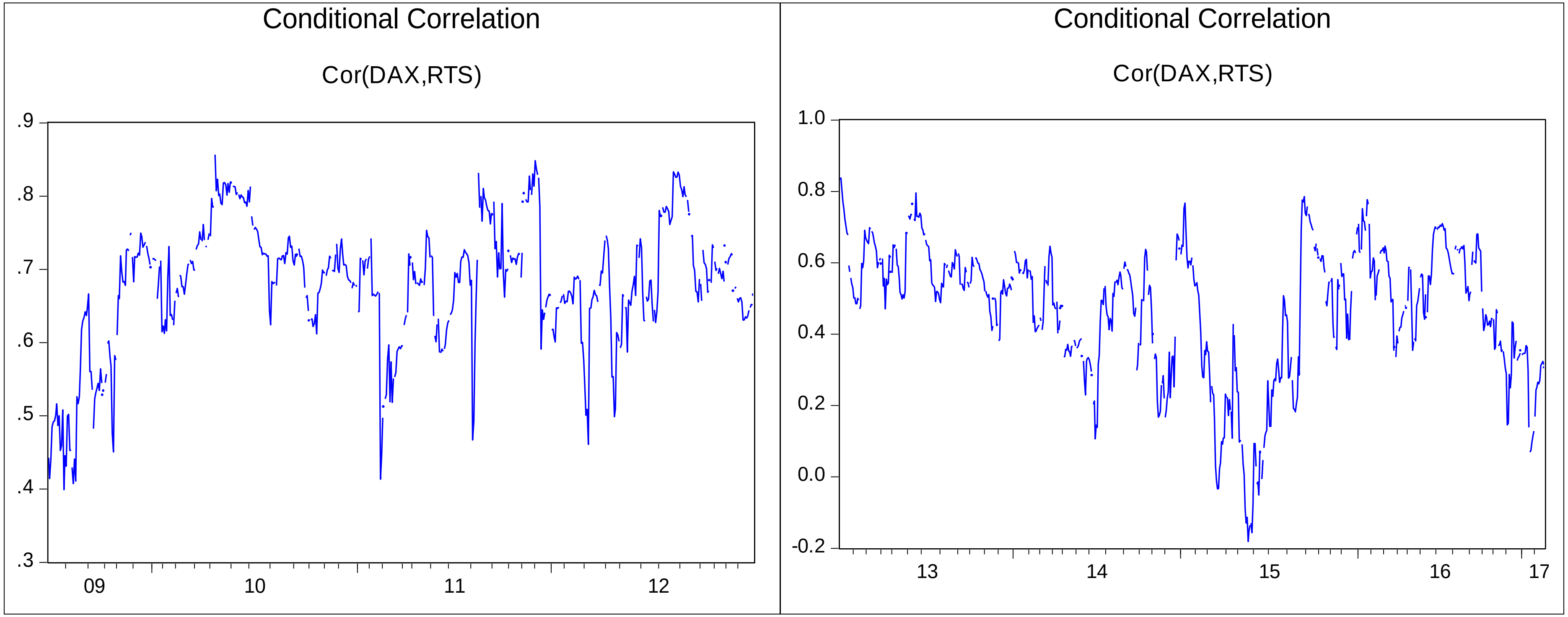

Figure 6-16: Estimated Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis' Period (left) and 'Post-crisis' Period (right) where DAX represents the Eurozone Stock Market, and RTS represents the Russian Stock Market.

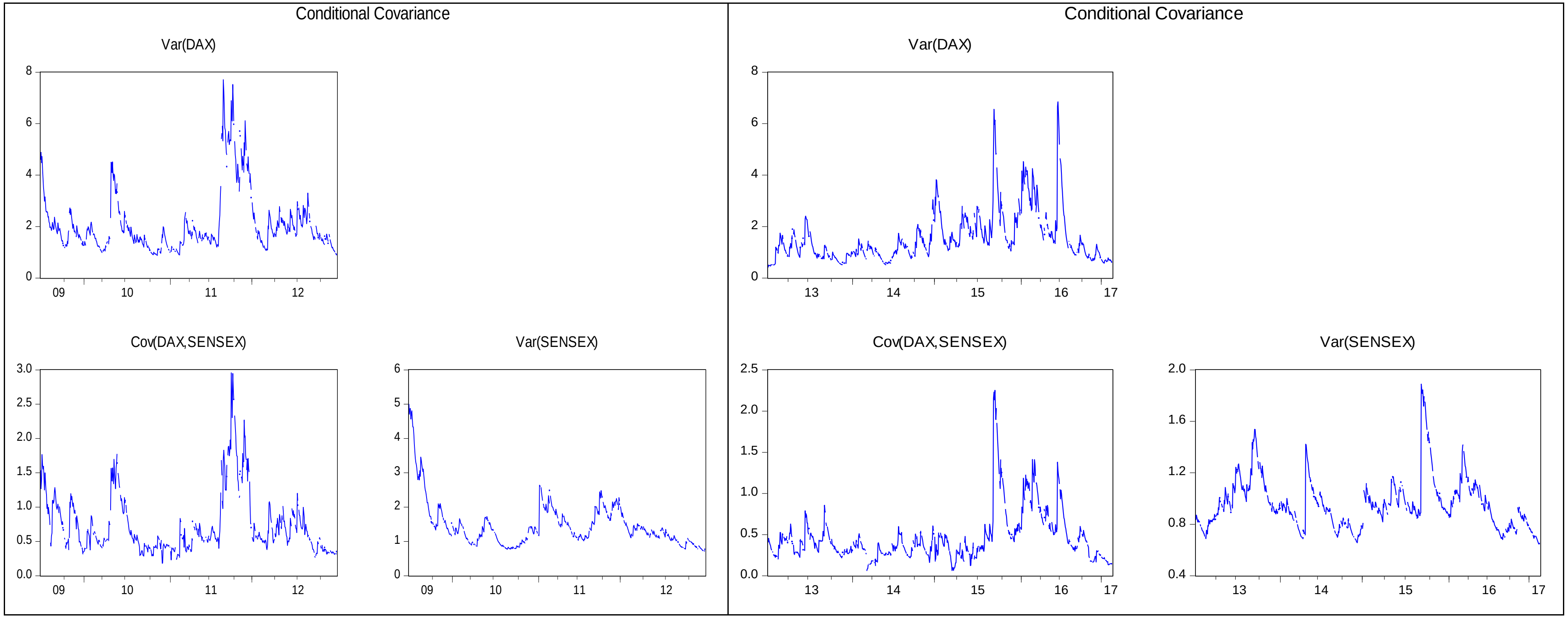

Figure 6-17: Estimated Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis' Period (left) and 'Post-crisis' Period (right) where DAX represents the Eurozone Stock Market, and SENSEX represents the Indian Stock Market.

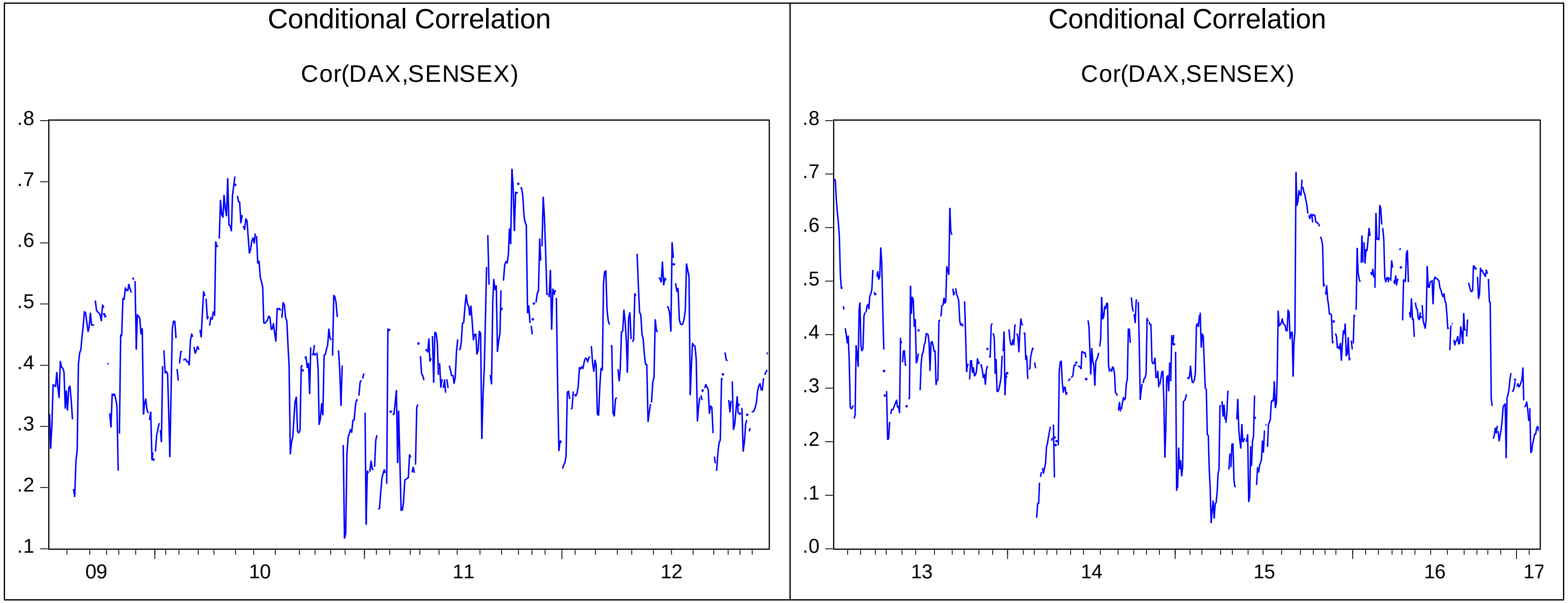

Figure 6-18: Estimated Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis" Period (left) and 'Post-crisis' Period (right) where DAX represents the Eurozone Stock Market, and SENSEX represents the Indian Stock Market.

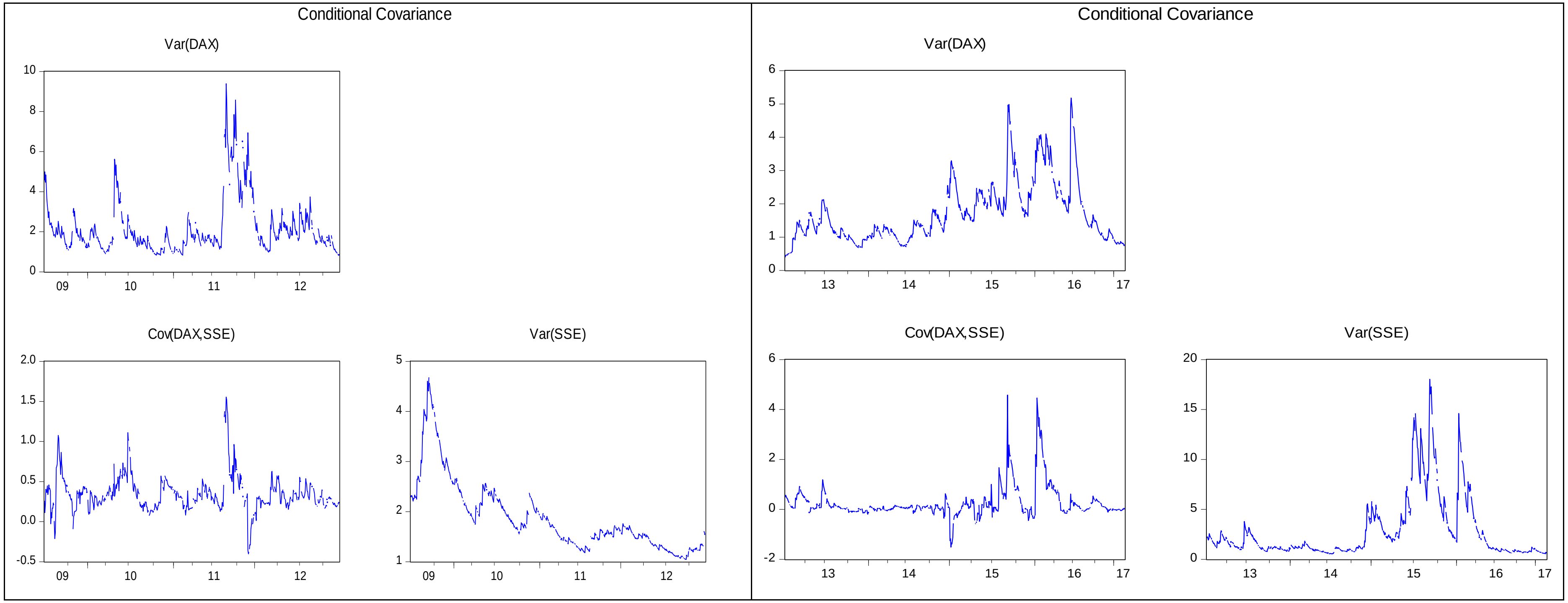

Figure 6-19: Estimated Conditional Variance and Covariance using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis' Period (left) and 'Post-crisis' Period (right). DAX represents the Eurozone Stock Market, and SSE represents the Chinese Stock Market.

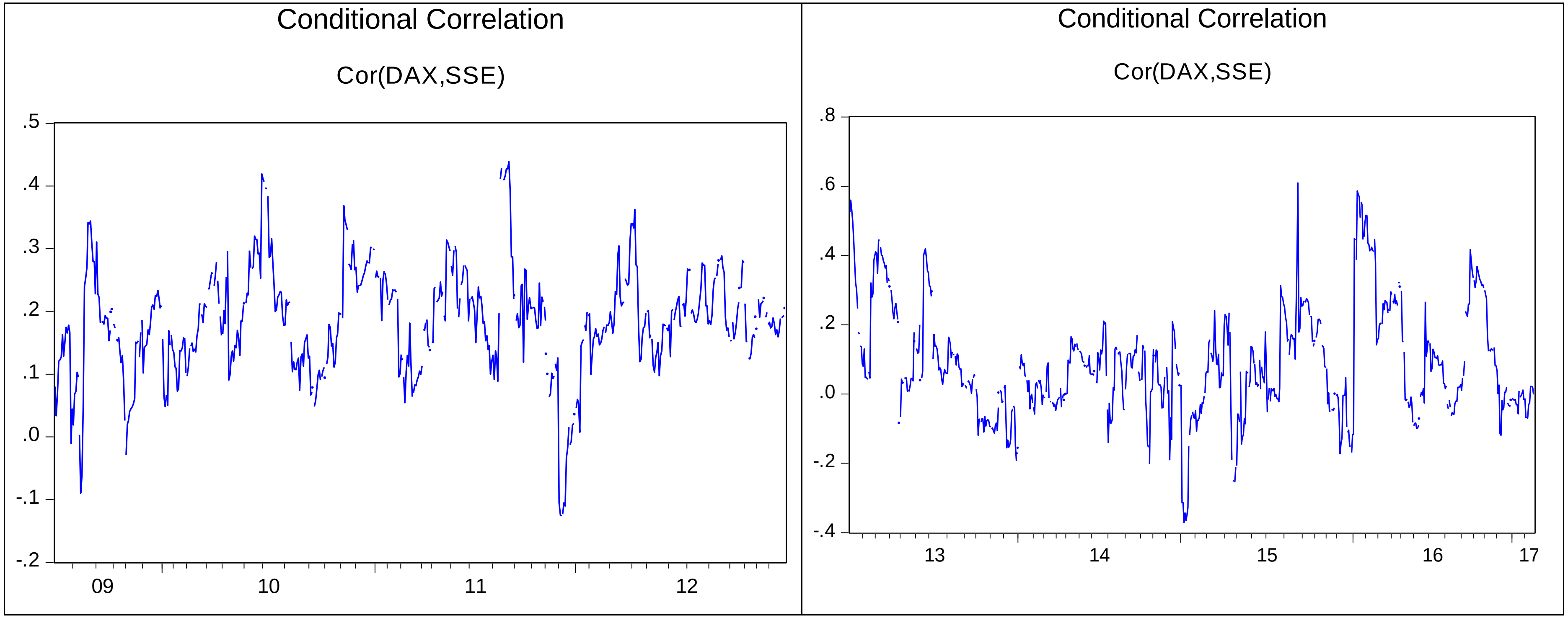

Figure 6-20: Estimated Conditional Correlation using Diagonal VECH GARCH under Student's t-distribution, for 'Crisis" Period (left) and 'Post-crisis' Period (right). DAX represents the Eurozone Stock Market, and SSE represents the Chinese Stock Market.

6.4.1.4 Diagnostic Test for Diagonal VECH GARCH model

After fitting the VECH GARCH model, the adequacy specification of the model is assessed. The results of the Box-Ljun statistic on standardised squared residual are presented in Table 6-7 and 6-10 for all periods.

Table 6-7: Bivariate Box-Ljung Q-statistics for Standardised Squared Residuals with the S&P500 During the Sub-prime 'Pre-crisis' Period

	Q(12)	P-value	Qs(12)	P-value
BOVESPA	54.09565	0.2530	55.09829	0.2240
JSE	**120.0738**	0.0000	**121.3784**	0.0000
RTS	**61.11083**	0.0000	**61.40027**	0.000
SENSEX	**107.7304**	0.0000	**109.2486**	0.000
SEE	51.52512	0.3376	52.33589	0.3094

Source: Estimation.

Table 6-8: Bivariate Box-Ljung Q-statistics for Standardised Squared Residuals with the S&P500 During the Sub-prime 'Crisis' Period

	Q(12)	P-value	Qs(12)	P-value
BOVESPA	**142.8892**	0.0000	**144.9792**	0.0000
JSE	**169.9933**	0.0000	**1717.566**	0.0000
RTS	**203.8055**	0.0000	**206.5476**	0.0000
SENSEX	**123.2985**	0.0000	**124.4808**	0.0000
SEE	**92.90075**	0.0001	**94.143190**	0.0001

Source: Estimation.

Table 6-9: Bivariate Box-Ljung Q-statistics for Standardised Residuals with the DAX During the 'Crisis' Period

	Q(12)	P-value	Qs(12)	P-value
BOVESPA	**69.79463**	0.0216	**70.35902**	0.0194
JSE	60.89759	0.1001	61.46634	0.0917
RTS	84.49552	0.0009	**85.26545**	0.0007
SENSEX	79.44678	0.0029	**80.20438**	0.0024
SEE	61.4286	0.0923	61.94350	0.0851

Source: Estimation.

Table 6-10: Bivariate Box-Ljung Q-statistics for Standardised Residuals with DAX during the 'Post-crisis' Period

	Q(12)	P-value	Qs(12)	P-value
BOVESPA	**69.79463**	0.0216	**70.35902**	0.0194
JSE	**93.04752**	0.0001	**93.68747**	0.000C
RTS	**72.55502**	0.0126	**73.12232**	0.0112
SENSEX	**68.09358**	0.0297	**68.6298**	0.0269
SEE	**102.7376**	0.0000	**1003.5383**	0.000

Source: Estimation.

The results in Tables 6-7 to 6-10 suggest the existence of serial dependence in the bivariate return series as the p-value for the Q-statistics test is close to zero, hence the rejection of the null hypothesis that there no residual autocorrelation up to lag 12. This suggests that the fitted Diagonal VECH model could not remove the GARCH effect (heteroscedasticity). Attempts by the researcher to modify the model by assuming a normal Gaussian distribution and by estimating the model with asymmetries yielded similar results.

Figures 6-21 to 6-24 present autocorrelation and cross-correlation of the standardised residuals and the squared standardised residuals of the series. For some of the lags, the sample ACFs are within the distance between positive and negative 2 times standard deviation lines at 95% confidence level; this confirms that the diagonal VECH GARCH model did not remove GARCH effects.

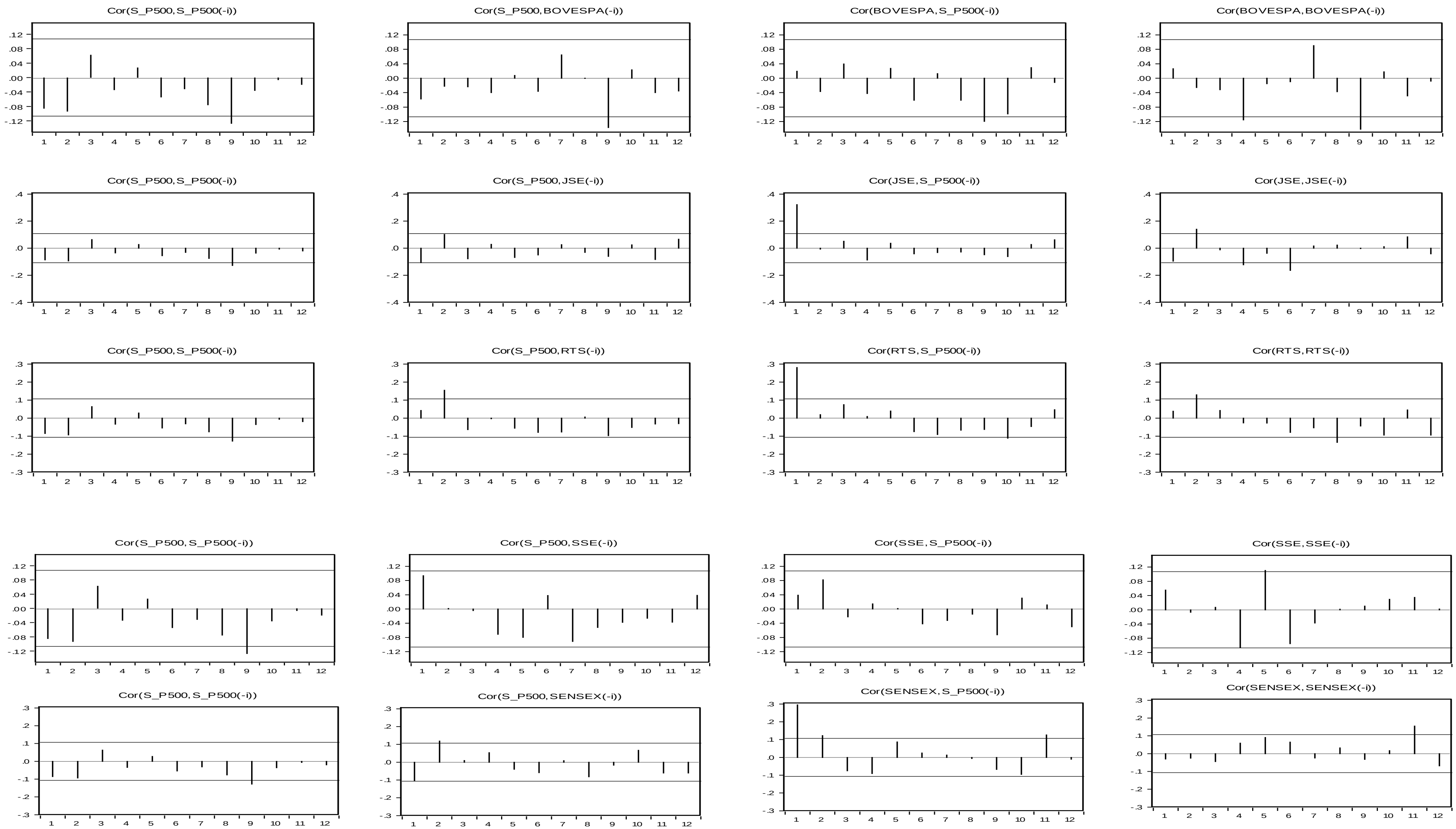

Figure 6-21: ACFs Standardized Residual of the Diagonal Bivariate VECH Model for the ‘Pre-crisis’ Period during the Sub-prime Crisis.

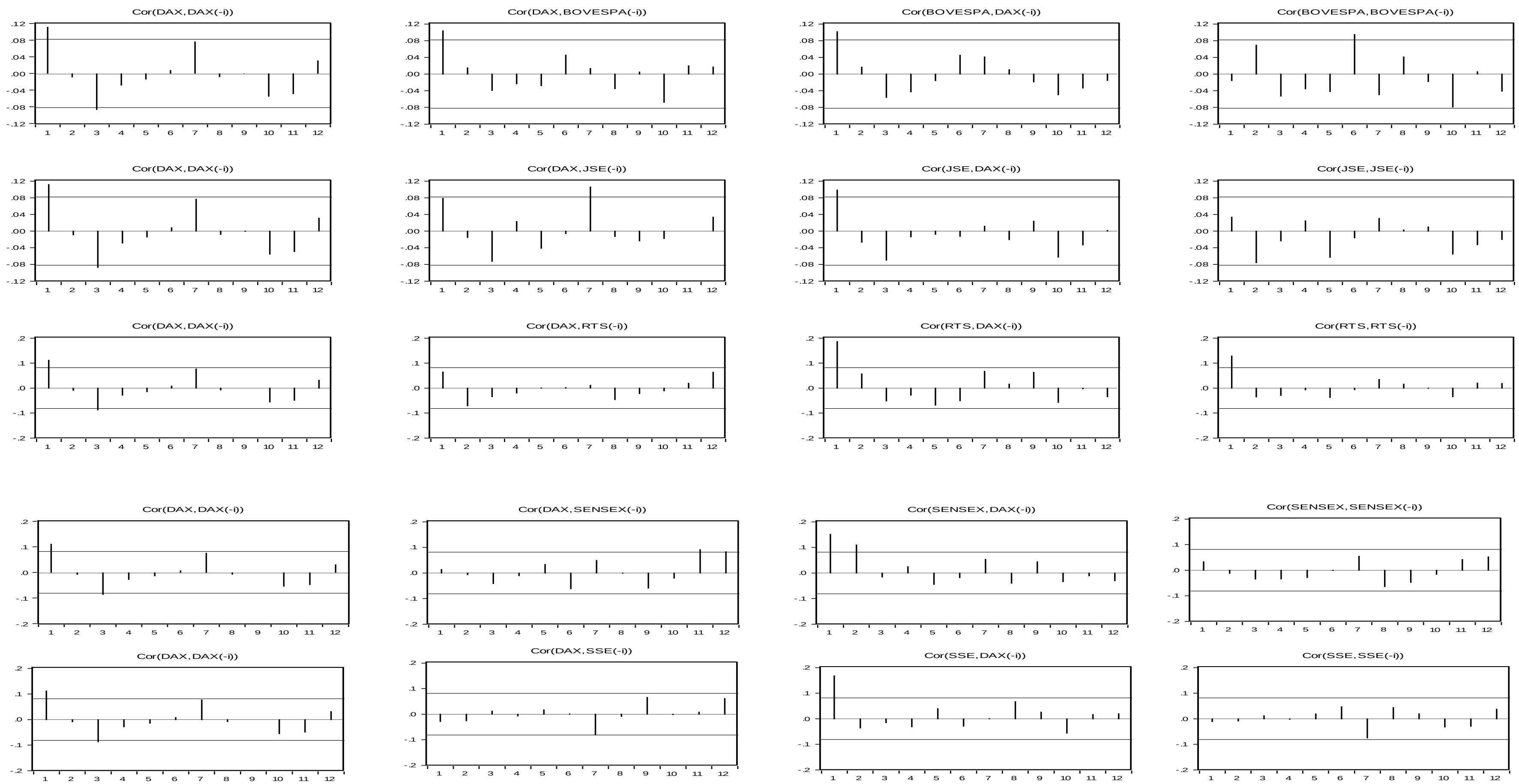

Figure 6-22: ACFs Standardized Residual of the Diagonal Bivariate VECH Model for the 'Crisis' Period during the Sub-prime Crisis.

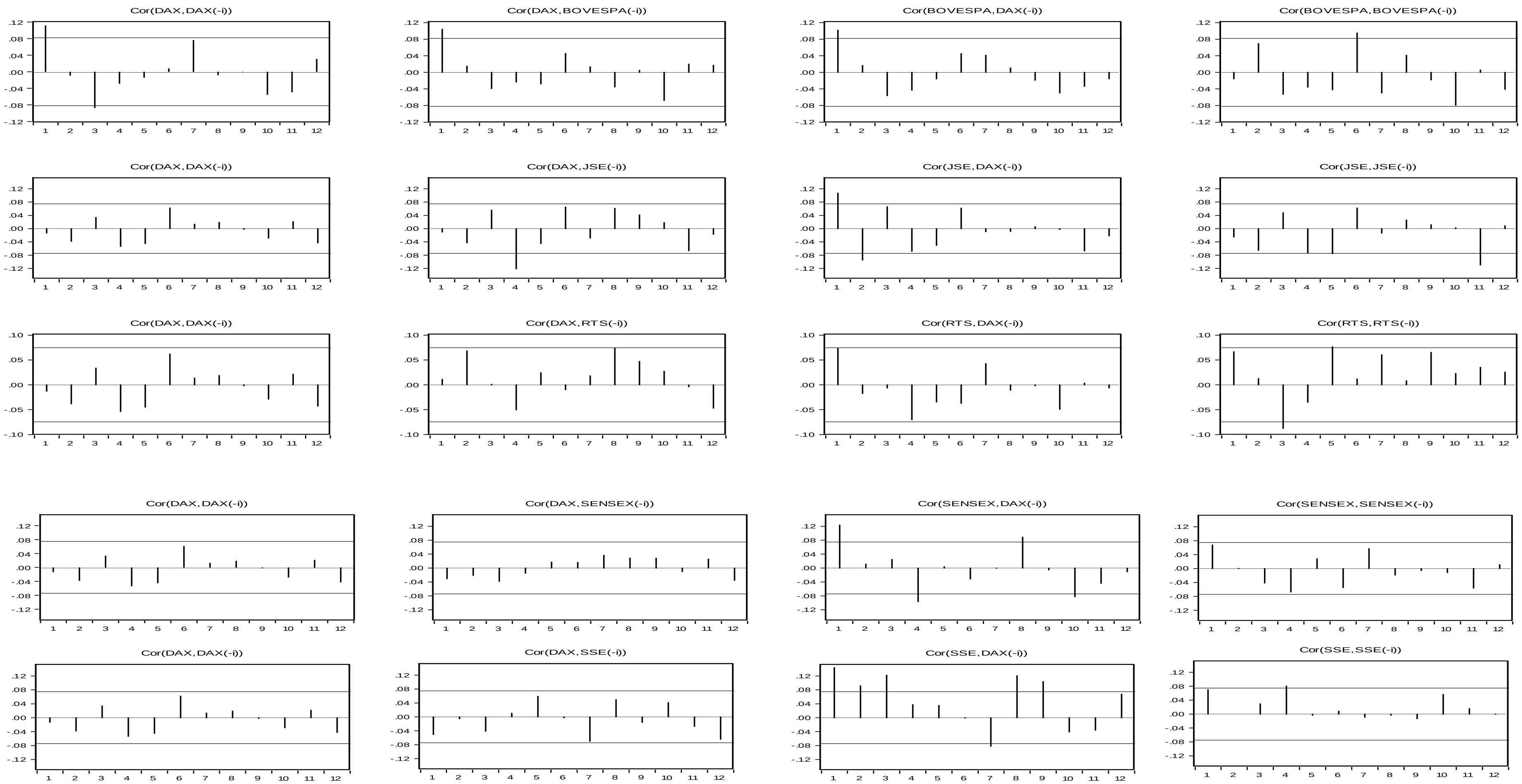

Figure 6-23: ACFs Standardized Residual of the Diagonal Bivariate VECH Model for the ‘Crisis’ Period during EZDC.

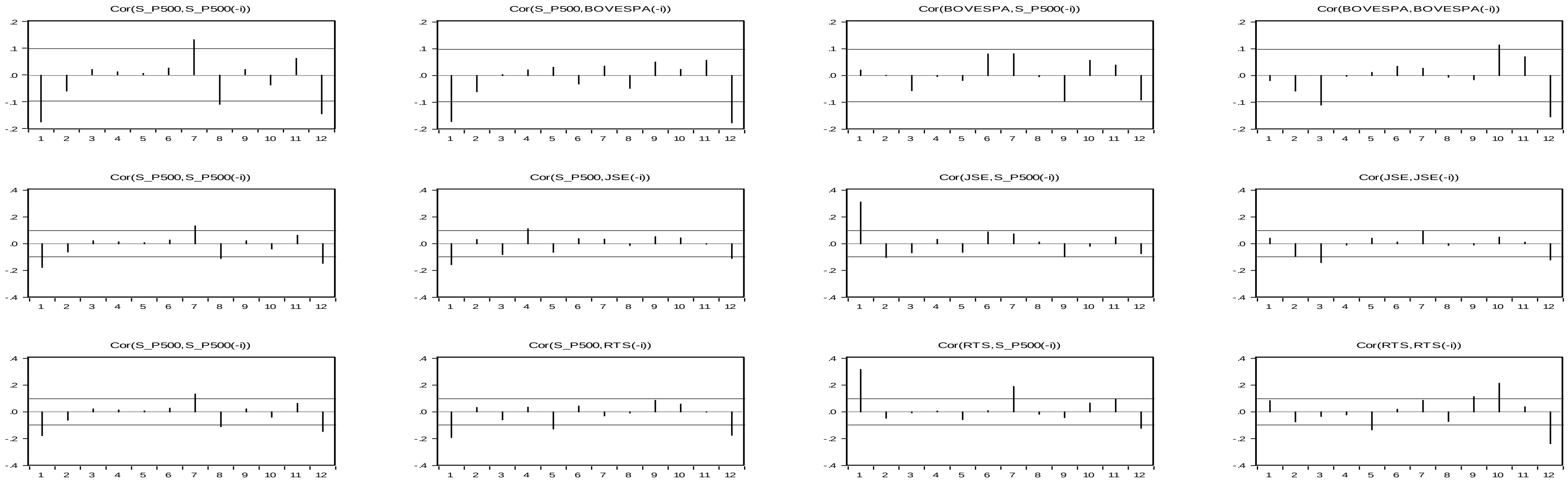

Figure 6-24: ACFs Standardized Residual of the Diagonal Bivariate VECH Model for the ‘Post-crisis’ Period during EZDC.

The drawback of the diagonal VECH models is that (i) they do not enforce positive definiteness and, (ii) they do not allow for complicated interactions among variables as the spillover effect is precluded by its structure where the only determinant of the variance of one series is its own shocks (Brook, 2014). Furthermore, the DVECH MGARCH models are less parsimonious and offer less flexibility of their specifications for a time-varying conditional covariance matrix of the disturbance. To circumvent these problems, the current study uses the DCC GARCH model as it allows correlations to be time-varying, in addition to the conditional variances.

6.4.2 ESTIMATIONS OF DCC GARCH MODEL

This section provides the estimation results for the mean, variance, and correlation model using the DCC GARCH model as introduced in the methodology section.

6.4.2.1 Estimations of DCC GARCH Model for Financial Contagion Following the Sub-prime Crisis

In order to examine financial contagion in BRICS stock markets following the sub-prime crisis in the US, the present study estimates the following coefficients: (i) the mean (Equation6.16), (ii) the variance (Equation 6.17), and (iii) the correlation model (Equation 6.23) using the DCC GARCH model. The coefficient was estimated for both the 'pre-crisis' and 'crisis' periods. The results for bivariate estimations of the DCC GARCH model between the S&P500 and individual BRICS stock markets indices are presented in Tables 6-11 through to Table 6-15.

Table 6-11: Estimation Parameters of Mean, Variance, and Correlation Models of Contagion with the U.S. as Source Country and Brazil as Target Country.

	Parameter	Pre-crisis			crisis		
		Estimate	SE	P-value	Estimate	SE	P-value
S&P500	α_0	**0.030612**	0.015175	0.043664	0.026354	0.019309	0.172304
	α_1	**0.088054**	0.040294	0.028869	**0.098974**	0.021360	0.000004
	β_1	**0.834843**	0.053447	0.000000	**0.896712**	0.019533	0.000000
BOVESPA	α_0	0.113157	0.120138	0.346246	0.112314	0.073492	0.126450
	α_1	**0.079405**	0.051562	0.123563	**0.084119**	0.024557	0.000614
	β_1	**0.875195**	0.079141	0.000000	**0.893265**	0.027903	0.000000
	θ_1	**0.048020**	0.016823	0.004312	**0.046595**	0.013976	0.000856
	θ_2	**0.939771**	0.023229	0.000000	**0.947932**	0.016114	0.000000
ρ_{ij} [corr(S&P500,BOVESPA)]				0.6150935	ρ_{ij} [corr(S&P500,BOVESPA)]		0.7678467
Maximized Log-likelihood				-889.6288	Maximized Log-likelihood		-1617.114

Source: Estimation.

Table 6-12: Estimation Parameters of Mean, Variance, and Correlation Models with the U.S. as Source Country and South Africa as Target Country

		Pre-crisis			Crisis		
	Parameter	Estimate	SE	P-value	Estimate	SE	P-value
S&P500	α_0	**0.030612**	0.015351	0.046139	0.026354	0.018993	0.165272
	α_1	**0.088054**	0.040324	0.028986	**0.098974**	0.021543	0.000004
	β_1	**0.834843**	0.053720	0.000000	**0.896712**	0.019551	0.000000
FTSE/JSE	α_0	0.034016	0.021301	0.110281	**0.058724**	0.030377	0.053210
	α_1	**0.165848**	0.048839	0.000684	**0.112168**	0.025988	0.000016
	β_1	**0.819095**	0.045508	0.000000	**0.869951**	0.025714	0.000000
	θ_1	0.004620	0.012811	0.718359	0.001380	0.020384	0.946037
	θ_2	**0.968608**	0.029602	0.000000	**0.887137**	0.887137	0.004369
ρ_{ij} [corr(S&P500,JSE)]				0.2400472	ρ_{ij} [corr(S&P500,JSE)]		0.4250802
Maximized Log-likelihood				-820.6837	Maximized Log-likelihood		-1655.506

Source: Estimation.

Table 6-13: Estimation Parameters of Mean, Variance, and Correlation Model with the U.S. as Source Country and Russia as Target Country

		Pre-crisis			crisis		
	Parameter	Estimate	SE	P-value	Estimate	SE	P-value
S&P500	α_0	**0.030612**	0.015287	0.045227	0.026354	0.019068	0.166942
	α_1	**0.088054**	0.040460	0.029530	**0.098974**	0.021298	0.000003
	β_1	**0.834843**	0.053555	0.000000	**0.896712**	0.019442	0.000000
RTS	α_0	**0.114489**	0.067514	0.089928	**0.078782**	0.047885	0.099921
	α_1	**0.125094**	0.048935	0.010579	**0.117498**	0.034544	0.000670
	β_1	**0.835400**	0.050359	0.000000	**0.875790**	0.027331	0.000000
	θ_1	0.005913	0.012067	0.624097	0.038157	0.046055	0.407381
	θ_2	**0.968719**	0.021778	0.000000	**0.815539**	0.250268	0.001119
ρ_{ij} [corr(S&P500,RTS)]				0.1464534	ρ_{ij} [corr(S&P500,RTS)]		0.3306286
Maximized Log-likelihood				-959.4556	Maximized Log-likelihood		-1839.87

Source: Estimation.

Table 6-14: Estimation Parameters of Mean, Variance, and Correlation Model with the U.S. as Source Country and India as Target Country

		Pre-crisis			crisis		
	Parameter	Estimate	SE	P-value	Estimate	SE	P-value
S&P500	α_0	**0.030612**	0.015344	0.046038	0.026354	0.019037	0.166241
	α_1	**0.088054**	0.040432	0.029416	**0.098974**	0.021347	000004
	β_1	**0.834843**	0.053672	0.000000	**0.896712**	0.019541	0.000000
SENSEX	α_0	**0.151964**	0.064974	0.019343	0.152778	0.130993	0.243491
	α_1	**0.154722**	0.053949	0.004132	**0.145174**	0.049816	0.003566
	β_1	**0.755650**	0.069218	0.000000	**0.842642**	0.052391	0.000000
	θ_1	0.000000	0.000029	0.999115	0.040532	0.028250	0.151350
	θ_2	**0.919327**	0.178326	0.000000	**0.850395**	0.064644	0.000000
ρ_{ij} [corr(S&P500,SENSEX)]				0.152096	ρ_{ij} [corr(S&P500,SENSEX)]		0.280337
Maximized Log-likelihood				-902.7562	Maximized Log-likelihood		-1818.645

Source: Estimation.

Table 6-15: Estimation Parameters of Mean, Variance, and Correlation Model with the U.S. as Source Country and China as Target Country

		Pre-crisis			crisis		
	Parameter	Estimate	SE	P-value	Estimate	SE	P-value
S&P500	α_0	**0.030612**	0.015344	0.046039	0.026354	0.019025	0.165987
	α_1	**0.088054**	0.040432	0.029417	**0.098974**	0.021456	0.000004
	β_1	**0.834843**	0.053672	0.000000	**0.896712**	0.019549	0.000000
SSE	α_0	0.085463	0.057525	0.137367	0.187103	0.155137	0.227796
	α_1	0.041964	0.027015	0.120334	**0.079929**	0.032844	0.014949
	β_1	**0.918015**	0.029109	0.000000	**0.893193**	0.035316	0.000000
	θ_1	**0.000000**	0.000158	0.999965	0.011784	0.016465	0.474168
	θ_2	0.919882	0.593842	0.121373	**0.964742**	0.040455	0.000000
ρ_{ij} [corr(S&P500,SSE)]				0.0234467	ρ_{ij} [corr(S&P500,SSE)]		0.03179588
Maximized Log-likelihood				-947.4045	Maximized Log-likelihood		-1887.203

Source: Estimation.

Tables 6-11 to 6-15 present a summary of the DCC model parameter estimates for both the 'pre-crisis' and the 'crisis' periods. Each table presents source-target pairs consisting of the U.S. and an individual BRICS market. Most of the parameter estimates for univariate GARCH (1,1) as represented in the diagonal elements of D_t in Equation 6.18 and 6.24 appear to be significantly different from zero at the 10% level of significance. This means that, following the sub-prime crisis in the US, equity markets in BRICS countries reacted to shocks emanating from the U.S. equity market, in both the ‘pre-crisis’ and ‘crisis’ periods.

The significant coefficients α_1 for most stock markets (except for China) are indicating the persistence of volatility which suggests possible transmissions of volatility from the U.S. stock market. The coefficient β_1 is also significant in most markets and indicates a large asymmetric impact, implying that BRICS stock markets are reacting to different sources of information from different markets and consequently adapting their portfolios. The DCC-GARCH (1, 1) parameters θ_1 and θ_2 are also presented in Tables 6-16 through 6-20. The parameters measure the impact of past standardised shocks (θ_1) and lagged dynamic conditional correlations (θ_2) on the current dynamic conditional correlations. The tables suggest that only θ_2 is significant in most BRICS equity markets, implying that it is the only one that has significant effects (except for China). Joint significance parameters θ_1 and θ_2 is only found in the Brazilian stock market. (Joint significance means that the DCC model is adequate at measuring both time-varying conditional correlations). The necessary condition of $\theta_1 + \theta_2 < 1$ holds for all sector pairs. It is worth noting that the mean value of the conditional correlation coefficient (ρ) for across pairs of stock market is of a higher magnitude in the ‘crisis’ period that the ‘pre-crisis’ period.

A plot of the estimated conditional correlations using the DCC model is presented in Figures 6-25 through 6-29. The general impression of the conditional correlations increased significantly during the ‘crisis’ period as compared to the ‘pre-crisis’ period. The conditional correlation reached its highest level towards the end of the year 2008, which corresponds with the bankruptcy filing of Lehman Brothers on September 15th 2008. Lehman Brothers was one of the oldest and largest investment banking firms in the world, and its collapse deepened the then -ongoing U.S. financial crisis.

Given the fact that conditional correlation coefficients increased considerably during the sub-prime crisis, — except for China (SSE) and Indian (SENSEX) —is an indication that financial contagion emanating from the U.S. took place in BRICS stock markets. For the Chinese market, the lack of contagion might be because strong government control of the Chinese stock market insulated the Chinese equity market from contagious effects from the US. Furthermore, as Naoui, Khemiri, and Liouane (2010) suggested, the decoupling of the Chinese market from financially contagious effects from the U.S. market can also be attributed to China’s growing economic strength at the time of financial contagion.

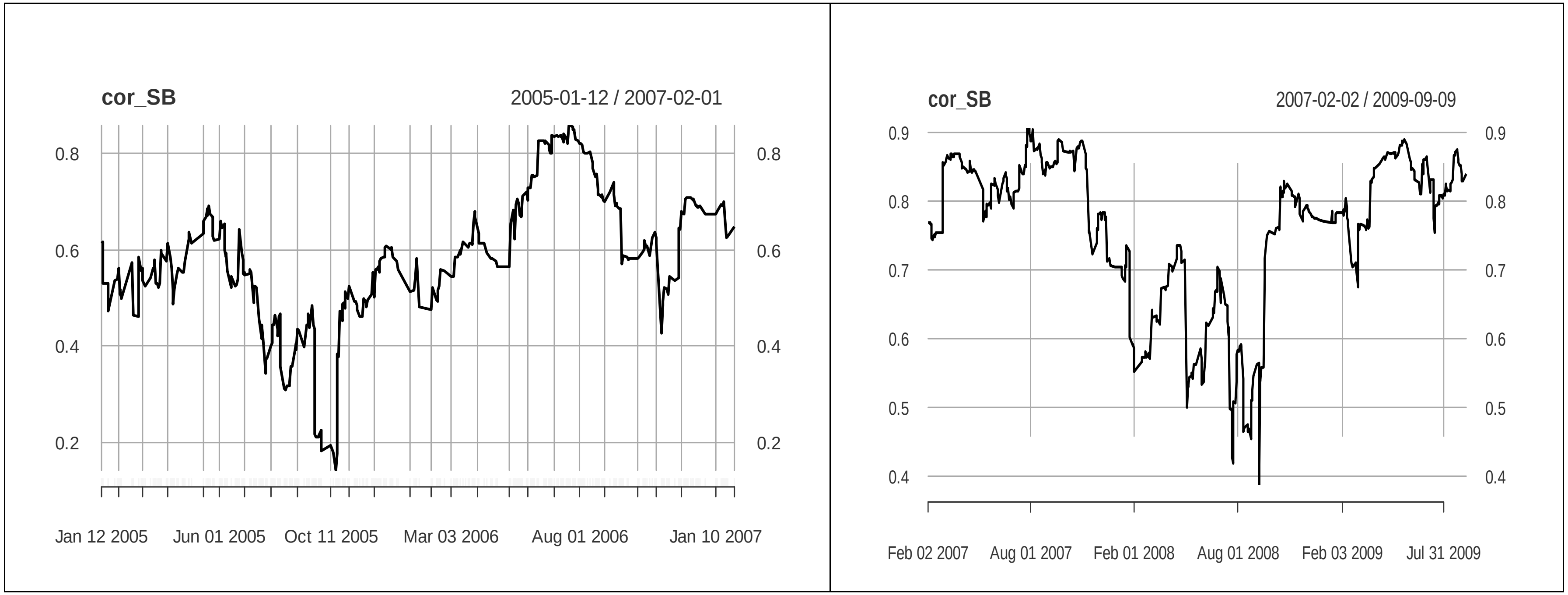

Figure 6-25: Estimated Conditional Correlation using DCC GARCH for ‘Pre-crisis’ Period (left) and ‘Crisis’ Period (right) between S&P500 (U.S.) and BOVESPA (Brazil).

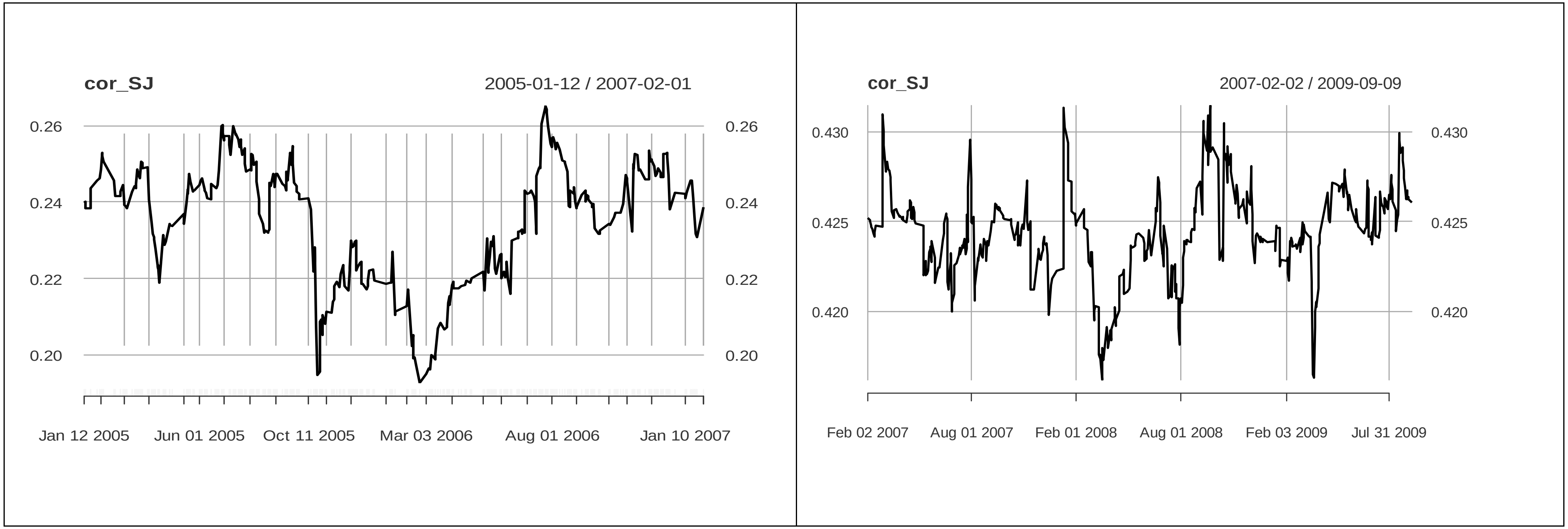

Figure 6-26: Estimated Conditional Correlation using DCC GARCH for ‘Pre-crisis’ Period (left) and ‘Crisis’ Period (right) between S&P500 (U.S.) and FTSE/JSE (South Africa).

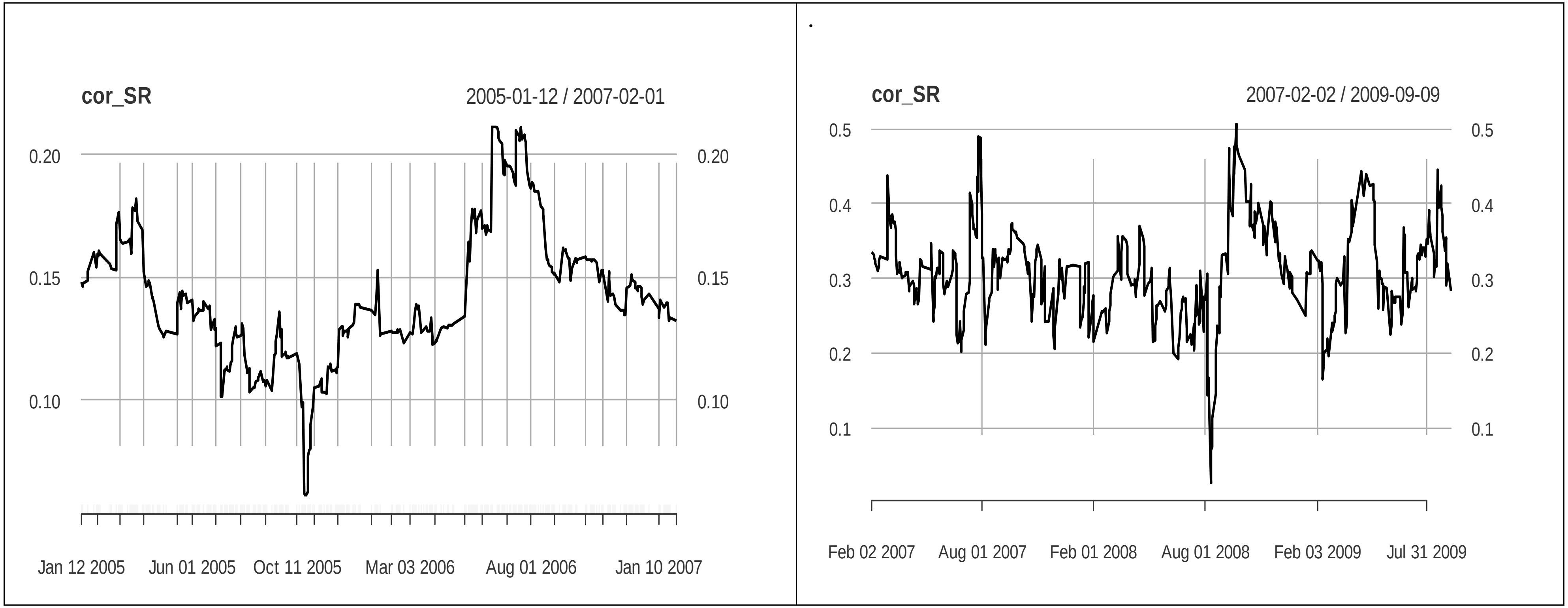

Figure 6-27: Estimated Conditional Correlation using DCC GARCH for 'Pre-crisis' Period (left) and 'Crisis' Period (right) between S&P500 (U.S.) and RTS (Russia).

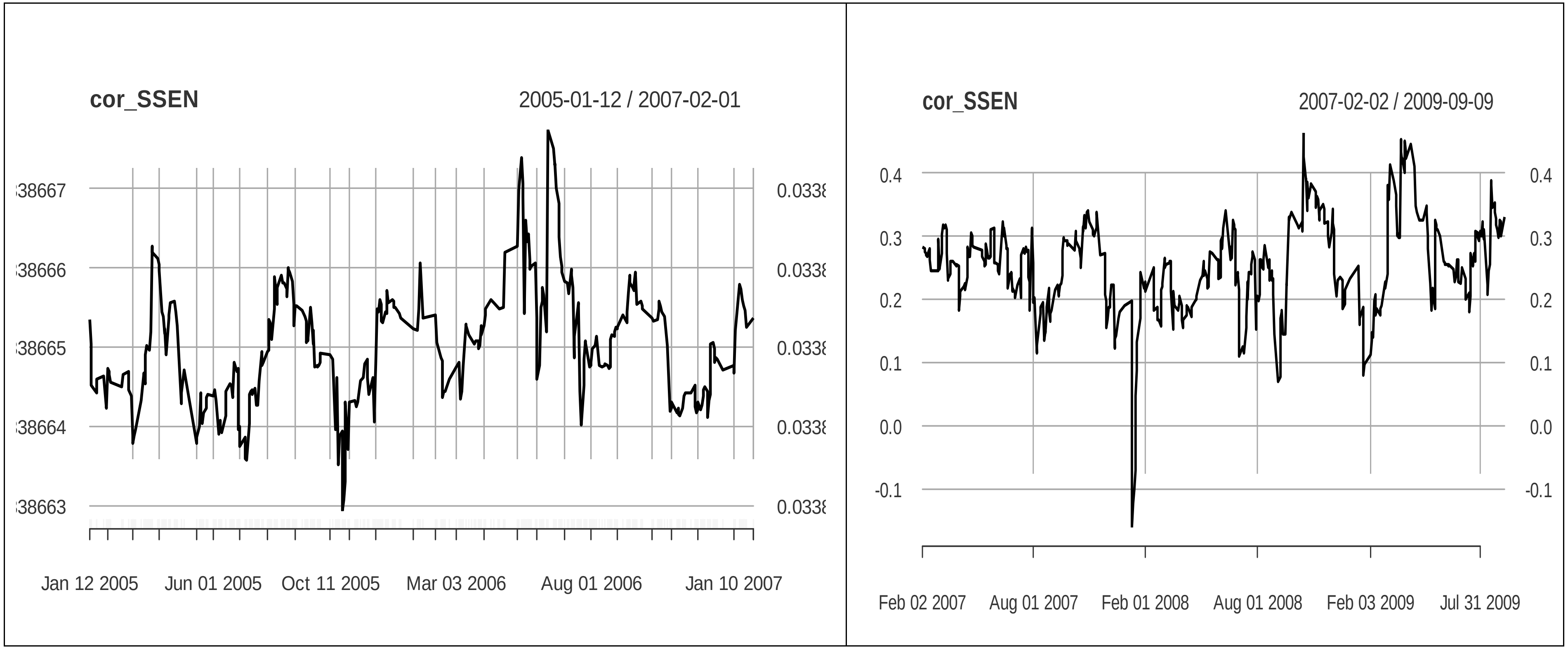

Figure 6-28: Estimated Conditional Correlation using DCC GARCH for ‘pre-crisis’ Period (left) and ‘crisis’ Period (right) between S&P500 (U.S.) and SENSEX (India).

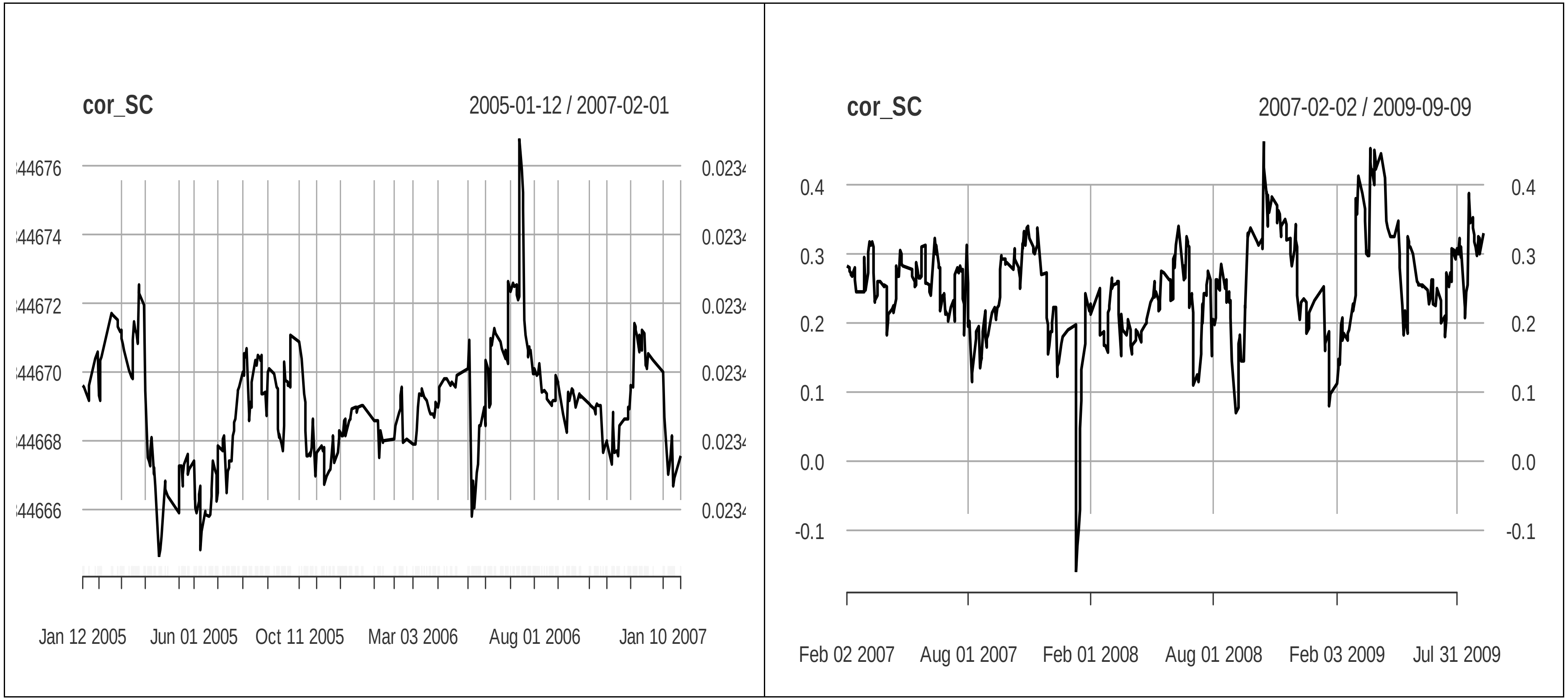

Figure 6-29: Estimated Conditional Correlation using DCC GARCH for 'Pre-crisis' Period (left) and 'Crisis' Period (right) between S&P500 (U.S.) and SSE (China).

6.4.2.2 ESTIMATIONS OF DCC GARCH MODEL FOR FINANCIAL CONTAGION FOLLOWING THE EUROZONE CRISIS

In order to examine financial contagion in BRICS stock markets following the Eurozone sovereign debt crisis in the Eurozone countries, the current study estimates coefficients for the mean (Equation 6.16), the variance (Equation 6.17) and correlation models (Equation 6.23) using the DCC GARCH model. The coefficient was estimated for both the 'crisis' and 'post-crisis' periods. The results for bivariate estimation between the DAX and individual BRICS stock market indices are presented in Table 6-16 through Table 6-20.

Table 6-16: Estimation Parameters of Mean, Variance, and Correlation Models of Contagion with the Eurozone Countries as Source Country and Brazil as Target Country.

	Parameter	crisis			Post-crisis		
		Estimate	SE	P-value	Estimate	SE	P-value
DAX	α_0	**0.103449**	0.055202	0.060928	0.043241	0.036482	0.235910
	α_1	**0.118185**	0.041146	0.004074	**0.120033**	0.051285	0.019258
	β_1	**0.830373**	0.055211	0.000000	**0.857878**	0.063436	0.000000
BOVESPA	α_0	**0.302310**	0.134154	0.024230	**0.100942**	0.044255	0.022551
	α_1	**0.138640**	0.053052	008968	**0.069881**	0.017837	0.000089
	β_1	**0.719771**	0.093178	0.000000	**0.887347**	0.029099	0.000000
	θ_1	0.007570	0.009694	0.434855	0.023470	0.020304	0.247730
	θ_2	**0.963034**	0.044093	0.000000	**0.809986**	0.075054	0.000000
ρ_{ij} [corr(DAX,BOVESPA)]				0.5760211	ρ_{ij} [corr(DAX,BOVESPA)]		0.3483692
Maximized Log-likelihood				-1961.107	Maximized Log-likelihood		-2374.321

Source: Estimation.

Table 6-17: Estimation Parameters of Mean, Variance, and Correlation Models of Contagion with the Eurozone Countries as Source Country and South Africa as Target Country.

	Parameter	Pre-crisis			crisis		
		Estimate	SE	P-value	Estimate	SE	P-value
DAX	α_0	**0.103449**	0.055671	0.063139	0.043241	0.036419	0.235103
	α_1	**0.118185**	0.041526	0.004426	**0.120033**	0.051302	0.019298
	β_1	**0.830373**	0.055782	0.000000	**0.857878**	0.063353	0.000000
FTSE/JSE	α_0	**0.053062**	0.026005	0.041308	**0.065181**	0.024784	0.008540
	α_1	**0.133186**	0.033212	0.000061	**0.120050**	0.032494	0.000220
	β_1	**0.818599**	0.042404	0.000000	**0.815082**	0.045588	0.000000
	θ_1	0.022089	0.021456	0.303233	**0.018138**	2.63951	0.008303
	θ_2	**0.657200**	0.162710	0.000054	**0.886743**	0.059042	0.000000
ρ_{ij} [corr(DAX,FTSE/JSE)]				0.708764	ρ_{ij} [corr(DAX,FTSE/JSE)]		0.6070643
Maximized Log-likelihood				-1651.724	Maximized Log-likelihood		-1941.868

Source: Estimation.

Table 6-18: Estimation Parameters of Mean, Variance, and Correlation Models of Contagion with the Eurozone Countries as Source Country and Russia as Target Country.

	Parameter	Pre-crisis			crisis		
		Estimate	SE	P-value	Estimate	SE	P-value
DAX	α_0	**0.103449**	0.055206	0.060948	0.043241	0.036727	0.239050
	α_1	**0.118185**	0.041843	0.004736	**0.120033**	0.051705	0.020261
	β_1	**0.830373**	0.055553	0.000000	**0.857878**	0.06390	0.000000
RTS	α_0	**0.181433**	0.181433	0.079663	0.079575	0.042561	0.061526
	α_1	**0.102632**	0.039802	0.009921	**0.088485**	0.026527	0.000851
	β_1	**0.848464**	0.054126	0.000000	**0.888743**	0.031128	0.000000
	θ_1	0.015472	0.014282	0.278659	0.034820	0.018758	0.063407
	θ_2	**0.952225**	0.065886	0.000000	**0.955482**	0.034678	0.000000
ρ_{ij} [corr(DAX,RTS)]				0.6441123	ρ_{ij} [corr(DAX,RTS)]		0.5007368
Maximized Log-likelihood				-2061.619	Maximized Log-likelihood		-2415.707

Source: Estimation.

Table 6-19: Estimation Parameters of Mean, Variance, and Correlation Models of Contagion with the Eurozone Countries as Source Country and India as Target Country.

	Parameter	Pre-crisis			crisis		
		Estimate	SE	P-value	Estimate	SE	P-value
DAX	α_0	0.103449	0.055092	0.060415	0.043241	0.036404	0.234914
	α_1	**0.118185**	0.040964	0.003913	**0.120033**	0.051374	0.019468
	β_1	**0.830373**	0.055130	0.000000	**0.857878**	0.063402	0.000000
SENSEX	α_0	0.030209	0.020288	0.136496	0.000851	0.005084	0.867025
	α_1	**0.060615**	0.018185	0.000858	0.000000	0.005018	0.999784
	β_1	**0.918141**	0.023983	0.000000	**0.999000**	0.000051	0.000000
	θ_1	0.024007	0.014774	0.104172	**0.018252**	0.007535	0.015429
	θ_2	**0.942609**	0.030984	0.000000	**0.966795**	0.014594	0.000000
ρ_{ij} [corr(DAX,SENSEX)]				0.3779123	ρ_{ij} [corr(DAX,SENSEX)]		0.4335689
Maximized Log-likelihood				-1915.086	Maximized Log-likelihood		-2043.774

Source: Estimation.

Table 6-20: Estimation Parameters of Mean, Variance, and Correlation Models of Contagion with the Eurozone Countries as the Source and China as Target Country.

	Parameter	Pre-crisis			crisis		
		Estimate	SE	P-value	Estimate	SE	P-value
DAX	α_0	0.103449	0.055289	0.061339	0.043241	0.036473	0.235793
	α_1	**0.118185**	0.041191	0.004115	**0.120033**	0.051445	0.019638
	β_1	**0.830373**	0.055243	0.000000	**0.857878**	0.063521	0.000000
SSE	α_0	0.040161	0.025166	0.110527	0.011841	0.015153	0.434542
	α_1	**0.046338**	0.017495	0.008083	**0.083509**	0.035720	0.019395
	β_1	**0.932619**	0.021889	0.000000	**0.915491**	0.037649	0.000000
	θ_1	0.000000	0.000009	0.999784	0.007978	0.026099	0.759836
	θ_2	**0.914852**	0.087708	0.000000	**0.735407**	0.303205	0.015290
ρ_{ij} [corr(DAX,SSE)]				0.1797751	ρ_{ij} [corr(DAX,SSE)]		0.1333193
Maximized Log-likelihood				-2052.647	Maximized Log-likelihood		-2339.518

Source: Estimation.

Tables 6-16 to 6-20 present a summary of the DCC model parameter estimates for both the 'crisis' and the 'post-crisis' periods. Each table presents source-target pairs consisting of the DAX composite index as a proxy of the Eurozone (continental Europe) stock markets, and individual indices from BRICS stock markets. Most of the parameter estimates for univariate GARCH (1,1), as represented in the diagonal elements of D_t in equation 6.18 and 6.21, appear to be significantly different from zero at the 10% level of significance. This means that, following the sovereign debt crisis in the Eurozone countries, equity markets in BRICS countries reacted equally to shock emanating from European equity market, in both the ‘crisis’ and ‘post-crisis’ periods.

The significant coefficient α_1 for most stock markets (except China) are indicating the persistence of volatility, which suggests possible transmissions of volatility from the European stock markets. The coefficient β_1 is also significant in most markets and indicates a large asymmetric impact, implying that BRICS stock markets are reacting to different sources of information from different markets and consequently adapting their portfolio. The DCC-GARCH (1,1) parameters θ_1 and θ_2 are presented in Tables 6-28 through 6-32; they measure the impact of past standardised shocks (θ_1) and lagged dynamic conditional correlations (θ_2) on the current dynamic conditional correlations. The tables suggest that only θ_2 is significant in most BRICS equity markets, implying that it is the only one that has significant effects (except for China). Joint significance parameters θ_1 and θ_2 are only found in the Indian and the South African stock markets in the ‘post-crisis’ period. This means that the DCC model is adequate in these two countries’ stock markets. It is worth noting that, unlike the case of the sub-prime crisis, there are no significant differences between the mean value of the conditional correlation coefficient (ρ) in the ‘crisis’ period compared to the ‘post-crisis’ period.

A plot of the estimated conditional correlations by the DCC model is presented in Figures 5-54 through 5-58. The general impression of the conditional correlations is that there are no significant differences during the ‘crisis’ period as compared to the ‘post-crisis’ period. This means that BRICS countries were insulated from the adverse effects of the Eurozone sovereign debt crisis that took place in Europe. These results differ with Gencer and Demiralay (2016) who surveyed financial contagion in the emerging markets during the European sovereign debt crisis and the global financial crisis at the aggregate and disaggregate level and found that the emerging equity markets were more integrated with the U.S. than with Europe. However, they noted that contagion incidences took place only during the European sovereign debt crisis.

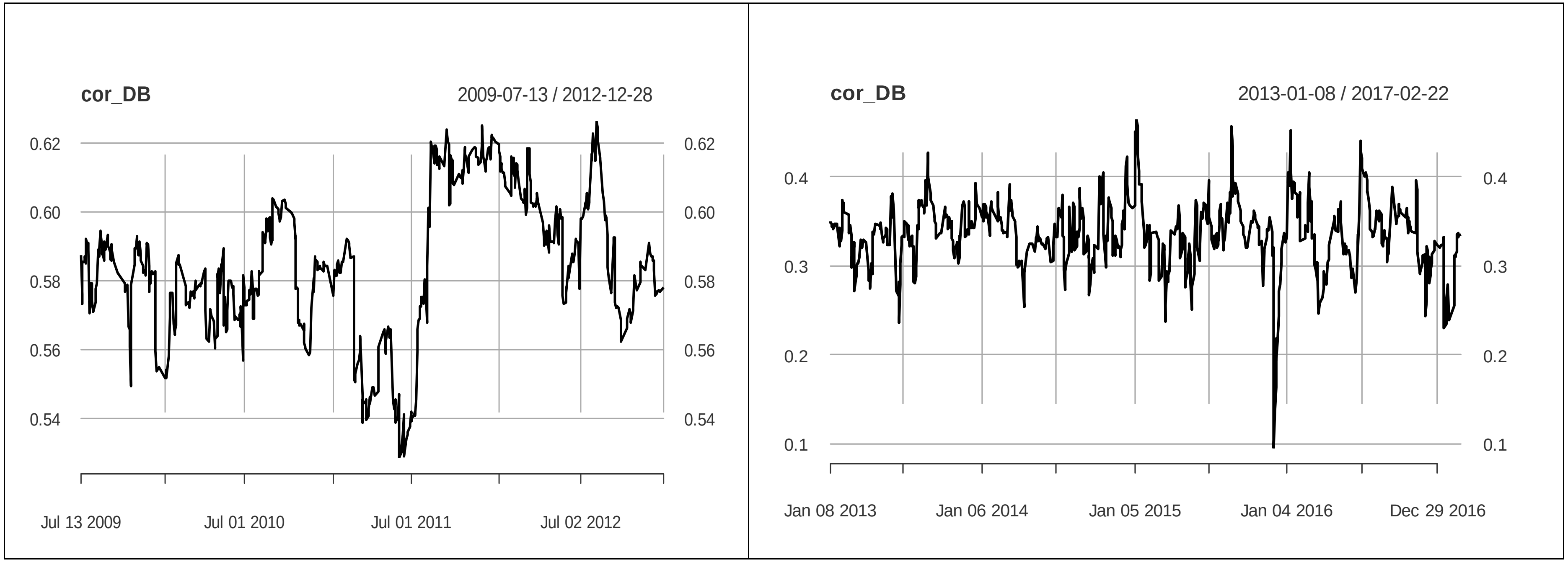

Figure 6-30: Estimated Conditional Correlation using DCC GARCH for ‘Crisis’ Period (left) and ‘Post-crisis’ Period (right) between DAX (Eurozone) and BOVESPA (Brazil).

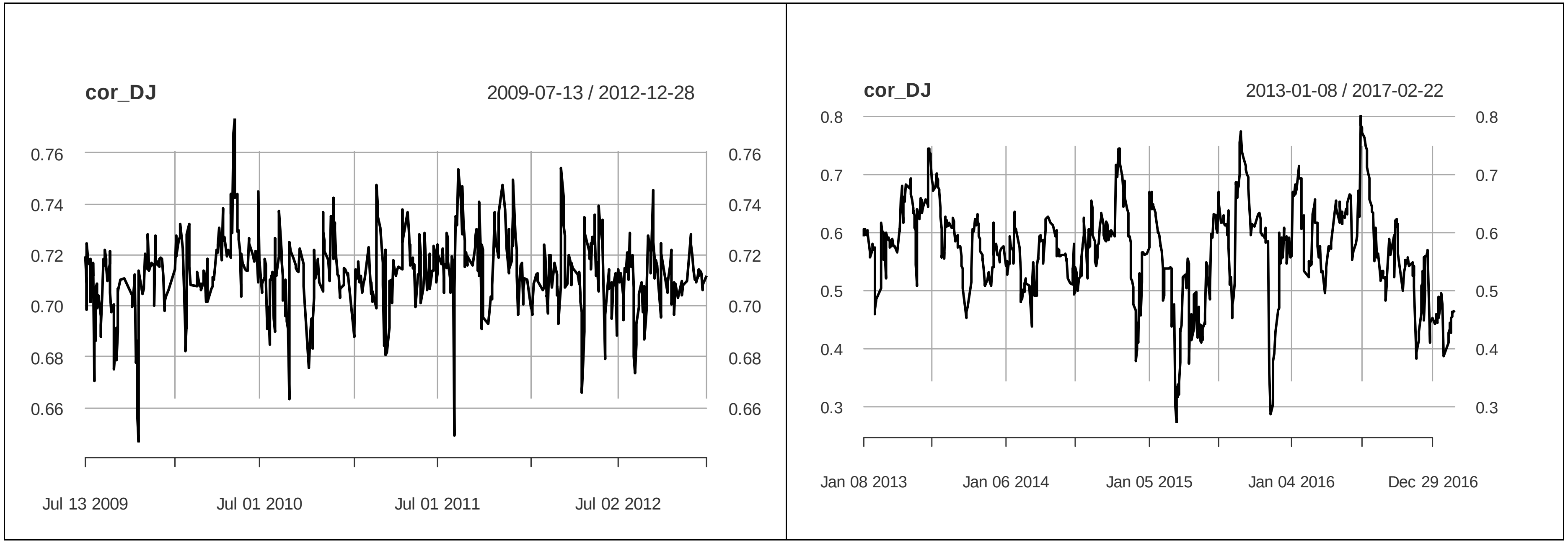

Figure 6-31: Estimated Conditional Correlation using DCC GARCH for 'Crisis' Period (left) and 'Post-crisis' Period (right) between DAX (Eurozone) and FTSE/JSE (South Africa).

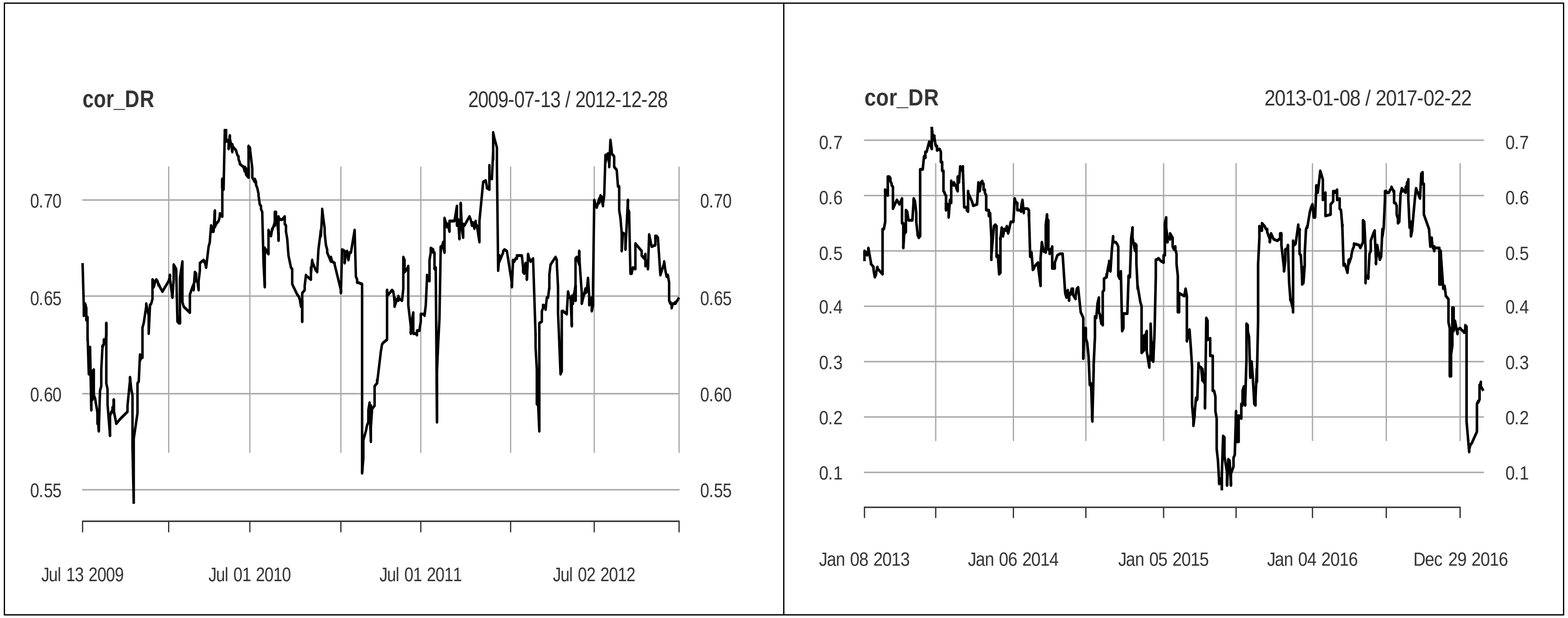

Figure 6-32: Estimated Conditional Correlation using DCC GARCH for ‘Crisis’ Period (left) and ‘Post-crisis’ Period (right) between DAX (Eurozone) and RTS (Russia).

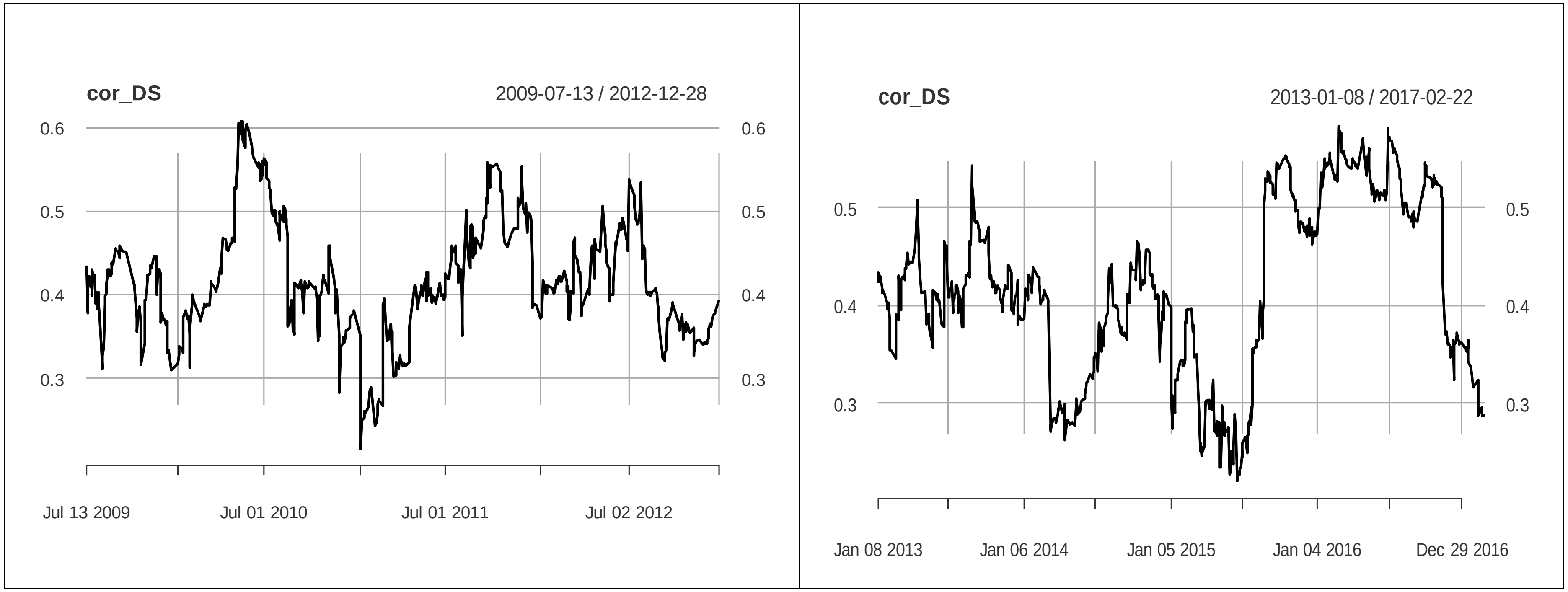

Figure 6-33: Estimated Conditional Correlation using DCC GARCH for 'Crisis' Period (left) and 'Post-crisis' Period (right) between DAX (Eurozone) and SENSEX (India).

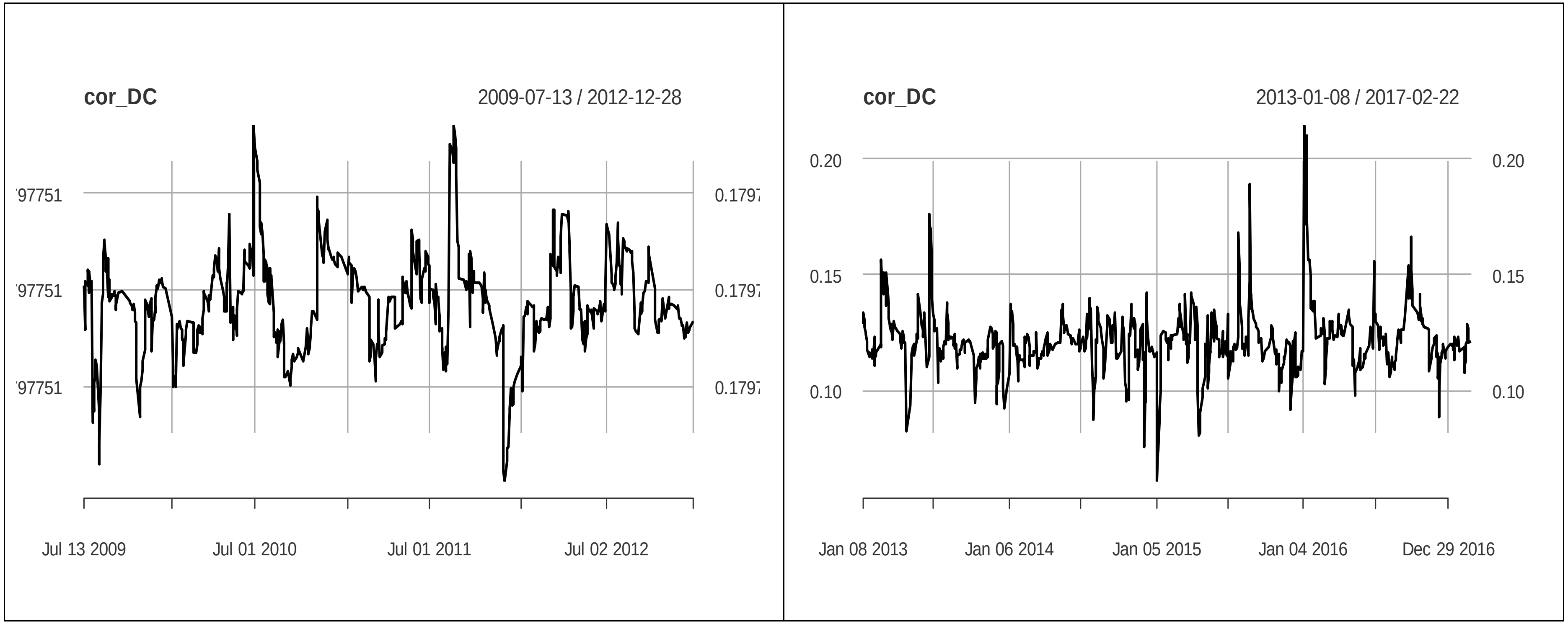

Figure 6-34: Estimated Conditional Correlation using DCC GARCH for ‘Crisis’ Period (left) and ‘Post-crisis’ Period (right) between DAX (Eurozone) and SSE(China).

6.4.2.3 Diagnostic Test for DCC GARCH Models

Once the model had been fitted the adequacy of the model was investigated using the standardised residuals of the fitted model. To test for serial correlation the present study used the univariate Ljung-Box test on each of the BRICS market return's standardised residuals. A summary table of the Ljung-Box statistic is presented in Table 6-21. From the Table it can be seen that the null hypothesis of no serial correlation is accepted since all the p-values are > 0.05. Hence the conclusion that the DCC GARCH model is adequate, as it removed serial correlation.

Table 6-21: Summary Table for the DCC Model Diagnostics under the Ljung-Box Test

		Sub-prime crisis		Eurozone sovereign debt crisis	
		Pre -crisis	crisis	crisis	Post- crisis
S&P500	Q statistic	0.012853	1.5144	—	—
	P-value	0.9097	0.2185	—	—
DAX	Q statistic	—	—	0.49813	0.046066
	P-value	—	—	0.4803	0.8301
BOVEPA	Q statistic	0.31599	0.25192	0.52054	0.036344
	P-value	0.574	0.6157	0.4706	0.8488
FTSE/JSE	Q statistic	2.1996	0.041909	0.0026452	0.12791
	P-value	0.138	0.8378	0.959	0.7206
RTS	Q statistic	0.13508	0.18682	0.23033	0.036344
	P-value	0.7132	0.6656	0.6313	0.8488
SENSEX	Q statistic	0.012853	0.24291	0.090002	0.00084586
	P-value	0.9097	0.6221	0.7642	0.9768
SSE	Q statistic	0.0013051	0.029202	0.23067	2.7207
	P-value	0.9712	0.8643	0.631	0.09905

Source: Estimation.

6.5 CHAPTER SUMMARY

This chapter presented a discussion on the use of multivariate GARCH models to examine the volatility spillover in BRICS countries in the wake of the U.S. sub-prime and the Eurozone sovereign debt crises. For each crisis the data were divided into two periods, (i) the turbulent period and (ii) the stable period.

Students' t-distribution Bivariate GARCH models were utilised to examine the dynamic cross-correlation between the U.S. and Eurozone as source markets and individual BRICS stock markets as target markets. In this regard, bivariate Diagonal VECH GARCH and DCC GARCH models were used to estimate the volatility and correlations of the BRICS returns. It was found that for both models there was a presence of cross-conditional volatility. The results also showed that the cross-conditional volatility coefficient is high in magnitude during periods of financial upheaval compared to a tranquil period, hence the conclusion that there was financial contagion during the U.S. sub-prime crisis (except in China).

As for the sovereign debt crisis in the Eurozone countries, equity markets in BRICS countries seemed to react equally (in both the 'crisis' and 'post-crisis' periods) from shocks emanating from European equity market. Hence the conclusion that there was no contagion in BRICS countries following the Eurozone sovereign debt crisis.

Diagnostic tests were carried out on the GARCH models to check for the adequacy of the models. The results of the tests showed that the bivariate GARCH models were sufficient for estimating the volatility and conditional correlations of the BRICS returns.

CHAPTER SEVEN

MULTI-TIMESCALE ANALYSIS FOR FINANCIAL CONTAGION IN BRICS EQUITY MARKETS DURING FINANCIAL CRISES

This chapter achieves Objective Four (*To investigate the presence of time-frequency correlations in BRICS stock markets, following the financial crises that took place in the U.S. and Eurozone countries*). The chapter uses the time-frequency decomposition of the wavelet approach to investigate lead and lag dynamics in BRICS stock markets. The analysis is conducted in the wake of recent financial crises emanating from the advanced market from the U.S. and Eurozone countries.

A better appreciation of time-frequency decomposition of return series within BRICS stock markets is crucial to efficient portfolio diversification. Furthermore, an understanding of lead-lag dynamic offers more insights to policymakers for potential decoupling or coupling strategies to protect the BRICS markets from the contagious effects emanating from developed markets (Fernández-Macho, 2012). The current chapter is divided into five sections. It begins with a contextual background on the wavelet approach to test contagion. Section two presents the main empirical models and the estimation methodology used. Section three analyses and discusses the time series data used in this chapter, covering descriptive statistics and preliminary analysis of data. The empirical results obtained from the analysis are presented in section four. The chapter concludes with a summary.

7.1 CONTEXTUAL BACKGROUND

The idea of multi-scale features is a familiar concept in financial time series. This is because there are several structures in any given time series, with each occurring on a different time scale. Wavelet techniques have the perceived ability to break down time series into several sub-series that may be associated with a specific time scale. By decomposing time series on different scales, one may expect to obtain a better understanding of the data (Fernández-Macho, 2012). And as Ranta (2010:2) maintains this allow a research to" picks up the best of both worlds, introducing an intelligent compromise between time and frequency analysis".

Unlike the Fourier methods which are hindered by the need for stationarity, wavelets often function naturally in the context of non-stationary time series. The maximal overlap discrete wavelet transform (MODWT) formulated by Percival and Walden (2000) is one of the wavelet methods commonly used in economics and finance. The MODWT is a modification of the ordinary discrete wavelet transform. Despite the fact that this transformation is non-orthogonal[25] the MODWT has appropriate attributes such as smoothness and the ability to analyse non-dyadic processes[26] that are important in econometric analysis.

As mentioned above, the popularity of wavelet models in economics and finance stems from the fact that the models can decompose processes on different time scales, but still preserve time. The decomposition process provides an efficient way to detect changes over time while maintaining randomness. This locality property and the ability to stationarise data make wavelets a suitable model for examining stochastic non-stationary processes in econometrics.

7.2 METHODOLOGY[27]

The wavelet variance estimators, wavelet correlation, wavelet cross-correlation and wavelet coherence analysis are discussed in this section.

7.2.1 WAVELET MODELS

The true dynamic structure of the relationship between variables varies over different time scales. However, most econometric models focus on a two-scale analysis — short-run and long-run. This is mainly due to a paucity of empirical tools. Of late, wavelet analysis has attracted attention in the fields of economics and finance as a means of filling this gap (In and Kim, 2013).

Wavelet analysis, according to Ranta (2010), decomposes variables into sub-time series. With these decompositions, researchers can capture both time series and frequency domain simultaneously. Thus, wavelet analysis provides the ability to observe the multi-horizon nature of co-movement, volatility and lead-lag relationships. For these reasons, wavelet analysis can

[25] Orthogonality means “uncorrelated.” An orthogonal model means that all independent variables in that model are uncorrelated. If one or more independent variables are correlated, then that model is non-orthogonal.
[26] A dyadic process is one that is a multiples of two.
[27] This section relies heavily on Ranta (2010).

be perceived as a kind of "lens" that enables researchers to take a close- up look at the details and draw a holistic image at the same time (Hashim and Masih, 2015).

Wavelet models are appropriate for the current study because not only do they allow the conducting of a lead/lag analysis[28], but they also enable the chronological specifications of variables to be examined, especially decomposition into sub-time series and the localisation of the interdependence between time series (Hashim and Masih, 2015).

Wavelet analysis entails estimating an initial series onto a sequence of two basic functions, known as wavelets. The two basic functions are the father wavelet (also known as the scaling function), φ, and the mother wavelet (known as thewavelet function), ψ. The mother wavelet can be scaled and translated to form the basis for the Hilbert space L^2 ($\mathbb{R}$) of square-integrable functions.

The following functions can define the father and mother wavelets:

$$\phi_{j,k}(t) = 2^{\frac{j}{2}}\phi\left(2^{j}t - k\right) \quad \text{...(7.1)}$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi\left(2^{j}t - k\right) \quad \text{...(7.2)}$$

where j = 1, ..., J is the scaling parameter in a J-level decomposition, and k is a translation parameter ($j,k \in \mathbb{Z}$). The long-run trend of the time series is depicted by the father wavelet, which integrates to 1. The mother wavelet, which integrates to 0, expresses fluctuations from the trend.

7.2.2 THE MAXIMAL OVERLAP DISCRETE WAVELET TRANSFORM (MODWT)

According to Abdullah, Saiti, and Masih (2016), both the Discrete Wavelet Transform (DWT) and the Maximal Overlap Discrete Wavelet Transform (MODWT) can decompose the sample

[28] It should be drawn to the reader's attention that while interpreting the result of wavelet phase-difference in the field of finance and economics, the leading role of one market over another market does not necessarily imply that there is a specific causality between the two. We should interpret with caution that the two markets, in fact, co-move with one market taking a leading role over another (Dewandaru, Masih, and Masih, 2018).

variance of a time series. However, the MODWT gives up the orthogonality property of the DWT to gain other features. Hashim and Masih (2015) highlight the advantages of MODWT over DWT as follows: (i) the MODWT can handle any sample size regardless of whether or not the series is dyadic (that is of size 2^{J0}, where $J0$ is a positive integer number); (ii) it offers increased resolution at higher scales as the MODWT oversamples the data; (iii) translation-invariance ensures that MODWT wavelet coefficients do not change if the time series is shifted in a 'circular' fashion; (iv) the MODWT produces a more asymptotically efficient wavelet variance than the DWT. The MODWT was chosen for the current study.

The MODWT estimator of the wavelet correlation is specified as follows:

$$\rho_{xy}(\lambda_j) = \mathrm{Corr}(\omega_{ijt}, \widetilde{\omega}_{ijt}) = \frac{\mathrm{Cov}(\omega_{ijt}, \widetilde{\omega}_{ijt})}{\sqrt{\mathrm{Var}(\omega_{ijt})\mathrm{Var}(\widetilde{\omega}_{ijt})}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. (7.3)$$

where ω_{ijt}represents the scale of the wavelet coefficientλ_j obtained by applying MODWT. The decomposition of the time series using MODWT is done with Daubechies least asymmetric (LA) wavelet filter of length 8.

7.2.3 WAVELET VARIANCE AND WAVELET CORRELATION

The MODWT can break down a sample variance of a series on a scale-by-scale basis since MODWT is energy conserving.

$$\|X^2\| = \sum_{j=1}^{j_o} \|\widetilde{W}_j\|^2 + \|\tilde{V}_{j_o}\|^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. (7.4)$$

From equation 7.4 above a scale-dependent analysis of variance from the wavelet and scaling coefficients is derived as follows:

$$\tilde{\upsilon}_X^2 = \|X^2\| - \overline{X}^2 = \frac{1}{N}\sum_{j=1}^{j_o} \|\widetilde{W}_j\|^2 + \frac{1}{N}\|\tilde{V}_{j_o}\|^2 - \overline{X}^2 \quad \ldots\ldots\ldots\ldots .. (7.5)$$

Percival and Walden (2000) highlight that wavelet variance is defined for both stationary and non-stationary processes by letting $\{X_t: t = ..., -1, 0, 1, ... \}$ be a discrete parameter real-valued stochastic process whose d th-order differencing will give a stationary process

$$Y \equiv (1-B)^d X_t \equiv \sum_{k=0}^{d} \binom{d}{k} (-1)^k X_{t-k} \qquad \text{……………………………………………..(7.6)}$$

with spectral density function (SDF) $S_Y(.)$ and mean μ_Y. Let $S_X(.)$denote the SDF for $\{X_t\}$, for which $S_X(f) = S_Y(f)/D^d(f)$, where $D(f) \equiv 4sin^2 (\pi f)$. Filtering $\{Xt\}$ with a MODWT Daubechies wavelet filter. $\{\tilde{h}_{j,l}\}$ of width $L \leq 2d$, a stationary process of *j*th-level MODWT wavelet is derived as follows:

$$\overline{W}_{j,t} \equiv \sum_{l=0}^{L_{j-1}} \tilde{h}_{(j,l)} X_{t-1}, \text{ t=...,-1,0,1...} \qquad \text{……………………………………………..(7.7)}$$

where $\overline{W}_{j,t}$ is a stochastic process achieved by filtering $\{X_t\}$ with the MODWT wavelet filter $\{\tilde{h}_{j,l}\}$ and $L_j \equiv (2^j - 1)(L-1) + 1$.

With a series which is the realisation of one segment (with values $X_0, ..., X_{N-1}$) of the process $\{X_t\}$. Under condition $M_j \equiv N - L_j + 1 > 0$ and that either $L > 2d$ or $\mu_x = 0$ (realisation of either of these two conditions implies $E\{\overline{W}_{j,t}\} = 0$and therefore $\upsilon_X^2(\tau_j) = E\{\overline{W}_{j,t}\}$), an unbiased estimator of wavelet variance of scale τ_j $\left(\upsilon_X^2(\tau_j)\right)$ is given by (Percival and Walden, 2000):

$$\hat{\upsilon}_X^2(\tau_j) = \frac{1}{M_j} \sum_{t=L,-1}^{N-1} \widetilde{W}_{j,t}^2 \qquad \text{……………………………………………..(7.8)}$$

where $\{\widetilde{W}_{j,t}\}$are the *j*th-level MODWT wavelet coefficients for time series

$$\left(\widetilde{W}_{j,t} \equiv \sum_{l=0}^{L_{j-1}} \tilde{h}_{(j,l)} X_{t-1 \text{ modN}}, \text{ t=0,1...,N-1}\right) \qquad \text{……………………………………………..(7.9)}$$

It can be proved that the asymptotic distribution of ˆ$\hat{\upsilon}_X^2(\tau_j)$ is Gaussian, which allows the formulation of confidence intervals for the estimate (Percival, 1995; Dajčman, 2013). Given two stationary processes $\{X_t\}$ and $\{Y_t\}$, whose *j*th-level MODWT wavelet coefficients are $\{\overline{W}_{X,j,t}\}$and $\{\overline{W}_{Y,j,t}\}$an unbiased covariance estimator $\hat{\upsilon}_{XY}(\tau_j)$ is specified by (Percival, 1995):

$$\hat{\upsilon}_{XY}(\tau_j) = \frac{1}{M_j}\sum_{t=L_j-1}^{N-1} \widetilde{W}_{j,t}^{(X)}\widetilde{W}_{j,t}^{(Y)} \qquad \text{……………………………………(7.10)}$$

$$= cov\{\overline{W}_{X,j,t}, \overline{W}_{Y,j,t}\}$$

with $M_j \equiv N - L_j + 1 > 0$ being the number of non-boundary coefficients at the jth-level. The MODWT correlation estimator for scale τj can be obtained by using the wavelet covariance and the square root of wavelet variances:

$$\hat{\rho}_{X,Y}(\tau_j) = \frac{\hat{\upsilon}_{X,Y}(\tau_j)}{\hat{\upsilon}_X(\tau_j)\hat{\upsilon}_Y(\tau_j)} \qquad \text{……………………………………..(7.11)}$$

where $|\hat{\rho}_{X,Y}(\tau_j)| \leq 1$. The wavelet correlation is analogous to its Fourier equivalent, the complex coherency (Gençay, Selçuk and Whitcher, 2003).

Computation of confidence intervals is based on Percival (1995) and Percival and Walden (2006), with the random interval

$$\left[tan\,h\left\{h[\rho_{\mathrm{XY}}(\tau_j)] - \frac{\Phi^{-1}(1-p)}{\sqrt{N_j - 3}}\right\}, tanh\left\{h[\rho_{\mathrm{XY}}(\tau_j)] + \frac{\Phi^{-1}(1-p)}{\sqrt{N_j - 3}}\right\}\right] \qquad \text{…..(7.12)}$$

capturing the right wavelet correlation and providing an approximate 100(1 – 2p)% confidence interval.

7.2.4 WAVELET CROSS-CORRELATION

Cross-correlation is a method in wavelet analysis which consists of estimating the degree to which two time series are correlated. The series can be shifted (either lag [π is then negative] or lead [π is then positive]) and then the correlation between the two-time series computed. Cross-correlation analysis allows us to identify which series return innovations are leading the other’s return innovations, with the latter time series considered as lagging. The size and significance of cross-correlation indicate whether the leading time series has predictive power for the lagging time series. Just as the usual time-domain cross-correlation is used to determine the lead/lag relationships between two time series, the wavelet cross-correlation will provide a lead/lag relationship on a scale-by-scale basis. The MODWT cross-correlation for scale τj at lag π is formulated as:

$$\rho_{\pi,XY}(\tau_j) = \frac{cov\left\{\overline{W}_{j,t}^{(X)}, \overline{W}_{j,t+\pi}^{(Y)}\right\}}{\left(var\left\{\overline{W}_{j,t}^{(X)}\right\} var\left\{\overline{W}_{j,t+\pi}^{(Y)}\right\}\right)^{\frac{1}{2}}} \quad \text{…………………………………………..(7.13)}$$

where $\overline{W}_{j,t}^{(X)}$ are the *j*th-level MODWT wavelet coefficients of time series $\{Xt\}$, at time *t*, and $\overline{W}_{j,t+\pi}^{(Y)}$ are the *j*th-level MODWT wavelet coefficients of time series $\{Yt\}$ lagged for π time units. Wavelet cross-correlation takes values, $-1 \leq \hat{\rho}_{\pi,XY}(\tau_j) \leq 1$, for all τ and j. This can be shown using Cauchy-Schwartz inequality.

7.2.5 WAVELET COHERENCE

The current study also uses a bivariate framework called wavelet coherence to examine the interaction between two time series, and how closely a linear transformation relates them. The wavelet coherence of two time series is specified as follows:

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{xy}(s)\right)\right|^2}{S(s^{-1}|W_n^x(s)|^2)S\left(s^{-1}\left|W_n^y(s)\right|^2\right)} \quad \text{..................................(7.14)}$$

where S is a smoothing operator, s is a wavelet scale, $W_n^x(s)$ is the continuous wavelet transform of the time series *X*, $W_n^y(s)$is the continuous wavelet transform of the time series *Y*, and $W_n^{xy}(s)$is a cross-wavelet transform of the two time series *X* and *Y* (Saiti, Bacha and Masih, 2016).

7.3 DATA

The data used in this chapter are similar to those used in Chapter Five, as they comprise daily closing stock price indices from BRICS, German and the United States stock markets spanning the period from 11th of January, 2005 to 26th of December, 2017 (providing 2, 443 daily observations for each market). The ‘target’ stock market indices examined are those in Brazil (São Paulo Stock Exchange/Bolsa de Valores de São Paulo index, BOVESPA), China (Shanghai Stock Exchange index, SSE), India (Bombay Stock exchange index, SENSEX), Russia (Moscow Exchange index, RTS) and South Africa (Johannesburg Stock Exchange All share index, FTSE/JSE. The daily stock price index of the United States, the S&P 500, and the

German DAX Composite indices are used as proxies for ‘source’ markets. Descriptive statistics for the data are similar to the ones presented in Chapter Five Table 5-1.

7.4 RESULTS OF WAVELET ANALYSIS

The results of the wavelet analysis used to investigate financial contagion in BRICS countries is divided into two sections. The first section uses wavelet approaches to analyse financial contagion in the wake of the sub-prime crisis while the second section uses a wavelet model to investigate financial contagion in the wake of the EZDC.

7.4.1 WAVELET ANALYSIS FOR THE SUB-PRIME CRISIS

In order to analyse financial contagion during the sub-prime crisis, a MODWT transformation was performed on a pair of the indices return series of the U.S. and individual BRICS stock markets. The MODWT used the Daubechies least asymmetric filter, with a wavelet filter length of 8(LA) to examine financial contagion in the wake of the sub-prime crisis. The maximum level of MODTW is 8($J_0 = 8$). The wavelet analysis was performed with eight scales that span from two- day to one-and-a-half year dyadic steps (2-4 days, 4-8 days, 8-16 days, 16-32 days, 32-64 days, 64-128 days, 128-256 days and 256-512 days). Scales are presented on the horizontal axis and correlations on the vertical axis. To analyse statistical significance, 95% confidence intervals are used.

It can be seen in Figures 7-1 to 7-5 that the wavelet correlations between the U.S. and BRICS stock markets are significantly positive except for the Chinese stock market. The correlations tend to increase as the scale increases. However, there is a sharp decrease on scale 7 (but for the Russian stock market the sharp decrease is recorded at scale 5); after that the correlation increases again, reaching values close to unity at scale 8. This implies that discrepancies between the pairwise equity markets (between individual BRICS countries and the U.S.), do not dissipate for less than a year. In other words, for the more extended period, the correlation between the U.S. and BRICS equity markets (except for the Chinese market) should not be ruled out. This can also be interpreted as perfect integration between the U.S. and BRICS equity markets, in the sense that the returns obtained in BRICS markets can be totally determined by the overall performance in the U.S markets at horizons longer than a year (Fernández-Macho, 2012).

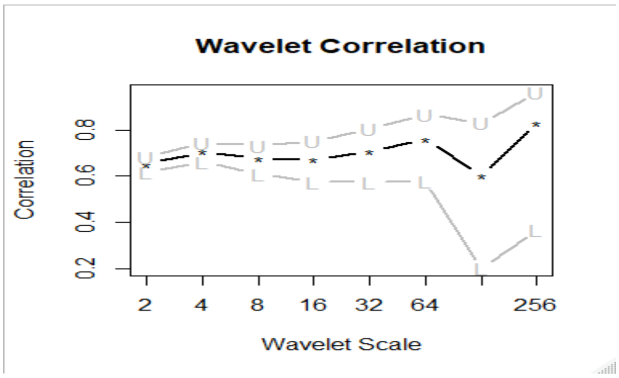

Figure 7-1: Correlation of S&P500 and BOVESPA at Different Time Scales

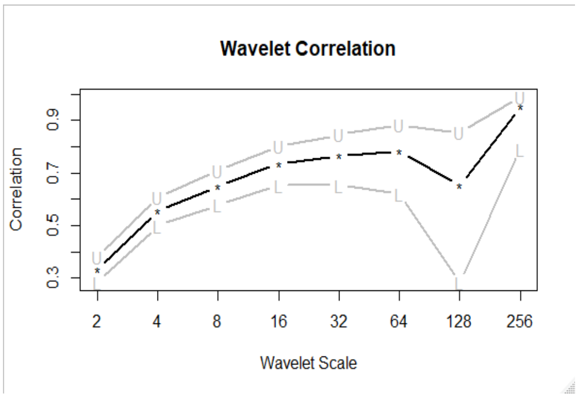

Figure 7-2: Correlation of S&P500 and FTSE/JSE at Different Time Scales

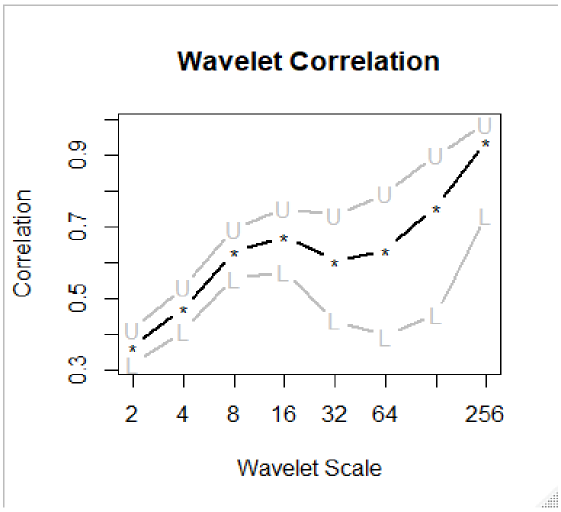

Figure 7-3: Correlation of S&P500 and RTS at Different Time Scales

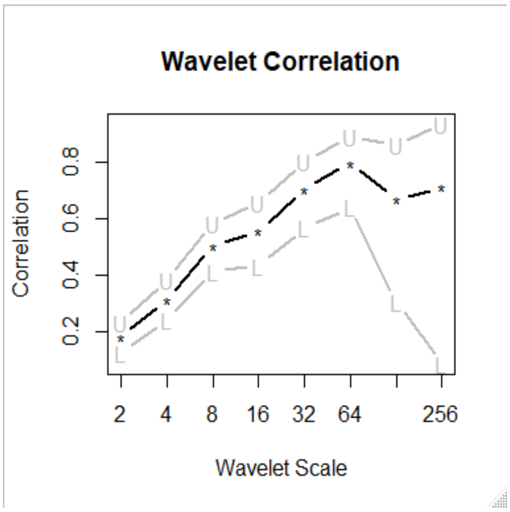

Figure 7-4: Correlation of S&P500 and SENSEX at Different Time Scales

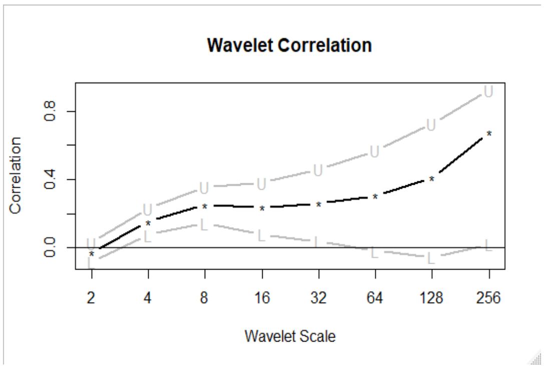

Figure 7-5: Correlation of S&P500 and SSE at Different Time Scales

The study also examined pairwise cross-correlations between the S&P500 and individual BRICS markets at all periods with the corresponding approximate confidence interval against lead time and lags for the different wavelet scales up to 33 days. The study thus calculates the cross-correlation of pairs of stocks market returns series first by lagging the second time series by 33-time units. The study then sequentially repeats the calculation of the cross-correlation for other time shifts (from 32-time units to the leads of 33-time units). If the curve is significant on the left, the first variable, i.e. S&P500, is leading. Conversely, if the curve is significant on the right side of the graph, the second variable, i.e. individual BRICS market, is leading. It can be seen from Figure 7-6 to 7-10 that at the shortest scales, i.e. scales 1 to 4, the cross-correlations around the time shift of $\pi = 9$ and $\pi = -9$ are significant and positive. It can also be seen that at the short scale the graphs are slightly skewed to the right, indicating that the S&P500 leads individual BRICS indices.

The coarse scales — particularly scales 5 and 6 — achieve the highest correlation at a time shift of $\pi = 30$ and $\pi = -30$ (with the Chinese equity market being an exception). It should also be noted that, in most instances, scales 5 and 6 have symmetrical distributions; hence, the study could not identify any lead/lag relationship at these time horizons. It can also be seen that scale 7 for most index-pairs has a significant negative wavelet cross-correlation on the right-hand side with implications that the individual BRICS markets lead the US market. As for scale 8, there is no clear evidence of a lead-lag relationship expect for India, where a significantly negative relationship is identified with the SENSEX leading the S&P500. Finally, the contemporaneous time scale correlation between the series indicates the presence an anti-correlation relationship.

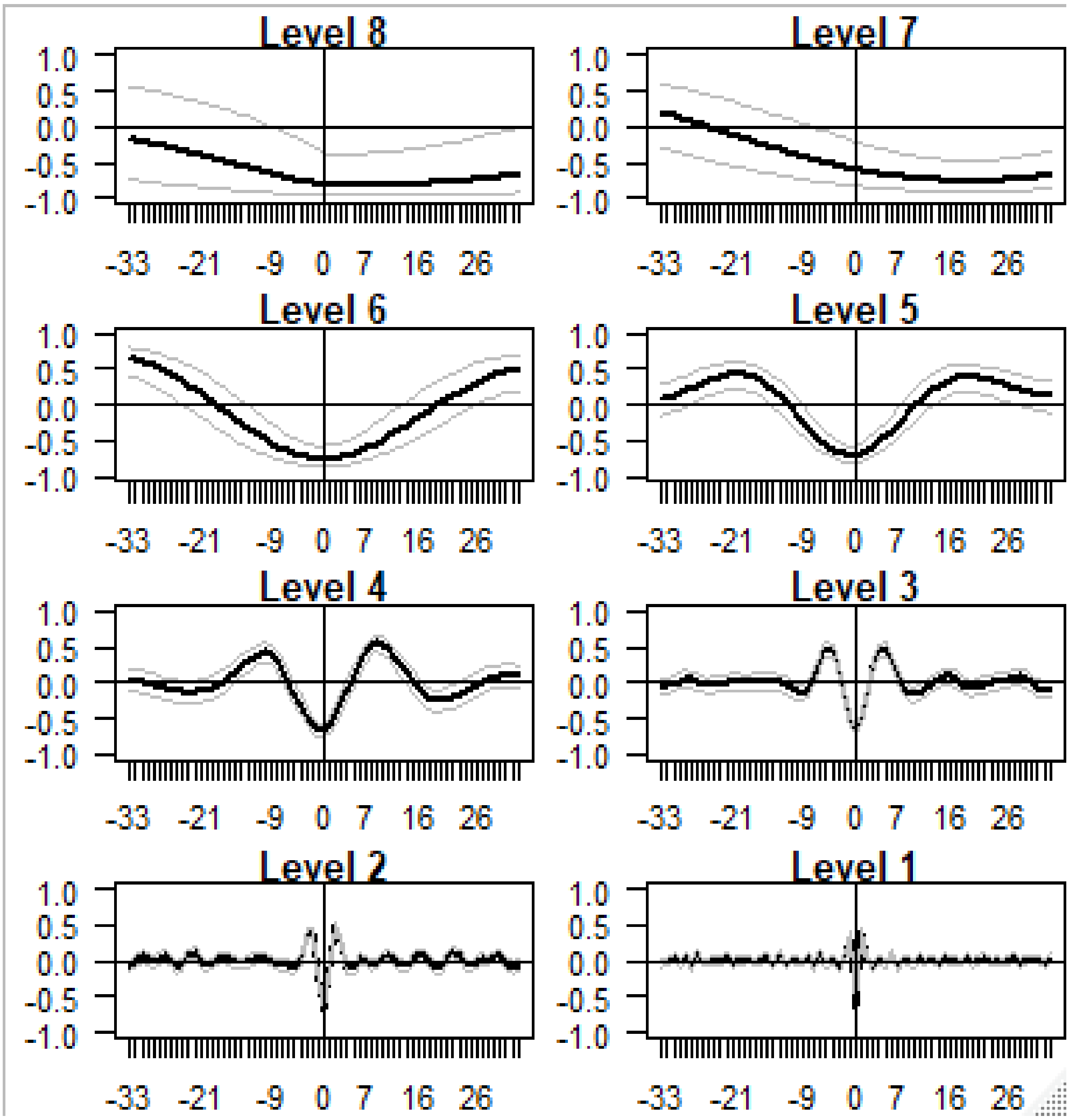

Figure 7-6: Cross-Correlation Between the Return Series of S&P 500 and BOVESPA

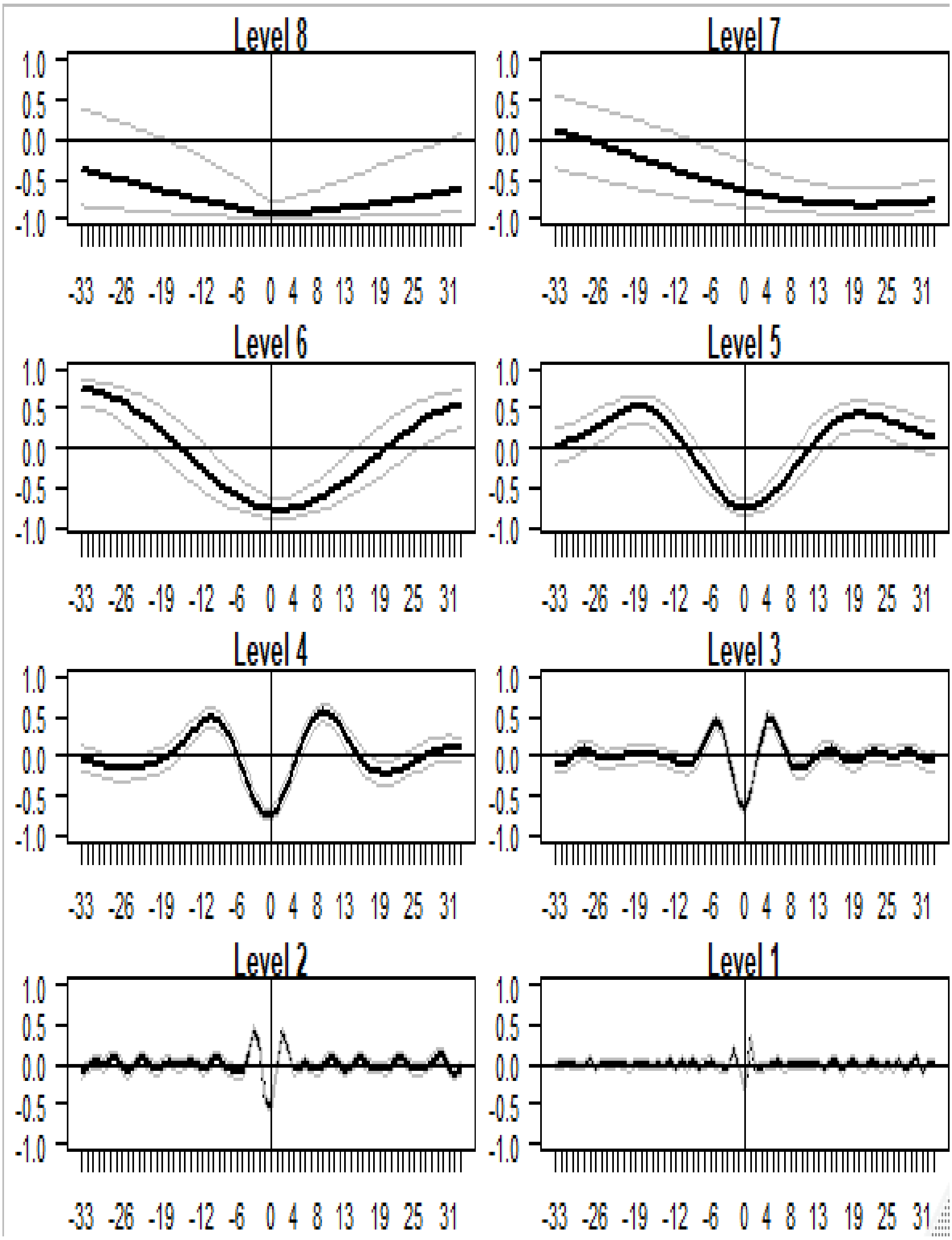

Figure 7-7: Cross-Correlation Between the Return Series of S&P 500 and FTSE/JSE.

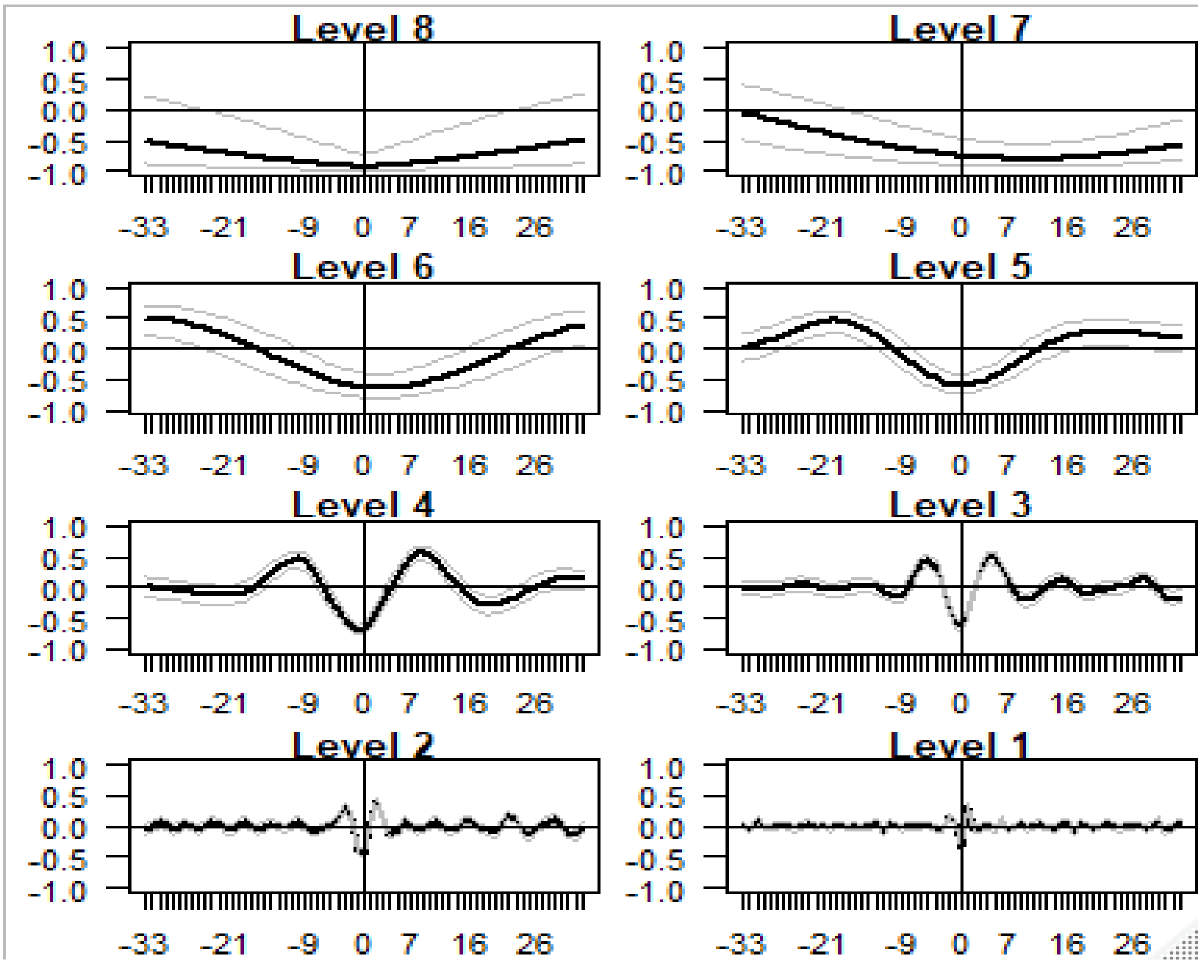

Figure 7-8: Cross-Correlation Between the Return Series of S&P 500 and RTS.

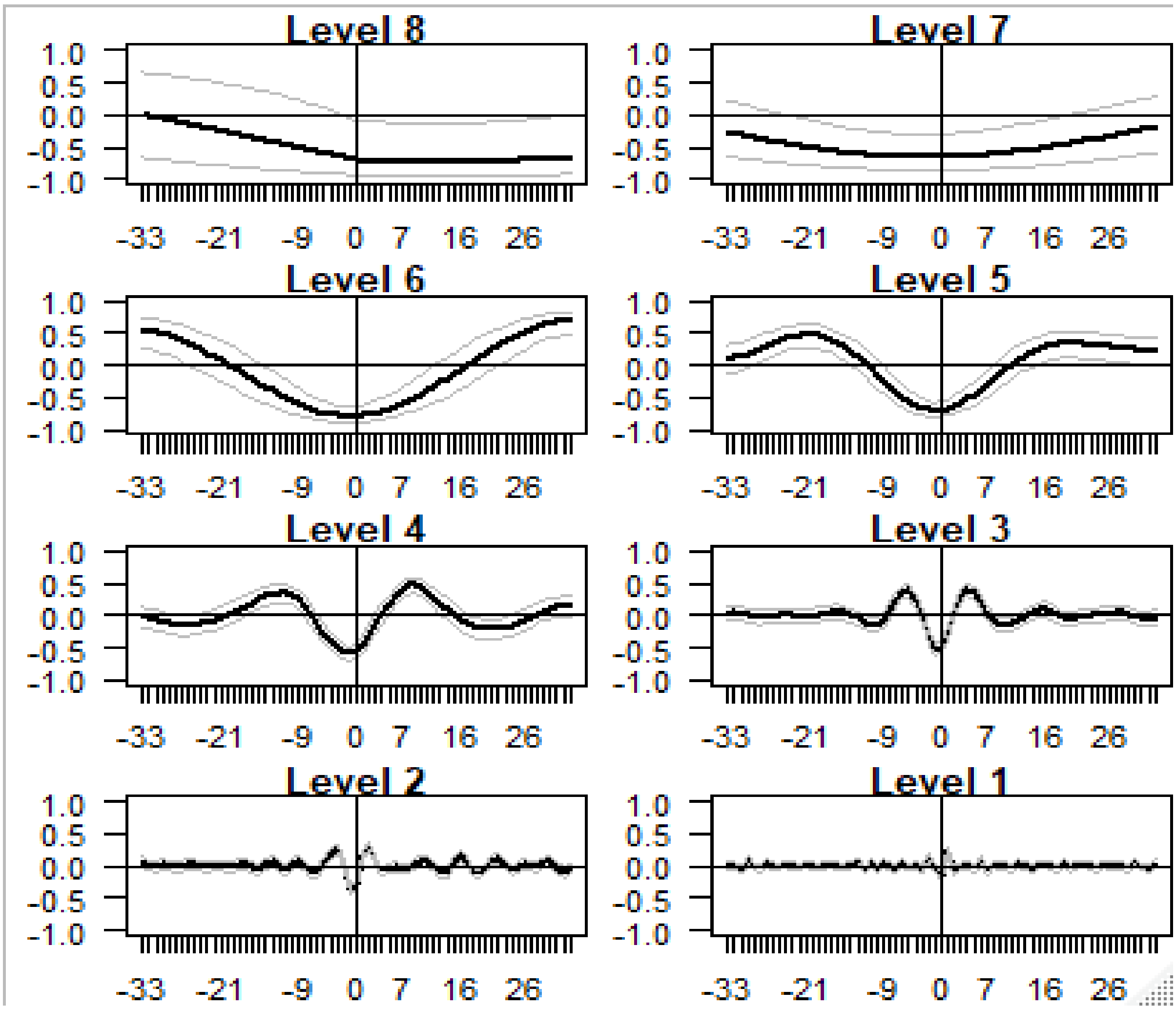

Figure 7-9: Cross-Correlation Between the Return Series of S&P 500 and SENSEX.

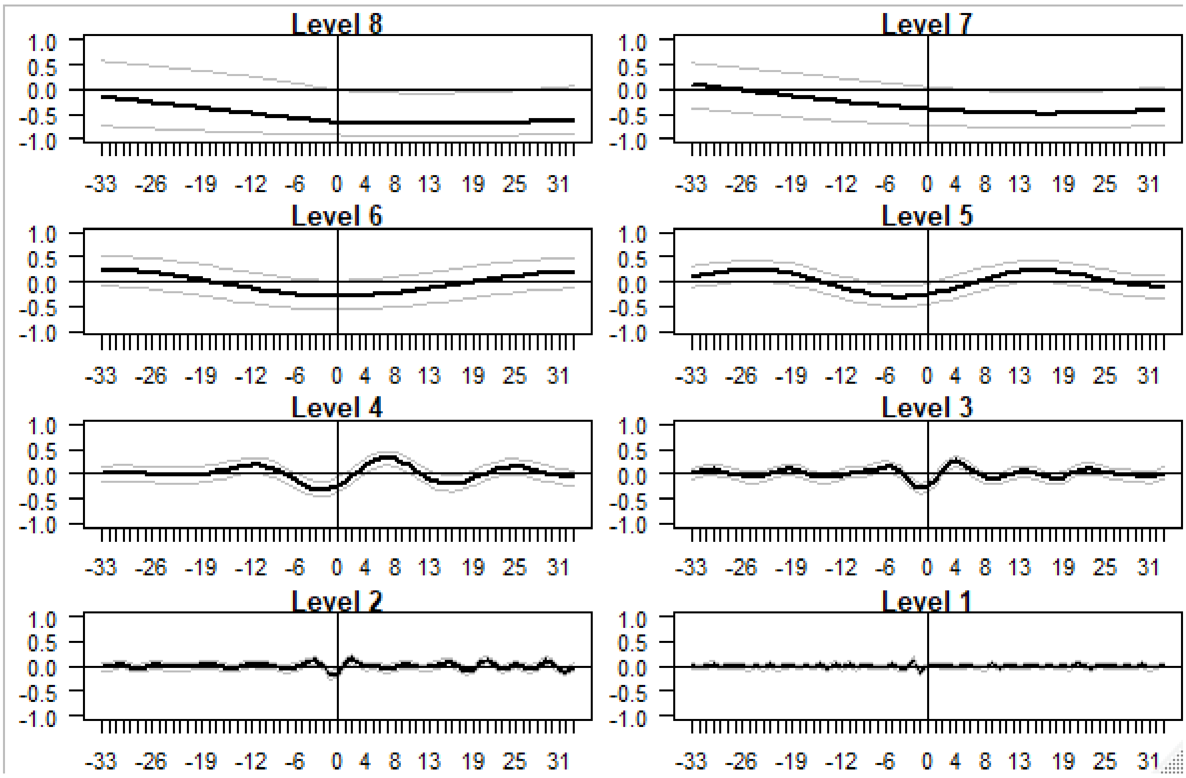

Figure 7-10: Cross-Correlation Between the Return Series of S&P 500 and SSE.

Figures 7-11 to 7-15 present the estimated cross wavelet coherence contour plots, from index-pairs between S&P 500 and individual BRICS equity markets. The values for the 5% significance level represented by the curved line are obtained from Monte Carlo simulations. The name of the variable presented first is the first series (i.e. S&P 500) while the other one is the second series (i.e. individual BRICS markets). In wavelet coherence mapping, time is displayed on the horizontal axis — which is converted to time units (daily) — whereas the vertical axis shows the frequency (the lower the frequency, the higher the scale). One should note that the vertical axis, in our case of financial time series, can be interpreted as a period in days or as the investment horizon in days. Therefore, the higher the frequency, the lower is the investment period. The current study can therefore distinguish different scales in the frequency domain as short-term investment horizon from (beginning up to 16), medium-term investment horizon (from 32 days up to one year) and long-term investment horizon (beyond one year).

In Figures 7-11 to 7-15 warmer colours (red) signify regions with major interrelation, while colder colours (blue) signify minor dependence between the series. Cold regions outside the significant areas represent time and frequencies with no dependence in the series. Arrows in the wavelet coherence plots represent the lead/lag phase relations between the observed series.

Arrows point to the right (left) when the time series are in-phase[29] (anti-phase). When the two series are in-phases it indicates that they move in a similar direction and anti-phase means that they move in the opposite direction. Arrows pointing to the right-down (South-East) or left-up (North-West), indicate that the first variable is leading, while arrows pointing to the right-up (North-East) or left-down (South-West) show that the second variable is leading.

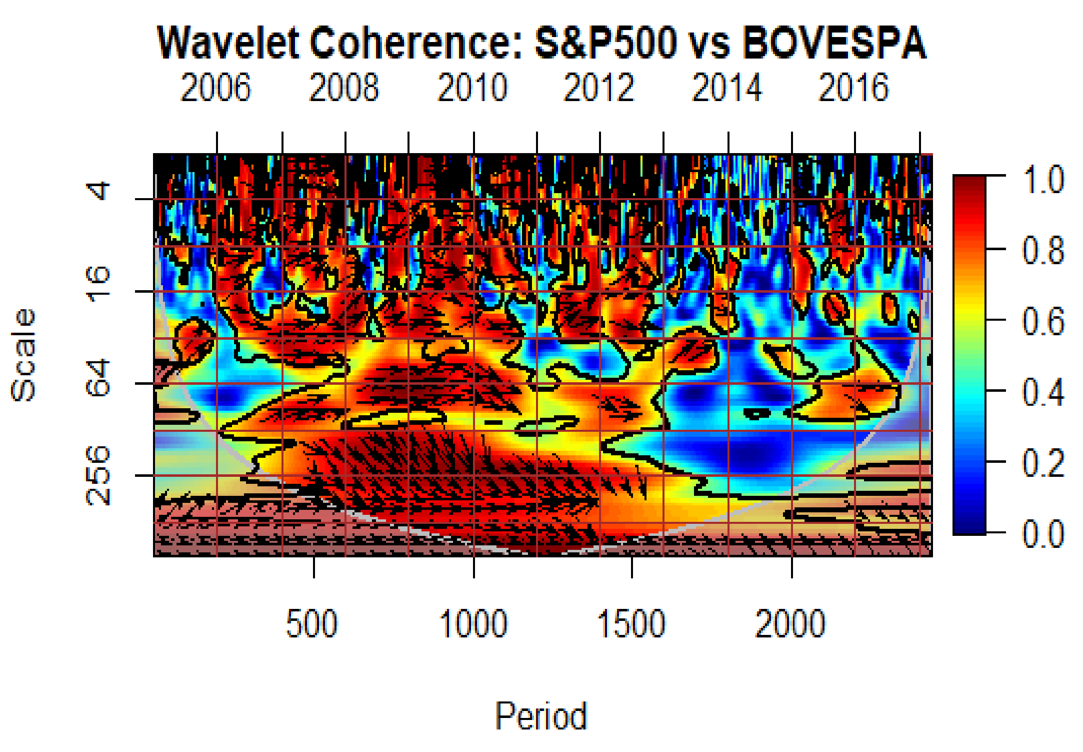

Figure 7-11: Wavelet Coherence Between the U.S. and Brazilian Stock Markets.

[29] The in-phase and anti-phase phenomena depicts positive and negative co-movements respectively.

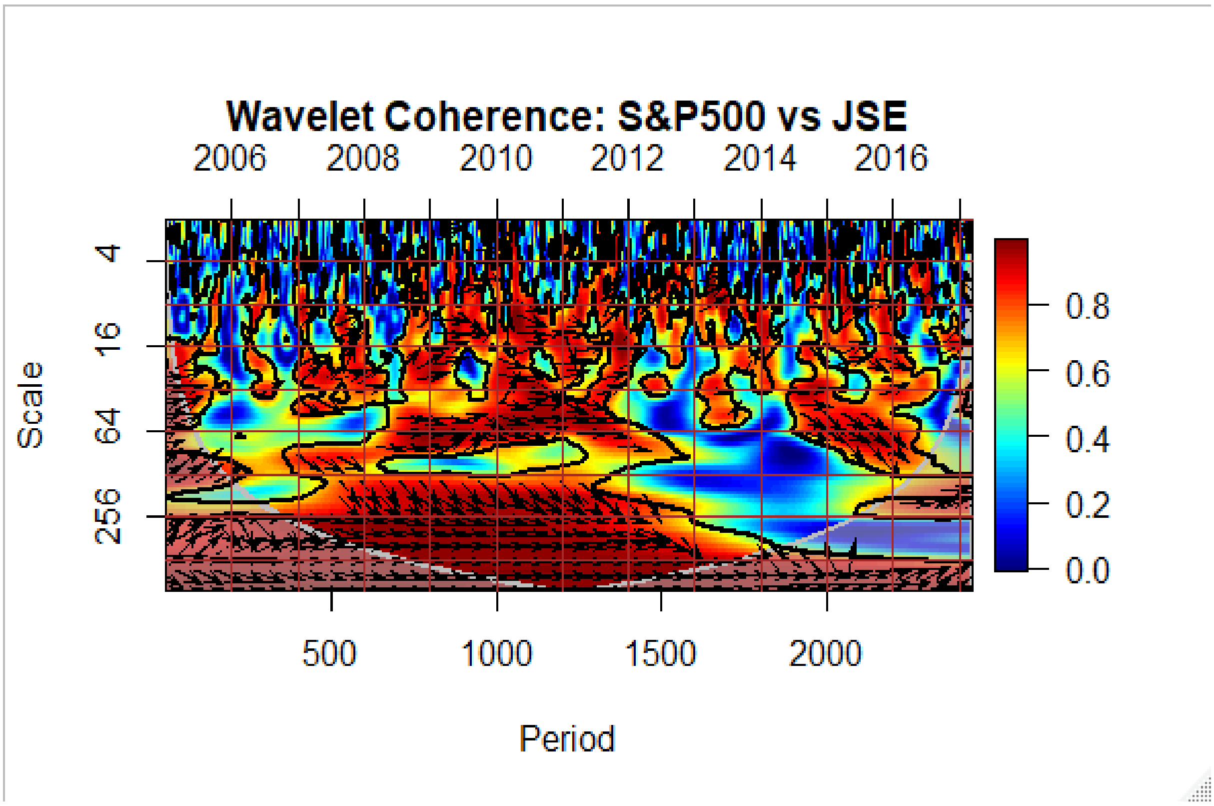

Figure 7-12: Wavelet Coherence Between the U.S. and the South African Stock Markets.

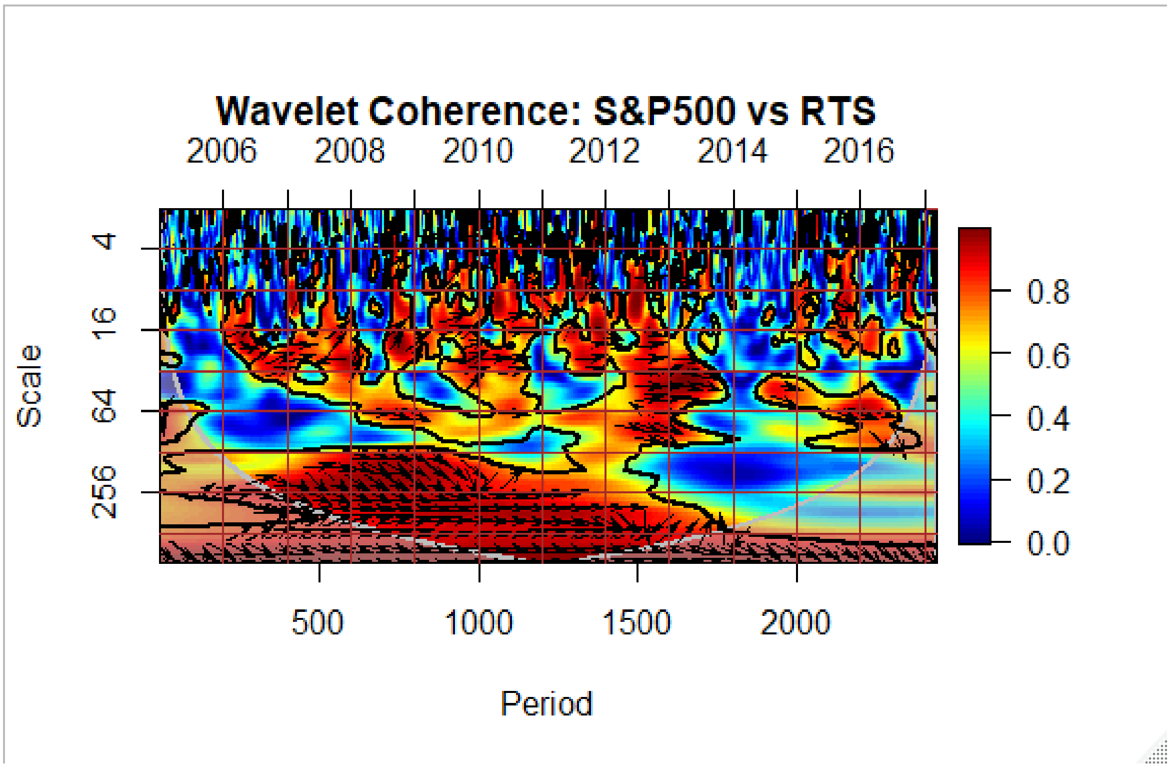

Figure 7-13: Wavelet Coherence Between the U.S. and Russian Stock Markets.

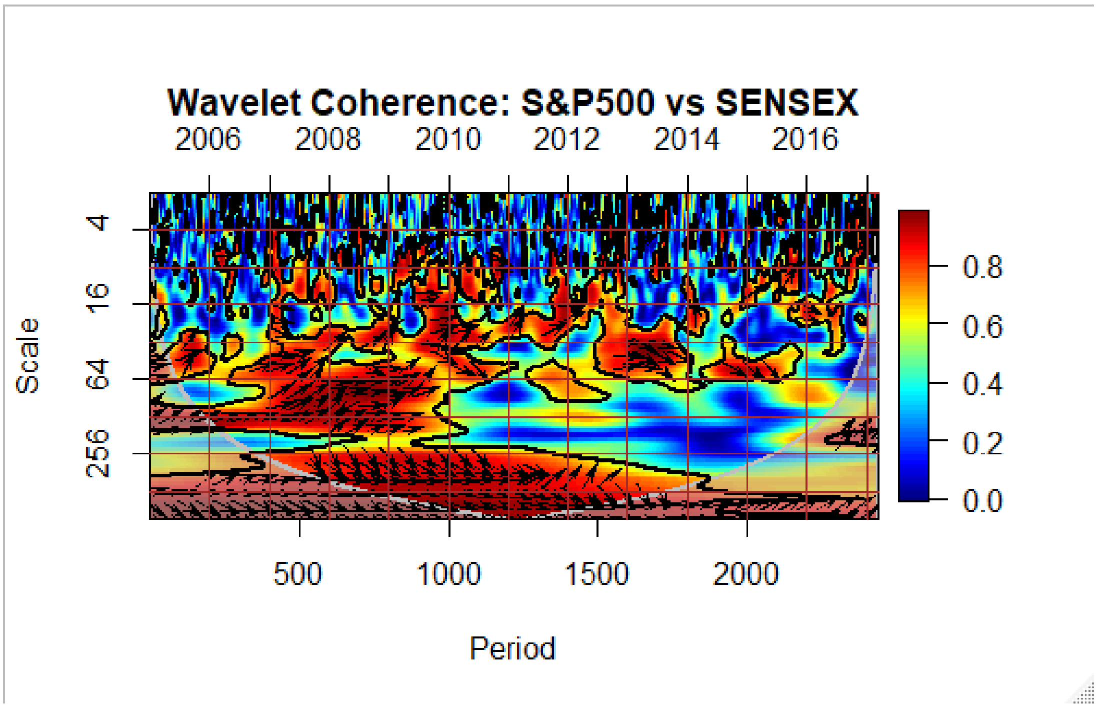

Figure 7-14: Wavelet Coherence Between the U.S. and Indian Stock Markets.

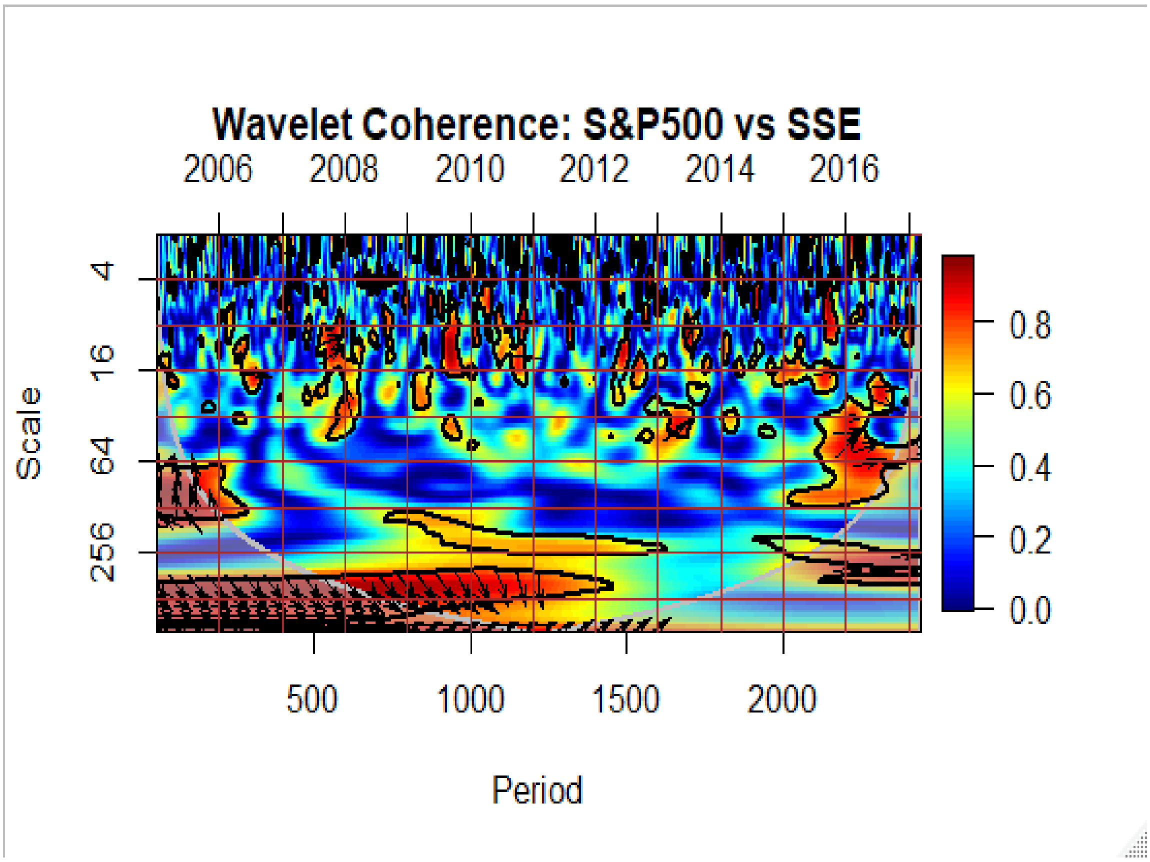

Figure 7-15: Wavelet Coherence Between the U.S. and Chinese Stock Markets.

It can be seen from Figure 7-11 to Figure 7-15 that the direction of the arrows at different frequency bands differs over the study period. The sub-prime 'crisis' period (between January 2008 and December 2010), is characterised by warmer colours in most of the pairwise relationships, China being the exception. One should also note the high correlation during periods of high correlation, especially in the medium-term horizon; the arrows mainly point South-East, indicating a positive correlation with the S&P 500 leading.

Regarding the index-pair of S&P 500 and BOVESPA (in Figure 7-11), high correlation in all-time horizons (short-term, medium-term and long-term) can be identified, for the period between 2008 and the beginning of 2013, which is the 'crisis' period. The presence of high correlation at lower scales (short-time horizon) indicates the presence of the pure form of contagion (Saiti *et al.*, 2016). Figure 7-11 also displays the heating of the map during the 'crisis' period for the long-term horizon (256-512 days holding periods). The high correlation in the long-term horizon is indicative of co-movement due to fundamentals. It is also worth noting that during the 'crisis' period the direction of the arrows point South-East, indicating a positive correlation, with the S&P500 leading the BOVESPA.
The contours plot for the pairwise relationship between S&P500 and FTSE/JSE, S&P500 and RTS, and S&P 500 and SENSEX, are displayed in Figures 7-13, 7-14 and 7-15, respectively. The contour plots for these three index-pairs display similar trends, where high correlation is identified in the short- term horizon starting from scale 2 (i.e. from 4 days up to 32). This is indicative of the presence of the pure form of contagion. High correlation is also identified in the long-term horizon, indicating co-movement due to fundamentals. The low correlation recorded on the first scale (i.e. 2 to 4 days) may be attributed to the geographic distance and the differences in trading hours between the U.S. and these three countries. It is also worth mentioning that high positive correlations are recorded in the medium-term horizon for the period between 2008 and 2012 for the FTSE/JSE, between 2012 and 2013 for the RTS, and between 2006 and 2010 for the SENSEX. The high correlations in the medium-term horizon also indicate co-movement due to fundamentals.

The picture changes quite dramatically when one looks at the relationship between the U.S. and the Chinese stock markets. Figure 7-15 displays the wavelet coherence between the S&P500 and the SEE. The contour plot in Figure 7-15 shows a sea of blue in all time horizons; this indicates a low correlation between the two markets. The only significant correlations are recorded in the long-term horizon during the ‘crisis’ period where the arrows point southeast, indicating that the S&P 500 leads the SSE.

One should also notice another heating of the map, in the short-term horizon around between the years 2015 and 2016; this period coincides with a period that Irwin (2018) dubbed a “mini-recession” in the US. A warmer colour in the short-term horizon can be identified in pairwise relationships between S&P 500 and BOVESPA, S&P 500 with FTSE/JSE AND S&P 500 with RTS. This suggests the presence of pure contagion around this period.

7.4.2 WAVELET ANALYSIS FOR THE EUROZONE SOVEREIGN DEBT CRISIS

The MODWT used the Daubechies least asymmetric filter with a wavelet filter length of 8(LA) to examine financial contagion in the aftermath of the Eurozone sovereign debt crisis. The maximum level of MODTW is 8 ($J_0 = 8$). The wavelet analysis was performed with eight scales that span from two- day to one-and-a-half year dyadic steps (2-4 days, 4-8 days, 8-16 days, 16-32 days, 32-64 days, 64-128 days, 128-256 days and 256-512 days). Scales are presented on the horizontal axis and correlations on the vertical axis. To analyse statistical significance, 95% confidence intervals are used.

It can be seen in Figures 7-16 to 7-20 that the wavelet correlations are all significantly positive except for the Chinese stock market. The correlations tend to increase as the scale increases. However, there is a sharp decrease on scale 7 (except for the Russian stock market where the sharp decrease is recorded at scale 5); after that the correlation increases again, reaching values close to unity at scale 8. This implies that discrepancies between the Eurozone and BRICS equity market, do not dispel for a period of less than a year. In other words, for the more extended period, the correlation between the Eurozone and BRICS equity markets (except the Chinese market) should not be ruled out. This can also be interpreted as perfect integration between the Eurozone and BRICS equity markets, given that the returns in BRICS stock markets can be totally determined by the overall performance in the Eurozone stock market at horizons longer than a year.

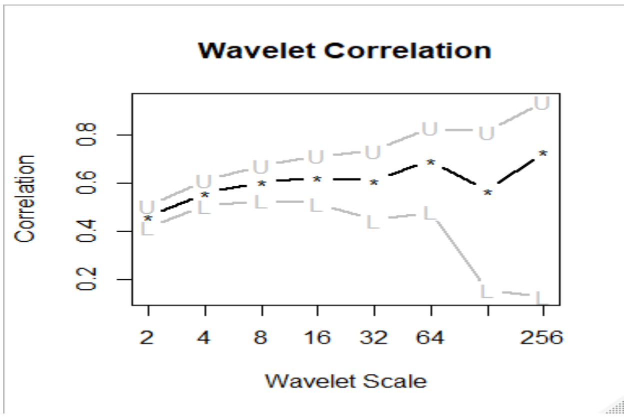

Figure 7-16: Correlation of DAX and BOVESPA at Different Time Scales.

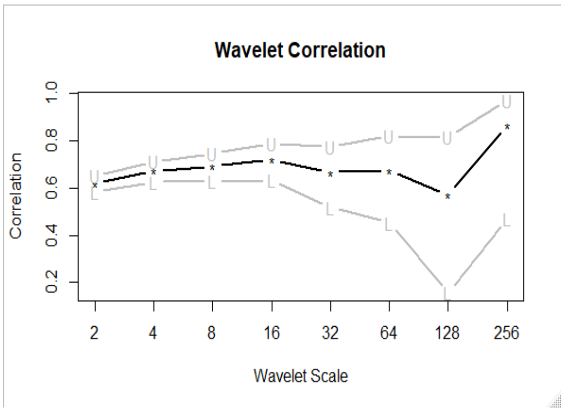

Figure 7-17: Correlation of DAX and FTSE/JSE at Different Time Scales.

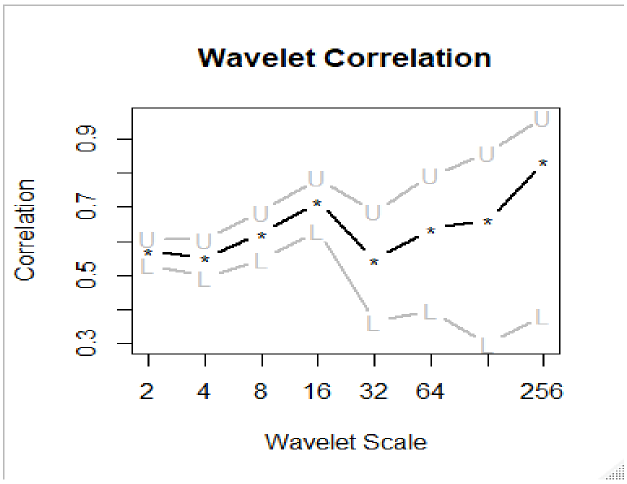

Figure 7-18: Correlation of DAX and RTS at Different Time Scales.

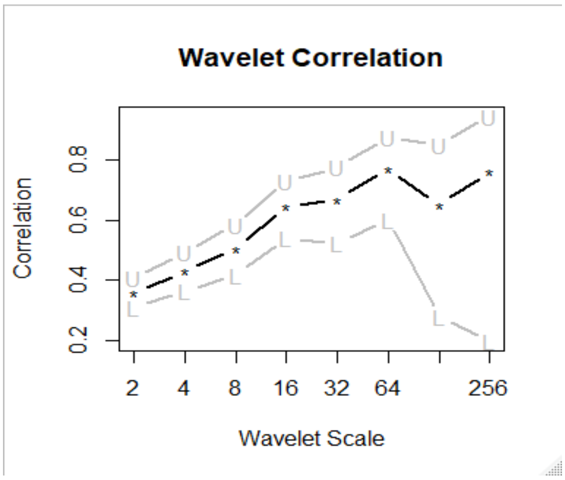

Figure 7-19: Correlation of DAX and SENSEX at Different Time Scales.

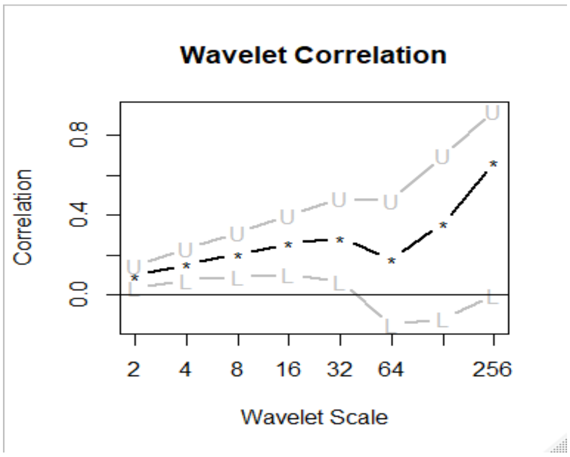

Figure 7-20: Correlation of DAX and SSE at Different Time Scales.

As in the case of the sub-prime crisis, the study also examined pairwise cross-correlations between the DAX and individual BRICS markets at all periods with the corresponding approximate confidence interval against lead time and lags for the different wavelet scales to 33 days. It can be seen from Figures 7-21 to 7-25 that at the shortest scales, i.e. scales 1 to 4, the cross-correlations around the time shift of $\pi = 9$ and $\pi = -9$ are significant and positive. It can also be seen that at the short scale the graphs are slightly skewed to the right, indicating that the DAX leads individual BRICS indices.

The coarse scales — particularly scales 5 and 6 — achieve the highest correlation at the time shift of $\pi = 21$ and $\pi = -21$ (with the Chinese stock market being an exception). It should also be noted that in most instance, scales 5 and 6 have symmetrical distributions; hence, the study could not identify any lead/lag relationship. It can be seen that for pairwise stock indices scale 7 there is a significant negative wavelet cross-correlation on the right-hand side, with implications that the individual BRICS market leads the Eurozone market. As for scale 8 there is no clear evidence of a lead-lag relationship. Finally, the contemporaneous time scale correlation between the series indicates that the values of the wavelet correlation coefficients at lag 0 have an anti-correlation relationship.

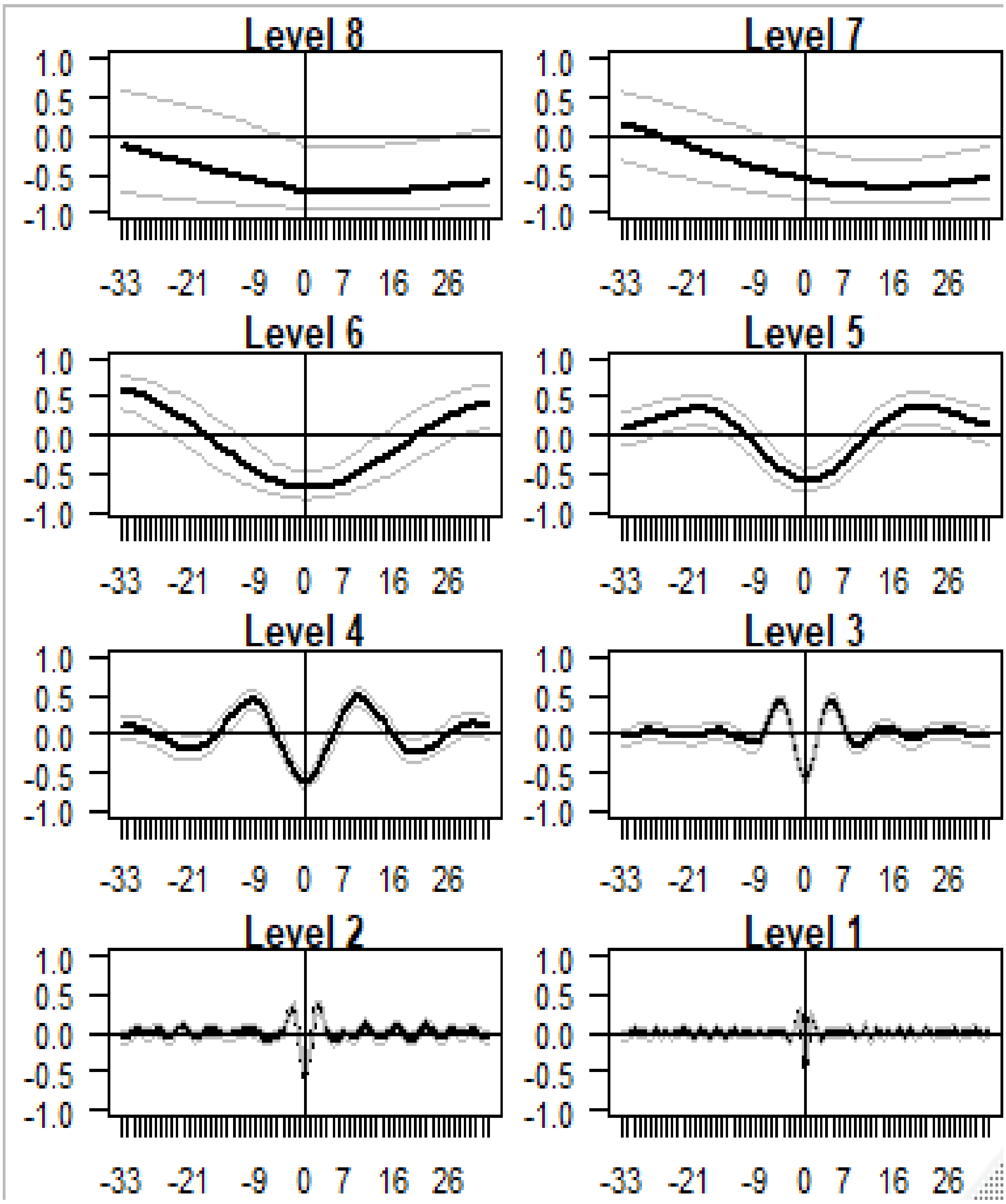

Figure 7-21: Cross-correlation Between the Return Series of DAX and BOVESPA.

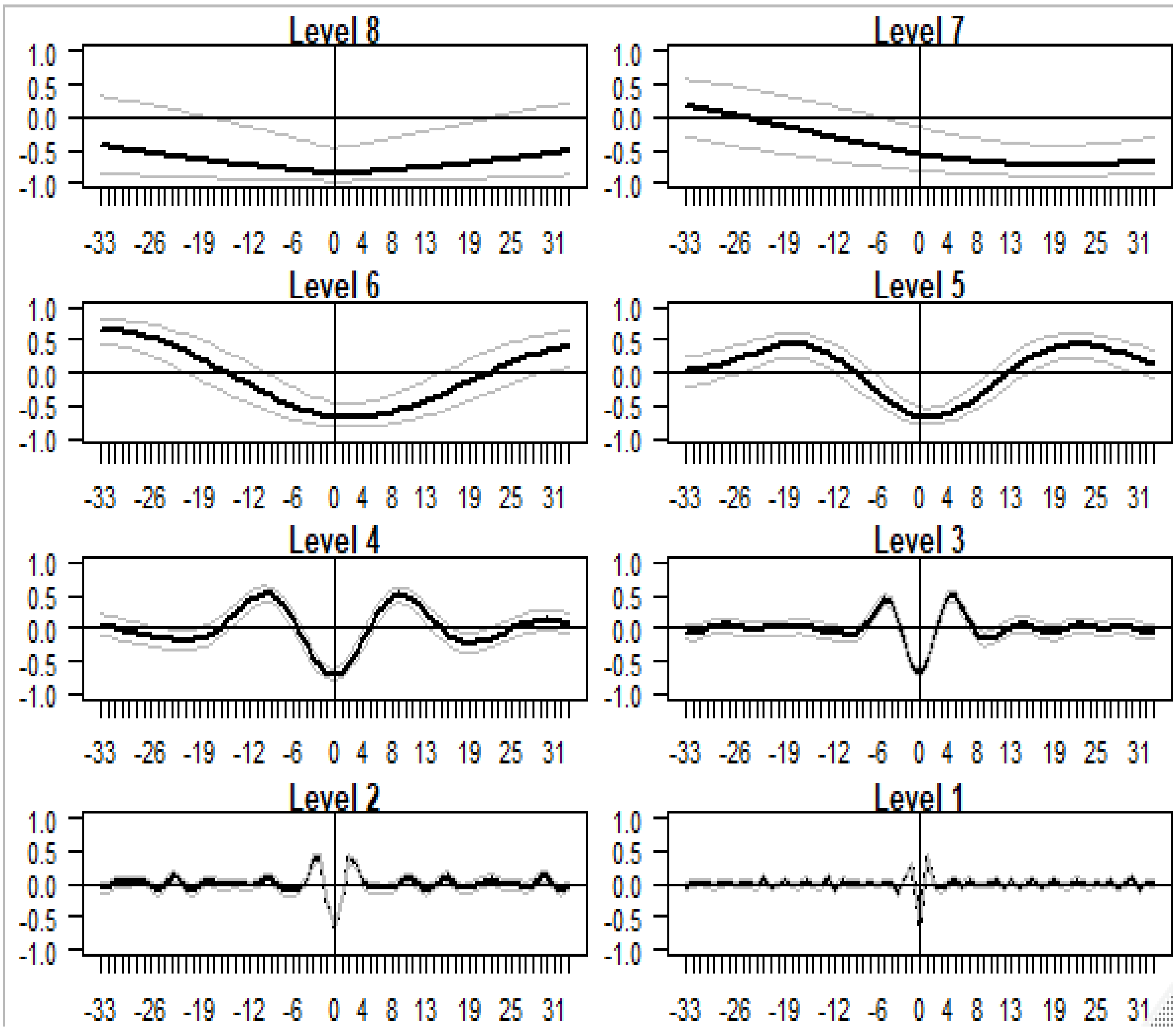

Figure 7-22: Cross-correlation Between the Return Series of S&P500 and FTSE/JSE.

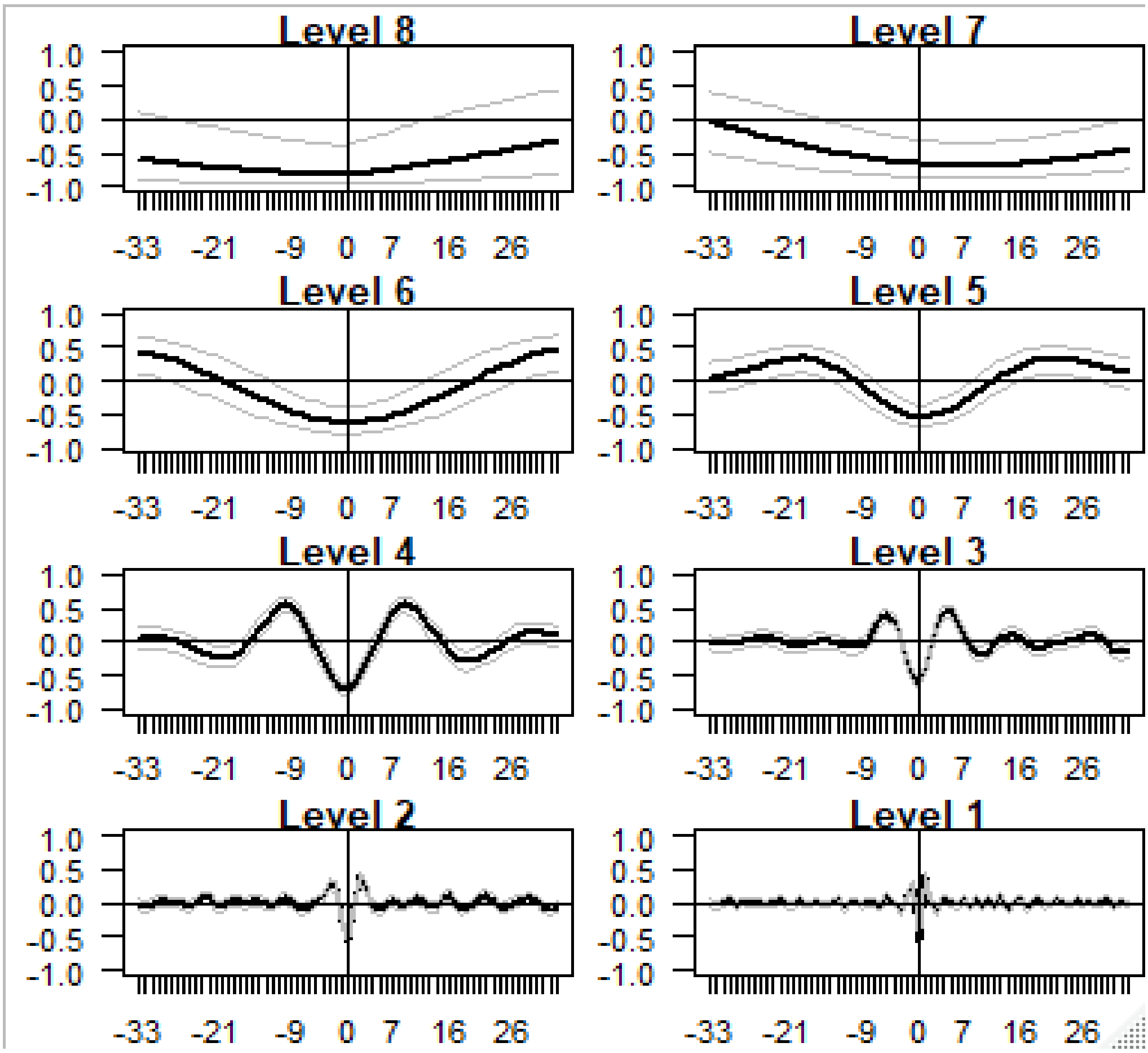

Figure 7-23: Cross-correlation Between the Return Series of DAX and RTS.

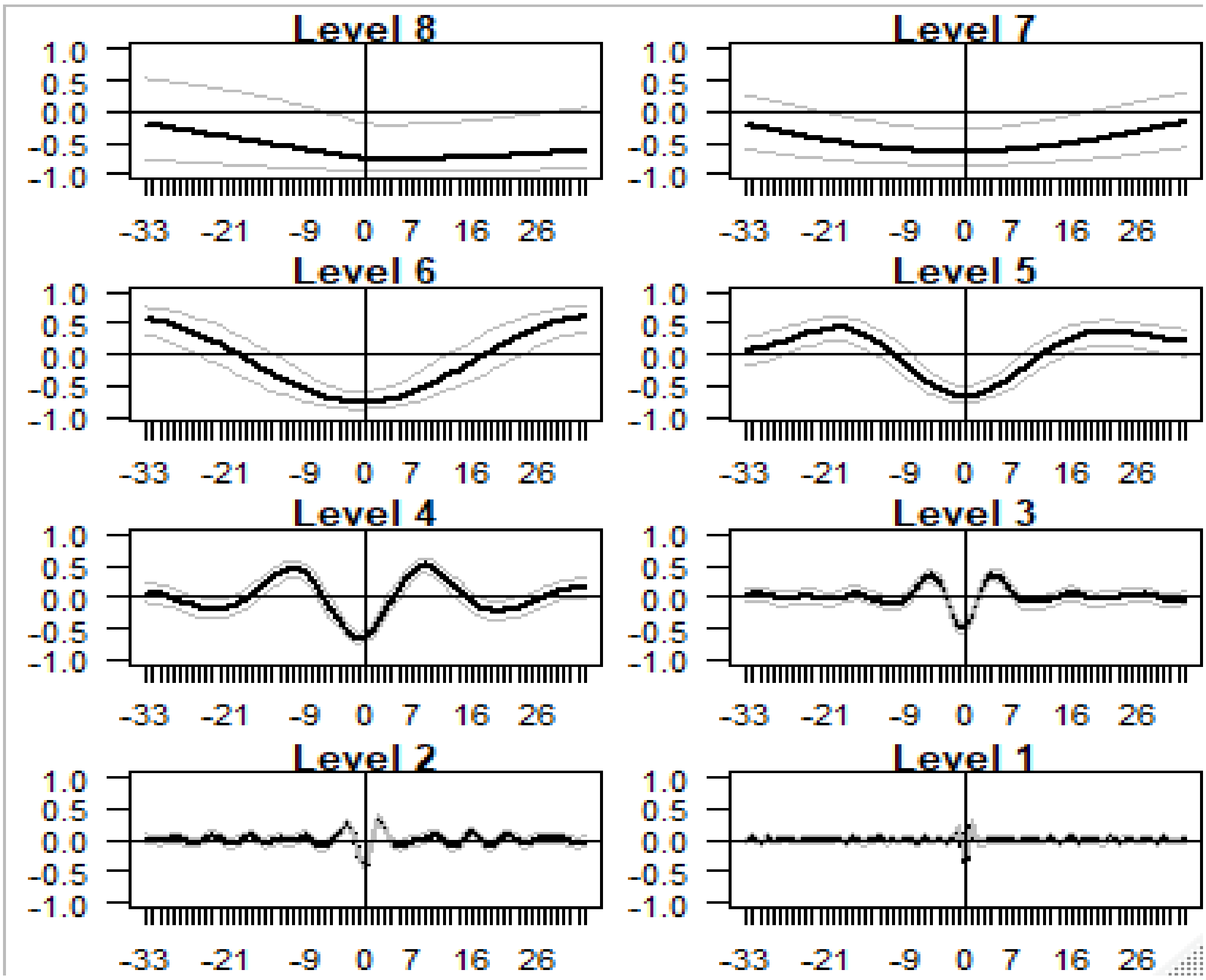

Figure 7-24: Cross-correlation Between the Return Series of DAX and SENSEX.

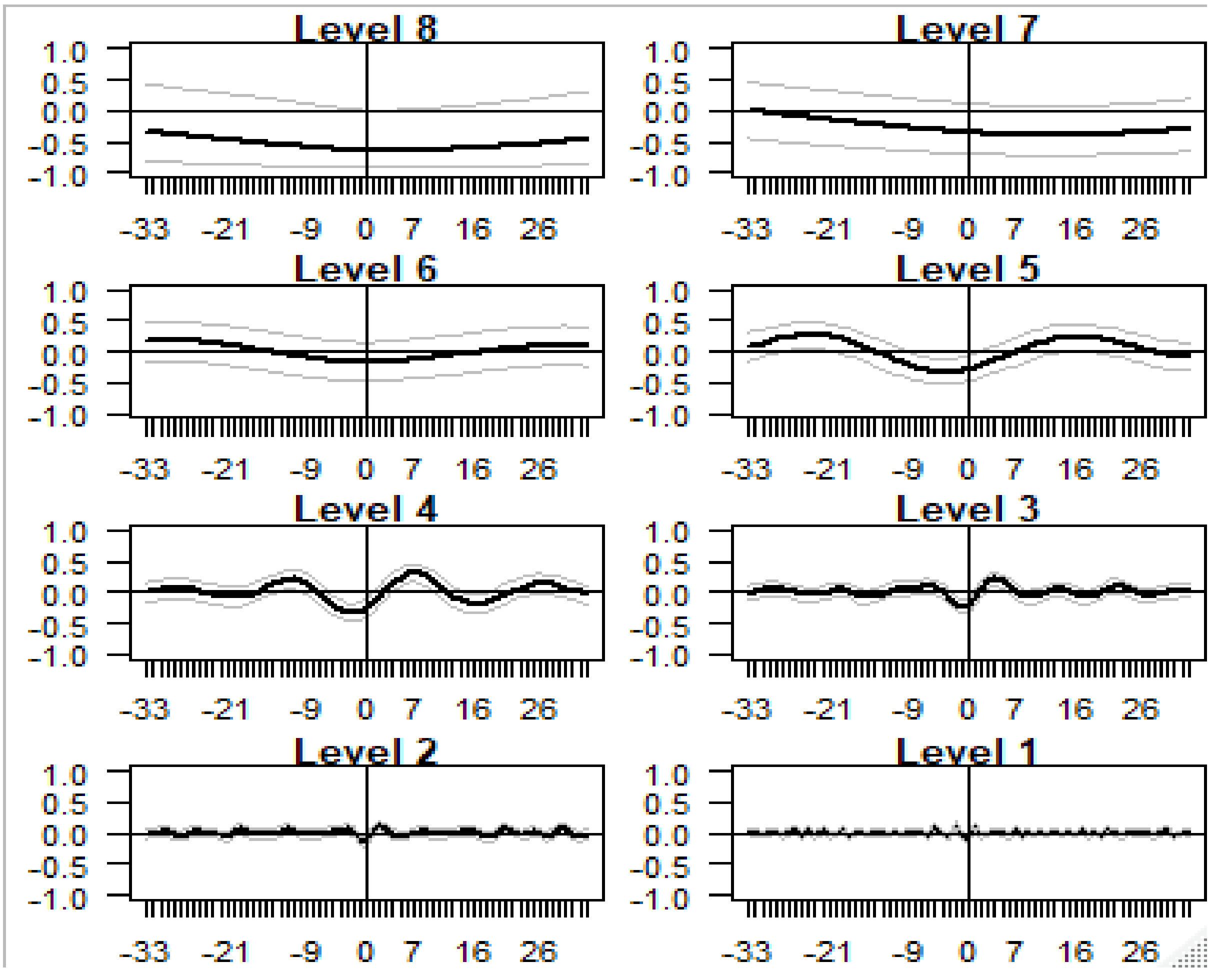

Figure 7-25: Cross-correlation Between the Return Series of DAX and SSE.

Figure 7-26 to Figure 7-30 present the estimated wavelet cross-coherence contour plots from the index -pairs of the DAX and individual BRICS equity markets. It can be seen that the Eurozone 'crisis' period (between July 2009 and December 2012), is characterised by warmer colours in most of the BRICS stock markets, China being the exception This indicates a high correlation during this period. One should also note that for high correlation during these periods, especially in the medium-term horizon, the arrows mainly point South-East, indicating a positive correlation with DAX leading.

Figures 7-26 and 7-30 also display the correlation of the index-pairs from DAX with JSE and DAX with RTS respectively. High correlation in alltime horizons (for short-term to long -term) can be identified for the Eurozone crisis period. High correlation in lower scales (short- time horizon) indicates the presence of contagion. It is also worth noting that during the 'crisis' period the direction of the arrows points South-East, indicating a positive correlation, with the DAX leading the JSE and the RTS. In the case of South Africa and Russia, the high correlation in the short-term horizon, which suggests the presence of pure contagion, can be explained by the fact that Eurozone countries have consistently remained significant trading partners for those two countries throughout the study.

As for the contour plots for the pairwise relationships between the index-pairs of DAX with BOVESPA, DAX with SENSEX and DAX with SSE, those are displayed in Figures 7-30, 7-33 and 7-34 respectively. The plots display relatively low correlation in the short term-horizon. Consequently, the current study could not find evidence of pure contagion in these three countries following during the Eurozone sovereign debt crisis.

The only significant correlation is recorded in the long-term horizon during the Eurozone crisis. The high correlation in the long-term horizon is indicative of co-movement due to fundamentals.

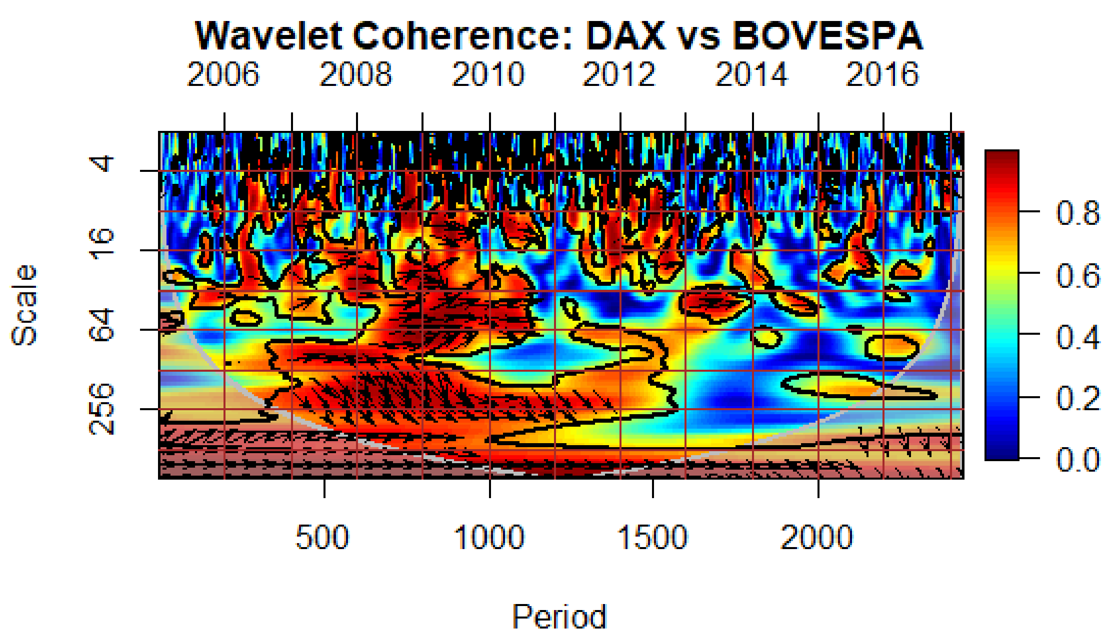

Figure 7-26: Wavelet Coherence Between the Eurozone and Brazilian Stock Markets.

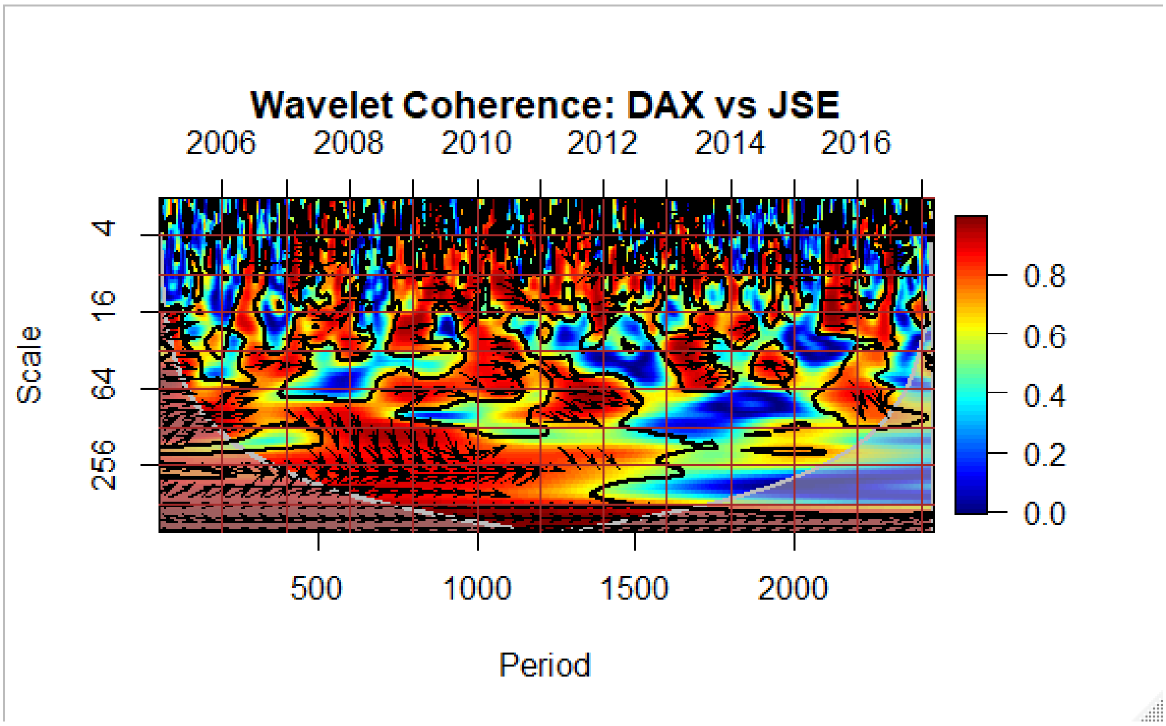

Figure 7-27: Wavelet Coherence Between the Eurozone and South African Stock Markets.

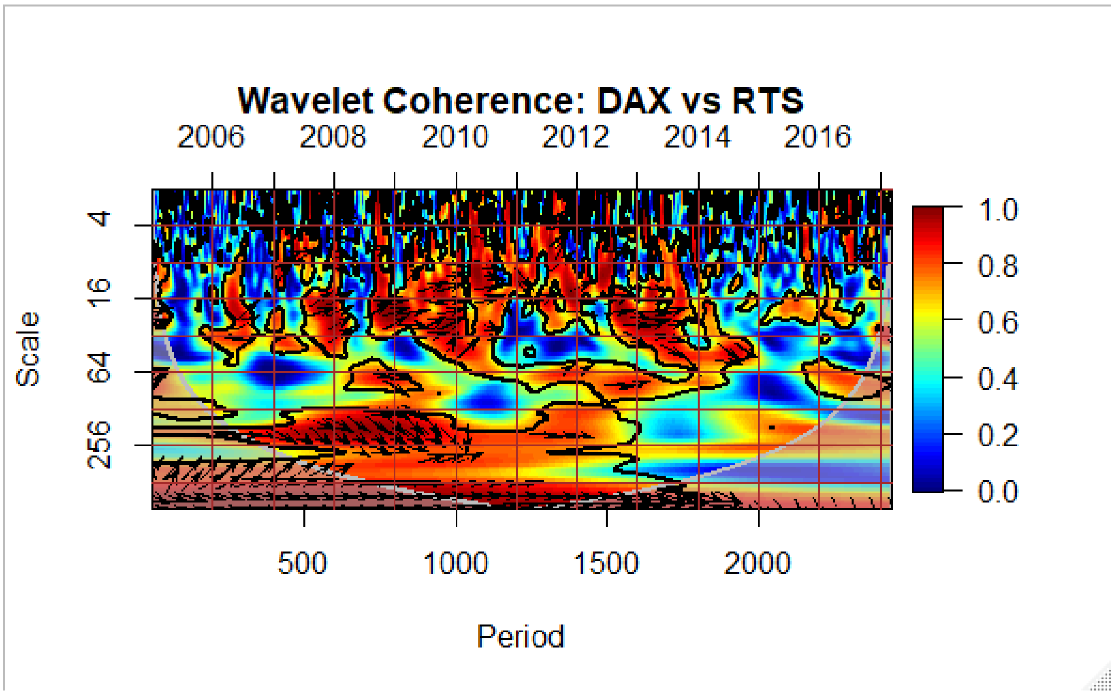

Figure 7-28: Wavelet Coherence Between the Eurozone and Russian Stock Markets.

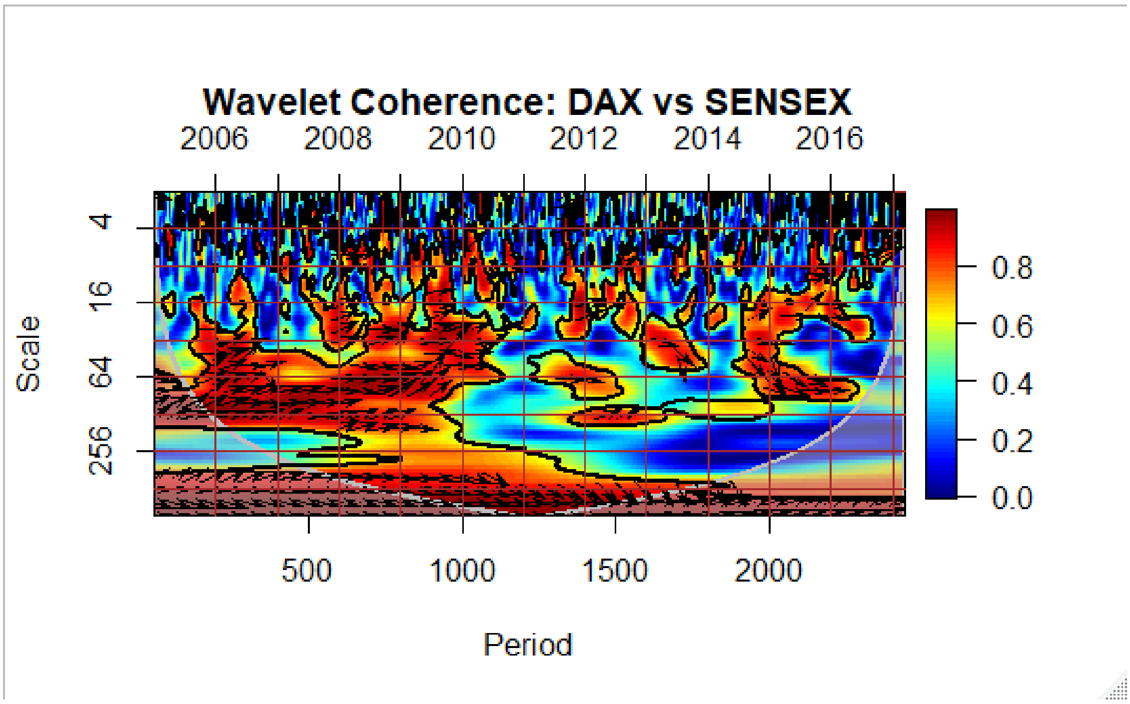

Figure 7-29: Wavelet Coherence between the Eurozone and Indian Stock Markets.

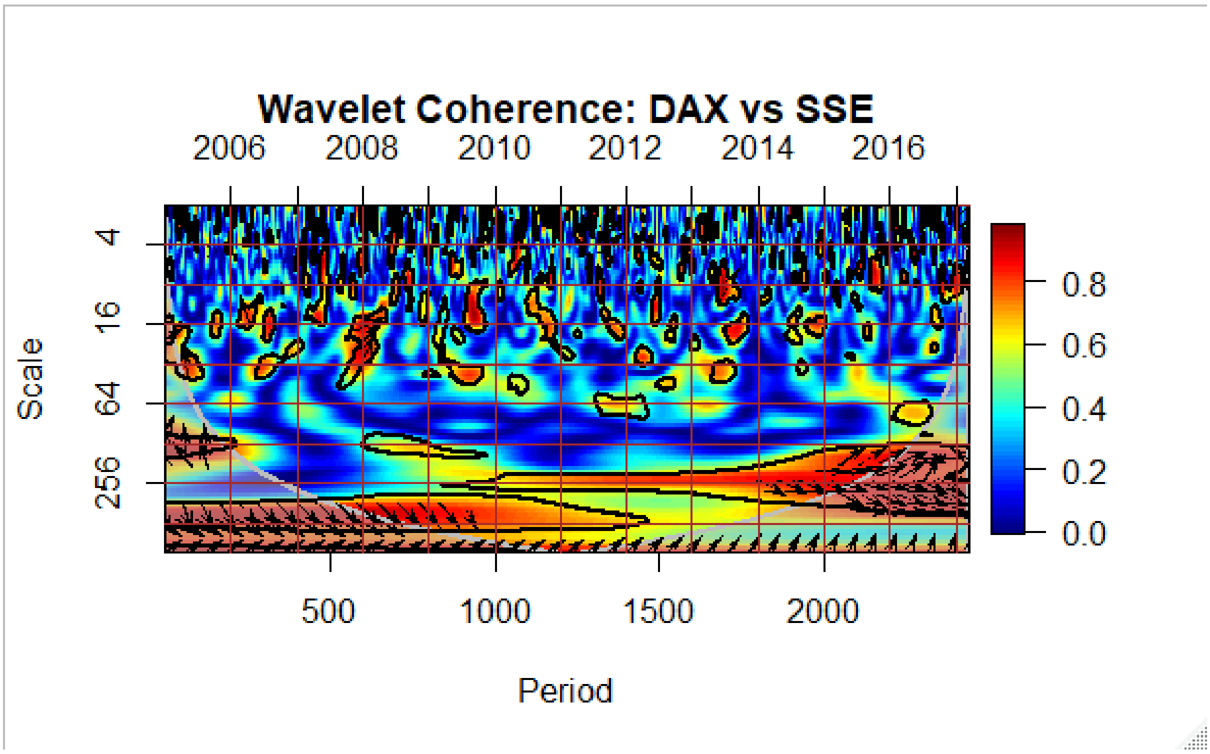

Figure 7-30: Wavelet Coherence between the Eurozone and Chinese Stock Markets.

7.5 CHAPTER SUMMARY

This chapter presented results of wavelet analysis for a multiscale interdependence of BRICS equity markets, *vis à vis* the source countries (U.S. and Eurozone countries) in the aftermath of the sub-prime and Eurozone crises.

For the sub-prime crisis emanating from the U.S. stock market, index-pairs consisting of the U.S. and individual BRICS equity market returns were analysed. using both wavelet cross-correlation and wavelet coherence analysis. The wavelet cross-correlation analysis shows evidence of positive cross-correlation between the U.S. and individual BRICS stock markets, and the cross-correlation was identified in both short and coarse scales, with the U.S. leading BRICS countries. Cross-correlation between the U.S. and China could not be established. The wavelet coherence analysis provides shreds of evidence of heterogeneous patterns in linkages between BRICS countries; a high correlation was identified for the short-term horizon in all stock markets except China. High correlation in the short-term horizon indicates the presence of financial contagion, hence the present study concluded that financial contagion took place between the U.S and BRICS equity markets (except the Chinese market).

Regarding the EZDC, the wavelet cross-correlation analysis showed evidence of co-movement and volatility spillover in the short scales with the DAX leading the BRICS market indices. For coarse scale, a significant negative wavelet cross-correlation was identified on the right-hand side with implications that the individual BRICS market leads the Eurozone market.

Wavelet coherence results also showed evidence of high correlation at a lower scale between the Eurozone stock market and individual stock markets of Brazil, South Africa, and Russia. It is also worth noting that during the ‘crisis’ period the direction of the arrows points South-East, indicating a positive correlation, with the DAX leading the JSE and the RTS. For the Brazilian, Indian and Chinese stock markets, no correlation was identified in the short scale period; hence the conclusion that no financial contagion took place in the Indian and the Chinese equity markets following the Eurozone sovereign debt crisis.

CHAPTER EIGHT

SUMMARY CONCLUSIONS AND POLICY RECOMMENDATIONS

This chapter provides an overall synthesis of the seven earlier chapters and summarises the entire thesis and the results which addressed the research questions of the study. The chapter also makes a number of specific policy recommendations based on the findings in the study and provides suggestions for future research directions. The summary of the study is presented in section one, the summary of the findings and conclusions are provided in section two, policy recommendations are outlined in section three, and the limitations of the study as well as suggestions for future research are provided in section four.

8.1 SUMMARY OF THE STUDY

The present study examines the pure form of contagions in the BRICS countries, namely Brazil, Russia, India, China, and South Africa. Pure form refers to the propagations that are not related to shocks in macroeconomic fundamentals, and are solely the result of irrational phenomena, such as panics, herd behaviour, loss of confidence and risk aversion.

The choice of the countries was motivated by the fact that these emerging countries have stronger partnerships through the BRICS association. Additionally, these countries come from various continents across the world. This allowed the study to have a worldwide overview of how contagions are transmitted, not only in one region but across regions.

The main objective of this study was to examine co-movement and volatility spillover in BRICS countries from 'source' markets of the U.S. and Eurozone countries. Specifically, the study sought to accomplish the following objectives:

1. To examine the salient characteristics of equity markets in BRICS countries.
2. To investigate the nature of volatility of stock market returns in BRICS countries during periods of financial turmoil.
3. To examine the presence of time-varying conditional correlations in BRICS equity market returns, in the wake of the financial crises that took place in the U.S. and Eurozone countries.

4. To investigate the presence of time-frequency correlations in BRICS stock markets, following the financial crises that took place in the U.S. and Eurozone countries.

The following four econometric models were formulated and utilised by the study: (i) GARCH (1, 1) and its extensions; (ii) the diagonal VECH GARCH (1, 1); (iii) the Dynamic Conditional Correlation GARCH; (iv) wavelet analysis. The estimation techniques employed can be described as being both descriptive and econometric.

The first objective (*To examine the salient characteristics of equity markets in BRICS countries*) was attained using descriptive statistics by means of graphical representation and tables.

The second research objective (*To investigate the nature of volatility of stock market returns in BRICS countries during periods of financial turmoil*) was attained using the Univariate GARCH (1,1) model and its extensions, namely the EGARCH (1,1) and GJR GARCH (1,1). In this regard the persistence of volatility and asymmetric effects of news on conditional volatility in BRICS equity market returns were estimated.

The third research objective (*To examine the presence of time-varying conditional correlations in BRICS equity market returns, in the wake of the financial crises that took place in the U.S. and Eurozone countries*) was accomplished using two estimations of multivariate GARCH methodologies, namely: (i) VECH GARCH (1,1), (ii) DCC GARCH (1,1).

The fourth research objective (*To investigate the presence of time-frequency correlations in BRICS stock markets, following the financial crises that took place in the U.S. and Eurozone countries*) was accomplished using MODWT wavelet analysis.

8.2 FINDINGS AND CONCLUSIONS OF THE STUDY

The findings of the study are presented in four categories to reflect the objectives.

8.2.1 FINDINGS AND CONCLUSIONS ON SALIENT CHARACTERISTICS OF EQUITY MARKETS IN BRICS COUNTRIES

The BRICS stock markets are among the most developed stock markets, and BRICS countries all have at least one stock exchange that is ranked among the world's top 20 bourses (by market capitalisation), with China and India becoming the world powerhouses in the global market.

Stock markets in BRICS countries are heterogenous as they differ in their structural characteristics, economic policies, and geopolitical importance. Chinese and Russian markets are still in the maturing process as they only reopened recently after decades of communist regimes that prohibited security markets. Brazilian, Russian and South African stock markets are dominated by natural resource-based stocks and are well-known commodity exporters. Among the BRICS stock markets, China's market has experienced the most rapid growth in the past 20 years.

India and Brazil are relatively more domestic demand-driven markets. This can be explained by the fact that both experienced a more rapid economic recovery from the 2008 financial crisis than did advanced and other emerging market economies. Trading and settlement in BRICS bourses are done using the latest technologies, to keep in line with global developments, with the Indian stock market leading the way in this regard.

8.2.2 FINDINGS AND CONCLUSIONS ON THE NATURE OF VOLATILITY IN THE STOCK MARKET RETURNS OF BRICS COUNTRIES

This subsection presents the findings on the nature of volatility in BRICS countries using the Univariate GARCH (1,1) models and their extensions, namely the EGARCH (1,1) and GJR GARCH(1,1)

8.2.2.1 Findings and Conclusions on the GARCH (1,1) Estimation Model on Volatility Clustering

Having conducted two preliminary tests, namely, (i) the unit root which showed that all variables are stationary at level, and (ii) the normality test using theQ-Q plot which highlighted that all return series did not follow the normal Gaussian distribution. The vanilla GARCH model was estimated using a student's t-distribution, as a substitute for the normal distribution.

The GARCH (1,1) results indicated the presence of volatility clustering in all return series, meaning that days of large movement are followed by days with the same feature. The presence of persistence of volatility justifies the use of a GARCH-type model to model volatility in BRICS stock markets.

Several diagnostic tests were also conducted to check the appropriateness of the GARCH (1,1) model, in this regard, several diagnostic tests were carried out on the fitted GARCH (1,1) model, including: (i) the JB test, (ii) the Ljung-Box test, and (iii) the ARCH-LM test. The results showed that, with the exception of the JSE and SSE, no heteroscedasticity was left in the fitted model. The LM ARCH test statistic was also not significant, indicating the absence of autoregressive conditional heteroskedasticity (ARCH) in the fitted residual. The value of the Box-Ljung test statistic Q (24) and Qs (24) were also not statistically significant for all market returns (with the minor exception of SEE and RTS); this is evidence of little or no serial correlation in the fitted residuals.

8.2.2.2 Findings and Conclusions on EGARCH (1,1) and GJR GARCH(1,1,1) Estimation Model on Leverage Effects

As in Vanilla GARCH(1,1), EGARCH (1, 1) and GJR GARCH(1,1,1) the models were estimated using a student's t-distribution. Even though all parameter estimates for EGARCH were found to be significant at conventional levels, the stationarity condition ($\alpha + \beta < 1$) was violated. For this reason, the study concludes that EGARCH cannot be used to test the leverage effect.

As for the GJR model, the asymmetry coefficients γ are positive and statistically significant at the 5% level in all markets except the Chinese market. The with the latter, GJR GARCH the model is explosive. Furthermore, the parameter estimate of the asymmetric coefficient γ is negative in the case of China. The current study hence concludes that asymmetric effects of news on conditional volatility are prevalent in all of the BRICS equity markets except the Chinese market.

8.2.3 FINDINGS AND CONCLUSIONS REGARDING CO-MOVEMENT AND VOLATILITY SPILLOVER IN BRICS EQUITY MARKETS

This subsection presents the findings on co-movement and volatility spillover in BRICS equity markets using (1) the diagonal VECH GARCH (1,1), and (2) the DCC GARCH(1,1) models.

8.2.3.1 Findings and Conclusions on Diagonal VECH GARCH (1, 1) Estimation Model on Co-movement and Volatility Spillover

In order to detect financial contagion emanating from the U.S. following the sub-prime crisis, the present study divided the data into two sub-periods, namely, (i) the 'pre-crisis'(stable) period and (ii) the 'crisis'(turmoil) period to detect the change in correlation between the two sub-periods.

The 'pre-crisis' period parameter estimated for the diagonal VECH GARCH model indicates that cross-innovation spillover coefficients are significant at the 5% level and their magnitude is lower compared to own-innovation spillover coefficients (except for BOVESPA). Based on the magnitudes of the estimated cross-volatility coefficients, innovation in all of the BRICS stock indices are influenced by the instability from the U.S. stock market, but the own-volatility shocks are relatively bigger than the cross-volatility shocks. During the 'pre-crisis' period, the cross-conditional volatility coefficients were higher in magnitude compared to the coefficient for own-conditional volatility (GARCH effect), implying that precedent shocks occurring from the U.S. markets have a more significant impact on BRICS stock markets than own-lagged market volatility. Parameter estimates for the 'crisis' period are similar to the ones obtained in the 'pre-crisis' period; the current study found that the parameter estimates for the 'crisis' period were high in magnitude compared to the 'pre-crisis' period hence, the conclusion that financial contagion took place in the BRICS equity market (except for the Chinese market) in the wake of the sub-prime crisis in the U.S.

In order to detect financial contagion emanating from the Eurozone countries following the sovereign debt crisis, the present study divided the data into two sub-periods, namely, (1) the ‘crisis’(turmoil) period, and (2) the ‘post-crisis’(stable) period to detect a change in correlation between the two sub-periods.

For the ‘crisis’ period, parameter estimated for diagonal VECH GARCH model indicate a cross-innovation spillover coefficients that are significant at the 5% level and their magnitude is lower compared to own-innovation spill-over coefficients. Based on the magnitudes of the estimated cross-volatility coefficients, innovation in all of the BRICS stock indices are influenced by the instability from the European stock market, with the cross-volatility shocks are relatively bigger than the own-volatility shocks. Similarly, GARCH effect coefficients are lower compared to cross- conditional volatility coefficients in the case of South Africa, India and China, suggesting that precedent shocks occurring from the Eurozone market have a greater impact on BRICS stock markets than own lagged market volatility.

Parameter estimates for the ‘post-crisis’ period are similar to the ones obtained in the ‘crisis’ period. The current study found there is no significant difference between that the parameter estimates for the ‘crisis’ period and the ‘post-crisis’ period; hence, the study could not confirm that financial contagion took place in the BRICS equity markets following the Eurozone sovereign debt crisis.

After fitting the VECH GARCH models, the adequacy specification of the model was assessed. In this regard, The Ljung- Box statistics on standardised squared residuals were used, and the results suggest the existence of serial dependence in the bivariate return series as the p-value for the Q-statistics test is close to zero, hence the rejection of the null hypothesis that there no residual autocorrelation up to lag 12. This suggests that the fitted Diagonal VECH model could not remove the GARCH effect (heteroscedasticity). Attempts by the researcher to modify the model by assuming a normal Gaussian distribution and by estimating the model with asymmetries yielded similar results. Given the fact that the VECH GARCH does not remove the GARCH effect, the model has been used in this study only as a secondary method.

8.2.3.2 Findings and Conclusions on DCC GARCH (1, 1) Estimation Model on Co-Movement and Volatility Spillover

In order to detect financial contagion emanating from the U.S. following the sub-prime crisis, the present study divided the data into two sub-periods, namely, (i) the 'pre-crisis'(stable) period and (ii) the 'crisis'(turmoil) period to detect a change in correlation between the two sub-periods. Parameter estimates for the DCC GARCH model on both the 'pre-crisis' and 'crisis' period indicated that the lagged dynamic conditional correlations on the current dynamic conditional correlations were significant in most BRICS equity markets. Joint significance of the parameters measuring the impact of past standardised shocks and lagged dynamic conditional correlations on the current dynamic conditional correlations were only found in the Brazilian stock market.

The mean value of the conditional correlation coefficient across pairs of stock markets is of a higher magnitude in the 'crisis' period than the 'pre-crisis' period (except China) hence the study deduced that financial contagion took place in BRICS equity market. A plot of the estimated conditional correlations by the DCC model also confirmed these results.

In order to detect financial contagion emanating from the Eurozone countries following the sovereign debt crisis the present study divided the data into two sub-periods, namely, (i) the 'crisis' (turmoil) period, and (ii) the 'post-crisis' (stable) period to detect a change in correlation between the two sub-periods.

Parameter estimates for the DCC GARCH model on both the 'crisis' and 'post-crisis' period indicated that the lagged dynamic conditional correlations on the current dynamic conditional correlations were significant in most BRICS equity markets. Unlike the case of the sub-prime crisis, there are no significant differences between the mean value of the conditional correlation coefficient (ρ) in the 'crisis' period compared to the 'post-crisis' period. A plot of the estimated conditional correlations by the DCC model also confirmed these results.

Once the DCC GARCH model had been fitted the adequacy of the model was investigated using the standardised residuals. To test for serial correlation, the study used the univariate Ljung-Box test on each of the BRICS market returns' standardised residuals. The null hypothesis of no serial correlation was accepted since all the p-values are> 0.05. To test for constant correlation, the study used the LM test by Engle and Sheppard (2001).

8.2.4 FINDINGS AND CONCLUSION ON THE NATURE AND THE DIRECTION OF VOLATILITY SPILLOVER IN BRICS EQUITY MARKETS

This subsection presents the findings on nature and direction of volatility spillover in BRICS equity markets using MODWT wavelet analysis.

8.2.4.1 Wavelet Variance and Wavelet Correlation

For all series used in the study, the wavelet correlations are all significantly positive except for the Chinese stock market. The correlations tend to increase as the scale increases. However, there is a sharp decrease in scale 7; thereafter, the correlation increases again, reaching values close to unity at scale 8. This implies that discrepancies do not dissipate for a period of less than a year.

8.2.4.2 Wavelet Cross-Correlation

The wavelet cross-correlations analysis showed evidence of positive cross-correlation between the U.S. and individual BRICS stock markets. The cross-correlation was identified in both short and coarse scales, with the U.S. leading BRICS countries. Cross-correlation between the U.S. and China could not be established as the results were not significant on the scale-by-scale analysis.

Regarding the Eurozone sovereign debt crisis, the wavelet cross-correlation analysis shows evidence of co-movement and volatility spillover in the short scales, with the Eurozone stock markets leading the BRICS stock market. For a coarse scale, a significant negative wavelet cross-correlation was identified on the right-hand side, with implications that the individual BRICS markets lead the Eurozone market.

8.2.4.3 Wavelet Coherence

Using wavelet coherence mapping the study shows that the wavelet coherence analysis provides pieces of evidence of heterogenous patterns in linkages between individual BRICS markets and the US. A high correlation was identified for the short-term horizon in all stocks markets except China. This is in an indication of presence of financial contagion.

Regarding the Eurozone sovereign debt crisis, the wavelet coherence analysis showed evidence of financial contagion in South Africa, and Russia, as their stock market indices display high correlation with the DAX in lower scales (short-time horizon). It is also worth noting that during the ‘crisis’ period the direction of the arrows points South-East, indicating a positive correlation, with the DAX leading the JSE and the RTS. For the Brazilian, Indian and Chinese markets, no correlation was identified in the short scale period, hence the conclusion that no financial contagion took place in the those equity markets following the Eurozone sovereign debt crisis.

8.3 LIMITATIONS OF THE STUDY

Our research is based on an array of assumptions, and choices made in order to derive the results presented in the analysis. The results should not be accepted at face value but rather be interpreted in light of the assumptions underlying them.

First, using daily time series data presents challenges due to trading hour differences, however, as Saleem (2008) stressed, this represents a relative problem given the fact that the current study used value-weighted indices for different regions. Second, software limitations reduced the ability of the researcher to do a thorough diagnostic analysis for multivariate GARCH models. Third, the models have been applied in their vanilla versions. That is, in the case of the DCC and BEKK model, only the most recent ARCH and GARCH terms have been included for their autoregressive representation. While it is unlikely that higher terms would have led to significant performance improvements, the current study cannot reject this hypothesis empirically. The same holds for asymmetric GARCH models.

8.4 RECOMMENDATIONS FOR FUTURE RESEARCH

The current study aimed to provide a deeper understanding of pure or fundamental contagion among the BRICS equity markets due to common shocks triggered by two major crises worldwide. The study intended to establish the medium of transmission of either pure contagion or fundamental contagion / interdependence.

Since volatility spillover between the BRICS equity markets and U.S. market is unidirectional the implications thereof are that firstly policymakers, investors and regulatory authorities should focus more on monitoring the volatility of the U.S. equity market as effort by BRICS authorities to stabilise volatility in their stock markets is futile since the volatility comes from outside.

Secondly, regulatory authorities should come up with initiatives that enable investors to reduce significant risk exposure by formulating sound risk management policies and macroprudential regulations.

Thirdly, BRICS countries should formulate and implement reliable hedging strategies against the contagious effects of the U.S. stock market on BRICS stock markets.

Fourthly, financial liberalisation processes need to be an integral part of the financial restructuring process, given the fact that financial integration can weaken and render vulnerable the emerging economies stock markets, due to their interdependencies with the world market. The strengthening of the requirement for the proper implementation of market liberalisation and the need for gradual deregulation is required.

Lastly, despite governments in BRICS countries taking steps to mitigate contagion-related risks from the U.S. market, there is still evidence of pure contagion in BRICS markets that emanates from the U.S. Additional best practices and tools are needed to address the current fissures. Global measures could include improving risk management and better mechanisms of private and counterparty risk sharing, reduction of systemic risk (for example the use of prudential regulations and the use of very-low risk assets), and the establishment more cautious financing facilities.

Given the fact that the current study could not identify financial contagion in Brazilian, Chinese and Indian stock markets emanating from Eurozone countries, the implication is that policymakers need to pay due attention to idiosyncratic shock channels in responding to volatility spillover.

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