COMMODITY PRICE VOLATILITY, STOCK MARKET PERFORMANCE AND ECONOMIC GROWTH: EVIDENCE FROM BRICS COUNTRIES

By

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ABSTRACT

The study investigated the nexus between commodity price volatility, stock market performance, and economic growth in the emerging economies of Brazil, Russia, India, China, and South Africa (the BRICS) predicated on two hypotheses. First, the study hypothesised that in modern integrated financial systems, commodity price volatility predisposes stock market performance to be non-linearly related to economic growth. The second hypothesis was that financial crises are an inescapable feature of modern financial systems. The study used daily data on stock indices and selected commodity prices as well as monthly data on national output proxies and stock indices. The study analysed data for non-linearities, fractality, and entropy behaviour using the spectral causality approach, univariate GARCH, EGARCH, FIGARCH, DCC-GARCH, and Markov Regime Switching (MRS) – GARCH. The four main findings were: first, spectral causality tests signalled dynamic non-linearities in the relationship between the three commodity futures prices and the BRICS stock indices. Second, the predominantly non-linear relationship between commodity prices and stock prices was reflected in the nexus between the national output proxies and the indices of the five main commodity classes. Third, spectral causality analysis revealed that the causal structures between commodity prices and national output proxies were non-linear and dynamic. Fourth, the Nyblom parameter stability tests revealed evidence of structural breaks in the data that was analysed. The DCC-GARCH model uncovered strong evidence of contagion, spillovers, and interdependence. The study added to the body of knowledge in three ways. First, micro and macro levels of commodity price changes were linked with corresponding stock market performance indicator changes. Second, unlike earlier studies on the commodity price – stock market performance – economic growth nexus, the study employed spectral causality analysis, single - regime GARCH analysis, Dynamic Conditional Correlation (DCC) – GARCH and a two-step Markov – Regime – Switching – GARCH as a unified analytical approach. Third, spectral causality graphs depicting relationships between stock indices and national output proxies revealed benign business cycle effects, thus, contributing to broadening the scope of business cycle theory.

Key Terms: BRICS, commodity price volatility, EGARCH, FIGARCH, MRS-GARCH, spillovers, relationship, stock market performance, economic growth

ABSTRAK

Die studie het die kommoditeitsprys-onbestendigheid, aandelemarkprestasie en ekonomiesegroei-verband in die ontluikende ekonomieë van Brasilië, Rusland, Indië, China en Suid-Afrika (BRICS) ten opsigte van twee hipoteses ondersoek. Eerstens het die studie veronderstel dat, in moderne geïntegreerde finansiële stelsels, kommoditeitsonbestendigheid daartoe lei dat aandelemarkprestasie nielineêr met ekonomiese groei verband hou. Die tweede hipotese was dat finansiële krisisse ŉ onafwendbare kenmerk van moderne finansiële stelsels is. Die studie het daaglikse data oor voorraadindekse gebruik en kommoditeitspryse asook maandelikse data oor nasionale uitsetaanduiders en voorraadindekse geselekteer. Die studie het data met betrekking tot nielineariteite, fraktaliteit en entropiegedrag ontleed deur gebruikmaking van die spektraalkousaliteitsbenadering, eenveranderlike GARCH EGARCH, FIGARCH, DCC-GARCH en Markov-regimeskakeling (MRS-) GARCH. Die vier belangrikste bevindings was: eerstens, spektralekousaliteit-toetse het dinamiese nielineariteite in die verhouding tussen drie grondstoftermynpryse en die BRICS-aandelekapitaalindekse aan die lig gebring. Tweedens is die oorwegend nielineêre verwantskap tussen kommoditeitspryse en aandelepryse weerspieël in die verband tussen die nasionale uitsetaanduiders en die indekse van die vyf belangrikste kommoditeitsklasse. Derdens het spektrale kousaliteit aan die lig gebring dat die kousale strukture tussen kommoditeitspryse en nasionale uitsetaanduiders nielineêr en dinamies is. Vierdens het die Nyblom-parameterstabiliteitstoetse bewyse aan die lig gebring van strukturele onderbrekings in die data wat ontleed is. Die DCC-GARCH-model het sterk getuienis van besmetting, oorlope en onderlinge afhanklikheid blootgelê. Die studie het op drie maniere tot die kenniskorpus bygedra. Eerstens is mikro- en makrovlakke van kommoditeitsprysveranderinge gekoppel aan ooreenstemmende aandelemark-prestasieaanwyserveranderinge. Tweedens, in teenstelling met vroeëre studies oor die verband tussen kommoditeitsprys-aandelemarkprestasie en ekonomiese groei, het die studie spektralekousaliteit-ontleding, enkelregime- GARCH-ontleding, dinamiese voorwaardelike korrelasie (DCC-) GARCH en ’n tweestap- MRS-GARCH as ’n verenigde analitiese benadering gevolg. Derdens het spektralekousaliteit-grafieke wat verhoudings tussen aandele-indekse en nasionale uitsetaanduiders uitbeeld, gunstige sakesiklus-effekte blootgelê, en sodoende daartoe bygedra om die bestek van die sakesiklusteorie te verbreed.

Sleutelterme: BRICS, kommoditeitsprys-onbestendigheid, EGARCH, FIGARCH, MRS-GARCH, oorlope, verwantskap, aandelemarkprestasie, ekonomiese groei

IQOQO

Isifundo socwaningo siye saphenya ukuntenga kwentengo yempahla, indlela izimakethe zesitoko ezisebenza ngayo kanye nokukhula komnotho wochungechunge lwamazwe asathuthukayo kwezomnotho anjenge*Brazil*, i-*Russia*, i-*India*, i*China* kanye neNingizimu Afrika (BRICS) yakhelwe phezu kwesisekelo samahayipothesisi amabili. Kokuqala, isifundo socwaningo sibeka leyo hayipothesisi ngokwezinhlelo zesimanje ezihlangene zezimali, isimo esintengayo sentengo yempahla sibeka engcupheni ukusebenza kwezimakethe zezitoko ukuba zingahambi ngendlela elindelwe (*linear*) ehambisana nokukhula komnotho. Ihayipothesisi yesibili yona yayithi izinkinga zezimali ziyingxenye engagwemeki lula yezinhlelo zezimali zesimanje. Isifundo socwaningo sisebenzise idatha yezinsuku zonke yezilinganiso zesitoko kanye nezintengo ezikhethiweyo zezimpahla kanye nedatha yenyanga yomkhiqizo wezwe kanye nezibalo zesitoko. Isifundo socwaningo siye sahlaziya idatha yokwenzeka kwezinto zingalindelwe (*non-linearities*), yesimo esingejwayelekile kanye nokuziphatha ngendlela engafanele ngokusebenzisa indlela eyimbangela, i--*univariate GARCH*, i-*EGARCH*, i-*FIGARCH*, i-*DCC-GARCH* kanye ne--*Markov Regime Switching (MRS-) GARCH*. Izinto ezine ezitholakele yilezi ezilandelayo: yokuqala, yizinhlelo zokuhlola, phecelezi, *spectral causality tests* eziye zaveza izinguquko ezingalindelwe zobudlelwano obuphakathi kwezinhlelo ezintathu zezintengo zempahla esikhathini esizayo kanye nezibalo zezitokwe ze-*BRICS.* Okwesibili, ubudlelwano obukade bukhona bezinto ezingalindelwe obuphakathi kwezintengo zempahla kanye nezintengo zezitoko babubonakala kwinsika yobudlelwano bezinto ezimele imiphumela kanye nezibalo zezigaba zezimpahla ezinhlanu. Okwesithathu, uhlaziyo lwe-*spectral causality* luveza izakhiwo eziyimbangela ephakathi kwezintengo zezimpahla kanye nezinto ezimela imikhiqizo yezwe ukuthi ibe yileyo engalindelwe kanye neguquguqukayo. Okwesine, izinhlelo zokuhlolwa phecelezi, i-*Nyblom parameter stability tests* ziye zaveza ubufakazi bezigaba zesakhiwo kwidatha ehlaziyiwe. I-*DCC-GARCH model* iye yaveza ubufakazi obuqinile obumayelana be--*contagion*, *spillovers* kanye nokusebenzisana kwangaphakathi (*interdependence*). Ucwaningo lwengeza phezu kolwazi ngezindlela ezintathu. Okokuqala, amazinga amancane namakhulu ezinguquko zezintengo zezimpahla bezihambisana nezinguquko zezinkomba zokusebenza kwezimakethe zesitoko. Okwesibili, Lokhu akufani nezifundo zocwaningo zokuqala ezimayelana nentengo yempahla – izinga lokusebenza kwemakethe yesitokwe – uhlelo oluyinsika yokukhula komnotho *commodity price–stock market performance–economic growth nexus)*, ucwaningo luye lwasebenzisa uhlaziyo lwe--*spectral causalityanalysis*, i-*single-regime GARCH analysis*, i-*dynamic conditional correlation (DCC-) GARCH* kanye ne--*two-step MRS-GARCH* njengendlela ehlangene yokuhlaziya. Okwesithathu, amagrafu e-*spectral causality* akhombisa izinhlelo zobudlelwano obuphakathi kwezibalo zesitoko kanye nezinto ezimele imiphumela yemikhiqizo yezwe equkethe imithintela yebhizinisi ejikelezayo, yona enomthelela ekukhuliseni kobukhulu bethiyori yesayikeli yebhizinisi.

Amagama asemqoka: I-BRICS, ukuntengantenga kwentengo yempahla, i-*EGARCH, FIGARCH, MRS-GARCH*, *spillovers*, ubudlelwano, isimo sokusebenza kwezimakethe zesitoko, ukukhula komnotho

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DEDICATION

I dedicate this thesis to God the Father - my Creator, Jesus Christ - my Saviour, and the saints of the Most High God.

DECLARATION

Name: **IAN NDLOVU**

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Title: Commodity Price Volatility, Stock Market Performance and Economic Growth: Evidence from BRICS Countries.

I declare that the above thesis is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

I further declare that I submitted the thesis to originality checking software and that it falls within the accepted requirements for originality.

I further declare that I have not previously submitted this work, or part of it, for examination at Unisa for another qualification or at any other higher education institution.

I Ndlovu 19 June 2019

SIGNATURE DATE

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ADF –	Augmented Dickey Fuller test
AIC –	Akaike Information Criterion
APARCH –	Asymmetric Power ARCH
AR –	Autoregressive model or filter
ARCH –	Autoregressive Conditional Heteroscedasticity
ARCH – LM –	ARCH Lagrange Multiplier (LM) test
ARDL –	Autoregressive Distributed Lag model
ARIMA –	Autoregressive Integrated Moving Average
ARMA –	Autoregressive Moving Average
ASEAN –	Association of South East Asian Nations
BDS –	Brock-Dechert-Scheinkman test
BEKK-GARCH –	Baba, Engle, Kraft and Kroner - GARCH
BIS-	Bank of International Settlements
BRICS –	Brazil, Russia, India, China and South Africa
BSE –	Bombay Stock Exchange
CCC -	Constant Conditional Correlation model
CE –	Cointegrating Equation
CGARCH –	Component GARCH
CHARMA –	Conditional Heteroscedasticity ARMA
CUSUM-	Cumulative Sum control chart
DCC-GARCH –	Dynamic Conditional Correlation GARCH

DFH-	Demand Following Hypothesis
ECB-	European Central Bank
ECOWAS –	Economic Community of West African States
EGARCH –	Exponential GARCH
EMH -	Efficient Markets Hypothesis
ESTAR –	Exponential STAR GARCH
ETN-	Exchange Traded Notes
ETP-	Exchange Traded Products
EU –	European Union
FAVAR-	Factor-Augmented VAR
FEM-	Fixed Effects Model
FIAPARCH –	Fractionally Integrated Asymmetric Power ARCH
FIEGARCH –	Fractionally Integrated Exponential – GARCH
FIGARCH-BBM –	Fractionally Integrated GARCH – Baillie - Bollerslev – Mikkelsen
FIGARCH-Chung –	Fractionally Integrated GARCH – Chung
FRED –	Federal Reserve Economic Data
GARCH –	Generalised Autoregressive Conditional Heteroscedasticity
GARCH – MEAN –	GARCH in Mean
GDP –	Gross Domestic Product
GED-	Generalised Error Distribution
GFC –	Global Financial Crisis
GJR – GARCH -	Glosten, Jaganathan and Runkle - GARCH
GO-GARCH-	Generalised Orthogonal GARCH

HGARCH –	Hyperbolic GARCH
HQIC –	Hannan-Quinn Information Criterion
IMF –	International Monetary Fund
ISE-100-	Istanbul Stock Exchange 100 index
JSE –	Johannesburg Stock Exchange
JSEFT –	JSE Financial Times index
KSE-	Karachi Stock Exchange
LSTAR-FIPGARCH –	Logistic STAR – Fractionally Integrated Power GARCH
MENA –	Middle East and North Africa
MGARCH –	Multivariate GARCH
MRS – GARCH –	Markov Regime Switching – GARCH
NIC –	News Impact Curve
NM-GARCH –	Normal Mixture – GARCH
NNGARCH –	Neural Network – GARCH
PP –	Phillips Perron test
QGARCH –	Quadratic GARCH
REM –	Random Effects Model
RS-BEKK-GARCH –	Regime Switching – BEKK-GARCH
RTSI –	Russian Trading System (cash) Index
S&P 500 –	Standard and Poor's 500
SLH-	Supply Leading Hypothesis
SA –	South Africa
SADC –	Southern African Development Community

SBIC –	Schwarz Bayesian Information Criterion
SIC-	Shibata Information Criterion
SSEC –	Shanghai Stock Exchange Composite index
STAR –	Smooth Transition Autoregressive model
SVAR –	Structural Vector Autoregressive
TGARCH –	Threshold GARCH
UNCTAD –	United Nations Conference on Trade and Development
US –	United States
USA –	United States of America
VAR –	Vector Autoregressive
VECM –	Vector Error Correction Model
WTI –	West Texas Intermediate crude oil

CHAPTER ONE:
INTRODUCTION AND BACKGROUND

1.0 Introduction

International trade in commodities has played a significant role in economic growth and development of many countries for hundreds of years (Powell, 2015; Emara, Simutowe, and Jamison, 2015). Nevertheless, over time commodity markets have remained largely segmented from banks, stock markets, and other financial markets. Segmentation has persisted despite the fact that some links have existed between commodity markets and other sectors of the macro-economy. In the past 15 years, the global economy has witnessed increased financialisation of commodity markets as well as their integration into the financial sector, especially stock markets (Zaremba, 2016).

This thesis contributes to the debate on commodity price volatility and financialisation of commodity markets by postulating that in modern integrated financial systems, commodity price volatility causes stock market performance indicators to be aligned to economic growth in a non-linear manner. Non-linear behaviour patterns exhibited by commodity prices over time have been corroborated by several researchers such as Uddin (2016), Irandoust (2016), Powell (2015), and Bhanumurthy *et al.* (2013). A number of studies from the 1970s to date have long demonstrated a linear neoclassical finance-growth relationship pertaining to the stock market development – economic growth nexus (Tinavapi, 2017; Pan and Mishra, 2016; Best and Francis, 2015).

1.1 Background to the Study

The finance-growth nexus has engaged theorists and researchers for more than a century (Adusei, 2018; Fanta, 2015; Barajas *et al.*, 2013; Stolbov, 2012; Yu *et al.*, 2012; Levine, 1996, 1997, 2004; Al-Yousif, 2002; Schumpeter, 1912; Bagehot, 1873). The conventional and mainstream view for many years has been that financial sector development and a sustained shift of financial structures augur well for growth in national output (Paun *et al.,* 2019; Zingales, 2015; Madichie *et al.*, 2014; Kagochi, 2013; Hongbin, 1998). That operational viewpoint has partly been the inspiration behind financial sector liberalisation policies in several emerging economies including some African economies (Škare, Sinkovic, and Porada-Rochon, 2018; Owusu and Odhiambo, 2013; Makina, 2005; Levine and Zervos, 1998; De Melo and Tybout, 1986; Fry, 1978).

Empirical studies on the nexus between key financial market performance indicators and economic growth proxies have yielded ambiguous or indeterminate results (Ginevičius *et al.,* 2019; Adusei, 2018; Hassan *et al.*, 2010; Acaravci, 2009; Caporale *et al.*, 2009; Afaro *et al.*, 2006; Levine, 2005; and Christopoulos and Tsianos, 2004). The preponderant view based on the seminal work of Gurley and Shaw (1955) has nevertheless favoured a proposition of a unidirectional causality from economic growth to financial sector development (Shaw, 1973; Goldsmith, 1969; Kar and Pentecost, 2000; McKinnon, 1973; Pagano, 1993; Jeanneney *et al.*, 2006 and Odhiambo, 2009).

A theoretical explanation of the links between economic growth and financial sector development has followed four main strands according to the mainstream literature. The first view is that of the supply-leading hypothesis (SLH) which sees financial development being a forerunner of economic growth. Primarily, financial sector development is seen as having a positive effect on economic growth (Škare *et al.,* 2018). Greenwood and Jovanovich (1990) observe that a contending viewpoint is the demand-following hypothesis (DFH) which views the real sector as a driver of financial development (Rajan and Zingales, 1998). The third view is that there is a bi-directional causality between economic growth and financial development (Ginevičius *et al.,* 2019). That school of thought is seen in the literature as a compromise between the supply-leading and the demand-following hypotheses (Ikhide, 2015; Dermiguc-Kunt and Levine, 2008; Luintel and Khan, 1999). Finally, there is the independence/independent hypothesis that maintains that financial deepening and economic growth are causally independent (Ikhide, 2015; Habibullah and Eng, 2006; Atje and Jovanovic, 1993).

The main contentions in the study cover the supply-leading hypothesis and the demand-following hypothesis.

1.1.1 The Supply Leading Hypothesis

The supply leading hypothesis (SLH) argues for a causal relationship from financial development indicators to real economic growth indicators (Chow, Vieito, and Wong, 2018; Banerjee and Ghosh, 2010). The SLH indicates that the direction of causality runs from the financial sector to the real sector of the economy (King and Levine, 1993; Levine and Zervos, 1998; Yartey, 2008). If stated differently, that perspective asserts that the deliberate creation of financial institutions and markets increases the supply of financial services which in turn catalyses growth in the real sectors of the economy.

Consequently, policies that improve financial structures and institutions in the economy are held to be a corollary for improving overall economic activity (Chow, *et al.,* 2018). The SLH is the theoretical underpinning that undergirded financial liberalisation policies of the 1990s and early 2000s in many emerging economies as originally espoused by McKinnon (1973) and Shaw (1973).

1.1.2 The Demand-Following Hypothesis

The demand-following hypothesis (DFH) of the finance-growth nexus postulates a causal relationship from real economic growth to financial growth, that is, it clearly states that as the real sector of the economy develops, increased demand for financial services induces growth in the latter (Best and Francis, 2015; Banerjee and Ghosh, 2010). Patrick (1966) views the finance-growth controversy from a different perspective. According to Patrick's (1966) hypothesis, the direction of causality between financial sector development and economic growth changes over time depending on the course of development (Adeyeye, et al., 2015; Odhiambo, 2008). In Patrick's world view, financial development is capable of inducing real innovation of investment before sustained economic growth gets underway and as such growth occurs, the supply-leading impetus gradually diminishes in importance as the demand-following response becomes more dominant (Odhiambo, 2008).

1.1.3 Major Functions of Financial Systems

Several studies conducted in the discipline of the finance-growth nexus have identified four major functions performed by financial institutions in any given economy. First, financial intermediaries are seen as channelling funds between lenders and borrowers (Khan *et al.,* 2015; Acaravci *et al.*, 2007). Second, there is a group of researchers and experts that underscore the risk transformation role of financial institutions which entails converting risky investments into relatively risk-free ones (Adusei, 2018; Adrian and Shin, 2010; Allen and Santomero, 2001; Scholtens and Wensveen, 2000; 2003). Conversion may involve lending to multiple borrowers in a bid to spread risk (Adrian and Shin, 2010). Third, in modern economies, banks and other deposit-taking financial institutions have been providing convenience denomination which involves matching small deposits with large loans and large deposits with small loans (Maggiori, 2017; Boulika and Trabelisi, 2002). Fourth, financial institutions raise capital for businesses, mobilise savings for investment, facilitate the growth of corporate entities and help governments to raise capital for development projects (De Gregorio and Guidotti, 1995).

1.1.4 The Finance – Commodity Market Nexus

One key feature of modern financial systems is that over the past two decades, they have become intertwined with commodity markets (Goldstein and Yang, 2019). Modern commodity markets have increased in sophistication due to the increased flow of information across the globe necessitated by rapid changes in technology (Jena and Goyari, 2016; Silvennoinen and Thorp, 2010, Aghion *et al.*, 2005; Bordo *et al.*, 2001; Du, *et al.*, 2011). The global integration of commodity markets has increased the complexity of price discovery mechanisms and processes, credit crisis events, business cycles, and financial crises (Chari and Christiano, 2017; Gorton and Rouwenhorst, 2007, Yilmazkuday and Akay, 2008; Dhaoui and Khraief, 2014; Diaz Alejandro, 1985). The rapid development of derivative products based on commodities traded in global markets has over the years amplified financial crises. Research efforts on the impact of commodity market financialisation and commodity price volatility on financial stability have yielded inconclusive results (Chari and Christiano, 2017; Irwin *et al.,* 2012; Jiménez-Rodríguez and Sanchez, 2005).

Recent empirical studies have discovered different patterns of non-linearity in the relationship between financial development and economic growth using different indicators of financial development (Jobarteh and Kaya, 2019; Soedarmono, Hasan, and Arsyad, 2017; Doumbia, 2015; Hung, 2009). Studies by Soedarmono *et al.* (2017), Bonato and Taschini (2015), De Gregorio and Guidotti (1995), Deidda and Fattouh (2002), Rioja and Valev (2004), Stockhammer, (2010) and Shen and Lee (2006) have confirmed that the finance-growth relationship is non-linear. Such studies have been conducted across countries, periods or stages of economic growth. Chen *et al.* (2006) employed a threshold autoregressive (TVAR) approach in order to examine the possibilities of a non-linear relationship between stock returns and output growth in the four East Asian economies of Taiwan, Japan, Korea, and Malaysia. The empirical findings of the study confirmed the existence of an asymmetric relationship between stock returns and industrial production growth (a proxy for output growth) in the four East Asian economies (Chen *et al.,* 2006).

1.2 Motivation of the Present Study

The present study departed from contemporary research effort in that it sought to investigate the nexus among financialised commodity markets, stock markets, and economic growth in terms of both observed and unobserved factors. Consequently, the theoretical and empirical posture of the study was to model the relationship among commodity prices, stock market performance indicators, and economic growth proxies during periods of crises and financial market correction (Errunza and Hogan, 1998). A study by Awartani, Maghyereh, and Ayton (2019) that sought to establish the nexus between oil price changes and national output proxied by industrial output in five Middle – East North Africa (MENA) countries of Saudi Arabia, Egypt, Kuwait, the United Arab Emirates, and Tunisia, had three main findings. First, results showed that output growth in MENA countries benefits from higher oil prices and is inversely related to a decline in prices. Second, the influence of oil price changes was found to be asymmetric as output responds faster to oil price increases than decreases. Third, the results showed that the long-run influence to a rise in oil price is also higher, though a considerable amount of time elapses before that influence is felt (Awartani *et al.,* 2019).

The study also departed from the empirical literature in that it sought to discover using a micro-perspective how, in the context of increasingly integrated emerging economies, commodity market financialisation links with stock market performance as measured by stock price returns (Gayi, 2015; Garcia and Perron, 1996). This is in contrast with much of contemporary research output which is predominantly linear and neoclassical, and has approached the finance-growth nexus from static causal and correlative perspectives relying heavily on standard *a priori* variable relationships (Fry,1978; 1980; Galbis, 1977). The study was thus less inclined to dwell on short-run and long-run equilibrium relationships among commodity price, stock market performance and economic growth indicators as its primary goal. The study sought to map in time and space (using the BRICS to represent the dimension of space), the dynamics of commodity market financialisation and stock market performance under volatile macroeconomic conditions.

1.2.1 Problem Statement

The subject of economic growth in developing economies is a well-debated and well-documented but highly controversial subject in the extant literature (Khatun and Bist, 2019; Al-Jafari, 2018; Ibrahim and Alagidede, 2016). The controversy associated with the subject of economic growth arises because of three major reasons. First, economic growth invariably entails either extracting resources from the natural environment or relying on the natural environment to facilitate economic activites (Al-Jafari, 2018). The second reason is anchored on the fact that economic growth has a multiplicity of factors that determine it, ranging from financial development to governmental environmental policies (Khatun and Bist, 2019; Al-Jafari, 2018; Biplob and Halder, 2018). Third, economic growth and some of its key determinants such as financial development, capital account openness, state of technology, investment including foreign direct investment as well as monetary factors such as interest rates, the inflation rate, and domestic credit are characterised by significant volatility and fluctuations that apparently mirror business cycle activity (Dey and Sampath, 2018; Abarche and Sarquis, 2017; Mensi *et al.*, 2018; Bonga-Bonga, 2015; He *et al.*, 2014).

In attempting to establish the nexus between stock market performance and economic growth the contemporary literature on emerging economies has not paid much attention to the relationship between volatile commodity prices and stock market performance indicators (Guo and Tanaka, 2019; Rioja and Valev, 2004; Sims, 1980). The finance-growth literature focusing on emerging economies has not adequately probed the extent to which commodity price volatility impacts the stock market performance – economic growth nexus (Biplob and Halder, 2018; Banerjee and Ghosh, 2010; Aziakpono, 2007; Alfaro *et al.*, 2006; Demirguc-Kunt and Levine, 1996). Ever since Solow (1956) developed and advanced an endogenous economic growth model identified as the Solow growth model, there has been a lot of research and analytical activity attempting to fit the finance-growth relationship to the long-run neo-classical framework (Beck and Levine, 2004; Levine and Zervos, 1998, 1998b; Demirgunt-Kunt and Levine, 1996).

Since the 1980s, many cross-country studies have also been undertaken to investigate the relationship between finance and economic growth (Jobarteh and Kaya, 2019; Senbet and Otchere, 2008; Chang and Velasco, 2001 and Bencivenga *et al.*, 1995). Most of the cross-country studies have neglected three basic issues. First, the robustness of a positive link between financial development and economic growth and its universality has been questioned (Driffill, 2003; Manning, 2003). Second, in an attempt to establish an equilibrium relationship between financial sector development and economic growth, much of the finance-growth literature has neglected the disruptive effects of financial development and financial integration on economic growth (Brezigar-Masten *et al.*, 2011; Mendoza *et al.*, 2009; Aziakpono, 2007 and Alexander and Lazar, 2006). History has demonstrated that as financial systems evolve, they experience crises and disruptions which usually harm economic growth. There is, however, controversy as to whether crises and disruptions emanating from the financial sector have long-run effects on economic growth or not (Nkoro and Uko, 2013; Ahmad and Malik, 2009).

The third issue is that cross-country studies that attempt to establish a link between financial development and economic growth have not addressed adequately observed and unobserved differences that characterise any arbitrary grouping of countries for purposes of econometric analysis (Barajas *et al.*, 2013; Panizza and Presbitero, 2013). Panizza and Presbitero (2013, p. 18) argue that, 'at the cross-country level, there is a negative correlation between the presence of state-owned banks and each of financial development and economic growth.'

Several researchers have provided evidence for the fact that highly integrated and globalised financial and economic systems are more prone to contagion and spillovers of volatility once a crisis is triggered in a major economy (Quoreshi, Uddin and Jienwatcharamongkhol, 2019; Gencer and Hurata, 2017; Bonga-Bonga, 2015 and Ijumba, 2013). The extent to which financial systems of emerging economies are integrated and the impact of such integration on commodity price discovery and dissemination processes has been the subject of empirical investigation for many years. For instance, Jacks *et al.* (2009) examined the link between commodity price volatility and world integration since 1700 and made an emphatic assertion that commodity markets of poor and less developed economies are generally more volatile than richer ones. They point out that such volatility impedes their growth (Jacks *et al.*, 2009). Jacks *et al.* (2009) also argue that specialisation due to the industrial revolution and other economic events, coupled with globalisation contributed to a reduction in commodity price volatility thereby fostering economic growth in emerging economies.

Taking the analysis, a step further, Cavalcanti *et al.* (2011) sought to establish the impact of the level and volatility terms of trade (TOT) on economic growth and on the three channels of growth that they identified, namely, total factor productivity, human capital acquisition and physical capital acquisition. The import of their study was to argue for the hypothesis that volatility, as opposed to the ubiquity of resources, drives the "resource curse" paradox. Contrary to the foregoing arguments, Caballero and Cowan (2007) while acknowledging that ordinarily, inflows of financial capital from other economies to emerging ones lead to increased volatility, have argued empirically that financial hedging strategies used by global market participants have been documented to reduce that volatility. What can be distilled from the foregoing is that previous empirical studies have not fully unpacked how financial market integration predisposes commodity markets to become financialised in emerging and transition economies and if such is the case, how such a link explains commodity and stock price volatilities. Empirical studies have also not exhaustively established the link between the integration of financial systems of emerging economies and the long memory features that are exhibited by commodities and financial asset returns. Put differently, the pertinent questions that need to be addressed by the empirical literature, which this study grappled with are: Have the long memory features of commodity and related asset prices increased with increased integration in global financial markets or there is no relationship between the two variables? How has increased long-range dependence between commodity and stock returns impacted the stock market performance-economic growth relationship?

In order to tackle observed and unobserved differences and effects associated with economic crises events in different economic systems, the study used frequency-domain causality analysis which converts time series data into different scales or angular frequencies identified by the Greek letter omega (ω) (Ronderos, 2016; Breitung and Candelon, 2006). The analytical information gain of spectral causality analysis was three-fold. First, the frequency-domain analytical approach transformed the Granger-causality measure from a static one to a dynamic one which changes as angular frequency, and hence time also changes. Second, frequency-domain analysis facilitated the inclusion of exogenous variables in analysing the causality for any pair of economic variables. The exogenous variables used in frequency domain analysis were of both daily and monthly data frequencies. The daily exogenous commodity variables were log-returns of gold, corn and West Texas Intermediate (WTI) crude oil. The monthly exogenous variables used in spectral causality analysis included four classes of commodity price indices, namely, the Commodity Beverage price index (denoted by cbev in Chapter 6), Commodity Agricultural Raw Materials price index (denoted by cagric), Commodity Industrial Inputs price index (denoted by cindus) and Commodity Metals price index (denoted by cmetal).

Thus, the dynamism of causal structures between any pair of variables of the study was enhanced by the fact that causality was analysed in the context of changes in commodity prices in both domestic and international economic environments. Third, the time-varying Granger causality measure obtained from spectral causality analysis brings to the foreground the importance of business cycle effects in determining both the short-run and long-run behaviour of financial and macroeconomic variables. The importance of business cycle activity to commodity price discovery and dissemination processes in emerging economies is probed in chapters two and four of the study. This study was, therefore, based on the assumption that business cycle activity in developing economies captures both explicit and underlying economic factors that impact the relationship among commodity price volatility, stock market performance, and economic growth.

1.2.2 Motivation for the choice of BRICS countries

Brazil, Russia, India, China, and South Africa constitute an important economic bloc commonly referred to as the BRICS. According to Marquand (2011), the economic bloc initially consisted of Brazil, Russia, India, and China (the BRIC) before the controversial inclusion of South Africa. Even though the BRICS is a fairly young economic bloc, its importance to researchers investigating economic growth, financial development, commodity trade dynamics, and international macroeconomic policies has increased over the past decade (Melis and Bonga-Bonga, 2019; Menon, 2017; Mminele, 2016; Matovska, et al., 2014; Fanta, 2015). Mminele (2016, p. 2) argues that, 'increased globalisation has meant that the BRICS has become an important source of global growth and political influence.' It is vitally important for researchers, policy makers, and other stakeholders to accurately understand key factors that determine capital market performance and the growth of BRICS economies.

Al-Jafari (2018) analysed the key determinants of economic growth in BRICS countries using the panel data and error correction models. The study found that only foreign direct investment had a significant positive long-run effect on economic growth, while investment in information and technology, the inflation rate, and economic size were found to have a significant negative long-run effect on the growth of the BRICS (Al-Jafari, 2018). Only the size of the economy was found to have a significant negative short-run effect on economic growth with the rest of the factors having an insignificant effect in the short-run (Al-Jafari, 2018). In addition to the foregoing exegesis, Awolusi and Mbonigaba

(2019) have observed that the diverse nature of institutional characteristics within the BRICS family implies that sustainable economic growth is now a major problem.

A study by Bonga-Bonga (2015) meant to shed more light on contagion and interdependence among BRICS stock markets, using the Vector Autoregressive – Dynamic Conditional Correlation – Generalised Autoregressive Conditional Heteroscedasticity (VAR-DCC-GARCH) model, showed evidence of cross-transmission of volatility among some member states such as Brazil and South Africa. The same study demonstrated that the South African economy is vulnerable to and affected by crises emanating from countries such as Russia, China, and India, while the reverse is not the case (Bonga-Bonga, 2015). This makes the study of the finance-growth relationship within the BRICS not only an empirical issue fascinating to those in the academic community, but also a pertinent issue with far-reaching policy implications (Bonga-Bonga, 2015). The controversies associated with the phenomenon of economic growth among the BRICS have been exercabated by the fact that these economies have for many years relied on extractive primary and secondary industries to facilitate their growth and the consequent need to deepen international trade relationships with other countries to ensure sustainable growth (Bosepung, 2017; Singh and Singh, 2016; Nashier, 2015). The implication of the foregoing is that the economic growth trajectory of the BRICS has been punctuated by frequent volatility due to volatile commodity prices, the occurrence of financial crises, and uncertainty associated with foreign direct investment (Škare and Stjepanovic, 2015; Karanasos et al., 2016; Istomina, 2013).

It is a fact documented in the empirical literature that contagion and volatility transmission among the BRICS have tended to increase during episodes of crisis (Chibani, 2017; Gencer and Hurata, 2017; Castro, Pacheso and Rosales, 2017; Singh and Singh, 2016; Bonga-Bonga, 2015). The foregoing discussion brings to the fore two important questions pertaining to the behaviour of BRICS capital markets during crisis periods that need to be addressed. First, do stock return volatilities and time-varying correlations change significantly during episodes of financial and economic crisis? Second, can the Efficient Markets Hypothesis (EMH) be relied upon to describe and make predictions about stock return behaviour during episodes of financial crisis? The study addressed these two questions by recourse to the Fractal Markets Hypothesis (FMH). The Fractal Markets Hypothesis is an analytical framework that has been gaining currency and traction in explaining the dynamics of non-linearity, contagion and interdependence among stock markets of emerging and transition economies in the past decade (Han, Wang, and Xu, 2019; Sarpong, 2017; Camelia, Cristina and Amelia, 2017; Kristoufek, 2013). Han *et al.* (2019, p. 1) undertook a study of the "…the daily return series of four main indices, including Shanghai Stock Exchange Composite Index (SSE), Shenzhen Stock Exchange Component Index (SZSE), Shanghai Shenzhen 300 Index (SHSE-SZSE300), and CSI Smallcap 500 index (CSI500) in Chinese stock market from 2000 to 2018 by multifractal detrended fluctuation analysis (MF-DFA)." During the whole study period, the daily return series of China's four main indices exhibited significant multifractal properties with the Shenzhen Stock Exchange Component Index (SZSE) having the highest multifractal properties (Han *et al.,* 2019). It is exigent to observe that the higher the multifractal properties exhibited by a given stock exchange index the lower the market efficiency of the particular stock market, *ceteris paribus*. The implication is that, the Shenzhen Stock Exchange Component Index (SZSE) exhibited the lowest market efficiency (Han *et al.,* 2019). Han *et al.* (2019, p. 1) ascribe the different multi-fractal properties of the four indices to two main factors, namely, long-range correlation which is also known as the long memory feature and 'fat-tail characteristics of the non-Gaussian probability density function.'

1.3 Objectives of the Study

The study consisted of one primary objective and four secondary objectives.

1.3.1 Primary Objective

The main objective of this study was to analyse how the nexus between volatile commodity prices and stock market performance indicators impacts the relationship between stock market performance and economic growth in the BRICS countries.

1.3.2 Secondary Objectives

The main objective of the study was achieved by pursuing the following specific objectives. The secondary objectives were:

i. To find out the extent to which volatile commodity prices explain the dynamic link between national output proxies and stock market performance indicators.
ii. To establish the effects of different financial crisis episodes on stock market volatility dynamics.
iii. To determine the extent to which volatility transmission and interdependence among stock markets of developing countries are impacted by financial crises.
iv. To examine the implications of the non-linear stock returns volatility on financial market efficiency.

1.4 Research Questions

This study consisted of four research questions which are listed below.

i. To what extent do volatile commodity price signals account for dynamic links between national output proxies and stock market performance indicators?
ii. How do different financial crisis episodes impact stock market volatility dynamics?
iii. How do financial crises impact volatility transmission and interdependence among stock markets of developing countries?
iv. What are the implications of the non-linear stock return volatility on financial markets efficiency?

1.5 Propositions of the Study

Aliyev (2019) has observed that many studies have relied on linear methods to model market efficiency. This has been done by a number of researchers even though diverse financial econometrics studies on efficiency have revealed that financial time series exhibit non-linear patterns due to different reasons (Aliyev, 2019; Chang, Aye and Gupta, 2014). It is a well-documented fact that financial markets of emerging and transition economies are characterised by long memory, contagion, thin trading, and 'fat-tail characteristics of the non-Gaussian probability density function' (Han, *et al.,* 2019; Sarpong, 2017, Bonga-Bonga, 2015; Kristoufek, 2013). Given the foregoing, the Efficient Markets Hypothesis (EMH) cannot be relied upon to accurately characterise stock market efficiency, and by corollary, the risk-return profiles of different financial assets traded on different emerging economy stock markets (Han, *et al.,* 2019; Caporale, Gil-Alana, Plastun, 2018; Rizvi and Arshad, 2016; Mynhardt, Plastun and Makarenko, 2014). An analysis of the degree of persistence of market fear in the VIX index over the 2004-2016 period by Caporale *et al.* (2018) showed that during tranquil and normal periods the market fear factor displayed anti-persistence while during episodes of crisis the level of persistence increased significantly. This has significant implications for market efficiency, and hence the risk-return profiles of financial assets associated with the VIX index (Caporale et al., 2018).

A study by Cong (2017) analysed the volatility persistence performance of stock returns around the 2008 financial market crash for Brazil, Russia, India, and China (BRIC) stock markets. Results of the study showed that volatility persistence became stronger with the onset of the global financial crisis (GFC) of 2007-2008 and dissipated during the recovery phase (Cong, 2017). Cong (2017) also found evidence of leverage effects during the crisis period implying that negative shocks had a stronger effect on conditional volatility than positive shocks. Bouoiyour and Selmi (2016) sought to discern the strength and magnitude of causality between BRICS' stock returns and the real oil price using the Breitung and Candelon (2006) frequency domain approach. On the basis of data spanning the 1994-2015 period, the results of the study showed that the impact of the oil price on stock returns is not uniform across the BRICS (Bouoiyour and Selmi, 2016). Long term hidden factors were found to be significant determinants of the Chinese share market. Results of the study showed that slowly fluctuating components of the oil price exert a significant influence on real stock returns in Brazil and Russia, while quickly fluctuating components of the oil price exert a notable influence on real stock returns of India and South Africa (Bouoiyour and Selmi, 2016).

Given the foregoing arguments, the study envisaged the use of Brazil, Russia, India, China, and South Africa (BRICS) economies to test the following two major hypotheses:

Hypothesis One (1): *In modern integrated financial systems, commodity price volatility predisposes stock market performance to be non-linearly related to economic growth.*

The import of the above hypothesis is that in modern integrated financial systems, operations of volatile commodity markets cannot be divorced from stock market activities and that this determines the non-linear relationship between stock market performance and economic growth. It is averred that the non-linearities that exist in the stock market performance – economic growth nexus are linked to changes in the business cycle as has been corroborated by some of the empirical literature (Gubler and Hertweck, 2013). Different types of GARCH models that were used to link commodity prices volatilities to stock market performance indicators also shed more light on the non-linearities that exist in the relationship between stock market performance and economic growth.

Hypothesis Two (2): *Financial crises especially those manifesting as either stock market crises or stock market corrections are associated with volatility in commodity markets and are thus an inescapable feature of modern financial systems.*

The import of the above null hypothesis is that since most developing countries depend mainly on commodities as a key driver of economic activity, and given that commodity prices are by nature volatile, this may explain the instability of emerging economy stock markets. It was expected that the correlation and conditional volatility of the main commodity indices obtained using the dynamic conditional correlation (DCC) model, Fractionally Integrated GARCH (FIGARCH) models and the Markov Regime Switching GARCH (MRS-GARCH) would provide an insight on the spill-overs, contagion, and fractality among different commodity and stock markets (Satoyoshi and Mitsui, 2011). Empirical results from different GARCH models (as specified in Chapter 5) confirmed the non-linear relationship between stock market performance and economic growth.

1.6 Significance of the Study

The present study, in contrast with much of mainstream and contemporary research on the finance-growth nexus, primarily focused on the importance of disequilibria, crises, corrections, and uncertainty on the performance, risk, and development of financial structures as well as the volatility of economic growth indicators. This approach took into account the noisiness of financial data, the complexity of financial structures as well as the dynamic nature of commodity markets from a systems perspective. This approach contrasts with the predominantly linear causality approaches.

The study's hypothetical posture was that even if the pattern of causality is established between financial development and economic growth indicators, this yields little or no insights about how deviations from such patterns due to financialisation of commodity markets impact short-run and long-run economic growth. Derivatives markets (often linked to commodity markets) have grown in importance in some developing and middle-income economies. The study was predicated on the fact that there has been limited research on how activities of those markets impact the finance-growth nexus in general, and the stock market performance-economic growth nexus in particular.

The present study probed the impact of the commodity market financialisation phenomenon on short-run and long-run economic growth without assuming a neoclassical growth context or paradigm. This approach creates room for the consideration of the stock market – commodity market – economic growth nexus from a dynamic perspective that is not encumbered by restrictive neoclassical growth theoretical perspectives.

1.7 Thesis Structure

This thesis comprises eight chapters which are briefly described below:

Chapter 1: Background and Introduction

This chapter gives background to the study by providing the motivation of the study through theoretical and empirical literature review. The chapter also explains the problem statement that provides the rationale for the pursuit of the study. Research objectives and the two research hypotheses of the study are clearly stated in Chapter One.

Chapter 2: Market Efficiency, Commodity Price Theory, and Stock Market Performance - This chapter explores historical and contemporary theoretical issues on the finance growth nexus. The chapter reviews literature on market efficiency, theories of commodity futures markets and the role of financial repression on commodity markets. The chapter also reviews the literature on the role of informational frictions on commodity markets. The chapter discusses how commodity market activity impacts the relationship between stock market performance and economic growth.

Chapter 3: Commodity Market Financialisation and Volatility Issues

This chapter discusses various perspectives on the concept of commodity market financialisation. It explores the implications of increased integration of commodity markets to stock markets in the global economy in general and the BRICS economies in particular.

Chapter 4: The BRICS and their Stock Markets

The chapter explores the size and contribution of the BRICS to the global economy. The chapter explores the trajectory of the economic performance of the BRICS countries since the 20th century. The phases of development of the financial sector in general and the stock markets of the BRICS, in particular, are discussed in this chapter. The chapter analyses how financial integration dynamics impinge on financial sector development in the context of commodity-driven economic growth.

Chapter 5: Research Methodology

This chapter is divided into two major segments. The first segment reviews the theoretical and empirical literature on models that other researchers have used to study the link among commodity price volatility, stock market performance and economic growth. The second segment describes and explains the empirical approach that was adopted for the study. Different models are specified and justified for the study in the context of both theoretical and empirical literature.

Chapter 6: Empirical Analysis: Pre-Estimation Diagnostics and Spectral Causality Tests

This chapter presents and discusses the descriptive statistics of both daily and monthly data series used in the study. The chapter also presents and explains the results of Phillip-Perron (PP) and Augmented Dickey Fuller (ADF) unit root test procedures, Johansen cointegration analysis, Granger time-domain causality tests as well as spectral causality test results are presented and discussed in this chapter.

Chapter 7: Empirical Analysis: GARCH Models, Tests, and Discussion

The chapter presents and analyses empirical results of the univariate GARCH (1, 1), the exponential GARCH (EGARCH), the Fractionally Integrated GARCH (FIGARCH), the DCC-GARCH (1, 1) and the Markov Regime Switching (MRS) – GARCH models. Results of corresponding diagnostic and robustness tests are also presented in Chapter 7.

Chapter 8: Conclusions, Recommendations and Directions for Future Research

In Chapter 8 research conclusions are proffered in the light of the past and current discourse on the finance-growth relationship in the context of commodity market price volatilities. The chapter also discusses how the study contributes to the body of knowledge in the context of the finance-growth nexus and commodity price volatility. The chapter ends with suggestions for future research.

1.8 Chapter Summary

Chapter 1 introduced the study by delineating the background to the study and the motivation of the study in terms of the statement of the problem. The chapter provided the empirical rationale for the choice of BRICS economies as the case of the study. The chapter outlined four secondary objectives that underpinned the primary research objective. The chapter also developed the theoretical framework that undergirded the two main propositions of the study. Chapter 1 discussed the significance of the study and also provided a detailed structure of the whole thesis.

CHAPTER TWO:
MARKET EFFICIENCY, COMMODITY PRICE THEORY, AND STOCK MARKET PERFORMANCE

2.0 Introduction

Chapter 2 explores historical and contemporary issues on the finance-growth nexus within the context of financialised commodity markets and integrated stock markets. The chapter reviews the ideas, concepts, and empirical findings of various researchers who have investigated and examined the relationship between finance and economic growth in general, and stock market performance and economic growth in particular.

2.1 Financial Development and Efficiency Issues

Section 2.1 provides working definitions and explanations of key terms and concepts that comprise the finance-growth nexus and issues surrounding this important topic in the literature. The terms to be explained in the subsequent sections include financial sector development, market efficiency, information asymmetry, credit market frictions, and financial repression.

2.1.1 Financial Sector Development

Financial sector development involves improvements in the parameters that characterise and define a financial system such as efficiency, effectiveness and quality of services, and products. Financial development can also be perceived as a process of reducing the costs of acquiring information, enforcing contracts, and making transactions and results in the emergence of financial contracts, markets, and intermediaries (Puatwoe and Piabuo, 2017; Adnan, 2011; Levine, 2004; Christopaulos and Tsionas, 2004). Different types and combinations of information, enforcement, and transaction costs in conjunction with different legal, regulatory, and tax systems have motivated distinct financial contracts, markets, and intermediaries across countries and throughout history.

Much of past research has tended to be mainly based on standard quantitative indicators of financial development available for a broad range of countries (Moyo *et al.,* 2018; Levine, 2004; Bonin and Wachtel, 2003; Levine and Zervos, 1998; Demirguc-Kunt and

Levine, 1996). These include the ratio of financial institutions' assets to GDP, the ratio of liquid liabilities to GDP, credit to the private sector as a percentage of GDP, and the ratio of deposits to GDP.

2.1.2 Market Efficiency

It is imperative to examine financial sector development taking into account the concept of market efficiency. According to Dimson and Mussavian (1998, p. 91) "the term efficiency is used to describe a market in which relevant information is impounded into the price of financial assets." Sewell (2011) argues that an efficient market is one in which the prevailing price 'fully reflects' an information set. To put it differently, the price of a security or financial instrument in an efficient market (that is, an informationally efficient market) would thus be unaffected by the revealing of the information set to all the participants in such a market (Sewell, 2011). The concept of market efficiency was anticipated in a seminal study undertaken by Bachelier (1900) on speculation in financial markets. In the 1960s, the American Nobel prize-winning economist, Eugene Fama proposed and published the Efficiency Markets Hypothesis (EMH) which has become the bedrock of modern portfolio theory (Fama, 1970). It is important to observe that the seeds of the efficient market hypothesis date back to the 1600s (Sewell, 2011; Fama, 1965a, 1965b, 1976a, 1976b; 1991).

The most important assumptions that underpin Fama's theory are those of inherently efficient markets, rational expectations of all participants in such markets, and the notion that security prices reflect all available information (Fama, 1970). The logic behind this model is usually demonstrated by fitting a random walk model whose primary import is to depict subsequent price changes as reflecting a random departure or disturbance from previous prices (Fama, 1965b).

Fama (1965a) identified three forms of market efficiency and these are the strong form, semi-strong form, and the weak form of efficiency. The strong form of efficiency is where all available public or personal as well as confidential information is reflected in the security's price (Fama, 1965a, 1965b, 2013). This type of efficiency precludes a scenario in which investors attain a comparative advantage (compared to others participating in the same market) and is taken as a deterrent to insider trading (Narasimhan and Titman, 1993). This degree of market efficiency implies that an investor's access to information cannot facilitate the achievement of an above-average return (Fama, *et al.,* 1969). Under the strong form efficiency world view it is impossible to "beat the market" since stocks or shares are always traded at their fair value making it impossible to buy undervalued shares or sell securities at inflated prices (Jensen, 1978). This implies that for a stock market with strong form efficiency, arbitrage is impossible. Market efficiency in the context of arbitrage has been defined as a scenario in which after the discovery or emergence of arbitrage opportunities, the market reverts to normal without an extra cost to any investor (Samuelson, 1965). The opposite situation which implies market inefficiency from Samuelson's perspective is when price differences (or arbitrage opportunities) persist for a long period (Samuelson, 1965).

The semi-strong efficiency means that a security's price (for example, a share price) reflects all publicly available information and this implies that investors cannot gain abnormal returns from their investment activities (Nwaolisa and Kasie, 2012). Malkiel (2005) demonstrated that for the financial year ending on 31 December 2003 nearly 75 percent of the mutual funds holding shares of large firms were outperformed by the Standard and Poor's 500 stock index which in a way proves that investors cannot on average consistently 'beat the market.' The weak form of efficiency claims that all previous share prices (that is history) are a reflection of today's price. The implication is that technical analysis cannot enable one to predict future price movements of a stock or security (Nwaolisa and Kasie, 2012).

Using the Capital Asset Pricing Model (CAPM) as an analytical framework, DeGennaro and Robotti (2007) are of the view that financial market friction refers to anything that interferes with trade. They assert that in a financial market with frictions, investors cannot costlessly adjust their holdings because of taxes and transaction costs (DeGennaro and Robotti, 2007). Financial market frictions, especially transaction costs, depend in part on the market structure. Market structure, in turn, depends on both the risk of the traded asset and trading volume. Other examples of frictions include agency and information problems, non-traded assets, asset indivisibility, taxes, and regulations. A tool that has been used to measure the severity of frictions is the average level of bank charges levied by the banking sector.

2.2 Theories of Efficiency of Commodity Futures Market

Section 2.2 explores theories of efficiency in the context of commodity futures markets. The fact is that while commodity markets the world over may have similarities, they also possess marked differences. This has spawned diverse models of commodity market efficiency whose overarching goal is to explain commodity market dynamics and how commodity markets link with other sectors of individual economies and the global economy as a whole. When trade is taking place in a market or rather for trade to take place, the dissemination of information about the trades being executed is a corollary of such market activities. Information dissemination, therefore, occurs concomitantly with trades being executed because economic agents engaging in such trades must be aware of the trades they participate in prior to or at the point at which they willingly participate. Such a line of argument provides the rationale for the link that is purported to exist in much of the theoretical and empirical literature between concepts of efficiency and information (Vo *et al.,* 2019; Goldstein and Yang, 2017; Serletis and Scowcroft, 1991). Serletis and Scowcroft (1991) have observed that recent advancements in the theory of cointegration have been used to verify the notion that futures commodity markets are efficient. Against the backdrop of advancements in cointegration and other theories, it is now possible to empirically test the presence of time-varying risk-premia predicated upon the belief of market efficiency.

2.2.1 The Fractal Markets Hypothesis (FMH)

One of the most fundamental functions of modern financial systems and markets is to facilitate information discovery (Vo *et al.,* 2019; Hu and Xiong, 2013). Over the past 40 years, most financial modelling systems have been undergirded by a hypothesis called the Efficient Markets Hypothesis (EMH). Blackledge (2010) has argued that the EMH has one major flaw that is the statistical belief that economic and financial processes can be conceptualised as random variables that are independently and identically distributed (i.i.d.) and are hence, normally distributed. Several empirical studies based on different countries have proved that many economic processes do not follow the bell-shaped normal distribution (Yin *et al.,* 2017; Blackledge, 2013; Panas and Ninni, 2010). The normality assumption underpinning the EMH explains the empirically documented inefficient forecasting abilities of modelling systems based on this popular but flawed hypothesis especially during times of crises, market corrections, and increased volatility in financial markets.

Peters (1991) formalised fractal theory as “borrowed” from such scientific disciplines as biology, botany, marine biology, and the study of coastlines into the Fractal Markets Theory (FMT). Peters (1991) developed the FMT borrowing from the broader framework of chaos theory to capture fully the role of investment horizons and liquidity for individual and market investors. Fractal Markets Theory (FMT) has the potential to yield new insights to the study of financial markets because the theory has two elements missing from previous theories, namely, the role of market liquidity and the related impact of information in financial asset price determination (Anderson and Noss, 2013). The Fractal Markets Hypothesis (FMH) retains the ‘smoothness and symmetry at a distance’ features of previous hypotheses that underpin asset price determination theories such as the Efficient Markets Hypothesis (EMH) and the homogeneity hypothesis. Additionally, the FMH has the added advantage of capturing the self-repeating behaviour which different economic variables such as asset return price data, business cycle activity, and the volatility of commodity markets exhibit (Barna *et al.,* 2016; Anderson and Noss, 2013). Barna *et al.* (2016) have argued that the fractal markets hypothesis has greater potential in explaining more clearly and robustly financial market imperfections such as ‘fat-tail’ effects, stochastic volatility, and self-similarity. In their analysis, Barna *et al.* (2016) found evidence of fractal features displayed by nine important emergent markets, ‘non-persistence’ for emergent markets in Europe and Asia which contrasted with statistically significant signs of local persistence exhibited by Latin American markets.

Commodity futures markets represent an important constituent of global financial markets which enables farmers and producers in their capacity as commercial hedgers to hedge commodity price risk according to insights from hedging pressure theory *a la* Keynes (1930), Hicks (1939), and Hirshleifer (1988) as cited in Hu and Xiong (2013). In the steady state, it is expected that futures markets just like other types of markets in an economy, ought to be efficient. Rao (2017) argues that the market forces of self-interest, competition, and the equilibrium between supply and demand have all a stabilising impact on prices in the market which in turn implies an efficient market. Rao (2017) further opines that the notion of a market's efficiency is linked to the market's ability to communicate relevant information to market participants or agents. Fama (1991, p. 1575) as cited in Rao (2017, p. 3) argues that since market efficiency per se is not directly testable, what is tested can only be whether asset prices properly reflect all relevant information.

The occurrence, frequency, and persistence of financial and economic crises in different parts of the world have caused some researchers to question the efficacy of the mainstream Efficient Markets Hypothesis (EMH) as articulated by some of the empirical literature (Blackledge, 2010). Some researchers have begun to doubt the ability of EMH to explain the likelihood, determinants, and consequences of financial crises when and wherever they occur (Yin *et al.,* 2017; Panas and Ninni, 2010).

2.2.2 Commodity Price Volatility: Long-memory, Non-linearities and Fractal Features

Tansuchat *et al.* (2009) have argued, based on findings of an earlier study by Poon and Granger (2003), that volatility is not necessarily the same as risk. If volatility is viewed as uncertainty, it becomes an important constituent of investment management, portfolio construction, option pricing, and risk management (Tansuchat *et al.,* 2009). Most studies focusing on volatility have tended to explore features of return series such as volatility clustering, time-varying conditional moments, long-memory persistence, and asymmetric patterns which in turn are evidence of the violation of the normality assumption (Tansuchat *et al.,* 2009). The study of price-volume correlation is critical in enhancing understanding of market fluctuations that are linked to commodity price volatility (Cheng *et al.,* 2013; Qiu *et al.,* 2011; He and Chen, 2010 and Arnold and Vrugt, 2006). Cheng *et al.* (2013), Yuan *et al.* (2012), Fleming and Kirby (2011), He and Chen (2011), Power and Turvey (2010) and Serletis and Andreadis (2004) have demonstrated that an accurate understanding of the price mechanism of any commodity market type is not possible while ignoring the study of the price-volume correlation. A discussion paper written by Ahti (2009) examined the erratic behaviour of commodity prices taking the rational expectations of competitive storage models as a point of departure. Competitive storage models postulate that non-linear commodity pricing processes are engendered by storage behaviour in the economy. The study was able to produce robust state of the art feedforward artificial neural networks that have more explanatory and forecasting power compared to standard models that had been proposed to explain base metal commodity market dynamics (Ahti, 2009).

Some recent studies on commodity futures price discovery processes and price transmission are based on a technique called multifractal detrended fluctuation analysis of ubiquitous and non-stationary time series data obtained from financial and commodity markets (Kantelhardt *et al.,* 2002). Such studies include the Bolgorian and Raei (2011) empirical analysis of the trading behaviour of individual and institutional investors plying their trade on the Tehran stock market. The empirical analysis of Bolgorian and Raei (2011) amply demonstrates through multifractal detrended fluctuation analysis (MFDA) that for both individual and institutional investors, long-term correlation adequately explains multifractality. It was also found that the S&P 500's fat-tailed probability distribution was a source of multifractality on the Tehran Stock Exchange (TSE). A similar study that employed detrended fluctuation analysis (DFA) but with special focus on the Korean agricultural market, found strong evidence of volatile financial data (including stock indices, commodity prices, and foreign exchange rates) to be highly correlated while the correlation in time of the return series of the same variables was found to be statistically insignificant (Kim *et al.,* 2011). The same study found evidence that Korean agricultural market prices exhibit a multifractal structure (Kim *et al.,* 2011).

Cheng *et al.* (2013) undertook a test of the 'long memory feature between price and trading volume of China's metals futures market.' Study results demonstrated that a period sensitive long memory feature existed that was corroborated by evidence from the analysis of the source of multifractality. This study brings to the fore the importance of fractal markets theory and other non-linear theories in enhancing understanding of how metal futures markets behave (Cheng *et al.,* 2013). A study conducted by Abdullahi *et al.* (2014) that relied on GARCH models to verify the presence of long memory in the West Texas Intermediate (WTI) and Brent crude oil futures provided strong evidence in support of long-term dependence in returns for both markets at different maturities. The study also detected the presence of asymmetric leverage effect in oil futures prices for both WTI and Brent oil markets, and empirical evidence corroborated the presence of a similar pattern of returns volatility at different maturities which apparently invalidates the Efficient Markets Hypothesis (EMH) (Abdullahi *et al.,* 2014). In the same spirit, Block *et al.* (2016) sought to understand the dynamic linkages that exist between OPEC and non-OPEC oil producers using wavelets methodology. The advantage of wavelet analysis is that it decomposes the series into different scales, thus facilitating a detailed frequency analysis of the volatility transmission process in the oil market. The main finding of the study was that the correlation between OPEC and non-OPEC price volatilities is not constant but it is frequency sensitive (Block *et al.,* 2016). It was observed that there was evidence of the existence of volatility adjustment mechanisms since the wavelet correlation apparently grew at the lower frequencies (Block *et al.,* 2016).

Elder and Jin (2007) sought to verify whether agricultural commodity futures are fractionally integrated as claimed by the extant literature using the Geweke-Porter-Hudak (1983) wavelet estimator. Their empirical results corroborated the fact that the volatilities of the futures exhibited the characteristic of self-similarity which in the extant literature is taken to be evidence of persistent long memory with an unconditional variance which is finite (Elder and Jin, 2007). Power and Turvey (2010) sought to verify the existence of long memory or long-range dependence among 14 agricultural commodity and energy futures prices employing the improved Hurst coefficient (H) estimator. The use of the improved Hurst coefficient (H) estimator was justified by information gains from the potential of the wavelets to capture self-similarity and facilitate stability tests of the H (Power and Turvey, 2010). The main findings of the study were that 9 out of 14 commodities had a non-stationary H while all the 14 commodities exhibited long-range dependence which is evidence of long memory or persistence of the data series (Power and Turvey, 2010).

2.2.3 Commodity Price Volatility and the Theory of Storage

The theory of storage is used by financial economists and other scholars to describe the features that are observed in commodity markets across the globe. According to Toyne

(2002), the theory of storage asserts that commodity price volatility is negatively related to inventories. This means that as inventories decrease, maybe due to increased aggregate expenditure in the economy or subdued production due to the obsolescence of plant and machinery in the economy, spot prices become relatively more volatile than futures prices, and the reverse is true (Toyne, 2002).

Geman and Smith (2013) argue that the theory of storage makes two major contributions to the empirical literature on the commodity market and price volatility. First, the theory of storage predicts that when there is a situation of scarcity, that is, when inventories are low, spot prices will be greater than futures prices, and therefore, by corollary spot price volatility will exceed futures price volatility, *ceteris paribus* (Geman and Smith, 2013). Second, during episodes of no scarcity, that is, when commodity inventories are either stable or accumulating the implication is that both spot prices and spot price volatility will remain fairly stable and subdued (Geman and Smith, 2013). Geman and Smith (2013) statistically tested the veracity of the two predictions using six base metals traded on the London Metal Exchange (LME), namely, zinc, lead, nickel, aluminium, copper, and tin and found strong evidence that back the two major claims of storage theory as articulated in the foregoing discussion.

The main building block of the theory of storage is a concept known as the Basis which is defined as 'the difference between contemporaneous futures and spot prices' (Fama and French, 1987). The main variables of the theory of storage may be defined *a la* Fama and French (1987) in the following manner - the futures price at the time 't' for delivery of a commodity at T may be defined implicitly as $F_{(t, T)}$. In the same manner, the spot price at time 't' may be defined as S_t. Basis may then be defined as:

Basis = $[F_{(t, T)} – S_t]$ ………………***(1)*** which may also be expressed as:

Basis = $[F_{(t, T)} – S_t]/[S_t]$ …………***(2)***

According to Fama and French (1987) basis is explained by three factors which are changes in interest rates, costs of warehousing and convenience yields. In the spirit of the preceding exposition, the marginal convenience yield [C (t, T)] may arise since some inventories such as wheat and soya beans are used in the production of intermediate goods such as flour and soya bean oil respectively (Fama and French, 1987). Thus, the marginal convenience yield [C (t, T)] of such commodities would be deriving from their economic value or their potential and real contribution to further production in the economy.

It is instructive to observe that different commodity supply conditions have significant implications on commercial consumer inventory decision making and futures prices. When, for instance, a particular commodity is characterised by a high level of supply, and hence justifies that rational commercial users of that commodity maintain low working inventories, this causes futures prices to be in contango. The market state of normal contango refers to a situation in which the futures prices are trading higher than the expected spot price of a commodity (Agarwal, 2017). The market state of normal backwardation is a scenario in which the futures prices are trading below the expected spot price of a commodity (Agarwal, 2017).

Carpantier and Dufays (2012, p.1) have observed that ‘one implication of the theory of storage is that commodity price volatility should increase when inventories are low.’ According to the empirical literature, the volatility of spot and futures prices tends to be low implying that futures premiums increase to the full cost of storage (Carpantier and Dufays, 2012). In contrast, if supplies of a certain commodity traded in international commodity futures markets are constrained, purchasing managers or commercial users of the commodity naturally feel compelled to build production inventory levels so as to secure the availability of the commodity (Carpantier and Dufays, 2012). The implications of this scenario are that futures prices of the commodity in question tend toward backwardation. The other consequence is that volatility of cash and the nearby futures prices rises in relation to more distant futures contracts (Power and Robinson, 2013).

The original theory of storage was the brain-child of Holbrook Working in 1933 (Working, 1933). After the original treatise, there was a steady growth in research output with each research paper contributing new insights to the overall model of storage in a bid to better explain the determination of commodity prices and their volatility, inventory investment, national output growth, and the stability of financial markets (French, 1986; Hazuka, 1984; Hansen and Hodrick, 1980; Working, 1948, 1949; Telser, 1958, 1967; Brennan, 1958; Kaldor, 1939). The theory of storage since its inception by Working (1933) and as further developed by other researchers is presented in Table 2.1.

Table 2. 1: Development of the Theory of Storage from 1933 to the late 1990s

Author	Contribution to the theory of storage literature
Holbrook Working (1933)	Originally developed the theory of storage for commodity markets
Nicholas Kaldor (1939)	Introduced the notion of convenience yield
Michael J. Brennan (1958)	Estimated the demand and supply curves for storage
F. H. Weynar (1968)	Related convenience yield to the probability of inventory stockout
Eduardo S. Schwartz (1997)	Modelling of yield as a mean-reverting stochastic process

Source: Researcher tabulation based on Working (1933), Brennan (1958), Schwartz (1997), Liu and Tang (2010) and other sources

Over the years more robust empirical examination has been undertaken by different researchers building on the classical theory of storage to partly explain commodity price variations and fluctuations. Fama and French (1987) employed descriptive statistics and regression analysis to test the purported link between inventory seasonals and seasonals in the marginal convenience yield and in the basis, which has already been tackled in the foregoing discussion. The major finding of the study was that futures prices have the power to forecast spot prices of selected commodities (Fama and French, 1987). Commodities such as broilers, eggs and hogs (pigs) exhibited strong forecast power (SF) and ranked among the top four commodities in terms of basis variability (Fama and French, 1987). Commodities with the time-varying expected premium feature were found to be lumber and soya oil. Minerals such as copper, gold, and platinum displayed relatively low basis variability and were not very useful in terms of forecast power and premiums (Fama and French, 1987).

2.2.4 The Risk Premium Theory

The risk premium theory as it relates to commodity markets was developed by researchers to explain the impact of risk aversion in the determination of commodity prices (Hur, Chung and Liu, 2018). The standard theory postulates that the existence of uncertainty results in a risk premium in a commodity's price or in commodity futures prices if investors are on average risk averse. According to Ruuska (2011) if the risk-averse investor takes on risk by purchasing a certain commodity or commodity futures, that investor does so based on a profit which is essentially the risk premium. In line with mainstream corporate finance literature, risk can be appropriately decomposed into systematic and non-systematic risk (Waemustafa and Sukri, 2016; Brown *et al.,* 1988; and Damodaran, 1999). Non-systematic risk can be neutralised by employing a well-diversified portfolio since it arises when commodity price fluctuations occur as a result of factors peculiar to only a particular commodity or commodity class (Ruuska, 2011; Carow *et al.,* 1999). Various scholars agree that systematic risk cannot be neutralised since it is associated with price variations that impact all financial markets, and hence all financial asset and commodity classes (Waemustafa and Sukri, 2016; Ederington and Lee, 1996; Brown *et al.,* 1988). The foregoing argument presupposes that commodities can be aggregated into distinct non-overlapping classes. The existence of risk in the dealings of agents in local and globalised commodity markets provides a rationale for the appetite of such agents or investors to hedge their asset value as a technique of offsetting any price risk. The foregoing implies that a futures contract is akin to acquiring an insurance policy since it transfers the price risk to an economic agent who is both willing and most probably equipped to handle such a risk for due compensation which in this case is a premium (Malhotra, 2015).

In order to develop the theory of risk premium further, it is imperative to note that the central message of the Efficient Market Hypothesis (EMH) is that at maturity, the futures and spot prices must be equal, that is,

$$S_T = F_T \quad \text{..................} \textbf{\textit{(3)}}$$

where S_T is the spot price of an asset or a commodity at maturity, while F_T is the futures price.

If the two prices diverge from each other, then arbitrage opportunities would by definition exist for some investors. According to Goss (1983, 1986) financial markets (including those whose underlying assets are commodities or commodity-based financial instruments) use the available information to actively take part in the spot price discovery processes. The existence of many (maybe different) futures prices (for the same financial asset) to compare with one spot price at maturity implies that the difference between the spot price at maturity and futures prices may be expressed as follows:

$$S_T - F_{(T-x,\, T)} \ldots\ldots\ldots\ldots \textbf{\textit{(4)}}$$

The fact that there are many futures prices prior to the maturity of an asset implies that the time index associated with the variable "F" the futures price must be changed from 'T' to 'T-x' as captured by Equation 4 (Anthropelosa, Kupperb and Papapantoleon, 2015; Ruuska, 2011). It is important to observe that from an empirical viewpoint, a difference deviating from zero is not unusual. The buyer of commodity futures is normally motivated by an average investor's desire to profit from a spot price increase. The increase in an asset's spot price is a necessary condition to facilitate investor retention or holding of assets. If the expected future spot price is $E_t\,[S_T]$, for the buyer of the futures contract to earn a positive yield in the future, then the futures price must be less than the investor's expectation of the future spot price as expressed in the inequality labelled 5.

$$F_{(T-x,\, T)} < E_t\,[S_T] \ldots\ldots\ldots\ldots\ldots \textbf{\textit{(5)}}$$

If inequality (5) holds, then commodity market investors must by corollary expect to receive a risk premium. If a commodity investor's expectations are the sum of the futures price plus a positive risk premium, then this can be expressed as:

$$F_{(T-x,\, T)} + P_t = E_t\,[S_T] \ldots\ldots \textbf{\textit{(6)}}$$

If P_t the risk premium is made the subject of the formula, then

$$P_t = E_t\,[S_T] - F_{(T-x,\, T)} \ldots\ldots\ldots \textbf{\textit{(7)}}$$

Equation (7) simply reveals that the risk premium that the buyer of the futures contract expects from the market is the difference between the expected future spot price and the price of the futures contract.

2.3 Empirical Evidence on the Efficiency of Commodity Markets

A number of commodity market efficiency studies from the early 1990s have tended to test empirically whether futures prices are unbiased predictors of spot prices. Such empirical tests are predicated on the belief that markets are efficient and that risk premia are zero or absent (Beck, 1994). It is worth noting that the hypothesis of no risk premia implies risk neutrality. Beck (1994) explains that given this premise cointegration techniques may be used to test for market efficiency. Much empirical research and experimentation have been conducted to test the efficiency of commodity markets. Singh and Singh (2014) have observed that it was Samuelson (1965) who first analysed futures prices as a potential predictor of future spot prices of a given contract and empirically proved that they follow a martingale. He and Holt (2004) conducted a study whose primary goal was to critically examine the efficiency of forest commodity futures markets. The study was predicated upon the belief that a well-functioning futures market ameliorates welfare losses for both producers and consumers which occur as a result of production and/or consumption fluctuations occasioned by volatility in commodity markets which are typically characterised by speculative behaviour among key agents (He and Holt, 2004).

Alvarez-Ramirez *et al.* (2010) empirically examined market inefficiencies with a special focus on the detection of autocorrelations in price time series. The researchers tested the notion that in the special case of crude oil markets, there has been a preponderance of empirical evidence that apparently roots for the belief that there is support for weak efficiency over a wide range of time-scales. In an investigation using lagged detrended fluctuation analysis (DFA) ostensibly to detect delay effects in price autocorrelations for data spanning the period 1986-2009, Alvarez-Ramirez *et al.* (2010) proved the existence of important deviations from efficiency and linked them to lagged autocorrelations.

There are several studies that have been conducted to understand the dynamics of energy consumption and macroeconomic performance (Tang and Tan, 2012, Cunado and Perez de Garcia, 2005). Zuykov (2005) analysed the efficiency of the futures market in the context of the deregulated electricity industry. The analysis which included France and Austria used data from the European Energy Exchange (EEX) for Germany and data from NordPool for Norway (Zuykov, 2005). The study's main finding was that NordPool was more efficient than the German base and the reasons proffered for NordPool's efficiency were high trading volume which, in 2003, was estimated at 545 terawatts (Tw), lower transaction costs, higher liquidity, and greater diversity of derivatives or contracts traded (Zuykov, 2005). An earlier study focusing on lead-lag relationships between futures and spot prices for oil (also an energy commodity) using the multivariate Johansen cointegration technique yielded two insights, namely, that futures prices lead spot prices and that contracts with shorter time to expiration are led by futures contracts with a longer time to the expiry date (Asche and Guttormsen, 2002). Deans (2015) argues that in developing economies thermal coal is a bulk commodity that facilitates electricity or power generation. It is further observed that thermal coal is a leading source of electricity for many emerging and transition economies including China and India (Deans, 2015, Steckel, *et al.,* 2015).

A seminal study by Nielsen and Schwartz (2004) sought to contribute to the theoretical and empirical literature on commodity pricing, by incorporating a nexus between the spread of forward prices and spot price volatility implied by the theory of storage using daily copper spot and forward prices. The model predicated on the Gibson-Schwartz (1990) two-factor model, was estimated using the Kalman filter technique and established a statistically significant link between the forward spread and volatility (Nielsen and Schwartz, 2004). The estimated model also corroborated the efficacy of the Gibson-Schwartz (1990) model in pricing forward contracts.

Soni (2013) conducted tests to detect the presence and efficacy of non-linear dependence in the rate of return series for four commodity exchange indices. The empirical study employed six different tests to detect the existence of non-linearity based on asymptotic theory and bootstrap analysis. One of the main findings of the study is that for metal and energy indices non-linearities exist even after taking into account linear serial correlations from the analysed data (Soni, 2013). This finding disproves the postulation of the weak-form market efficiency for the metal and energy sectors of commodity markets in India (Soni, 2013). The picture for the agricultural commodity spot prices was the opposite of the scenario for metals and energy.

Wang and Ke (2005) sought to ascertain the efficiency of the Chinese wheat and soya bean futures markets using the Johansen cointegration approach for three different cash markets and six different forecasting horizons spanning 1 week to 4 months. Their empirical findings corroborated those of later investigators for the Indian and emerging markets in that evidence was found that supports the existence of a long-run equilibrium relationship between the futures price and cash price for soya beans (Wang and Ke, 2005). Weak-form efficiency in the soya beans futures market in the short-run was supported by the empirical analysis. The same study found that the wheat futures market is inefficient owing to government intervention and what the authors call over-speculation (Wang and Ke, 2005). Since there is generally no consensus about whether markets are efficient or not, some authors have chosen different theoretical frameworks to study financial market operations, asset price determination processes and relationships between different financial markets variables. Ramirez *et al.* (2015) in a study that sought to understand the dynamics of the agricultural commodity futures contracts applied the adaptive market efficiency hypothesis (AMEH). The analysis applied a battery of non-linear tests ostensibly to uncover non-linear dependence in the return series of eight agricultural commodity futures contracts (Ramirez *et al.,* 2015). Results obtained from Hinich portmanteau bicorrelation tests provide evidence of the phenomenon of non-linear serial dependence with non-overlapped time windows ranging from 2.63 percent of the total windows for soya beans oil to 9.87 percent for eggs.

Inoue and Hamori (2014) examined the market efficiency of the commodity futures market in India. The methodology of the study involved estimating the long-run relationship between multi-commodity futures and spot prices employing the dynamic ordinary least squares and the fully modified ordinary least squares econometric techniques to test for the weak-form type of market efficiency (Inoue and Hamori, 2014). The main finding of the study was that the main indices had a long-run association and that subsample data since July 2009 apparently supported the conclusion that the commodity futures market was efficient (Inoue and Hamori, 2014). Kristoufek and Vosvrda (2014) examined the market efficiency of 25 commodity futures whose spectrum encompassed energies, soft commodities, metals, grains, and other agricultural commodity markets. The analysis involved ascertaining 'contributions of the study to the long-term memory, fractal dimension and approximate entropy to the total inefficiency' (Kristoufek and Vosvrda, 2014, p. 50). Using the Efficiency Index, the key findings of the study were that energy commodities are the most efficient, with livestock agricultural commodities being the least efficient (Kristoufek and Vosvrda, 2014). The study conducted by Haq and Rao (2014) focusing specifically on agricultural commodity futures in India, employed cointegration and error correction models to examine both short-run and long-run dynamics among the Indian agricultural commodity futures. The empirical results showed that market efficiency for each commodity is a long run feature with inefficiencies being exhibited in the short-run (Haq and Rao, 2014). This finding echoes an earlier observation by McKenzie and Holt (1998) that the time dimension at times signals that markets may be efficient and unbiased in the long-run, while exhibiting short-run inefficiencies.

The economy of India has presented a unique case to study commodity market growth and issues related to the efficiency of different commodity market strands. A recent study reveals that between 2004 and 2013 inclusive, total traded contracts witnessed a Compound Annual Growth Rate (CAGR) of nearly 67 percent (Parasuraman and Rao, 2014). The efficiency of commodity markets in emerging economies has also been analysed in the context of existing theoretical models such as the cost-of-carry model.

Harper *et al.* (2015) examined the weak-form of efficiency of the Efficient Market Hypothesis (EMH) focusing on silver as a commodity. The study used parametric and non-parametric tests to prove that the silver futures market exhibited the weak-form of efficiency during the study period which implies that no one could use historic prices to predict the future price movement of silver futures (Harper *et al.,* 2015). It is imperative to observe that even though the EMH still has a lot of currency and weight in contemporary finance discourse, some recent academic work has proffered alternatives to it. For instance, Kristoufek (2013) demonstrated using the fractal markets hypothesis (FMH) as a basis and the continuous wavelet transform methodology that specific investment horizons (that is, short investment horizons) predominate during turbulent economic times.

In the same vein, Parasuraman and Rao (2014) examined the efficiency of commodity markets in India against the backdrop of the accelerated proliferation of innovative financial instruments that have entered the Indian capital markets. The Parasuraman and Rao (2014) study sought to build on and improve on earlier studies that examined market efficiency such as Crowder and Phengpis (2005), Kellard *et al.* (1999), Beck (1994) and Serletis and Scowcroft (1991). Their empirical results refuted the cost-of-carry model given a single hypothesis and joint hypothesis tests implying that evidence of market efficiency was weak at the time of the data analysis (Parasuraman and Rao, 2014). In contrast, Narsimhulu and Satyanarayana (2016) sought to discern the efficiency of commodity futures in India in discharging price discovery and risk management functions with special focus on three agricultural commodities, namely, Chana, Chilli, and Turmeric. The study involved carrying out Johansen cointegration analysis, Vector Error Correction modelling (VECM), Wald Chi-square tests, and Granger Causality tests of the daily closing prices of spot and futures markets for the period 2004- 2013 inclusive, obtained from the National Commodity & Derivatives Exchange (NCDEX) Ltd (Narsimhulu and Satyanarayana, 2016). Empirical evidence supported a long-run relationship between spot and futures prices of Chilli, Chana, and Turmeric. The VECM revealed the direction of long-run causality to be from futures prices to spot prices for Chilli and Turmeric with Chana showing evidence of a bidirectional causal relationship between futures and spot returns (Narsimhulu and Satyanarayana, 2016). The study revealed that commodity futures hedging is more effective when it is done with near-month futures contracts.

2.3.1 The Special Case of Oil Market Efficiency

Crude oil is a composite commodity with a significant impact on global economic activity and affects even the price volatility of other commodities together with their relevant derivative markets. Crude oil has many interesting features that make it attractive to global economic activities. These features include the fact that crude oil is a liquid mineral, a unique source of energy, exists in abundance in some regions of the world while in most parts of the world, crude oil either does not exist or has not yet been discovered. Crude oil is a raw material for a diverse and broad range of petrochemical industries. All these and other features of oil partially explain why the prices of crude oil as quoted in international markets tend to be more volatile together with the prices of related derivative financial instruments. The link between oil markets and the wider economy has been a subject of much controversy in both the theoretical and empirical literature. Much of what is known about oil price and oil market dynamics is still in a state of flux, though a lot of progress has been achieved by researchers in explaining the sources of and the impact of oil price volatility.

Prior to the onset of the Global Financial Crisis (GFC), Coppola (2008) undertook a study of the cointegrating relationships between spot prices and futures prices of oil under the cost of carry theoretical framework. The primary focus of the study was to estimate models that could be used to forecast out of sample spot and futures oil price movements using the Vector Error Correction Model (VECM) and the Random Walk model (RWM) (Coppola, 2008). The study found that in-sample, a significant variation in oil prices can be explained by information gleaned from the futures market and that out-of-sample, price movements of near term (that is, 1-month) futures contracts were explained better by VECM than the RWM (Coppola, 2008).

A study published towards the end of Global Financial Crisis (GFC) by Charles and Darne (2009) tested the applicability of the random walk model (RWM) to crude oil markets using daily observations from 1982 to 2008 gleaned from two of the most important crude oil markets in the global economy, namely, the U.K. Brent and the U.S. West Texas Intermediate (WTI). The modelling process was predicated on the weak efficiency market hypothesis which was tested using non-parametric variance ratio tests according to Wright (2000) and Belaire-Franch and Contreras (2004). The empirical results reveal that Brent crude oil is weak-form efficient while the WTI crude oil market was apparently inefficient for the sub-period ranging from 1994 to 2008. This may indicate that the deregulation of the oil industry is yet to bear fruits in terms of making returns of the WTI crude oil market less predictable (Charles and Darne, 2009).

An empirical study of the market efficiency of oil spot and futures prices was conducted by Lean *et al.* (2010) employing the mean-variance (MV) and stochastic dominance (SD) statistical methods. The study period was from 1989 to 2008 and the study made use of West Texas Intermediate (WTI) crude oil data. The major finding of the study was that mean-variance (MV) and stochastic dominance (SD) relationships do not exist between the spot and futures indices for crude oil (Lean *et al.,* 2010). This implies that the spot oil and the futures oil markets do not dominate each other. Therefore, it can be statistically and validly concluded that arbitrage opportunities do not exist between the two markets since discerning investors participating in the two markets are indifferent between them (Lean *et al.,* 2010). The main findings of the Lean *et al.* (2010) study are apparently echoed by the Wang *et al.* (2011) study that employed DFA and detrended cross-correlation analysis (DCCA) to empirically test the autocorrelations and cross-correlations of West Texas Intermediate (WTI) crude oil spot and futures return series. Their empirical results showed that the autocorrelations and cross-autocorrelations are persistent for time scales shorter than a month and there is anti-persistence for time scales longer than a month but shorter than a year (Wang *et al.,* 2011). The study also found that for time horizons longer than a year there was evidence of the efficient operation of the crude oil markets corroborated by the fact that the series were neither autocorrelated nor cross-correlated (Wang *et al.,* 2011).

In contrast to the Lean *et al.* (2010) empirical analysis, Liu *et al.* (2013) undertook empirical analysis in which they tested the null hypothesis that the world oil market is "one great pool" against the negation of the null hypothesis. The analysis was facilitated by examining the extent to which China's oil market is integrated into four major crude oil markets. Using a non-linear correlation measure, Liu *et al.* (2013) found more statistically significant evidence in support of price co-movement between China's and international crude oil prices in the long run than in the short term. Evidence from the implemented threshold error correction model (TECM) further demonstrated that long-run equilibrium relationships are characterised by marked asymmetric effects whose existence is regime-dependent (Liu *et al.,* 2013). Using BEKK-GARCH as the analytical framework, volatility spillover was found to be unidirectional from benchmark markets to China's oil market. The maintained hypothesis of "one great pool" was thus rejected on the basis of empirical findings (Liu *et al.,* 2013).

2.4 Financial Repression and Commodity Markets

According to the literature, financial repression occurs when governments implement policy measures that channel productive funds to themselves which in an unregulated or deregulated market framework would otherwise go to the private and other non-government sectors (Reinhart and Sbrainca, 2015; Denizer, *et al.,* 1988). According to Yulek (2017, p. 1390) "financial repression policies (lowering real interest rates, selective credits and other restrictions on financial markets, products and institutions) have been widely discussed in the economic literature during the last four decades." Hileman (2016, p. 6) defines "financial repression …. as any measure taken by central authorities that directs lendable funds towards the sovereign's publicly issued debt, often on attractive terms (below market)." It is imperative to note that financial systems of developing or emerging economies usually have characteristics of restriction or repression such as burdensome reserve requirements, foreign exchange controls, interest rate ceilings, taxation of the financial markets or financial market transactions and government regulation of bank balance sheet composition (Yulek, 2017; Denizer *et al.,* 1988).

Fry (1982) cited in Yulek (1996) argues that in most transition economies, financial markets are shallow with the dominant feature being high levels of financial repression due to financial restrictions that exist in such economies. Yulek (1996) further argues that central bank intervention and operations meant to positively impact the real economy may worsen the opaqueness of financial markets. In this scenario, the impact of monetary policy and other policy instruments becomes uncertain and indeterminate. This finding has recently been corroborated by an analysis of the nexus between financial repression and economic growth undertaken by Huang and Wang (2010). After constructing an appropriate financial repression index and employing time series and panel data modelling methods, Huang and Wang (2010) establish that in 1978, financial repression held down economic growth (as measured by the GDP growth rate) by between 9 and 10.9 percentage points. The same study also found that in contrast financial liberalisation increased China's economic growth by 4 percentage points although constraints to economic growth still remain (Huang and Wang, 2010). The rationale for these results has been provided by Xu and Gui (2013, p. 385) who observe that, "China exhibits the typical symptoms of a financially repressed economy, such as regulated interest rates, a dominance of state ownership, and managed credit allocation."

The main reasons that motivate governments of different countries to regulate financial markets are generally not well understood and basically explain the controversy surrounding the subject of financial repression. Prior to the 1970s, the discourse on the role of government in financial markets generally favoured financial restrictions in capital-scarce economies based on the premise that money supply would be better controlled and that investment saving targets would be higher than in liberalised or deregulated financial systems (Denizer *et al.,* 1988). The neoclassical justification for government intervention in financial markets is predicated on the belief that money and "productive" capital are perfectly substitutable. In the Tobin (1965) monetary-growth perspective, a rise of the return on capital relative to the return on money implies a shift from money to capital in household portfolios, higher capital-to-labour (capital intensity) ratios and improvements in labour productivity. The corollary of this thesis is that reducing interest rates through interest rate ceilings coupled with optimal inflation levels would spur economic performance (Denizer et al, 1988). In contrast, the McKinnon (1973) and Shaw (1973) framework departs from the neoclassical approach to developing countries on the backdrop of the argument that a repressed financial sector discourages both saving and investment because the rates of return are lower than what they could potentially be in a competitive or deregulated financial sector. In a McKinnon – Shaw world money and capital are viewed as complements in contrast to the neoclassical world view which posits that the two variables are substitutes (McKinnon, 1973, p. 60; Shaw, 1973, pgs. 81-82). In such a system, financial intermediaries do not function at their full capacity and fail to channel savings into investment efficiently. Common measures of financial repression include the reserve requirements set by the central bank, level of interest rate ceilings and the base interest rate.

In the early 1980s, critics of the McKinnon-Shaw framework argued that raising institutional interest rates might negatively affect savings, investment, and economic growth. Critics who hold variants of this view include Hastings (1993), Wade (1990), Diaz-Alejandro (1985) and van Wijnbergen (1985). A study of the newly industrialising East

Asian economies revealed that certain levels of government intervention in financial markets may actually have welfare enhancing effects (Yulek, 2017; Wade, 1990; Amsden, 1989 and van Wijnbergen, 1985).

2.5 Informational Frictions and Commodity Markets

Various models have been propounded by different scholars in a bid to explain why real-world commodity and financial markets depart from the idealistically imagined and projected world of the Efficient Market Hypothesis (EMH) (Bejarano *et al.,* 2016; Kwon and Lee, 2016; Sockin and Xiong, 2015; Hugonnier *et al.,* 2012; DeGennaro and Roboti, 2007). Informational frictions fall under the broad category of what is known as financial market frictions. Financial market friction refers to any factor or event which interferes with trade, be it trade in commodities or financial instruments or both (DeGennaro and Robotti, 2007). This world view of frictions that occur when trades take place is what is envisaged by the Capital Asset Pricing Model (CAPM). Bejarano *et al.* (2016) analysed how persistent commodity price changes characterising small but resource-rich economies impact the macroeconomy when economic agents face financial and informational frictions. The study involved the estimation of the informational and financial friction model, using Colombian data, which reproduced the boom-bust foreign borrowing pattern linked to the business cycle in developing economies (Bejarano *et al.,* 2016).

The empirical literature has over the years developed a well-knit and elegant theoretical framework that serves two main purposes. First, such a theoretical framework analyses how information aggregation is facilitated by trading in centralised asset markets and secondly, how such trading helps market participants to overcome the informational frictions they face (Asriyan, Fuchs, and Green, 2019; Grossman and Stiglitz, 1980 and Hellwig, 1980). The *a priori* theoretical expectation of basic commodity market microeconomics is that a higher commodity price signals a strengthening global economy which motivates each commodity producer to produce more goods (Sockin and Xiong, 2015).

Several empirical studies have been undertaken by different researchers on the nexus between informational frictions and commodity market price discovery processes (Goldstein and Yang, 2016; Goldstein and Yang, 2019). Sockin and Xiong (2015)'s study develops a model underpinned by a tractable log-linear equilibrium in a bid to analyse the impact of informational frictions in commodity markets. Their study involved aggregating dispersed information about the global economy's strength for goods producers characterised by complementarity (Sockin and Xiong, 2015). The main finding of the study was that commodity prices are signals that guide production decisions and patterns of commodity demand (Sockin and Xiong, 2015). The estimated model revealed that informational noise originating from supply shocks and futures market trading has important feedback effects on commodity demand and spot prices (Sockin and Xiong, 2015). The caveat to the main findings is that different types of shocks in commodity markets are not publicly observable to all relevant and key market participants.

2.6 Commodity Volatility Issues, Stock Market Performance and Economic Growth

The growth in importance of commodity markets since the 1990s and the subsequent integration of different commodity markets into mainstream financial markets has created possibilities of a nexus between commodity markets (and hence different commodity price indices) and economic growth. The interdependence that has been proven to exist between commodity markets in different economies partially explains why over time the economic growth variable tends to exhibit significant volatility in different countries (Abarche and Sarquis, 2017; Chukwuemeka, 2016; Dabusinskas *et al.,* 2012; Hamilton, 2011 and Imbs, 2002). Dabusinskas *et al.* (2012) investigated the impact of macroeconomic volatility on economic growth for a panel of 121 countries for a period spanning 1980 and 2010. Their results confirmed earlier findings by Ramey and Ramey (1995) who found that macroeconomic volatility has a negative impact on economic growth (Dabusinskas *et al.,* 2012).

Researchers such as Bernanke (2010), Anson (1998), Mork (1989), Barro (1984), Burbridge and Harrison (1984) and Darby (1982) have at different times explored the theoretical dynamic causal effects of commodities such as oil on output and inflation. In the same spirit, authors such as Huang *et al.* (2005), Cologni and Manera (2008) and Leduc and Sill (2004) have sought to understand the role of macroeconomic policies adopted by various governments to deal with price and output volatility in oil markets.

Other researchers have sought to explore the links that may exist between oil prices on the one hand, and the terms of trade and trade accounts of oil-importing economies on the other hand (Husain *et al.,* 2008 and Dohner, 1981). Empirical investigations by Mory (1993), Lee *et al.* (2001), Cunado and Perez de Garcia (2003) and Hamilton (2009) have been undertaken to understand the impact of oil price shocks on several macroeconomic indicators such as national income (GDP), investment, level of employment, Balance of Payments (BOPs), interest rates and inflation. An analysis of the impact of oil price on the Stock Index for Kuwait conducted by Hayky and Naim (2016) using a Markov Switching Model to investigate regime shifts between low and high volatility regimes revealed that the stock market index responds differently to the oil price variable in different regimes. The study also demonstrated that during the high regime period, the relationship between the oil price variable and the stock market index is positive and statistically significant while during the low regime period there is no statistically significant relationship between the two macroeconomic variables (Hayky and Naim, 2016).

2.6.1 Commodity Prices, Stock Market Development, and Economic Growth

A study of the commodity-finance-growth nexus shows that there is a paucity of both theoretical and empirical literature on this nascent but important strand of the debate in financial economics. It is a fact that both theoretical and empirical literature already exists on the nexus between commodity prices and stock performance indicators (Youssef and Mokni, 2019; Morema and Bonga-Bonga, 2018; Wai, 2015). It is also a fact that there is a huge library of extant literature from 2000 to 2015 on the purported link between finance and growth or more specifically on the nexus between financial sector development and economic growth (Fanta, 2015; Barajas *et al.*, 2013; Stolbov, 2012; Yu *et al.*, 2012; Levine, 2004; Al-Yousif, 2002). In fact, the finance-growth nexus is one of the most researched topics in both theoretical and empirical financial economics and international corporate finance (Fanta and Makina, 2017; Fanta, 2015). A number of single and cross-country studies have been undertaken with the overarching aim of proving or disproving the purported link between financial development and economic growth (Barajas, 2013; Odhiambo, 2008; Senbet and Otchere, 2008; Levine, 2004).

The trade in commodities is as old as humankind because people need commodities for their upkeep (Keong *et al.,* 2014; Gorton and Rouwenhorst, 2007). Much of economic activity is delicately and intimately undergirded by a robust trade in primary and intermediate (or semi-processed) commodities. It is nearly impossible to imagine how any economy in the world would thrive or even survive for even the shortest periods without trade in commodities (Keong *et al.,* 2014). Even though commodities in general and trade in commodities, in particular, are necessary for modern economies to grow and sustain growth, it is noteworthy that trade in commodities started to grow at an accelerated pace from the early 1990s onwards (Gorton and Rouwenhorst, 2007). This accelerated growth in trade in commodities was partly facilitated by a phenomenon known as 'financialisation of commodity markets' that improved linkages between commodity markets and the mainstream financial sector.

'Financialisation of commodity markets' also known as the 'financialisation hypothesis' has been viewed by Carmona (2015) as the reduction of virtually all value, including the value attached to commodities and their markets, into financial instruments. It is a fact corroborated by a number of researchers that since the early 1990s the importance of commodity markets has increased, and that commodity markets are now more integrated into globalised financial markets (Irwin *et al.,* 2012; Dore, 2000 cited in Falkowski, 2011; Cashin *et al.,* 2004 and Gorton and Rouwenhorst, 2007). In the past, that is, prior to the accelerated growth of the 1990s, commodity markets were largely segmented from financial markets and as a result there was little or insignificant co-movement between commodity prices and stock prices (Cheng and Xiong, 2014; Gorton and Rouwenhorst, 2006; Gorton *et al.,* 2007 and Erb and Campbell, 2006). Researchers such as de Roon *et al.* (2000), Bonato and Taschini (2015) have in different ways argued that increased financialisation of commodity markets has been predicated on the fact that commodity prices provide investors with a risk premium for commodity price risk. It is important to observe at this juncture that according to UNCTAD's Trade and Development Report (2009) the build-up, progression and eruption of the 2007-2009 global financial crisis (GFC) was paralleled by an unusually sharp increase and strong reversal in prices of internationally traded primary commodities anchored by minerals, especially crude oil.

Killian (2009) and UNCTAD's Trade and Development Report (2009) have observed that during approximately 78 months between 2002 and mid-2008, the International Monetary Fund (IMF)'s overall commodity price index rose steadily, and nominal commodity prices nearly quintupled. Any attempts to link speculation and commodity price volatility have been met with scepticism owing to the belief that financial investors who effect spot prices only participate in commodity futures, and related derivative markets to ensure delivery and holding of physical commodities in their inventories (Ekeland *et al.,* 2015; Irwin *et al.,* 2009 and Alquist and Kilian, 2007). Krugman (2008) has argued that the speculative activity in the oil market that drives prices above their fundamental equilibrium level normally causes market imbalances and over-supply which ultimately leads to inventory accumulation. This argument has been negated by the fact that during the Global Financial Crisis (GFC) of 2007-2008 sharp increases in oil prices occurred without any inventory accumulation.

It is instructive to observe that despite evidence provided in the foregoing analysis, there is still a paucity of empirical evidence that links commodity prices, stock market performance indicators, and economic growth. Most recent studies that have made attempts to link commodity markets to the finance – growth nexus have been mainly trade-related studies (Tsaurai, 2018; Khan and Qayyum, 2007). Khan and Qayyum (2007) undertook a study of the nexus between trade, finance and economic growth in Pakistan. The empirical analysis that involved CUSUM and CUSUMQ stability tests of the estimated equations revealed that both trade and financial liberalisation play a crucial role in enhancing long-run growth in Pakistan (Khan and Qayyum, 2007). Jamel and Maktouf (2017) sought to establish the nexus between economic growth, financial development and trade openness among other factors in European countries. Jamel and Maktouf (2017) used ordinary least squares (OLS) predicated on the Cobb-Douglas production function to verify the nexus between economic growth (GDP), Carbon-dioxide (CO2) emissions (to proxy environmental degradation), financial development, and trade openness for 40 European economies for the period 1985-2014. Granger causality tests showed that bidirectional causality existed between the following pairs of variables: GDP and the pollution proxy (CO2 emission), GDP and financial sector development, GDP and trade openness (Jamel and Maktouf, 2017).

Deaton (1999) evaluated the link between commodity prices and economic growth in Africa, and found that attempts to leverage on the proceeds of commodity exports to facilitate the industrialisation process have been hindered by a lack of growth in real commodity prices. Cavalcanti *et al.* (2012) employed the General Method of Moments (GMM) coupled with a cross-sectionally augmented version of the pooled mean group econometric method of Pesaran *et al.* (1999) to examine the impact of the level and volatility of commodity terms of trade on economic growth for a sample of 118 countries. The study was predicated on three perceived channels of economic growth which are total factor productivity, physical capital accumulation and human capital acquisition (Cavalcanti *et al.,* 2012). A direct relationship was established between terms of trade growth and real output per capita, though terms of trade growth volatility were found to negatively impact economic growth through the lower physical capital accumulation growth channel (Cavalcanti *et al.,* 2012). The main conclusion of Cavalcanti *et al.* (2012) was that terms of trade volatility as opposed to abundance only, drives the 'resource curse' paradox. The 'resource curse' paradox, also known as the paradox of plenty, refers to the failure by many resource-rich economies to optimally benefit from their natural resource base in terms of tangible and sustainable public welfare improvements (Natural Resource Governance Institute, 2015).

Zapata *et al.* (2012) conducted a two-pronged study which analysed the cyclical link between stocks and commodities, and the role of commodity and agribusiness indices in portfolio allocation. The analysis revealed that over a 140-year period a high negative correlation existed between stock and commodity prices (Zapata *et al.,* 2012). The study also found that the commodity and stock markets have alternated in price leadership with 29-32-year cycles (Zapata *et al.,* 2012). Mongale and Eita (2014) analysed the nexus between commodity prices and stock market performance in South Africa using quarterly time series data spanning the period 1994-2013 based on the Engle-Granger two-step methodology. The study demonstrated that there is a direct relationship between commodity prices and stock market performance which implies that an increase in prices of commodities is linked to an appreciation in stock market performance (Mongale and Eita, 2014). Mongale and Eita (2014) also demonstrated that stock market performance and macroeconomic performance proxies such as money supply and the exchange rate are positively related in South Africa. Table 2.2 summarises some of the studies that have established the nexus between Commodity Prices, Stock Market Performance and Economic Growth.

Table 2. 2: The nexus between Commodity Prices, Stock Market Performance and Economic Growth from the Extant Literature

Authorship	Goals/ Objectives	Case Studies	Methods	Findings and Conclusions
Khan and Qayyum (2007)	Nexus between trade, finance and economic growth	Pakistan	CUSUM and CUSUMQ stability tests of the estimated equations	Both trade and financial liberalisation play a crucial role in enhancing long run growth
Cavalcanti *et al.* (2012)	Impact of the level and volatility of commodity terms of trade on economic growth	118 countries	GMM underpinned by Pesaran (1999)'s cross-sectionally augmented version of the pooled mean group	First, direct relationship between terms of trade growth and real output per capita. Second, terms of trade growth volatility negatively impact economic growth mainly through the lower physical capital accumulation growth channel. Third, terms of trade volatility drive the 'resource curse' paradox.
Zapata *et al.* (2012)	cyclical link between stocks and commodities and the role of commodity and agribusiness indices in portfolio allocation	Mainly the United States (U.S)	Linear programming, Minimization of Total Absolute Deviations (MOTAD) and Target MOTAD to conduct return-risk analysis	First, 140-year period a high negative correlation has existed between stock and commodity prices. Second, commodity and stock markets have alternated in

				price leadership with 29-32-year cycles.
Jamel and Maktouf (2017)	Nexus between mainly economic growth, financial development and trade openness	40 European economies	Ordinary Least Squares (OLS) predicated on the Cobb-Douglas production function	bidirectional causality between GDP and the pollution proxy (CO2), GDP and financial development, and GDP and trade openness
Mongale and Eita (2014)	Nexus between commodity prices and stock market performance	South Africa	Engle-Granger two step methodology. Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin test statistics for unit root tests	Direct relationship between commodity prices and stock market performance

Source: Researcher compilation using various cited sources

Table 2.2 demonstrates the gap that exists in the empirical literature in terms of establishing the nexus between commodity price volatility, stock market performance and economic growth. Table 2.2 shows that research efforts that have sought to establish the nexus among volatile commodity prices, stock market performance and economic growth are inedaquate.

2.6.2 Non-linearities in Commodity Futures and Stock Market Performance

Several studies have been conducted to discern any non-linearities that exist between commodity futures prices and stock market performance indicators (Youssef and Mokni, 2019; Azar and Chopurian, 2018; Sinha and Mathur, 2013). Such studies have demonstrated the inherent volatility of commodity futures prices. The same studies have proven the fractality of commodity futures prices which may be taken as proof of persistence or anti-persistence as well as long-memory and self-similarity.

In recent years, there has been an increase in research output that has focused on linking different derivatives in the context of the broad theme of financial market development (Storm, 2018; Djenic, Popovcic-Avric and Barjaktarovic, 2012; Sundarum, 2012; Alquist and Kilian, 2007). It is in this regard that Noman and Rahman (2013) sought to discern the long-run relationship between a set of 19 Exchange Traded Notes (ETN) and their underlying commodity futures indices predicated on the financialisation of commodity futures markets hypothesis. The study involved an analysis of linearities or non-linearities that existed in the data. The study employed the Engle-Granger cointegration framework which permits both linear and non-linear adjustment via the error correction term of the estimated model (Noman and Rahman, 2013). Study results showed that there is a long-run relationship between ETN prices and the values of their underlying commodity indices. Noman and Rahman (2013) attributed non-linearities exhibited by the long-run adjustment process between the markets to the fact that the process of the creation and redemption of the share units of the ETN is characterised by a time lag.

An analysis of cross-market linkages and contagion characterising the oil and stock markets by Bampinas and Panagiotidis (2017), provides evidence in support of the argument that these two markets behave as a "market of one" due to commodity market financialisation. It is important to note that the model estimated by Bampinas and Panagiotidis (2017) sought to capture crucial stylised features of stock and oil returns which include 'fat tails' or leverage effects by estimating the marginal model of their returns as an ARMA (p, q) – GARCH (1, 1) model with a white noise process that follows a skewed Student - t distribution. The local Gaussian correlation methodology provided evidence of cross-market linkages between spot and futures markets on the one hand and stock markets on the other hand (Bampinas and Panagiotidis, 2017). Evidence was adduced to support the occurrence of contagion and spillovers between the US stock markets and all the benchmark oil markets. Empirical evidence provided by Bampinas and Panagiotidis (2017) for all the four major crises studied validated the hypothesis of flight from stocks to oil occasioned by financial crisis. In contrast, an earlier study by Iscan (2015) which sought to establish the relationship between commodity prices and stock prices using Johansen cointegration techniques for the case of Turkey found no evidence of a long-run relationship between the two variables.

Creti *et al.* (2012) analysed the link between price returns of 25 commodities and stocks with special emphasis on energy raw materials. Data analysis based on the dynamic conditional correlation (DCC) GARCH model showed that the correlations linking commodity and stock markets are time varying with a tendency to be highly volatile during crisis episodes such as the Global Financial Crisis (GFC) of 2007-2008 (Creti, *et al.,* 2012). The high volatility of dynamic conditional correlations linking commodity and stock markets supports the hypothesis of the financialisation of commodity markets. The same analysis underscored the association of oil, coffee and cocoa with speculative activities, in contrast with gold which during the study period exhibited qualities of being a safe haven (Creti *et al.,* 2012).

2.7 Chapter Summary

Chapter has examined the body of theoretical and empirical literature that attempts to explain the dynamic finance-growth relationship as well as the commodity prices-finance nexus. This chapter also explored literature pertaining to the relationship between credit market frictions, financial markets efficiency and financial repression issues. The chapter reviewed theories and models of efficiency of commodity markets which have been proposed by different authors and researchers since 1933. Empirical evidence reviewed for this chapter demonstrated that commodity prices are characterised by non-linearities, fractality, and persistence as well as the unique feature of self-similarity found in commodity markets over time. Chapter three explores commodity market financialisation and volatility issues in detail. Chapter three explores how commodity market financialisation fits into the broader and overarching aim of the study which is to investigate and analyse how commodity market price determination processes and mechanisms link with more focused themes such as volatility, non-linearity and contagion in both commodity and the mainstream financial markets.

CHAPTER THREE:

COMMODITY MARKET FINANCIALISATION AND VOLATILITY ISSUES

3.0 Introduction

This chapter analyses the theoretical and empirical issues associated with commodity price volatility and commodity market financialisation. The chapter examines in detail the theoretical linkages among commodity price volatility, stock return behaviour and economic growth. The chapter also evaluates the veracity of the prevalent notion that commodity price volatility damages economic growth. The chapter discusses the role of financial investors in commodity markets, and how such a role impacts financial market development in general, and stock market performance in particular.

3.1 The Concept of a Commodity – A Commodity Taxonomy

Academics have failed to reach a consensus on the main differences between commodities and financial assets. The main problem encountered in endeavouring to define commodities is that commodities are the subject of study by scholars from diverse disciplines. The study of commodities is a matter of interest in disciplines ranging from the natural sciences to political science. Nassim Nicholas Taleb in a preface to a text by Geman (2005) observes that an economist may view a commodity as a consumption asset whose scarcity greatly impacts local (or national) development as well as global development. Nassim Nicholas Taleb observes that an ecologist's viewpoint of a commodity may be that it is a natural good whose original integrity needs to be preserved (Geman, 2005).

Uebele (2012) argues that the catch-all term 'commodity' is used to refer to a homogeneous good or product that is not a true asset. The distinction between a commodity and a financial asset is that the latter generates a stream of consumption or a stream of cashflows that can be used to purchase commodities, while a commodity is normally itself purchased for consumption purposes (Uebele, 2012). A financial asset such as a bond or a stock generates or at least is expected to generate a flow of benefits.

Some commodity market scholars believe that establishing the dichotomy between a consumption good and a true asset may contribute to understanding commodity market bubbles or bubbles in commodity prices (Cheng and Xiong, 2014; Uebele, 2012 and Geman, 2005). Establishing the dichotomy between a commodity and a financial asset is imperative given advances in financial markets due to rapid changes in technology, and the controversial phenomenon of financialisation of commodity markets (Zaremba, 2016).

3.2 Financialisation of Commodity Markets

The increasing importance of commodity markets to modern economies and their integration into globalised financial markets have led to a process known as commodity market financialisation (Dwyer *et al.,* 2012). This process entails the increasing dominance of the finance industry in the sum total of economic activity, of financial controllers in the management of corporations, of financial assets among total assets, of market securities and particularly equities among financial assets and of the stock market as a market which determines corporate strategies (Dore, 2000 cited in Falkowski, 2011; Gorton and Rouwenhorst, 2007 and Cashin *et al.,* 2004).

According to Carmona (2015) financialisation – also called the financialisation hypothesis- means the reduction of virtually all value of commodities into financial instruments. This definition agrees with the perspective that commodity market financialisation is a process by which commodity futures become a popular asset class for portfolio investors, just like stocks and bonds (Cheng and Xiong, 2014). Kang *et al.* (2016, p.3) have argued that financialisation of commodity markets, which is facilitated by financial integration, is an “important ingredient for investors seeking to diversify their investment portfolios.”

The financialisation of commodity markets has sparked a debate on whether the financialisation of commodity markets distorts commodity prices (Cheng and Xiong, 2014). Falkowski (2011) argues that even though the market forces of demand and supply determine price formation for specific commodities, other factors such as world events, human psychology (including fear or anxiety due to uncertainty) and expectation of future profits also determine commodity prices and their volatility. Quoting the Commodity Futures Trading Commission (2008) report, Falkowski (2011) observes that different commodity index-related instruments bought by institutional investors rose in value terms from US$15 billion in 2003 to US$200 billion in mid-2008. This demonstrates that over the years spanning the early 2000s, the pace of financialisation of commodity market financialisation accelerated.

3.3 Commodity Markets Since 1800

Global trade in commodities has existed from antiquity. The trade in commodities is an important source of revenue for many developing and emerging economies. For instance, oil is the backbone of economic activities in a number of Middle Eastern and the Persian Gulf economies. Rapid oil price increases in global markets have accounted for improvements in economic growth (Calvacanti *et al.,* 2015; Kinfack and Bonga-Bonga, 2015). The level of sophistication of commodity markets has, however, changed over time. In the past 15 to 20 years commodity futures markets have developed quite markedly in a number of developing and emerging economies. In India, for instance, in recent years there has been a significant inflow of investment towards a commodities futures market (Jena, 2016).

Several authors have attested to the fact that commodity prices have experienced recurrent jumps at irregular intervals in history (Calvacanti *et al.,* 2015; Pirrong, 2012). The long history of volatility in commodity prices includes dramatic jumps in the 1860s, 1910s, 1940s and the 1970s (Jacks, 2017). According to Uebele (2012), there is a view he terms the classic view which sees the last 25 years of the 19th century as a defining period in determining international trade in commodities and commodity market integration. Authors such as O'Rourke (1997) and Harley (1980, 1988) are of the view that reduced transport costs directly linked to the 'transport revolution' which was characterised by an improvement in transport infrastructures, provided a basis for accelerated trade in commodities and commodity market integration. Using data stretching from the 1800s and 67 annual series of wheat prices in the United States of America (USA) and Europe modelled by a multilevel dynamic factor model, Uebele (2012) found evidence of commodity price volatility which is linked to international business cycles.

Pirrong (2012) observes that even though international trade in commodities started in antiquity, the study of commodity prices has been something of what he terms an 'academic stepchild.' Much academic effort in an attempt to better understand the mechanics of diverse commodity markets is in the domain of specific disciplines such as agricultural economics (Pirrong, 2012). This phenomenon may be partially explained by the niche role of commodities in the broader scope of financial market operations.

Some scholars have linked trade in commodities, especially grains and other agricultural products with the agricultural revolution, which started in earnest before the 1800s when feudalism was effectively succeeded by capitalism (Jacks *et al.,* 2011; O'Rourke and Mitchell and Milke, 2005 cited in Aksoy and Beghin, 2005; Williamson, 2004 and Timmer, 1988). O'Rourke and Williamson (2004) are of the opinion that in a post-Malthusian world, commodity trade can no longer be explained by a linkage between real wages (or factor prices) and factor endowments but by the Industrial Revolution and the opening up of the economy to the rest of the world. Jacks *et al.* (2011) maintain that trade in commodities has tended to be characterised by price volatility since 1700 but that the phenomenon of commodity price volatility is more pronounced in developing or emerging economies than in developed or advanced economies. They further argue that commodity price volatility in developing countries actually impedes economic growth in the same economy (Jacks *et al.,* 2011).

Major financial institutions such as Goldman Sachs, Citibank and Morgan Stanley started venturing seriously into commodity markets, notably the energy sector, as a new avenue for making profits in the 1990s and the 2000s (Pirrong, 2012). The increased participation of mainstream financial institutions has been coupled with the entry of many investors into commodity markets. This has greatly enhanced the level and intensity of competition that characterises local and international commodity markets (Calvacanti *et al.,* 2015; Dhaoui and Khraief, 2014).

The entry of financial institutions from the early 1990s to the early 2000s has facilitated the evolution and the accelerated development of some products and innovations in the financial sector. A good instance to illustrate this point is the development of the Petrodollars and Eurodollars markets that are closely linked to recent fast paced changes in international trade and international finance. In the 15 years preceding 2014, oil exporting economies experienced windfall gains in revenue due to a sustained rise in the price of oil in global markets (Higgins *et al.,* 2006). The accumulated foreign currency reserves in oil exporting countries, otherwise known as petroleum exporting countries, has led to a phenomenon which in the literature is known as “petrodollar recycling” (Lubin, 2007; Higgins *et al.,* 2006). Lubin (2007) observes that the pool of Petrodollars which is available for recycling or further use in international trade and international finance exceeds United States Dollar (USD) 1 trillion. For Middle Eastern oil exporters alone, this pool was close to approximately USD 600 billion. In the years post the global financial crisis of 2007-2008, this figure was growing rapidly, even though by 2014 oil prices began to decline in international markets.

3.4 Commodity Types and Indexes in the Global Economy

There are different types of commodities that are traded by different economies. The theoretical and empirical literature identifies four main groups of traded commodities. The first class comprises agricultural commodities which include grains, food and fibre as well as livestock and meat. The second group is that of energy commodities which include oil, ethanol, natural gas, propane, purified terephthalic acid (PTA) and electricity. The third class consists of metals that have two categories, namely, industrial metals and precious metals. The last group with no identifiable common class name is also important in international commodity trade and is simply identified as other commodities and these include palm oil, rubber, wool, and amber.

3.4.1 Agricultural Commodities

Agricultural commodities generally fall under two categories, which are the grains, food and fibre, and livestock and meat. The main commodities traded under the grains, food, and fibre category are maize (called corn in the United States – (US)), oats, rice, soya beans (called soybeans in the US), soya bean-meal, wheat, milk, cocoa, cotton, sugar, and frozen concentrated orange juice. The livestock and meat category include pigs (also known as hogs) and cattle. In a research study aimed at reviewing contemporary issues in agricultural commodity markets, Vijayshankar and Krishnamurthy (2012) have observed that such markets have grown in size and complexity. The growth in size and complexity of Indian agricultural commodity markets has not only been in terms of the range and volume of the commodities traded but also in terms of regulatory reforms and the emergence of new marketing channels.

In line with the foregoing narrative, a study of trade and investment links undertaken by Zafar (2007) observes that industrialisation driven by trade between China and Sub-Saharan African economies totalled more than US$50 billion with a bias towards trade in primary raw material types of commodities. Zafar (2007) further opines that demand for commodities from the Chinese economy has contributed to an upward swing in commodity prices, which has been positively correlated with a boost in real Gross Domestic Product (GDP). A study by Jordaan and Grove (2007) based on the selected field crops in South Africa revealed that the volatility in prices of white maize, yellow maize and sunflower varies over time. The same study found that the volatility in the prices of wheat and soya beans was constant over time, which contrasted with the price of white maize which was found to be the most volatile in the study (Jordaan and Grove, 2007).

A study by Gilbert and Morgan (2010) revealed that even though food prices have been high in recent years, the notion that food price volatility is also high is rather misplaced because analysis reveals that price volatility has generally been lower over the two most recent decades preceding the study than previously. The study, therefore, concludes that with the exception of rice, even the prices of grains have displayed greater variability, it has not been out of line with historical experience (Gilbert and Morgan, 2010). Researchers such Gilbert (2010) and Abbot *et al.* (2009) have argued that accelerated economic growth in China and some Asian economies, depreciation of the US dollar and diversion of food crops into biofuel production partially explains the sustained increase in prices between 2006 and mid-2008.

In a study that sought to examine the role of the agriculture sector in business cycles, Da-Rocha and Restuccia (2002) observe that the agricultural sector whose employment tends to be counter-cyclical, is more volatile than the rest of the economy. Bhanumurthy *et al.* (2013, p. 1) in their analysis of the impact of weather shocks on price formation in spot and futures markets for food in India, found that “the transmission of these shocks to short-term (spot) price movements was unclear.” They concluded that the weak price-discovery mechanism could explain the high price volatility of agricultural commodities (Bhanumurthy *et al.,* 2013).

Ncube *et al.* (2013) investigated the extent to which volatility and co-movement in commodity prices are determined by macroeconomic fundamentals and the stability of the joint commodity movements during periods of economic downturn which include recessions. Their study analysed the covariances of crude oil prices, viz-a-viz, two distinct agricultural commodity groups, namely, coffee, cotton, cocoa comprising the first group and wheat, corn, and palm-oil constituting the second group (Ncube *et al.,* 2013). Using a model based on earlier work by Deb *et al.* (1996), Ncube *et al.* (2013) employed a VAR model of pairwise conditional commodity prices covariances derived from their MGARCH regressions. One of the key findings of the study from impulse-response analysis was that, 'a 0.25-point impulse to the probability of a recession produces a 5 percent spurt in the covariance between the percentage price changes of cocoa and crude oil after a period of two quarters' (Ncube *et al.,* 2013, p. 10).

The Ncube *et al.* (2013, p.12) study's main conclusion was that "macroeconomic fundamentals play a critical role in explaining the volatility in commodity prices." The fact that oil and other commodity prices tend to be determined by macroeconomic fundamentals is corroborated by a study which was undertaken by Tverberg (2013) of Business Insider who discovered that oil and energy use tend to move together with the global economy's Gross Domestic Product (GDP). The three economic variables tend to rise and fall together as captured by business cycles which according to economic theory have four main phases which are the recovery, boom, recession and trough or depression. Arezki *et al.* (2014) used a large dataset of monthly prices covering the period 2002-2011 to examine the relative volatility of commodity prices. Their main finding was that, on average, "prices of individual primary commodities are less volatile than individual manufactured goods prices" (Arezki *et al.,* 2014, p. 939).

Figure 3.1 depicts oil and energy for the whole world, viz-a-viz, world GDP.

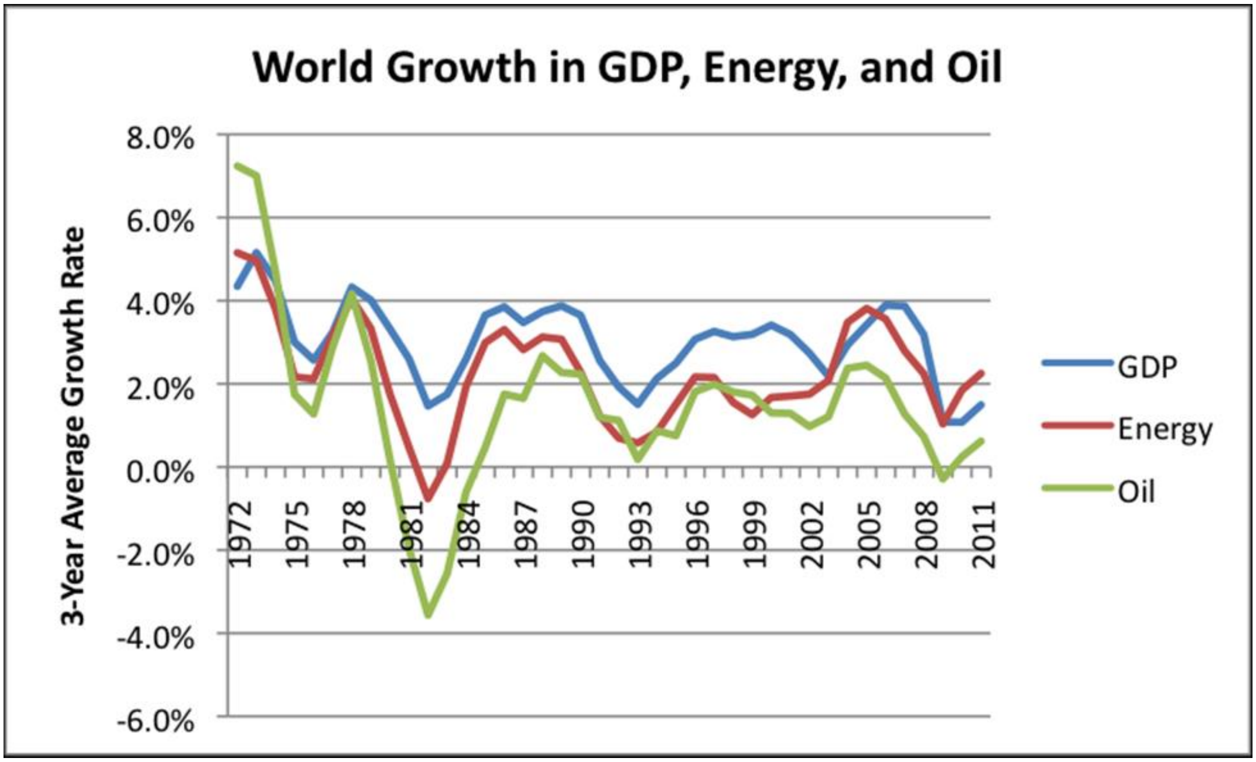


Figure 3. 1: Oil and Energy Use versus Global GDP changes since 1972, Sources: Tverberg (2013), BP's 2012 Statistical Review of World Energy, USDA Economic Research data

Figure 3.1 demonstrates that GDP, oil, and energy-use tend to move together over time. The figure also shows that changes in oil and energy usage tend to slightly precede changes in world output or global GDP (Tverberg, 2013). For instance, a decline in oil and energy usage in the period 1974-1976 was apparently associated with a concomitant decline in global GDP. A drastic decline in oil usage in the years 1980-1984 was also linked to a decline in global GDP growth from approximately 4 percent in 1978 to approximately 1.8 percent in 1982. The behaviour of the three macroeconomic variables for the global economy is also confirmed for China, which is one of the world's largest economies.

Figure 3.2 depicts the behaviour of the three variables for China's economy.

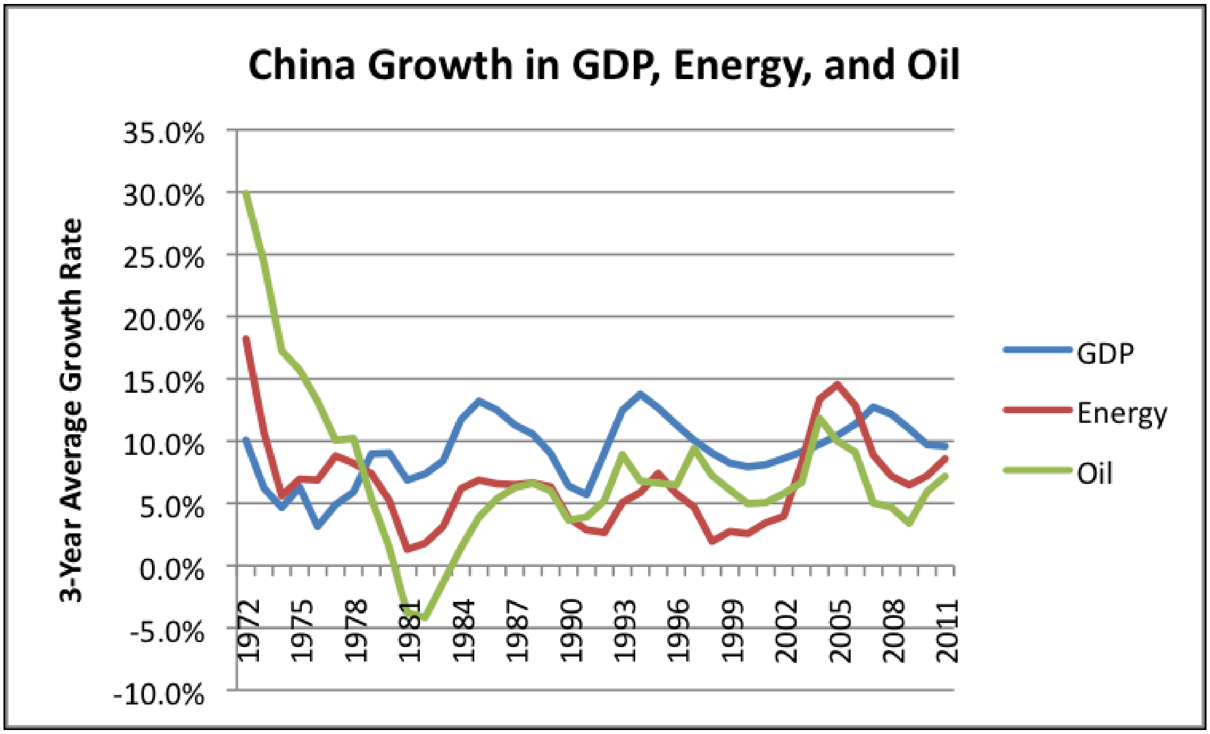


Figure 3. 2: Oil and Energy Use versus China's GDP changes since 1972, Sources: Tverberg (2013), BP's 2012 Statistical Review of World Energy, USDA Economic Research data

Figure 3.2 also shows that around 1982 there was a drastic decline in oil usage which was associated with a decline in energy usage in the Chinese economy. Nevertheless, the GDP series curve shows that China's national output experienced a relatively localised and temporary shock in 1981 which was followed by an upsurge in China's national output. It is notable that for China's economy the co-movement between GDP and energy and oil usage is not as pronounced and strong as for the world economy, but still there is evidence of co-movement among the three main macroeconomic fundamentals. The propensity of the three main economic variables to move together seems to partially support Ncube *et al.* (2013)'s main finding that oil and other commodity price variations tend to be determined by macroeconomic fundamentals.

3.4.2 Energy Commodities

Energy-oriented commodities include oil, natural gas, and ethanol, among others. It is a fact that does not need overemphasis that oil and natural gas are important raw materials or contributors to economic activity in different parts of the world (UNCTAD, 2011; 2012; Dwyer *et al.,* 2012 and Hamilton, 1983). Petroleum products such as petrol (or gasoline), diesel, paraffin, motor oil and grease to mention just a few, drive economic activities in virtually all modern economic systems all over the world (UNCTAD, 2011). UNCTAD (2012) observes that energy prices have repercussions on activities of financial markets especially futures markets where oil futures are traded regularly (Holloway and Wright, 2012). An empirical study by Holloway and Wright (2012) on commodity prices and financial markets found evidence of increased involvement of financial investors in financial markets where contracts on commodities including oil are traded and that financial investors provide additional liquidity and improved price discovery in those markets. In line with foregoing arguments, in a study of financialisation of commodity markets in India, Jena (2016, p. 147) has observed that in recent years there has been what he has styled "a huge inflow of investment towards commodities futures market in India." The study observes that significant inflows of investment into commodities futures in India have been accompanied by high prices and volatility of those prices which has sparked a debate on whether financialisation distorts commodity markets (Jena, 2012). Evidence in some emerging economies has shown that in times of financial crisis investors usually prefer to invest in commodity markets (Jena, 2016; Dhaoui and Khraief, 2014; Holloway and Wright, 2012).

The increased participation of financial investors in commodity markets has led to a number of claims about the impact of such activity on commodity price volatility. Investors that commit themselves to energy commodities such as oil or natural gas tend to fall into two categories, namely, those who invest in individual commodities or those who invest in commodity indices in a bid to avoid storage costs, convenience yield and marketing expenses (Jena, 2016). Albert and Xiong (2001) argue that to investors a diversified index acts like a channel whose role is to correlate commodity prices with prices of other assets in their portfolios. The relationship between commodity markets and financial markets (especially stock markets) is not homogeneous in all economies, rather it varies from one economy to another due to differences that exist among different countries.

Büyükşahin and Harris (2011, p. 167) observe that “the coincident rise in crude oil prices and increased number of financial participants in the crude oil futures market from 2000-2008 has led to allegations that "speculators" drive crude oil prices.” In 2008 the price of crude oil continued to rise until it was US$147 per barrel in July of the same year (Büyükşahin and Harris, 2011). This led to a renewed debate on whether “speculators” drive crude oil prices in global markets. In their analysis of data obtained from the U.S. Commodity Futures Trading Commission (CFTC), Büyükşahin and Harris (2011) found little evidence that speculators (proxied by hedge funds and other non-commercial positions) Granger-cause crude oil price changes. It is noteworthy that energy prices are more often than not characterised by conditional mean and volatility that are driven by seasonal trends due to factors such as weather, demand, and storage level seasonalities (Martínez and Torró, 2014).

Figure 3.3 depicts the volatility of the Brent – Crude oil price index from 1987 to 2019.

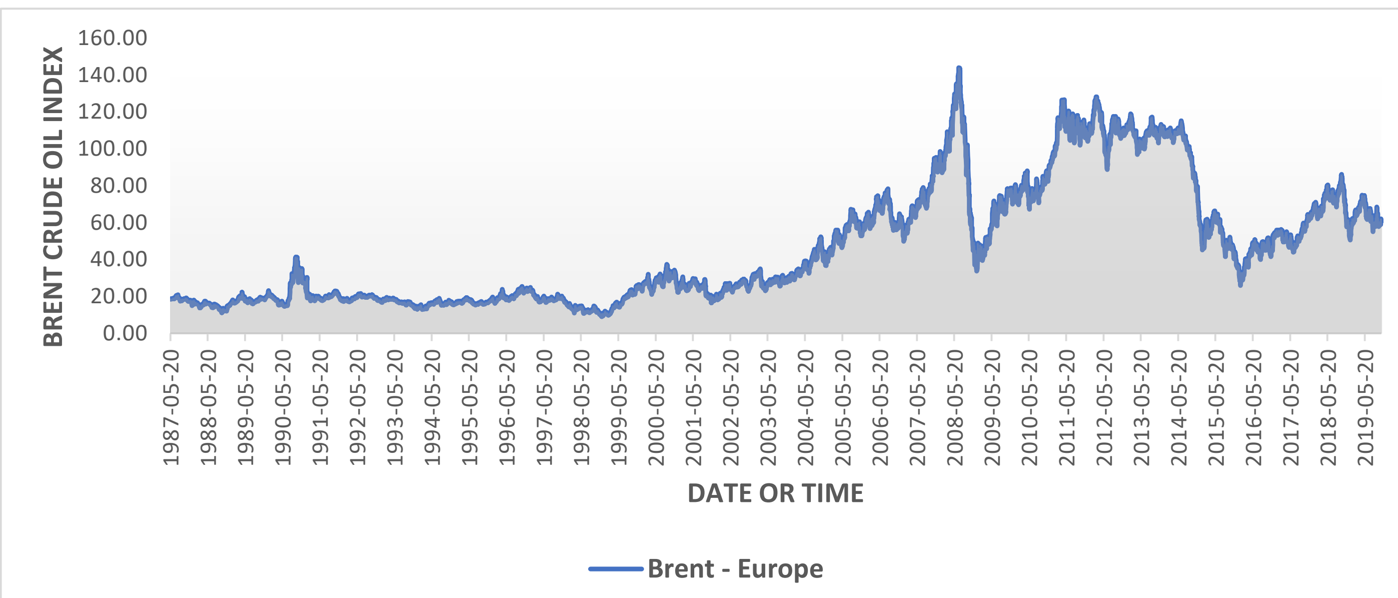


Figure 3. 3: Crude Oil Prices: Brent - Europe,

Source: Researcher Compilation using Data from the U.S. Energy Information Administration (2019)

Figure 3.3 displays the trajectory of the Brent – crude oil price index from 1987 to 2019. The graph shows that from 20 May 1987 to 20 May 1999, the Brent – crude oil price index was characterised by low volatility, though there was a localised spike between 20 May 1990 and 20 May 1991. It is important to observe that the Brent oil price index was characterised by an upward trend from May 2000 to May 2008. Coincidentally, oil price volatility increased during the period May 2000 to May 2008, evidently because of the onset of the global financial crisis (GFC) (Gencer and Hurata, 2017). The volatility profile of the Brent crude oil price index from 1987 to 2019 makes it imperative clearly define the volatility measure beyond the notion that it is standard deviation from the expected return of an index under consideration (Moledina *et al.,* 2004). Moledina *et al*. (2004) argue that standard deviation as a measure of volatility likely overstates the actual volatility, and therefore, conclude that if volatility is split into its predictable and unpredictable components, then there is little evidence that volatility has been increasing over the years. Other researchers hold a contrary view about oil price volatility implying that oil price volatility (and by corollary, commodity price volatility) remains an inconclusive topic of study (Adjasi, 2009; Pindyck, 2004 and Benavides, 2004).

Tverberg (2012) provides logical arguments backed by evidence to support the notion that a decline in oil supply can be expected to reduce the ability of economies to use debt for leverage or investment purposes. According to contemporary empirical evidence, the inescapable corollary of this fact is that reduced oil supply combined with a decline in leverage may (and usually) occasions an economic recession (Tverberg, 2012). In developing small open economies (DSOE) such disruptions to overall economic activities are usually amplified owing to the fact that in recent years global trade and financial capital movement are more integrated (Febiyansah, 2017). Even though the South African (SA) economy normally ranks number two in terms of Gross Domestic Product (GDP) in Africa, it may be considered a small economy by global standards.

Thus, the impact of an oil supply induced recession on an emerging economy like South Africa may be more pronounced, even though this may depend on other local macroeconomic and other factors (Gossel and Biekpe, 2013). This may be the case given the fact that the recent trend for a number of emerging economies, including South Africa is that there has been huge capital movement especially in the form of foreign direct investment (FDI) which has contributed somewhat to spurring economic growth (Febiyansah, 2017).

There has been quite a bit of controversy in the empirical literature about whether electricity can also be considered a commodity. There is neither doubt nor any meaningful argument about the fact that electricity is a form of energy, but the main argument centres on the extent to which electricity is a commodity. Barlow (2002) observes that electricity is continuously generated and consumed but cannot be economically stored. The fact that electricity cannot be economically or sustainably stored implies that the usual arbitrage-based methods may not be applicable for pricing electricity derivative contracts (Bessembinder and Lemmon, 2002). Secondly, it has been argued even though electricity can be (and is actually) transported at high speeds, it has a rather localised market. Using simple demand and supply analysis as a foundation, Barlow (2002) obtained a diffusion (that is, jumpless) model for spot prices which exhibited price spikes for the Alberta and California markets. It is noteworthy that there are many different models of spot power (or electricity) prices all of whose aim is to provide a better understanding of the behaviour of electricity prices over time. These models are affected by industry specific factors as well as the regulatory framework that governs electricity or power markets. In North America, some electricity markets are still regulated while others were deregulated a number of years ago (Barlow, 2002; The Regulatory Assistance Program (RAP), 2011).

In their paper based on a competitive rational expectations model of spot and forward prices of many storable and/or convertible commodities, Routledge *et al.* (2001) have shown that electricity (taken as a "downstream commodity") has empirical features similar to those of other commodities such as natural gas and other fuel (considered as "upstream commodities"). These empirical features include mean-reverting prices, price dependent heteroscedasticity, skewness and electricity-fuel correlations that are characterised by instability (Routledge *et al.,* 2001). Even though the foregoing holds, electricity has its unique features which include the fact that spot prices are volatile (Bessembinder and Lemmon, 2002; Longstaff and Wang, 2004). Conejo *et al.* (2010, p. 235) reveal that pool electricity prices tend to be volatile while the prices of the futures-market products are comparatively more stable. These researchers further observe that, "Electricity market agents engage in both pool and futures market transactions seeking to maximize their respective profits/utilities for a given risk level on profit variability" (Conejo *et al.,* 2010, p.235). Engaging in two markets may either have complementary or trade-off effects on the portfolios of the market participants. The effects on agents' portfolios are not homogeneous since market conditions differ from one market to another due to industry-specific factors and other systemic factors such as regulation and policy issues that affect different markets.

3.4.3 Metals and Other Commodities

A large proportion of global trade involves metals and other commodity flows between nations and different economic regions. Literature generally identifies two main groupings of metals, namely, industrial metals and precious metals. Copper, lead, zinc, tin, aluminium, nickel, and cobalt are some of the more common industrial metals that are in high demand in different parts of the world especially in fast developing East Asian economies like China, Japan and South Korea (Anderson and Gilbert, 1988). In a study using a factor-augmented VAR model (FAVAR) to examine linkages across non-energy commodity price developments (which included prices of metals), Lombardi *et al.* (2012) found evidence that exchange rates and economic activity affect individual non-energy commodity prices. The research's other key finding was that common trends captured by food and metals factors affect individual commodity prices (Lombardi *et al.,* 2012). The same study could not establish any econometrically viable link between non-oil commodity prices on the one hand and oil prices and interest rates on the other hand (Lombardi *et al.,* 2012). Therefore, an argument for strong spillovers from oil to non-oil commodity prices could not be sustained given these findings.

3.5 Commodity Price Volatility Issues

A precise definition of commodity price volatility has been elusive in much of the mainstream literature on the subject. Be that as it may, a number of researchers have proffered some definitions that give an insight into the controversies that are associated with the subject of commodity price volatility. The term commodity price volatility is a composite one whose constituents are commodity and price volatility. The term 'commodity' has been defined in the preceding sections and, therefore, it behoves this section to define price volatility. Price volatility refers to a statistical measure of the dispersion of returns for a given security's price or market index (Demirer *et al.,* 2019). Price volatility can be measured using the standard deviation or the variance between returns from that same security's price or market index. The empirical finance literature reveals that price volatility is a measure of the degree of risk or the riskiness of a security (Wright, 2011; Figlewski, 1997; Benavides, 2004).

The empirical literature is inconclusive about the relationship between volatility and financial markets. The findings of Moledina *et al.* (2004) reveal that standard deviation as a measure of volatility likely overstates the actual volatility and hence is an inaccurate measure of commodity price volatility. This implies that policy interventions such as countercyclical payments and buffer stocks may be in some respects misplaced (Wright, 2010).

Figure 3.4 below shows the volatility of the global price for wheat for the period ranging from October 1989 to January 2019.

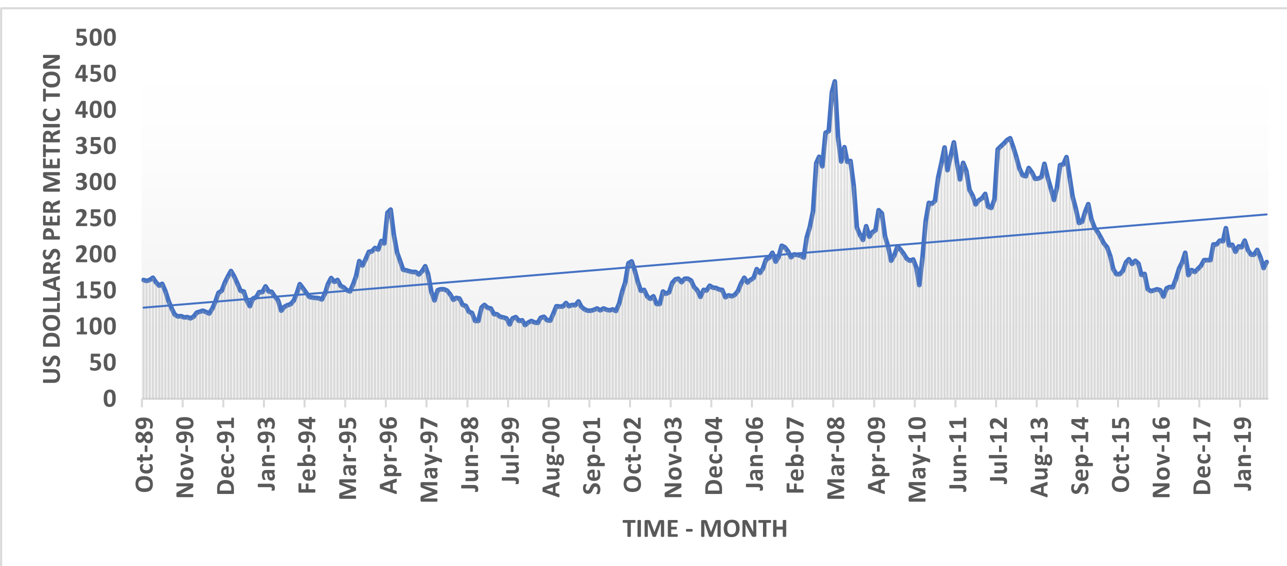


Figure 3. 4: Wheat Monthly Price - US Dollars per Metric Ton,

Source: Researcher Compilation using data from Bloomberg; US Department of Agriculture; World Bank

Description of the series: *Wheat, No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico, US Dollars per Metric Ton*

There are two striking features about the wheat's monthly price, first, the magnitude of volatility in wheat prices was relatively low from June 1989 to July 2006. In the 1995 – 1996 agricultural season, there was a localised spike in wheat monthly prices which pales into insignificance when compared to the wheat prices spanning July 2007 and July 2011. Second, the latter part of the wheat price series (January 2006 to August 2013) is characterised by increased volatility with a significant spike in 2008. The wheat price series generally followed an upward trend as shown by the trend line.

The behaviour of the wheat monthly price time series depicted by Figure 3.4 may suggest conditional volatility. This viewpoint has been corroborated by Benavides (2009, p. 41) in an examination of "the volatility accuracy of volatility forecast models for the case of corn and wheat futures price returns." The analysis by Benavides (2009) showed that the composite forecast model was the most accurate one (compared to the univariate GARCH model and the multivariate GARCH model of the BEKK variety) having the lowest mean-square-errors. Silvennoinen and Terasvirta (2009) posit that the Baba-Engle-Kraft-Kroner (BEKK) model defined formally in Engle and Kroner (1995) may be viewed as a restricted version of a Vector Error Correction Model (VECM). This is consistent with a study by Dawson (2015, p. 20) which employed 'an exponential generalised autoregressive conditional heteroscedasticity (EGARCH) model with a constant (price) elasticity of variance (CEV) and a broken trend' to show that highly persistent volatility was coupled with a structural break in the time series.

It has been established in the foregoing discussion that oil prices tend to be volatile, though the extent of the volatility over time is still a subject of controversy in the literature (Huchet-Bourdon, 2011; Miguez and Michelena, 2011; Moledina *et al.,* 2004). In an examination of commodity price volatility in Argentina, Miguez and Michelena (2011) discovered that United States (US) interest rate and inflation dynamics, weather conditions related to Pacific Ocean currents, economic growth of developing economies and level of available inventories are some of the key factors that determine volatility of prices for corn, wheat, sorghum, rice, soya beans, and other agricultural products.

3.6 Evidence from Selected Countries on Commodity Price Volatility Issues

This section reviews empirical studies on the relationship between stock prices, exchange rates, commodity prices and other macroeconomic variables for Pakistan, India, China, South Africa, and the BRICS. The reviewed studies used different methodologies ranging from non-linear Generalised Autoregressive Conditional Heteroscedasticity (GARCH) to Stochastic Volatility models. Empirical results generally reveal that the relationship between commodity prices and exchange rates impact investor efforts in diversifying their assets classes that include both real and financial assets (Ahmed *et al.,* 2017).

3.6.1 Evidence from Europe

Zivkov *et al.* (2016) analysed the Dynamic Conditional Correlation (DCC) between stock returns and exchange rates for the Czech Republic, Hungary, Poland, and Russia. The persistence of long memory and the existence of the asymmetric effect in all asset markets implies that the DCC - Fractionally Integrated Asymmetric Power Autoregressive Conditional Heteroskedasticity (DCC-FIAPARCH) model was deemed to be the most appropriate model for the data. DCC parameters revealed that during major crisis periods time-varying behaviour was significant especially during the Global Financial Crisis (August 2007-November 2009) and the European sovereign debt crisis which lasted from November 2009 to April 2010 (Zivkov *et al.,* 2016; Federal Reserve Board of St. Louis, 2009). The results of the same study also revealed that exchange rate conditional volatility has a higher influence on the Dynamic Conditional Correlation than stock conditional volatility (Zivkov *et al.,* 2016).

Several studies have demonstrated the strong link that exists between commodity prices and stock prices or returns. The scales of academic effort have tended to tilt in favour of examining the link between oil prices and stock prices or stock returns. This has been necessitated by the fact that oil as a source of energy powers many diverse economic activities, unlike other commodities that tend to have a narrow range of uses. In an empirical study examining the link between oil price shocks and real stock market returns in Greece, Papapetrou (2001) found evidence of the suppressive effects of positive oil price shocks on the real stock market returns variable. The findings of Park and Ratti (2008) from an investigation of the impact of oil price shocks on stock market returns of

13 European countries and the United States of America (USA) revealed that oil price shocks have a negative effect on stock returns of oil importing countries. In contrast, the impact of oil price shocks was found to be positive on oil exporting countries.

In a study of effects of oil price shocks on stock market volatility in Europe, Degiannakis *et al.* (2014) found that 'the aggregate demand oil price shocks are a statistically significant variable in explaining current and forward-looking volatilities.'

3.6.2 Oil Price Dynamics and Macroeconomic Variables in the MENA Region

Several studies have been conducted by different researchers in a bid to unravel the link between oil price dynamics and economic growth in Middle Eastern economies. Mohammed *et al.* (2016) conducted a study based on the eight Middle East and North African (MENA) economies, namely, Algeria, Iran, Egypt, Saudi Arabia, Turkey, Tunisia, Kuwait, and Morocco. Using quarterly data from the last quarter of 1994 to the second quarter of 2015, Mohammed *et al.* (2016) employed the panel Autoregressive Distributed Lag (Panel ARDL) model and concluded that there were short-run cross section dynamic relationships between oil on the one hand and economic growth, the consumer price index, money market rate and market capitalization on the other hand. The same study also concluded that in the long run, the consumer price index and stock market capitalization exhibit a cointegrating relationship with oil prices (Mohammed *et al.,* 2016). Nevertheless, no long-run equilibrium relationships could be established between oil price changes, economic growth, and the monetary policy variable.

An empirical study by Eryigit (2012) whose primary objective was to unravel the link among interest rates, exchange rates, Istanbul Stock Exchange market index (ISE-100) and oil price using the vector autoregressive (VAR) technique found that there is a dynamic relationship among the study variables. In the same spirit, Berk and Aydogan (2015) employed a vector autoregressive model with data comprising of Brent crude oil prices and Istanbul Stock Exchange National Index returns of the period spanning 2 January 1990 and 1 November 2011 inclusive. Unlike the Eryigit (2012) study, Berk and Aydogan (2015) incorporated into their model formulation a liquidity proxy variable. The main findings of the study were that there was little evidence supporting rational evaluation of oil price shocks in the context of the stock market in Turkey and that global liquidity conditions played a more significant role in explaining stock market return variations (Berk and Aydogan, 2015). Ozturk's (2015) vector autoregressive study of the nexus between oil price shocks and macroeconomic variables underpinned by Granger causality tests, found that positive oil price shocks reduce money supply and industrial production while Turkish imports increase in response to a negative oil price shock. The study also found that oil price shocks Granger-cause variations in imports and industrial production in Turkey (Ozturk, 2015).

Chatziantoniou *et al.* (2013) used a Structural VAR model to examine the relationship among oil price shocks, tourism variables and economic factors in four European countries which are part of the Mediterranean economic region. In agreement with Kilian (2009), Chatziantoniou *et al*. (2013, p. 331) add to the empirical literature by identifying, 'three oil price shocks, namely, supply-side, aggregate demand and oil specific demand shocks.' Their major findings were, first that oil-specific shocks impact the inflation variable and the tourism sector equity index simultaneously. Second, the study revealed that aggregate demand oil price shocks have either a direct or indirect lagged effect on tourism generated income and economic growth. There was, however, no evidence that was found to corroborate the hypothesis that supply-side shocks trigger any responses from the remaining variables under study (Chatziantoniou *et al.,* 2013).

3.6.3 Evidence from BRICS economies

Several studies have been conducted by different researchers in an attempt to discover the magnitude and nature of the relationship between commodity price volatility and macroeconomic fundamentals such as stock market return behaviour, investment, interest rates, exchange rates and the Balance of Payments (BOPs) components like the current account. Over the past 15 years, the BRICS (originally BRIC) have grown to be a force to reckon with in the global economy. The demand for and consequently the consumption of commodities by BRICS economies has increased tremendously in the past 20 years. Rapid economic growth in India and China has been one of the key drivers of the increase in the demand for commodities from global markets. According to the BP Statistical Review of World Energy Markets (2004) cited in Masih *et al.* (2010), in 1990 India and China accounted for approximately 5 percent of global petroleum use. By 2003 these two giant economies accounted for more than 10 percent of global oil consumption (Masih *et al.,* 2010).

Bouri *et al.* (2017) examined the predictive power of implied volatility in commodity and major developed stock markets under the analytical framework of Ahelegbey *et al.* 's (2016) newly developed Bayesian Graphical Vector Autoregressive (BVAR). The study finds 'evidence that the predictability of individual implied volatilities in BRICS is basically determined by implied volatilities attributable to both regional and global stock markets, and that the role of commodity market volatility is marginal in general for BRIC, except for South Africa' (Bouri *et al.,* 2017, p. 1).

Radulescu, Panait and Voica (2014) have argued that the global financial crisis had no strong effect on the BRICS group. It is averred that BRICS economies actually performed better than developed countries (Radulescu *et al.,* 2014). Balcilar *et al*. (2014) have, however, argued that the economic performance of most emerging economies including the BRICS was characterised by notable volatility during the period of the global financial crisis which may be suggestive of different phases of the business cycle. Energy resources or commodities account for much of the variations in economic performance in many emerging and developing economies. A study conducted by Balcilar *et al.* (2014) using the South African economy as a case study, reveals that oil price shocks are among the main factors that have been identified in the recent empirical and theoretical literature as being important in explaining phases of a typical business cycle. The researchers observe that oil price shocks as a key determinant of business cycles in emerging economies have not received the attention they deserve in the theoretical and empirical literature (Balcilar *et al.,* 2014). The researchers used a Bayesian Markov switching vector autoregressive (MS-VAR) model and data spanning 1960 to 2013 and found that oil prices have predictive power for real output under the low growth regime (Balcilar *et al.,* 2014).

Negi (2015) examined the impacts of oil price on the GDP of Brazil, Russia, India and China (BRIC), four of the world's largest and fastest-growing economies. The study used Ordinary Least Squares (OLS), the Fixed Effects Model (FEM) and the Random Effects Model (REM) in an attempt to examine the relationship between oil price and national income (GDP) (Negi, 2015). The major findings of the study were that GDP and oil price have a positive relationship. The coefficients were negative for India and China, which implies that if the oil price increases, Indian and China's GDP is likely to decline. In contrast, for Russia and Brazil positive coefficients apparently indicate that an increase in oil price is associated with increases in GDP.

3.7 Evidence from Pakistan and other Emerging Asian Economies

Ahmed *et al.* (2017, p.109) assert that 'investors are always attracted to those sectors of the economy where they get a maximum return at an acceptable level of volatility and where an increase in price shows a consistent trend.' The veracity of this assertion is debatable and can only be corroborated by or rejected on the basis of empirical evidence. Ahmed *et al.* (2017) undertook their empirical study in Pakistan based on monthly time series data covering the period January 2005 to December 2015. The results of a vector autoregressive model coupled with impulse-response analysis showed that stock returns significantly determine the variation or shock in oil prices, gold prices and exchange rates (Ahmed *et al.,* 2017). In a study analysing the dynamic relationship between exchange rates and stock prices for selected emerging Asian economies, Abbas (2010) discovered that in Pakistan and Sri Lanka, Granger causality runs from stock prices to exchange rates. In contrast, the same study found that in India, the direction of causality ran from exchange rates to stock prices. There was, however, no long-run causality between stock prices and exchange rates for Pakistan, Sri Lanka, Indonesia and Korea (Abbas, 2010).

A study by Abbas *et al.* (2017) examining the long-run association between the stock market, money market, and foreign exchange market in Pakistan using the Johansen-Juselius procedure found one cointegrating vector from the trace test. The same study also found that the Error Correction Term (of -1) was negative and statistically significant for all variables during the study period which may attest to the presence of long-run causality connection among the selected variables (Abbas *et al.,* 2017). Pairwise Granger causality test results indicated that there were statistically significant variations in the causal relationship during the military regime and democratic administration. Rahman and Uddin (2009) investigated the interactions between stock prices and exchange rates in India, Bangladesh, and Pakistan. Their analysis showed that there is no long run association or causality between stock prices and exchange rates for the three emerging economies (Rahman and Uddin, 2009). Abbas and Mcmillan (2014) examined the equilibrium relationship between money supply, the stock price index, the foreign exchange rate and interest rates, and found that there is a significant long-run relationship among the variables. Using a VAR model, the study found that money supply and exchange rates are significant determinants of fluctuations of the Karachi Stock Exchange (KSE) 100 index while the interest rate variable is not.

In an examination of the impact of a number of stock market price indices and macroeconomic variables on the Thai stock market using the GARCH-M model, Chancharat et al (2007, p. 2) discovered that 'changes in stock returns in Malaysia, Singapore and Indonesia before the 1997 crisis, and changes in Singapore, the Philippines and Korea after 1997 instantaneously influenced the Thai stock market.' The same researchers found that volatility clustering and a GARCH-M model were present prior to the 1997 crisis and that five Thai macroeconomic variables impacted stock returns during the pre-1997 crisis and post-1997 crisis period (Chancharat *et al.,* 2007). In contrast, analyses of the effect of domestic macroeconomic factors on stock return volatility for the United States by Schwert (1989) and Flannery and Protopapadakis (2002) found weak evidence of such factors being able to predict inherently volatile stock market returns.

Rashid and Muhammad (2002) employed the Johansen cointegration procedure, the vector error correction modeling technique and pairwise Granger causality to examine the relationship between exchange rates and stock returns for India, Pakistan, Bangladesh and Sri Lanka. They found no short-run association between stock returns and exchange rates. They also found no long-run relationship between the aforementioned variables for all the four economies under study (Rashid and Muhammad, 2002). Huy (2016) analysed the relationship between exchange rates and stock prices using the Johansen and Juselius (1990) cointegration approach and the Toda and Yamamoto (1995) short-run dynamic causality test procedure. The study found that there was a unidirectional Toda-Yamamoto causal relationship from stock prices to exchange rates for Vietnam and that long-run association exists between the two variables according to the maximum eigenvalue and trace tests of the Johansen-Juselius procedure (Huy, 2016).

In a study that made use of unit root, cointegration tests, vector error correction, block exogeneity and impulse response analysis among other techniques, Lee and Zhao (2014) found that for China, 'long-run causality ran from exchange rates to stock prices in Chinese stock markets.' This contrasted with short-run causality which was found to be strongly from Japanese Yen and Korean Won exchange rates to stock prices in the case of the Shangai Stock Exchange (Lee and Zhao, 2014). The same study found out that the impact of the Global Financial Crisis of 2007 to 2009 on China's stock markets was not statistically significant. An analysis of the short-term and long-term effects of oil price shocks on the Chinese economy using a Structural Vector Autoregressive (SVAR) model found that oil price increases have negative repercussions on output and investment and a positive effect on interest rates and rate of inflation (Tang *et al.,* 2010). In a study examining the global effects of China's export-led economic growth strategy, Ahuja and Nabar (2012) found that a percentage point reduction in China's investment is associated with global economic growth reduction of just less than one-tenth of a percentage point.

Masih *et al.* (2010) sought to understand the links which exist among interest rates, economic activity, real stock returns, oil price volatility and real oil prices in Korea using the VEC model underpinned by impulse response analysis and variance decomposition. Their findings echoed and corroborated findings of earlier studies in that oil price volatility was found to be a dominant factor in explaining real stock returns and that this dominance tended to increase over time (Masih *et al.,* 2010). The study also revealed that for Korea oil price volatility had the potential to affect the time horizon of investment and that this makes it necessary for firms to adjust their risk management procedures accordingly.

3.8 Commodity Market Financialisation and the Finance-Growth Nexus

In a study testing the hypothesis that financial investors are less concerned with fundamentals and, therefore, impede the price discovery process, Dwyer *et al.* (2012) found no evidence that supports the notion that financialisation has been the main driver of commodity price developments in the 2000s. This key finding of Dwyer *et al.* (2012) was confirmed by the study of Jena (2016) who examined the financialisation of commodity markets in India using time series methods. The study found a strong correlation between the commodity index price and the stock index price, and the direction of causality was from commodity index price to stock index price but the reverse was not (Jena, 2016). Thus, no statistical evidence was found to support the notion that commodity markets in India are financialised. The study was based on testing the relationship between futures markets and spot markets for commodities using data from the International Monetary Fund (IMF) and other sources. The standard view in the empirical finance literature is that if decision-making by financial investors or speculators reflects informed perspectives about economic or market fundamentals governing commodity markets, financialisation may positively facilitate price discovery (Dwyer *et al.,* 2012 and UNCTAD, 2011).

An empirical study of how economic growth links with the agricultural and petroleum subsectors of the Nigerian economy by Okunola (2017) revealed that there is a long run association among the three variables. The study further revealed that for the Nigerian economy both sectors have a significant positive association with economic growth (Okunola, 2017). It is imperative to observe that the volume and product composition of an economy's commodity trade is one of the key determinants of its vulnerability to commodity price volatility (UNCTAD, 2012). Ewepu (2016) reports that the Central Bank of Nigeria (CBN) revealed in 2016 that the share of the agricultural sector on Gross Domestic Product (GDP) had increased from 23.86 percent in the fourth quarter of 2014 to 24.18 percent. It is further revealed that the agricultural sector of the Nigerian economy was larger than the manufacturing and oil sectors combined (Ewepu, 2016). This may partially explain the positive short-run and long-run association between the agricultural sector and economic growth in Nigeria.

The findings discussed in the preceding section are corroborated by a trend study of the contribution of the Nigerian agricultural sector spanning 53 years from 1960-2012 that demonstrated through regression analysis that agriculture has a positive relationship with GDP and its contribution is statistically significant with a coefficient of 0.664 (Ahungwa *et al.,* 2014). This implies that if agriculture increases by 1 percent, GDP may increase by 0.664 percent compared to other sectors of the economy, *ceteris paribus*. This finding has been reinforced by a recent study by Riti *et al.* (2016) that found that the agricultural, manufacturing, and telecommunication sectors of the Nigerian economy have a statistically significant contribution at 5 percent level of confidence and that the three sectors of the economy Granger-cause Nigerian economic growth. The common thread in the foregoing analysis is the agricultural sector whose contribution to the economy is not only significant in statistical terms but actually drives employment and economic growth (proxied by changes in GDP) in Nigeria. This puts into perspective the importance of agricultural commodity price volatility to Nigeria's overall economic stability.

3.9 Commodity Price Volatility and Fluctuations of Macroeconomic Indicators

The point of departure of the foregoing discussion from the mainstream theoretical and empirical literature in the finance-growth nexus is that commodity price volatilities and stock market performance are in reality not linearly related to each other. In fact, the review of empirical literature in the preceding sections has amply demonstrated that commodity markets are by nature volatile and that there is interdependence or close association between them and financial markets especially stock markets. It, therefore, begs the question of how stock market performance can be adequately and realistically conceptualised as being linearly related to economic growth given its interconnectedness with volatile commodity markets. As a corollary of this argument is the subsequent question of whether national income, as measured by Gross Domestic Product (GDP) or another appropriate measure such as industrial output, is itself not volatile or rather whether it has not been volatile over time in many emerging and even developed countries. A study conducted by Hamilton (1983) of the relationship between oil price volatilities and the performance of the macroeconomy concluded that all recessions experienced by the United States (US) with exception of one since the Second World War were preceded by a dramatic increase in the price of crude oil. The study concluded that the correlation between crude petroleum price changes and economic recessions was statistically significant and non-spurious lending credence to the belief that there was a strong link between oil price volatility and performance of the macroeconomy which existed prior to 1972 and even afterwards as corroborated by subsequent research based on the US economy (Ju *et al.,* 2016; Ozturk, 2015; Shahbaz *et al.,* 2013; Hamilton, 1983).

In another study, Hamilton (2009) has argued that oil price shocks could affect the economy through their effects on demand and supply. An earlier study by Loungani (1986) cited in Hamilton (2009, p. 5) “demonstrated that oil-induced sectoral imbalances contributed to fluctuations in U.S. unemployment rates.” This may partially explain the empirically verified non-linear relationship between oil price fluctuations or shocks and economic growth as measured by changes in GDP.

An empirical examination of the impact of energy use on selected macroeconomic fundamentals in China using the ARDL bounds technique to cointegration by Shahbaz *et al.* (2013) confirmed a long-run relationship among the variables. Shahbaz *et al.* (2013, p. 8) concluded that “energy use, financial development, capital, exports, imports and international trade have a positive impact on economic growth.” The conclusion reached by Shahbaz *et al.* (2013) agrees with Nikolaos and Renatas (2015) whose main finding was that there is a dynamic link between stock returns, commodity price volatility and currency markets. The researchers’ further finding was that dynamic spillovers had time- and event-specific patterns (Nikolaos and Renatas, 2015). An investigation of the nexus between commodity prices and exchange rate volatility in South Africa by Arezki *et al.* (2012) revealed that prior to capital account liberalisation the causality ran from the South African Rand to gold price volatility and vice versa post-liberalisation. This demonstrates that the link between commodity price shocks and macroeconomic fundamentals is not restricted to energy commodities but includes gold and other non-energy minerals as well.

3.10 Context of The Study in Light of Literature Review

Many empirical studies have satisfactorily established the long memory features of developing economy and advance economy stock markets (Ali *et al.,* 2017; Ahamed *et al.,* 2015; Mukherjee *et al.,* 2011; Tan and Khan, 2010; Triki and Selmi, 2009; Cheong; 2008; Kang and Yoon, 2008; Cotter, 2002; Cohay *et al.,* 1995; Low, 1991; Joyeux and Granger, 1980). Nevertheless, mainstream empirical research on stock market performance and price volatility is largely silent on the impact of commodity prices on the long run features of stock market performance.

Much empirical work conducted in the past has tended to focus on unravelling the dynamic correlations that presumably exist between commodity and equity returns (Ishfaq *et al.,* 2018; Behmiri *et al.,* 2016; Lombardi and Ravazzolo, 2013; Bhardwaj and Dunsby, 2013; Rossi, 2012; Nilsson and Thulin, 2012; Sieczka and Hołyst, 2009). The studies that have attempted to correlate different commodity pairs have tended to focus on specific commodities, for instance, sugar and coffee, gold and crude oil, crude oil and platinum, copper and gold and so on (Alfsen and Nisja, 2017). Contemporary research has not done much to establish the correlation among different commodity classes. In addition, mainstream empirical studies have not conclusively linked indices of specific commodity sub-groups with stock performance indicators. More specifically empirical studies have not addressed adequately the two hypothetical questions which are – what is the magnitude and nature (linear or non-linear) of the correlation among indices of the four main commodity classes? – and to what extent do the main indices representing the four main commodity classes correlated with the performance of different developing economy stock markets?

Several studies have been conducted by different researchers worldwide on the nexus between stock indices and bond yields in times of financial and economic crises. It is important to observe that not much research has been undertaken on the nexus between stock indices and commodities that are intimately linked to financial instruments in the context of financial and economic crises (Tsoutsas, 2017). A study undertaken by Pesonen (2017) has revealed that correlations between commodity futures and equity prices change markedly during periods of stock market crises. Correlations between crude oil futures and aggregate U.S. equities obtained from the Cappiello *et al.* (2006) DCC GARCH model increased significantly during periods of financial turmoil (Pesonen, 2017). This has implications for the hedging activities of international investors. What the Pesonen (2017) study as well as other studies have not established is whether the increased cross-correlation is accounted for by increased financialisation of commodity markets (Lideus and Engberg, 2013; Ramsland and Hostvedt, 2014). More pertinently, the question which needs to be addressed more exhaustively is whether the phenomenon of commodity market financialisation has implied a strengthening of the cross-market linkages between:

a) Different types of commodity markets, for instance, crude oil and the energy sector or crude oil and gold or,
b) Commodity markets and equities market.

The present study addressed the above two-pronged question.

3.10 Chapter Summary

Chapter 3 explored the commodity taxonomy according to the theoretical literature. The controversies that accompany any attempt to give a precise definition of a commodity were briefly explained. The chapter also explained the consequences, according to the empirical literature, of the financialisation of commodity markets with a specific focus on developing and emerging economies such as India and Nigeria. The relationship between agriculturals (or the agricultural sector), oil (or mining sector), and economic growth was assessed using empirical evidence from Nigeria. Conclusions of the theoretical and empirical literature about the relationship between commodity markets financialisation and commodity price volatility, and how these two variables impinge on economic growth are inconclusive. Chapter four reviews literature on the BRICS economies and their stock markets.

CHAPTER FOUR: THE BRICS ECONOMIES AND THEIR STOCK MARKETS

4.0 Introduction

Brazil, Russia, India, China, and South Africa (BRICS) are an important bloc in the determination of world economic growth, international financial flows, international trade in commodities and other types of goods and investment levels in the global economy. This chapter pursues three main goals. First, this chapter gives an overview of each of the economies that make up the BRICS. Second, the chapter reviews the theoretical and empirical literature on the interdependence and contagion among financial markets of BRICS economies. In the same vein, the chapter also explores the extent to which BRICS financial markets are integrated into financial markets of the rest of the world (and especially those of the most economically advanced nations). The current chapter examines the extent to which international trade in commodities and commodity-based financial instruments explain any linkages, interdependence, and contagion within the BRICS economic bloc and the rest of the world. Third, the chapter analyses the extent to which financial crises and international commodity price dynamics affect financial and commodity market integration, and hence assesses the veracity of the notion of increased financialisation of commodity markets in the context of BRICS countries.

4.1 The BRICS Economic Bloc

The study focused on “BRICS” economies mainly because they are emerging economies that have interesting features. This economic bloc was originally called “BRIC” since it initially comprised of Brazil, Russia, India and China before the controversial inclusion of South Africa (Marquand, 2011). The acronym “BRICs” was ‘coined' by economist Jim O’Neill in 2001 in a report on the importance of Brazil, Russia, India and China (O’Neill, 2001). It is noteworthy that BRICS are all developing or newly industrialised countries which over the past 20 years have grown at a phenomenal pace, only for some of them to slow down in the past few years (Chaudhary *et al.,* 2012). All the five-member states constituting the BRICS are also part of the G-20 grouping of leading economies of the globe. China and India have a combined population that constitutes more than 30 percent of the world population currently estimated at seven (7) billion people. Therefore, the five economies that constitute the BRICS have a formidable market for goods and services whose full potential is yet to be tapped fully.

Even though the BRICS is a fairly young economic bloc, its importance when considering such topics as economic growth, financial development, financial integration, international trade in commodities and international macroeconomic policies, has captured and retained the interest of many researchers worldwide (Menon, 2017; Fidrmuc *et al.,* 2013; Gauteng Province – Provincial Treasury, 2013; Gong and Kim, 2013; Akin and Kose, 2008 and Georgieva, 2006). Different scholars have invariably underscored the importance of the BRICS countries in the global economy (Wang *et al.,* 2017; De Castro, 2013; Prasad, 2013). According to Marquand (2011), the BRICS economies had US$4 trillion in foreign currency reserves. In contrast, the United States (US) and some European countries were as of 2011 still battling the repercussions of the 2007-2008 global financial crisis, mainly characterised by a burgeoning sovereign debt crisis and subdued economic growth rates. The share of the BRICS countries, vis-a-vis, the rest of the world is displayed in Figure 4.1

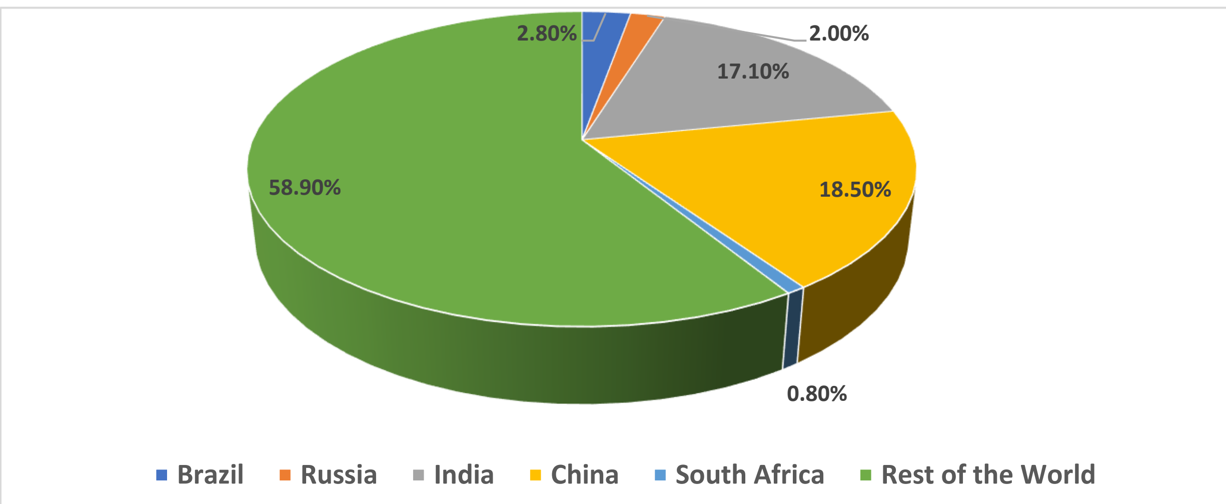


Figure 4. 1: BRICS and Rest of the World Population Distribution,

Source: Researcher Compilation using data from BRICS Joint Statistical Publication (2017)

Figure 4.1 shows that China is the most populous BRICS country followed by India. South Africa has the lowest population within the BRICS economic family. In aggregate terms, BRICS countries account for approximately 41.1 percent of the world's population. The combined nominal Gross Domestic Product (GDP) of the BRICS was estimated at approximately US$18.5 trillion in 2017 (Statistics South Africa, 2018). Matovska *et al.* (2014) have observed that with the exception of Russia, the other countries constituting the BRICS, namely, Brazil, India, China and South Africa are largely emerging economies which may be considered as new powers because of their increasing impact on international developments, international relations and global economic trends.

The facts and figures provided in the foregoing analysis provide a rationale for choosing the BRICS as the focus of the present study on the commodity price volatility-stock market performance-economic growth nexus.

4.1.1 Brazil

Brazil is a country that has undergone many changes since 1950. The population of Brazil has experienced a tremendous growth since 1950. Figure 4.2 shows Brazil's population growth trend since 1950.

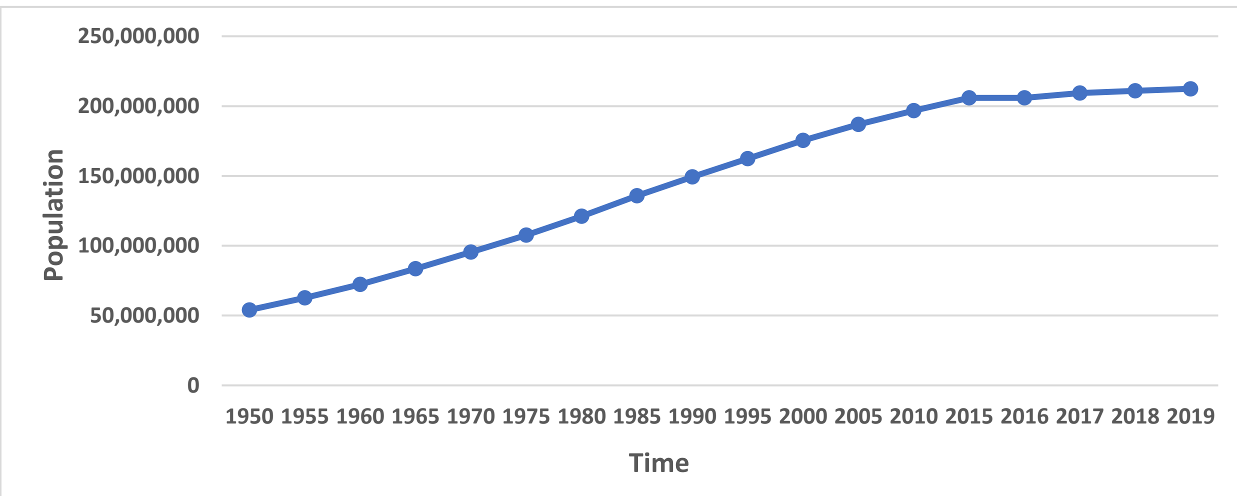


Figure 4. 2: Brazil Population Since 1950,

Source: Researcher Compilation using data from the World Population Review (2019)

Baer (2008) reveals that in 1900 the total population of Brazil was 17.4 million. Figure 4.2 shows that Brazil's population grew steadily from 1950 to 2010. Figure 4.2 shows that Brazil's population started to plateau in 2015.

Brazil is the largest economy in South America with Gross Domestic Product (GDP) estimated at US$ 1.796 trillion by the World Bank (Internet World Stats, 2017; World Bank, 2016; Basu *et al.,* 2013; Georgieva, 2006). Brazil has undergone different phases of economic growth and development since 1981.

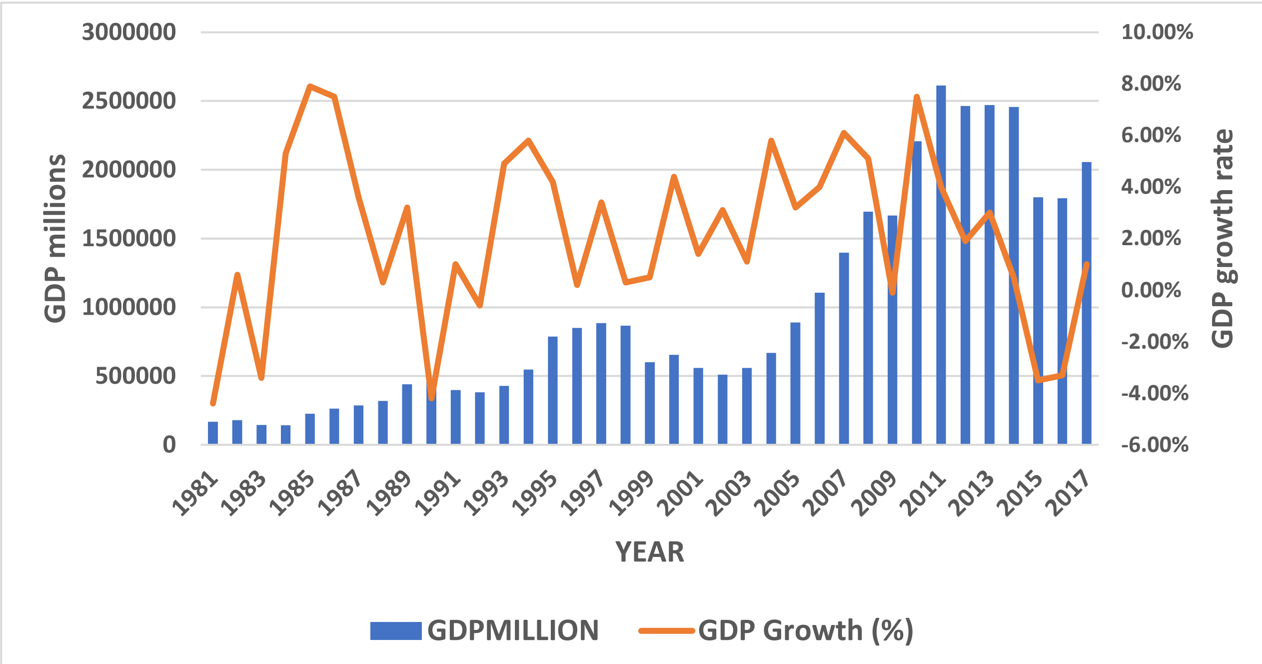


Figure 4. 3: Annual Rates Economic Growth Rates From 1981 To 2019,

Source: Researcher Compilation using Data from countryeconomy.com

Figure 4.3 shows that Brazil's economy performance exhibited an upward trend between 1981 and 2017, though there were localised variations or volatility in the GDP series. The GDP growth rate curve shows that Brazil's economic growth exhibited signs of mean reversion between 1981 and 2017.

Brazil is a country that is rich in natural resources, is largely land-abundant and has a fairly diversified skills base powering a broad range of economic activities (Jenkins, 2012; Georgieva, 2006). Despite the abundance of natural resources and the fair supply of labour which could potentially spur sustained economic activity, Brazil has for many years been plagued by a multiplicity of economic and other types of problems that have militated against consistent and sustained economic growth (Kon, 2016; Sarti and de Mendonca, 2014; Proni, 2010; Polaski *et al.,* 2009; Baer, 2008; Evangelist and Sathe, 2006; Barbosa, 1998).

According to different researchers, Brazil as a modern developmental state has a lot of potential to completely industrialise and raise most of its economic indicators to a high level given certain conditions (Proni, 2010; Sarti and de Mendonca, 2014). Some of the conditions that have been analysed by different researchers include policy consistency, a congenial environment for Foreign Direct Investment (FDI), economic integration issues, resolution of certain systemic issues like occasional institutional failures, and trade related conditions (Singh, 2016; De Castro, 2013; Singh and Dube, 2013). Empirical research has characterised Brazil's financial sector as fairly robust, though according to other scholars it still has a long way to go before it matches the level of financial breadth, depth, and sophistication of such economies as the United Kingdom (UK), United States (US), Japan, Singapore or Canada to mention a few economically advanced nations (Rashti *et al.,* 2014; Barbosa, 2011; Ahmad and Malik, 2009; Bittencourt, 2008; De Gregorio and Guidotti, 1995).

One of the key features of the economy of Brazil which has attracted and retained the interest of different scholars is its tendency to have periods of economic growth and consolidation which have been disrupted by episodes of crises ranging from currency crises to fully blown economic crises (De Mendonca *et al.,* 2012; Sobreira and de Paula, 2010; De Matos, 2003). Be that as it may, Sobreira and de Paula (2010) argue that the Brazilian banking system was characterised by good performance during the global financial crisis of 2008-2009 and that it cannot be validly averred that the system was in danger of collapse during the crisis period. The researchers further assert that, despite the confidence crisis faced by the banking system and which was exacerbated by the collapse of Lehman Brothers and other big global financial institutions, the system showed a great deal of resilience during the period under review (Sobreira and de Paula, 2010). It has been argued that the high degree of regulation, the presence of market discipline and transparency of Brazil's financial system partially explains why there was lower volatility in the stock market during the subprime crisis induced global financial crisis of 2008-2009 (De Mendonca *et al.,* 2012). Ozdemir (2014) argues that the fact Brazil had pursued what is termed “neo-developmentist” economic strategies partially explains why the performance of the Brazilian economy was satisfactory during the global financial crisis.

The short to medium-term effects of the 1998-1999 currency crisis and the global financial crisis of 2007-2008 on the Brazilian economy underline the importance of contagion and negative external shocks owing to adverse economic events emanating from other economies in South America or even from further afield (de Mendonca *et al.,* 2012; Sobreira and de Paula, 2010; Bittencourt, 2008). A case in point is the global financial crisis of 2008-2009 which to a certain extent negatively impacted several macroeconomic indicators in Brazil such as financial sector stability, employment levels, interest rates, and inflation levels (Arturo, 2011; Sobreira and de Paula, 2010 and Blanco, 2009).

Rapoza (2014) observed that the depreciation of the Argentina peso in 2014 which caused a significant decline in the country’s foreign currency reserves by 20 percent to approximately US$34 billion had potential of transmitting negative shocks to the Brazilian economy even though the latter had foreign currency reserves estimated at above US$300 billion in 2014. Rapoza (2014) further argues that the reasons for Brazil’s subdued economic performance are not difficult to discover. The study points out that since 1985, Brazil and Argentina have grown closer in terms of economic ties with combined imports and exports between the two economies being steady at between 15 and 17 percent since Argentina’s 2002 debt default (Rapoza, 2014). Nassif *et al.* (2013) used the Kaldor–Thirlwall theoretical and empirical framework in a bid to discover economic forces that underpin long-run economic development and behaviour of productivity in Brazil. Their study revealed that by 2013 Brazil had entered a phase of early deindustrialisation and that income elasticity of demand for imports between the periods 1980-1998 and 1999-2010 increased from 1.97 and 3.36 (Nassif *et al.,* 2013). The period under review was styled that of falling behind for Brazil relative to the global economy and what is termed the ‘international economic frontier.’

It has been argued that economic crises in Brazil could potentially negatively affect her neighbours’ economies such as Argentina (Garcia, 2016). Argentine Chancellor Susana Malcorra quoted by Garcia (2016) argued that “…When you have a partner that accounts for almost 40% of your trade balance, in a complex economic situation, lack of growth has a real and direct impact…." This shows that the resilience of the Brazilian economy benefits her major trading partners like Argentina and other Latin American economies such as Mexico, Bolivia, Venezuela, and Chile.

Naoui *et al.* (2010) undertook a Dynamic Conditional Correlation (DCC) analysis of financial contagion among six developed economies and ten emerging economies including Brazil. Their empirical results showed that the effect of the subprime mortgage crisis and its global financial crisis aftermath was to amplify dynamic conditional correlations during the period ranging from August 1, 2007, to February 26, 2010 (Naoui *et al.,* 2010). The same study also demonstrated that economies of Brazil, Mexico and Argentina had a high condition correlation, which reached 80 percent, with American financial markets during the subprime mortgage crisis (Naoui *et al.,* 2010). Candelaria (sa) examined time-varying correlation between the returns of the NASDAQ telecommunication index and the stock indices of Argentina, Brazil and Mexico. The study employed the DCC-GARCH methodology to examine the time-varying correlations paying particular attention to two different economic turmoil periods, namely, the bust in the telecommunications sector of 2001 and the subprime mortgage crisis-induced U.S. great recession of 2007-2009 (Candelaria, [sa]). The study found evidence of movement in the same direction of the NASDAQ telecommunications index and the stock indices of Brazil, Argentina, and Mexico. The global financial crisis period of 2007-2009 was found to be much more volatile than the tech bust of 2001.

4.1.2 Russia

Russia is a fairly large and expansive country whose land area is 1712.5 million hectares according to 2015 statistics (Federal State Statistics Service, 2016). Russia with a diverse population estimated at above 144 million and Gross Domestic Product (GDP) of about US$1.2837 trillion is one of the most important economies in Asia and the world (World Bank, 2017 and Federal State Statistics Service, 2016). The post-Soviet Russian economy was one of the fastest-growing economies during the 1998-2008 period, buoyed by economic reforms and significant growth in the energy sector (Cooper, 2009). The economy was, however, hard hit by the global financial crisis of 2007-2009 and experienced a significant economic downturn. According to Cooper (2009) economic growth in Russia averaged 6.9 percent between 1998 and 2008.

Russia is considered in the literature as the economically transformed remnant of the now-defunct Union of Soviets Socialist Republics (USSR) which existed for many years during the 20th century to foster the so-called scientific socialist and communist ideology (Dabrowski, 2004; Strayer, 2001; Gros and Steinherr, 1991 and Fischer, 1992). Immediately prior to and after the collapse of communism in the USSR in 1989, Russia embarked on a broad programme of reforms termed *perestroika* and *glasnost*. After the formal collapse of communism in 1989, Russia began to pursue economic reforms in a bid to catch up with other major economies of the world (Fischer, 1992). In the contemporary world, Russia has been perceived by the empirical literature to be straddled somewhere between communist ideology and market-led economic policies (Deshpande, 2015; Kim, 2015; Cooper, 2013). As a developmental state, the Russian economy is considered to be an upper-middle income economy which is in transition, though it is fairly advanced in terms of a number of different indicators (Kim, 2015; Roaf, *et al.,* 2014; Gregory and Lazarev, 2004; Kotz, 1999 and Åslund, 1999).

In the years preceding 2007, the Russian economy was characterised by fast growth that Beck *et al.* (2007) have linked to the rise in the price of crude oil in global markets. Using the Vector Error Correction Model (VECM) as the analytical framework, Beck *et al*. (2007) have demonstrated that Russia's fast economic expansion has been facilitated by what they term 'singular factors' such as the unprecedented increase in oil prices which confirm Russia's dependency on oil and that oil is the mainstay of economic activity. There has been empirical confirmation of symptoms of what is termed the "Dutch disease" in Russia which has been characterised by a growing services sector, slowdown in the performance of the manufacturing sector and an appreciation of the real exchange rate (Ito, 2017; Dulger *et al.,* 2013; Benedictow *et al.,* 2013 and Beck *et al.,* 2007).

A macro-econometric analysis predicated on estimating 13 equations covering variables such as government spending and revenue, interest rates, the labour market, and prices of commodities for the period first quarter of 1995 to first quarter 2008, reveals that the Russian economy is prone to significant volatility in oil price (Benedictow *et al.,* 2013). Ito

(2017) undertook a study whose main focus was to ascertain whether the Russian economy has been experiencing the “Dutch disease” or deindustrialisation. The main findings of the study were that there is a positive correlation between manufacturing output and oil price (Ito, 2017). The study also revealed that both manufacturing output and the real effective exchange rate tend to be positively associated with a slight rise in industrial sector performance occurring as a results of real exchange rate appreciation. Foreign Direct Investment (FDI) inflows were revealed to be an insignificant contributory factor to the manufacturing output variable and that the Russian government has in the past resorted to restrictive fiscal policy following an increase in manufacturing output (Ito, 2017). According to the World Bank (2016), during the period 2011-2016, the Russian economy was characterised by declining unemployment from approximately 7 percent to slightly above 5 percent.

The empirical literature has sought a deeper understanding of the oil-growth nexus in the context of macroeconomic modelling (Dreger *et al.,* 2016; Sabitova and Shavaleyeva, 2015; Mironov and Petronevich, 2015; Benedictow *et al.,* 2013). Ono (2017) conducted a study on the finance-growth nexus in Russia using the Vector Error Correction Model (VECM) analytical framework taking into account oil prices and foreign exchange rates. The study period was split into two subperiods, namely, 1999 to 2008 called subperiod 1 and 2009 to 2014 identified as subperiod 2. Empirical results from subperiod 1 corroborated the demand-following hypothesis in that economic growth was found to Granger-cause money supply and bank lending (Ono, 2017). Results for subperiod 2 revealed that causality runs from economic growth to bank lending with no evidence of causation running from money supply to economic growth (Ono, 2017). It is imperative to note that much of Russia’s economic growth has been natural resource-driven. Nevertheless, during the period 2014-2016 Russia experienced increased pressure from economic sanctions, volatile and declining oil prices, and a dampening of aggregate demand especially in China due to sluggish economic growth (Nesvetailova, 2015). Nesvetailova (2015) opines that the bias of Russia’s economy towards oil and gas exports constitutes a ‘resource curse’ and links it to the slow pace of modernisation of Russia into a diversified and industrialised economy.

4.1.3 India

India is a diversified and rapidly growing emerging economy whose global impact has steadily increased in the past two decades owing to a multiplicity of economic, technological, environmental, and geopolitical factors. India's economy is the second largest among the BRICS economies in terms of Gross Domestic Product (GDP) estimated at US$2,264 trillion (World Bank, 2016). According to Das and Mohapatra (2017) accelerated economic growth has catalysed India's integration to the global economy. International trade measured as a summation of imports and exports expressed as a percentage of India's Gross Domestic Product (GDP) has increased from 14.1 percent in the 1980-1984 period to 51.3 percent for the period spanning 2011-2015 (Das and Mohapatra, 2017). Foreign Direct Investment (FDI) as a percent of GDP over the corresponding periods improved from 0.03 percent to 1.7 percent (Das and Mohapatra, 2017).

The Indian economy has a sizeable agricultural sector dominated by the production of food crops such wheat, maize, rice and millets; plantation crops such as coffee, coconut, rubber and tea; horticulture crops such as fruits and vegetables and cash crops such as sugarcane, tobacco, jute and cotton. Given this background it is to be expected that volatility in agricultural commodity prices is an important issue to the Indian economy. For instance, a study by Chandrasekhar (2013) reveals that higher food prices while negatively affecting those whose larger proportion of income is devoted to food, have not been helpful to farmers that produce food crops either.

India's economic growth has been partly underpinned by a surge in stock or capital market activity over the past 20 years (Devi and Hinduja, 2018; Didier and Schmukler, 2013). India's economic expansion has been characterised by growth in the trading of derivative financial instruments such as stock index futures, stock index options, currency futures, and interest rate futures (Nandy (Pal) and Chattopadhyay, 2014). An analysis of the stock market return for India undertaken by Nandy (Pal) and Chattopadhyay (2014) for the period from 1 April 1996 to 31 March 2012, using the GARCH (1, 1) model demonstrates the existence of time-varying persistence of stock market volatility for the period under consideration. These findings have been corroborated by Sinha and Agnihotri (2016) who found evidence of negative conditional correlation between volume traded and the return of the large-cap index using the bivariate Glosten–Jagannathan–Runkle (GJR) GARCH methodology based on the Constant Conditional Correlation (CCC) model of Bollerslev (1990). Sinha and Agnihotri (2016) also found evidence of significant persistence in volatility, mean-reversion of returns, and asymmetry in the market. A study by Kaur (2004) interrogating time-varying volatility of stock markets in India based mainly on Sensex and Nifty returns demonstrate that 'day-of-the-week', the 'weekend effect' and the 'January effect' were not present while there was evidence of intra-week and intra-year seasonality in return and volatility measures. The empirical findings were rather indeterminate and mixed on return and volatility spillover between the United States (US) and Indian capital markets.

A study by Chittedi (2015) assessing the degree of contagion between India and the USA during the global financial crisis of 2007-2009 using Engle's (2002) DCC-GARCH to capture time-varying correlations, revealed a statistically significant increase of the correlation coefficient between the Indian and U.S. markets during the crisis period, vis-à-vis, the pre-crisis period. This proves that the contagion and interdependence between the U.S. and Indian markets intensified with the onset of the financial crisis.

An empirical study of the relationship between anomalous market movements and the rolling settlement based on three market series, namely, BSE Sensex, S & P CNX Nifty and S & P CNX 500 for the period spanning April 1997 to December 2001 for the pre-rolling settlement period and the period January 2002 to March 2007 for the post-rolling settlement period found evidence which differed from that of developed capital markets (Chander and Mehta, 2007). Evidence of the weekend effect was corroborated by statistically significant documented lowest Friday returns in the pre-rolling settlement period. Empirical results pertaining to the post-rolling settlement period confirmed those from other markets in that Friday returns were highest while those of Monday were lowest (Chander and Mehta, 2007).

4.1.4 China

China's economy has grown in importance in world affairs over the past 40 years. According to Pomenkova *et al.* (2014) over the past 20 years China has developed to be the second largest economy after the United States (U.S.) and the largest exporter of goods and services.

A wavelet spectrum analytical approach to discerning globalisation and business cycles for China and seven leading industrialised economies in the world (the G7) has revealed that China's cyclical development was markedly different from that of the G7 (Pomenkova *et al.,* 2014). This is in harmony with the findings of other researchers such as He and Wei (2012), Artis and Akubo (2012) who have found little or no evidence of Asian countries' dependability on global cycles, vis-à-vis, other advanced economies. The rapid economic development of China characterised by a positive and sustained economic growth rate over the past two decades has made the as yet nascent and indeterminate understanding of the degree of synchronisation of China's business cycle with those of other economies imperative. Even though international trade between China and G7 countries has increased over the past two decades, empirical evidence underpinned by wavelet spectrum analysis demonstrates that overall synchronisation of China's economic (GDP) growth with G7 economies is quite low (Pomenkova *et al.,* 2014).

Even though researchers such as He and Wei (2012) have found little evidence of China's and other Asian economies' dependability on global economic cycles, researchers such as Zhiang *et al.* (2010) have found evidence of bubble development processes and bubble burst events in Chinese capital markets which are in line with financial economic developments elsewhere in the world such as the global financial crisis. In a study predicated upon the 'theory of rational expectation bubbles, imitation and herding of investors and traders school of behavioural finance, the statistical physics of bifurcations and phase transitions, and the log-periodic power law (LPPL) model,' Jiang *et al*. (2010) found that the Shanghai Stock Exchange Composite Index (SSEC) and the Shenzhen Stock Exchange Component Index (SZSC) exhibited two bubbles with the first developing from mid-2005, bursting in October 2007 and the second bubble developing from November 2008, bursting in August 2009. Such findings are in harmony with empirical results obtained by Zhou and Sornette (2006b) who accurately predicted the peak of the U.S. housing bubble (see also Bastiaensen *et al.,* 2009 and Sornette *et al.,* 2009).

China is heavily involved in international commodity trade because of its rapid economic growth which it has sustained for more than two decades. The Chinese economy is, however, more resilient to commodity price shocks compared to other major economies. A study by Broadstock and Filis (2014) examining time-varying correlations between different oil price shocks, identified by Kilian (2009) as supply-side, aggregate demand and oil-market specific demand using a Scalar-BEKK model, found that China is apparently more resilient to oil price shocks than the United States (US).

4.1.5 South Africa's Economic and Financial Systems

South Africa is the smallest of all the BRICS economies in terms of three main fundamental measures which are population, Gross Domestic Product (GDP) and breadth and depth of financial markets. It was controversially incorporated into the economic bloc in 2010 (Onyekwena *et al.,* 2014). Onyekwena *et al.* (2014) observe that South Africa accounts for approximately 33 percent of economic activity in Sub-Saharan Africa and 80 percent of the South African Development Community (SADC) economic activity or GDP. Unlike many African countries, South Africa has an abundance of mineral and natural resources, and is characterised by well-developed financial, transport, energy and tourism sectors (Onyekwena *et al.,* 2014). A recent study has provided an international trade rationale for the inclusion of South Africa in the BRICS alliance by pointing out that prior to 2010, the trade balance between South Africa and the BRIC bloc switched from a deficit to a surplus and that the BRIC alliance substituted the European Union as South Africa's major trading partners (Onyekwena *et al.,* 2014). The share of the BRICS alliance in global trade grew from US$16 trillion which was 14 percent in 2008 to US$18.1 trillion which was 17 percent in 2012 (Industrial Development Corporation, 2014, p. 3).

The South African economy dates its existence from antiquity, even though a number of modern researchers and scholars trace the development of South Africa as a modern developmental state to 1652 when Dutch traders and explorers arrived in modern day Cape Town which was called then the Cape of Good Hope (South African Reserve Bank, 2011, Rossouw, 2009). South Africa is ranked as the most industrialised economy in

Africa and is generally considered to be an upper-middle-income economy (Luiz, 2016 and Bojetic and Fedderke, 2006). The other African economies considered to be upper-middle-income are Gabon, Botswana, and Mauritius.

Rossouw (2009) reveals that the first bank in colonial South Africa was Lombaard Bank which was established on 23 April 1793 in Cape Town. Even though this bank was wholly owned and controlled by the Cape Colonial Government, it was a commercial bank as opposed to being a central bank (Rossouw, 2009). The demise of Lombaard Bank due to failure to meet legal requirements led to the formation of other commercial banks (Rossouw, 2009). According to Gelb (1984) the South African Reserve Bank (SARB) was established on 30 June 1921 in Cape Town according to the Currency and Banking Act (No. 31 of 1920) (South African Reserve Bank, 2011). Parsons (1983) reveals that the famous British economist John M. Keynes, Jan Smuts, and Louis Botha had a significant input in the development of the South African Reserve Bank (SARB) after the end of the First World War. The banking system in South Africa was dominated by commercial banks up to the 1950s, when other types of banks began to develop (South African Reserve Bank, 2011 and Rossouw, 2009).

There is a lot of controversy in academic circles pertaining to the trajectory of South Africa as a developmental state. McKenzie and Mohammed (2016) argue that South Africa is a more unequal society post-apartheid than what it was during the heinous period of apartheid with a Gini Coefficient of 0.7. Laubscher (2013) reveals that the Gini Coefficient of income inequality ranges between 0.6 and 0.7 depending on the method of calculating it. A Gini Coefficient is an index or statistic that is used to measure income inequality in an entire country by distilling it into a single measure. The statistic owes its origin to the work of an Italian statistician called Corrado Gini who published a seminal paper in 1912 entitled “Variability and Mutability” (Luebker, 2010).

South African economic growth generally trended upwards between 1981 and 2011, buoyed by a sustained growth in private sector investment during the same period. Fanta and Makina (2017) have found evidence of a link between bond market development and economic growth in South Africa. The same study did not observe similar effects for bank and non-bank financial intermediaries and the stock market (Fanta and Makina, 2017).

This important finding raises the fundamental question of the role that bond markets play in South Africa's GDP growth which financial intermediaries and equity markets do not play. This is depicted in Figure 4.4:

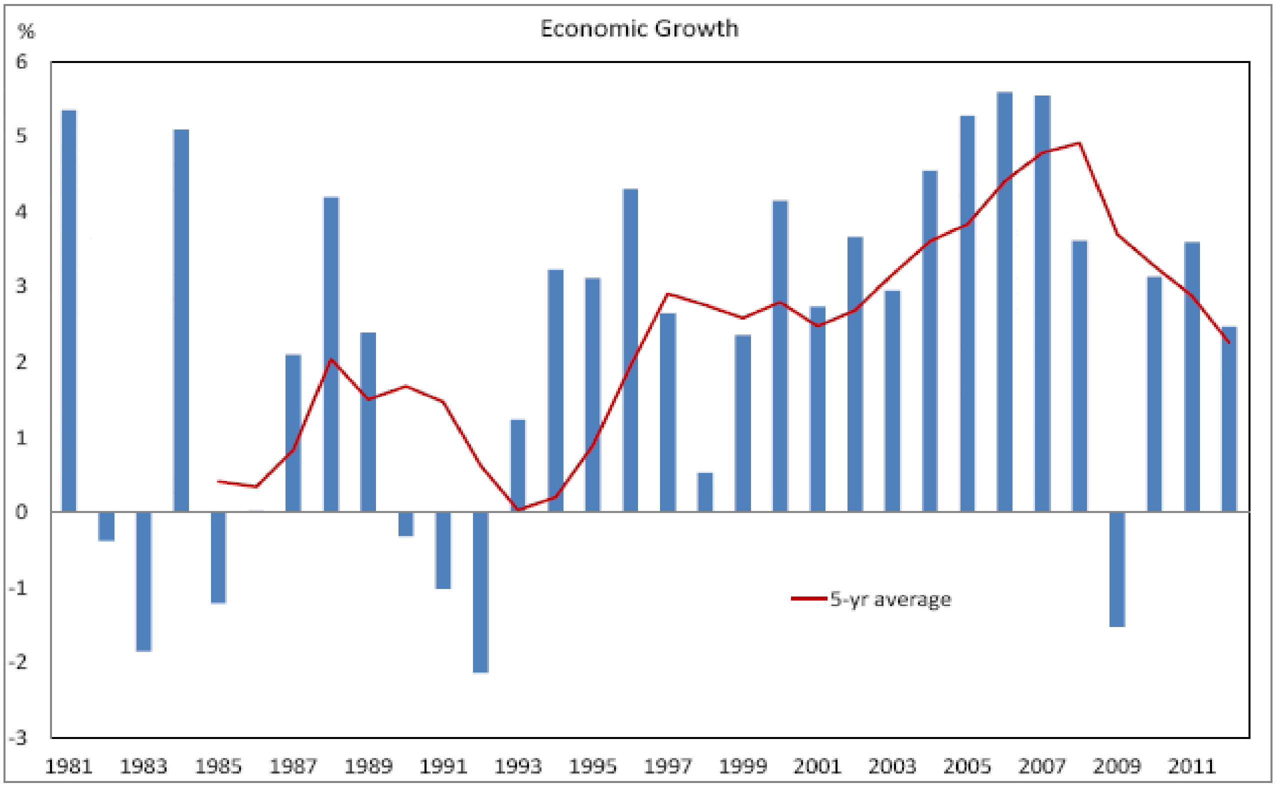


Figure 4. 4: South Africa's Economic Growth between 1981 and 2011, Source: Laubscher (2013)

Figure 4.4 reveals certain key features about South Africa's economic growth story. First, between 1981 and 1992, growth in South African national income was characterised by significant fluctuations, 1981 had a peak economic growth rate of slightly more than 5 percent, while the years such as 1982, 1983, 1985, 1990 and 1991 actually registered negative economic growth rates. Second, the picture and trajectory of economic growth started to improve towards independence in 1994, with 1993 registering an economic growth rate of slightly above 1 percent. Third, the upward trend in GDP growth was sustained between 1994 and 2007 before the economy experienced a short-lived recession between 2007 and 2009 in high probability owing to the global financial crisis of 2007-2008.

Private sector investment also grew during the period 1981-2011 which may partially explain why South African national income actually had an upward trend especially post-apartheid as observed in the above analysis. Figure 4.5 shows the trajectory of the private sector and public-sector investment spending during the period under review.

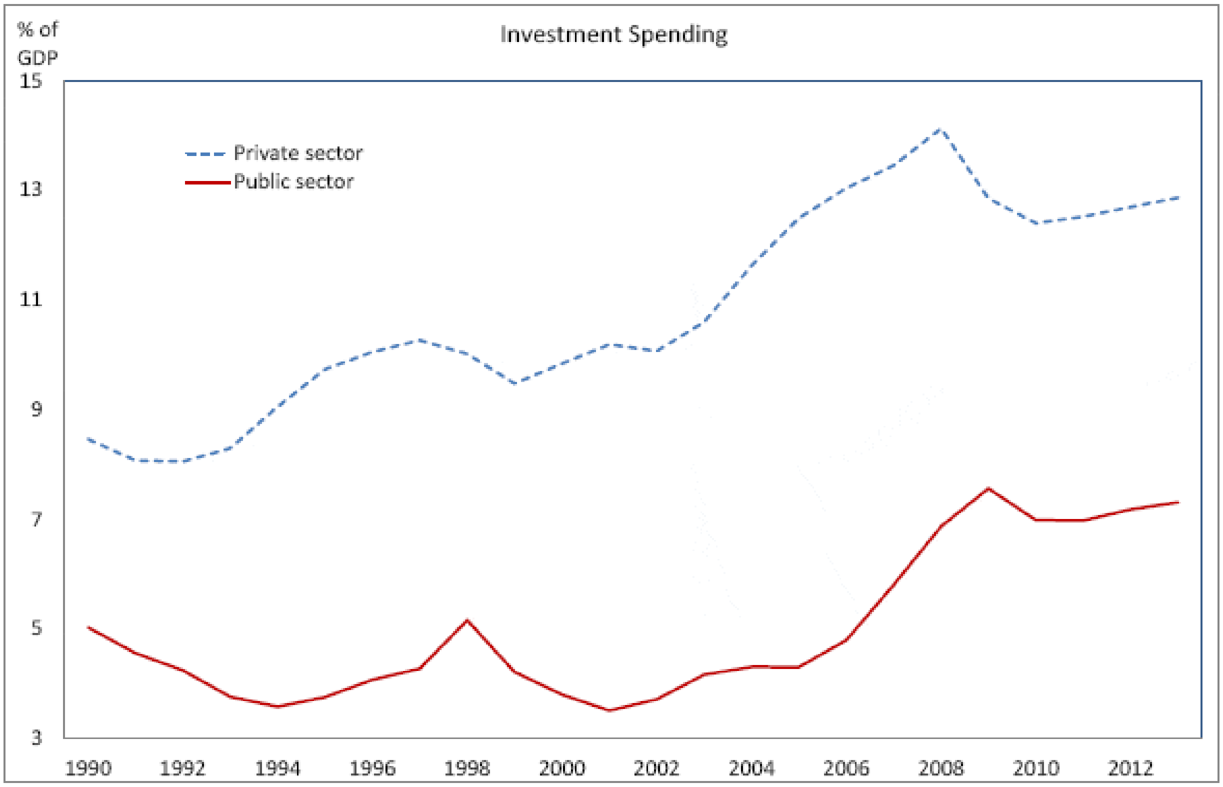


Figure 4. 5: Private Sector and Public-Sector Investment between 1990 and 2012, Source: Laubscher (2013)

Figure 4.5 shows that in South Africa the private sector has dominated investment spending compared to public sector investment since 1990. Laubscher (2013) has mentioned 'new business opportunities, increased competition, a predominantly business-friendly and fairly predictable policy environment up to 2007, and a reduction in the cost of capital in response to lower inflation,' as some of the key factors that explain the upward trend in both private sector and public-sector investment spending. Despite high levels of crime and corruption, the South African economy has been one of the most attractive economies in Sub-Saharan Africa owing to a combination of investor friendly policies and relatively advanced and highly developed infrastructure (Gupta and Ziramba, 2009; Akinboade and Makina, 2010). Several empirical studies have partially attributed sustained positive rates of economic growth to what is termed the 'democracy dividend' after 1994 even though the democracy-economic growth nexus is associated with a lot of controversies (FauNattrass, 2014; Seekings, 2014; lkner and Loewald, 2008). Faulkner and Loewald (2008) have identified political change and in particular the transition to democracy as catalysing economic growth in South Africa.

Between 2006 and 2008 there was a short-lived reversal of the gap between government revenue and government expenditure all measured as a percentage of GDP (Idenyi *et al.,* 2016; Alm and Embaye, 2011 and Nyamongo *et al.,* 2007). Nyamongo *et al.* (2007) investigated the government revenue – expenditure nexus under the vector autoregressive (VAR) framework. Johansen tests revealed that study variables are cointegrated which signals a long-run association between government expenditure and government revenue. The trough associated with private sector investment owing to the recession occasioned by the global financial crisis during the period 2007-2009 is also partially reflected in the downward trend in government revenue as a percentage of GDP (Verick and Islam, 2010; Baxter, 2009).

It is instructive to note that when the African National Congress (ANC) came into power in 1994, the South African economy was dominated by interwoven conglomerates or large corporates operating under oligopolistic market circumstances (McKenzie and Mohammed, 2016 and Newman *et al.,* 2010). The abandonment of apartheid brought corporate restructuring and internationalisation which in turn presented South African conglomerates and other firms with new threats and opportunities. The financial system was not exempt from the changes which began to prevail post-apartheid and the structural changes that were introduced to the South African economy, even though some scholars are quick to point out that the fundamental neo-liberal posture of many South African industries and the financial system did not really change but actually became more integrated to the global economic and financial system (McKenzie, 2016; Mohammed, 2016 and Padayachee, 1989).

The South African economy is fairly diversified even though it is sensitive to commodity price movements in global markets owing to the predominance of minerals in economic activity (Keeton, 2016; Wenzel, 2014; Baxter, 2013 and Ngandu, 2005). A study by Stilwell (2004) underpinned by input-output analysis revealed that in 2002, South Africa exported 87.5 percent of its platinum production. The new “Scramble for Africa”, in part undertaken by some of the BRICS economies such as China, Russia and India, has been necessitated by the vast natural resources’ potential of the continent (Wenzel, 2014). South Africa was incorporated into the original BRIC grouping also because of the mineral wealth that its economy is endowed with. South Africa is the leading producer of gold globally (Neingo and Tholana, 2016 and Premoli, 2011).

4.2 Interdependence, Contagion, and Spillovers among the BRICS

Several studies have been undertaken in recent years by different researchers with the broad objective of discovering the links and interdependence that exist among BRICS economies (Bonga-Bonga, 2015). Bonga-Bonga (2015) analysed the magnitude of the transmission of financial shocks between South Africa and other economies within the BRICS family using data spanning 1996-2012. The study used the VAR-DCC-GARCH composite model and found that there is strong evidence of cross-transmission and dependence between South Africa and Brazil (Bonga-Bonga, 2015). The same empirical study revealed that the South Africa economy was more prone to and affected by crises emanating from the Asian economies of Russia, China and India but the reverse was not the case (Bonga-Bonga, 2015).

Different studies have tended to focus on different specific themes. For instance, an analysis by Export-Import Bank of India (2015) reveals that developing countries have emerged in recent years as what is termed “regional and global growth engines” characterised by higher rates of economic growth than developed countries. According to 2015 statistics, the BRICS account for 22.5 percent of world output, 17.2 percent of global trade and over 40 percent of the world’s population (Export-Import Bank of India, 2015). This signifies that the BRICS together with other emerging and developing economies are fast becoming an economic force to reckon with.

In an analysis of the relationships that exist among the stock markets of Russia, Brazil, Argentina, South Africa and China, Padmanabhan *et al.* (2015) observe that China is the world’s leading investor and the leading contributor to global economic growth. In the

1990s, the Chinese stock market was viewed as more of a gambling arena (specifically a casino) due to the market power previously exercised by insiders and speculators. This situation changed with the reforms of the past decade which ensured that even though the Chinese stock market is part of relatively closed system, it is now relatively more efficient compared to those of advanced Western economies (Padmanabhan *et al.,* 2015).

4.3 Financial Integration and Economic Growth Issues

Financial integration is an important topic in the literature on the finance-growth nexus. According to Tayebi and Fakhr (2009) financial market integration is important in the context of monetary policy which is best implemented through an efficient financial system. Since financial integration affects the structure of the financial system which in turn affects financial stability, therefore, regulators and central banks monitor integration to better inform policy formulation and policy implementation (Tayebi and Fakhr, 2009). According to the literature, Singapore is one of the economies which is most integrated with the rest of the world, with near-perfect financial integration. According to the Monetary Authority of Singapore (2000, p.i), the Singaporean economy maintains open capital as well as current accounts characterised by "no restriction on movements of portfolio capital and direct investment."

The question which normally arises when one considers stock market return and commodity price volatility issues is that of the extent of the stock market and wider financial market integration within the BRICS economic bloc. A number of researchers have analysed the topic of financial market integration among the BRICS and other economies from different perspectives (Bosepung, 2017; Singh and Singh, 2016; Padmanabhan *et al.,* 2015; Gregoryev, 2010). In a study predicated on Cheung and Ng's (1996) causality-in-mean/variance test, Gregoryev (2010) sought to measure the effect of the oil price variable on cross-market linkages between stock markets of BRICS and selected developed country mature stock markets. The study found evidence that the oil price variable complemented cross-market linkages for country pairs with similar oil status and economic profile (Gregoryev, 2010).

In a study seeking to ascertain the extent of financial integration between BRICS' stock markets on the one hand and the US and the UK stock markets on the other hand, using correlation analysis and Johansen cointegration test, Nashier (2015, p.65) found 'evidence of short-term static and long-term dynamic integration between the stock markets' of the two distinct economic regions. This means that there are limited diversification or arbitrage opportunities linked to speculative activities between the BRICS' stock markets and the US and UK stock markets. It is important to observe that the increased pace of globalisation has also concomitantly increased the extent of involvement of investors in foreign stock markets (Nashier, 2015). Dasgupta (2014) employed the Johansen-Juselius and Engle-Granger analytical approaches with data consisting of daily closing values of the BRIC indices spanning 1st January 2003 and 31st December 2012. The major aim of the study was to ascertain the extent and direction of integration and dynamic links among different economies within the BRIC economic bloc. The study found evidence of both short-run and long-run unidirectional and bidirectional causality between Indian and Brazilian stock markets, the Chinese stock market was found to Granger-cause changes in the Brazilian stock market which in turn was linked to the Russian capital markets (Dasgupta, 2014).

4.4 Financial Crises and the BRICS

Financial crises are a constant feature of financial market operations and dynamics. Financial markets of both emerging and developed economies have in the past been associated with financial crises. A financial crisis is often viewed in the literature as a state of panic in the financial markets characterised by a run on banks, massive selling off of shares by investors or withdrawal of savings from the financial sector (Claessens, 2013; Allen, 2009 and Crotty, 2009). The theoretical and empirical literature has tended to link financial crises with a crisis of expectations in which investors in a particular market or market segment begin to expect the value of financial assets to go down (Škare and Stjepanović, 2015). One of the major functions of financial markets is to manage risks that are associated with different financial assets (Sakyi, *et al.,* 2014). Prudent risk management is a function that financial markets must discharge diligently and at all times because any lapse in risk management systems may inadvertently lead to massive avoidable losses (Mehran and Mollineaux, 2012). It is imperative to emphasise that prudent and meticulous risk management does not necessarily eliminate risks that are associated with financial assets and financial market operations (Dionne, 2013; Kashyap, 2010 and Jorion, 2009). Jorion (2009) argues that even if risk management is executed flawlessly, there is no guarantee that huge losses will not occur. This indicates that as long as financial markets operate under socio-economic and political conditions characterised by uncertainty, there will always be a risk (Sakyi *et al.,* 2014) and potential for financial services, and other types of firms to make significant losses. Big losses in business have been linked to business decision making and a sudden downturn in economic conditions which predispose private sector organisations to make losses (Jorion, 2009). A healthy financial system is one in which different types of risk are kept at manageable levels (Kashyap, 2010 and Oldfield and Santomero, 1997). Dugguh and Diggi (2015) have argued that the need for commercial banks to ensure stable and successful business has necessitated restructuring, reviewing and updating of risk management strategies.

The empirical literature has revealed that financial crises tend to be linked to the different phases of the business cycle (Kirkpatrick, 2009). Disruptions experienced in the financial system have been shown to have a significant impact on real economic variables. A study by Milio *et al.* (2014) reveals that the global financial crisis of 2007-2008 was still being felt as recently as 2014, because the crisis quickly spread to, and affected the real economy exacerbating business losses, a decline in household demand as well as subdued investment activity in different economies. As a consequence of the financial crisis, the European Union (E.U.)'s GDP declined by slightly more than 4 percent and industrial production fell by 20 percent (Milio, *et al.,* 2014). Business cycles are defined as systematic fluctuations in business and economic activity which are characterised by four major phases, namely, the boom, recession, depression and the recovery stage (Milio *et al.,* 2014).

4.4.1 Financial Crises – Empirical Evidence

Several empirical studies have been undertaken by different scholars in an attempt to understand the impact of financial crises on the BRIC. These various studies have yielded mixed findings. When the global financial crisis of 2007-2009 started and progressed right through 2009, there were genuine fears that it would drag the United States (US) and the global economy down the steep path towards a severe economic depression (Molano, 2009). The mechanism by which the effects of a financial or an economic crisis are transmitted from one economy to another is called contagion. According to Forbes and Rigobon (2002) as cited in Karanasos *et al.* (2016) contagion is “the significant increase in cross-market linkages after a shock to one country.”

Banerjee and Vashisth (2010) observe that while the erstwhile engine of the world economy, the US showed signs of a slowdown in the period 2007-2009, the BRIC economies exhibited steady growth. While acknowledging that the global financial crisis of 2007-2008 had an indirect impact on the BRIC, Banerjee and Vashisth (2010) argue that the severity of the impact on this economic bloc was far much less, vis-à-vis, many developed and emerging economies across the globe. They observe that the resilience of the BRIC in general and their unique features as a heterogenous economic bloc made the economic downturn shallow and ensured speedy and strong economic recovery (Banerjee and Vashisth, 2010). It has been observed that 18 percent of India’s GDP is accounted for by agriculture and that the sector accounts for 52 percent of the employment of labour (Banerjee and Vashisth, 2010). In contrast, the Chinese economy has manufacturing accounting for the lion’s share with a 48.1 percent share of China’s GDP and employing 22 percent of the total labour-force (Banerjee and Vashisth, 2010). The foregoing argument about the resilience of the BRIC is corroborated by empirical evidence presented by Molano (2009) who observes that Brazil, for instance, had a US$2.3 billion trade surplus. The study, nevertheless, points out that since exports to the United States dropped by 36 percent and embarkations to the European Union (EU) declined by 27.4 percent, a current account deficit would be expected for 2009 (Molano, 2009). These facts and figures partially explain the resilience of the BRIC economies given the global financial crisis of 2007-2008.

In contrast to the foregoing perspective about the resilience of the BRICS, in a study that included South Africa, Istomina (2013) argues that despite having large current account surpluses and huge foreign exchange reserves, the BRIC economic bloc was not shielded from external economic threats. A review of UNCTAD statistics by Istomina (2013) shows that GDP growth for most emerging economies generally declined by between 5 percent and 15 percent for the period 2007-2009. This shows that the global financial crisis had a significant impact on economic performance in most emerging economies. Istomina (2013) identifies three major channels of contagion linking developed and developing economies. These are foreign trade, capital flows and stress co-movement (Istomina, 2013). It is important to observe that China and India are fast growing and export-oriented economies that naturally experience the repercussions of financial and economic crises from other countries via mainly the foreign trade and capital flows channels (Bansal, 2012). Bansal (2012) argues that the global financial crisis of 2007-2009, coupled with the consequent economic slowdown of the major trading partners of India have conspired to bring about tough challenges to India's international trade activities. The decline of the global trade volume growth rate from 7.3 percent in 2007 to 2.8 percent in 2008 underscores the negative repercussions of the global financial crisis on world trade (Bansal, 2012). India's exports and imports reduced from 28.87 percent and 35.38 percent respectively for the 2007-2008 period to 12.21 percent and 18.85 percent respectively for the 2008-2009 national income accounting period (Bansal, 2012). In the same vein, Istomina (2013) argues that globalisation and securitisation have accelerated the interconnectedness of the global financial system, thereby increasing moral hazard. It has been argued that economies that experienced a small impact of the global financial crisis benefited from the cushion effect of accumulated foreign exchange reserves (Istomina, 2013).

4.4.2 Econometric Studies Linking Financial Crises, Volatility and Performance of BRICS

Several econometric studies have been conducted by different researchers in a bid to understand the factors that explain stock market volatility in emerging financial markets. A bivariate Exponential GARCH (EGARCH) study undertaken by Bhar and Nikolova (2009) examined the level of integration and the dynamic relationship between the BRIC economies, their regions and the global economy at large. The major findings of this study were that the Indian economy exhibited the highest level of regional and global integration, followed by Brazil, Russia and lastly China (Bhar and Nikolova, 2009). The same study also found evidence of “a negative relationship between the location conditional volatility of India with that of the Asia-Pacific region …” (Bhar and Nikolova, 2009, p. 203). Kishor and Singh (2017) used a GARCH model to facilitate an empirical examination of the volatility of stock prices for the BRICS spanning four years, from January 2007 to December 2010. Their study specifically examined the difference in the stock return volatility of the respective BRICS stock indices during and after the US subprime mortgage crisis of 2008 on an individual basis (Kishor and Singh, 2017). The study found that BRICS with the exception of the Russian stock market had been significantly affected by news of a recession in the US stock market occasioned by the subprime crisis. Even though stock market volatility had changed quite markedly during the crisis and recovery phases, these changes were heterogeneous and depended to a larger extent upon the individual markets (Kishor and Singh, 2017).

Mensi *et al.* (2014) relied on data spanning September 1997 to September 2013 to analyse the impact of global factors on BRICS stock markets using quantile regression. The global factors isolated by the study include the S&P 500 index, the commodity markets, the global stock market uncertainty and the U.S. economic policy uncertainty. Empirical results show that since the onset of the global financial crisis, BRICS stock markets exhibited asymmetric dependence on the global stock market which remained unchanged during the study period (Mensi *et al.,* 2014). The results of the analysis also showed that oil prices exhibited a symmetric tail independence with markets of Brazil, Russia, India and China, with South Africa being an exception (Mensi *et al.,* 2014). This was despite the fact that oil and BRICS markets dependence significantly increased from the commencement of the global financial crisis onwards. Mensi *et al.* (2014) further revealed that gold price returns move together with the returns of the BRICS markets at both the upper and lower tails with the exception of Russian and Chinese markets. The degree of the co-movement was revealed to have declined since the onset of the global financial crisis. The quantile econometric analysis found no evidence of economic policy uncertainty having any significant impact on the BRICS stock markets during the study period (Mensi *et al.,* 2014).

A study by Singh and Kaur (2015) established that the US subprime crisis spill-overed the returns and volatility from the US stock market to economies that are integrated to the US. The study used the Spillover Index and an econometric method called Tri-Variate Vector Autoregression to establish a unidirectional causality from the US market to the Indian and Chinese markets, and unidirectional causality was found to be running from the Chinese market to the Indian market during the 2007 to 2009 period (Singh and Kaur, 2015). The Singh and Kaur (2015) study used Threshold Generalised Autoregressive Conditional Heteroskedasticity [TGARCH (1, 1)] to estimate the time varying risk parameters. The Spillover Index revealed that the cross-market effect on the volatility reduced over the 2007-2009 period owing to the increasing impact of past volatility and the existence of the 'leverage effect' (Singh and Kaur, 2015). Mensi *et al.* (2015) investigated the asymmetric linkages between the five BRICS' stock markets and three country risk ratings, namely, financial, economic and political risk, taking into account significant global economic and financial factors. The empirical examination employed the dynamic panel thresholds models and found evidence of asymmetry more often than not (Mensi *et al.,* 2015). It was discovered that the statistical significance and the signs of the effects of the aforementioned risk ratings on BRICS stock market returns tended to differ across the lower and upper regimes (Mensi *et al.,* 2015). It was observed that drops in the BRICS markets were caused by increases in implied volatility.

A study by Syriopoulos *et al.* (2015) examined the dynamic risk-return features of BRICS capital markets by modelling potential time-varying correlations and volatility spillover effects with the US stock market. Using VAR (1)-GARCH (1, 1) methodology, the study found evidence of 'significant return and volatility transmission dynamics between the BRICS and US stock markets and business sectors (Syriopoulos *et al.,* 2015).' Given the 2008 financial market crash as a backdrop, Cong (2017) analysed stock market volatility persistence performance using the GARCH and EGARCH models. Empirical results demonstrated a universal trend that persistence in volatility was strengthened by the occurrence of the crisis and dissipated as the economy moved to the recovery phase (Cong, 2017). In other words, unconditional volatility tended to be higher during the crisis period than during other phases of the business cycle. Cong (2017) also demonstrated that the EGARCH had better goodness of fit for the sample analysed than the GARCH model. Chkili and Nguyen (2014) sought to ascertain the dynamics that explain the link between exchange rates and stock returns under conditions of regime-switching for the BRICS economies. Their analysis showed that BRICS' stock returns evolve according to a low volatility regime and a high volatility regime (Chkili and Nguyen, 2014). According to the estimated Markov switching VAR models, stock markets have more influence on exchange rates during tranquil and turbulent periods (Chkili and Nguyen, 2014).

Hunzinger *et al.* (2014) undertook an empirical study of volatility skews of indices of security exchanges of BRICS economies for the period spanning 01 March 2009 to 27 March 2014. The study period was the post-global financial crisis of 2007-2008. In their study, Hunzinger *et al.* (2014) argue that the shapes of volatility skews of a security exchange index can reveal crucial information about the volatility and liquidity of a local market. The return time series of an index and the country's central bank rate was used to obtain the volatility skew of an index. Demand for and supply of in-the-money and out-of-the-money options are normally deduced by volatility skews and this helps fund managers in deciding whether to write a call option or a put option (Hunzinger *et al.,* 2014). Volatility skews also help in the pricing of options in financial markets. The empirical results obtained from the risk-neural historical probability distribution (RNHD) model show that Brazil's volatility skew generally lies above those of other BRICS economies due to it having the highest interest rate compared to other BRICS members (Hunzinger *et al.,* 2014). Even though India has the second highest interest rate within the BRICS family, its volatility skew is lowest.

Tripathy (2017) used GARCH, CHARMA, APARCH and CGARCH models to investigate whether BRIC countries stock market volatility move together. The study had three major findings. First, the study found evidence of the presence of asymmetric and leverage effects in all BRIC countries' stock market return, second, the component of time varying long-run volatility is more persistent in the stock markets of China and Russia (Tripathy, 2017). Finally, the analysis demonstrated that volatility shocks are quite persistent in all the stock markets of BRICS countries. This implies that over time the volatility pattern is changing over. Karanasos *et al.* (2016) used the multivariate FIAPARCH approach to model financial markets with dynamic correlations in times of crisis. The study was predicated on data obtained from eight national stock market indices' daily returns for the period 1988-2010. The analysis found significant cross effects, asymmetric volatility, long range volatility dependence and negative shocks. The analysis also found evidence of continuous herding behaviour among investors during times of high volatility and increased contagion effects between the markets as shown by higher dynamic correlations of the stock markets after the crisis event (Karanasos *et al.,* 2016).

4.5 Context of the Study in Light of The Literature

The study bridged gaps that exists in the empirical literature in a number of ways. First, unlike previous studies that adopted either a single GARCH model or a few GARCH models to analyse BRIC and BRICS stock market volatility dynamics, the present study bridges the gap in the literature by studying the five BRICS using a number of GARCH models as well as spectral analysis. The study by Bhar and Nikolova (2009) is a case in point of a study which relied primarily on a single GARCH model, that is, the bivariate EGARCH model to examine the level of integration and the dynamics of the relationship among the BRICS and the global economy. A study that relies on a single model, for instance, EGARCH in the case of Bhar and Nikolova (2009), stands or falls on the basis of the merits and demerits of the adopted methodology.

A study by Tripathy (2017) relying on four models, namely, GARCH (1, 1), CHARMA, APARCH and CGARCH has demonstrated that results obtained from one method tend to be confirmed or disproved by findings from another model or models. This gives the research a balanced picture of the phenomenon being studied. Nevertheless, even the use of four or more GARCH models does not give a complete picture of stock price volatility dynamics as long as all the models used are all single regime GARCH models. There is a need for findings from single regime GARCH models to be verified by multiple regime GARCH models. It is for this reason that the current study uses GARCH (1, 1), Fractionally Integrated GARCH (FIGARCH-BBM and FIGARCH-Chung), EGARCH and DCC – GARCH whose results are then verified using Markov-Switching GARCH (1, 1) assuming a Gaussian distribution and another Markov – Switching GARCH model assuming non-normal error distributions such as the skewed Generalised Error Distribution (GED) and the Student t distribution.

Most empirical studies that have been reviewed on the subject matter of commodity price volatility, stock market development and economic growth tend to rely heavily on the normal distribution and Student t error distributional assumptions. This has a great impact on the final parameter estimates obtained for the variables of the study. It is an established fact in empirical finance research that the magnitude and sign of parameter estimates as well as their test statistic values are by necessity affected by the error distribution that the researcher chooses in fitting a model to a given dataset (Almarashi and Khan, 2019; Agboola *et al.,* 2019). The corollary of the foregoing argument is that the choice of the error distribution has great import on the final decisions that are made by the researcher when testing a given study's research hypotheses. It is in this light that this study also modelled BRICS stock return volatility dynamics relying on the Gaussian, Student t, Generalised Error Distribution (GED) and Skewed GED error distributional assumptions.

A review of the empirical literature on the nexus between stock market performance and economic growth reveals that no previous study has ever used spectral causality analysis to examine links between stock indices and national output proxies of economic growth. A review of empirical literature also reveals that no single study attempting to link commodity price volatility and stock market performance has ever straddled frequency-domain analysis and time-domain analysis (Breitung and Candelon, 2006). Straddling frequency-domain and time-domain analytical approaches improves the integrity and comparability of research findings.

A study of the nexus between COP/USD exchange rate and the COLCAP stock index of Colombia by Ronderos (2016) revealed that it is more beneficial to study cointegrated variables in the frequency domain so as to understand fully the trajectory of causality between the two variables in the context of business cycle activity. In light of the foregoing, the study examined the time and spectral causality among BRICS stock returns and returns of gold, corn and WTI crude oil for data of daily frequency. In the same vein, for monthly data the study examined both time-domain and frequency-domain causality among the BRICS stock price indices with four selected commodity class indices serving as external regressors. The four commodity class indices which served as external or independent regressors were incorporated to account for the impact of commodity price changes (or volatility) on the frequency-domain causality structures of BRICS monthly stock indices.

4.6 Chapter Summary

Chapter 4 gave an analytical overview of the BRICS interrogating issues such as the extent of financial market linkages, financial market interdependence, and contagion. The chapter also discussed the role of commodities markets in the context of their perceived financialisation and the impact of financial crises on BRICS economic growth and stock market performance. The motivation for studying BRICS economies is the realisation that key financial time series (of stock returns, derivatives, economic growth and so on) associated with them are characterised by regularity, stationarity (after necessary transformations) and historicity which facilitate the use of time series and frequency domain econometric approaches in a bid to better model price behaviour for prediction and risk management purposes (Izadi, 2009).

CHAPTER FIVE: RESEARCH METHODOLOGY

5.0 Introduction

Chapter 5 explains the research methodology that was used in the study. The chapter covers six main sections that constitute the entirety of the research methodology from conceptual issues to the limitations of the study. The main sections of the chapter are the review of methodological issues, the empirical approach adopted for the study, the theory that anchors the techniques of analysis adopted for the study, data sources, the main variables of the study, model selection, robustness checks, and limitations of the study. In essence, the overarching objective of this chapter is to explain how the theoretical and empirical literature was used to distil models that were deemed appropriate for the study.

5.1 Review of Methodological Issues

The ensuing sections review extant and contemporary literature on key methodological issues that are linked to the study. The main models that have been used by different researchers to study commodity price volatility are reviewed in the ensuing sub-sections.

5.1.1 Models of Commodity Price Volatility Applied by Different Researchers

Models that have evolved from the early 20th century to date in a bid to accurately capture commodity price determination and dissemination processes are as diverse as the commodities themselves. GARCH models, as they are commonly known are based on the seminal work of Engle (1982) who published a paper on autoregressive conditional heteroscedasticity (ARCH) modelling. It was Engle (1982) who discovered an attribute called volatility clustering associated with financial, commodity, and economic variables. Volatility clustering refers to a scenario in which significant changes, say in the price of a financial asset, are followed by significant changes in either sign or small changes tend to be followed by small changes (Engle, 1982). Bollerslev (1986) observes that the ARCH process introduced by Engle (1982) distinguishes between unconditional and the conditional variance. This distinction permits the conditional variance to change over time as a function of past errors (Bollerslev, 1986). It is essential to note that when the ARCH model is used in empirical studies, a relatively long lag structure in the conditional variance equation becomes a necessity with the corollary of the imposition of a fixed lag structure so as to prevent variance estimates becoming negative (Bollerslev, 1986; Engle, 1982; 1983 and Engle and Kraft, 1983). Different GARCH models form the bedrock of commodity pricing in modern global financial and commodity markets. It has been observed in real world commodity and financial markets that commodity and financial asset behaviour usually exhibit long memory or persistence features which necessitate the extension of the ARCH class of models to take into account longer memory and a more flexible lag structure (Bollerslev, 1986). Bollerslev (1986) argues that given an error term modelled conditional on a given information set, it is plausible to envision a generalised conditional heteroscedasticity (GARCH, p, q) process. Such a GARCH process allows lagged conditional variances to augment the ARCH (q) modelling of the conditional variance as a linear function of past sample variances within the framework of an adaptive learning mechanism (Bollerslev, 1986).

The classical GARCH model by Bollerslev (1986) has been criticised by a number of researchers and improved upon especially on its stringent non-negativity conditions. Researchers such as Nelson and Cao (1992) as well as He and Terasvirta (1999) have demonstrated through their respective studies that a possibility exists econometrically to obtain more dynamic and representative autocorrelation structures of squared returns by relaxing the stringent non-negativity assumption. Karolyi (1995) also demonstrated using a multivariate GARCH model of the spillover of stock returns and volatility between the United States (U.S.) and Canada that cross-market dynamics in volatility to a certain extent explain the magnitude and persistence of return innovation that originates from either of the two markets under study.

Over the years, ARCH/GARCH modelling has evolved into many different types of models that all retain the fundamental assumption of modelling the conditional variance as a function of past sample variances or lagged conditional variances with variations being introduced to account for nuances that exist for different commodity and financial asset classes. A study by Chang *et al.* (2009) modelled long memory volatility in 16 agricultural futures returns ranging from corn (or maize) to palm oil using three fractional GARCH models. The three fractional GARCH models used in the study are Fractionally Integrated

GARCH (FIGARCH) by Baillie *et al.* (1996), Fractionally Integrated Exponential GARCH (FIEGARCH) by Bollerslev and Mikkelsen (1996) and the Fractionally Integrated Power ARCH (FIAPARCH) model by Tse (1998). The estimated fractional GARCH models were compared to the classical GARCH model by Bollerslev (1986), Exponential GARCH (EGARCH) by Nelson (1991), and the Asymmetric Power ARCH model by Ding *et al.* (1993). Fractional GARCH models introduce the 'd' parameter to model long term dependence. Chang *et al.* (2009) specified and estimated the FIGARCH (1, d, 1) and FIEGARCH (1, d, 1) which outperformed their GARCH (1, 1) and EGARCH (1, 1) counterparts for the specified 16 agricultural commodity futures returns.

According to Li *et al.* (2016) commodity price volatility modelling facilitates the forecasting of aspects of the entire distribution of price changes such as the absolute magnitude and the quantiles of that distribution. This signifies that when commodity price volatility is adequately and accurately modelled, uncertainty and risks that are associated with that uncertainty can be mitigated accordingly and timeously. Since it is a fact that has been repeatedly established by different researchers that agricultural commodity prices tend to exhibit time-varying variance or time-varying volatility, this signals that GARCH models are appropriate for modelling those prices for both developing and developed economies (Li *et al.,* 2016, Aradhyula and Holt, 1988). Han *et al.* (1990) cited in Li *et al.* (2016) demonstrated that the quarterly aggregate U.S. farm price index displayed time-varying volatility. Li *et al.* (2016) basing on previous empirical research used a mixture of two normal distributions to model volatility in equity markets. A number of researchers before Li *et al.* (2016) have employed the Normal Mixture (NM)-GARCH (1, 1) model. They include Haas *et al.* (2004) and Alexander and Lazar (2006) who have documented performance gains from the generalised two-component NM-GARCH (1, 1) model compared to both symmetric and skewed Student's t-GARCH models when used to model exchange rate volatility. The former model was found to be more efficient in modelling time-varying conditional skewness and kurtosis, thus enabling the estimated model to better account for heterogeneous market shocks (Li *et al.,* 2016). The estimated NM-GARCH (1, 1) model efficiently predicted that an expected negative price shock occasions a higher volatility persistence, while greater responsiveness of volatility was found to be linked to a positive price change (Li *et al.,* 2016). Chang (2012) used a flexible regime-switching EGARCH model with Student-t distributed error terms to examine whether regime volatilities and basis impact the observed behaviour of crude oil futures returns, taking into account moments such as mean, variance, skewness, kurtosis as well as the feature of heavy-tailedness. A study by Abdullahi *et al.* (2014) modelled the long memory feature in the volatility of West Texas Intermediate (WTI) and Brent Crude oil futures returns using GARCH, EGARCH, APARCH, FIGARCH, FIEGARCH, FIAPARCH and Hyperbolic GARCH (HYGARCH) models. The empirical results revealed strong evidence of long-term dependence of returns of different maturities for both WTI and Brent Crude oil markets. The asymmetric leverage effect was also found to be present in both oil markets.

Few researchers have experimented with artificial neural networks in the context of modelling oil price volatility (Matar *et al.,* 2013). Matar *et al.* (2013) have cited Ou and Wang (2011) who assert that a model which is a hybrid of neural networks with GARCH has improved effectiveness in estimating extreme values of oil price volatility compared to standard GARCH models and is less prone to misspecification. Table 5.1 provides a summary of the main GARCH models applied to volatility modelling of oil, equity, agricultural, and currency markets by different researchers in empirical financial economics.

Table 5. 1: Summary of ARCH/GARCH models applied to Volatility Modelling

MODEL	Model Features
Autoregressive Conditional Heteroscedasticity (ARCH)	The conditional volatility is a linear function of past volatility and innovation (Engle, 1982)
Asymmetric Power ARCH (APARCH)	This model can well express the Fat tails, Excess kurtosis and Leverage Effects that empirical evidence has documented to be common in financial time series (Ding, Granger and Engle, 1993).

(Standard) GARCH	It is Generalised ARCH which has two components: The conditional volatility is a linear function of past volatility and innovation. These models are more effective in modelling short-term volatility compared to long-term volatility (Bollerslev, 1986).
Fractionally Integrated GARCH (FIGARCH)	A non-linear model that captures long memory shocks effectively. Unlike IGARCH, it provides a slow decay of shocks over time (Baille *et al.,* 1996). This model has an infinite variance which is its major drawback and limits its applications. To cater for this, usually hyperbolic GARCH may be used.
Threshold GARCH (TGARCH)	TGARCH adds another residual term to the standard GARCH to account for asymmetrical behaviour in volatility; this term is only present if the residual is negative (Zakoian, 1994).
Glosten, Jagannathan, and Runkle (GJR) – GARCH	GJR-GARCH - add another residual term to the standard GARCH to account for asymmetrical behaviour in volatility; this term is only present if the residual is negative. Has better forecast performance due to the inclusion of the leverage effect (Glosten *et al.,* 1993)
Exponential GARCH (EGARCH)	A non-linear model that is effective in accounting for asymmetric behaviour in volatility by examining the ratio of the residual and the volatility at *t-1*. While

	linear GARCH models often restrict coefficients to be positive, this model removes this restriction (Nelson, 1991).
Quadratic GARCH	Generalizing from the model of Takaishi (2010) the QGARCH may be explained as follows: In the original standard GARCH model specified by Bollerslev (1986), the GARCH (1, 1) can modelled thus: Let x_t be an asset return observed at time t which can be transformed into: $y_t = x_t - \bar{x}$ ……………………...(i) In the GARCH model y_t can be decomposed as: $y_t = \delta_t \varepsilon_t$ where ε_t ~ N(0, 1)….(ii) Generalizing from the original formulation of the GARCH model, the GARCH (1, 1) will be having the following volatility response function: $\sigma_t^2 = \omega + \alpha y_{t-1}^2 + \beta \sigma_{t-1}^2$ ………..(iii) Equation 3 is held to be symmetric under positive or negative observations of y_t . In contrast, the QGARCH model like other extensions of the original GARCH accommodates leverage effects after negative or positive news or return information: $\sigma_t^2 = \omega + \gamma y_{t-1} + \alpha y_{t-1}^2 + \beta \sigma_{t-1}^2$

	Where γy_{t-1} introduces the asymmetry into the model.
Hyperbolic GARCH (HYGARCH)	This model is a mixture of standard GARCH, IGARCH and FIGARCH models. This model provides the same slow decay of shocks that is present in FIGARCH, while maintaining the favourable stationarity features of the standard GARCH model (Davidson, 2004).
GARCH-in-Mean (GARCH-M)	GARCH-M allows for the mean of the returns to be a function of the conditional volatility. This accounts for risk aversion as the computed returns increase during periods of high volatility (Engle, Lilien and Robins, 1987)
Multivariate GARCH	This class of GARCH models incorporates time-varying conditional covariance of returns. These models are useful when simultaneously computing the volatility of multiple assets (Bollerslev, Engle and Wooldridge, 1988). The BEKK version of MGARCH was proposed by Engle and Kroner (1995).
Component GARCH (CGARCH)	This model is a specific formulation of GARCH (2, 2). It improves the modelling of long-term effects by decomposing the model into long-run and short-run components (Ding and Granger, 1996).
Neural Network-GARCH (NN-GARCH)	A hybrid model that incorporates neural networks with GARCH estimates the

	extreme values of volatility more effectively than GARCH models alone (Donaldson and Kamstra, 1997). Neural Network GARCH has been extended to NN- APGARCH (Bildirici and Ersin, 2009; 2012).
Normal Mixture (NM) – GARCH	It uses a mixture of two normal distributions to model volatility in equity, commodity and currency markets (Lee and Lee, 2009).

Source: Adapted from Matar *et al.* (2013), Li *et al.* (2016), and various other sources

Table 5.1 shows that while standard GARCH model specifications tend to be efficient and effective in modelling short-term volatility, they are ineffective in capturing long-term dependence and persistence in asset prices or the volatility of their returns. The evolution of different GARCH models that seek to capture commodity price (or return) behaviour is justified by the fact that volatility as a feature of commodity and financial asset price behaviour has different properties. Such properties include persistence, leverage effect, mean reversion, and probable vacillations between high and low volatility regimes (Matar *et al.,* 2013; Hamilton, 1989; 1994). All models explained in Table 5.1 have one drawback in that they model volatility clustering, asymmetry, and non-linearity for a single regime. They, therefore, have lower forecasting power compared to their dual and multi-regime switching volatility counterparts covered in the subsequent section. The following section covers the Smooth Transition Autoregressive (STAR) model family and its neural network and GARCH extension which has evolved since 1994 in an attempt by financial econometricians to explain the aforementioned volatility features in an environment where commodity and financial asset prices experience regime shifts over time.

5.1.2 Smooth Transition and GARCH Models of Commodity Market Volatility

There has been steady research output within the past ten years of smooth transition models (STM) which have been proposed by different researchers in a bid to accurately model the volatility of commodities, currencies, inflation, financial assets, and other macroeconomic variables. Variants of the smooth transition model (STM) are actually extensions of the Smooth Transition Autoregressive (STAR) model. The STAR model and its extensions have been proposed by different researchers to capture better the non-linearity of financial asset and commodity prices. Some experts in the field of financial econometric modelling have observed that these types of models have improved forecasting powers or abilities (Dijk *et al.,* 2002). According to Bildirici and Ersin (2014), one major advantage of the STAR model is that it nests several non-linear models such as the SETAR and TAR models which are modelled by means of identity functions.

Researchers such as Lin and Terasvirta (1994), and Terasvirta (1994) have observed that incorporating a transition function that switches smoothly in value terms between one and zero enables the STAR model to replicate actual movements between the two data structures. Balagtas and Holt (2009) as cited in Sanders and Baker (2012) used the STAR modelling approach to examine the commodity terms of trade and the phenomenon of the decrease of relative prices of certain primary commodities.

In a study whose major goal was to estimate the impact of U.S. markets on the UK stock market, Aslanidis *et al.* (2003) employed the smooth transition autoregressive model to ascertain the role of different potential transition variables in generating non-linearity in the movement of U.K. stock prices. Redrado *et al.* (2009) employed a smooth transition vector autoregressive (STVAR) model to account for the financialisation of commodity markets which are characterised by heterogeneity in agent behaviour and non-linearity. The STVAR methodology was found to be beneficial in distinguishing those variables that impact long-run equilibrium or “fundamental” price dynamics from short-run deviations with respect to that long-run equilibrium. The study revealed that high discrepancies between spot and long-run equilibrium or “fundamental” prices tend to be corrected relatively fast in contrast to small misalignments that tend to be characterised by persistence over time due to the lack of an endogenous force correcting such misalignments (Redrado *et al.,* 2009).

Empirical modelling by Bildirici and Ersin (2009), which dates back to the late 1990s has contributed much to the extension of a class of NN-GARCH model originally proposed by Donaldson and Kamstra (1997). Empirical experimentation with Logistic-STAR-GARCH-NN family models helped Bildirici and Ersin (2009) in more accurately accounting for non-linear dynamics and the leptokurtic distribution of petrol prices. The fractionally integrated and the asymmetric power versions of the standard LSTAR-GARCH-NN models were found to possess more power in forecasting petrol prices (Bildirici and Ersin, 2009).

Table 5. 2: Summary of STAR Models and their Extensions

Model	Model Features
STAR	They are a class of smooth transition and regime-switching models that account for autoregressive features in different types of financial time series data (Terasvirta, 1994).
LSTAR	The logistic smooth transition autoregressive (LSTAR) model is a type of non-linear model with a more different multiperiod forecasting mechanism compared to their linear counterparts.
ESTAR-GARCH	This is Exponential STAR-GARCH
LSTAR-GARCH	The Logistic STAR – GARCH model
LSTAR-FIGARCH	The fractionally integrated version of the Logistic STAR - GARCH
LSTAR-FIPGARCH	The fractionally integrated version of the Logistic STAR – Power GARCH

LSTAR-FIAPGARCH	The fractionally integrated version of the Logistic STAR – Asymmetric Power GARCH (APGARCH) model of Ding et al (1993). The APGARCH model was applied by Tse and Tsui (1997) to the modelling of daily Malaysian - U.S. and Singapore - U.S. exchange rate data.

Source: Adapted from Bildirici and Ersin (2009), Bildirici and Ersin (2014), Bauwens *et al.* (2006) and Various Sources

Chan and McAleer (2002) have argued that little is known of the (stationary) Smooth Transition Autoregressive–GARCH (STAR-GARCH) model or the consistency, asymptotic normality, and finite sample features of the estimators of this model. Chan and Theoharakis (2009) have argued that the formulation and parameterisation of STAR - GARCH models are fraught with many numerical challenges whose causes are unknown. In their paper, Chan and Theoharakis (2009) demonstrated that the use of the Quasi-Maximum Likelihood Estimator (QMLE) to obtain stable parameter estimates has attendant difficulties associated with it. First, experimentation has revealed flatness of the log-likelihood functions of Exponential STAR – GARCH (ESTAR-GARCH) around the global optimum in the vicinity of the true values of the transition rates. The implication of this, is that the use of conventional gradient-based optimization algorithms to maximize the log-likelihood functions as a means of estimating transition rates is fraught with difficulties (Chan and Theoharakis, 2009). Secondly, in addition to being flat around the local optima, the surfaces of the log-likelihood functions of the Logistic STAR-GARCH (LSTAR-GARCH) have been found to be lumpy meaning that the choice of transition functions predispose the shapes of the log-likelihood functions. The corollary is that reparameterisation can transform the shapes of the log-likelihood functions.

5.1.3 Markov Switching Models of Volatility

Different processes in biology, ecology, economics, politics, and empirical finance evolve with discrete changes in outcomes. The phenomenon of business cycles (including price cycles of different types of commodities) is normally associated with episodes (or regimes) of recessions and expansions. From a depression/ trough the economy progresses through expansion, peak/ boom, and recession or contraction, then the cycle starts all over again. When economic variables fluctuate between a high state (linked to expansion) and a low state (linked to contraction or recession), moments associated with such variables such as means, variances and other parameters such as skewness and kurtosis will also be changing across states (also called episodes or regimes).

Given the foregoing, the estimation problem becomes two-pronged. First, the researcher is faced with the problem of estimating when regimes change. This aspect of the problem locates estimation in the locus of probability. Second, the financial econometrician has to estimate the values of the parameters associated with each episode or regime. The corollary of the foregoing is that questioning when episodes change is akin to interrogating the period of time that regimes persist.

In order to answer the when and what value questions associated with regime changes in modelling of business cycles, asset price and other variables' behaviour, researchers normally use Markov-transition models. The merit of Markov-transition models is that the probability of regime change is estimated as the means, variances and other moments of study variables are being estimated.

In order to conceptualise how the Markov-transition model accounts for regime changes that may describe the price behaviour of given commodity, researchers hypothesise a scenario in which the price of crude oil vacillates between the high and low states, implying that the simple Markov-switching model will be transitioning between only two states. The states do not necessarily need to be two. They can be more than two.

Table 5. 3: Estimated Transition Probabilities for Hypothetical Changes in Crude Oil Price

FROM/TO

State	**Low**	**High**
Low	0.79	0.11
High	0.67	0.33

Source: Researcher's Hypothetical Example

Let the change in the price of crude oil hypothetically start at the low state. The probability of transitioning from the low state to the yet low state is 0.79. In other terms, once the price of crude oil is at a low state, it tends to remain there. Nevertheless, the probability of the oil price process transitioning from the low state to the high state is 0.11. It is noteworthy that the high state does not have the same persistence as the low state. The process of crude oil price change has a probability of 0.67 of reverting from the high state to the low state in the next phase or period.

Table 5.3 describes a price change process that is hypothetically abrupt or sudden and as such the probability instantly changes. Markov models of this type are dynamic models. It can also be useful to conceptualise changes in the price of crude oil as being somewhat smooth instead of being abrupt. In this regard, Markov models can model the transition probabilities associated with smoother crude oil price changes as an autoregressive process.

Different researchers have over the years grappled with the issue of substantial persistence in high-frequency financial time series data (So *et al.,*1998; Lamourex and Lastrapes, 1990 and Chou, 1988). These different authors have tackled issues such as structural changes in the volatility process, the impact of occasional discrete shifts on algorithms meant to determine parameter levels as well as volatility persistence in the context of economic changes and sudden or abrupt market events. Fong and See (2002) used a Markov switching model to account for the conditional volatility of crude oil futures prices. The flexible generalised regime-switching model set-up that they employed allowed sudden or abrupt changes in mean and leptokurtosis (Fong and See, 2002). The main finding of the study was that within a high volatility regime, regime persistence was likely to be increased by a negative basis than a positive basis which corroborates empirical studies based on the theory of storage such as Fama and French (1988) and Ng and Pirrong (1994).

Marcucci (2005) compared the descriptive and forecasting properties of different GARCH models in modelling of financial time series data from a one-day to a one-month horizon. Markov Regime-Switching GARCH (MRS-GARCH) models outperformed all standard GARCH models at shorter horizons while asymmetric GARCH models performed better at longer horizons. Choi and Hammoudeh (2010) augmented antecedent regime-switching studies on West Texas Intermediate (WTI) crude oil. Their empirical analysis revealed the possibility of two volatility regimes for commodities such as gold, silver, copper, crude oil (both WTI and Brent) and S&P 500 index characterised by varying high-to-low volatility ratios (Choi and Hammoudeh, 2010). Their main findings were that the dynamic conditional correlations (DCCs) among all the commodities under study were increasing since the 2003 Iraq War but were declining with the S&P 500. Financial and geopolitical crises were found to be significant in determining volatility persistence and changes in the S&P 500. In a study of the volatility dynamics of short-term interest rates, Smith (2012) undertook empirical analysis predicated on a comparison of Markov-Switching and Stochastic Volatility Diffusion Models. Study results showed that single-regime models display interest rate volatility as an explosive process in contrast with Markov-switching model estimates which reasonably fitted the data and had better forecasting ability (Smith, 2012). A study of the German Stock Market Index the DAX undertaken by Reher and Wilfling (2011) was anchored on a flexible general Markov-switching GARCH model with the ability of specifying complex GARCH equations in two distinct Markov regimes and modelling of say an exponential GARCH model in the first state and a standard GARCH specification in the second Markov-regime. The model proposed by Reher and Wilfling (2011) was found to exhibit better performance compared to conventional Markov-switching GARCH models.

Different researchers have employed different forms of the regime-switching volatility model. For instance, Lee and Yoder (2005) used the Markov regime switching BEKK-GARCH model which resolved the path-dependency problem (that usually afflicts the bivariate RS-BEKK-GARCH) by recombining the covariance term in the conditional variance-covariance matrix. The RS-BEKK-GARCH was found to be more effective in carrying out-of-sample hedging for both maize and nickel data (Lee and Yoder, 2005). Gupta *et al.* (2018) used the Markov-switching model so as to empirically discern the contemporaneous and dynamic relationships between crude oil and selected energy products from oil, namely, gasoline (petrol), diesel and Automatic Transmission Fluid (ATF). Evidence was found for a contemporaneous relationship among the energy commodities when the energy market is in both the bull and bear states. In contrast to the foregoing, Abul and Perry (2015) sought to depart from the mainstream by modelling volatility dynamics and risk measures using the underutilized Generalised Orthogonal GARCH (GO-GARCH) to account for volatilities and conditional correlations between stock prices, oil prices, VIX, gold prices and bond prices of emerging markets. The dynamic conditional correlations and optimal hedge ratio out-of-sample forecasts were constructed using the empirically documented rolling window analytical approach (Abul and Perry, 2015). The empirical results were found to be resilient and robust to the choice of model refits, forecast length and a wide range of distributional assumptions. The merit of GO-GARCH volatility modelling is that first, it is a natural generalization of the orthogonal-GARCH model which in terms of empirical estimation is nested in the more general BEKK model which has been tackled in the preceding discussion. Second, "the potentially large covariance matrices can be parameterized with a fairly large degree of freedom while estimation of the parameters remains feasible (van der Weide, 2002, p. 549)."

5.1.4 Wavelet Analysis of Volatility, Spillovers and Interdependence

It is imperative to define wavelet analysis before wavelet analysis is applied to the modelling of volatility, contagion and interdependence among commodities and markets. The term wavelet analysis is a composite of two words, namely, wavelet and analysis. Wavelet analysis is the study of wavelets wherever they occur in a bid to understand dynamics of correlation and transmission of signals either in nature, artificial environments like laboratories or in economic systems. Wavelet analysis is a natural progression from Fourier analysis. According to Morin (2009, p. 1), "Fourier analysis is the study of how general functions can be decomposed into trigonometric or exponential functions with definite frequencies."

Wavelet analysis compensates for the weaknesses of Fourier analysis. Rua (2012) has ably argued that one major drawback of Fourier analysis is the time-invariant nature of the frequency content of the signal decomposed from the Fourier transform. This obviously incapacitates Fourier analysis from reproducing diverse commodity price signals because more often than not, they exhibit time-varying features. Put differently, Fourier analysis can tell the researcher how much of each frequency exists in the commodity price signal but it fails to tell him or her when in time these frequency components exist (Rua, 2012, Rua and Nunes, 2012). This leaves the researcher with an incomplete picture of commodity price behaviour and hence, whatever results are derived from any analysis predicated on the Fourier transform, lack completeness to facilitate accurate and timeous portfolio construction, hedging, and pricing strategies by commodity and financial market players. It is because of the foregoing that many researchers primarily focused on commodity and financial asset price behaviour have found wavelet analysis to be useful in decoding commodity and financial asset price behaviour. Wavelet analysis has also been used in empirical studies to deduce the dynamic nature of the correlation between economic variables as was the case with a study by Dahir *et al.* (2018) who used wavelet analysis to deduce the link between exchange rates and stock prices in BRICS economies in both the time and frequency domains.

Ismail *et al.* (2016) studied the daily stock return behaviour of four African countries' stock market indices for a period spanning 02 January 2000 and 31 December 2014 using standard GARCH (1, 1) model, vis-à-vis, the Maximal Overlap Discreet Wavelet Transform (MODWT) – GARCH (1, 1) model. Empirical results proved that both model specifications fit the data well, though MODWT-GARCH (1, 1) model generated more accurate forecasts of observed returns compared to the standard GARCH (1, 1) which underestimated the observed returns (Ismail *et al.,* 2016).

5.2 Commodity Markets, Stock Market Performance, and Economic Growth Issues

Section 5.2 reviews studies on the nexus between commodity price volatility and stock return volatility to map the conceptual framework that governed the study.

5.2.1 The Nexus Between Commodity Prices and Stock Returns

There has been a lot of research output in recent years interrogating the relationships that exist between commodity prices of various types and stock return volatilities. Part of the research effort has focused on the subject of volatility transmission between markets and between countries (Gargano and Timmermann, 2012; Silveinnoinen and Thorp, 2009). Silveinnoinen and Thorp (2012) examined bivariate conditional volatility and correlations dynamics for individual commodity futures and financial assets for 20 years spanning May 1990 and July 2009 using Dynamic Smooth Transition Conditional Correlation – GARCH (DSTCC-GARCH). Their study showed that there was evidence of increasing integration between different types of commodities and financial markets (Silveinnoinen and Thorp, 2009). In contrast to Silveinnoinen and Thorp (2009), Lombardi and Ravazzolo (2013) used time-varying Bayesian Dynamic Conditional Correlation (Bayesian DCC), specifically Bayesian VAR-DCC to model volatilities and correlations between equity and commodity prices. The main finding of the Bayesian DCC study was that correlating commodity and equity prices yielded more accurate point and density forecasts which particularly improves portfolio allocation (Lombardi and Ravazzolo, 2013). The empirical literature has established that commodity and equity prices have become increasingly correlated in the past ten years (Gorton and Rouwenhorst, 2006; Kilian and Park, 2009; Cassassus and Higuera, 2011). In fact, Buyusahin and Robe (2012) apparently argue for a link between greater speculative activities and increased correlations between commodity and equity prices. It remains to be fully explored how different commodity classes are correlated within individual economies and across international boundaries, not only in the time domain but in both the time and frequency domains. An exploration of correlation structures between commodity and equity markets on the one hand, and different commodity classes in both time and frequency domains can only be fully undertaken using spectral analysis and Markov-switching volatility modelling.

According to Onwumere *et al.* (2018, p.199), volatility transmission can be defined as "the means, medium or channel through which financial shocks move across borders." It is a fact that has been established by the extant literature on volatility transmission, spillovers and contagion that due to the forces of globalisation and the greater generation and dissemination of information, modern economies have become more integrated and interdependent. This underlines the importance of accurately discerning the impact of commodity and stock market linkages on the macroeconomy at both the local economy and international economy levels (Bonga-Bonga, 2015). Structural Vector Autoregressive Dynamic Conditional Correlation – GARCH (SVAR-DCC-GARCH) was used by Bonga-Bonga (2015) and Boubaker and Raza (2017) to detect interdependence and contagion among the BRICS' stock markets.

5.2.2 The nexus between stock market development and economic growth

Different researchers have sought to establish the link that exists between stock market development proxies and economic growth proxies. In seeking to discern the exact relationship between the two sets of variables, it becomes apparent that one model cannot fit the diverse measures and proxies of stock market development and economic growth.

Hoque and Yakob (2016) used Granger causality tests, the Autoregressive Distributed Lag (ARDL) model, and multivariate regression to analyse the role of foreign capital inflows and exchange rates on the nexus between stock market development and economic growth. The main findings of their study were that stock market development promotes economic growth while capital inflows inhibit economic growth since they worsen Malaysia's indebtedness to other economies (external debt increases) (Hoque and Yakob, 2016). A similar study by Hoque *et al.* (2018) using the ARDL and hierarchical regression methodology analysed the nature and extent of endogeneity among Foreign Direct Investment (FDI), economic growth and stock market development. The key results of the study are that there is a short-run and long-run bidirectional relationship among FDI, stock market development and economic growth in Bangladesh. Hoque *et al.* (2018) also found that while FDI partially mediated the stock market development – economic growth nexus, political instability in Bangladesh hindered both stock market development and economic growth.

5.3 Empirical Approach for the Study

Section 5.3 explains the empirical approach adopted to model the main variables of the study. The following subsections cover issues such as the research design, the theoretical framework underpinning empirical analysis, data sources, descriptive data analysis procedures, and the main models specified for the study. The section concludes with an explanation of the criteria that the researcher used to select the optimum lag length for cointegration analysis and Granger causality tests.

5.3.1 Research Design

The study adopted a quantitative research design that is predicated on a hypothetico-deductive research philosophy. According to several philosophers, the hypothetico-deductive approach also synonymous with the scientific method has seven major steps that are involved in validating or invalidating a theory (McPherson, 2001; Edwards, 1972; and Platt, 1964). It must be pointed out that McPherson (2001) is at loggerheads with the Popperian perspective on hypothesis formulation and testing because it is rooted in the falsifiability of a hypothesis. The seven steps of the scientific method which were followed in the study are – first, the identification of a broad research area which in this case is the finance-growth nexus, second, the definition of the problem statement which in the context of the study is analysing the links among commodity price volatility, stock market development and economic growth. The third step is developing hypotheses upon which the entire study is anchored. The study is anchored on two hypotheses which are stated and explained in Chapter 1. The remaining four steps of the scientific method are – determination of the measures, data collection which takes into account data sources, data analysis and interpretation of the results of the study. Chapter 5 explains how measures were determined, data collection methods and sources as well as data analysis procedures. The study operationalised the quantitative research design by following the experimental approach. After the specification of models of correlation and volatility, the study proceeded to the conduct of statistical and econometric experiments. The results obtained from these experiments were subjected to robustness and diagnostic checks to facilitate the reporting of estimated parameters with robust standard errors.

5.3.2 The Theoretical Framework Underpinning Empirical Analysis

The researcher predicated the data analytical methods used in the study on the broad framework of the Fractal Markets Hypothesis (FMH) due to the short-comings of the Efficiency Markets Hypothesis (EMH). An earlier discussion on the credibility of the Efficient Markets Hypothesis (EMH) as an explanation of the efficiency of commodity and stock markets observed that the theory fails because of its fundamental assumption that all participants have rational expectations (Fama, 1970). Recent empirical studies have demonstrated that the behaviour of commodity and stock prices does not conform to the random walk statistical model (Rehman et al., 2018; Anderson and Noss, 2013). Blackledge (2010) argues that the operational view that economic and financial processes are independent and identically distributed (i.i.d.), and hence conform to the bell-shaped normal distribution is flawed. Given the 'non-normal' behaviour of asset prices in general, Barna *et al.* (2016) have argued that the fractal markets hypothesis has greater potential to yield insights pertaining to financial markets characterised by imperfections such as "fat-tail" effects, stochastic volatility, and self-similarity. In this regard, an empirical study by Barna *et al.* (2016) found evidence that nine emergent markets exhibited fractal features with Latin American markets displaying statistically significant signs of local persistence.

Aktan, Sahin and Kucukkaplan (2017), Yin et al. (2017), and Panas and Ninni (2010) have expressed doubts about the efficacy of the Efficient Markets Hypothesis (EMH) in accurately accounting for the efficiency of emerging economy financial markets as well as the likelihood, determinants, and effects of financial crises. Cong (2017) analysed the volatility persistence performance of stock returns of Brazil, Russia, India, and China (BRIC) stock markets around the 2008 financial market crash. Empirical results showed that volatility persistence became stronger with the onset of the global financial crisis (GFC) of 2007-2008 and dissipated during the recovery phase (Cong, 2017). An analysis of cross-market linkages and contagion between commodity and mainstream financial markets during crisis periods has buttressed the notion that oil and stock markets at times behave as a "market of one" due to commodity market financialisation (Bampinas and Panagiotidis, 2017). Both oil and stock returns were found to be characterised by 'fat tails' which implied leverage effects associated with the impact of news on stock and oil markets (Bampinas and Panagiotidis, 2017).

The methodology used by most researchers to discern fractal features, persistence, non-linearities, and other stylised features of stocks, exchange rates, and commodity returns includes frequency domain causal tests, EGARCH, Fractionally Integrated GARCH (FIGARCH) as well as Markov Regime Switching (MRS) GARCH (Kishor and Singh, 2017; Karanasos et al., 2016; Ronderos, 2016; Syriopoulos et al., 2015; Mensi et al., 2014). The present study adopted frequency domain causality to discern non-linearities between stock indices and national output proxies, and GARCH modelling to analyse the volatility dynamics of BRICS stock returns. This contrasts with previous studies that adopted exclusively GARCH (Tripathy, 2017) or frequency domain analysis (Ronderos, 2016) to account for non-linearities, volatility persistence, and fractality of commodity returns, stock returns, and exchange rates.

5.3.3 Data Sources and Variables

The study was entirely based on secondary data that was obtained from diverse sources. The study focused on the following broad variables in an attempt to settle the main research question and address the two major hypotheses:

a) Commodity prices – agricultural, metal, energy and other commodity prices,
b) Stock market indices,
c) Industrial output: the index of manufacturing to proxy for low frequency economic growth figures.

The secondary data used for modelling and statistically discerning relationships between the main variables of study was obtained from various sources. The daily and monthly stock market indices were obtained from the investing.com website. The futures prices of West Texas Intermediate (WTI) crude oil, corn (or maize) and gold were also obtained from the investing.com website. Industrial production and manufacturing Purchasing Managers Indices (PMI) for Brazil, Russia, India and South Africa were obtained from the Federal Reserve Bank of St. Louis and the investing.com websites. China’s Retail Sales growth figures were obtained from the investing.com and China Internet Watch websites.

West Texas Intermediate (WTI) crude oil monthly price index data (denoted by crudeoil) was obtained from the websites of NYMEX-CME Group, US Energy Information Administration and indexmundi website. Price index data for the four commodity classes used in spectral causal analysis was obtained from Econstats, Federal Reserve Bank of St. Louis and indexmundi websites (the specific links are captured under Appendix H. The four commodity class indices are the Commodity Beverage price index (denoted by cbev in Chapter 6), Commodity Agricultural Raw Materials price index (denoted by cagric), Commodity Industrial Inputs price index (denoted by cindus) and Commodity Metals price index (denoted by cmetal). Some of the detailed weblinks to the data used in the study are listed under Appendix H.

Tables 5.4 shows the monthly variables that were analysed for the study.

Table 5. 4: Monthly Data Variables of the Study

Country	**Output Proxy**	**Stock Index**
Brazil	BRZY	BOV
Russia	RUSSIAPTI	RTSI
India	INDIAPTI	BSE
China	CHRETAIL	SSEC
South Africa	SAMANUF	JSEFT
Indices of Five Commodity Classes		
Commodity Class	**Index**	**Code**
Beverages	Commodity Beverage price index	cbev
Agricultural Raw Materials	Commodity Agricultural Raw Materials price index	cagric
Metals	Commodity Metals price index	cmetal
Industrial Inputs	Commodity Industrial Inputs price index	cindus
Crude Oil	West Texas Intermediate (WTI) future prices	crudeoil

KEY:
BRZY – Production in Total Manufacturing for Brazil,
RUSSIAPTI – Production of Total Industry in Russian Federation,
INDIAPTIA – Production of Total Industry index in India,
CHRETAIL – China’s Retail Sales growth rate,

SAMANUF – Total Manufacturing Production for South Africa,
BOV – Bovespa monthly index,
RTSI – Russia Trading System Index monthly,
BSE – S & P BSE Sensex,
JSEFT- Johannesburg Stock Exchange – Financial Times Index

Source: Researcher Compilation

Table 5.5 shows the list of countries or markets and their respective log-returns. Volatility modelling just like other types of econometric modelling, normally requires stationary data. Log-returns of stock and commodity price indices have the characteristics of stationarity and mean reversion which are essential for building stable statistical and econometric models (Mills, 1999).

Table 5. 5: BRICS log-returns

Stock Indices			Commodity Futures Prices	
Country	**Log-Return**		**Market**	**Log-Return**
Brazil	Logbov		US Corn Future	logcorn
Russia	Logrtsi		Comex Gold Futures	loggold
India	Logbse		West Texas Intermediate (WTI - NYMEX) crude oil	logcrude
China	logshang or logshng			
South Africa	Logjse			
United States	logdow			

Source: Researcher Compilation

5.3.4 Justification for the Chosen Variables

The following segments of the study explain why the study made use of the variables chosen in the light of empirical literature. The subsections provide empirical justification for the variable classes that have been chosen for statistical analysis and econometric modelling.

5.3.4.1 Commodity Prices – agricultural, metal, energy, food and others

Since the current study is primarily focused on how commodity price volatility links with stock market performance, it is imperative that prices and price indices of different commodity classes form the bedrock of the study. The study specifically focuses on and includes indices for the agricultural, metal, energy, food, and other sectors that are the common denominator of all modern and integrated economies. A study by Arfaou and Rejeb (2017) showed that oil and stock prices have a negative relationship which is in contrast with the positive impact of gold prices and the United States dollar (USD) on stock prices. The same researchers also found that oil futures prices and Chinese oil gross imports impacted the spot price of oil (Arfaou and Rejeb, 2017). Arfaou and Rejeb (2017, p. 278) thus concluded that "indirect effects always exist which confirm the presence of global interdependencies and involve the financialisation process of commodity markets." Researchers such as Handika and Ashraf (2018) demonstrated that the lower realised volatility of financialised commodity returns was caused by higher realised volatility of NASDAQ return series. This was in contrast with the finding that "higher realised volatility of SP500 return causes higher realised volatility of financialised commodity return" (Handika and Ashraf, 2018, p.153). The common denominator of virtually all previous research just reviewed is that commodity market price volatilities and commodity indices (used as a barometer for discerning commodity market financialisation) are specified as endogenous variables together with stock indices as well as other macroeconomic factors.

The present study departed from earlier studies by specifying different commodity index classes as exogenous variables in testing for spectral causality between national output proxies and stock market indices. The rationale of exogenising commodity market indices is the belief that it would assist in deducing the impact of commodity market volatilities and commodity market financialisation on the stock market – economic growth nexus. The fundamental assumption underpinning the analytical approach of the present study is that exogenising commodity market financialisation (proxied by different commodity index classes) facilitates an accurate account for non-linearities between national output proxies and stock indices of BRICS countries. It must be observed that there is a paucity of literature that empirically analyses how the phenomenon of commodity market financialisation from an aggregate commodity class perspective impacts the stock market performance – economic growth relationship.

5.3.4.2 Stock Exchange Indices and Stock Returns

The primary focus of the study was to discern the links between commodity prices and stock returns and/or stock indices. The null hypothesis is that commodity price – stock return/stock index interaction is linear. The alternative hypothesis is that commodity price-stock return/stock index interactions or correlations are non-linear as has been proven by many studies before the current one. It is postulated that if the commodity price-stock return interaction is non-linear, then it must by necessity lead to non-linear interactions or non-linear correlation dynamics between stock market performance indicators and the proxies of economic growth. Given the foregoing, it is thus pertinent to include stock returns and stock exchange indices in experimentation involved in the current study (Kang *et al.,* 2017; Iscan, 2015; Wang *et al.,* 2012; Tang, *et al.,* 2010 and Chuku *et al.,* 2010). In an empirical analysis of the dynamic interaction and time-varying dynamics between global commodity prices, global stock volatility, domestic output and consumer prices, Kang *et al.* (2017) discovered, firstly, that a gradual and endogenous adjustment process characterises the interaction between stock volatility and commodity price shocks and the impact of these two variables on the macroeconomy. Second, they discovered that the effects of global stock volatility were magnified by, and hence, greater during the global financial crisis of 2007- 2009 compared to other economic episodes. Third, the researchers demonstrated experimentally and empirically that endogenous commodity price responses amplified the effects of global stock volatility on the domestic output of the U.S.A. (Kang *et al.,* 2017).

5.3.4.3 Industrial Output Indices

Industrial output indices (IOI) were used in the study to proxy for levels of economic activity. Indices of manufacturing, as they are known in some economies, have two major advantages compared to Gross Domestic Product (GDP) or any aggregate measure of the level of economic activity. These advantages are that IOI usually have relatively higher frequency compared to their GDP or economic aggregate counterparts as they are computed and calculated monthly. Secondly, indices of industrial or manufacturing activity for different economies tend to have a strong positive correlation with the national income aggregates such as GDP or Gross National Product (GNP). Some researchers examined the nexus between stock market performance and industrial production in different countries. Singh *et al.* (2016) analysed the importance of the industrial production index in the context of economic growth. They observed that the industrial sector plays a very critical role in the growth of the Indian economy (Singh *et al.,* 2016). In the same vein, Forson and Janrattanagul (2014) relied on the Toda and Yamamoto's augmented Granger causality test to evaluate the importance of the industrial output index in explaining stock market movements. The researchers discerned unidirectional causality from Industrial Production (IP) to the Thai Stock Exchange index (SETI). Nwaolisa and Chijindu (2016) assessed causality between the industrial production index and Nigeria's stock market liquidity. Their study revealed that the index of industrial production Granger causes stock market liquidity in Nigeria (Nwaolisa and Chijindu, 2016). The present study was thus inspired by empirical work reviewed in the foregoing discussion to use industrial output indices as proxies for overall economic activity in modelling non-linearities between stock indices and national output proxies in BRICS.

5.3.5 Lag Length Selection

An empirical analysis of commodity price volatility, stock market development and economic growth makes it a necessity to choose the most suitable lag length to estimate the best model. Four basic criteria have been proposed in statistics and econometrics and these are the Akaike Information Criterion (AIC), Schwarz's Bayesian Information Criterion (SBIC), Shibata Information Criterion (SIC), and the Hannan-Quinn Information Criterion (HQIC). Lag selection criteria was useful for cointegration analysis and Granger causality tests.

The SBIC imposes stricter penalties to avoid overfitting and is more preferred for empirical studies with large samples (Koehler and Murphree, 1988). The HQIC imposes a penalty for adding more regressors to the model in an attempt to minimise the value of the residual sum of squares (Hannan and Quinn, 1979). Practical experimentation with empirical data has, nevertheless, revealed that the HQIC, and the SBIC are not as asymptotically efficient compared to the AIC (Burnham and Anderson, 2002).

Different empirical studies demonstrate that in practice the AIC, HQIC and SBIC are all preferred since they collectively provide a trade-off between goodness of fit and the complexity of the model (Gujarati, 2004). Gujarati (2004) opines that there is an apparent trade-off between goodness of fit and model complexity. The four information criteria have the ensuing formulas or formulae. AIC is given by the following formula:

$$\ln AIC = \left(\frac{2k}{n}\right) + \ln\left(\frac{RSS}{n}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{\textit{1}}$$

where: 2k/n is the penalty factor

The SBIC is given by the following formula:

$$\ln SIC = \frac{k}{n} \ln n + \ln\left(\frac{RSS}{n}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{\textit{2}}$$

where: k/n ln n is the penalty factor.

SBIC poses a stricter penalty than the AIC and both models are good for in-sample and out-of-sample forecasting.

The HQIC is given by the following formula:

$$HQ(p) = \ln \left|\sum(p)\right| + \frac{2\ln(\ln(T))}{T} pM^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{\textit{3}}$$

The lowest lag length given by each of these criteria will be used in this study, per country. Several scholars have used this approach including Vinayagathasan (2013) and Buckle *et al.* (2016). If the three criteria yield different optimal lag lengths, the researcher could take the one with the lowest lag length even though most contemporary researchers prefer SBIC.

The point of departure of the Shibata information criterion (SIC) is the Akaike Information Criterion (AIC) whose essence is captured by equation 1 (Shibata, 1976). Shibata (1976, p. 125) has pointed out that 'it is difficult when samples are small to evaluate analytically the properties of the Akaike Information Criterion (AIC).' Shibata (1976, p. 125), nevertheless, concedes that the AIC 'balances the risk associated with the bias when a lower order is chosen as well as the risk incurred due to the increase of variance when a higher order is chosen' by the researcher. The researcher employed unrestricted Vector Autoregressive (VAR) models for different variable groups to facilitate optimal lag length selection for Johansen cointegration analysis and Granger causality tests. The detailed results of VAR modelling for optimal lag selection are captured in three Tables under Appendix I.

5.4 Preliminary Data Analysis Issues

The ensuing subsections of the study explain how data analysis was conducted in terms of descriptive statistics, correlation analysis, and diagnostic tests. The section concludes with an explanation of dating procedure of the data series used, and the justification for the choice of dates.

5.4.1 Descriptive Statistics Analysis

The data collected from secondary sources were initially analysed using descriptive statistical means. The first stage of descriptive statistical analysis involved trend analysis. This involved plotting original data series and log-returns series in graphical presentations. The study also involved computing and presenting the main descriptive statistics measures such as mean, median, maximum, minimum, standard deviation, skewness, kurtosis and Jarque-Bera statistics. The rationale of calculating and presenting these descriptive statistics measures was to discern the extent of central tendency and dispersion of different data series. This helps the researcher to discern similarities and differences among different types of variables being studied. The main descriptive statistics are presented and analysed in Chapter Six. It should be observed that detailed inference and hypothesis testing are usually not possible from descriptive statistical analysis alone. Descriptive statistics may, therefore, be perceived as providing a foundation upon which to base further econometric analysis.

5.4.2 Correlation, Autocorrelation and Partial Autocorrelation Analysis

The purpose of correlation analysis is rooted in a desire on the part of the researcher to discern the strength and direction of a linear relationship between any two economic variables that are being studied. The study involving calculating Pearson correlation coefficients using EViews and Microsoft Excel software packages. The results from such computations were obtained together with corresponding probability values. The relevant probability values facilitated tests of the statistical significance of calculated correlation coefficients. The null hypothesis in correlation analysis normally maintains that there is no linear association between any two financial economics variables, while the alternative hypothesis simply negates the null hypothesis. The decision-making rule is to retain or fail to reject the null hypothesis if a calculated correlation coefficient has a probability value greater than 0.05. Otherwise, the researcher fails to accept the null hypothesis, that is, if the calculated correlation coefficient has a probability value which is less than 0.05 the researcher rejects the null hypothesis and concludes that the linear association between the two variables being analysed is statistically significant. Results of correlation analysis for the study are shown in tables in Chapter Six. Statistically insignificant results are highlighted to facilitate easy isolation from the statistically significant results.

The study also involved the computation and compilation of the correlelogram and partial correlelogram graphs for the log-returns of BRICS stock indices using the Stata version 14 software package. The autocorrelation and partial autocorrelation analysis results are presented in Appendix A which comprises ten graphs. The first pair of graphs, namely, A1 and A2 represent the Bovespa's correlelogram and partial correlelogram graphs respectively. The second pair of graphs, namely, A3 and A4 represent Russia's RTSI correlelogram and partial correlelogram graphs respectively. The third set of graphs, namely, A5 and A6 represent India's BSE Sensex's correlelogram and partial correlelogram graphs respectively. The fourth set of graphs, namely, A7 and A8 represent Shanghai Composite Index's correlelogram and partial correlelogram graphs respectively. The fifth set of graphs, namely, A9 and A10 represent South Africa's JSE Index's correlelogram and partial correlelogram graphs respectively. Autocorrelation and partial autocorrelation graphs that constitute Appendix A helped the researcher in the specification of different GARCH models employed in the study to map and describe the volatility dynamics of the BRICS stock returns. The graphs provided an intuitive basis for deciding the number of autoregressive and moving average terms to provision for parsimonious GARCH models that are presented and discussed in Chapter 7.

5.4.3 Diagnostic Tests

The study involved unit root, Johansen's cointegration, and Granger causality tests. The purpose of unit root tests is to statistically deduce whether a time series variable is non-stationary. If a variable is non-stationary, then it is said to possess a unit root. The maintained (null) hypothesis is normally defined as a statement that the series has a unit root, while the alternative hypothesis normally argues for either strict stationarity or trend stationarity depending on the particular type of test that the researcher adopts. The study used the Augmented Dickey – Fuller (ADF) which is based on the works of Dickey and Fuller (1979). The original Dickey-Fuller (DF) test was augmented by Said and Fuller (1984) to cater for data series that generally conform to an ARMA structure of unknown dimensions in terms of the autoregressive and moving average terms. If we consider an autoregressive scheme of order 1 expressed as follows:

$$z_t = \varphi z_{t-1} + \varepsilon_t \quad \text{.......................................} \mathbf{4}$$

The hypothesis to test is cast as follows:

H_0: $\varphi = 1$

H_1: $\varphi < 1$

The Dickey – Fuller test is a t-test for H_0. Alternatively, the test cast be expressed as:

$$\Delta z_t = (\varphi - 1) z_{t-1} + \varepsilon_t$$

$$= \pi z_{t-1} + \varepsilon_t \quad \text{..} \mathbf{5}$$

Where $\pi = \varphi - 1$

$= \varphi(1)$

The hypothesis would then be cast as follows:

H_0: $\pi = 0$

H_1: $\pi = 1$

The Dickey – Fuller test statistic for the null hypothesis is a t – test whose value is:

$$\hat{\tau} = \frac{\hat{\varphi} - 1}{se(\hat{\varphi})}$$

$$= \frac{\hat{\pi}}{se(\pi)}$$

It should be noted that the asymptotic distribution of $\hat{\tau}$ is not normal. The deterministic components input in the test equation generally determine the resultant distribution. The augmented version of the Dickey – Fuller test commonly known as the Augmented Dickey – Fuller (ADF) test (Said and Dickey, 1984) generally follows an autoregressive moving average (ARMA) structure. Given data with an ARMA structure, the test regression equation to be estimated to facilitate hypothesis testing is as follows:

$$z_t = \beta ' D_t + \varphi z_{t-1} + \sum_{m=1}^{p} \varphi_m z_{t-m} + \varepsilon_t \quad \text{.......6}$$

Where D_t is a vector of deterministic terms that include the constant and the trend terms. The ARMA structure of the errors is approximated by the *p* lagged difference terms - Δz_{t-m}. The error term is assumed to be serially uncorrelated and homoscedastic. The ADF test statistic is expressed as follows:

$$ADF_t = t_{\varphi=1}$$

$$= = \frac{\varphi - 1}{se(\varphi)}$$

The test statistic for the general case is:

$$ADF_n = \frac{T(\varphi - 1)}{1 - \psi_1 - \psi_2 - ... - \psi_{p-1} - \psi_p}$$

The study also made use of the Phillips – Perron (PP) unit root test which is based on the work of Phillips and Perron (1988). The Phillips – Perron (PP) test may be viewed as the non-parametric alternative of the ADF unit root test. The PP – test equation may be generally stated as:

$$z_t = \alpha + \rho z_{t-1} + \varepsilon_t \quad \text{..7}$$

The term ρ in equation 7 is meant to correct for serial correlation and heteroscedasticity in the error term. The ρ is also held to be non-parametric which makes it robust to the presence of serial correlation and heteroscedasticity. The ADF test has, however, been criticised for lack of power to detect the scenario when the actual (or estimated) ρ is close to the null value, that is, when $\rho < 1$, but very close to 1. Generally, many tests suffer from this deficiency as the actual parameter value becomes asymptotically close to the null value. The ADF and PP test results are presented and discussed in Chapter 6.

The study also used the Johansen cointegration procedure to test for the presence of long-run association among economic variables. According to Hjalmarsson and Österholm (2007) the starting point for Johansen methodology is a vector autoregressive of order p which is given as:

$$y_t = \mu + A_t y_{t-1} + \ldots + A_p Y_{t-p} + \varepsilon_t \quad \text{.............................}\mathbf{8}$$

Where y_t is an *n x 1* vector of economic variables integrated of order 1, that is, I (1) and ε_t is an *n x 1* vector of innovations. The Johansen cointegration test used in the study was done by means of the Trace Test and the Maximum Eigenvalue test. According to Hjalmarsson and Österholm (2007) the equations of the two tests are as follows:

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i) \quad \text{..........................}\mathbf{9}$$

$$J_{\max} = -T \ln(1-\hat{\lambda}_{r+1}) \quad \text{................................}\mathbf{10}$$

Where T is the sample size, $\hat{\lambda}_i$ is the *i-th* largest canonical correlation. According to Hjalmarsson and Österholm (2007) the hypothesis for the Trace Test is mounted as follows:

H_0: cointegrating vectors are r

H_1: cointegrating vectors are n

The hypothesis for the maximum eigenvalue test is cast as follows:

H_0: cointegrating vectors are r

H_1: cointegrating vectors are r+1

The results of Johansen cointegration tests of daily and monthly variables are presented in Chapter 6.

The study also involved the conducting of Granger causality tests. Given two variables x_t and y_t, x_t Granger causes y_t if x_t helps predict y_t at some stage in the future (Sørensen, 2005). Wiener (1956) argued that if knowledge of a certain time series (Time series B) improves the prediction of the time series under consideration (Time Series A), then the former has a causal influence on the latter. Lin (2008) reveals that Granger causality tests are predicated on two major assumptions. First it is assumed that the past causes the present or the future simply because the future cannot for all practical purposes cause the past. But expectations formed in the past about the future may have had an influence on the past (when it was still the present) (Lin, 2008). Second, the information contained in the cause of an effect is so unique that it is not found elsewhere (Lin, 2008). The Granger Causality test procedure is illustrated through an example that relates to this study. If we assume a test for causality between India's national output proxy (INDIAPTI) and India's Stock Index (BSE), then the Granger Causality test equations can be expressed as follows:

$$INDIAPTI_t = \sum_{i=1}^{n} \gamma_i BSE_{t-i} + \sum_{i=1}^{n} \beta_i INDIAPTI_{t-i} + \delta_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{\mathit{11}}$$

$$BSE_t = \sum_{i=1}^{n} \varphi_i BSE_{t-i} + \sum_{i=1}^{n} \theta_i INDIAPTI_{t-i} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{\mathit{12}}$$

Where δ_t and ε_t are uncorrelated.

The hypothesis is expressed as follows:

H_0: There is no causality between INDIAPTI and BSE variables

H_1: There is causality between INDIAPTI and BSE variables

The study had four likely hypothesis testing conclusions for each pair of study variables flowing from Granger causality tests as adapted from Gujarati (2003):

1. If the estimated coefficients on lagged BSE (in equation 11) are statistically different from zero as a group (that is, $\sum \gamma_i \neq 0$) and the set of coefficients on

lagged INDIAPTI (in equation 12) is not statistically different from zero as a group (that is, $\sum \theta_i = 0$), then there is *unidirectional causality from BSE to INDIAPTI.*

2. If the estimated coefficients on lagged BSE (in equation 11) are not statistically different from zero (that is, $\sum \gamma_i = 0$) and the set of coefficients on lagged INDIAPTI (in equation 12) is statistically different from zero as a group (that is, $\sum \theta_i \neq 0$), then there is *unidirectional causality from, INDIAPTI to BSE*.
3. If both sets of estimated coefficients on lagged BSE and lagged INDIAPTI are significantly different from zero, then there is *bilateral causality* or the system is said to have *feedback*.
4. The fourth and final scenario is one of independence which implies that sets of INDIAPTI and BSE coefficients are all statistically insignificant.

Granger causality tests conducted for the study were implemented through an F-test whose statistic according to Gujarati (2003) is expressed as follows:

$$F = \frac{RSS_R - RSS_{UR/m}}{RSS_{UR} / (n-k)}$$

where RSS_R – Restricted Residual Sum of Squares

RSS_{UR} – Unrestricted Residual Sum of Squares

m and (n-k) - are degrees of freedom,

n – is the number of observations,

m - is the number of lagged BSE terms,

k - is the number of parameters estimated in the unrestricted regression.

The procedure outlined in the foregoing exposition was generalised for the other variables of study such as RUSSIAPTI, RTSI, BRZY, BOV and CHRETAIL. The results of time-domain Granger causality tests are presented and discussed in Chapter 6.

5.4.4 Choice of Dates and Time Periods of the Data Series

The empirical models of the present study used two datasets, namely, the monthly dataset (1990-2018) and the daily dataset (2000-2018). The ensuing discussion provides empirical justification for the use of the two datasets for the models of the study.

The dating of data series for purposes of data analysis was largely influenced by the research topic and research objectives. First, the study sought to explore the extent to which commodity market financialisation explains the commodity market – stock market relationship. This objective could not be fully explored using a short data series. Since commodity market financialisation is, according to Dwyer *et al.* (2012), a process that has spanned decades since the early 1980s, it stands to reason that to understand its impact fully the data series has to be of reasonable duration. Most studies on commodity market financialisation, stock market performance and economic performance have tended to use daily or monthly time series data covering any period between 10 years and 30 years (Ahmed *et al.,* 2017; Abbas *et al.,* 2017; Zivkov *et al.,* 2016; Rahman and Uddin, 2009 and Chancharat *et al.,* 2007). In line with the empirical literature, spectral causality analysis between national output proxies and stock indices covered the period January 1990 - October 2018 after repeated cycles of experimentation to better account for non-linear dynamics between the two sets of variables in the context of business cycle activity. It is important that most industrial output indices of many emerging economies, including the BRICS started being systematically published from 1990. It is also essential to observe that prior to 1990, Russia was part of the USSR, therefore, any industrial output figures for Russia prior to 1990 would not give an accurate picture of industrial activity, and hence economic growth.

GARCH analysis of the volatility dynamics of BRICS stock returns used daily data spanning the period 2000-2018 given the foregoing arguments based on the empirical literature. The choice of the period for daily data analysis was also informed by practical considerations such as dates or periods of crisis episodes such as the oil price bubble also called the energy crisis (2003-2009), subprime mortgage crisis (2007-2010), the European sovereign debt crisis (2009-2011) and China's stock market correction (2017).

This period was deemed sufficient to cater for most of the important economic events such as the 1994 economic crisis in Mexico, the 1997 Asian financial crises, the 1998 Russian financial crisis, 1998-1999 Ecuadorian financial crisis, the Argentine economic crisis (1999-2002), the United States (US) sub-prime mortgage crisis of 2007-2010 and the European sovereign debt crisis. As aforementioned, the period January 1990 – October 2018 is replete with crises of different types and magnitude. This facilitated a thorough examination using spectral causality analysis and selected GARCH models to unravel the indirect impact of the different crises on the non-linear dynamics between stock market performance proxies and economic growth proxies.

5.5 Empirical Model of the Study

This section explains all the models that were estimated for the present study in light of the empirical literature. This study involved spectral causality analysis of both daily and monthly data. It is through an approach adapted from Ronderos (2016) that non-linearities between national income proxies and stock market indices were discerned. The estimated models are displayed graphically in Chapter 6. The study also the involved estimation of GARCH models. The estimated GARCH models and their relevant diagnostic test results are presented and discussed in Chapter 7.

5.5.1 Spectral Analysis of Log-returns, National Output Proxies and Stock Market Indices

The study was concerned with modelling causality in the frequency domain among the five BRICS stock log-return series and the log-returns of three commodity futures prices, namely, gold, WTI crude oil and corn (or maize). This implies that the study sought to discern non-linearities in the causal relationships among the five BRICS stock indices. This was done to also assess the role of observed and unobserved heterogeneities in the context of the volatile commodity markets. The model that was used to facilitate frequency domain causal analysis was adapted from a study by Ronderos (2016). The model specification procedure and the analysis of Ronderos (2016) were based on the theoretical framework of Breitung and Candelon (2006). The maintained hypothesis of the study was that if one variable Granger-causes the other within a specified frequency range (given the underlying influence of the four commodity classes incorporated as external regressors), this implies that commodity – driven business cycle activity may have been impactful on the direction of causality within the specified frequency range. The reverse would obviously be true of the alternative hypothesis which has to be by definition a negation from or a departure from the null hypothesis.

Breitung and Candelon (2006) are some of the researchers who formalized the frequency domain approach to analyzing short-run and long-run causality. Their approach was based on earlier works by Geweke (1982) and Hosoya (1991), who proposed measures of causality in the frequency domain. The model for analyzing causality in the frequency domain may be formally presented in the following steps. First, it is postulated that:

Let $z_t = [x_t, y_t]'$ which is a two-dimensional vector of time series with time t = 1, 2, 3, …, T.

$\Theta(L)z_t = \varepsilon_t$ ……………………………………***13***

where equation 13 expresses the vector z_t as having a finite-order vector autoregressive (VAR) form of representation.

$\Theta(L) = I - \Theta_1 L - \ldots - \Theta_p L^p$ is a 2 x 2 lag polynomial with $L^k z_t = z_{t-k}$.

It is further assumed that:

$E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_{t'}) = \Sigma$ where the matrix Σ must be positive definite.

Breitung and Candelon (2006) have observed that for ease of exposition any deterministic terms in equation 13 can be dispensed with, though in practical empirical scenarios the model would normally have a constant, trend or dummy variables depending on what is being modelled or the scope of the model.

In their exposition of frequency-domain causality, Breitung and Candelon (2006) further postulated that let the Cholesky decomposition $G'G = \Sigma^{-1}$ yield the lower triangular matrix G, such that:

$E(\eta_t \eta_t') = I$ and $\eta_t = G_t$………………… ***14***

If the system is characterised by stationarity, then the moving average (MA) rendering of the system is as follows:

$$z_t = \Phi(L) = \begin{pmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

$$= \Psi(L)\eta_t = \begin{pmatrix} \Psi_{11} & \Psi_{12} \\ \Psi_{21} & \Psi_{22} \end{pmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{\textit{15}}$$

where $\Phi(L) = \Theta(L)^{-1}$ and $\Psi(L) = \Phi(L)G^{-1}$.

The above representation can be used to obtain the spectral density of x_t which in this case is:

$$f_x(\omega) = \frac{1}{2\pi}\{|\Psi_{11}(e^{-i\omega})|^2 + |\Psi_{12}(e^{-i\omega})|^2\}$$

Geweke (1982) and Hosoya (1991) used the above exposition of the spectral density of the random variable x_t to define the spectral causality measure as:

$$M_{y\to x}(\omega) = \log\left(\frac{2\pi f_x(\omega)}{|\Psi_{11}(e^{-i\omega})|^2}\right)$$

$$= \log\left(1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{\textit{16}}$$

The frequency domain causality measure is zero if $|\Psi_{12}(e^{-i\omega})|^2$. The implication is that the variable y does not cause variable x at frequency ω. The preceding exposition is a summary of the derivation of frequency-domain causality measure. The current study used Eviews software Spectral Causality add-in by Ronderos (2016) to calculate the tabular schedules of pairwise Granger-causality for calculated angular frequencies (ω). The frequency domain causality graphs were also computed using the Spectral Causality – Add-in and they presented and discussed in Chapter 6.

5.5.2 Univariate GARCH Modelling of the BRICS stock returns

The basic building block that was used by the study in modelling the volatility dynamics of the BRICS stock indices is the stock return. According to Perrelli (2001) and Fryzlewicz (2007), the basic formula for computing the return (and hence, log-return) of a financial asset's price series can be derived through the following two major steps. First, we assume that there is P_k, where k = 0, 1, 2, …, n-1, n, is the time series of a financial asset's prices. Instances of financial asset prices may be daily quotes on a stock index, a share, commodity futures, or a currency exchange rate. In the context of the study, the asset return or more accurately, the asset's log-return refers to the log-return of the daily stock indices of the five chosen BRICS stock indices, namely, the Bovespa for Brazil, the RTSI for Russia, the BSE Sensex for India, the SSE Composite Index for China, and South Africa's JSE index. The study also made use of the daily log-returns of gold, crude oil and US corn futures to represent commodities.

In line with standard practice in the empirical literature, the study did not model the original price or the original index series because such price series normally exhibits unit-root behaviour and therefore, cannot be modelled as stationary (Fryzlewicz (2007). The log-return of a financial asset's price series, P_k is calculated as follows:

$$X_t = \log P_t - \log P_{t-1} = \log\left(\frac{P_t}{P_{t-1}}\right) \quad \text{...} \mathbf{17}$$

The log-returns obtained using equation 17 two attractive features which inspired their choice for the study. First, they have the feature of being additive compared to other measures such as the relative return $\left(\frac{P_t - P_{t-1}}{P_{t-1}}\right)$. The second merit of the log-return is that they generally tend to be stationary at level the logarithm is implicitly first-difference already. This is confirmed by unit root test results presented in Chapter 6.

The study analysed the volatility dynamics of commodity markets and stock markets of BRICS countries using the univariate GARCH model. The study used the GARCH (1, 1) model originally developed by Bollerslev (1986) because it is a model which is considered highly parsimonious by many researchers since it uses only three parameters in the conditional variance equation (Rossi, 2004; Terasvirta, 2006 and Zivot, 2008). The GARCH model is based on Engle's (1982) ARCH model. According to Perrelli (2001) the basic building block of Engle's (1982) ARCH model is a non-linear process which can be expressed as follows:

$$X_t = \varepsilon_t \sqrt{\alpha \varepsilon_{t-1}^2} \quad \text{...}\textbf{\textit{18}}$$

The process X_t specified in equation 18 is linear in mean but non-linear in variance. Given GARCH Equation 1 Engle's (1982) ARCH model meant to capture serial correlation in volatility can be expressed as:

$$\sigma^2 = \omega + \alpha(L)\eta_t^2 \quad \text{.......................................}\ \textbf{\textit{19}}$$

Where $\alpha(L)$ represents the polynomial lag operator and $\eta_t \mid \psi_{t-1} \sim N(0, \sigma_{t-1}^2)$ is the innovation in the asset return being studied. The ARCH model by Engle (1982) has a number of weaknesses. First, the ARCH model assumes that positive and negative shocks to a given system have the same effects on volatility. This is the case because volatility is postulated to depend on the square of previous shocks. Squaring previous shocks would obviously render all results positive. Second, the ARCH model has a higher likelihood of overpredicting volatility. This is the case because a typical ARCH model responds slowly to large isolated shocks to any return series being studied. Third, a typical ARCH model provides a mechanical, non-flexible way of describing the behaviour of the conditional variance. Fourth, calculations become cumbersome and non-trivial if the polynomial presents a high order. The aforementioned weaknesses justified the adoption of the Generalised ARCH (GARCH) model and its extensions in the present study instead of ARCH models.

The univariate GARCH model by Bollerslev (1986) was proposed to facilitate calculations when the polynomial represents a high order. The Generalised Conditional Heteroscedasticity (GARCH) model is of the following form:

$$\sigma_t^2 = \omega + \beta(L)\sigma_{t-1}^2 + \alpha(L)\eta_t^2 \quad \text{..}\textbf{\textit{20}}$$

The GARCH (p, q) model specification follows an Autoregressive Moving Average (ARMA) process. The $\beta(L)$ term of order *p* represents the Autoregressive part, while the

$\alpha(L)$ term of order q represents the moving average part. The following conditions to ensure the positivity of the conditional variance process should be satisfied:

$$\omega > 0, \ \alpha \geq 0 \text{ and } \beta \geq 0$$

It is conventional practice in GARCH modelling to assume that $\alpha + \beta < 1$. This implies that the persistence of the GARCH model must be less than unit (1) to prevent the conditional variance from becoming explosive, that is, to ensure weak stationarity of the conditional variance process.

The results from the univariate GARCH model were subjected to standard robustness and diagnostic tests. The Nyblom's test of parameter stability revealed that for China the GARCH (1, 1) model yielded unstable conditional variance parameters (Nyblom, 1989). Gram and Thomassen (2015) have observed that the Nyblom's stability test which is used to discern structural stability of parameters in the in-sample period is an indicator of the existence of structural breaks in the data under consideration. The GARCH (1, 1) specification yielded a model for India for which only the logdow variable was stable in terms of the Nyblom parameter stability test. This implies that nearly all variables specified for India's conditional mean equation were unstable, that is, they had structural breaks and all parameters of the conditional variance equation were also unstable implying that they exhibited structural breaks as well. These mixed results which are reported in detail in Chapter 7 provided the basis for experimentation with chosen extensions of the original GARCH (1, 1) such as EGARCH, FIGARCH, DCC-GARCH and MRS-GARCH.

5.5.3 Exponential GARCH (EGARCH) modelling of BRICS stock returns

The News Impact Curve diagnostic tests showed that there was evidence of sign bias for Brazil's Bovespa, India's BSE Sensex, China's Shanghai Stock Exchange (SSE) Composite index and South Africa's JSE index. The News Impact Curve diagnostic test results showed that there was significant asymmetry in the volatility dynamics of the BRICS with the exception of Russia. That is what inspired this study to implement EGARCH to model the volatility dynamics of BRICS stock returns.

Nelson (1991) proposed the EGARCH model to deal with the leverage effect of news. Generally, according to the literature bad news are expected to exert more impact on the volatility dynamics of stock returns than the occurrence of good news (Engle and Ng, 1993). The original non-symmetric EGARCH model by Nelson (1991) models the volatility of an asset's returns as follows:

$$\log(\sigma_t^2) = \alpha_0 + \alpha_1 f(\varepsilon_{t-1}/\sigma_{t-1}) + \beta_1 \log(\sigma_{t-1}^2) \quad \text{......................} \textit{\textbf{21}}$$

Where $f(\varepsilon_{t-1}/\sigma_{t-1}) = \theta_1\varepsilon_{t-1}/\sigma_{t-1} + (|\varepsilon_{t-1}/\sigma_{t-1}| - E|\varepsilon_{t-1}/\sigma_{t-1}|)$

According to Mills (1999), *f(.)* is the news impact curve whose purpose is to relate revisions in the conditional volatility which is given by $\log(\sigma_{t-1}^2)$ to the news which is represented by ε_{t-1}. Elsewhere it has been proven that *f(.)* embodies an asymmetric response since $\delta f/\delta\varepsilon_{t-1} = \theta_1 + 1$ if $\varepsilon_{t-1} > 0$ and $\delta f/\delta\varepsilon_{t-1} = \theta_1 - 1$ if $\varepsilon_{t-1} < 0$. It flows from the foregoing exposition that conditional volatility will be minimised when there is no news in the market or economy, that is, $\varepsilon_{t-1} = 0$. This non-symmetry feature is an important stylised fact characterizing many asset returns including stock indices because it allows conditional volatility to respond more quickly to downturns than to corresponding upsurges in the market (Mills, 1999). This feature is what is conventionally called the 'leverage' effect in the empirical literature. Mills (1999) observes that *f* (ε_{t-1}) is a strict white noise process with zero mean and constant variance. This predisposes the volatility process $\log(\sigma_t^2)$ to be an Autoregressive Moving Average (ARMA) (1, 1) process whose stationarity is attained when $\beta_1 < 1$. The results of EGARCH modelling of BRICS stock returns are presented and analysed in Chapter 7.

5.5.4 Modelling Long Memory – The Fractionally Integrated GARCH (FIGARCH) model

The study made use of two FIGARCH models, namely, Fractionally Integrated GARCH – Baillie-Bollerslev-Mikkelsen (FIGARCH-BBM) and Fractionally Integrated GARCH – Chung (FIGARCH-Chung). The FIGARCH model is used to model the long-range dependence feature that is at times exhibited by returns of certain financial assets such as stock indices, currencies and shares. This phenomenon was first observed by Ding *et al.* (1993) who basing on a data series spanning the period 1928-1991 discovered that the first negative autocorrelation of the squared return of the S&P 500 occurred at lag 2598 (Mills, 1999). Additional evidence of long-range dependence in conditional volatility was obtained by Mills (1996) who analysed the daily returns of the FT30 index for the period 1935-1994 and discovered that although the fitted autocorrelations decline quickly at first, they fall slowly as the lag increases. It is this feature that the study sought to discern and explain by employing the two versions of the FIGARCH model.

The outline of the FIGARCH model by Baillie *et al.* (1996) which was adopted for the study is predicated on the standard GARCH (1, 1) process which may be modelled as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 \text{ .... } \mathbf{22}$$

The main restriction imposed on the model expressed by equation 22 is that all the three parameters to be estimated must be non-negative. This implies that $\alpha_0 > 0$, $\alpha_1 > 0$ and $\beta_1 > 0$. In line with the exposition of Mills (1999) the GARCH (1, 1) process outlined in *GARCH EQ. 5* may be generalised into a GARCH (p, q) process which is expressed as follows:

$$\varepsilon_t^2 = \alpha_0 + (\alpha(B) + \beta(B)\varepsilon_{t-1}^2 + \upsilon_t - \beta(B)\upsilon_{t-1} \text{ .... } \mathbf{23}$$

It is important to observe that ε_t^2 ~ ARMA (m, p), where m = max (p, q). According to Mills (1999) the GARCH (p, q) process expressed in equation 23 can be weak stationary if and only if $\alpha(B) + \beta(B)$ occur outside the unit circle. This implies that $\alpha(1) + \beta(1) < 1$. Equation 24 may be extended to yield the FIGARCH (1, d, 1) by introducing the fractional differencing term on both sides of the equation as follows:

$$\Delta^d \varepsilon_t^2 = \alpha_0 + (\alpha(B) + \beta(B)\Delta^d \varepsilon_{t-1}^2 + \upsilon_t - \beta(B)\upsilon_t \text{ .... } \mathbf{24}$$

Mills (1999) elaborates equation 24 from the exposition of Baillie *et al.* (1996) as follows:

$$\sigma_t^2 = \alpha_0 + (1-\Delta^d)\varepsilon_t^2 - (\beta_1 - (\alpha_1 + \beta_1)\Delta^d)\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \text{............}\mathbf{\mathit{25}}$$

Baillie *et al.* (1996) cited in Mills (1999) demonstrated that the FIGARCH (p, d, q) class of processes depicted by equation 25 is strictly stationary for $0 \le d \le 1$ but not weakly stationary over the same range of the fractional difference term d.

In 1999 a serious drawback of the FIGARCH – BBM was pointed out by Chung (1999). Al-Hajieh (2017, p. 202) points out that "there is a structural discrepancy in the FIGARCH – BBM measurement." It has been pointed out that the ARFIMA formulation of the conditional mean is actually incomplete which makes interpretation of estimated parameters intractable (Al-Hajieh, 2017). This observation prompted Chung (1999) to propose the following FIGARCH process:

$$\phi(L)(1-L)^d(\varepsilon_t^2 - \sigma^2) = [(1-\beta(L)](\varepsilon_t^2 - \sigma_t^2) \text{.......} \mathbf{\mathit{26}}$$

Where σ^2 is the unconditional variance of ε_t^2. If the model presented in equation 26 is subjected to variance targeting this would imply replacing the population σ^2 with its sample equivalent (Al-Hajieh, 2017). The conditional variance of FIGARCH-Chung can therefore be expressed as:

$$\sigma_t^2 = \sigma^2 + \{1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\}(\varepsilon_t^2 - \sigma^2) \text{......}\mathbf{\mathit{27}}$$

Chung (1999) demonstrated that $\sigma^2 > 0$ and $0 \le \phi_1 \le \beta_1 \le d \le 1$ are sufficient conditions to ensure positivity of the conditional variance when p = q = 1 (Al-Hajieh, 2017).

The study estimated FIGARCH – BBM and FIGARCH – Chung models using the maximum likelihood technique. Strong convergence of estimated model parameters was ensured by the use of numerical derivatives. Robust standard errors were guaranteed by the use of the Sandwich formula.

5.5.5 Modelling of Spill-overs, Contagion, and Interdependence – VAR-DCC-GARCH

The study involved experimenting with various formulations of Engle (2002) Dynamic Conditional Correlation (DCC) GARCH. The main advantage of DCC-GARCH as Engle (2002) has argued is that DCC estimators have the flexibility of univariate GARCH while foregoing the complexity of conventional multivariate GARCH models. The DCC-GARCH model form by Engle (2002) assisted in modelling contagion, spill-overs and interdependence that characterise not only commodity and stock price behaviour of the BRICS but of the modern integrated and globalised economy. In line with contemporary studies this study adopted the Vector Autoregressive – Dynamic Conditional Correlation – GARCH approach (VAR-DCC-GARCH) to model dynamic volatility spill-overs, linkages and contagion between BRICS equity markets (Dey and Sampath, 2018; Mensi *et al.,* 2018; Ling and McAleer, 2003; Bonga-Bonga, 2015 and Gamba-Santamaria *et al.,* 2017). The implementation of the VAR-DCC-GARCH model is a two-step process which implies that even the model specification must have two segments that link to each other.

Adapting the approach of Dey and Sampath (2018), the study formally specifies the conditional mean part of the VAR-DCC-GARCH model as a VAR (1, 1) process as follows:

$$X_t = \phi_0 + \sum_{i=1}^{n} \phi_i X_{t-i} + \theta Z_t + \gamma_t, \gamma_t \mid \Omega_{t-1} \sim N(0, V_t) \qquad \textbf{28}$$

$$\gamma_t = v_t \sigma_t \qquad \textbf{29}$$

where X_t is a 5-variable vector of log-returns of BRICS stock indices. The order of log-returns in the vector of stock index variables is as follows: Brazil, Russia, India, China and South Africa. The Z_t represents a vector of deterministic and exogenous variables, γ_t is a term representing residuals which combine both the white noise process v_t and the heteroscedastic component which is σ_t. The parameters ϕ_0, ϕ_i and θ are to be estimated. The residuals obtained from equations 28 and 29 at the first stage serve as inputs into the univariate conditional variance model specified for each BRICS stock market log-return. The study relied on the univariate GARCH (1, 1) specification expressed as:

$$\sigma_t^2 = \omega + \beta(L)\sigma_{t-1}^2 + \alpha(L)\eta_t^2$$

The parameter ω is the constant of the variance equation which represents a kind of 'ambient volatility' while β represents adjustment to past shocks and α represents adjustment of current volatility to squared innovations.

The last stage in VAR-DCC-GARCH estimation comprises the computation of the time-varying conditional correlation matrix from the conditional variance. This is expressed as:

$$H_t = D_t R_t D_t \text{ ....} \textbf{\textit{30}}$$

where: - $D_t = diag(h_{11t}^{1/2}...h_{nnt}^{1/2})$ and D_t represents the diagonal matrix of conditional variances. R_t is a square positive definite N x N correlation matrix and is defined as $R_t = (1-a-b)\bar{R} + a\Psi_{t-1} + bR_{t-1}$.

The restrictions imposed on the estimated model are that the parameters *a* and *b* are non-negative scalars such that their sum $a + b < 1$. $\bar{R}$ represents a scalar for constant conditional correlation. It can be non-trivially verified that if a = b = 0, then $\bar{R}$ = R.

Bonga-Bonga (2015) explains that: $$\Psi_{ij,t-1} = \frac{\sum_{m=1}^{M} u_{1,t-m} u_{j,t-m}}{\sqrt{(\sum_{m=1}^{M} u_{i,t-m}^2)(\sum_{h=1}^{M} u_{j,t-h}^2)}} \text{ ....} \textbf{\textit{31}}$$

and $u_{it} = \gamma_{it} / \sqrt{h_{iit}}$.

In line with the procedure of Dey and Sampath (2018) the study estimated the DCC-GARCH (ENGLE) – GARCH via the quasi-maximum likelihood estimation (QMLE) technique using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. The results of the estimated model and diagnostic test results are presented and discussed in Chapter Seven (7).

5.5.6 Markov Regime Switching – GARCH Modelling of BRICS Stock Returns

The study examined the effects of regime changes on volatility through Markov Regime Switching – GARCH (MRS – GARCH) modelling. Lamoureux and Lastrapes (1990) argue on the basis of empirical evidence that MSGARCH models are more superior to their single-regime counterparts in explaining volatility persistence as well as other stylised facts of stock returns. This finding was corroborated by Ardia (2009) who employed a Bayesian MRS GARCH model. Evidence was found of the volatility of the Swiss Market Index being asymmetric with statistically significant evidence of regime changes as well (Ardia, 2009).

The MRS-GARCH models implemented for the study are akin to those implemented by Zhang *et al.* (2015) specified in line with Klaassen (2002) and Haas *et al.* (2004). Klaassen (2002) and Haas *et al.* (2004) assumed that the innovation, ε_t, of the MRS – GARCH follows a student t distribution characterised by v degrees of freedom. Equations 32, 33 and 34 capture the conditional mean, conditional variance (which is assumed to follow a GARCH process) and the expectation of squared innovations:

$$r_t = \mu_t^{(i)} + \varepsilon_t = \delta^{(i)} + \varepsilon_t, \varepsilon_t = \eta_t \sqrt{h_t} \text{ ....} \textbf{\textit{32}}$$

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)} \varepsilon_{t-1}^2 + \beta_1^{(i)} E_{t-1}\{h_{t-1}^{(i)} \mid S_t\} \text{ ....} \textbf{\textit{33}}$$

$$E_{t-1}\{h_{t-1}^{(i)} \mid S_t\} = P_{ii,t-1}[(\mu_{t-1}^{(i)})^2 + h_{t-1}^{(i)} + P_{ji,t-1}[(\mu_{t-1}^{(j)})^2 + h_{t-1}^{(i)}] - [P_{ii,t-1}\mu_{t-1}^{(i)} + P_{ii,t-1}\mu_{t-1}^{(i)}]^2 \text{ ....} \textbf{\textit{34}}$$

Where i, j = 1, 2 denotes the two regimes of the MRS – GARCH model.

$$= \Pr(S_t = j \mid S_{t+1} = i, \varsigma_{t-1}) = \frac{P_{ji}(\Pr(S_t - j \mid \zeta_{t-1})}{\Pr(S_{t+1} = i \mid \varsigma_{t-1})} = \frac{P_{ji} P_{j,t}}{P_{i,t+1}}$$

ς_{t-1} represents information at time *t-1*, that is, the immediate past.

Zhang *et al.* (2015) employed WTI data for k days following Klaassen (2002) in defining the time *t*, *k*-step-ahead volatility forecast as follows:

$$\hat{h}_{t,t+k} = \sum_{\tau=1}^{k} \hat{h}_{t,t+\tau} = \sum_{\tau=1}^{k} \sum_{i=1}^{2} \Pr(S_\tau = i \mid \varsigma_{t-1}) \hat{h}_{t,t+\tau}^{(i)}$$

Where:

$\hat{h}_{t,t+\tau}^{(i)} = \alpha_0^{(i)} + (\alpha_1^{(i)} + \beta_1^{(i)}) E\{h_{t,t+\tau-1}^{(i)} \mid S_{t+\tau}\}$ is the τ-step-ahead volatility forecast of regime *i* at time *t*.

The study deviated from the student t distribution originally assumed by Klaassen (2002) and Haas *et al.* (2004) for the innovation ε_t. MRS – GARCH modelling for the study consisted of two phases. The first phase involved estimating the symmetric normal distribution MRS – GARCH model for all the BRICS using R software to obtain robust standard error estimates. This was done so that parameter estimates assuming symmetry for the error distribution would serve as a benchmark for the skewed MRS-GARCH estimates. The second phase of the MRS – GARCH model estimation was experimentation with various error distributions which are skewed and choosing those formulations that had the best fit in terms of the log-likelihood and information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). In the final analysis, the skewed Generalised Error Distribution (skewed GED) was adopted for Brazil, Russia, India, and China. The student t error distribution originally assumed by Klaassen (2002) and Haas *et al.* (2004) was retained for South Africa. The MRS – GARCH model results are presented and discussed in Chapter 7 of the study.

5.5.7 Robustness Tests of Estimated GARCH models

The GARCH models estimated for the study were subjected to a number of standard tests that include the Nyblom parameter stability test (Nyblom, 1989). This is a standard test to ascertain the parameter which was first proposed by Nyblom (1989). The non-technical null hypothesis of the Nyblom's test is that estimated parameters are stable which is cast against the alternative that parameter estimates are unstable. The technical null hypothesis of the test is that parameters are time-invariant for observations that are obtained sequentially in time. The alternative hypothesis is that the parameter process conforms to a martingale. In probability and statistical theory, a martingale refers to a stochastic process for which at any given point in time, the conditional expectation of the next observation's value in the sequence is equal to the current value taking into account all prior or previous values. The results of Nyblom parameter stability tests are presented and discussed in Chapter 7 of the study.

The estimated GARCH models were also subjected to Box-Pierce Q tests for autocorrelation of squared standardised residuals. Lobato (1999) has questioned the assumption of the independence of squared residuals when applied to financial time series data. Lobato (1999) has argued that most financial time series data tend to have highly correlated squared residuals. Be that as it may, it is standard procedure in volatility modelling to subject the squared residuals of an estimated GARCH model to autocorrelation testing (Tafeyi and Ramanathan, 2012; Ijumba, 2013; Bonga-Bonga, 2015). The present study, therefore subjected the estimated GARCH models to both the Ljung – Box Q test and the Box-Pierce Q Test. The Ljung – Box test was used to test for autocorrelation for the DCC-GARCH model. The univariate GARCH, FIGARCH-BBM and FIGARCH-Chung were all subjected to the Box – Pierce autocorrelation test procedure. The results of autocorrelation tests are presented in and explained in Chapter 7.

The univariate GARCH (1, 1) Model was subjected to Engle's ARCH Lagrange – Multiplier (LM) test. The purpose of this test was to deduce whether the five-daily log-return series displayed ARCH effects to justify the implementation of the GARCH zoo of models. The results obtained are reported and discussed in Chapter 7 of the study.

One hypothesis of the study averred that stock market development and economic growth indicators have non-linear relationships. This hypothesis was cast at the nascent stages of the research as a departure from the Efficient Markets Hypothesis (EMH). After the study fitted the daily log-return data to the Engle (2002) DCC-GARCH model, the estimated dynamic conditional correlations of the 10 pairs of BRICS economies were subjected to the Brock – Dechert-Scheinkman (BDS) test as a way of discerning whether the apparent non-linear dynamics were indeed non-linear from a statistical perspective. This was also done in an attempt to deduce fractality that may characterise BRICS stock markets. The results of the BDS test for non-linearities and fractality are displayed and discussed in Chapter 7.

5.6 Limitations of the Study

The study encountered various challenges and limitations. The researcher relying on the empirical literature and repeated experimentation managed to surmount some of the more serious challenges encountered. Other challenges were, however, not resolved and this study humbly believes that future studies of an interdisciplinary nature may unravel some of the issues encountered.

The study encountered three main limitations. The first limitation of the study that was encountered by the researcher is the fact that macroeconomic variables do not usually occur in the same frequency to facilitate statistical and econometric analysis of relationships among variables. Since one of the objectives of the study was to link stock market performance with economic growth, it was also logical that measures of stock market performance would be linked to the economic growth rate which according to the empirical literature is normally proxied by the Gross Domestic Product (GDP) growth rate or Gross National Product (GDP) growth rate (Sobrecarey, 2015 and Gamolya, 2006). It is clear that stock market performance indicators such as log-returns and stock market capitalization usually occur at a higher frequency than economic growth proxies such as the GDP growth rate. The resolution of this problem could have involved transforming low-frequency data to a higher frequency through splining techniques such as the constant, quadratic, linear, cubic, point, Denton or Chow-Lin that are available in Eviews software. Unfortunately, as observed by some researchers, these techniques normally interfere with and distort the 'natural' behaviour of the error term (Revesz, 2015 and Burden *et al.,*1981). This study thus avoided using techniques that would distort the error term (and by extension residuals). Industrial output indices were used as a proxy for the low-frequency GDP growth rate statistics. The merits of industrial output indices have been explained in an earlier discussion under section 5.3.3.3. The second limitation of the study is the use of secondary data whose integrity depends on the institutions that compiled the data. The merit of the secondary data used in the study is that most of it was gathered by reputable national and international institutions such as the stock markets of the respective BRICS countries, the International Monetary Fund and the United States (US) Federal Reserve System. The data series from one source were compared with the data that the researcher obtained from other sources. This enabled the researcher to rely on multiple data sources to fill in gaps in data series that were analysed.

The third limitation of the study is the period chosen for the data analysis. Spectral analysis of monthly data used data series which covered the period January 1990 to October 2018. This means that the findings and conclusions of the study are in fact limited to the time period chosen since observations that occurred before 1990 were excluded from the analysis based on monthly data. It is enlightening to observe at a philosophic level that there exists no time series study that can cover all of the material time in studying a particular phenomenon. This is the case because of two main reasons. First, data for such an exercise would for all practical purposes not be available. Second, a dataset whose observations are asymptotically approaching infinite is not even desirable because it would be virtually impossible to analyse it to deduce any meaningful econometric relationships among the variables concerned. The study thus relied on the empirical literature and data availability considerations to delimit the time scope of the study. This is explained under section 5.4.4.

5.7 Chapter Summary

Chapter 5 provides a detailed review of several GARCH volatility as well as smooth transition models that are used to model the volatility dynamics of commodity and stock globally. The chapter explained in detail the empirical approach for the study, data sources and the main variables of the study, model selection, robustness checks and limitations of the study. The chapter also provided the theoretical and empirical context for the models that were employed to interrogate the two main hypotheses and the three secondary objectives that underpinned the present study. A case was made for the unified single-regime GARCH, two-regime Markov-Regime-Switching (MRS) as well as the VAR-DCC-GARCH model that was specified for the study. Chapter 6 presents and discusses the descriptive statistics, unit root test, cointegration test, time-domain causality and spectral causality test results.

CHAPTER SIX: EMPIRICAL ANALYSIS: PRE-ESTIMATION DIAGNOSTICS AND SPECTRAL CAUSALITY TESTS

6.1 Introduction

Chapter 6 analyses and presents the results of the study obtained using methodological approaches explained in Chapter 5. The first segment of the chapter comprises graphical presentation and analyses of trends of the BRICS' stock returns series, selected commodity indices as well as log-return series of West Texas Intermediate (WTI) crude oil, gold and corn. The second segment of Chapter 6 consists of an analysis of descriptive statistics and basic diagnostic tests that the different variables were subjected to. The last segment of this chapter presents and discusses spectral causality test results for daily and monthly data.

6.1 Trend Analysis of the Main Indices

This section has two categories, namely, an analysis of the trends of daily stock return and selected commodity price series. The second category is a graphic presentation and analysis of the monthly stock return series of the BRICS and seven commodity classes based on data from the International Monetary Fund (IMF). Figure 6.1 presents a set of graphs constructed from raw daily stock price indices of the BRICS, and the Dow Jones index.

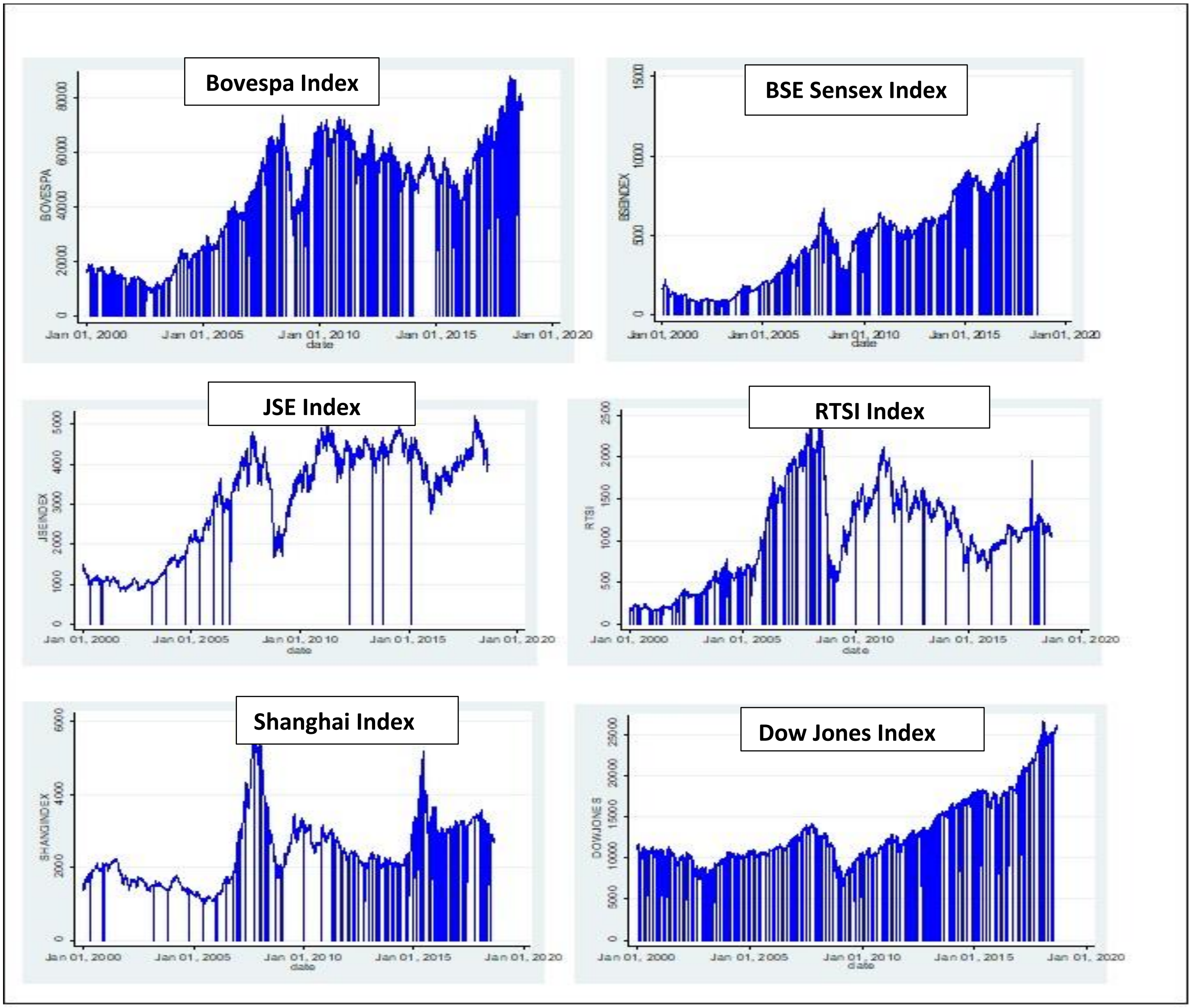


Figure 6. 1 – Bovespa, Bseindex, Jseindex, rtsi, shangindex, Dow Jones, Source: Researcher Compilation

The daily stock index series of the five BRICS economies, and the Dow Jones Index series which is included as a control, show substantial volatility in daily stock prices for all the six indices included in this analysis. It is apparent from Figure 6.1 that the six stock markets, while exhibiting a certain common trend, have substantial dissimilarities, and nuanced differences. Brazil's Bovespa index displayed a clear upward trend between January 2000 and September 2018. There was, however, marked and significant volatility in the index during the period under consideration. India's Bseindex also exhibited an upward trend between 2000 and 2018, with marked volatility during the global financial crisis period (2007-2008), which was triggered by the US subprime mortgage crisis. South Africa's JSE index exhibited an overall upward trend just like Brazil's Bovespa and India's Bseindex, but there was a significant downturn followed by a sustained rally in the JSE index between 2007 and 2011. The marked deep and increased volatility in the JSE index during the period 2007-2009 was evidently linked to the global financial crisis whose repercussions on the global economy have been well documented in empirical literature (Bonga-Bonga, 2015; Ijumba, 2013 and Nikkinen *et al.,* 2013).

Russia, though part of the Group of Seven plus one powerful and advanced economies, is heavily reliant on natural gas and other mineral resources for most of its economic activities. It is, therefore, not surprising that Russia's RTSI index can be calibrated into two significant phases. First, between January 2000 and October 2006, the RTSI exhibited strong, sustained and significant growth characterised by an overall upward trend, which was nevertheless abruptly terminated by the onset of the global financial crisis which was triggered by the US subprime mortgage crisis (Sheu and Liao, 2011 and Nikkinen *et al.,* 2013). The second phase of the RTSI index, nevertheless shows that the negative ramifications of the global financial crisis did not hinder a quick recovery of the Russian stock as evidenced by the upsurge recorded between 2009 and 2011. The recovery was, however, dampened by a modest, yet steady downturn which spanned the period October 2010 to August 2016. Russia possesses a unique and peculiar economy in the sense that it has its own historical features. The history associated with the Russian economy partly explain its structural rigidities and oligopolistic nature, as well as sensitivities to certain socio-economic and political events associated with Eastern and Western Europe (Ericson, 2008; Kudrin and Gurvich, 2015).

China's Shanghai Index (Shangindex) exhibits a significant difference from the other four BRICS stock indices which have been tackled in the foregoing analysis. There are basically two features that can be picked from the Shangindex. First, there is no statistically discernible upward or downward trend in China's Shangindex. The index, though displaying high and low moments like other indices, was to a larger extent flat for the period under review, that is, from January 2000 to September 2018. This phenomenon may be due to the fact that China's economy was to a larger extent shielded from negative world economic events such as the global financial crisis of 2007-2009 and Europe's sovereign debt crisis of 2009-2010 by its protected and state-oriented capitalistic nature (Bao and Yang, 2013; Li, *et al.,* 2012). A number of researchers such as Li *et al.* (2012), Adas and Tussupova (2016) and Haasbroek and Gottwald (2017) have amply argued and empirically demonstrated that China's financial sector was moderately impacted by the global financial crisis though Chinese exports were hurt by the crisis. The second feature that can be gleaned from the Shangindex is that marked short-lived high volatility corresponding to the onset of the global financial crisis was followed low volatility for the period 2009-2014. It was during this period that even though economic growth in China remained positive, it was largely subdued compared to the years preceding the global financial crisis and Europe's sovereign debt crisis.

The Dow Jones Industrial Average (Dow Jones) which is included in this analysis as a control and in a bid to capture the influence of the United States (US) economy. It presented an upward trend between January 2000 and September 2018. The US's Dow Jones index just like other indices that have been graphed in the foregoing analysis was apparently affected adversely by the global financial crisis of 2007-2008, though the US stock market appears to have recovered remarkably well as evidenced by a sustained rally and upsurge between November 2009 and September 2018. The six indices under consideration, namely, Bovespa, Bseindex, JSEindex, RTSI, Shangindex and the Dow Jones exhibited different volatility features and trends, though all of them were apparently significantly affected by adverse economic, political and social events.

Figure 6.2 shows the stock returns of the six indices under consideration.

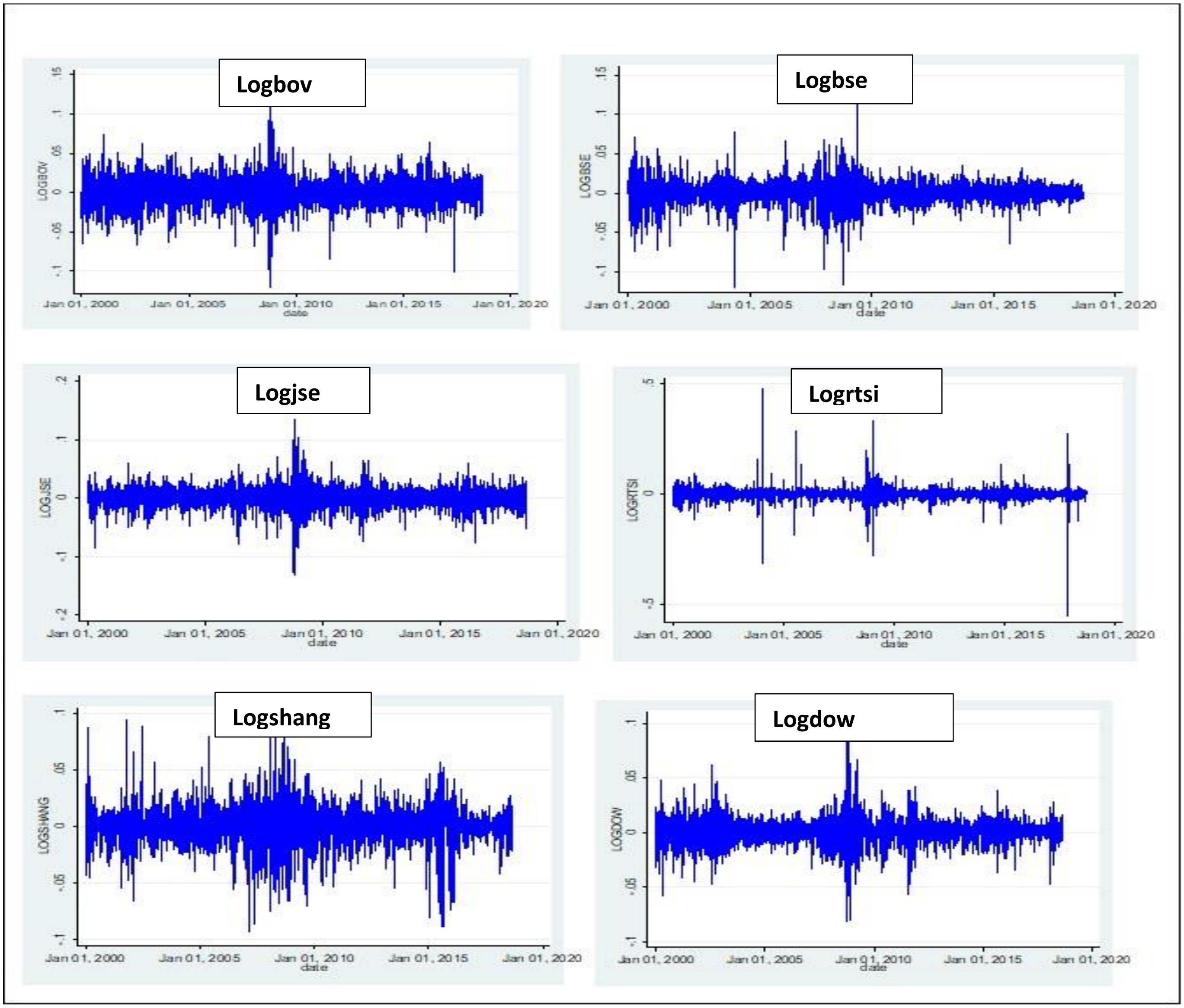


Figure 6. 2: Log-returns of the Six indices,

Source: Researcher Compilation

The key feature of the log-return plots of the index series show statistical features of weak or covariance stationarity as well as mean reversion, though they have idiosyncratic differences owing to individual peculiarities and nuanced experiences of the six economies represented by the six indices. The plots of the log-return series clearly bring out the adverse effects of the global financial crisis of 2007-2008 on the stock markets of all the six economies under review. There was evidently a spike in the volatility of the log-returns for Brazil, India, South Africa, China and the United States (US). Russia's RTSI shows a less clear picture of the negative ramifications of the global financial crisis as there were apparently early crisis or downturn-oriented events in the early 2000s and around 2017. The log-return series of China (logshang) exhibits significant volatility clustering especially for the periods 2006 to 2010 and January 2015 to September 2015 respectively. The log-returns series of stock markets of Brazil, India, South Africa and the United States (US) also exhibited volatility clustering to different degrees.

6.2 Commodity Price Trend Analysis

Section 6.2 explores the trends in commodity prices that were chosen for the study because of their significance in global economic activity in general, and the BRICS economies in particular. The commodity price series include that of crude oil, gold and United States (US) corn futures prices which have been dealt with considerably in the empirical literature (Karali and Thurman, 2010; Kang and Ratti, 2013; Raza and Shahbaz, 2016). Karali and Thurman (2010) employed the generalised least squares method to distinguish time-to-delivery effects, seasonality, calendar trend, and volatility persistence for corn, soya beans (called soybeans in the USA), wheat and oats. Raza and Shahbaz (2016) employed the non-linear Autoregressive Distributed Lag (ARDL) approach to amply demonstrate that gold prices have a positive impact on large emerging BRICS stock markets prices.

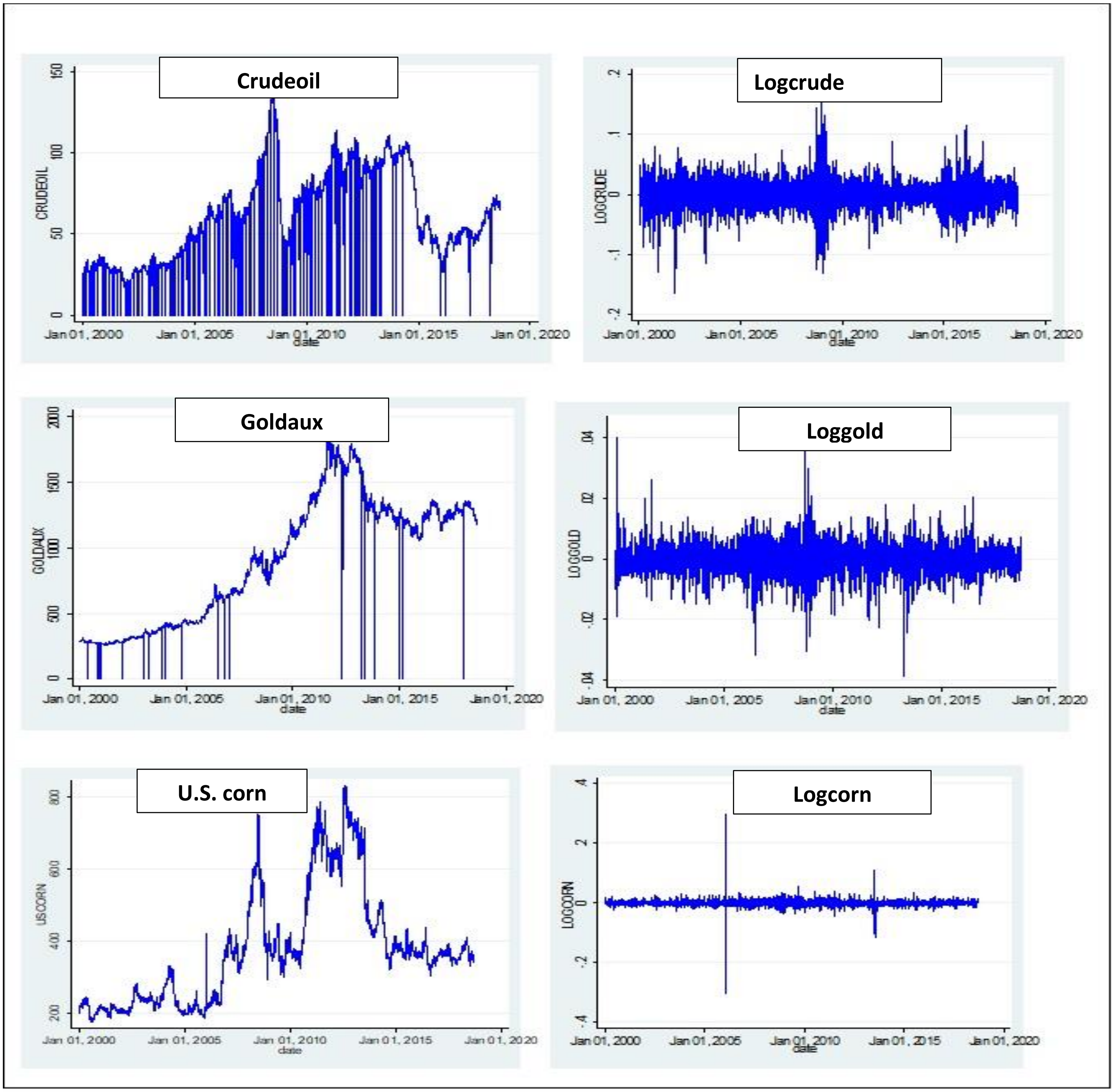


Figure 6. 3: Trend Analysis of crude oil, gold and corn prices,

Source: Researcher Compilation

Figure 6.3 indicates both raw and log return series of West Texas Intermediate (WTI) crude oil, gold and United States corn (also called maize). The respective raw plots of the three selected daily series show significant and marked volatility in the prices of WTI crude oil, gold and corn. The prices of gold and corn showed an overall upward trend between

03 January 2000 and 03 September 2018. There was increased volatility in the prices of both commodities during the global financial crisis period (2007-2008) evidently owing to a significant slowdown, and downturn in global economic activity (Ratti and Vespignani, 2015; Kang and Ratti, 2013). The raw price plot of WTI crude oil displayed the most volatility of all the three series with no straightforward or clear trend. The shape displayed by raw crude oil price plot confirm the phenomenon of volatility clustering clearly depicted by the plot of the log-return series for the study period. It is imperative to observe that both gold and crude oil prices are characterised by volatility clustering. In the United States (US) just like other leading global commodity producers, market prices are normally characterised by volatility.

According to some researchers such as Silvennoinen and Thorp (2010), Gorton and Rouwenhorst (2007) and Du *et al.* (2011), the phenomenon of commodity price volatility has in recent years been exacerbated by the financialisation of commodity markets which has been characterised by increased integration of commodity markets into the mainstream financial markets.

6.3 Descriptive Statistics of the Study

The descriptive statistics are presented in five tables which are Table 6.1 that captures selected variables of daily raw data, Table 6.2 that covers log-return information, and Tables 6.3, 6.4, and 6.5 that summarise monthly data series of the present study.

Table 6. 1: Descriptive Statistics Raw Data Series

	BOVESPA	JSEINDEX	BSEINDEX	RTSI	SHANGINDEX	DOWJONES	CRUDEOIL	USCORN	GOLDAUX
Mean	41908.44	3093.879	4519.752	1026.017	2311.348	12683.75	62.06370	375.5423	905.2457
Median	48622.00	3585.490	4651.135	1058.200	2185.525	11350.65	59.34000	358.2500	942.0500
Maximum	87652.60	5207.140	12035.70	2487.920	6092.060	26616.71	145.3000	831.2500	1900.490
Minimum	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	174.7500	255.5500
Std. Dev.	22393.91	1331.334	3079.451	581.7914	1005.851	4840.665	27.08566	158.8438	466.0065
Skewness	-0.270627	-0.478581	0.395347	0.094029	0.416998	0.302345	0.349011	0.935781	0.038820
Kurtosis	1.873541	1.724993	2.187128	2.168948	4.063964	4.231691	2.155783	3.020362	1.654281
Jarque-Bera	317.7097	517.0449	261.5851	147.6832	371.7576	382.9756	244.0875	712.6014	369.6058
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	2.05E+08	15104315	22065428	5009014.	11284000	61922084	302995.0	1833397.	4419409.
Sum Sq. Dev.	2.45E+12	8.65E+09	4.63E+10	1.65E+09	4.94E+09	1.14E+11	3580862.	1.23E+08	1.06E+09
Observations	4882	4882	4882	4882	4882	4882	4882	4882	4882

Source: Researcher Calculations

Table 6.1 summarises basic descriptive statistics for the main BRICS stock indices, namely, Bovespa, JSEIndex, BSEIndex, RTSI, Shangindex, and Dow Jones (a control variable). Table 6.1 also presents a summary of descriptive statistics for prices of WTI crude oil, United States (US) corn and gold. The summary of the statistics shows that all the nine variables do not follow a normal distribution since all the respective Jarque-Bera statistics are statistically significant at 5 percent level of significance. The arithmetic mean values for the variables under review were as follows – Brazil’s Bovespa has an average value of 41908.44 for the period January 2000 to September 2018. South Africa’s JSEIndex has an average of 3093.879 for the same period. The rest of the variables have the following estimates – the average for India’s BSEIndex is 4519.752, the average for Russia’s RTSI is 1026.017, the average for China’s Shanghai index (Shangindex) is 2311.348 and the Dow Jones index averaged 12683.75 for the same period.

The prices of WTI crude oil, gold, and US corn averaged $62.06370, $375.5423 and $905.2457 respectively. The variables being reviewed were slightly positively skewed with the exception of Brazil's Bovespa index and South Africa's JSE Index which are slightly negatively skewed. The excess kurtosis statistics for Bovespa, JSE index, BSE Sensex index, RTSI, crude oil and gold are all negative which implies that these variables have thinner tails than the tails of a normal distribution. Excess kurtosis is a statistic which is used to deduce the peakedness of the distribution of a given series. Its formula is – excess kurtosis equals calculated kurtosis minus 3. If the excess kurtosis is zero, it means the data series conforms to a normal distribution. If the excess kurtosis is positive, this means that the data series has fatter or heavier tails than the tails of a normal distribution. Negative excess kurtosis, therefore, implies a platykurtic distribution of the data series, further implying that the data series under consideration has a distribution with thinner tails than the tails of a normal distribution.

Table 6. 2: Descriptive Statistics of Log-returns of the nine variables

	LOGBOV	LOGJSE	LOGBSE	LOGRTSI	LOGSHANG	LOGDOW	LOGCRUDE	LOGCORN	LOGGOLD
Mean	0.000288	0.000221	0.000324	0.000348	0.000116	0.000162	8.39E-05	5.34E-05	0.000127
Median	0.000000	0.000000	0.000000	0.000192	0.000000	0.000000	0.000000	0.000000	0.000120
Maximum	0.136766	0.134436	0.154902	0.480459	0.094008	0.105083	0.164097	0.296172	0.045328
Minimum	-0.120961	-0.131487	-0.119364	-0.551956	-0.092562	-0.082005	-0.165445	-0.305943	-0.038546
Std. Dev.	0.016827	0.016974	0.014122	0.026376	0.014961	0.010863	0.022767	0.010059	0.004729
Skewness	-0.088210	-0.323011	-0.383603	-0.501106	-0.322412	-0.040364	-0.111875	-0.787296	-0.116785
Kurtosis	7.619581	8.456940	11.85554	87.50572	8.708956	12.33891	7.678519	340.1455	9.802827
Jarque-Bera	4347.351	6142.275	16071.79	1452847.	6714.372	17742.35	4462.677	23122278	9424.908
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.406524	1.081088	1.583718	1.699156	0.566519	0.790483	0.409480	0.260529	0.618699
Sum Sq. Dev.	1.382038	1.406279	0.973486	3.395728	1.092470	0.575930	2.530054	0.493873	0.109146

Observations	4882	4882	4882	4882	4882	4882	4882	4882	4882

Source: Researcher Calculations

Table 6.2 displays Jarque-Bera statistics that clearly show that none of the nine daily logreturn series is normally distributed. The log-return descriptive statistics for the six main indices and three commodity prices are different from the raw data in two respects. First, all the nine variables are slightly negatively skewed. Second, the two series differ in terms of excess kurtosis. This has implications on the types of models that best account for the behaviour of the data series under consideration.

Logcorn has the highest kurtosis at 340.1455 while logbov has the least kurtosis which is 7.6195 which implies that the log-return series for U.S. corn has the fattest-tailed distribution. The log-return series of the Bovespa index has the least fat-tailed distribution of all the nine variables under consideration.

Table 6. 3: Monthly data summary of descriptive statistics of stock indices

	BOVESPA	BSESENSEX	JSEFT	RTSI	SSEC
Mean	30699.73	11344.86	20234.27	700.4382	1852.300
Median	22189.00	5622.845	11011.36	506.2850	1669.980
Maximum	87424.00	38645.07	59772.83	2459.880	5954.770
Minimum	0.000000	676.2300	0.000000	0.000000	0.000000
Std. Dev.	25761.71	9906.041	18663.54	654.4061	1103.396
Skewness	0.330095	0.873698	0.672590	0.629727	0.602219
Kurtosis	1.632709	2.557141	2.100348	2.188852	3.370552
Jarque-Bera	33.23524	46.84717	37.75556	32.35371	22.89337
Probability	0.000000	0.000000	0.000000	0.000000	0.000011
Sum	10622106	3925322.	7001058.	242351.6	640895.7
Sum Sq. Dev.	2.29E+11	3.39E+10	1.20E+11	1.48E+08	4.20E+08
Observations	346	346	346	346	346

Source: Researcher Calculations

Table 6.3 shows that the average monthly indices for Bovespa, BSESensex, JSEFT, RTSI and SSEC are 30699.73, 11344.86, 20234.27, 700.4382 and 1852.300 respectively. These average monthly indices for the period January 1990 to October 2018 are comparable to the daily averages for the same variables for the period January 2000 to September 2018 presented on Table 6.1 and explained earlier. Table 6.3 shows that the variables - Bovespa, BSESensex, JSEFT, RTSI and SSEC are not normally distributed as confirmed by the individual Jarque-Bera statistics. Table 6.4 has five output proxies for the BRICS economies. The study analysed the output proxies for Brazil, China, India, Russia and South Africa (SA). Brazil's manufacturing Purchasing Managers

Index (PMI) is coded as brzy, China's Retail Sales index is coded as chretail, India's manufacturing Purchasing Managers Index (PMI) is coded as indiapti, Russia's manufacturing Purchasing Managers Index (PMI) is coded as russiapti. South Africa's output proxy is manufacturing Purchasing Managers Index (PMI) which is coded as samanuf.

Table 6. 4: Descriptive Statistics of Output Proxies

	BRZY	CHRETAIL	INDIAPTI	RUSSIAPTI	SAMANUF
Mean	90.73206	0.122009	56.86330	72.30713	89.56881
Median	92.04510	0.117500	51.57385	79.37430	90.80760
Maximum	115.6069	0.374000	115.0131	108.3042	111.0093
Minimum	0.000000	0.000000	0.000000	0.000000	0.000000
Std. Dev.	15.82367	0.072034	34.65812	29.64366	12.32021
Skewness	-0.584031	0.408420	-0.158266	-1.298774	-2.358232
Kurtosis	4.681615	3.688008	1.944603	4.087267	17.20107
Jarque-Bera	60.43749	16.44340	17.50265	114.3156	3228.113
Probability	0.000000	0.000269	0.000158	0.000000	0.000000
Sum	31393.29	42.21500	19674.70	25018.27	30990.81
Sum Sq. Dev.	86384.09	1.790145	414408.9	303167.6	52366.70
Observations	346	346	346	346	346

Source: Researcher Calculations

The average figures for the output proxies for Brazil, China, India, Russia and South Africa are 90.73, 0.122, 56.86, 72.31 and 89.57 respectively. The statistic for China requires explanation since it uniquely differs from other statistics. The monthly proxy which was chosen for China's output growth is China retail sector growth (chretail). Thus, the average of 0.122 is an average growth rate which is to be distinguished from proxies of the other four members of the BRICS which are indices. The average of 0.122 simply implies that the average growth rate of the retail sector in China was 12.2 percent for the period January 1990 to October 2018. This gives an indication of the fast pace at which China's economy grew between 1990 and 2018.

Table 6.5 shows a summary of monthly statistics for the seven commodity classes. The seven commodity classes are cagric representing the agricultural sector, cbev representing the food and beverages sector, cmetal representing industrial metals, comfuel representing the fuel industry in general, comnonfuel representing the nonfuel sector, crudeoil representing the petroleum or crude oil sector and cindus representing the industrial manufacturing sector.

Table 6. 5: Descriptive statistics of seven commodity classes

	CAGRIC	CBEV	CMETAL	COMFUEL	CINDUS	COMNONFUEL	CRUDEOIL
Mean	74.22509	68.35188	61.49829	61.83225	109.2337	69.99480	47.41038
Median	74.27000	64.37000	49.38000	47.54500	95.20000	60.19000	34.10500
Maximum	134.5600	124.8100	126.2600	173.4300	217.0700	128.5000	132.8300
Minimum	44.88000	34.77000	29.12000	15.93000	64.46000	39.89000	10.41000
Std. Dev.	17.82198	22.17870	27.64380	38.72289	37.57245	23.52135	31.92364
Skewness	0.702428	0.354091	0.646211	0.716358	0.821039	0.633194	0.767544
Kurtosis	3.414993	2.079920	2.074694	2.305131	2.553131	2.186428	2.318400
Jarque-Bera	30.93582	19.43467	36.42437	36.55372	41.75232	32.66294	40.67048
Probability	0.000000	0.000060	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	25681.88	23649.75	21278.41	21393.96	37794.85	24218.20	16403.99
Sum Sq. Dev.	109579.9	169703.7	263642.0	517314.5	487032.7	190872.6	351596.0
Observations	346	346	346	346	346	346	346

Source: Researcher Calculations

Table 6.5 shows that the index of commodities associated with industry (cindus) have the highest average of 109.2337 with the commodity metals sector recording the lowest average for the period under review of 61.498. The average of 47.41 is actually an average price per barrel of crude oil which is properly read as $47.41 for the period January 1990 to October 2018. It is, therefore, not an index, hence its exclusion in a characterisation of indices of different commodity categories. This implies that strictly speaking, Table 6.5 actually depicts six commodity classes, including crude oil because it is an important commodity which directly and indirectly drives activity in virtually all sectors of modern economies. The Jarque-Bera statistics for the seven commodity classes confirm that all the data series are not normally distributed at 5 percent level of significance. All the seven variables are slightly positively skewed with negative excess kurtosis except for cagric representing commodities of the agricultural sector whose excess kurtosis is slightly positive.

6.4 Correlation statistics of the study

The study also involved a computation of different sets of correlation figures which are presented in the tables below, namely, Tables 6.6, 6.7, and 6.8 respectively.

Table 6. 6: Correlation Matrix of Daily Raw Data

	BOVESPA	BSEINDEX	JSEINDEX	RTSI	SHANGINDEX	DOW JONES	USCORN	CRUDEOIL	GOLDAUX
BOVESPA	1.000000 -----								
BSEINDEX	0.722000 [0.0000]	1.000000 -----							
JSEINDEX	0.819256 [0.0000]	0.769968 [0.0000]	1.000000 -----						
RTSI	0.647059 [0.0000]	0.426000 [0.0000]	0.757341 [0.0000]	1.000000 -----					
SHANGINDEX	0.494965 [0.0000]	0.476911 [0.0000]	0.489777 [0.0000]	0.438129 [0.0000]	1.000000 -----				
DOW JONES	0.552990 [0.0000]	0.728215 [0.0000]	0.554777 [0.0000]	0.223491 [0.0000]	0.349179 [0.0000]	1.000000 -----			
USCORN	0.579931 [0.0000]	0.400825 [0.0000]	0.703244 [0.0000]	0.652182 [0.0000]	0.261778 [0.0000]	0.169323 [0.0000]	1.000000 -----		
CRUDEOIL	0.628472 [0.0000]	0.376613 [0.0000]	0.769433 [0.0000]	0.784041 [0.0000]	0.258559 [0.0000]	0.156971 [0.0000]	0.780551 [0.0000]	1.000000 -----	
GOLDAUX	0.751548 [0.0000]	0.718509 [0.0000]	0.873468 [0.0000]	0.595450 [0.0000]	0.346001 [0.0000]	0.467730 [0.0000]	0.824200 [0.0000]	0.686139 [0.0000]	1.000000 -----

KEY: […] shows probability values of the correlation coefficients

Source: Researcher Calculations

Table 6.6 shows that according to raw data, Brazil's Bovespa index is strongly positively correlated with other indices and the three commodities, namely, U.S. corn, crude oil and gold. The correlation coefficients range from the highest of 0.819 between Bovespa and South Africa's JSE index to the lowest of 0.4949 between Bovespa and China's Shanghai index (Shangindex). It is notable that all the variables are strongly positively correlated with each other and all the correlation coefficients are statistically significant.

The BSE Sensex index is also positively correlated with the JSE index, Russia's RTSI, China's Shanghai index (Shangindex), the Dow Jones index, U. S. corn, crudeoil and gold. South Africa's JSE index is also positively correlated with Russia's RTSI, China's Shangindex, Dow Jones, US corn, crude oil and gold with the highest correlation coefficient being between the JSE index and gold (goldaux) which is 0.8735 and the lowest being between the JSE index and Shanghai index (Shangindex) which is 0.4898.

South Africa is the leading producer of gold globally, hence the fact that the highest correlation is naturally between the JSE index and the gold price which is 0.8735. Russia's RTSI is naturally strongly positively correlated with crude oil price with a correlation coefficient of 0.7840 because the Russian economy is a predominantly energy dependent economy.

China's Shanghai index (Shangindex) is moderately positively correlated with the Bovespa index and the JSE index with correlation coefficients of 0.4950 and 0.4898 respectively. Among commodities, the Shanghai index is weakly positively correlated with all the three commodities being analysed. Table 6.7 shows correlation analysis results for log-return data for the nine variables. The correlation coefficients, radically different from those of raw data in that they are generally low, with three correlation between logdow and loggold being negative (-0.022149) and statistically insignificant.

Table 6. 7: Correlation matrix of log-return data

	LOGBOV	LOGBSE	LOGJSE	LOGRTSI	LOGSHANG	LOGDOW	LOGCRUDE	LOGGOLD	LOGCORN
LOGBOV	1.000000 -----								
LOGBSE	0.221448 0.0000	1.000000 -----							
LOGJSE	0.434556 0.0000	0.326231 0.0000	1.000000 -----						
LOGRTSI	0.149985 0.0000	0.160345 0.0000	0.245743 0.0000	1.000000 -----					
LOGSHANG	0.114696 0.0000	0.168846 0.0000	0.152963 0.0000	0.061744 0.0000	1.000000 -----				
LOGDOW	0.557558 0.0000	0.191733 0.0000	0.372897 0.0000	0.102692 0.0000	0.051324 0.0003	1.000000 -----			
LOGCRUDE	0.215509 0.0000	0.111425 0.0000	0.280763 0.0000	0.072476 0.0000	0.064739 0.0000	0.177889 0.0000	1.000000 -----		
LOGGOLD	0.104199 0.0000	0.052673 0.0002	0.235091 0.0000	0.023488 0.1008	0.038758 0.0068	-0.022149 0.1218	0.216722 0.0000	1.000000 -----	
LOGCORN	0.085667 0.0000	0.035395 0.0134	0.116785 0.0000	0.044490 0.0019	0.020499 0.1521	0.076171 0.0000	0.148827 0.0000	0.134090 0.0000	1.000000 -----

Source: Researcher Calculations

The correlation coefficients between logshang and logcorn; and logrtsi and loggold are also statistically insignificant as shown in Table 6.7.

Table 6. 8: Correlation Matrix of Monthly Data

	BOVESPA	BRZOUTPUT	BSESENSEX	INDIAPTI	JSEFT	SAMANUF	SSEC	CHRETAILGR	RTSI	RUSSIAPTI
BOVESPA	1.000000 -----									
BRZOUTPUT	0.790939 [0.0000]	1.000000 -----								
BSESENSEX	0.909774 [0.0000]	0.616649 [0.0000]	1.000000 -----							
INDIAPTI	0.876688 [0.0000]	0.844562 [0.0000]	0.827650 [0.0000]	1.000000 -----						
JSEFT	0.903894 [0.0000]	0.675829 [0.0000]	0.979778 [0.0000]	0.880490 [0.0000]	1.000000 -----					
SAMANUF	0.604693 [0.0000]	0.814195 [0.0000]	0.511986 [0.0000]	0.803558 [0.0000]	0.596667 [0.0000]	1.000000 -----				
SSEC	0.840346 [0.0000]	0.694811 [0.0000]	0.779840 [0.0000]	0.794044 [0.0000]	0.785331 [0.0000]	0.619505 [0.0000]	1.000000 -----			
CHRETAILGR	0.153382 [0.0042]	0.272898 [0.0000]	0.047016 [0.3833]	0.175328 [0.0011]	0.027693 [0.6077]	0.185897 [0.0005]	0.156195 [0.0036]	1.000000 -----		
RTSI	0.164888 [0.0021]	0.375339 [0.0000]	-0.117549 [0.0288]	0.194524 [0.0003]	-0.057905 [0.2828]	0.349430 [0.0000]	0.319366 [0.0000]	0.125574 [0.0195]	1.000000 -----	
RUSSIAPTI	0.748224 [0.0000]	0.787823 [0.0000]	0.704075 [0.0000]	0.833382 [0.0000]	0.740409 [0.0000]	0.697169 [0.0000]	0.729052 [0.0000]	0.470856 [0.0000]	0.240668 [0.0000]	1.000000 -----

Key - […] probability value of the correlation coefficient

Source: Researcher Calculations

Table 6.8 shows that there is strong statistically significant positive correlation among all the variables analysed for monthly data. The correlation coefficients were very high especially between Brazil's Bovespa and India's BSE Sensex (0.9098), Bovespa and South Africa's JSE index (0.90389), Bovespa and China's SSEC index (0.84035), JSE index and BSE Sensex (0.9797), JSE index and India's output proxy (Indiapti) with a correlation coefficient of 0.8805 as well as India's index and output proxy (Indiapti) whose correlation coefficient is 0.8277.

6.5 Unit Root Test Results

This section presents unit root test results. The study used the Augmented Dickey Fuller (ADF) and the Phillips-Perron unit root test procedures to discern the stationarity levels of the variables of the study. Since the study used both daily and monthly data, the results presented are for daily and monthly data.

Table 6. 9: Unit Root Test Results for Raw Daily Data

Test / Variable	Augmented Dickey Fuller (ADF) Test		Phillips-Perron Test	
	At level	1st difference	At level	1st difference
bovespa	-2.715779 [0.2301]	-23.21674** [0.0000]	-84.5115* [0.0001]	*No need to test*
bseindex	-4.183906* [0.0047]	*No need to test*	-96.57098* [0.0001]	*No need to test*
jseindex	-2.654383 [0.2560]	-33.49941** [0.0000]	-10.77318* [0.0000]	*No need to test*
rtsi	-3.672602* [0.0242]	*No need to test*	-14.76735* [0.0000]	*No need to test*
shangindex	-4.207711* [0.0006]	*No need to test*	-31.14871* [0.0000]	*No need to test*
Dow Jones	-1.691580 [0.7552]	-25.53256** [0.0000]	-96.99481* [0.0001]	*No need to test*
crudeoil	-1.963828 [0.6203]	-54.09092** [0.0000]	-1.959766 [0.6225]	-77.60440** [0.0001]

uscorn	-2.021130 [0.5890]	-79.38014** [0.0001]	-1.998566 [0.6014]	-79.51824** [0.0001]
goldaux	-1.226954 [0.9041]	-69.75658** [0.0000]	-1.223011 [0.9049]	-69.75658** [0.0000]

Key - * significant at level, ** significant after 1st differencing & […] probability value of the t-statistic

Source: Researcher Calculations

Table 6.9 shows that according to the ADF test Bovespa is stationary after first differencing while the Phillips-Perron (PP) test indicates that the index series is stationary at level. Both the ADF and the PP tests concur that the BSE Sensex index, RTSI, Shangai index series are stationary at level. The ADF test indicates that the JSE and Dow Jones indices are stationary after first differencing while the PP test shows that the indices are stationary at level. Finally, both the ADF unit root test and the PP test show that the commodity price series included in the study, namely, gold, U.S. corn and crude oil price series are all stationary after first differencing.

The results below are for daily log-return data for all the nine variables that were analysed in the current study.

Table 6. 10: Unit Root Test Results for Log-Return Data

Test / Variable	Augmented Dickey Fuller (ADF) Test		Phillips-Perron Test	
	At level	1st difference	At level	1st difference
logbov	-70.21385* [0.0001]	*No need to test*	-70.37685* [0.0001]	*No need to test*
logbse	-64.78064* [0.0001]	*No need to test*	-64.69226* [0.0001]	*No need to test*
logjse	-67.64145* [0.0001]	*No need to test*	-67.70613* [0.0001]	*No need to test*
longrtsi	-53.79880* [0.0001]	*No need to test*	-69.17002 [0.0001]	*No need to test*

logshang	-68.75279* [0.0001]	*No need to test*	-68.80801* [0.0001]	*No need to test*
logdow	-54.28583* [0.0001]	*No need to test*	-75.01739* [0.0001]	*No need to test*
logcrude	-72.06543* [0.0001]	*No need to test*	-72.12409* [0.0001]	*No need to test*
logcorn	-56.28493* [0.0001]	*No need to test*	-85.50798* [0.0001]	*No need to test*
loggold	-71.04956* [0.0001]	*No need to test*	-71.05063* [0.0001]	*No need to test*

Key - * significant at level; […] probability value of the t-statistic

Source: Researcher Calculations

Table 6.10 shows that as per *a priori* expectations all the log-return series of the nine variables of the study are stationary at level. This makes log-return series of the study variables more attractive than raw data for modelling, simulation and forecasting purposes (Akpan and Moffat, 2017; Ahmed and Suliman, 2011; Minovic, 2008). These unit root test results partly created the basis for GARCH modelling, including Dynamic Conditional Correlation (DCC) GARCH modelling as well as spectral density analysis that were conducted for the purposes of the study.

Table 6.11 displays unit root test results for monthly data which was also relied upon to provide illumination on the main study hypotheses and research objectives. The unit root test results for monthly data are akin to those of daily data in the sense that both the Augmented Dickey Fuller (ADF) and the Phillips-Perron tests were utilized to derive a clear picture of the stationarity of the variables of the study.

Table 6. 11: ADF and PP tests for unit root – monthly data

Test / Variable	Augmented Dickey Fuller (ADF) Test			Phillips-Perron Test	
	At level	1st difference	2nd difference	At level	1st difference
bovespa	-2.650009 [0.2585]	-16.01232** [0.0000]	*No need to test*	-2.598747 [0.2812]	-15.84627** [0.0000]
brzy	1.516981 [1.0000]	-3.201299 [0.0859]	-6.417265*** [0.0000]	1.078430 [0.9999]	-7.897525** [0.0000]
bsesensex	-1.559322 [0.8069]	-18.134** [0.0000]	*No need to test*	-1.55932 [0.8069]	-18.13415** [0.0000]
indiapti	-0.437518 [0.9859]	-18.60236** [0.0000]	*No need to test*	-0.448027 [0.9854]	-18.60346** [0.0000]
ssec	-18.10713* [0.0000]	*No need to test*	*No need to test*	-3.73874* [0.0211]	*No need to test*
chretail	-32.00496* [0.0000]	*No need to test*	*No need to test*	-5.23027* [0.0001]	*No need to test*
russiapti	-1.587963 [0.7961]	-11.11712** [0.0000]	*No need to test*	-1.672288 [0.7616]	-11.11633** [0.0000]
jseft	-2.198012 [0.4887]	-20.22348** [0.0000]	*No need to test*	-2.141625 [0.5202]	-20.22124** [0.0000]
samanuf	-0.480356 [0.9841]	-19.45460** [0.0000]	*No need to test*	-0.253544 [0.9916]	-19.45486** [0.0000]
cagric	-2.139646 [0.5213]	-8.746750** [0.0000]	*No need to test*	-1.817841 [0.6942]	-12.62523** [0.0000]
cbev	-2.318972 [0.4220]	-14.44217** [0.0000]	*No need to test*	-1.954009 [0.6237]	-14.36986** [0.0000]
cmetal	-2.502544 [0.3268]	-12.72407** [0.0000]	*No need to test*	-2.396571 [0.3807]	-12.84309** [0.0000]
comfuel	-2.866248 [0.1750]	-11.79535** [0.0000]	*No need to test*	-2.573238 [0.2930]	-11.83513** [0.0000]
cindus	-1.861884 [0.6720]	-12.93259** [0.0000]	*No need to test*	-1.906596 [0.6489]	-13.25619** [0.0000]

comnonfuel	-2.478490 [0.3387]	-11.20731** [0.0000]	*No need to test*	-1.956960 [0.6222]	-11.44222** [0.0000]
crudeoil	-3.016731 [0.1291]	-11.79993** [0.0000]	*No need to test*	-2.282234 [0.4421]	-11.34307** [0.0000]

Key - * significant at level, ** significant after 1st differencing and * significant after 2nd differencing; […] probability value of the t-statistic**

Source: Researcher Calculations

Table 6.11 shows that virtually all the 16 variables whose monthly data series are being analysed are integrated of order 1, that is, I (1). This means that virtually all the 16 variables are stationary after first differencing. There is, by and large, an agreement between the Augmented Dickey-Fuller test and the Phillips-Perron test. The only exception is Brazil's proxy for national output (brzy) which according to the ADF test becomes stationary after 2nd differencing though the Phillips-Perron test shows that the variable is stationary after 1st differencing.

The next section presents and briefly explains the results of cointegration tests that were conducted as part of this study. This study used the Johansen cointegration test procedure to discern the long-run association or relationship among the variables in both the daily and monthly data series. This test is important for vector autoregressive modelling, structural vector autoregressive modelling, impulse response analysis and the fitting of various self-exciting models that have been developed by researchers over the years and are documented in many econometric journal articles, books and university modules.

6.6 Johansen cointegration test results

This section presents and explains results of the Johansen cointegration test procedure. The test for long-run association among economic and financial variables is an important step in coming up with a robust econometric model.

Table 6. 12: Johansen cointegration test results – daily data

Data series: Bovespa, BseIndex, JSEIndex, RTSI, Shangindex, Dow Jones, UScorn, Crudeoil, Goldaux

Lag interval (in first differences): 1 to 4

	Trace Test			Maximum Eigenvalue Test		
Hypothesised Number of C.E.'s	**Eigenvalue**	**Trace Statistic**	**Prob. Value**	**Eigenvalue**	**Maximum Eigenvalue**	**Prob. Value**
*None**	0.119769	1720.843	1.0000	0.119769	622.1627*	0.0001
*At most 1**	0.090905	1098.680*	0.0001	0.090905	464.8056*	0.0001
*At most 2**	0.050009	633.8747*	0.0001	0.050009	250.2034*	0.0000
*At most 3**	0.036476	383.6714*	0.0001	0.036476	181.2170*	0.0001
*At most 4**	0.027752	202.4543*	0.0000	0.027752	137.2595*	0.0000
*At most 5**	0.009746	65.19483*	0.0005	0.009746	47.76565*	0.0000
At most 6	0.001968	17.42918	0.6083	0.001968	9.608445	0.7805
At most 7	0.001278	7.820734	0.4847	0.001278	6.236726	0.5830
At most 8	0.000325	1.584008	0.2082	0.000325	1.584008	0.2082

Source: Researcher Calculations

Table 6.12 shows that both the Trace and maximum eigenvalue tests confirm the existence of 6 cointegrating equations. This implies that there is long-run association among stock indices and the three commodity price series.

Table 6. 13: Johansen cointegration test results – log-returns

Data series: logbov logbse logrtsi logshang logjse logdow logcorn loggold logcrude

Lag interval (in first differences): 1 to 4

	Trace Test			Maximum Eigenvalue Test		
Hypothesised Number of C.E.'s	**Eigenvalue**	**Trace Statistic**	**Prob. Value**	**Eigenvalue**	**Maximum Eigenvalue**	**Prob. Value**
*None**	0.217084	8661.814	0.0000	0.217084	1193.548	1.0000
*At most 1**	0.206747	7468.265	0.0000	0.206747	1129.577	1.0000
*At most 2**	0.195275	6338.689	1.0000	0.195275	1059.552	0.0001
*At most 3**	0.183474	5279.137	1.0000	0.183474	988.5515	0.0001
*At most 4**	0.177014	4290.585	1.0000	0.177014	950.1155	0.0001
*At most 5**	0.169778	3340.470	0.0000	0.169778	907.4222	0.0001
*At most 6**	0.161702	2433.048	1.0000	0.161702	860.2123	0.0001

*At most 7**	0.152942	1572.835	1.0000		0.152942	809.5119	0.0001
*At most 8**	0.144881	763.3234	0.0001		0.144881	763.3234	0.0001

Source: Researcher Calculations

Table 6.13 shows that there are nine cointegrating equations. Both the trace test and the maximum eigenvalue test confirm that the long run association between the logarithmic variables can be captured by 9 cointegrating equations. This implies that when it comes to vector autoregressive modelling, the most appropriate technique is the vector error correction modelling.

Table 6. 14: Johansen cointegration test results – monthly data

Data Series: bovespa, brzy, bsesensex, indiapti, rtsi, russiapti, jseft, samanuf, ssec and chretail

	Trace Test				Maximum Eigenvalue Test		
Hypothesised Number of C.E.'s	**Eigenvalue**	**Trace Statistic**	**Prob. Value**		**Eigenvalue**	**Maximum Eigenvalue**	**Prob. Value**
*None**	0.190666	276.3867*	0.0003		0.190666	72.13629*	0.0080
*At most 1**	0.149796	204.2504*	0.0218		0.149796	55.33709	0.0980
At most 2	0.104059	148.9133	0.1631		0.104059	32.41532	0.6302
At most 3	0.090681	111.4440	0.2625		0.090681	24.06397	0.8227
At most 5	0.055761	54.96468	0.4205		0.055761	19.56526	0.7860
At most 6	0.040064	35.39942	0.4271		0.040064	13.94298	0.8266
At most 7	0.034436	21.45643	0.3298		0.034436	11.94947	0.5527
At most 8	0.027181	9.506961	0.3206		0.027181	9.397187	0.2546
At most 9	0.000322	0.109773	0.7404		0.000322	0.109773	0.7404

Source: Researcher Calculations

In Table 6.14, the unrestricted cointegration rank test (trace) shows that there are two cointegrating equations at 0.05 level of significance. On the other hand, the maximum eigenvalue test shows that there is one cointegrating equation.

It is not sufficient to deduce whether there is long-run association among variables of study or not. It also important to statistically test the direction of causality among economic variables. The present study used the Granger causality test procedure to discern the direction of causality among variables.

6.7 Granger Causality in the Time Domain – daily log-return data

Section 6.7 of the chapter presents results of causality test results in both the time domain and the frequency domain. The results of time domain Granger causality test results are shown in Tables 6.15.

Table 6. 15: Granger causality test results – daily log-return data

Null Hypothesis	Observations	F-Statistic	Prob. Value	Decision
LOGBSE does not Granger Cause LOGBOV	4880	2.58570	0.0754	*1-way causality*
LOGBOV does not Granger Cause LOGBSE		56.3827	6.E-25	
LOGRTSI does not Granger Cause LOGBOV	4880	1.01744	0.3616	*1-way causality*
LOGBOV does not Granger Cause LOGRTSI		57.4626	2.E-25	
LOGSHANG does not Granger Cause LOGBOV	4880	0.30428	0.7377	*1-way causality*
LOGBOV does not Granger Cause LOGSHANG		20.2710	2.E-09	
LOGJSE does not Granger Cause LOGBOV		3.26320	0.0383	*2-way causality*
LOGBOV does not Granger Cause LOGJSE	4880	141.160	3.E-60	
LOGDOW does not Granger Cause LOGBOV	4880	2.82195	0.0596	*No causality*
LOGBOV does not Granger Cause LOGDOW		0.89018	0.4106	
LOGCORN does not Granger Cause LOGBOV	4880	1.18993	0.3043	*No causality*
LOGBOV does not Granger Cause LOGCORN		1.55770	0.2107	
LOGGOLD does not Granger Cause LOGBOV	4880	1.31263	0.2692	*No causality*
LOGBOV does not Granger Cause LOGGOLD		13.1892	2.E-06	
LOGCRUDE does not Granger Cause LOGBOV	4880	0.35022	0.7046	*1-way causality*
LOGBOV does not Granger Cause LOGCRUDE		5.97694	0.0026	
LOGRTSI does not Granger Cause LOGBSE	4880	1.76059	0.1721	*No causality*
LOGBSE does not Granger Cause LOGRTSI		2.41768	0.0892	
LOGSHANG does not Granger Cause LOGBSE	4880	5.75019	0.0032	*2-way causality*
LOGBSE does not Granger Cause LOGSHANG		6.85852	0.0011	

LOGJSE does not Granger Cause LOGBSE	4880	31.3302	3.E-14	*1-way causality*
LOGBSE does not Granger Cause LOGJSE		1.30795	0.2705	
LOGDOW does not Granger Cause LOGBSE	4880	69.9593	1.E-30	*1-way causality*
LOGBSE does not Granger Cause LOGDOW		0.24512	0.7826	
LOGCORN does not Granger Cause LOGBSE	4880	1.03946	0.3537	*No causality*
LOGBSE does not Granger Cause LOGCORN		2.10525	0.1219	
LOGGOLD does not Granger Cause LOGBSE	4880	1.38729	0.2498	*No causality*
LOGBSE does not Granger Cause LOGGOLD		1.28683	0.2762	
LOGCRUDE does not Granger Cause LOGBSE	4880	0.15071	0.8601	*No causality*
LOGBSE does not Granger Cause LOGCRUDE		1.68000	0.1865	
LOGSHANG does not Granger Cause LOGRTSI	4880	0.90252	0.4056	*No causality*
LOGRTSI does not Granger Cause LOGSHANG		2.99282	0.0502	
LOGJSE does not Granger Cause LOGRTSI	4880	10.7864	2.E-05	*1-way causality*
LOGRTSI does not Granger Cause LOGJSE		1.07583	0.3411	
LOGDOW does not Granger Cause LOGRTSI	4880	51.2087	1.E-22	*1-way causality*
LOGRTSI does not Granger Cause LOGDOW		0.91580	0.4003	
LOGCORN does not Granger Cause LOGRTSI	4880	3.10770	0.0448	*1-way causality*
LOGRTSI does not Granger Cause LOGCORN		0.97544	0.3771	
LOGGOLD does not Granger Cause LOGRTSI	4880	6.55784	0.0014	*1-way causality*
LOGRTSI does not Granger Cause LOGGOLD		0.25181	0.7774	
LOGCRUDE does not Granger Cause LOGRTSI	4880	16.7432	6.E-08	*1-way causality*
LOGRTSI does not Granger Cause LOGCRUDE		1.06949	0.3433	
LOGJSE does not Granger Cause LOGSHANG	4880	29.9351	1.E-13	*1-way causality*
LOGSHANG does not Granger Cause LOGJSE		2.31664	0.0987	
LOGDOW does not Granger Cause LOGSHANG	4880	35.5285	5.E-16	*1-way causality*
LOGSHANG does not Granger Cause LOGDOW		0.33643	0.7143	
LOGCORN does not Granger Cause LOGSHANG	4880	1.16742	0.3113	*No causality*

LOGSHANG does not Granger Cause LOGCORN		0.15160	0.8593	
LOGGOLD does not Granger Cause LOGSHANG LOGSHANG does not Granger Cause LOGGOLD	4880	0.05504 2.94258	0.9464 0.0528	*No causality*
LOGCRUDE does not Granger Cause LOGSHANG LOGSHANG does not Granger Cause LOGCRUDE	4880	5.68241 0.12528	0.0034 0.8823	*1-way causality*
LOGDOW does not Granger Cause LOGJSE LOGJSE does not Granger Cause LOGDOW	4880	231.457 4.14265	9.E-97 0.0159	*2-way causality*
LOGCORN does not Granger Cause LOGJSE LOGJSE does not Granger Cause LOGCORN	4880	3.10588 0.71286	0.0449 0.4903	*1-way causality*
LOGGOLD does not Granger Cause LOGJSE LOGJSE does not Granger Cause LOGGOLD	4880	14.1984 1.60186	7.E-07 0.2016	*1-way causality*
LOGCRUDE does not Granger Cause LOGJSE LOGJSE does not Granger Cause LOGCRUDE	4880	7.12589 0.38316	0.0008 0.6817	*1-way causality*
LOGCORN does not Granger Cause LOGDOW LOGDOW does not Granger Cause LOGCORN	4880	1.05950 1.82941	0.3467 0.1606	*No causality*
LOGGOLD does not Granger Cause LOGDOW LOGDOW does not Granger Cause LOGGOLD	4880	3.35163 6.54503	0.0351 0.0014	*2-way causality*
LOGCRUDE does not Granger Cause LOGDOW LOGDOW does not Granger Cause LOGCRUDE	4880	1.47565 7.73243	0.2287 0.0004	*1-way causality*
LOGGOLD does not Granger Cause LOGCORN LOGCORN does not Granger Cause LOGGOLD	4880	4.33672 1.40621	0.0131 0.2452	*1-way causality*
LOGCRUDE does not Granger Cause LOGCORN LOGCORN does not Granger Cause LOGCRUDE	4880	0.70428 0.57552	0.4945 0.5624	*No causality*
LOGCRUDE does not Granger Cause LOGGOLD LOGGOLD does not Granger Cause LOGCRUDE	4880	1.46089 0.39520	0.2321 0.6736	*No causality*

Source: Researcher Calculations

Table 6.15 presents a summary of the Granger causality test results for daily log-return data used in the current study. Table 6.15 shows that there is two-way causation between logbse and logbov, logrtsi and logbov, logshang and logbov, logbov and logjse, logshang and logbse, logdow and logjse, loggold and logdow. The foregoing means that the log-returns of stock indices of India and Brazil, Russia and Brazil, China and Brazil, Brazil and South Africa, the United States (US) and South Africa Granger-cause variations or changes in each other and the scheme of causality is two-way. It is also of interest to note that there is two-way causality between gold log-returns and the log-returns of the Dow Jones industrial average.

It is also important to observe that log-returns of Bovespa index Granger-cause variations in the log-returns of West Texas Intermediate but the opposite is not the case, the log-returns of JSE index Granger-cause changes on those of the BSE Sensex index but the reverse is not the case and that Dow's log-returns Granger-cause changes in the log-returns of India's BSE Sensex index but the opposite is not the case. Other instances of one-way causality are – from log-returns of JSE index to Russia's RTSI index, from log-returns of Dow Jones index to Russia's RTSI, from the log-returns of United States corn to Russia's RTSI and the log-returns of gold to Russia's RTSI. This signifies that the variations in the log-returns of Russia's Trading System Index (RTSI) are affected by changes in the prices of U.S. corn and gold as well as the Johannesburg Stock Exchange (JSE) and Dow Jones indices.

It is imperative to also note that variations in log-returns of the Shanghai composite index are Granger-caused by changes in the Dow Jones industrial average and the WTI crude oil price variations.

6.8 Spectral causality test results of daily log-returns

The main advantage of spectral causality tests is that instead of yielding a single set of statistics for the entire series, the analysis is dynamic in that it assesses causality at different frequencies, that is, for different scales representing points in the time domain. Thus, the measure of causality is not static but changes as frequencies associated with the autoregressive and filtering processes of the original data change. This enables the researcher to fully understand the behaviour and power of the frequency causality from one variable to another variable from a signal perspective, with the entire series viewed as a spectrum (Sadoon, 2017; Renaud, 2015; Foresti, 2006).

Figures 6.4 to 6.9 show results of frequency domain Granger causality tests conducted on the main variables of the study in order to address the main objectives and hypotheses of the present study. Frequency domain causality tests are also known as spectral causality tests (Lin, 2008; Granger, 1969).

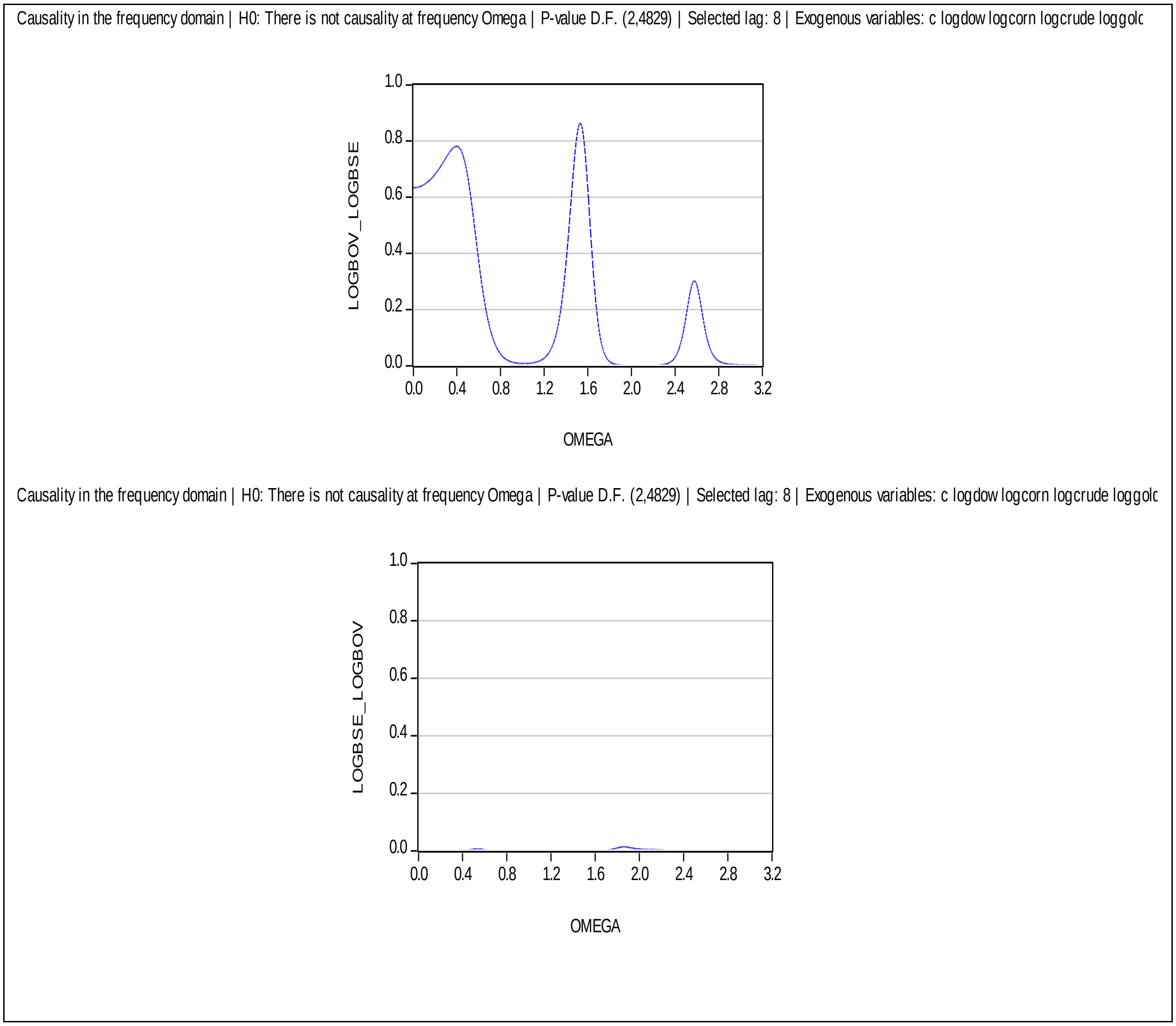


Figure 6. 4: LOGBSE versus LOGBOV,

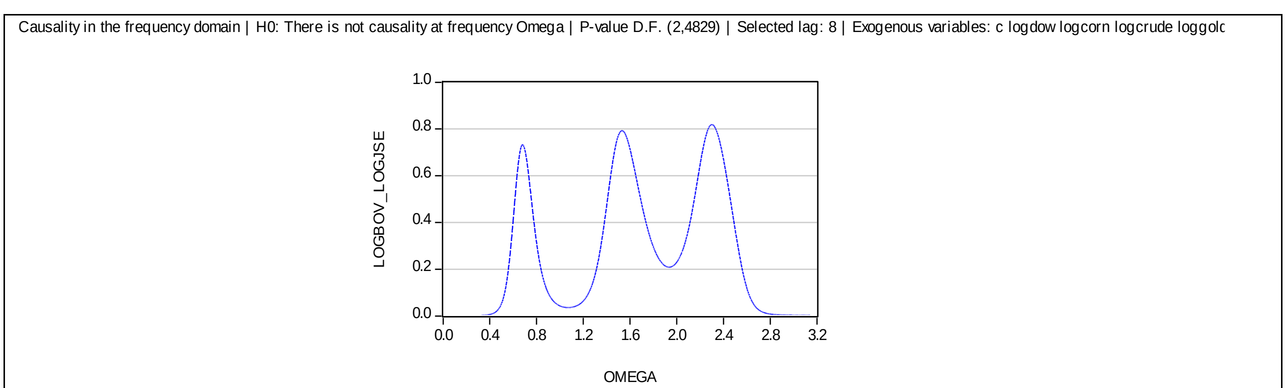
Source: Researcher Compilation

The top panel of Figure 6.4 corresponds to the hypothesis that the log-returns of the BSE Sensex index do not cause the log-returns of the Bovespa index at frequency omega. It can be readily observed that the BSE Sensex index does not Granger cause the Bovespa within the frequency range of 0.001287 to approximately 0.78 which corresponds to a cycle with a frequency of 4 days to 1220 days. The angular frequency range translates to the first three years of the series when analysed in the time domain. In other words, the BSE index does not Granger cause the Bovespa index for the first oscillation of the business cycle which endures from 2000 to 2003. This finding harmonizes with the finding of Granger causality in the time which retained the null hypothesis that the logBSE index does not Granger cause logBov index, that is, the daily log returns of the BSE Sensex index do not Granger cause the daily log returns of the Bovespa index.

In contrast to the results of static time domain Granger causality test results, spectral causality tests indicate that between the frequencies of 0.7851 and 1.2484, the BSE Sensex index Granger causes the Bovespa index. This signals that for the next two years from 2003 to 2005, the direction of causality changes from no causality to causality between the two variables. Thus, the oscillations of the business cycle are revealed not to be even by spectral causality test results.

The bottom panel of Figure 6.4 shows that the LOGBOV Granger causes LOGBSE at all frequencies which implies that the daily log-returns of the Bovespa index Granger cause the daily log-returns of the BSE Sensex index. This finding harmonizes with the main finding of Granger causality tests in the time domain which indicated that LOGBOV Granger causes LOGBSE. The implication is that, LOGBOV causes changes in LOGBSE in the short, medium and long terms. This has implications for investor decisions and portfolio allocation decisions (Bonga-Bonga, 2015).

Figure 6.5 shows the results of spectral causality tests between LOGBOV and LOGJSE.



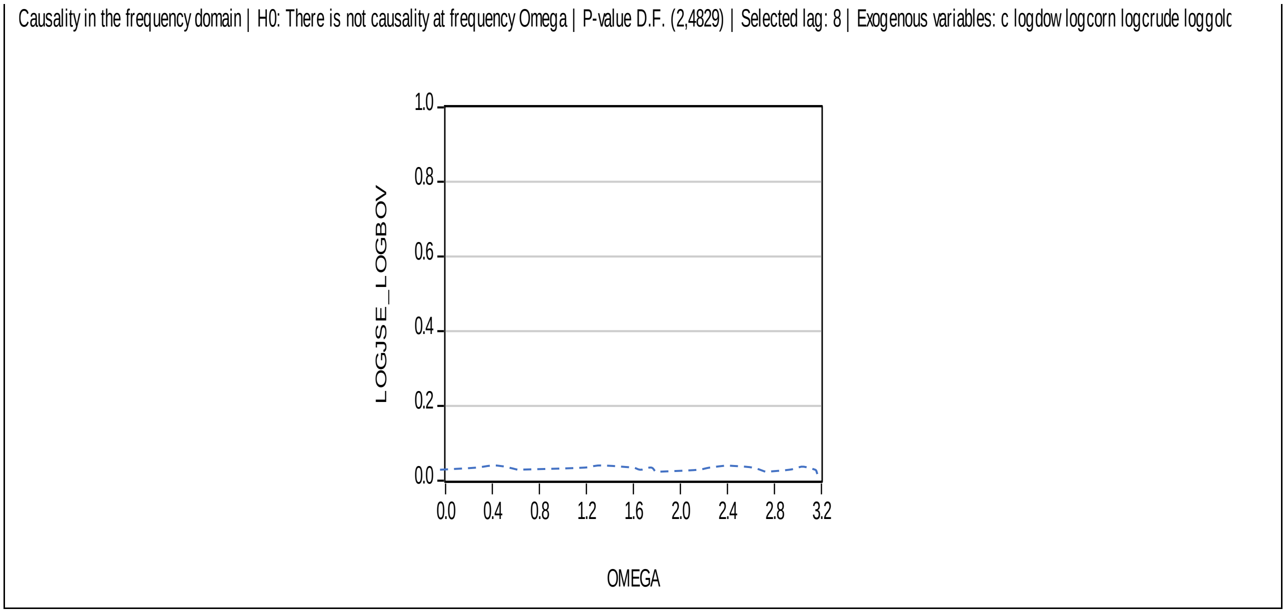


Figure 6. 5: LOGBOV versus LOGJSE,

Source: Researcher Compilation

The top panel of Figure 6.5 shows that log-returns of the JSE index Granger cause the log-returns of the Bovespa index for the frequency range of 0.00 to 0.4 which corresponds to the first two years of the data series, that is, from 2000 to 2001. The same panel shows that from the beginning of 2002 to approximately the beginning of 2004, LOGJSE does not Granger-cause LOGBOV. This apparently implies that cycles of causality alternate with non-causality between the daily log-returns of the two indices last two years. This is an interesting finding which contrasts with the main finding of Granger causality tests in the time domain which is that there is two-way causation between two variables. The single Granger-causality statistic for the whole series in favour of causality from LOGJSE to LOGBOV (and vice versa) hides the fact that in some frequency scales of the two series, LOGJSE actually does not Granger-cause LOGBOV.

The bottom panel of Figure 6.5 shows that for all frequency scales, LOGBOV Granger causes LOGJSE. In the bottom panel the spectral causality graph is almost resting on the horizontal axis which shows that logbov Granger-causes logjse for all angular frequencies. This confirms the result of Granger causality tests in the time domain.

Figure 6.6 displays spectral causality test results from LOGBOV to LOGRTSI and vice versa.

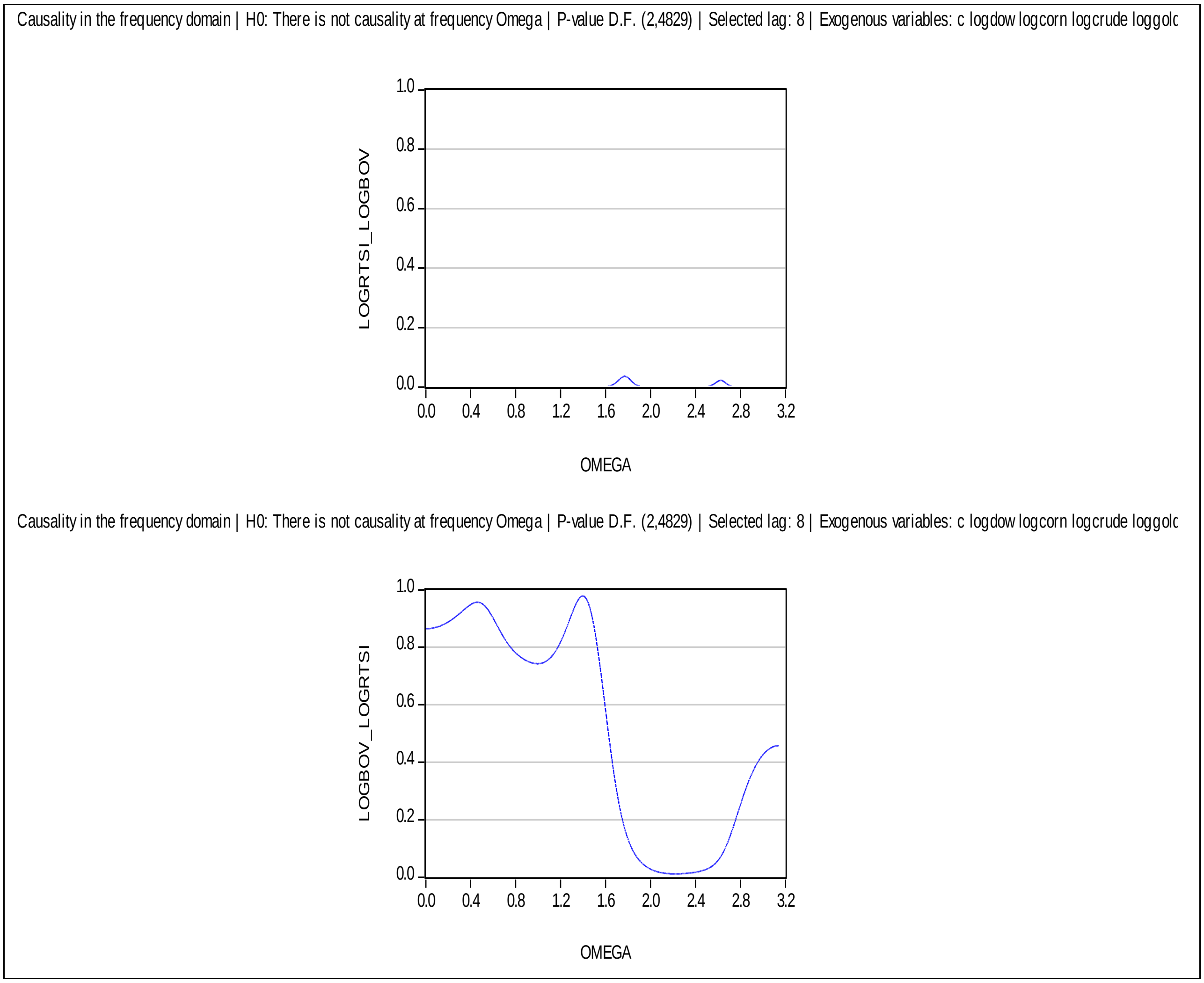


Figure 6. 6: LOGBOV versus LOGRTSI,

Source: Researcher Compilation

The top panel of Figure 6.6 shows that Brazil's Bovespa index Granger causes Russia's RTSI index for all frequencies which harmonizes with findings of causality tests in the time domain. In contrast, the bottom panel shows that LOGRTSI does not Granger cause LOGBOV for most of the angular frequencies of the data series, save for the frequency range of 1.92 to 2.58 which corresponds to a duration of approximately three years of the record of the study. This implies that from a frequency domain perspective, Russia's RTSI index Granger causes Brazil's Bovespa for the approximate period 2008-2011 viewed from a time domain perspective. This post-global financial crisis causality from LOGRTSI to LOGBOV is quite instructive. This may imply volatility transmission from Russia's stock market to Brazil stock market which is discussed in more detail in chapter 7 which presents and discusses the empirical results of Dynamic Conditional Correlation (DCC) GARCH analysis.

Figure 6.7 depicts the results of the spectral causality test from Brazil's Bovespa index (LOGBOV) to China's Shanghai index (LOGSHANG) and vice versa.

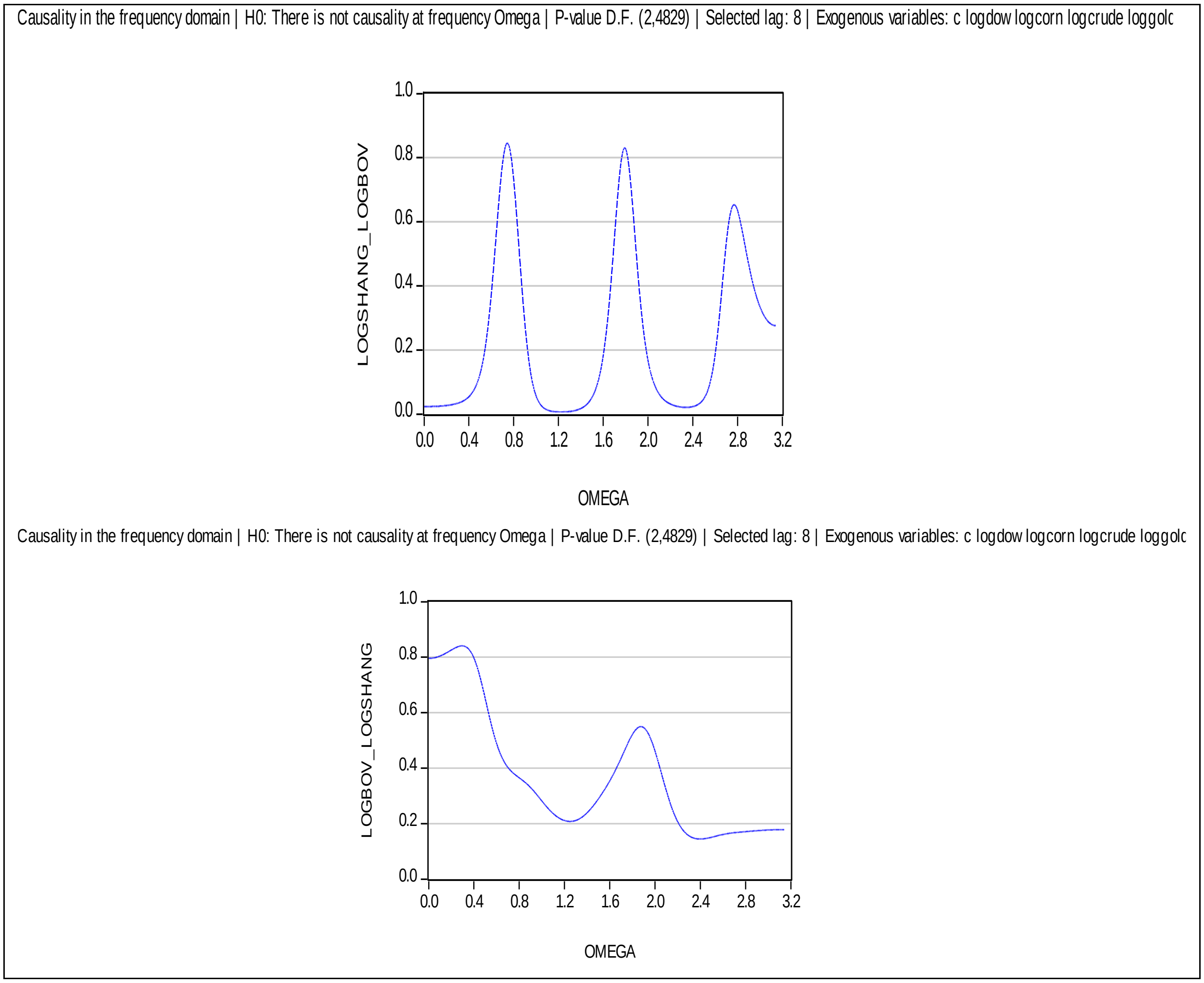


Figure 6. 7: LOGBOV versus LOGSHANG,

Source: Researcher Compilation

The top panel of Figure 6.7 shows that Brazil's LOGBOV Granger causes China's LOGSHANG in cycles of two years which are interspaced by non-causality which lasts more than two years but less than three years. Non-causality of LOGBOV to LOGSHANG is within frequency ranges of 0.387-1.0064 (which corresponds to just above 2 years) and 1.98-2.12 (which corresponds to 2 and ½ years). Data analysis results indicate that

Brazil's LOGBOV does not Granger cause China's LOGSHANG within the frequency range 0.00-0.5907 (which corresponds to the period 2000 to mid-2001). Spectral analysis results confirm the results of time domain Granger causality tests which revealed that there is no causality running from LOGSHANG to LOGBOV.

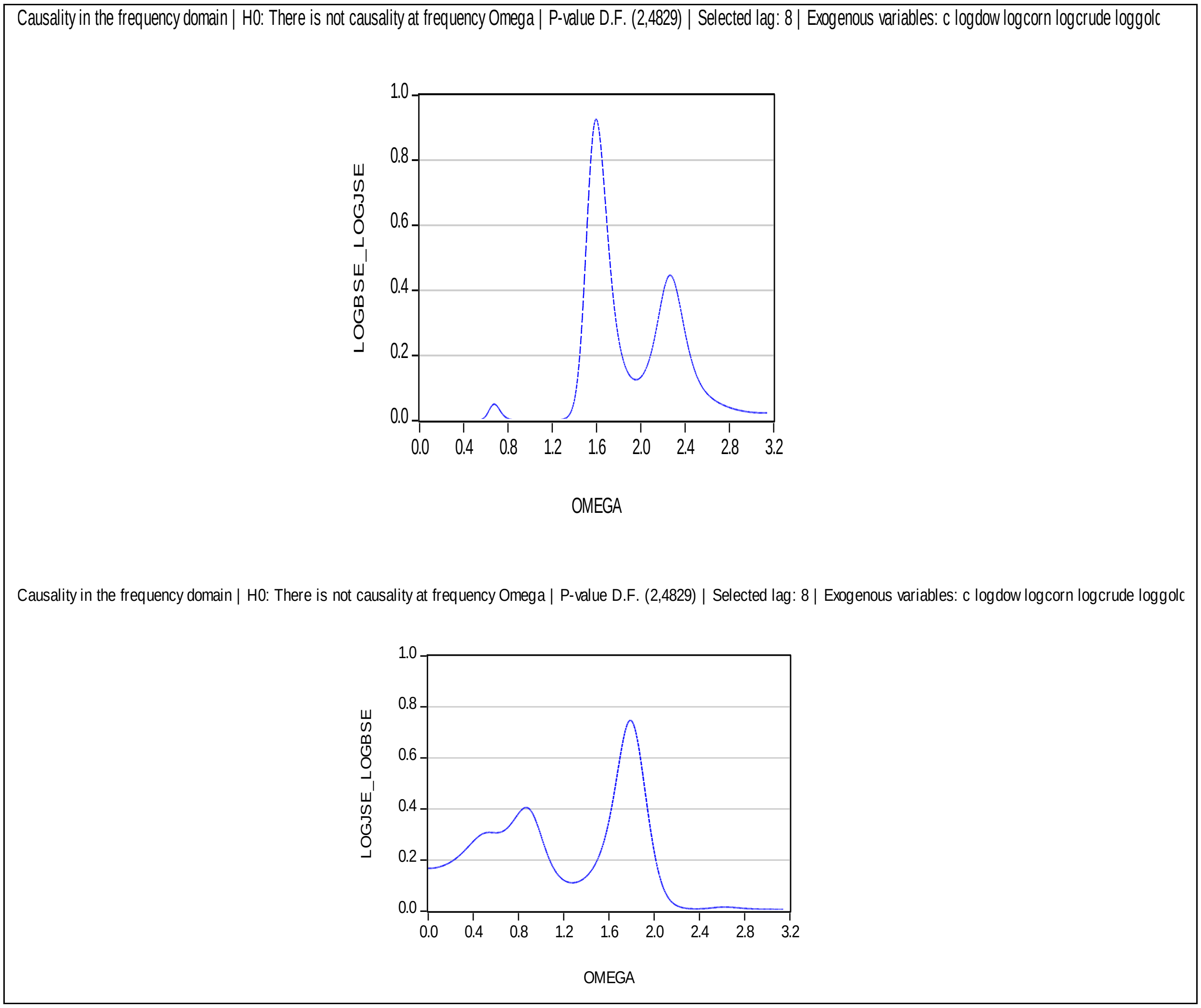


Figure 6. 8: LOGJSE versus LOGBSE,

Source: Researcher Compilation

The top panel of Figure 6.8 shows that South Africa's LOGJSE Granger causes India's LOGBSE within the frequency range of 0.00-1.3913 which corresponds to the period 2000-2006. This confirms earlier findings of time domain analysis that LOGJSE Granger causes LOGBSE though post 2006, according to spectral analysis there is no causality between the two variables up to mid-2011.

The bottom panel shows that LOGBSE does not Granger cause LOGJSE for frequency range 0.00-2.1274 which corresponds to the period 2000-2009 in the time domain.

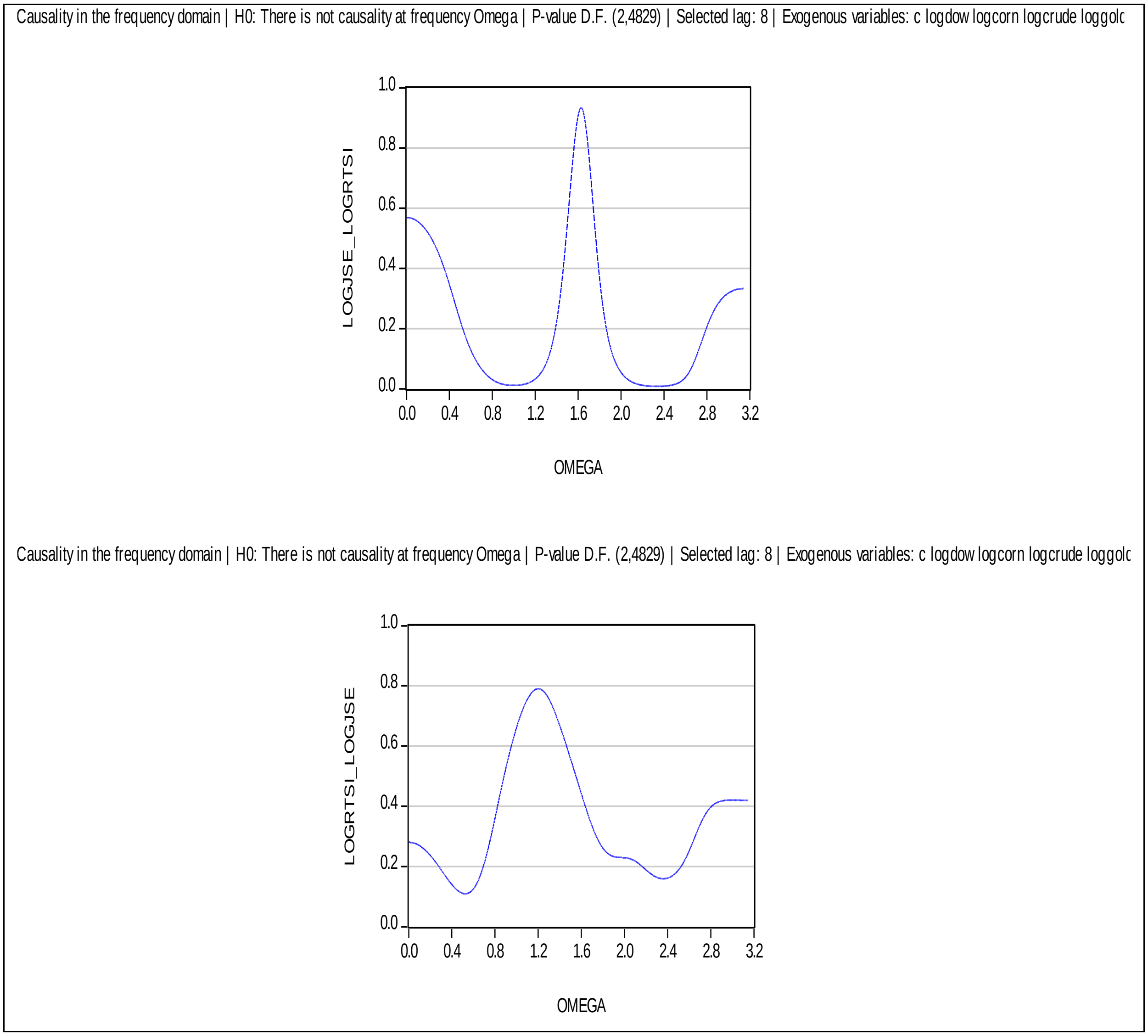


Figure 6. 9: LOGJSE versus LOGRTSI,

Source: Researcher Compilation

The top panel of Figure 6.9 shows that LOGRTSI does not Granger cause LOGJSE within the frequency range 0.0 and 0.7349 with causality ensuing for frequencies beyond 0.7349 up to 1.2471. In terms of periodicity, the frequency range 0.7362-1.2471 translates to the period 2003-2005. Beyond this frequency range, the pattern of causality apparently switches to non-causality cyclically. This finding is in contrast with the time domain causality test result which indicated that there is no causality from LOGRTSI to LOGJSE.

The bottom panel of Figure 6.9 indicates that for all the frequencies there is no causality from LOGJSE to LOGRTSI. This is in stark contrast to the main finding of time domain analysis which found evidence of Granger causality from LOGJSE to LOGRTSI.

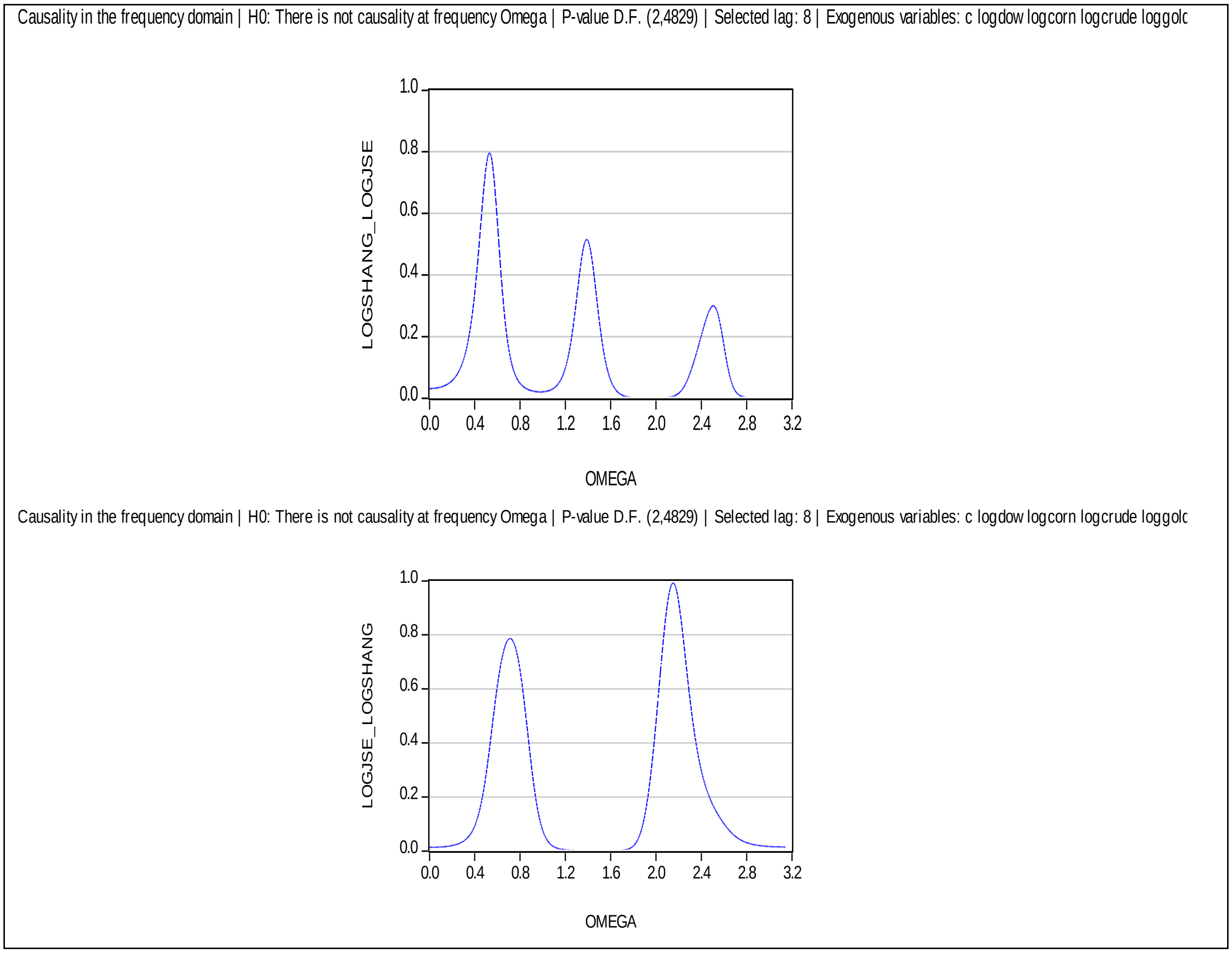


Figure 6. 10: LOGJSE versus LOGSHANG,

Source: Researcher Compilation

The top panel of Figure 6.10 reveals that the pattern of causality in the frequency domain from LOGJSE to LOGSHANG switches cyclically starting with causality at lower frequencies followed by no causality for frequencies between 0.4 and 0.6 beyond which causality commences again. This translates to a cyclical pattern of causality disrupted by non-causality of nearly 3 and half years in terms of the periodicity of the record of the study. The bottom panel also shows that causality from LOGSHANG to LOGJSE also varies cyclically with non-causality though the record indicates that causality lasts longer than non-causality.

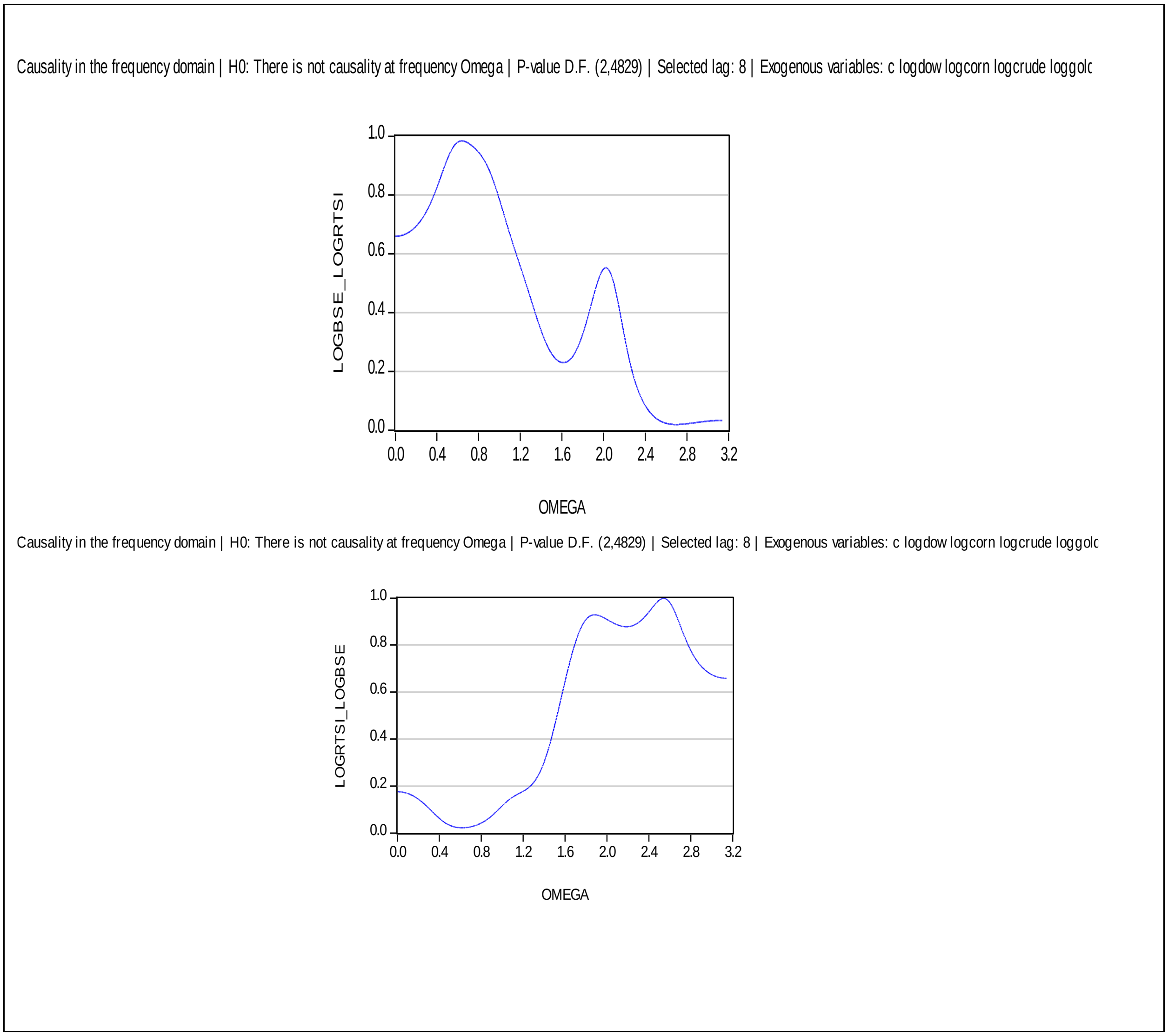


Figure 6. 11: LOGRTSI versus LOGBSE,

Source: Researcher Compilation

The top panel of Figure 6.11 shows that for all frequencies between 0.00 and 2.4723, LOGRTSI does not Granger cause LOGBSE which implies that from 2000 to 2010, the daily log-returns of Russia's RTSI index do not cause the daily log-returns of India's BSE Sensex index. This finding largely harmonizes with causality test results within the time domain which revealed that LOGRTSI does not Granger cause LOGBSE. In fact, Granger causality test results of the time domain reveal that there is no causality between the two variables.

According to the bottom panel of Figure 6.11 within the frequency range 0.00-0.4324, LOGBSE does not Granger cause LOGRTSI. After the omega frequency of 0.4324, causality ensues up to the frequency of 0.8301. This implies causality cycles of nearly two years disrupted by nearly two years of non-causality.

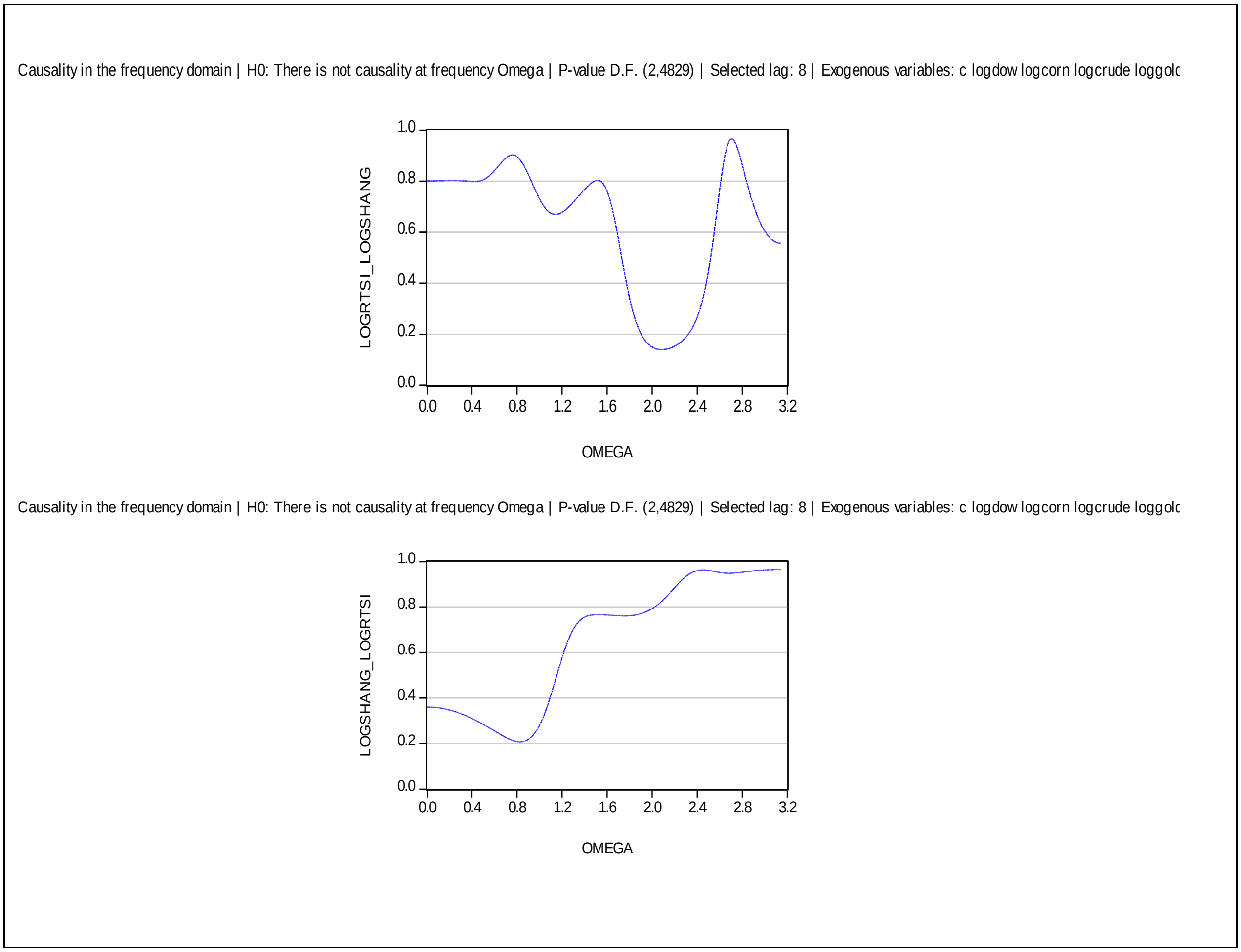


Figure 6. 12: LOGRTSI versus LOGSHANG,

Source: Researcher Compilation

The top and bottom panels of Figure 6.12 show that there is no spectral Granger causality between LOGRTSI and LOGSHANG for all angular frequencies. This confirms the results of time domain Granger causality tests.

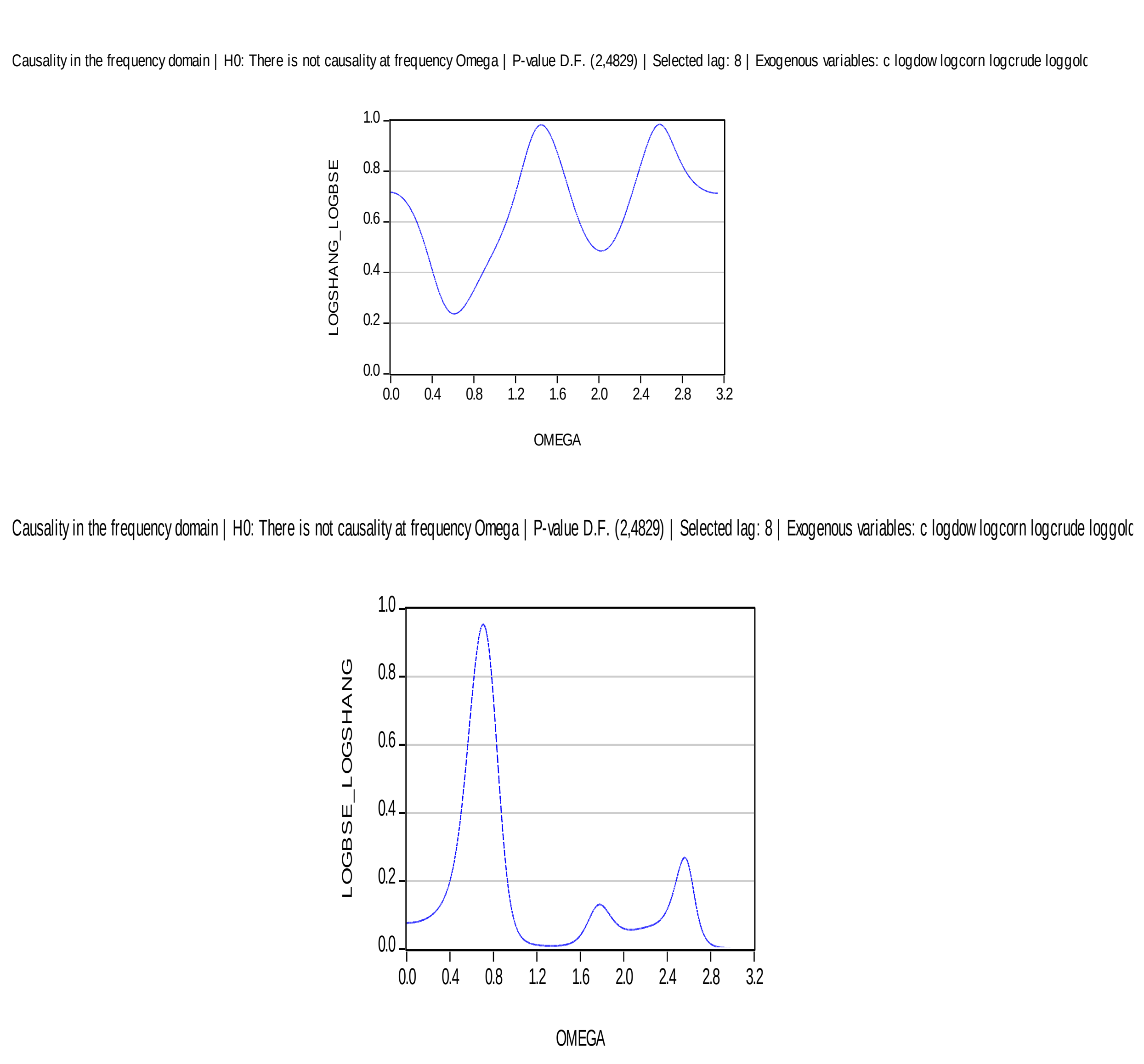


Figure 6. 13: LOGSHANG versus LOGBSE,

Source: Researcher Compilation

The top panel of Figure 6.13 indicates no causality from LOGBSE to LOGSHANG for all frequencies of the record of the current study. This contrasts with time domain results which give a picture of two-way causation between the two variables. The bottom panel shows that within the frequency range of 0.00-1.0283 (which translates to the period 2000-2004) China's LOGSHANG does not Granger cause India's LOGBSE. There is, nevertheless, evidence of causality from LOGSHANG to LOGBSE for frequencies between 1.0296 and 1.6203 which in time domain terms is the period between 2004 and 2011.

6.9 Non-linearities between stock indices and national output proxies

The present study departed from many contemporary studies on the finance-growth nexus in two main ways. First, the study did not make use of conventional proxies of financial development such as the ratio of broad money to Gross Domestic Product (GDP), Private sector credit to GDP, Stock Market Capitalization to GDP. These measures were not used because one of the main thrusts of the current study is to establish the nexus between commodity prices and stock market development. Commodity prices tend to yield high-frequency data yet stock market development to GDP is an annualised measure which cannot be accurately linked to the former. Thus, the present study opted to use log-returns of stock indices as a high-frequency alternative to the low-frequency stock market capitalization to GDP. Second, the present study contrasted the time domain causality test procedure with the frequency domain spectral causality test procedure (Liu and Molennar, 2016; He *et al.,* 2014; Priestly, 1981). Table 6.16 presents the results of Granger causality test in the time domain.

Table 6. 16: Time Domain Granger Causality test results

Null Hypothesis:	Observations	F-Statistic	Prob. value	Type of Causality
BRZY does not Granger Cause BOV	344	1.61864	0.1997	*No Causality*
BOV does not Granger Cause BRZY		1.88002	0.1542	
RUSSIAPTI does not Granger Cause RTSI	344	0.00545	0.9946	*No Causality*
RTSI does not Granger Cause RUSSIAPTI		0.30301	0.7388	
INDIAPTI does not Granger Cause BSE	344	6.72421	0.0014	*Two-way Causality*
BSE does not Granger Cause INDIAPTI		3.40132	0.0345	
CHRETAIL does not Granger Cause SSEC	344	0.85472	0.4263	*No Causality*
SSEC does not Granger Cause CHRETAIL		0.80279	0.4489	
SAMANUF does not Granger Cause JSEFT	344	7.76678	0.0005	*One-way Causality*
JSEFT does not Granger Cause SAMANUF		1.59487	0.2045	

Source: Researcher Calculations

Table 6.16 shows that according to static time domain analysis there is no causality between the stock index and output proxy for Brazil, Russia and China which contrasts with India for which there is two-way causation between the output proxy (INDIAPTI) and the stock index (BSE). Causality test results reveal that there is one-way causation between South Africa's manufacturing index and the JSE-Financial Times index (JSEFT) from the former to the latter in terms of direction.

The current study also examined the non-linear dynamics or relationship between proxies of national output, vis-à-vis, the respective stock indices of the BRICS. The ensuing sub-sections present and explain the linear and non-linear causal relationships between stock indices and national output proxies.

6.9.1 Spectral causality results for the BRICS

This section presents results of spectral analysis for Brazil. Figure 6.14 depicts a graphical plot of the dynamic frequency domain causality between Brazil's stock index, Bovespa and the national output proxy (BRZY).

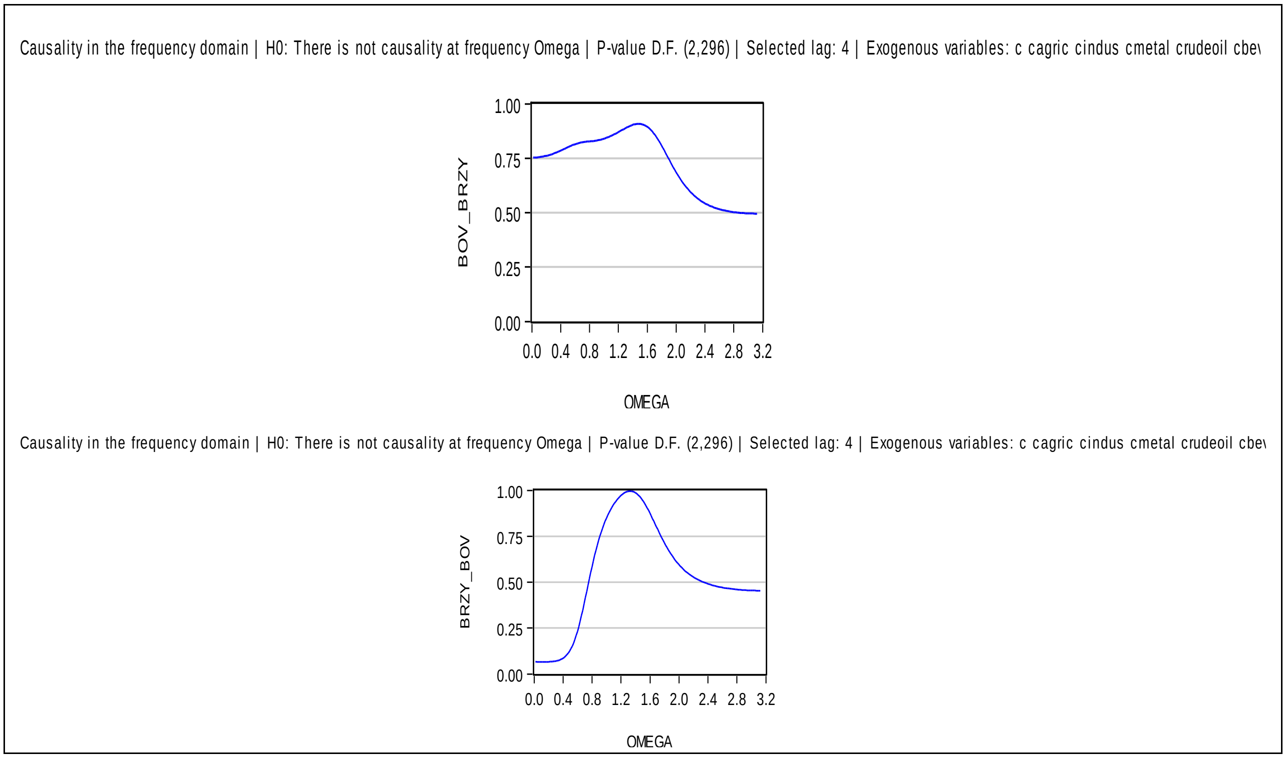


Figure 6. 14 – Spectral Analysis for Brazil – monthly data,

Source: Researcher Compilation

The top and bottom panels of Figure 6.14 show that for all frequencies there is no causality between Brazil's output proxy (BRZY) does not Granger and the Bovespa index (BOV).

Figure 6.15 depicts results of spectral causal analysis for Russia, that is, between Russia's RTSI stock index and the output proxy (RUSSIAPTI).

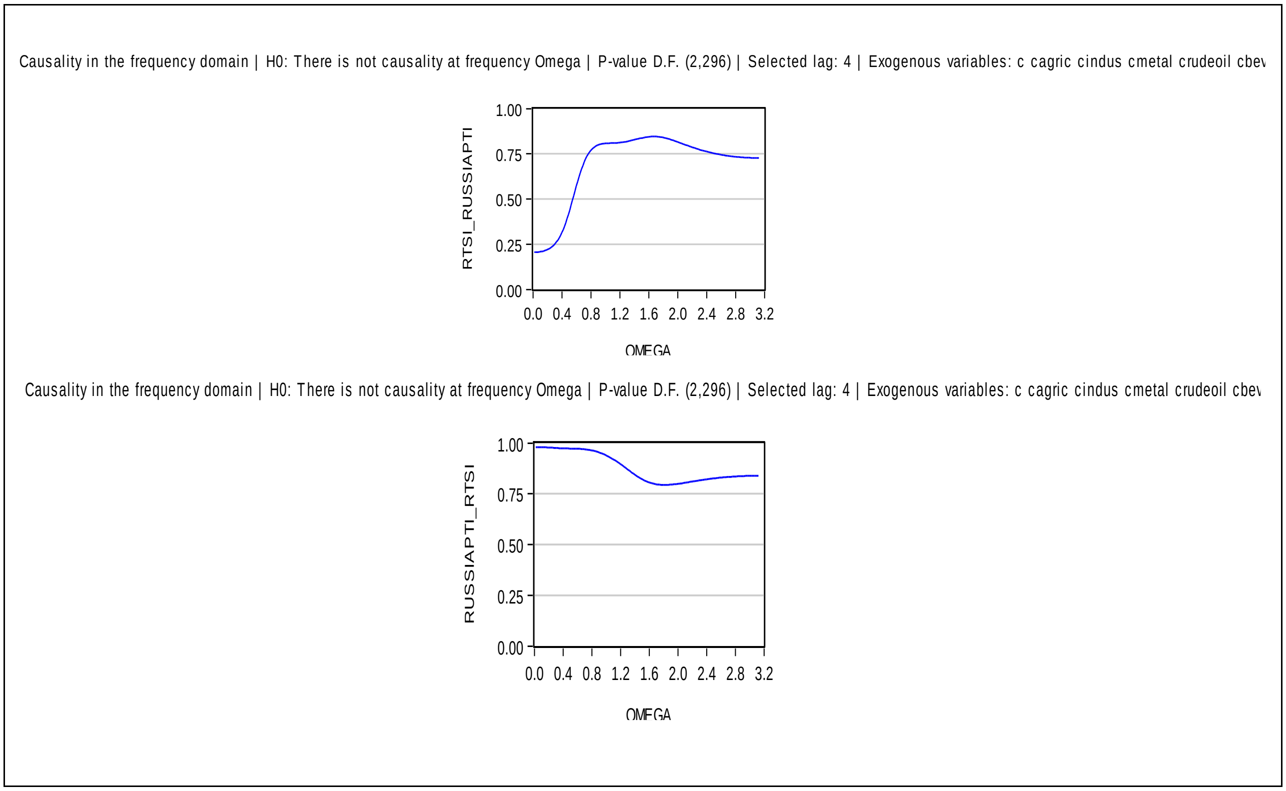


Figure 6. 15 – Spectral analysis results for Russia – monthly data,

Source: Researcher Compilation

Figure 6.15 also confirms time domain causality test results of no causation between Russia's RTSI index and the output proxy (RUSSIAPTI). Thus, there is no spectral causality between RTSI and RUSSIAPTI.

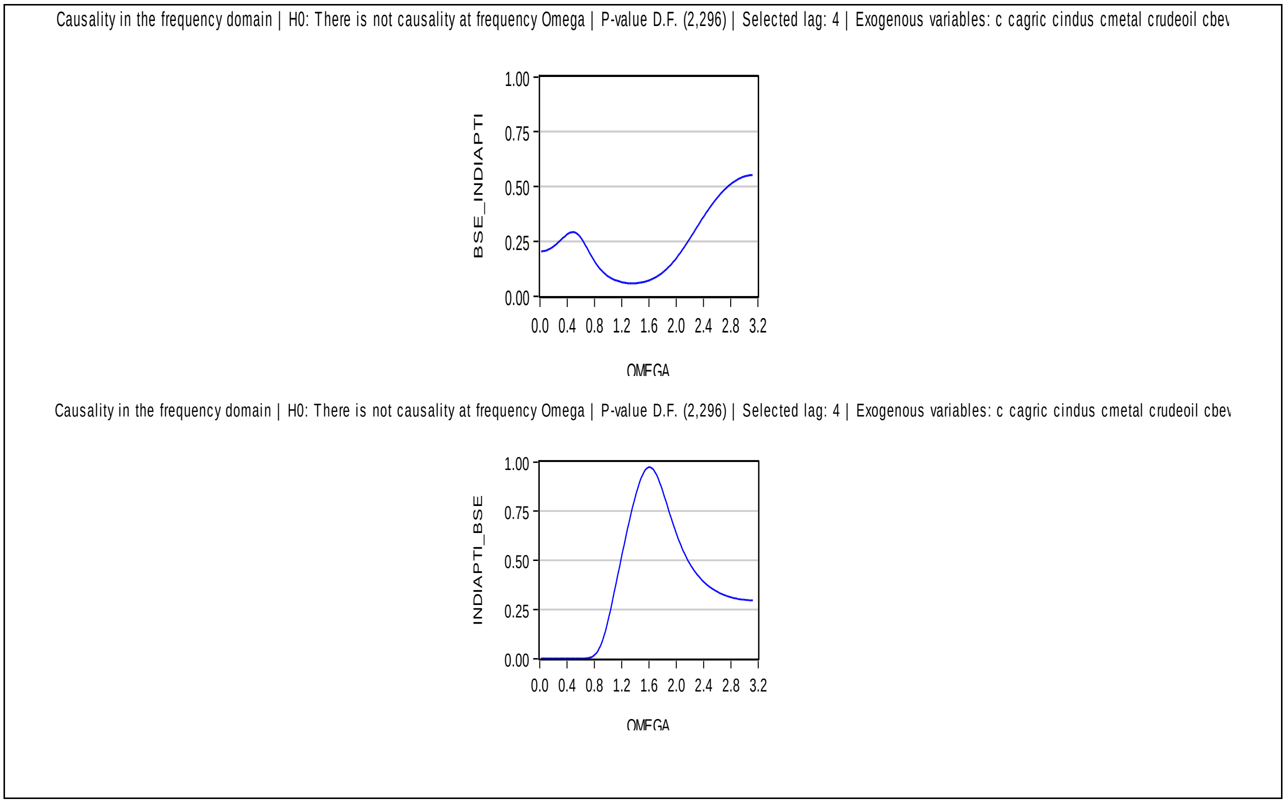


Figure 6. 16: Spectral causality between India – monthly data

Source: Researcher Compilation

The top panel of Figure 6.16 shows that India's output proxy (INDIAPTI) does not Granger cause the BSE Sensex index (BSE) for all frequencies of the data series, which in the language of spectral analysis is the entire record. The bottom panel of Figure 6.15 reveals that BSE Sensex index (BSE) Granger causes the output proxy (INDIAPTI) within the frequency range of 0.00-0.8535, which translates to causality between the two variables for the approximate period January 1990 – January 1998. Spectral causality analysis results contrast with the time domain result of two-way causation between the two variables.

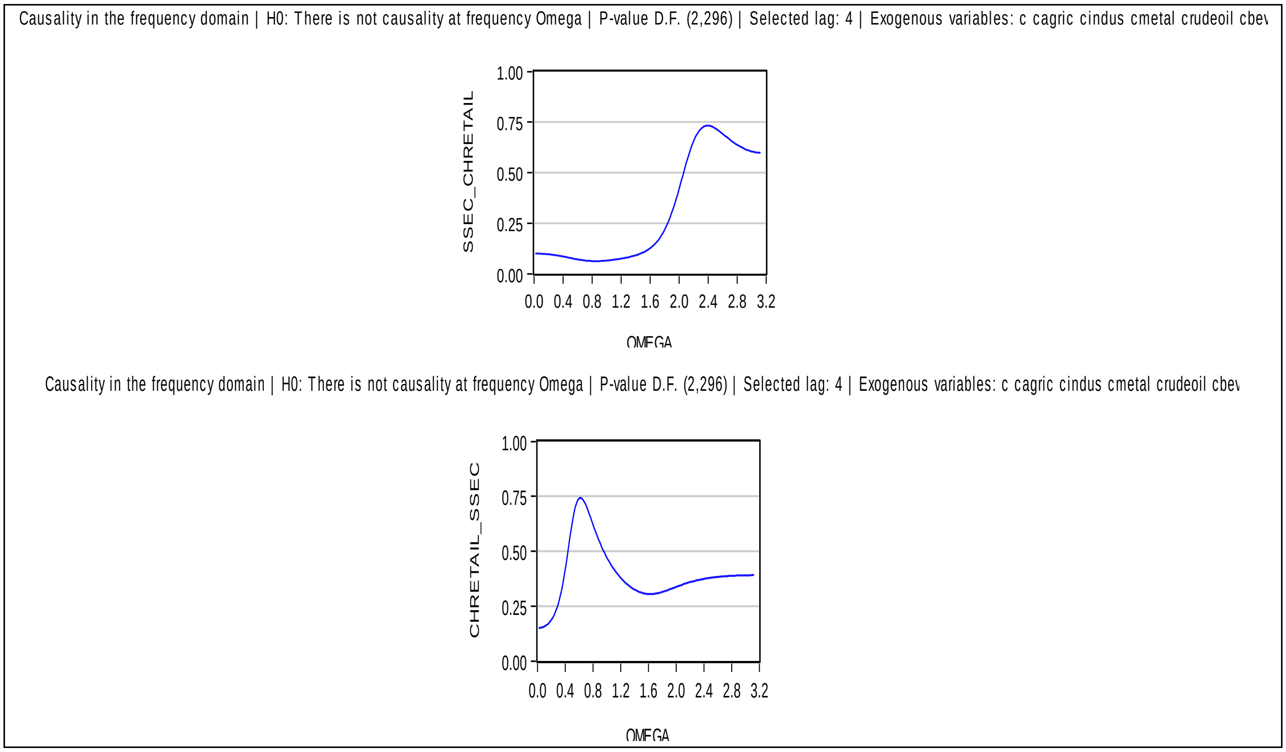


Figure 6. 17: Frequency domain causality test results for China

Source: Researcher Compilation

The top and bottom panels of Figure 6.17 show that there is no spectral causality between China's stock index (SSEC) and the output proxy (CHRETAIL). This finding confirms the time domain pairwise Granger causality test result of no causation between the two variables.

Figure 6.18 depicts the spectral (frequency domain) causality test results for South Africa's stock index (JSEFT) and the output proxy (SAMANUF).

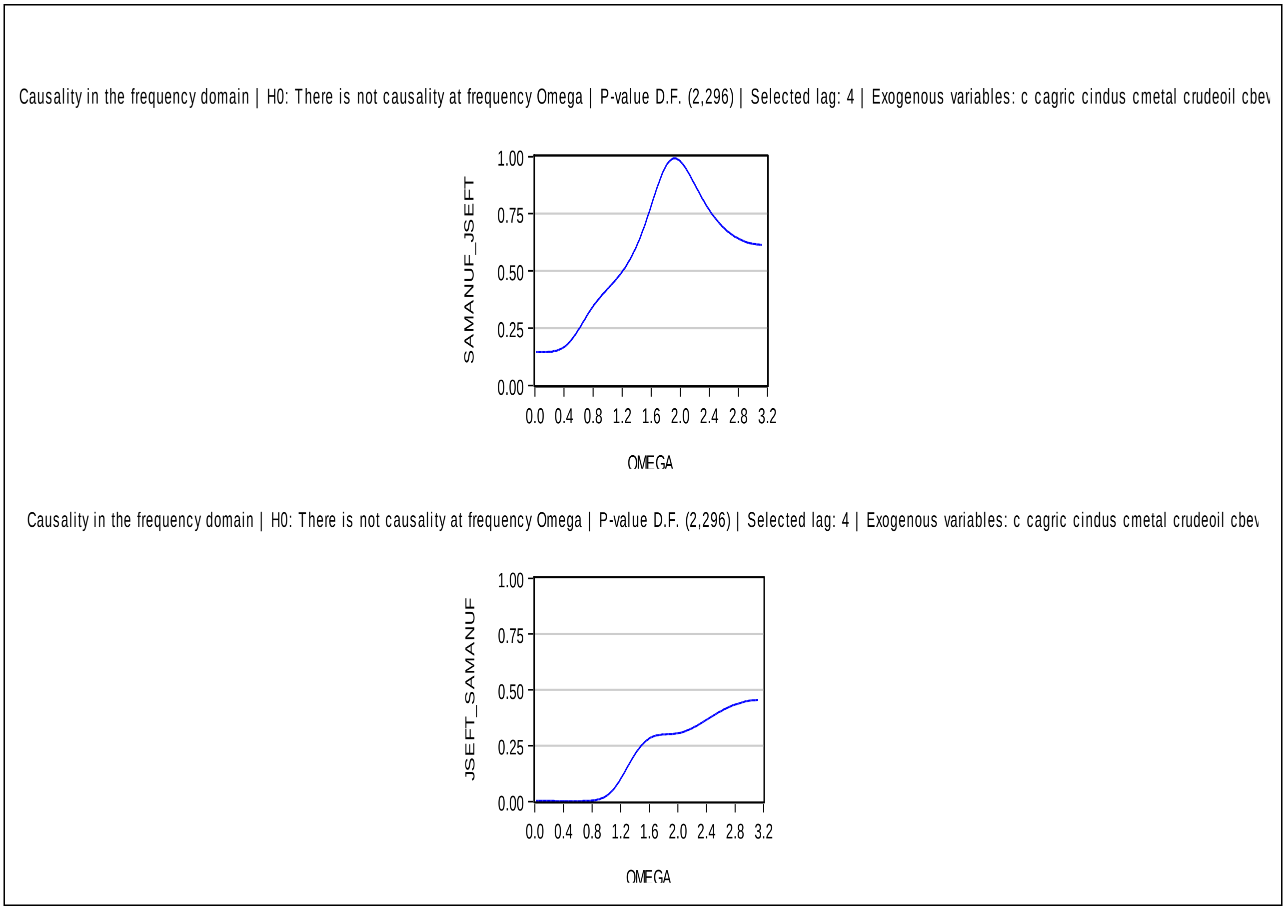


Figure 6. 18: Spectral causality test results for South Africa – monthly data

Source: Researcher Compilation

The top panel of Figure 6.18 shows that there is no spectral causality from South Africa's stock index (JSEFT) to the output proxy (SAMANUF). Nevertheless, the bottom panel shows that there is frequency domain causality from SAMANUF to JSEFT for the angular frequency range of omega 0.00 to omega 1.0533, which translates to a time period of January 1990 to October 2009. This implies that for the rest of the series, that is, from November 2009 to October 2018 there is no causality from the output proxy (SAMANUF) to the stock index series (JSEFT). In as much as spectral causality analysis finds evidence for causality from SAMANUF to JSEFT, this result confirms the main finding of time domain causal analysis which also reveals that the output proxy (SAMANUF) Granger causes the stock index (JSEFT).

6.9.2 Unique results – 'Cross spectral causality'

The ensuing section presents results of 'cross causality' which is defined in the context of the present analysis as a situation in which the stock index of one economy causes or is caused by the output proxy of another economy and vice versa. Figure 6.19, thus, depicts 'cross spectral causality' test results for China's output proxy (CHRETAIL), vis-à-vis, Brazil's stock index (BOV).

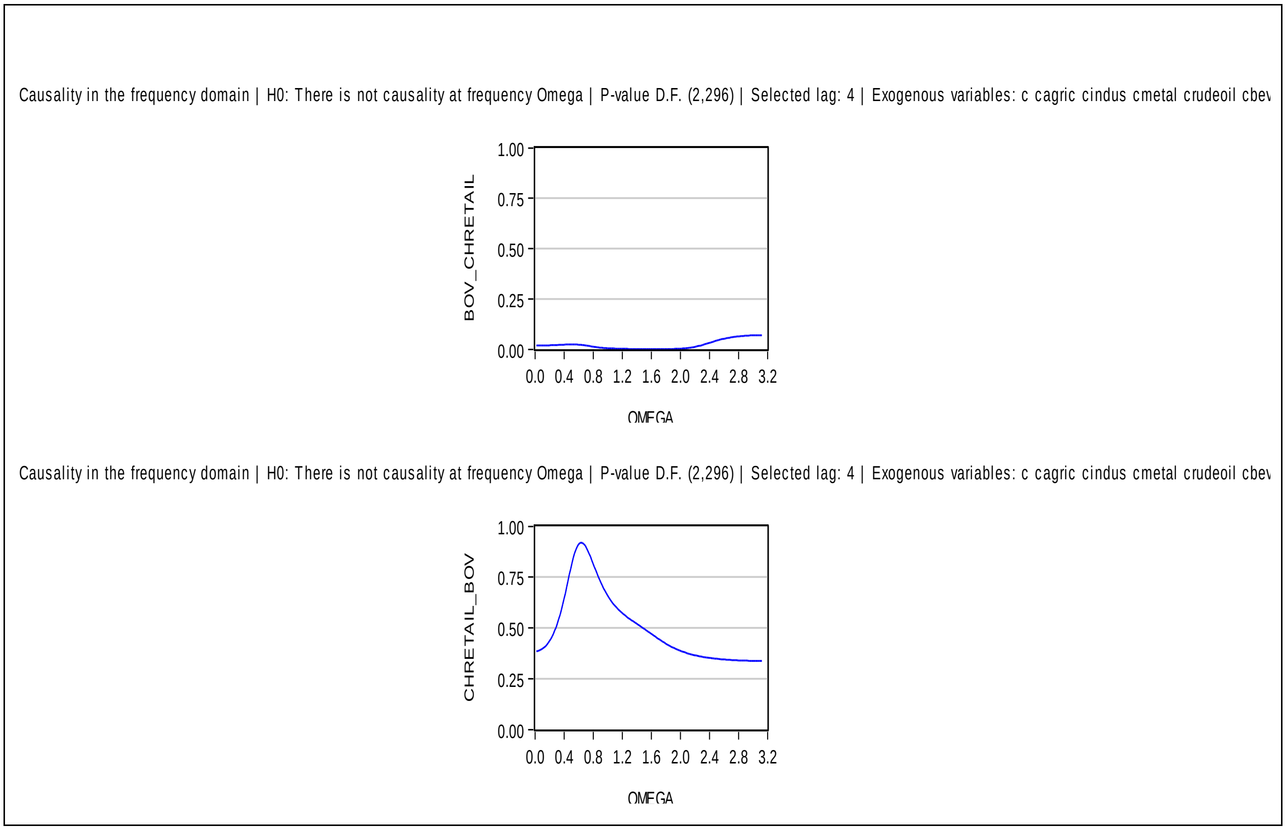


Figure 6. 19: China's output proxy versus Brazil's stock index (BOV)

Source: Researcher Compilation

The top and bottom panels of Figure 6.19 show that China's output proxy (CHRETAIL) Granger causes changes in Brazil's stock index (BOV) but the reverse is not the case. This implies that China's retail sales are a significant factor among the main drivers of Brazil's Bovespa index. This is not a far-fetched result because China does not only have the world's highest population making it potentially the biggest market for commodities, but China is also the second largest economy on earth (Lin, 2011).

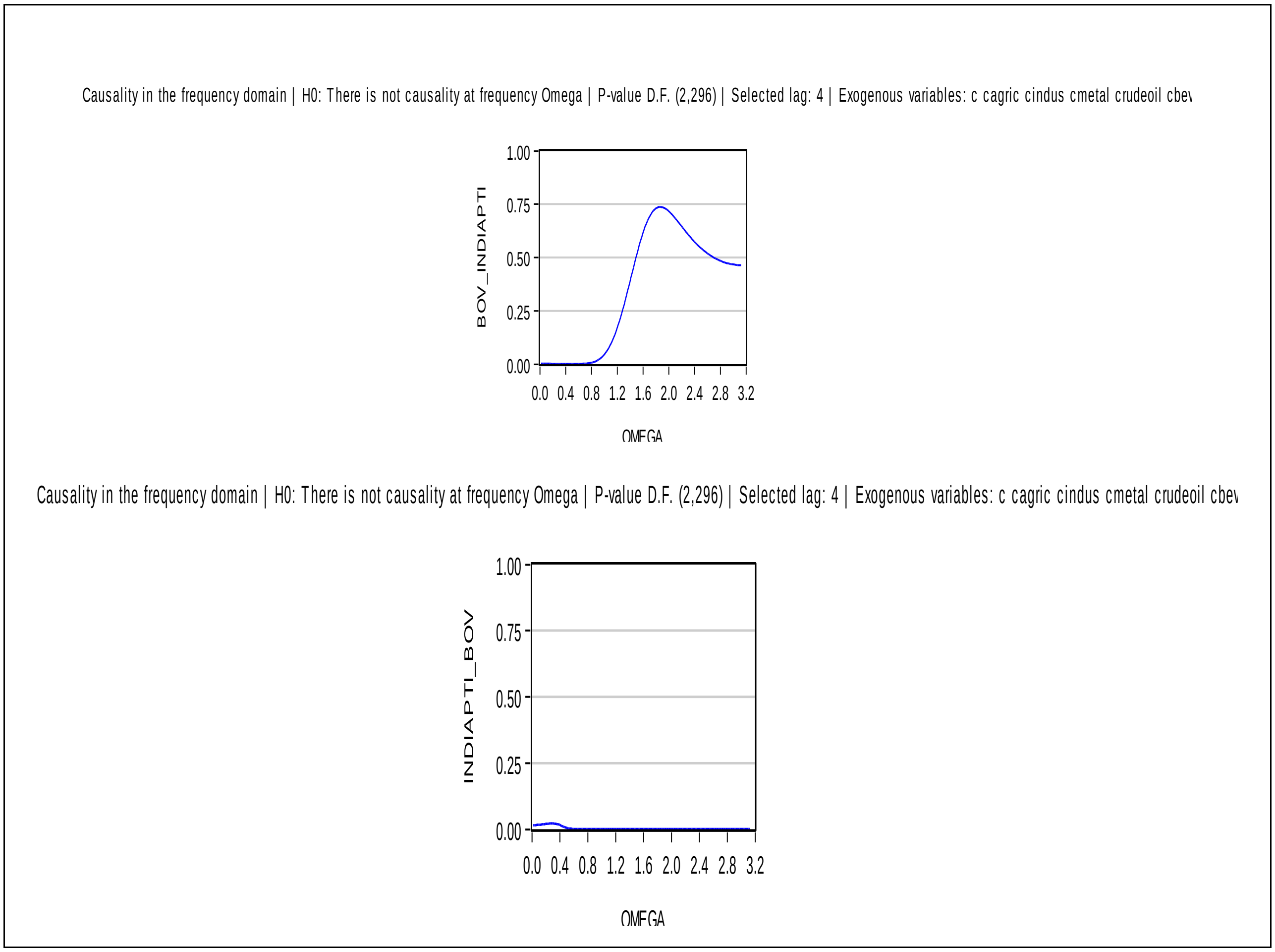


Figure 6. 20: 'Cross spectral causal' analysis - Brazil's BOV versus INDIAPTI, Source: Researcher Calculations

The top panel of Figure 6.20 shows that India's output proxy (INDIAPTI) Granger causes Brazil's stock index (BOV) with the frequency range – 0.00 to 0.9988 which translates to a time period of January 1990 to March 1999. The upward oscillation of the plot of frequencies, vis-à-vis, probability values may be reflective of changes in the business cycle for the corresponding time period. The bottom panel reveals that there is spectral causality from Brazil's stock index (BOV) to India's output proxy (INDIAPTI) for all frequencies which implies that the Bovespa index Granger causes India's national output for the whole record, that is, from January 1990 to October 2018.

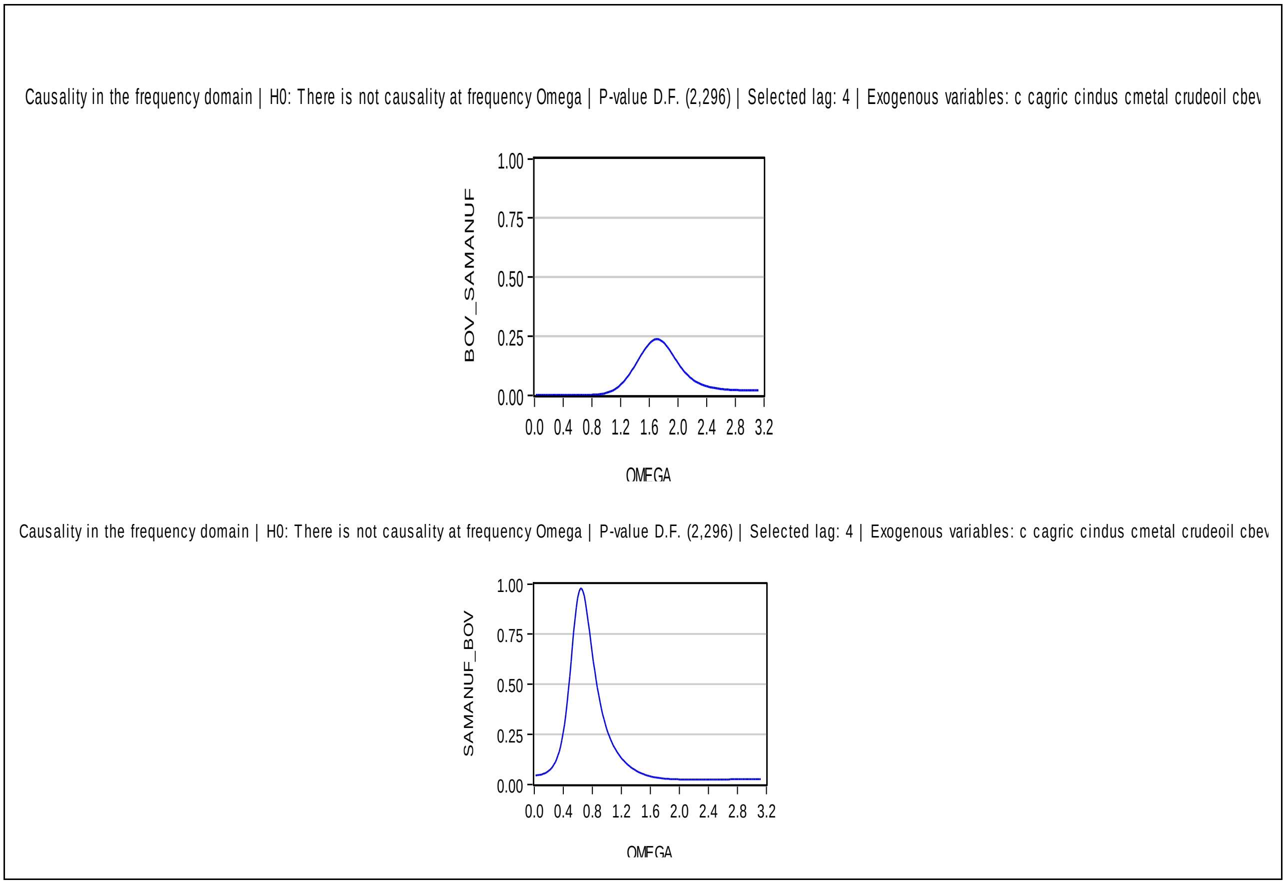


Figure 6. 21: South Africa’s output proxy (SAMANUF) versus Brazil’s BOV

Source: Researcher Calculations

Figure 6.21 shows that there is two-way spectral ‘cross-causality’ between South Africa’s output proxy (SAMANUF) and Brazil’s stock index (BOV) though the two-way causation does not hold for all frequencies as can be clearly seen from both the top and bottom panels of the figure. The import of the graphical results is that South Africa’s output is one of the main drivers of Brazil’s stock index – Bovespa and vice versa. The corollary from the foregoing is that dynamic linkages between these two members of the BRICS exist.

Figure 6.22 shows that South Africa’s JSEFT index Granger causes India’s national output (INDIAPTI) at the beginning and at the end of the record of study, implying a ‘middling’ period of non-causality from a frequency domain perspective. This means that there was ‘non-cross causality’ from the JSEFT index to India’s national output between 1995 and 2005.

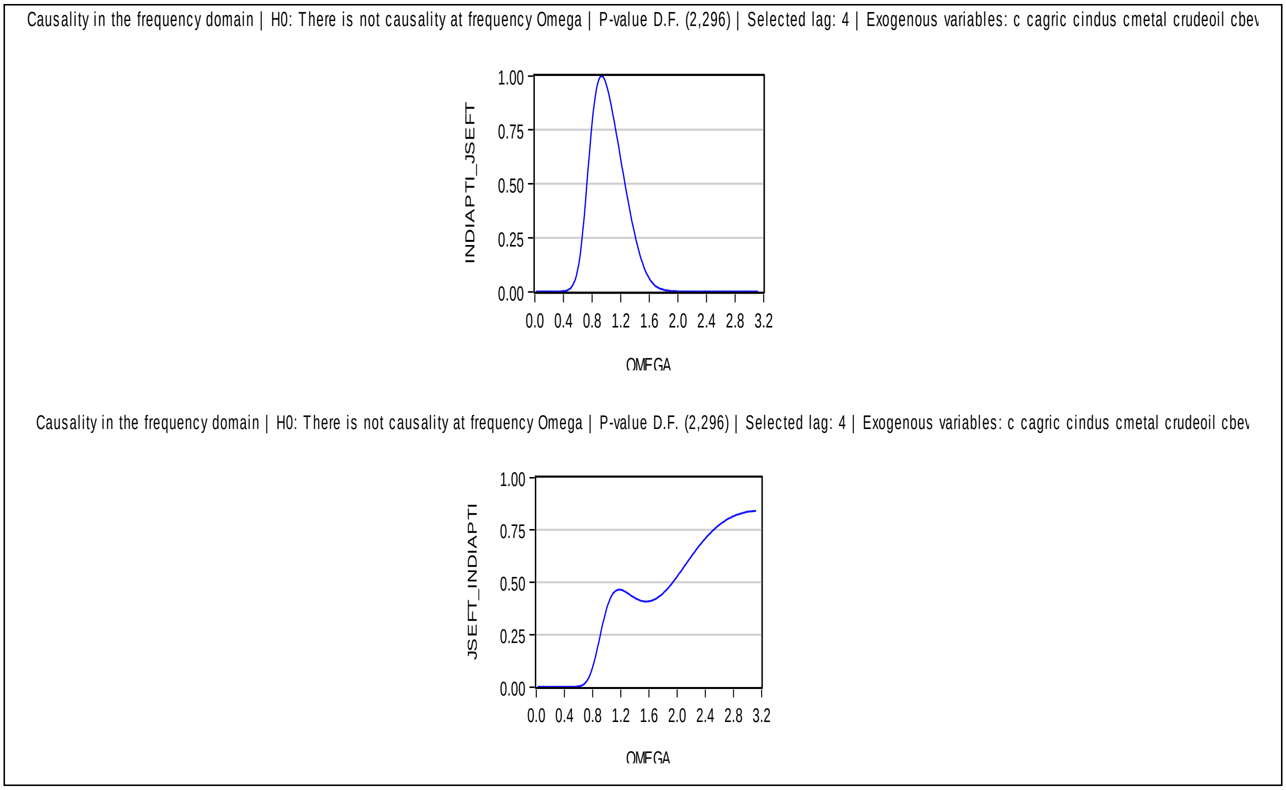


Figure 6. 22: India's output proxy, vis-à-vis, South Africa's Stock Market Index, Source: Researcher Calculations

The bottom panel of Figure 6.22 shows that India's national output (INDIAPTI) only Granger caused South Africa's JSEFT stock index at the beginning of the record, that is, from January 1990 to October 1996. For the remainder of the frequencies there is no causality from India's national output to South Africa's stock Index.

Figure 6.23 shows that South Africa's output proxy (SAMANUF) Granger causes India's BSE Sensex index (BSE) for frequencies that constitute the beginning of the record, that is, between January 1990 and January 2000. Beyond the first ten years of the data series there is, thus, no evidence of spectral causality between South Africa's national output and India's stock index (BSE).

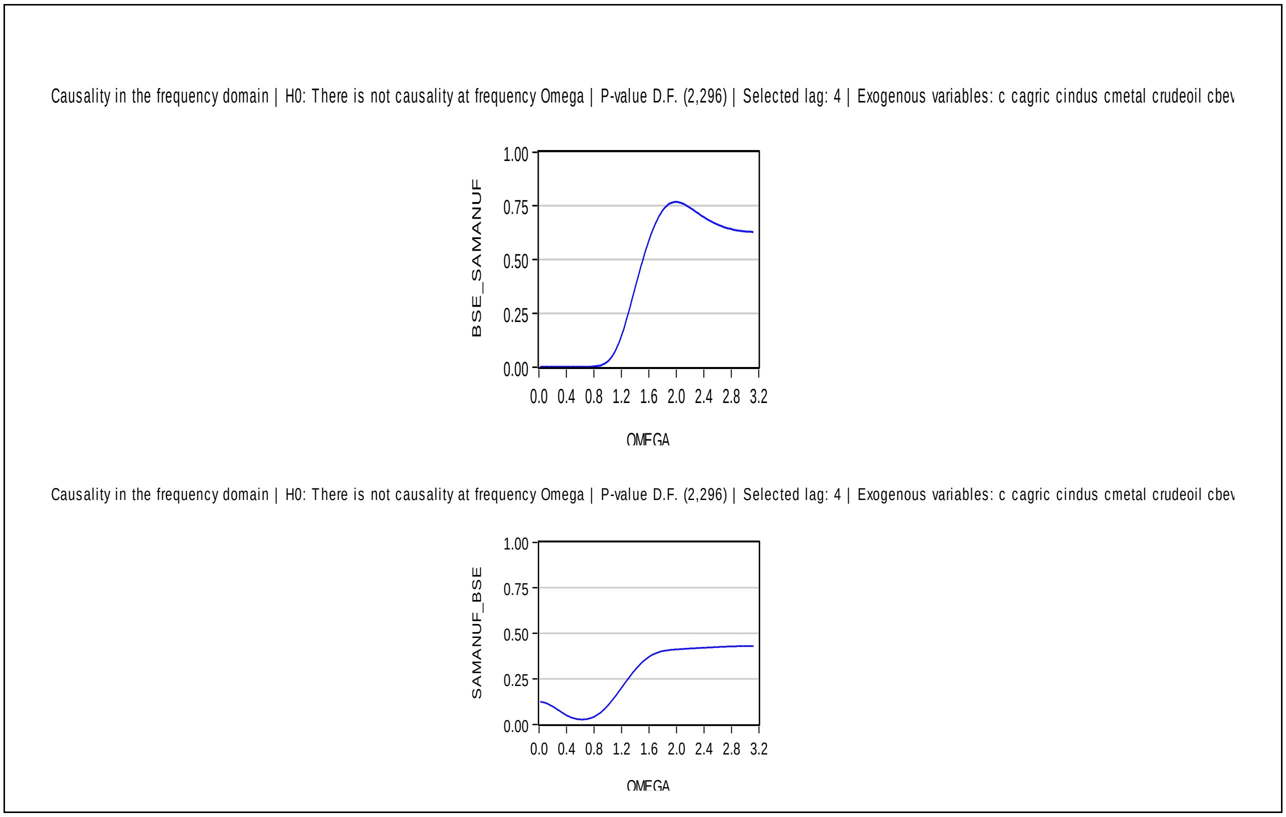


Figure 6. 23: South Africa's output versus India's BSE index,

Source: Researcher Calculations

The bottom panel of Figure 6.23 reveals that the BSE index Granger caused South Africa's national output for only a brief period captured by the frequency range from 0.4177 to 0.8353, that is, from January 1994 to October 1997.

International commodity price volatility and the onset of the East Asian currency crisis of 1997-1998 may be two of the factors that partly explain the attenuation of the causal relationship from India's BSE Sensex index and South Africa's national output. In the same vein, Harris (1999) argues that the transmission of the financial crisis from East Asia to Sub-Saharan Africa was limited to South Africa (SA) due to fairly developed financial markets found in SA.

6.13 Chapter Summary

This study was motivated by a desire to understand the nexus between commodity price volatility and stock market development on the one hand, and to discern how that nexus predisposes stock market indicators to be non-linearly related to national income. National income was proxied by different production and sales indicators. The study demonstrated using spectral analysis that the causal relationship between different stock market indicators and national income proxies is indeed dynamic and not static. Time domain Granger causality test results often give the impression that causality between any two variables can be adequately summarised and fully captured by a single figure or statistic. Results presented and discussed in section 6.9 amply demonstrated the non-linear and dynamic nature of the phenomenon of causality among different economic aggregates through frequency domain spectral causality tests. This has far reaching implications to individual and institutional investors in terms of strategic portfolio planning and diversification during periods of crises. The next chapter, that is, Chapter 7 presents the results of the study obtained from different types of GARCH models together with relevant robustness and diagnostic test results.

CHAPTER 7 - EMPIRICAL ANALYSIS: GARCH MODELS, TESTS AND DISCUSSION

7.0 Introduction

The purpose of Chapter 7 is to present and analyse different GARCH models that were fitted unto the daily log-return data of BRICS countries. The presentation and discussion commence with univariate GARCH analysis, progresses to DCC GARCH and climaxes with Markov-Switching GARCH. The chapter concludes with a summary section that discusses the contribution of the findings in the context of the extant and contemporary literature.

7.1 Univariate GARCH (1, 1) model results

It is a fact attested to by statistical history that autoregressive processes whose study was formalized by the seminal works of G. U Yule and J. Walker in the 1920s and 1930s form the foundation from which sprang the Autoregressive Conditional Heteroscedasticity (ARCH) model that was developed Engle (1982). Intermediating the development of the ARCH model were the Autoregressive Moving Average (ARMA) and the Autoregressive Integrated Moving Average (ARIMA) models which are attributed to G. E. P. Box and G. M. Jenkins (Box and Jenkins, 1976). The empirical results presented in this chapter are based on experimentation with different forms of the GARCH model mainly developed by Bollerslev (1986). The estimated models and their attendant diagnostics are based on different versions of the GARCH model under differing error distributional assumptions. Table 7.1 summarises the results of univariate GARCH analysis based on daily log-return data. Table 7.1 is a summary of five univariate GARCH (1, 1) models under the skewed student t distribution for Brazil, Russia and India, and the student t distribution for China and South Africa. The model results that are presented in Table 7.1 are the best estimated models in terms of convergence considerations, log-likelihood, information criteria, positive definiteness and the statistical significance of estimated parameters.

Table 7. 1: Univariate GARCH analysis results based on daily log-return data

	***Brazil* (*logbov*)**	***Russia* (*logrtsi*)**	***India* (*logbse*)**	***China* (*logshang*)**	***South Africa* (*logjse*)**	
	MEAN EQUATION	*MEAN EQUATION*	*MEAN EQUATION*	*MEAN EQUATION*	*MEAN EQUATION*	***Variable Name***
	0.000369 [0.0623]	0.000798* [0.0006]	0.000776* [0.0000]	0.000771** [0.0479]	0.000629* [0.0005]	***CONSTANT***
	0.136468* [0.0000]	0.044979* [0.0001]	0.037248* [0.0000]	0.022220* [0.0019]	0.108384* [0.0000]	***LOGCRUDE***
	0.042428 [0.1607]	0.036862 [0.1618]	*[INSIGN. OMITTED]*	-0.007836 [0.3161]	0.043835 [0.1728]	***LOGCORN***
	0.301537* [0.0000]	0.073834 [0.1257]	*[INSIGN. OMITTED]*	0.090102* [0.0086]	0.753068* [0.0000]	***LOGGOLD***
	0.020310 [0.6387]	-0.003264 [0.8339]	ARMA (0, 0) specified	0.182904* [0.0000]	ARMA (0, 0) Specified	***d-Arfima***
	0.674174 [0.0000]	-0.103896 [0.4215]	*Not applicable*	0.539189 [0.0000]	*Not applicable*	***AR(1)***
	-0.733516 [0.0000]	0.158548 [0.2030]	*Not applicable*	-0.705733 [0.0000]	*Not applicable*	***MA(1)***
PARAMETERS	*VARIANCE EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*	
C * 10^4	0.032781* [0.0022]	0.158548* [0.0002]	0.030457* [0.0000]	*OMITTED due to variance targeting*	0.042222* [0.0001]	
			LOGDOW -0.000638* [0.0000]	*Sigma^2* 0.000008		
ARCH (α1)	0.063648* [0.0000]	0.162548* [0.0000]	0.097060* [0.0000]	0.145723* [0.0000]	0.075035* [0.0000]	
GARCH (β1)	0.925018* [0.0000]	0.824464* [0.0000]	0.889133* [0.0000]	0.816415* [0.0000]	0.907963* [0.0000]	
	Asymmetry -0.037550** [0.0276]	*Asymmetry* -0.032412 [0.0527]	*Asymmetry* -0.050072* [0.0015]	*STUDENT(DF)* 3.621858* [0.0000]	*STUDENT(DF)* 8.833822* [0.0000]	
	Tail 7.196097 [0.0000]	Tail 3.922416 [0.0000]	Tail 5.289561 [0.0000]	*Not applicable*	*Not applicable*	
DIAGNOSTIC TESTS						
Log likelihood	13673.182	12712.207	15042.849	14563.358	13875.731	
Positivity constraint = α/[1-β]	0.848844	0.9260095	Not applicable [variance equation has a regressor]	0.793763107	0.815269945	
Persistence=	0.988666	0.987012	0.986193	0.962138	0.982998	

α + β						
4th moment of GARCH <1 Constraint	0.993225	-1.03422	Not applicable [variance equation has a regressor]	0.63124	0.984533	

***, **, *** indicates results are statistically significant at 1%; 5%; 10% level and [..] indicates probability value**

Source: Researcher Calculations

Table 7.1 summarises univariate GARCH analysis results for Brazil, Russia, India, China and South Africa (BRICS). The ARCH (LM) test shows all the five (5) daily log-return series had statistically insignificant (LM) F-statistics. This indicates that all the conditional variance equations were correctly specified. According to Minovic (2008) the ARCH (LM) test is used to examine whether the standardised residuals display ARCH behaviour. It is further argued that if the conditional variance equation is specified correctly, then standardised residuals should exhibit no ARCH effect (Minovic, 2008). Table 7.2 present a summary of the ARCH test results.

Table 7. 2: The ARCH Test of standardised residuals

ARCH TEST	South Africa	
ARCH 1-2 test	F(2,4875) = 1.2434	[0.2885]
ARCH 1-5 test	F(5,4869) = 0.88589	[0.4895]
ARCH 1-10 test	F(10,4859)= 0.59089	[0.8228]

ARCH Test	Brazil		Russia	
ARCH 1-2 test	F(2,4875) = 1.9984	[0.1357]	F(2,4354) = 0.14881	[0.8617]
ARCH 1-5 test	F(5,4869) = 0.84814	[0.5154]	F(5,4348) = 0.22403	[0.9523]
ARCH 1-10 test	F(10,4859)= 0.86254	[0.5680]	F(10,4338)= 0.23658	[0.9927]

ARCH TEST	India		China	
ARCH 1-2 test	F(2,4875) = 0.087810	[0.9159]	F(2,4875) = 0.35043	[0.7044]
ARCH 1-5 test	F(5,4869) = 0.32664	[0.8972]	F(5,4869) = 0.38052	[0.8624]
ARCH 1-10 test	F(10,4859)= 0.38658	[0.9531]	F(10,4859)= 0.34038	[0.9702]

(…, ...) indicates degrees of freedom and number of observations, […..] indicates probability value

Source: Researcher Calculations

The mean equation results show that for Brazil, the log-returns of the Bovespa index are positively impacted by the log-returns of WTI crude oil, US corn and gold. The coefficient of US corn futures is, however, statistically insignificant. The daily log-returns of Russia's RTSI index are also positively affected by the daily log-returns of crude oil, corn and gold, though it is only crude oil with a statistically significant coefficient. The coefficients of US corn and gold are statistically insignificant, vis-à-vis, the daily log-returns of Russia's RTSI index. Results show that the daily returns of China's Shangai index, logcrude and loggold are statistically significant, while logcorn is statistically insignificant. In repeated modeling until a convergent model was found, results showed that only crude oil is statistically significant in determining variations of the daily log-returns of India's BSE Sensex index. Table 7.1 actually shows that the daily log returns of US corn and gold were found to be insignificant in the context of the GARCH (1, 1) modeling, hence their exclusion from the model completely. The inclusion of these two variables in a simple GARCH (1, 1) model resulted in a model which failed to satisfy the condition for the existence of the fourth moment of a stable GARCH model. The daily log-returns of the Dow are statistically significant in determining the volatility of India's LOGBSE. Simple GARCH (1, 1) analysis showed that prices of both gold and crude oil are statistically significant variables in determining movements of the daily log-returns of the Johannesburg Stock Exchange (JSE) index. US corn was found to be statistically insignificant.

As shown in Table 7.1 all calculated ARCH and GARCH terms were found to be statistically significant. This implies that the estimated models are useful in describing the volatility dynamics of the five BRICS economies. The asymmetric GARCH (1, 1) model was found to fit data for Brazil and India. The coefficient for asymmetry was found to be statistically insignificant for Russia. The study relied on a simple symmetric Student t error distribution to model the volatility of the log-returns of China and South Africa. The following section presents results of Nyblom parameter tests of the GARCH (1,1) model displayed in Table 7.1.

7.1.1 Model Adequacy Diagnostic Tests of the univariate GARCH (1, 1) model

Table 7.3 presents the results of diagnostic tests of the GARCH (1, 1) models which are presented in Table 7.1.

Table 7. 3: Nyblom Test Results for the BRICS' GARCH (1, 1) models

Country	Type of Test	Variables	Nyblom Statistic	Decision
Brazil	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logcrude(M) logcorn(M) loggold (M) Cst(V) x 10^4 ARCH(Alpha1) GARCH(Beta1) Student (DF)	[0.34400] [8.88598] [0.24572] [0.68654] [0.08796] [0.19563] [0.13742] [0.26379]	*Only the coefficient of logcrude is unstable. All other estimated coefficients are stable.*
Russia	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logcrude (M) logcorn (M) loggold (M) d-Arfima AR(1) MA(1) Cst(V) x 10^4 ARCH(Alpha1) GARCH(Beta1) Asymmetry Tail	[1.26279] [0.10169] [0.16212] [0.60173] [0.11174] [0.08294] [0.08168] [0.31090] [0.48389] [0.52996] [0.38917] [0.68555]	*Only the coefficient of Constant of the mean equation is unstable. All other estimated coefficients are stable.*
India	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logcrude (M) Cst(V)x 10^4 logdow (V) ARCH(Alpha1) GARCH(Beta1) Asymmetry Tail	[0.77555] [1.15561] [1.74984] [0.23424] [1.60992] [1.20032] [1.26442] [0.96526]	*Only the coefficient of logdow is stable. All other estimated coefficients are unstable.*
China	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logcrude (M) logcorn (M) loggold (M) d-Arfima AR(1) MA(1) ARCH(Alpha1) GARCH(Beta1) Student(DF)	[0.21387] [0.24236] [0.11173] [0.11975] [0.06041] [0.03434] [0.02698] [3.01955] [4.18296] [1.55038]	*Estimated ARCH and GARCH coefficients are unstable while all other estimated coefficients are stable.*
South Africa	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logcrude (M) logcorn (M) loggold (M) Cst(V) x 10^4 ARCH(Alpha1) GARCH(Beta1) Student(DF)	[0.34400] [8.88598] [0.24572] [0.68654] [0.08796] [0.19563] [0.13742] [0.26379]	*Only the coefficient of logcrude is unstable. All other estimated coefficients are stable*

[…] indicates calculated Nyblom parameter stability statistic

Source: Researcher Calculations

The Null Hypothesis for all the tests presented in Table 7.3 is that the estimated parameter is stable. Table 7.3 shows that Nyblom's test of parameter stability revealed that the fitted GARCH (1, 1) models for Brazil, Russia and South Africa are, by and large, satisfactory since the estimated parameters of the fitted models are largely stable. India is a clear outlier since nearly all estimated parameters were unstable with the exception of the logdow which was included in the model as an external regressor in the conditional variance equation. The estimated coefficients for the ARCH and GARCH terms for China are found to be unstable according to Nyblom's parameter stability test. The estimated conditional variance equation is, thus, in adequate in fully explaining volatility dynamics of China's stock market given the time-varying feature of those dynamics. The failure of India's and China's fitted GARCH (1, 1) models to yield stable parameter after different permutations and combinations of models of the same flavour had been tried thus necessitated the estimation of other flavours/extensions of the GARCH model whose results are presented and discussed in the ensuing sections.

7.1.2 Autocorrelation Dynamics of the Estimated GARCH (1, 1) models

Table 7.4 presents a summary of the results of autocorrelation tests conducted on the standardised squared residuals using the Box/Pierce methodology. This method was used despite the misgivings of some researchers who believe that a related test called the Li-Mak test must be conducted on standardised residuals and squared standardised residuals in an attempt to discover whether the errors of the estimated model are correlated or uncorrelated (Fisher and Gallagher, 2012 and Li and Mak, 1994).

Table 7. 4: Q-Statistics on Squared Standardised Residuals

Country	Box/Pierce Statistic	Decision
Brazil	P-values adjusted by 2 degree(s) of freedom Q (5) = 6.78738 [0.0789927] Q (10) = 9.77391 [0.2812543] Q (20) = 18.7349 [0.4083172] Q (50) =76.1147 [0.0060083] ** H_0: No serial correlation ==> Accept H_0 when prob. is High [Q < Chisq(lag)]	*The results show that the residuals are largely uncorrelated though Q (50) has a statistically significant result*
Russia	P-values adjusted by 2 degree(s) of freedom Q (5) = 1.01558 [0.7974826] Q (10) = 25.4464 [0.0013055] ** Q (20) = 26.5983 [0.0868435] Q (50) =73.3213 [0.0107672] *	*The results are mixed as they show that for Q (5) and Q (20) residuals are uncorrelated while results for Q (10) and Q (50) they are correlated. This*

	H_0: No serial correlation ==> Accept H_0 when prob. is High [Q < Chisq (lag)]	*may be evidence of the long memory feature of conditional volatility.*
India	P-values adjusted by 2 degree(s) of freedom Q (5) = 8.02722[0.0454525] * Q (1[0.9927] [0.9927] = 11.5953[0.1701924] Q (20) = 26.4767[0.0893481] Q (50) = 60.929 [0.0996505] H_0: No serial correlation ==> Accept H_0 when prob. is High [Q < Chisq (lag)]	*The results show that the residuals are largely uncorrelated though Q (5) has a statistically significant result.*
China	P-values adjusted by 2 degree(s) of freedom Q (5) = 6.78738 [0.0789927] Q (10) = 9.77391 [0.2812543] Q (20) = 18.7349 [0.4083172] Q (50) = 76.1147 [0.0060083] ** H_0: No serial correlation ==> Accept H_0 when prob. is High [Q < Chisq(lag)]	*The results show that the residuals are largely uncorrelated though Q (50) has a statistically significant result. The serial correlation that becomes statistically significant for Q(50) may be evidence of long memory*
South Africa	P-values adjusted by 2 degree(s) of freedom Q (5) = 4.39827 [0.2215463] Q (10) = 5.72762 [0.6777122] Q (20) = 18.0189 [0.4544052] Q (50) = 44.7630 [0.6062683] H_0: No serial correlation ==> Accept H_0 when prob. is High [Q < Chisq(lag)]	*The results show that the residuals are largely uncorrelated. Thus, for the estimated GARCH (1, 1) model it can be assumed that errors are Independent and Identically distributed (i.i.d).*

[…] indicates probability value

Source: Researcher Calculations

Table 7.4 shows that only the fitted GARCH (1, 1) model for South Africa's JSE index can be said to satisfy the assumption of independent and identically distributed (i.i.d) random errors. It can, thus, be postulated that the estimated model can adequately describe both mean returns and the volatility of the JSE index and may be relied upon forecasting volatility dynamics to the near future normally postulated to be seven days for daily log-returns of stock indices (Kandananond, 2012; Gardner; 1983).

7.1.3 Diagnostic tests based on the news impact curve (EGARCH vs. GARCH)

The study also involved tests based on the news impact curve (EGARCH vs GARCH). Haas *et al.* (2006, p. 7) have argued 'that negative and positive shocks have an asymmetric impact on future volatility in the sense that negative news surprises increase volatility more than positive news surprises.' It is for this reason that the present study involved tests based on the news impact curve to determine the applicability and relevance of the EGARCH model formulation for the BRICS' log-return data. The results of the diagnostic tests are presented in Table 7.5.

Table 7. 5: The News Impact Curve Diagnostic Tests

Country	Type of Diagnostic Test			
	Sign Bias t-Test	**Negative Size Bias t-Test**	**Positive Size Bias t-Test**	**Joint Test for the Three Effects**
Brazil	0.80222 [0.42242]	1.34667 [0.17809]	3.03014* [0.00244]	15.29601* [0.00158]
Russia	0.03359 [0.97320]	0.15222 [0.87902]	0.39237 [0.69478]	0.22780 [0.97298]
India	1.11707[0.26397]	4.22957* [0.00002]	0.09666 [0.92300]	33.44670* [0.00000]
China	2.12214**[0.03383]	0.86218 [0.38859]	0.73305 [0.46353]	8.82124* [0.03176]
South Africa	0.50549 [0.61321]	1.13393 [0.25682]	3.28899* [0.00101]	18.63478* [0.00033]

[…] indicates probability value, * & ** indicates statistical significance at 1% and at 5% levels respectively

Source: Researcher Calculations

The results presented in Table 7.5 show that for Brazil's Bovespa log-returns the positive size bias, as well as the joint test for the three effects are statistically significant. The sign bias and negative size bias yielded statistically insignificant t-statistics. The news impact curve diagnostic tests yielded statistically insignificant t-statistics for all the scenarios of bias for Russia's RTSI index. This may imply that the GARCH (1, 1) model may be adequate, vis-à-vis, the EGARCH model or it may imply that other flavours of the GARCH zoo of models are applicable to the log-returns of RTSI. In the case of India, only the negative size bias test and the joint test for the three effects yielded statistically significant results. This may signal that the EGARCH model is actually more applicable to India's stock market than any other economy within the BRICS family. China's empirical results were also mixed with the sign bias test and the joint test yielding statistically significant results. This is reminiscent of the key findings for Brazil's and India's stock market volatility profile. Finally, the analysis whose results are shown in Table 7.5 shows that for South Africa's JSE index the positive size bias test and the joint test for the three effects returned statistically significant results.

It is imperative to observe that the diagnostic test results based on the News Impact Curve are not homogenous for the five BRICS economies owing to certain nuanced differences in their economic systems and their respective stock markets. This buttresses the assertion that even though the five economies of the current study may face the same economic events such as the global financial crisis (GFC), their individual responses are likely to differ in terms of timing, phase/duration, and magnitude. This may lend credence to the argument that the emerging BRICS economies are in fact fractal in structure and disposition (Gunay, 2015).

Gunay (2015) basing on the case of Brazil, Russia, India, China and Turkey (BRIC-T) and employing the Brock-Dechert-Scheinkman test, the Largest Lyapunov exponent and the Box-Counting method, has found weak evidence of the chaoticity and fractality of the BRIC-T stock markets. The following segment presents a summary of the EGARCH model which has been fitted into the log-return data of the five BRICS' stock markets.

7.2 Asymmetric univariate GARCH models

The present study also examined asymmetry and leverage effects in volatility for the daily log-returns using the Exponential GARCH (EGARCH) model developed by Nelson (1991). The main motivation for the implementation of EGARCH in the present study is that contemporary literature on volatility clustering has documented an asymmetry of volatility to shocks (Halunga and Orme, 2005). The results of the analysis are presented in Table 7.6.

Table 7. 6: EGARCH analysis results based on daily log-return data

	Brazil (logbov)	***Russia (logrtsi)***	***India (logbse)***	***China [logshang]***	***South Africa (logjse)***
	MEAN EQUATION	*MEAN EQUATION*	*MEAN EQUATION*	*MEAN EQUATION*	*MEAN EQUATION*
LOGBSE	0.045477* [0.0003]	0.082196* [0.0000]	*LOGBOV* 0.0035** [0.027735]	0.071771* [0.0000]	0.198442* [0.0000]
LOGJSE	0.180670* [0.0000]	0.190074* [0.0000]	0.170278* [0.0000]	0.058963* [0.0000]	*LOGBOV* *0.182065** *[0.0000]*
LOGSHANG	0.034591* [0.0006]	0.014954 [0.2171]	0.074428* [0.0000]	*LOGBOV* *0.021058*** *[0.0369]*	0.066840* [0.0000]
LOGRTSI	0.023474*	*LOGBOV*	0.014474*	0.004662	0.041472*

	[0.0009]	*0.042998* [0.0023]*	[0.0015]	[0.3270]	[0.0000]
LOGDOW	0.699557* [0.0000]	-0.003632 [0.8722]	0.048599* [0.0022]	-0.031479 [0.0567]	0.369603* [0.0000]
LOGCORN	0.008739 [0.5604]	0.042483** [0.0092]	0.005301 [0.7355]	-0.010707 [0.4846]	OMITTED
LOGCRUDE	0.040964* [0.0000]	0.021597** [0.0144]	0.002105 [0.7314]	0.011986 [0.0745]	0.070058* [0.0000]
LOGGOLD	0.184683* [0.0000]	-0.041135 [0.3163]	-0.084992* [0.0040]	0.029328 [0.3636]	0.665909* [0.0000]
VARIANCE EQUATION		*VARIANCE [EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*
CONSTANT(ω)	-0.297654* [0.0000]	-0.481908* [0.0000]	-0.366179* [0.0000]	-0.282463* [0.0000]	-0.209084* [0.0000]
ARCH (α)	0.142282* [0.0000]	0.248979* [0.0000]	0.208484* [0.0000]	0.208592* [0.0000]	0.099278* [0.0000]
LEVERAGE EFFECT (γ)	-0.036545* [0.0002]	-0.034092* [0.0001]	-0.089515* [0.0000]	-0.031058* [0.0020]	-0.070177* [0.0000]
GARCH(β)	0.978504* [0.0000]	0.961578* 0.0000	0.976248* [0.0000]	0.983202* [0.0000]	0.984955* [0.0000]
DISTRIBUTION	*GED* 1.442143* [0.0000]	*GED* 1.024890* [0.0000]	*STUDENT T* 5.634669* [0.0000]	*STUDENT T* 3.444105* [0.0000]	GED 1.503760* [0.0000]
α + β	1.120786	1.210557	1.184732	1.191794	1.084233
Loglikelihood	14574.21	12788.29	15308.72	14694.14	14492.29

***, ** & [..] indicates statistically significant result at 1% and 5% levels respectively as well as probability value**

Source: Researcher Calculations

Results of the estimated EGARCH (1,1) model estimated for the returns of the Bovespa, Russia's RTSI, India's BSE Sensex, China's Shangai and South Africa's JSE indices displayed in Table 7.6 indicate that all the estimated coefficients of the constant, the arch term, the GARCH term are statistically significant at 1% level of significance. Table 7.6 also shows that γ the parameter that captures the asymmetric leverage effect is negative and statistically significant for all the models of the BRICS stock markets. According to Ahmed and Suliman (2011, p.121) the 'negative sign for all the periods show that negative shocks mean a higher next period conditional variance than positive shocks of the same sign.' The significant negative leverage terms for the BRICS signal that negative news have more impact on volatility than positive news.

7.3 Long-memory and Forecasting – Evidence from FIGARCH analysis

It is a stylised fact documented in the empirical literature that commodity returns and stock returns are characterised by volatility clustering as well as volatility persistence. The feature of volatility persistence which characterises stock returns is also called long memory in the literature. There are a number of volatility models that have been suggested by different researchers so as to accurate model long-range dependence in mean and volatility of asset returns (Tafeyi and Ramanathan, 2012; Lopes, 2008; Baillie *et al.,*1996). Tafeyi and Ramanathan (2012) have argued that the long-memory characteristic of FIGARCH models predisposes them to be better and more efficient in modelling volatility in option prices, inflation and stock market returns compared to other GARCH models. In the same vein, Al-Hajieh (2017, p. 200) argues that different flavours of fractionally integrated GARCH models have superior predictive ability. The study thus involved estimating two versions of the Fractionally Integrated – GARCH (FIGARCH) for each of the five BRICS countries. FIGARCH-Baillie-Bollerslev-Mikkelsen usually abbreviated FIGARCH-BBM was proposed by Baillie *et al.* (1996), while FIGARCH-Chung was developed by Chung (1999) purportedly as a modification of FIGARCH-BBM ostensibly to improve its parameterisation problem. Tables 7.7 and 7.8 summarise the results of the FIGARCH-BBM and attendant diagnostic tests.

Table 7. 7: FIGARCH – BBM models for BRICS

	Brazil (logbov)	*Russia (logrtsi)*	*India (logbse)*	*China [dlogshng]*	*South Africa (logjse)*
	MEAN EQUATION	*MEAN EQUATION*	*MEAN EQUATION*	*MEAN EQUATION*	*MEAN EQUATION*
	Constant 0.000311 [0.0980]	*Constant* 0.000860* [0.0000]	*Constant* 0.000807* [0.0000]	*Constant* -0.000394** [0.0183]	*Constant* 0.000325 [0.0847]
	logrtsi 0.025362* [0.0005]	*Logbov* 0.048420* [0.0031]	*logbov* 0.044003* [0.0000]	*logshng_1* 3.445927** [0.0268]	*logbov* 0.331256* [0.0000]
	logbse 0.079349* [0.0000]	*Logbse* 0.100768* [0.0000]	*logrtsi* 0.013822 [0.0947]	*logrtsi* not specified	*logrtsi* 0.055545* [0.0004]
	logshng -0.366085 [0.3248]	*Logshang* -0.366957 [0.4196]	*logshng* -0.456080 [0.1369]	*logbse* not specified	*logshng* -0.435243 [0.3294]
	logjse	*Logjse*	*logjse*	*logjse*	*logbse*

	0.383361* [0.0000]	0.203340* [0.0000]	0.188493* [0.0000]	not specified	0.241387* [0.0000]
PARAMETER	*VARIANCE EQUATION*	*VARIANCE [EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*
CONSTANT(ω)*10^4	0.079597* [0.0082]	0.157091* [0.0002]	0.049123* [0.0043]	0.256041* [0.0000]	0.076248** [0.0114]
d.FIGARCH	0.384547* [0.0000]	0.996930* [0.0000]	0.447363* [0.0000]	0.381811* [0.0000]	0.358500* [0.0000]
ARCH (α)	0.306195* [0.0000]	-0.030843 [0.5199]	0.277121* [0.0017]	0.299212* [0.0000]	0.388906* [0.0000]
GARCH(β)	0.590405* [0.0000]	0.804228* [0.0000]	0.552949* [0.0000]	0.146518** [0.0233]	0.652941* [0.0000]
DISTRIBUTION	*STUDENT (DF)* 8.309163* [0.0000]	*STUDENT (DF)* 3.906987* [0.0000]	*STUDENT (DF)* 5.405363* [0.0000]	*STUDENT (DF)* 6.857907* [0.0000]	*STUDENT (DF)* 8.879820* [0.0000]
Information Criteria	Akaike *-5.738634* Shibata *-5.738642* Schwarz *-5.725310* Hannan-Quinn *-5.733958*	Akaike *-5.251296* Shibata *-5.251304* Schwarz *-5.237972* Hannan-Quinn *-5.246620*	Akaike *-6.249040* Shibata *-6.249048* Schwarz *-6.235716* Hannan-Quinn *-6.244364*	Akaike *-5.358285* Shibata *-5.358289* Schwarz *-5.348957* Hannan-Quinn *-5.355011*	Akaike *-5.795470* Shibata *-5.795479* Schwarz *-5.782147* Hannan-Quinn *-5.790794*
Loglikelihood	13989.312	12802.156	15232.661	13057.102	14127.766

***, ** indicates statistical significance at 1% and 5% levels, [..] indicates the probability value**

Source: Researcher Calculations

Table 7.7 displays a summary of the Fractionally Integrated-GARCH model results for the BRICS economies using different mean model specifications. The mean model specification was determined by the literature as well as practical imperatives such as convergence and model parsimony. The results in Table 7.7 clearly demonstrate that the log returns of the BRICS have long memory or persistence as corroborated by findings from other univariate GARCH models. This implies that the shock to an n-step ahead (future) volatility decays at a slower hyperbolic rate. The intuitive meaning of long-range dependence or long memory is that an unexpected shock to any of the BRICS stock indices has long lasting effects. The results captured in Table 7.7 confirm the findings of Singh (2018) who discovered that the volatility process of China's equity market is characterised by a long-run dependence structure. The results presented in Table 7.7

depart from most of the empirical literature in that for Brazil, Russia, India and South Africa, log returns of the stock indices of other members of the BRICS bloc are specified in the respective mean equations. This was done to ascertain the extent of integration or strength of linkages between different BRICS stock markets. The maintained hypothesis is that if any two economies have interlinked (and to some extent integrated) stock markets, then the log returns of one stock market index will explain the log-returns of another stock market index.

The FIGARCH-BBM results indicate five interesting facts about the BRICS. First, Brazil's log stock returns are explained by the log-returns of the stock markets of Russia, India and South Africa. The log returns of China's Shanghai composite index are statistically insignificant in explaining Bovespa's log-returns. Second, the log-returns of the Russia Trading System Index (RTSI) are determined by the log-returns of the Brazilian, Indian and South African stock markets. Third, the log-returns of India's BSE Sensex index are explained by the log-returns of Brazil's Bovespa and South Africa's JSE indices. Fourth, the log-returns of South Africa's JSE index are statistically explained by the log-returns of Bovespa, RTSI, and BSE Sensex indices.

Finally, the log-returns of China's Shanghai composite index were found to be statistically independent of the log-returns of other indices in repeated modelling under diverse error distributional conditions. This important finding contradicts earlier results published by Kishor and Singh (2017, p.38) who found that 'Chinese stock indices (are) significantly and positively correlated with Russian stock indices.' The study found no evidence to support such a conclusion either from the FIGARCH-BBM model or from correlation analysis whose results are presented in Chapter Six of this thesis. The statistically significant very low positive correlation coefficient of 6.17 percent or 0.061744 for China's Shanghai log-returns and Russia's RTSI log-returns as presented in Table 6.7 is evidence of a virtually insignificant positive association between the two stock markets. This finding for China is not amazing. China is an economy which for many years has been centrally planned with the government or governmental institutions playing a significant role in economic activities (Wang *et al.,* 2017 and Wang, 2009).

7.3.1 Diagnostic tests of the FIGARCH - BBM of the BRICS

A model in financial economics which is useful for describing and forecasting stock returns and their volatility is one which is characterised by stationarity of variables and residuals, the stability of parameters as well as good goodness of fit. The study, thus, conducted standard tests associated with the FIGARCH-BBM models.

Table 7. 8: Nyblom Parameter Stability Test Results for the FIGARCH - BBM

Country	Type of Test	Variables	Nyblom Statistic	Decision
Brazil	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst (M) logrtsi (M) logbse (M) logshng (M) logjse (M) Cst(V) x 10^4 d-FIGARCH ARCH(Beta1) GARCH(Beta1) Student (DF)	[0.16494] [0.19471] [0.37391] [0.25089] [0.48423] [0.43412] [0.49944] [0.50014] [0.65943] [0.59921]	*All the estimated coefficients are stable.*
Russia	*1% critical value = 0.75* *5% critical value = 0.47*	Cst (M) logbov (M) logbse (M) logshng logjse Cst(V) x 10^4 d-FIGARCH ARCH(Alpha1) GARCH(Beta1) STUDENT (DF)	[1.03922] [2.59857] [2.04330] [0.19786] [5.12601] [0.33825] [0.77995] [0.34039] [0.88826] [0.73675]	*Only the coefficient of logshng and the ARCH effect are stable. All other estimated coefficients are unstable, that is, they have structural breaks*
India	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logbov (M) logrtsi (M) logjse (M) Cst(V)x 10^-4 d.FIGARCH ARCH(Alpha1) GARCH(Beta1) Student (DF)	[0.51520] [0.38346] [0.20923] [0.89994] [0.20923] [0.99715] [0.96515] [0.53266] [0.31546]	*The two constant parameters, logbov, logrtsi, student (df) are stable. All other estimated coefficients are unstable, that is, they have structural breaks*
China	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) Logshng_1(M) d-FIGARCH Cst(V) x 10^-4 ARCH(Alpha1) GARCH(Beta1) Student(DF)	[0.06271] [0.11016] [1.74980] [0.95375] [0.46908] [0.52551] [0.78482]	*Estimated logshng, ARCH and GARCH coefficients are stable while the constant of the mean equation and student t are unstable, that is, they have structural breaks*

South Africa	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logbov (M) logrtsi (M) logbse (M) logshng (M) Cst(V) x 10^-4 d-FIGARCH ARCH(Alpha1) GARCH(Beta1) Student(DF)	[0.19505] [8.69716] [1.05348] [6.85133] [0.03175] [0.10389] [0.41287] [0.50719] [0.24496] [0.26090]	*Only logbov, logrtsi and logbse the coefficients are unstable. All other estimated coefficients are stable.*

[…] indicates calculated Nyblom parameter stability statistic

Source: Researcher Calculations

Table 7.8 shows mixed parameter stability test results. Some variables especially those specified for the mean equations are unstable for the BRICS respective stock markets. The merit of the estimated FIGARCH-BBM models for the BRICS is that virtually all GARCH parameters are stable, though the d-FIGARCH parameters for China, India and Russia are unstable. This may be due to the fact that the respective series are not characterised by one regime as assumed in conducting the univariate FIGARCH modelling exercise. The Markov – Switching GARCH model results presented in Tables 7.15 and 7.16 amply demonstrate that the data series spanning the period January 2000 to September 2018 are characterised by regime changes and breakpoints.

Table 7.9 presents the results of serial correlation tests that were conducted on the squared residuals of the FIGARCH-BBM models for the BRICS.

Table 7. 9: Serial Correlation Test Results for Squared Standardised residuals

Country	Box/Pierce Statistic	Decision
Brazil	--> P-values adjusted by 2 degree(s) of freedom Q(5) = 3.11891 [0.3736529] Q(10) = 7.23042 [0.5119885] Q(20) = 12.6495 [0.8119583] Q(50) = 35.2379 [0.9146992] H0 : No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)]	*The results show that the residuals are uncorrelated. Thus, for the estimated FIGARCH (1,d, 1) model it can be assumed that errors are Independent and Identically distributed (i.i.d).*
Russia	--> P-values adjusted by 2 degree(s) of freedom Q(5) = 0.787656 [0.8524171] Q(10) = 16.6180 [0.0343416]* Q(20) = 17.7683 [0.4710123] Q(50) = 81.3830 [0.0018632]** H0 : No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)]	*The results are mixed as they show that for Q (5) and Q (20) residuals are uncorrelated while results for Q (10) and Q (50) they are correlated. This may be evidence of the long memory feature of conditional volatility.*

India	--> P-values adjusted by 2 degree(s) of freedom Q(5) = 1.56904 [0.6664306] Q(10) = 3.02988 [0.9324686] Q(20) = 18.1530 [0.4456190] Q(50) = 39.4575 [0.8052583] H0 : No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)] ---------------	*The results show that the residuals are uncorrelated. Thus, for the estimated FIGARCH (1,d, 1) model it can be assumed that errors are Independent and Identically distributed (i.i.d).*
China	--> P-values adjusted by 2 degree(s) of freedom Q(5) = 7.53118 [0.0567627] Q(10) = 8.54538 [0.3820844] Q(20) = 13.1587 [0.7820581] Q(50) = 42.0423 [0.7144292] H0 : No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)]	*The results show that the residuals are uncorrelated. Thus, for the estimated FIGARCH (1,d, 1) model it can be assumed that errors are Independent and Identically distributed (i.i.d).*
South Africa	--> P-values adjusted by 2 degree(s) of freedom Q(5) = 5.92032 [0.1155520] Q(10) = 9.80626 [0.2788879] Q(20) = 23.2595 [0.1808129] Q(50) = 52.7892 [0.2942587] H0 : No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)]	*The results show that the residuals are uncorrelated. Thus, for the estimated FIGARCH (1,d, 1) model it can be assumed that errors are Independent and Identically distributed (i.i.d).*

[…] indicates probability value

Source: Researcher Calculations

Table 7.9 shows that with the exception Russia's FIGARCH-BBM model, Brazil's, India's, China's and South Africa's estimated FIGARCH-BBM models have uncorrelated residuals. This may indicate that the errors associated with those economies' log stock returns may be independent and identically distributed (i.i.d) from a Fractionally Integrated GARCH modelling perspective.

7.3.2 Persistence in Volatility Dynamics – Evidence from FIGARCH-Chung

The picture of the volatility dynamics of the stock returns of the BRICS would be incomplete if it were to be analysed from the perspective of Baillie *et al.* (1996)'s FIGARCH-BBM model. The study, thus, involved modelling BRICS' stock return behaviour and persistence using the FIGARCH-Chung originally developed by Chung (1999) in order to ameliorate parameterisation and other practical problems associated with FIGARCH-BBM estimation. Table 7.10 summarises the model results of the FIGARCH-Chung estimation procedure.

Table 7. 10: FIGARCH – Chung models for BRICS

	Brazil (logbov)	***Russia (logrtsi)***	***India (logbse)***	***China [dlogshng]***	***South Africa (logjse)***
	MEAN EQUATION	*MEAN EQUATION*	*MEAN EQUATION*	*MEAN EQUATION*	*MEAN EQUATION*
	Constant 0.000183 [0.3404]	*Constant* 0.000983* [0.0000]	*Constant* 0.000763* [0.0000]	*Constant* 0.000003 [0.4739]	*Constant* 0.000201 [0.0768]
	logrtsi 0.028156* [0.0000]	*AR(1)* -0.023694 [0.9083]	*Logbov* 0.044422* [0.0000]	*AR(1)* -0.019471 [0.1589]	*logbov* 0.252207* [0.0000]
	logjse 0.239796* [0.0000]	*AR(2)* -1.031760* [0.0000]	*Logjse* 0.189701* [0.0000]	*AR(2)* -0.010793 [0.4571]	*logrtsi* 0.052322* [0.0002]
	logdow 0.700857* [0.0000]	*AR(3)* -0.333477 [0.0677]	………………	*AR(3)* 0.009352 [0.4782]	*logbse* 0.237269* [0.0000]
	d.ARFIMA 0.056340 [0.2571]	*AR(4)* -0.479867** [0.0470]	……………….	*AR(4)* -0.011657 [0.3673]	*logdow* 0.370911* [0.0000]
	AR(1) -0.040137 [0.8730]	*MA(1)* 0.079238 [0.6920]	………………	*MA(1)* -0.972158* [0.0000]	*AR(1)* 0.407455 [0.0989]
	AR(2) 0.352703** [0.0111]	*MA(2)* 1.024423* [0.0000]	……………… …………………..	……………….. …………………	*AR(2)* 0.311301 [0.0635]
	MA(1) -0.083573 [0.7484]	*MA(3)* 0.370421** [0.0342]	……………………	…………………	*AR(3)* 0.014934 [0.3411]
	MA(2) -0.411842** [0.0122]	*MA(4)* 0.505693** [0.0341]	………………….	………………..	*MA(1)* -0.526310** [0.0333]
	……………………	……………………	…………………	………………..	*MA(2)* -0.301849 [0.1130]
PARAMETER	*VARIANCE EQUATION*	*VARIANCE [EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*	*VARIANCE EQUATION*
CONSTANT(ω) *10^4	Not specified	67.835907** [0.0239]	5.022591 [0.0776]	4.662229** [0.0210]	1.855421* [0.0000]
d.FIGARCH	0.296788* [0.0000]	0.629224* [0.0000]	0.442559* [0.0000]	0.439625* [0.0000]	0.226198* [0.0000]
ARCH (α)	*Set equal to zero to ensure positivity of variance equation*	0.081381 [0.1995]	*Insignificant in repeated modelling*	0.097097 [0.6726]	*Set equal to zero to ensure positivity of variance equation*

GARCH(β)	0.202874* [0.0000]	0.566793* [0.0000]	0.278755 [0.0001]	0.439140 [0.1322]	0.128091* [0.0018]
DISTRIBUTION	*STUDENT (DF)* 8.438643* [0.0000]	*STUDENT (DF)* 3.778015* [0.0000]	*STUDENT (DF)* 4.987007* [0.0000]	*STUDENT (DF)* 3.593000* [0.0000]	*STUDENT (DF)* 7.992385* [0.0000]
Information Criteria	Akaike *-5.959633* Shibata *-5.959645* Schwarz *-5.943645* Hannan-Quinn *-5.954022*	Akaike *-5.195094* Shibata *-5.195111* Schwarz *-5.176441* Hannan-Quinn *-5.188548*	Akaike *-6.248273* Shibata *-6.248277* Schwarz *-6.238946* Hannan-Quinn *-6.245000*	Akaike *-5.971976* Shibata *-5.971986* Schwarz *-5.957320* Hannan-Quinn *-5.966832*	Akaike *-5.851980* Shibata *-5.851996* Schwarz *-5.833327* Hannan-Quinn *-5.845433*
Loglikelihood	14529.67	12669.250	15227.793	14558.733	14269.422

***, ** indicates statistical significance at 1% and 5% levels, […] indicates the probability value**

Source: Researcher Calculations

Table 7.10 shows that different formulations of the FIGARCH – Chung model for individual BRICS economies were adequately catered for within the Student t error distributional framework. The five FIGARCH – Chung models presented on Table 7.10 were, from the vintage of the researcher, the best taking into account, autocorrelation and partial autocorrelation graphical analysis results as presented on Appendix A. Model formulation also took into account model parsimony, convergence issues, forecasting power or gains, parameter stability, log likelihood statistics and information criteria as measured by the Akaike, Shibata, Schwarz Bayesian and Hannan-Quinn criteria. According to the empirical literature the best model must, among other requirements, be able to minimise the information criteria selected by the research to compare different models. The FIGARCH – Chung models also yielded better in-sample conditional mean and conditional variance forecasts as well as out of sample forecasting.

The mean equation for Brazil reveals that Russia's logrtsi, South Africa's logjse, the United States' (US) logdow all have a statistically significant positive impact on Brazil's logbov. This implies that at 1 percent level of significance, the log-returns of Russia's, South Africa's and the US' stock markets have a statistically significant positive effect on the log-returns of Brazil's Bovespa index (represented by logbov). Distant past innovations of the estimated logbov model have a statistically significant impact on the log-returns of Brazil's stock market at a 5 percent level. This may be part of the evidence of the impact of persistence in volatility on stock market returns, *ceteris paribus*.

The volatility dynamics of Brazil are such that for the model to satisfy the positivity constraint, the ARCH term had to be suppressed implying that the final model that is found to be parsimonious is the FIGARCH (1, d, 0). The estimated model results in Table 7.10 show that both the d.FIGARCH and GARCH terms have a positive and statistically significant effect on the current volatility of the Brazilian stock market's log-return at a 1 percent level. This confirms findings from other models that there is long-range dependence in the returns and volatility of Brazil's stock market as ably demonstrated and argued by Calvacante and Assaf (2002). This evidence disproves the argument held by Fama (1965a, 1976a and 1991) that stock markets are efficient. The persistence of volatility actually proves that stock market return behaviour is fractal, non-linear and inefficient (Calvacante and Assaf, 2002).

The mean model which was fitted for the Russian stock market's log-returns is an ARMA (4, 4). The AR (2) term is statistically significant at a 1 percent level while the AR (4), MA (2), MA (3) and MA (4) are statistically significant at a 5 percent level. The import of this finding is that lags of the stationarised log-returns series (Autoregressive (AR) terms) and lags of the forecast errors (also called Moving Average (MA) terms) are statistically significant in determining current log-returns of Russia's RTS stock index (RTSI). This is also evidence of long-range dependence in stock returns from the vantage point of Russia's stock market.

The main parameters of Russia's FIGARCH (1, d, 1) model, with the exception of the ARCH term were all found to be statistically significant at 1 percent and 5 percent levels respectively as displayed in Table 7.10. This lends more credence to the belief that Russia's stock market is characterised by fractality, non-linearity, and inefficiency. This finding harmonises with the perspective of Ikeda (2017) who argues for the multi-fractality of the Russian stock price returns on the basis of the multifractal detrended fluctuation analysis (MFDFA) model.

The findings displayed in Table 7.10 reveal that the mean model of India's stock market index (the BSE Sensex) is determined by the stock returns of Brazil's and South Africa's stock markets. Repeated modelling experiments show that the FIGARCH (1, d, 0) model specification fits the data well in terms of meeting the positivity constraint, loglikelihood, parameter stability and goodness of fit test results that are shown in detail under Appendix B.1.

The mean model of China's stock market returns was specified as an ARMA (4, 1) taking into cognisance the autocorrelation dynamics as analysed and displayed graphically under Appendix A4. It is important to note that the AR terms, though positively related to the current differenced log-return for the Shanghai composite index, are actually statistically insignificant but have been kept in the model because of the forecasting gains of retaining those terms. The conditional mean and volatility forecasts of China's FIGARCH (1, d, 1) model are displayed graphically under Appendix D4 to corroborate the claim made in the foregoing analysis.

The return and volatility dynamics of log-return data from South Africa's Johannesburg Stock Exchange (JSE) index are such that an ARMA (3, 2) – FIGARCH (1, d, 0) model was found to be parsimonious and stable in terms of its parameters. This is corroborated by forecasting test results displayed under D5 respectively.

The FIGARCH – Chung models estimated for the BRICS whose results are summarised in Table 7.10 were all subjected to standard diagnostic tests. The results of Nyblom's parameter stability tests are summarised in Table 7.11.

Table 7. 11: Nyblom Parameter Stability Test Results for the FIGARCH – Chung

Country	Type of Test	Variables	Nyblom Stat.	Decision
Brazil	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst (M) logrtsi (M) logjse (M) logdow (M) d-ARFIMA AR (1) AR (2) MA (1) MA (2) d.FIGARCH GARCH(Beta1) Student (DF)	[0.40055] [0.59139] [0.26729] [1.77803] [0.21509] [0.26158] [0.24602] [0.22836] [0.35046] [0.22954] [0.11246] [0.92535]	*Of all the estimated coefficients only logdow is unstable. The student t (df) is also unstable.*

Russia	*1% critical value = 0.75* *5% critical value = 0.47*	Cst (M) AR (1) AR (2) AR (3) AR (4) MA (1) MA (2) MA (3) MA (4) Cst(V) x 10^4 d-FIGARCH ARCH(Alpha1) GARCH(Beta1) STUDENT (DF)	[1.38214] [0.10589] [0.59014] [0.14870] [0.36251] [0.10082] [0.62960] [0.18226] [0.34986] [0.99001] [1.85425] [1.14930] [2.22228] [2.06398]	*All estimated ARMA (4, 4) coefficients of the mean equation are stable except the constant. All parameters of the FIGARCH – Chung variance equation are not stable. This may be due to regime changes due to crises during the study period.*
India	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logbov (M) logjse (M) Cst(V)x 10^-4 d.FIGARCH GARCH(Beta1) Student (DF)	[0.53604] [0.39125] [0.91358] [0.38081] [0.08737] [0.55932] [0.38192]	*Only the estimated parameter of logjse is unstable. All other parameters are stable. This is a fairly stable model.*
China	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) AR (1) AR (2) AR (3) AR (4) MA (1) Cst(V) x 10^4 d.FIGARCH ARCH (Phi1) GARCH(Beta1) Student(DF)	[0.39789] [0.19051] [0.08643] [0.03610] [0.12676] [4.81136] [0.73348] [1.40641] [0.49926] [0.81170] [0.72208]	*Only the estimated coefficients of MA (1), di.FIGARCH, and GARCH (Beta1) unstable. All the other estimated coefficients are stable.*
South Africa	Nyblom Parameter Stability *1% critical value = 0.75* *5% critical value = 0.47*	Cst(M) logbov (M) logrtsi (M) logbse (M) logdow (M) AR (1) AR (2) AR (3) MA (1) MA (2) Cst(V) x 10^4 d-FIGARCH GARCH(Beta1) Student(DF)	[0.67175] [9.71092] [1.00112] [5.88856] [10.68438] [0.45076] [0.14440] [0.14074] [0.25754] [0.08487] [0.61407] [0.18660] [0.24558] [0.34174]	*With the exception of the constant and ARMA (3, 2) coefficients, all coefficients of log-returns of Brazilian, Russian, Indian and US stock markets specified in the mean equation are unstable. This may be due to structural breaks in them. All coefficients of the variance equation are stable.*

[…] indicates calculated Nyblom parameter stability statistic

Source: Researcher Calculations

Model adequacy tests yielded mixed results. Brazil and India have the most stable FIGARCH – Chung models characterised by instability in only one parameter estimate. This implies that the estimated models for Brazil and India can be relied on for in-sample and out-sample forecasting of the volatility of their respective stock market log returns. China has the third-best model in terms of parameter stability since only two estimated coefficients are unstable. This implies that conditional mean and variance forecasts obtained from China's FIGARCH-Chung model would yield satisfactory results. The fourth best FIGARCH-Chung model is that of South Africa, whose unstable parameter estimates are those of the mean equation. This implies that in-sample conditional variance forecasts obtained from South Africa's FIGARCH – Chung model may still be expected to be fairly accurate. The researcher would need to rely on a Markov – Switching GARCH model for conditional mean forecasts for South Africa which takes into account regime changes and structural breaks which may be contributing to mean equation parameter instability. The least stable FIGARCH – Chung estimated model is that of Russia. The estimated model for Russia has stable mean equation parameter estimates except for the estimate for the constant. This implies that the model may give satisfactory or fairly accurate conditional mean in-sample forecasts. Nevertheless, the main drawback of Russia's FIGARCH – Chung model is that all estimated parameters of the variance equation are unstable. This implies that in-sample and out-of-sample conditional variance forecasts need to be accepted with a caveat. These mixed results obtained from the FIGARCH – Chung modelling of BRICS stock market log returns partly influenced the choice and estimation of the DCC – GARCH and Markov – Switching models.

The study also involved testing for the serial correlation of squared standardised residuals using the Box/Pierce procedure. The table labelled Appendix B shows the Box/Pierce test results of the FIGARCH – Chung model specification. The results are mixed, mirroring results of other model specifications such as GARCH (1, 1) and FIGARCH – BBM which show for some stock markets such as that of Russia, India and China, evidence of both short-term stability and long memory features.

7.3.3 In-Sample Forecast Performance of FIGARCH – BBM and FIGARCH – Chung

The study also analysed the forecasting performance of the FIGARCH-BBM and the FIGARCH-Chung. The results of conditional mean and variance forecasts for the BRICS stock returns are shown in Appendices C and D. The results show that taking into consideration a four week (28 day) in-sample forecast period from 5 August 2018 to 2

September 2018, generally the FIGARCH – BBM and FIGARCH – Chung had similar and comparable forecast performance. Appendices C1 and C3 show that the conditional mean forecast estimated using the FIGARCH – BBM is fairly accurate in tracking the actual log-return behaviour of Brazil's Bovespa and India's BSE Sensex indices. This finding is similar to that of the FIGARCH – Chung model which yielded good in-sample conditional mean forecasts for the Brazilian and Indian stock market return processes respectively. The FIGARCH-BBM model was apparently not good in mapping accurately the conditional mean and volatility dynamics for China, though it yielded fair in-sample mean forecasts for the JSE index. In contrast, the FIGARCH-Chung yielded poor conditional mean forecast results for Russia's RTSI index compared to the FIGARCH-BBM which yielded fairly accurate in-sample conditional mean forecast results. It is noteworthy that while the in-sample forecast performance of the FIGARCH-BBM was poor for China's Shanghai Composite index, the forecast performance of the FIGARCH – Chung model was satisfactory for the same index. The conclusion of the study is that the two models complement each other and need to be used together as complements not as substitutes since they compensate for each other's weaknesses in terms of forecast performance.

The trend gleaned from general graphs that are presented under Appendix F is that there was a spike in volatility during the GFC period of 2007-2008.

7.4 Volatility Transmission and Interdependence among BRICS – Evidence from DCC-GARCH

This study involved estimating the Dynamic Conditional Correlation (DCC) – GARCH (1, 1) model in order to investigate volatility transmission and interdependence among the BRICS economies. The rationale that motivated the implementation of DCC-GARCH is twofold. First, basing on the empirical findings in a similar study by Bonga-Bonga (2015), this study maintains that an increase in correlation during certain documented crises signifies contagion. Second, the DCC-GARCH models estimated for this study sought to discern the effects of the US stock market which in the present study is proxied by the daily log-returns of Dow Jones Industrial average.

7.4.1 DCC GARCH model results

Table 7.12 presents a summary of the DCC model parameter estimates. In the modeling scheme of the current study the univariate GARCH (1, 1) parameter estimates for each of the BRICS log-returns represent the diagonal elements of the D_t as defined in Chapter 5, while θ_1 and θ_2 represent the DCC conditional correlation parameters.

Table 7. 12: DCC model parameter estimates for the BRICS daily log stock returns

Market	**Parameter**	**Estimate**	**Standard Error**	**p-value**	**Persistence**
Bovespa (Brazil)	constant	0.000006	0.000002	0.004417	
	A	0.062303	0.005856	0.000000	$\alpha + \beta =$
	B	0.915060	0.007496	0.000000	0.977363
RTSI (Russia)	constant	0.000030	0.000011	0.005402	
	A	0.147946	0.029700	0.000001	$\alpha + \beta =$
	B	0.810899	0.030053	0.000000	0.958845
BSE Sensex (India)	constant	0.000003	0.000002	0.121251	
	A	0.119578	0.026360	0.000006	$\alpha + \beta =$
	B	0.871152	0.025537	0.000000	0.99073
ShangaiSE (China)	constant	0.000000	0.000000	0.985367	
	A	0.065843	0.015625	0.000025	$\alpha + \beta =$
	B	0.908605	0.021512	0.000000	0.974448
JSE (South Africa)	constant	0.000004	0.000003	0.122746	
	A	0.066283	0.008281	0.000000	$\alpha + \beta =$
	B	0.916808	0.012651	0.000000	0.983091
DCC conditional correlation parameters	θ_1	0.005420	0.001178	0.000004	Stability: $\theta_1 + \theta_2 =$ 0.996809<1
	θ_2	0.991389	0.002395	0.000000	

Information Criteria	
Akaike	-34.950
Bayes	-34.875
Shibata	-34.951

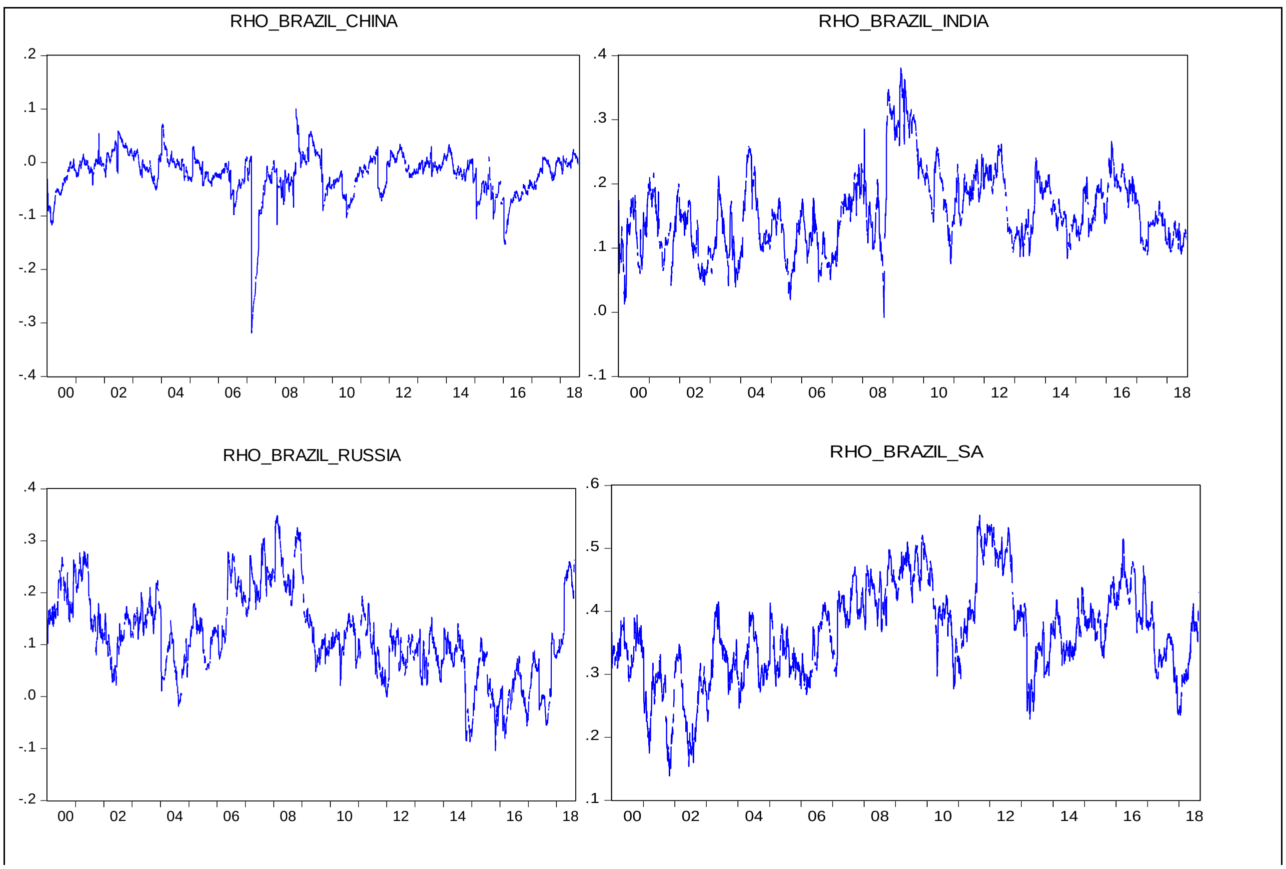
Hannan-Quinn	-34.924

Source: Researcher Calculations

Table 7.12 shows that all the ARCH and GARCH terms of the stock return series of the five BRICS' stock markets are statistically significant at the 1% level. This means the respective ARCH and GARCH terms are significant in explaining the volatility dynamics of the daily log-returns of the BRICS' stock markets. The statistical significance of the univariate GARCH parameters, namely, α and β captured in Table 7.12 reveals two stylised facts associated with emerging economy stock market performance. First, statistically significant univariate ARCH and GARCH parameters show that the conditional volatility of BRICS stock markets is highly persistent. China's Shangai Stock index exhibits the highest volatility persistence at 0.99073 while Russia's RTSI index exhibits the lowest volatility persistence at 0.958845. This result partially confirms the results of the GARCH (1, 1) model presented in Table 7.1 which was estimated by specifying more variables (including commodity price log-returns) for the conditional mean equation. Second, the results indicate that different stock markets are responsive to shocks received from other stock markets (Ijumba, 2013). It is imperative to note that the stability condition of the DCC model, which is $\theta_1 + \theta_2 = 0.991062<1$ is met which implies that the estimated correlation matrix P_t satisfies the requirement of positive definiteness.

7.4.1.1 Volatility Dynamics, Transmission, and Interdependence among BRICS

The crux of the current study is an examination of the nexus between commodity price volatility and stock market development. The current study departed from traditional measures of stock market development because those measures are not amenable to high frequency data. It is the belief of the current study that an investigation of the commodity price volatility – stock market development nexus is not the preserve of low frequency conceptualisations of stock market development. It is in this regard that the present study relied on log stock returns to proxy (or give a picture of) stock development in the high frequency domain. Dynamic Conditional Correlation (DCC) – GARCH analysis reveals interesting features about volatility transmission and contagion among BRICS' stock markets. This section does not rehash the causality issues which are examined both in the time series domain and the frequency domain in Chapter 6. The present discussion is concerned with distilling from DCC-GARCH analysis certain salient features that characterise emerging economy commodity and stock markets. The current study has confirmed claims of the empirical literature that volatility transmission and contagion is normally from more developed economies to less developed ones than vice versa (Bonga-Bonga, 2015 and Ijumba, 2013). The concomitance of increased contagion between emerging economies and increased commodity market integration globally has been styled by some studies on financialisation (Silvennoinen and Thorp, 2010). Figure 7.1 displays graphical plots of the estimated conditional correlations of the DCC model.



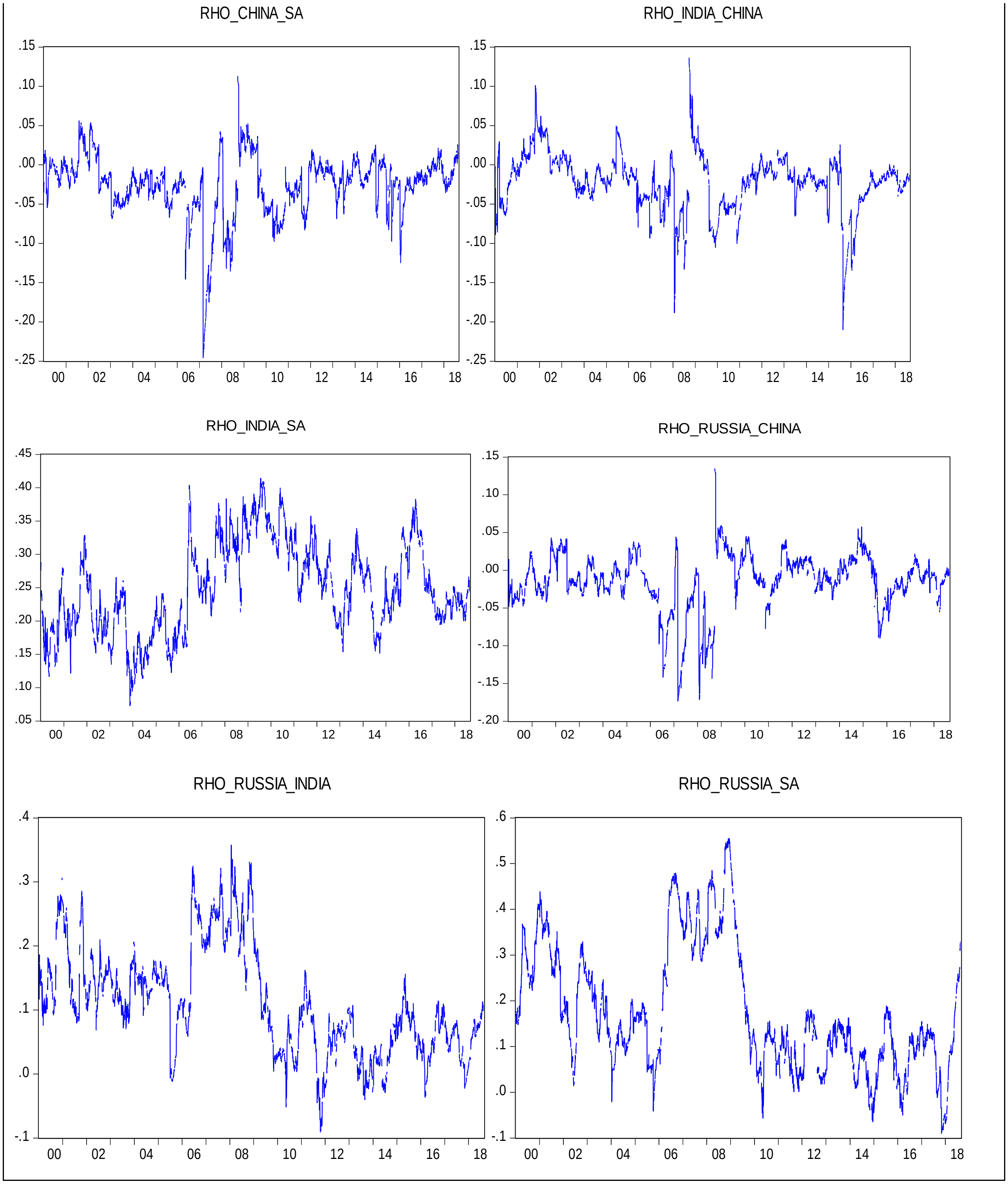


Figure 7. 1: Dynamic Correlations for Brazil, Russia, India, China & SA markets, Source: Researcher Compilation

Figure 7.1 shows that in virtually all the markets there was a decline in conditional correlation between 2000 and 2002. Brazil's and India's stock markets exhibited highly volatile correlation characterised by evidence of decoupling between the two stock markets on 15 September 2008. Brazil's and South Africa's stock markets had correlation that exhibited an upward trend between 2003 and 2008, with a peak in 2008 which was followed by a local minimum in 2010 which is one of the years of the European sovereign debt crisis (Rengasamy, 2012; Huang, 2013). It is, nevertheless, important to observe that Rengasamy (2012) basing on a sample bifurcated into two study periods and on the basis of Kolmogorov Smirnov and Shapiro-Wilk's tests argues that BRICS stock markets did not register negative returns during the 32 months study period. Such a finding does not adequately account for the localised downturn in dynamic correlations that obtained for the Brazilian and Indian, Brazilian and Chinese stock markets towards the end of 2010 as shown in Figure 7.1. According to the findings of Creti *et al.* (2012) the high levels of volatility in the dynamic conditional correlations may be taken as indirect evidence of how financialisation of commodity markets caused volatility of the equity markets of BRICS countries.

The general trend of the dynamic correlation between Bovespa index and the Shanghai index is upward for the period 2000-2009. The dynamic correlation between the Bovespa index and the Shanghai index attained a peak in 2009 the year of the climaxing of the global financial crisis (GFC) in the United States (US) economy which in the present analysis is proxied by the Dow Jones Industrial average. This shows that there was increased contagion between Brazil's stock market and China's stock market during the GFC period.

The increasing positive dynamic conditional correlations, during the Global Financial and European sovereign debt crisis, between Brazil and South Africa, Brazil and Russia, Brazil and India, Russia and South Africa, and Russia and India provide evidence of increased contagion between those economies. This shows that the repercussions of GFC and the European sovereign debt crisis were transmitted to the stock markets of Brazil, Russia, India, and South Africa. The Chinese stock market benefited from the protectionist policies of China's central government.

Figure 7.1 shows that beyond 2009 the correlation between Brazil's stock index and that of China follows a downward trend characterised by a significant decoupling of the two capital markets on 5 December 2016 since the dynamic correlation was 0.053 for that date. The most significant feature of the dynamic correlation between Brazil's stock market index and Russia's RTSI index is the peak it attained between the end of 2006 and the end of 2008. This was evidently as a result of the global financial crisis and owed to increased contagion between the two markets during the crisis period as ably demonstrated by Bonga-Bonga (2015) in a study to uncover the equity market contagion among BRICS economies.

The dynamic correlations of India versus China, Russia versus India, Russia versus South Africa and Russia versus China generally exhibited an upward trend between 2000 and 2006 which coincided with a period of increased financialisation of commodity markets globally (Silvennoinen and Thorp, 2010). Dynamic correlations between the four market combinations peaked around 2008 the year in which the negative repercussions of the US subprime mortgage crisis were felt in much of the global economy. The peaking of the dynamic correlations between different markets is evidence of contagion and increased interdependence among different BRICS stock markets during the crisis period. India versus South Africa experienced a peak in dynamic correlation on 16 June 2006 with a correlation statistic of 0.412 while China's stock market versus South Africa's stock market exhibited neither a downward nor an upward trend during the study period. The present study also shows that the South African currency crisis of 2001 had a negligible effect on the stock markets of BRICS economies, though the correlation between the Brazilian stock market and the South African stock market trended downwards from 2000 to November 2001.

It is imperative to observe that the peaking of dynamic correlations among different BRICS stock markets during the period 2006-2009 coincided with the phenomenon of volatility clustering which is analysed in detail in Chapter 6. The upward trend in dynamic correlations during the years preceding 2008 for different BRICS stock markets is evidence of increased portfolio diversification in anticipation of and as an attempt to mitigate the negative effects of the global financial crisis whose full impact was felt by the global economy in 2008.

7.4.2 The Brock-Dechert-Scheinkman (BDS) tests: Non-linearities and fractality of BRICS stock markets

The estimated dynamic conditional correlations presented graphically in Figure 7.1 were subjected to the BDS test for non-linearity which has been used in contemporary research as one of the techniques for detecting fractality and the chaoticity of commodity and financial markets. The ensuing presentation and discussion capture the salient features of the BDS tests on BRICS Dynamic Conditional Correlations (DCC's). The hypothesis that governs the BDS test is cast as follows:

- **Null Hypothesis (H_0):** The Data Generating Process or variable is linear
- **Alternative Hypothesis (H_1):** The Data Generating Process or variable is non-linear

Table 7. 13: BDS Test Results

DCC measure	Dimension	BDS Statistic	Prob. Value	Decision
RHO_BRAZIL_CHINA	2 3 4 5 6	0.190629 0.322607 0.412777 0.473414 0.513282	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*
RHO_BRAZIL_INDIA	2 3 4 5 6	0.194104 0.329022 0.421886 0.485067 0.527419	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*
RHO_BRAZIL_RUSSIA	2 3 4 5 6	0.192411 0.326121 0.418171 0.480630 0.522343	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*
RHO_BRAZIL_SA	2 3 4 5 6	0.190776 0.322731 0.412673 0.473142 0.512843	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*
RHO_CHINA_SA	2 3 4 5 6	0.193519 0.328059 0.420602 0.483632 0.525761	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*

RHO_INDIA_CHINA	2 3 4 5 6	0.192329 0.326393 0.418728 0.481647 0.523843	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*
RHO_INDIA_SA	2 3 4 5 6	0.193089 0.326826 0.418301 0.480242 0.521445	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*
RHO_RUSSIA_CHINA	2 3 4 5 6	0.196936 0.334110 0.428949 0.493802 0.537624	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*
RHO_RUSSIA_INDIA	2 3 4 5 6	0.200913 0.341349 0.439012 0.506533 0.552910	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*
RHO_RUSSIA_SA	2 3 4 5 6	0.200913 0.341349 0.439012 0.506533 0.552910	0.0000 0.0000 0.0000 0.0000 0.0000	*Conditional correlation is non-linear*

Source: Researcher Calculations

Table 7.13 shows that all ten dynamic conditional correlation combinations conform to a non-linear data generating process. This may be ample evidence that the dynamic conditional correlations based on the log-return series of the five BRICS stock markets are amenable to non-linear forces, chaotic behaviour and fractality as opposed to the concept of market efficiency which was postulated and promoted by Fama (1965b, 1976b, 1991).

7.4.3 DCC Model Stability Tests

This section presents the results of tests of the adequacy of the model on the basis of standardised residuals. The univariate Ljung-Box test is implemented on each of the BRICS standardised residuals to test for serial correlation. Table 7.14 summarises the Ljung-Box test results.

Table 7. 14: Q-Statistics on Squared Standardised Residuals

	Brazil	Russia	India	China	South Africa
Q-statistic	0.00017314	0.068052	0.14348	2.6263	0.021676
Prob. Value	0.9895	0.7942	0.7048	0.1051	0.883

Source: Researcher Calculations using R Software

The null hypothesis associated with the statistics displayed in Table 7.14 is:

- ***H₀:*** No serial correlation - the decision-making criterion is to accept H_0 if the probability value of the calculated Q-statistics of squared standardised residuals is greater than 0.05 or 5%.

According to analytical results displayed in Table 7.14, the null hypothesis is retained for all the log-return series. The main finding is that the squared standardised residuals are independent of one another. As a result, it is thus concluded that the errors of all the five BRICS' stock markets are independent and identically distributed (i.i.d). Thus, generally, the estimated DCC GARCH model may be averred to be adequate in terms of stability since there is not enough evidence of serial correlation between squared standardised residuals at 5 percent level of significance as displayed in Table 7.14.

It is imperative to underscore that even though all five stock indices exhibit highly persistent volatility according to the DCC-GARCH model, they are also characterised by certain nuanced differences and dissimilarities. This is apparently linked to the long memory features and possible evidence of fractality in the BRICS stock markets which has been documented in some of the extant literature.

7.5 BRICS' Stock Volatility Dynamics – Evidence from Markov – Switching (MS) GARCH Models

This section presents and explains the results of Markov Switching GARCH (MSGARCH) modelling of BRICS' log stock returns. MSGARCH modelling was employed to verify the persistence of conditional volatility of BRICS' log stock returns. A study by Bollerslev and Engle (1993) has revealed that co-persistence in variance has significant implications on asset pricing relationships and optimal portfolio allocation decision making. Lamoureux and Lastrapes (1990) observed that MSGARCH models are more superior than their single-regime counterparts in explaining the phenomenon of volatility persistence and other stylised features associated with stock returns. This finding is confirmed by Ardia (2009) who using a Bayesian estimation Markov-switching GARCH model found evidence of the volatility of the Swiss Market Index being asymmetric with the characteristic of experiencing regime changes as well.

It is important to observe that model estimation using China's Shanghai's Stock log-return data, both the normal and skewed normal conditional distributions returned parameter estimates with zero standard error. This may point to the fact that the aforementioned two variations of the normal distribution may not fit the sample data well. Under normal circumstances one would expect estimated parameters to have standard errors significantly different from zero to account for errors of measurement, recording or observation of sample data from a population (Ahn and Fessler, 2003; Ogata, 1978).

Table 7. 15: Parameter estimates by MRS-GARCH assuming a normal conditional distribution

Estimated Parameter	Brazil	Russia	India	China	South Africa
α (0, 1)	0.0000* [2.670e-03]	0.0000* [3.023e-11]	0.0000** [2.110e-01]	0.0000* [0.0000]	0.0000* [1.321e-02]
α (0, 2)	0.0000* [6.213e-03]	0.0000* [1.175e-02]	0.0000** [1.393e-01]	0.0000* [0.0000]	0.0000* [1.068e-02]
α (1, 1)	0.0211* [6.223e-03]	0.0949* [2.413e-07]	0.0500* [1.617e-03]	0.1999* [0.0000]	0.0145* [8.365e-02]
α (1, 2)	0.0674** [1.036e-01]	0.2580** [4.867e-01]	0.3205** [1.568e-01]	0.0588* [0.0000]	0.0716* [9.949e-02]
β_1	0.9642* [<1e-16]	0.8464* [<1e-16]	0.9162* [<1e-16]	0.5338* [0.0000]	0.9719* [<1e-16]

β2	0.9105* [<1e-16]	0.7419* [<1e-16]	0.6740* [<1e-16]	0.9397* [0.0000]	0.9161* [<1e-16]
P (1, 1)	0.9581* [<1e-16]	0.9796* [<1e-16]	0.7109* [3.012e-06]	0.4803* [0.0000]	0.9696* [<1e-16]
P (2, 1)	0.1731* [<1e-16]	0.8959* [<1e-16]	0.7461* [1.671e-04]	0.5391* [0.0000]	0.1091* <1e-16
SP_1	0.8049	0.9777	0.7207	0.5092	0.7819
SP_2	0.1951	0.0223	0.2793	0.4908	0.2181
Regime 1 Persistence	0.9853	0.9413	0.9662	0.7337	0.9864
Regime 2 Persistence	0.9779	0.9999	0.9945	0.9985	0.9877
Loglikelihood	13506.3882	12581.1423	14932.1635	14633.6539	13623.5679
AIC	-26996.7764	-25146.2847	-29848.327	-29251.308	-27231.136
BIC	-26944.8315	-25094.3398	-29796.382	-29199.363	-27179.191
Conditional distribution	Normal	normal	normal	normal	normal

*, ** & [..] denotes statistically significant at 1% and 5% level of significance as well as probability value, S.P. stands for Stable Probabilities

Source: Researcher Calculations using MSGARCH R package

The results of MSGARCH analysis presented in Table 7.16 were obtained by adapting models and techniques of Hamilton and Susmel (1994), Haas *et al.* (2004), Ghalanos (2017) and Ardia *et al.* (2018). In fact, the R package MSGARCH by Ardia *et al.* (2018) used for the analysis implements the model specification of Haas *et al.* (2004). It is important to observe that according to MSGARCH results, generally volatility persistence is high for virtually all the BRICS for the period of study. This confirms the results obtained from single regime GARCH schemes presented and analysed under sections 7.2 and 7.3 of this chapter. Be that as it may, it is imperative to emphasise that MSGARCH results shown in Table 7.15 reveal that, with the exception of Brazil, volatility persistence is shown to be increasing from regime 1 to regime 2. Results show that for Brazil persistence declined from 0.9853 to 0.9779 which is a marginal decline. Thus, it may be concluded that for Russia, South Africa, India and China as their respective stock markets transition from a regime of low volatility to a high volatility regime, persistence is more likely to increase evidently owing to the impact of negative shocks to the stock market system (Charles and Darne, 2014). The main insight from Markov Regime Switching GARCH estimation is that volatility persistence is not a static measure or concept but that it is dynamic since it changes with time and prevailing market and economic conditions. This finding corroborates Zaremba (2016)'s argument that rapid changes in financial markets, and by corollary commodity market integration and financialisation give rise to instability in the same markets.

Table 7. 16: Parameter estimates of the asymmetric MRS-GARCH model

Estimated Parameter	Brazil	Russia	India	China	South Africa
α (0, 1)	0.0000 [1.715e-13]	0.0001 [5.918e-05]	0.0000 [1.332e-15]	0.0000 [3.331e-15]	0.0000 [9.490e-05]
α (0, 2)	0.0000 [2.919e-04]	0.0000 [4.531e-02]	0.0001 [3.833e-04]	0.0000 [1.310e-04]	0.0000 [5.140e-03]
α (1, 1)	0.0249 [7.969e-07]	0.3353 [2.150e-03]	0.0271 [1.716e-09]	0.1386 [9.920e-07]	0.0288 [7.238e-03]
α (1, 2)	0.0685 [9.405e-04]	0.0685 [9.405e-04]	0.1214 [2.235e-05]	0.0291 [4.232e-04]	0.0674 [1.284e-03]
β_1	0.9668 [<1e-16]	0.5731 [<1e-16]	0.9669 [<1e-16]	0.7352 [<1e-16]	0.9555 [<1e-16]
β_2	0.8723 [<1e-16]	0.9191 [<1e-16]	0.7151 [<1e-16]	0.9388 [<1e-16]	0.9325 [<1e-16]
Nu1	1.0897 [<1e-16]	0.7005 [<1e-16]	1.0628 [<1e-16]	0.7002 [<1e-16]	10.0451 [1.318e-09]
Nu2	1.8072 [<1e-16]	1.8451 [<1e-16]	1.3990 [<1e-16]	1.5621 [<1e-16]	97.4379 [1.735e-01]
Xi1	0.9999 [<1e-16]	0.9999 [<1e-16]	0.9996 [<1e-16]	1.0000 [<1e-16]	Not Applicable
Xi2	0.9971 [<1e-16]	0.8229 [<1e-16]	0.9394 [<1e-16]	1.5621 [<1e-16]	Not Applicable
P (1, 1)	0.9835 [<1e-16]	0.9271 [<1e-16]	0.9818 [<1e-16]	0.9517 [<1e-16]	0.9937 [<1e-16]
P (2, 1)	0.0616 [<1e-16]	0.0466 [9.331e-03]	0.0470 [<1e-16]	0.1117 [<1e-16]	0.0753 [<1e-16]
SP_1	0.7891	0.3898	0.7211	0.698	0.9233
SP_2	0.2109	0.6102	0.2789	0.302	0.0767
Loglikelihood	13599.2086	12834.5872	15035.253	14844.3385	13642.1083
AIC	-27174.4171	-25645.1743	-30046.5061	-29664.6771	-27264.2166
BIC	-27096.4999	-25567.257	-29968.5888	-29586.7598	-27199.2855
Conditional distribution	Skewed GED	Skewed GED	Skewed GED	Skewed GED	Student t

***, ** & [..] indicates statistically significant at 1% and 5% level of significance as well as probability value**

S.P. stands for Stable Probabilities

Key assumptions are a skewed GED for the BRIC and a student t distribution SA

Source: Researcher Calculations using MSGARCH R package

Table 7.16 presents results of MSGARCH estimates assuming a skewed generalised error distribution (SGED) for Brazil, Russia, India and China; and a student-t distribution for South Africa's JSEFT log-return data.

MRS-GARCH model estimation using SA's JSEFT log-return data did not yield any convergence when the skewed generalised error distribution (SGED) was used. Therefore, the current study settled for the student t distribution whose main feature though symmetric is the fact that data exhibits heavier or fatter tails than the standard normal distribution. Thus, the JSE Financial Times' log returns are the only ones with a symmetric distribution. This is evidence that the BRICS economies are not a homogeneous lot but they are characterised by heterogeneity and certain nuanced differences. The stable probabilities of the asymmetric MRS-GARCH model show that Brazil's stock market is more likely to linger in regime 1 than in regime 2 given the respective probabilities of 78.9 percent and 21.1 percent respectively for the two states. The picture is somewhat different for Russia's stock market which has a higher probability of being remaining in a high volatility regime than in low regime one considering the stable probabilities of 0.3898 and 0.6102 for the two respective regimes. The stable probability results for the remaining three economies that constitute the BRICS conform more or less to the Brazilian scenario already explained in the foregoing analysis.

7.6 Conditional variance dynamics, kernel density plots and financial market fractality

The study involved a graphical analysis of the conditional variance dynamics and kernel density plots of the standardised residuals of the log-returns of the selected BRICS stock indices. The results of the analytical exercise are summarised under Appendix E. The graph depicted in Appendix E1 shows that the conditional variance of Brazil's Bovespa index spiked in 2008. The kernel density plot of standardised residuals comforms to a normal distribution with evidence of slight kurtosis around the zero mean. The graph depicted in Appendix E2 shows that the conditional variance of Russia's RTSI index spiked around 2003 and also in 2017 evidently after the imposition of United States sanctions and most probably due to the negative effects of the European Sovereign debt crisis (Tyll, *et al.,* 2018). The kernel density plot shows strong evidence of standardised residuals conforming to leptokurtic error distribution with fat-tails. Appendix E3 shows that the conditional volatility of India's BSE Sensex index spiked prior to 2005 and towards the end of the Global Finance Crisis (GFC) period, around 2009 to be specific. The kernel density plot of standardised residuals conforms to a heavy-tailed symmetric leptokurtic distribution. Appendix E4 depicts the Shanghai Composite index as being characterised by significant volatility clustering around the periods 2002-2003 and 2007-2008 respectively. It is germane to observe that China's stock market was largely shielded from the repercussions of the GFC.

Lastly, Appendix E5 shows the results of the conditional variance plot for South Africa's JSE index. The plot shows that there was a significant in conditional volational during 2008, the year which marked the peak of the GFC. The kernel density plot of standardised residuals shows evidence of a model of slight leptokurtosis in the error distribution. The kernel density plots of standardised residuals show that the GARCH family of models are indeed appropriate in modelling stock return conditional volatility. This was found to an important step since the study intended to forecast the conditional variance dynamics of all five BRICS members.

The findings of the Markov Regime Switching GARCH model provoke an age-old question which can be stated as follows: Are emerging economy financial and commodity markets fractal in nature and behaviour? Anderson and Noss (2013) have argued that the fractal markets theory can potentially yield insights to our understanding of financial markets dynamics and operation. The fractal markets hypothesis takes into account the role of market liquidity and the impact of (positive and/or negative) information in financial asset price determination and diffusion processes. The statistically significant estimated parameters of the two MRS-GARCH models presented on Tables 7.12 and 7.13 for the two separate regimes may be evidence of the fractality of BRICS' stock markets. Barna *et al.* (2016) have observed that self-repeating behaviour which may be associated with business cycle activity and the volatility of commodity markets may be a pointer to the fact that financial markets under consideration are actually fractal. It may, therefore, be concluded that volatility persistence and long memory features corroborated by the two strands of the MRS-GARCH model may point to the fact that emerging economy stock markets are characterised by fractality.

7.7 Chapter Summary

This chapter presented results from fitting different GARCH models such as the classical Gaussian GARCH (1, 1), EGARCH, FIGARCH-BBM, FIGARCH-Chung, DCC-GARCH and Markov-Switching GARCH models. Empirical results generally support the notion that there is an undeniable link among BRICS emerging economy stock markets. The linkages among BRICS stock markets are apparently sensitive to economic events that take place in commodity markets. The study also found that global financial, commodity and economic trends and events have a significant impact on the performance of BRICS economies in general. The chapter evaluated results of empirical analysis in the context of fractal markets which are characterised by a remarkable departure from homogeneity, efficiency and linearity. It is the posture of the study that commodity and financial market trends from 2000 to 2018 prove that heterogeneity, inefficiency and non-linearities characterise financial and commodity markets more as a rule than an exception contrary to what some of the extant literature postulates and supports. The next chapter presents the main conclusions of the study, policy recommendations and suggestions for future research.

CHAPTER EIGHT: CONCLUSIONS, RECOMMENDATIONS, AND DIRECTIONS FOR FUTURE RESEARCH

8.0 Introduction

Chapter 8 proffers conclusions to the study on commodity price volatility, stock market performance, and economic growth. Chapter 8 presents the main conclusions of the study that flow from the findings presented and discussed in Chapters 6 and 7. Previous studies on the nexus between commodity price volatility and stock market development paid little or no attention on four related themes which are the focus of the present study.

First, such studies have not analysed the impact that financialisation of commodity markets has on the commodity price – stock index relationship. Second, mainstream studies on the commodity price-stock market nexus have largely neglected the role of different types of crises on the stock market performance – economic growth nexus. Third, studies on non-linearities in the nexus between stock market performance and economic growth have largely neglected how different commodity classes influence the non-linear relationship between the two economic aggregates. Fourth, most frequency domain causality tests of the relationship between stock market performance indices and economic growth indicators have largely failed to harmonize or compare those findings with time domain causality test results. The present study bridged the four mentioned gaps in the empirical literature.

8.1 Financialisation of Commodity Markets and the Stock Market – Economic Growth Nexus

Even though there was animated debated in the past on the veracity of the notion of commodity market financialisation, in recent years the debate has shifted to measurement and modelling related imperatives pertaining to the financialisation of the commodity markets conundrum. Researchers such as Zaremba (2016), Dwyer *et al.* (2012), Carmona (2015) and Kang *et al.* (2016, p. 3) have linked the phenomenon of commodity market financialisation to rapid technological changes in the modern world, the role of forces of globalisation, and financial market integration on diverse commodity markets and the growth of derivative financial instruments that blur the dichotomy which in the past was purported to exist between commodity markets and financial markets.

Different studies have attempted to unravel the mystery of the connection between commodity market financialisation and economic growth by linking the former with banking and other financial systems found in different economies. There is little or no debate at present in the empirical literature on whether financial institutions trade commodity-based financial instruments. A simple research exercise reveals that commodities such as crude oil, copper, gold, iron, silver, platinum, gold, aluminium and zinc to mention a few, are traded in organized exchanges. The mere existence of the Chicago Board of Trade (CBOT), the South African Futures Exchange (which is part of JSE), the New York Mercantile Exchange (NYMEX), the Ghana Commodity Exchange (GCE), Egyptian Commodities Exchange (EGYCOMEX), Ethiopia Commodity Exchange and the Brazilian Mercantile and Futures Exchange (BMF) is proof that commodity markets are not only financialised but that their financialisation has mainstreamed trade in commodities into general economic activities that determine modern economic growth.

8.2 Stock Market Indices and Economic Growth Proxies – main conclusions

Researchers such as Falkowski (2011) and Cheng and Xiong (2014) have amply demonstrated the link between financialisation and the phenomenal growth in trade in commodities and commodity-backed financial instruments. What has remained controversial is how such a link impacts or distorts commodity price discovery and diffusion processes in different economies. This is the basis of the study of commodity price volatility, stock market performance and economic growth from the emerging economies' perspective. Chapter 6 presented results from causality tests in the time and frequency domains to prove the dynamic, non-linear, and at times indeterminate relationship between different stock market performance indicators and national output proxies of the BRICS economies.

Causality tests conducted on BRICS stock market performance indicators and national output proxies yielded three main findings. First, it was discovered that for Brazil and Russia both time-domain and frequency-domain analysis yielded the same conclusion of no causal relationship between their individual stock indices and their respective national output proxies. This coincidence between time domain analysis and frequency domain causality tests imply harmony between the static (time series) and dynamic (frequency domain) perspectives of causality among financial and macroeconomic variables. The conclusion from this finding is that time-domain Granger causality and frequency-domain Granger causality tests of the finance – growth nexus at times yield similar results. This shows that the two approaches to testing causality between any pair of macroeconomic aggregates may complement (or even confirm) each other.

Second, time-domain and frequency-domain causality tests conducted for India yielded different results. Time-domain test results indicated the two-way causation between the stock index for India (BSE Sensex) and the output proxy (INDIAPTI) while spectral causality test results were more dynamic. Spectral causality tests demonstrated that India's output proxy (INDIAPTI) does not Granger cause the BSE Sensex index (BSE) for the entire record (that is, for all the frequencies of the data series). On the other hand, India's BSE Sensex index was found to Granger-cause national output (proxied by INDIAPTI) for part of the record, that is, between omega frequency 0.00 and 0.8535 which in time-domain terms implies the period between January 1990 and January 1998. Spectral causality tests for India show that what from a time-domain perspective would be perceived as two-way causality between economic aggregates, may be partial causality.

Third, spectral causality tests conducted on the BRICS economies' output proxies and stock indices revealed what may be termed "cross-spectral causality". In studying cross-market linkages between different economies it may be necessary to unravel linkages that may exist between the economic growth measure of one economy and the stock market index of another economy. The null hypothesis governing such an exercise is that where cross-market linkages do not exist, spectral causality tests would yield graphs that depict non-causation between the economic growth proxy of one country and the stock index of another country. These cross-market linkages should not be viewed as only obtaining between the economic system of one country and the stock market of another country, but also between stock markets of two different countries. In light of the foregoing discussion, the study tested the relationship that may exist between, for instance, China's output proxy (CHRETAIL) and Brazil's stock index (BOV).

The key finding from the spectral causality test is that China's output Granger-causes Brazil's Stock index but the opposite is not the case. The spectral causality from China's output to Brazil's stock index was revealed to be partial, that is, not for the entire record of the data studied. The key conclusion from this finding is that underlying economic, financial, and other forces may account for partial causality in one direction only. Some researchers have ascribed such a situation to random political events. The shock to global financial markets caused by the social media assisted election of Donald Trump in 2016 as US President is a case in point (Pereira *et al.,* 2018, Palmlov, 2018 and Colonescu, 2018). Evidence has been provided supporting the notion that the election of Donald Trump even affected Indonesia's stock market (Sagita, 2017).

The import of the foregoing is that time domain causality tests and spectral causality tests are complementary. Frequency domain causality compensates for the static and summative nature of the time domain causality test results. The conclusion from the foregoing discussion is that frequency domain causality graphs demonstrate the non-linearities that exist between stock market performance (proxied by BRICS' stock indices) and economic growth (proxied by national output proxies).

It is important to observe that the frequency domain mapping of causality did not just focus on two variables *per se*, that is, the stock index and the national output proxy. Spectral graphs depicting the causal relationship between stock indices and national output proxies were calculated subject to different commodity classes acting as exogenous factors or regressors.

The foregoing necessitated that spectral Granger causality between any two indices was analysed in the context of processes obtaining in commodity markets. This, therefore, means that the dynamic frequency-domain Granger causality graphs presented in Chapter 6 under section 6.9 took into account commodity market dynamics in mapping relationships between stock market performance and economic growth proxies. It is a hypothesis which is implied in Chapter 6 under section 6.9 that commodity market dynamics (proxied by different commodity classes) impact the nexus between stock market performance and economic growth. On the basis of the preceding discussion, the present study concludes that commodity market dynamics partially explain non-linearities between stock market performance and economic growth.

8.3 Fractality, Non-linearity, and Possible Entropy in Financial Markets

Advocates of the efficient markets hypothesis (EMH) have long based their argument on the belief that stock markets are generally governed by the rational expectations of all market participants that predispose security prices to reflect all available information (Fama, 1965a, 1965b, 2013). All studies predicated on EMH have invariably yielded findings and conclusions that give the impression that the occurrence and persistence of crises is an aberration from the perceived norm of efficient and well-behaved financial markets and systems. One of the two hypotheses upon which the study is based is that financial crises especially those manifesting as either stock market crises or stock market corrections are an inescapable feature of modern financial systems.

The results obtained from the FIGARCH-BBM, FIGARCH-Chung, DCC-GARCH and Markov-Switching GARCH models showed that BRICS log-returns exhibit characteristics of non-linearity, volatility persistence, long-range dependence, and fractality. This proves that the argument that financial markets are efficient cannot be sustained empirically for emerging economies such as the BRICS.

The results of FIGARCH-BBM and FIGARCH-Chung models presented in Tables 7.7 and 7.10 demonstrate that emerging economy stock markets have characteristics of heterogeneity or dissimilarity in behaviour, non-linearity, fractality, return, and volatility persistence. The DCC-GARCH model estimates for the BRICS stock markets provided strong evidence of contagion, and interdependence, thus confirming findings of previous researchers (Bonga-Bonga, 2015 and Ijumba, 2013).

The GARCH analysis results, presented and discussed in Chapter 7, showed that while the global financial crisis (GFC) of 2007-2009 was indeed a global event, it did not have a homogenous impact on all the BRICS economies during the same period. China's economy was largely shielded from the destabilising effects of the GFC by government policies compared to other members of the BRICS economic bloc. This can be perceived from the relatively low volatility of the log-return series of Shanghai's composite index during the aftermath of the GFC compared to other BRICS economies such Brazil, India, South Africa and Russia whose stock log-return series were characterised by relatively higher volatility during the post-GFC period. The lack of homogeneity in response to the GFC among different BRICS members must by necessity prove that financial markets and systems are not only heterogeneous but are also characterised by fractality in terms of asset return behaviour.

Correlation analysis and modelling of China's and Russia's stock log-return series under the FIGARCH – BBM framework revealed that there is no statistically significant relationship between China's stock index and Russia's stock index. This finding contradicts earlier findings by Kishor and Singh (2017, p. 38) who averred that "Chinese stock indices (are) significantly and positively correlated with Russian stock indices." Correlation analysis of the two economies' respective stock indices revealed that even though the correlation coefficient was statistically significant at 6.17 percent or 0.061744, it is, nevertheless, too low. The economic and financial systems of Russia and China have significant differences owing to the fact that in China the government and government institutions play a more prominent role in economic activities compared to Russia which employs a mixture of free market policies and the command economy model.

The DCC-GARCH model revealed that for paired stock markets of Brazil and China, Brazil and India, China and South Africa, India and China, and Russia and China, the onset of and occurrence of the global financial crisis (GFC), caused significant decoupling of the aforementioned stock index pairs. This is an important finding which sheds light on the heterogeneous impact of the global financial crisis on different stock market pairs from a DDC-GARCH model perspective. The main conclusion from this finding is that significant financial crises such as the GFC are likely to trigger different and opposite reactions from different stock markets. The phenomenon of stock markets decoupling signals that when the log-returns of one market are improving, the log-returns of another market will be declining, *ceteris paribus*. The phenomenon of decoupling log stock returns also proves that asset return behaviour is not static but dynamic. This is the case since the decoupling between different stock market returns is usually brief and crisis-related. A possibility exists that the decoupling in financial asset behaviour may be crisis-driven since the phenomenon either dissipates or abruptly reverses once the impact of the crisis fades away.

8.4 The Study's Contribution to the Body of Knowledge

The study makes three main contributions to the body of knowledge. The first addition to knowledge is in linking the micro and macro levels of commodity price changes with their corresponding stock market performance indicator changes. This approach yielded results that demonstrated the impact of commodity price volatility at higher (that is, daily) and lower (that is, monthly) frequencies. Few or no studies comprising the reviewed extant literature juxtaposed higher and lower frequency data in a deliberate analysis of the impact of commodity price volatility on stock market performance indicators. In addition, a review of the contemporary literature on the nexus between commodity price volatility and stock market performance for emerging economies shows that virtually no studies ever attempted to verify the time-domain causality test results with the results of spectral causality tests. The study employed the spectral causality method which is similar to the approach adopted by Ronderos (2016) in establishing the link between the logarithm of the COP/USD floating exchange rate and the logarithm of Colombia's COLCAP stock index.

The second main contribution of the study to the stock of knowledge is methodological. A review of the empirical literature reveals that most mainstream and contemporary studies on the nexus between commodity price volatility and stock market performance for the BRICS have never unified spectral causality analysis, single - regime GARCH analysis, Dynamic Conditional Correlation (DCC) – GARCH and a two-step Markov – Regime – Switching – GARCH analytical approach within the context of a single study. This holistic approach was adopted to tap into the law of synergy which asserts that the whole is greater than the sum of its parts. The rationale for the use of diverse approaches to modelling the impact of commodity price volatility on stock market performance is that different methods compensate for each other's weaknesses in modelling the dynamics of market behaviour. The results that are obtained by the researcher are thus more likely to have minimum bias. The results obtained are likely to be less prone to extreme conclusions which is usually the case for those studies that lean heavily on one methodological approach or a single type of model.

The third contribution of the study to the body of knowledge is in extending our knowledge of business cycle theory in general, and business cycle behaviour in emerging economies in particular. The reviewed literature on the BRICS economies under Chapters 2, 3, and 4 demonstrated the phenomenon of commodity - driven business cycle activity. Spectral causality analysis on non-linearities between stock indices and national output proxies revealed that the strength of causality between any pair of study variables was not homogenous but tended to be oscillatory in nature. At times Granger – causality in the frequency domain tended to be self-attenuating, that is, it started only to stop after attaining a certain angular frequency. This was the case for India, that is, for the causality between India's output proxy (INDIAPTI) and India's stock index (BSE). It was also the case for South Africa, that is, for the causality between South Africa's output proxy (SAMANUF) and South Africa's stock index (JSEFT). This apparently "self – starting" and "self-terminating" frequency – domain causality behaviour may partially explain why the onset of downturns or recessions associated with business cycle activity in emerging economies is sometimes sudden only to terminate at an unforeseen point in time. This implies that much as economic agents may attempt to incorporate rational expectations into their appreciation of business cycle behaviour in emerging economies, those same economic agents may lack the means (and near perfect knowledge) to incorporate the dynamics of coupling and decoupling economic variables as economies progress through different phases of the business cycle.

8.5 Recommendations of the Study

The study makes recommendations to two sets of stakeholders based on the main research findings and conclusions. First, the study makes specific recommendations to different types of investors. Second, the study proffers recommendations to the BRICS and multilateral institutions like the World Bank and the IMF.

8.5.1 Recommendations to Portfolio Investors

One of the main findings of the study was that the prices of the three commodities selected for analysis, namely, crude oil, corn, and gold are positively correlated with the five BRICS' stock returns. Therefore, when the price of crude oil increases, the log-returns of the Bovespa index, for example, are likely to be increasing as well. Granger causality test results captured in Table 6.15 showed that the log-returns of the Bovespa index Granger cause variations in the WTI crude oil prices. Thus, a passive or indexed investor would be advised to invest in the WTI crude oil futures market when the Bovespa index is experiencing a rally, and liquidate the position to invest elsewhere when, the Bovespa index experiences a downturn. The corollary of the foregoing is that a discerning investor would not on the basis of correlation analysis and Granger causality test results invest in both the Bovespa index and the WTI crudeoil futures simultaneously. Positive correlation between any pair of financial assets means that one asset cannot be used to hedge against potential losses that may arise due to adverse price movements of another asset.

Study results also showed that all the BRICS' stock log-returns are positively correlated with each other. The implication from the foregoing is that it is not recommended that a fund manager invests in, for instance, both the Bovespa index and the Shanghai Composite index. This conclusion, and hence, recommendation has to be adopted with caution because correlation between any two financial assets may also be dynamic just like the causality measure.

One major weakness of static correlation statistics is that they do not take into account the dynamic behaviour of co-movement between any two financial assets due to inherent stochastic forces, political and economic uncertainty, psychological factors that impact trading in financial markets, mob or herding behaviour as well as hedonism that characterise diverse modern financial systems. The present study, thus, adopted DCC-GARCH analysis to discern the dynamic conditional correlations (DCCs) which are computed taking into account the volatility that is entrenched in the behaviour of, and pricing of, financial assets. Two main recommendations are made from DCC-GARCH analysis results that are presented and discussed in Section 7.4. First, given that the dynamic correlations between the Bovespa index and China's Shanghai index, South

Africa's JSE index and China's Shanghai index became negative at the onset of the global financial crisis, this means that an investor with positions in all the three stock indices would be having a balanced (or hedged) portfolio, *ceteris paribus*. Second, it is evident from results graphically displayed in Figure 7.1 for Brazil and India that during the European Sovereign Debt crisis of 2009-2011 the dynamic correlation between the Bovespa index and the BSE index was positive. The study, therefore, recommends that if a sovereign debt crisis was to occur in any major economy that is linked to the BRICS in the near future, a wise investor must ensure that the portfolio held does not consist of investments in both the Bovespa index and the BSE Sensex index due to losses that would likely arise out of such holdings.

Conditional mean and conditional variance forecasting results displayed under Appendices C show that on the basis of FIGARCH-BBM empirical models an investor would be able to reduce uncertainty if funds were invested in both the Bovespa index and the BSE Sensex index during the in-sample forecast period of 05 August 2018 to 02 September 2018. An analysis of Appendices C1 and C2 shows that during the forecast period FIGARCH-BBM empirical models yielded conditional mean forecasts that tracked the actual log-returns of the Bovespa and BSE Sensex indices quite well, though for India, the forecast conditional variance becomes quite explosive towards the end of the forecast period. The study, thus, recommends that trend traders rely on Fractionally Integrated volatility models like FIGARCH-BBM and FIGARCH-Chung to more accurately track the behaviour of stock indices so as to avoid making unnecessary losses. Such models take into account both the persistence, long memory, and hence, fractal features associated with emerging economy stock markets.

8.5.2 Recommendations to the BRICS and its International Stakeholders

It is important to observe that the study found that global financial and commodity markets are now more integrated than in the past. The evidence of this is the apparent increasing dynamic conditional correlations between Brazil and India, Brazil and Russia, Brazil and South Africa, India and China, India and South Africa during the global financial crisis (GFC) period and immediately after the GFC. The extent to which South Africa's JSE index and China's Shanghai index decoupled at the onset of the global financial crisis, imply that institutional investors including government sovereign funds in China and South Africa would be prudent to have some of their funds invested in both indices to hedge against potential losses due to exogenous crisis events.

The study also found that virtual all BRICS economies are prone to economic, political and financial events that occur in the United States of America (USA) and Europe. For instance, dynamic conditional correlations results presented in Figure 7.1 show that Brazil and South Africa, Brazil and Russia, Brazil and India, Russia and South Africa, and Russia and India experienced contagion during the global financial crisis and the European sovereign debt crisis. This indicates that the BRICS economic bloc needs to put in place economic policy measures individually and collectively to partially insulate themselves from the repercussions of negative economic and financial events emanating from the United States (US). China was, by and large, shielded from the consequences of the European sovereign debt crisis due to the centrally planned nature of the Chinese economy. This lends credence to the importance of government intervention in financial markets especially when they enter a crisis mode or when they fail.

The study recommends the improvement of the mandate of multilateral financial institutions such as the International Monetary Fund (IMF), the Bank of International Settlements (BIS), the European Central Bank (ECB), and the Federal Reserve System (the Fed) so that they are more proactive in monitoring levels of liquidity in developed economies. Too much liquidity in the US housing market triggered the GFC which destabilised many economies worldwide including some of the BRICS with the exception of China. Advanced financial econometric modelling systems which taken into account the long memory features, volatility persistence, and entropy behaviour of developed and emerging economy stock markets would provide a scientific basis for such liquidity monitoring efforts. The research and analytical effort would need to be inter-disciplinary and cross-country in order to yield forecasts and projections of financial indices' behaviour that can be relied upon to craft effective and efficient policies.

8.6 Suggestions for Future Study

The study was conducted under important time and financial constraints. There is need to probe the nexus between commodity markets and financial markets from an artificial neural perspective so that the dynamism of volatility persistence and long-range dependence in conditional variance dynamics may be fully explored. This requires time and funding. The study thus recommends that diverse faculty and researchers drawn from different emerging and advanced economies may need to collaborate on the important topic of commodity price volatility, stock market performance and economic growth from an interdisciplinary perspective.

There is a need to probe the full impact of United States (US) political events like elections and media pronouncements on international and commodity market behaviour before, during and after the occurrence of a financial or economic crisis. This may be done by blending the before – after experimental design with the phenomenological approach. The prevalence and recurrence of hedonism in financial markets during booms and busts that characterise economic activity imply that financial markets may have a consciousness which is at times disconnected from global economic and financial architecture. Studies have shown in political and other human sciences that where consciousness and behaviour flowing from that consciousness disconnects from the being or beings responsible for that behaviour, chaos and entropy results. The behaviour of complex financial markets cannot be fully understood by economists, mathematicians, and statisticians working in isolation. An inter-disciplinary cross-pollination of theoretical frameworks and methodologies may enrich findings of future studies.

Further studies may also explore the nexus among commodity price volatility, stock market performance, and economic growth using Bayesian statistical and econometric approaches. This would serve as a means of verifying the veracity of results obtained in the present study. The same research topic may be studied taking into account contagion among different economic blocs, like for example between the BRICS and the European Union (EU), the Economic Community of West African States (ECOWAS) and the BRICS, the SADC and the EU and so on. This would reveal whether such trade and economic blocs have any important impact on global economic activity.

8.7 Chapter Summary

On the basis of the main findings the study concludes that there is a non-linear relationship between commodity price volatility and stock market performance. The study concludes that the non-linearities that characterise the commodity price – stock market performance relationship predisposes the nexus between stock market performance and economic growth to be non-linear as well. The study concludes that in-sample forecast results show that the FIGARCH-BBM and the FIGARCH – Chung models complement each other and must not be viewed as substitute models. In general, empirical test results obtained from the two FIGARCH models show that the BRICS stock markets exhibited fractal behaviour during the study period (2000 to 2018). This demonstrates that BRICS stock markets, and by extension any emerging economy stock markets, lack the attributes of Efficient Markets as postulated by Fama and other advocates of the Efficient Markets Hypothesis (EMH). This has far-reaching implications in terms of portfolio management decisions as well as policy formulation and implementation.

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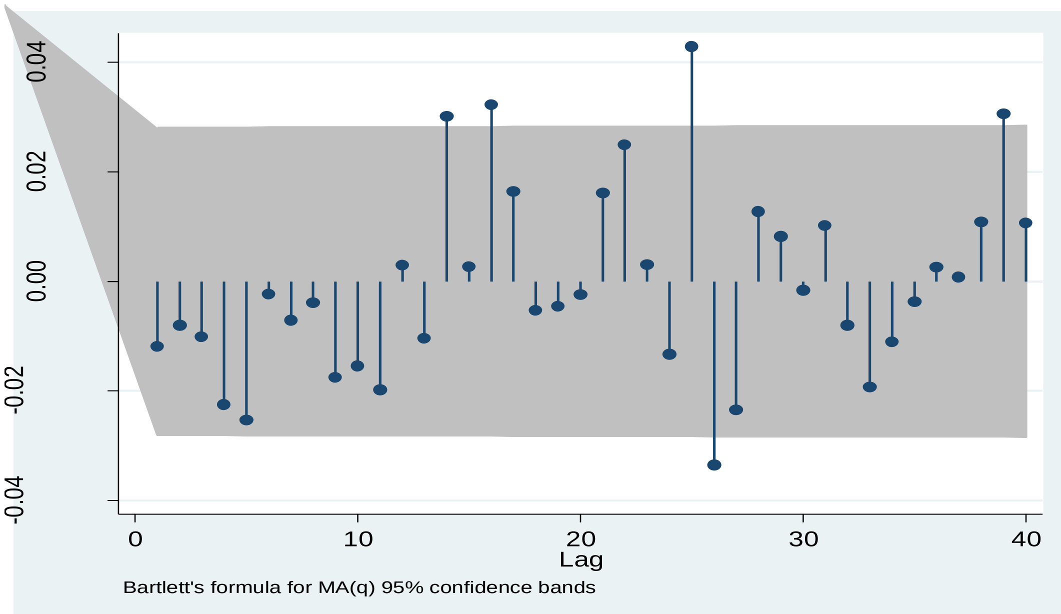
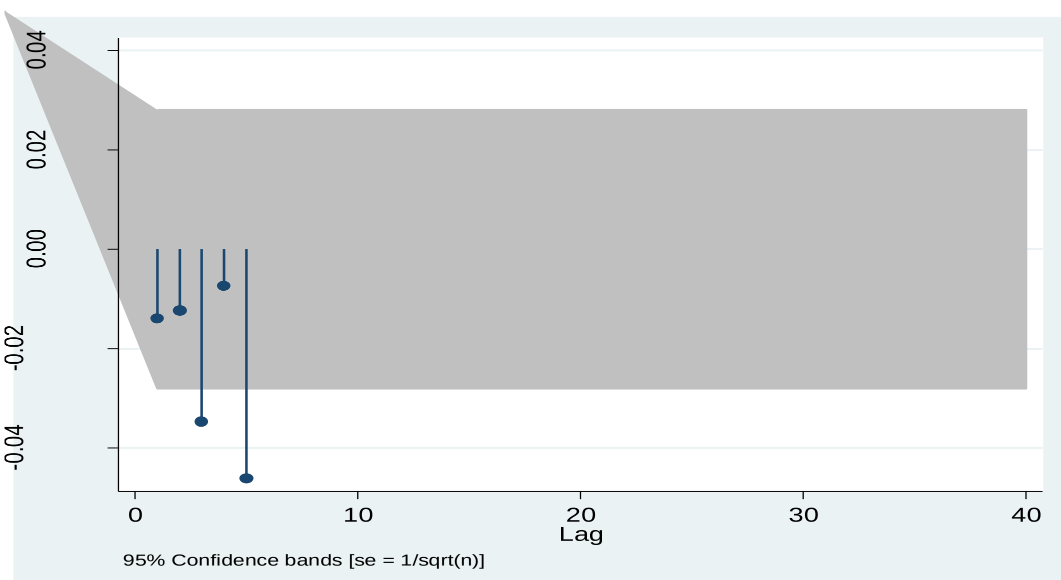
APPENDIX A – AUTOCORRELATION AND PARTIAL AUTOCORRELATION ANALYSIS GRAPHS

A. 1: Brazil Autocorrelation Analysis

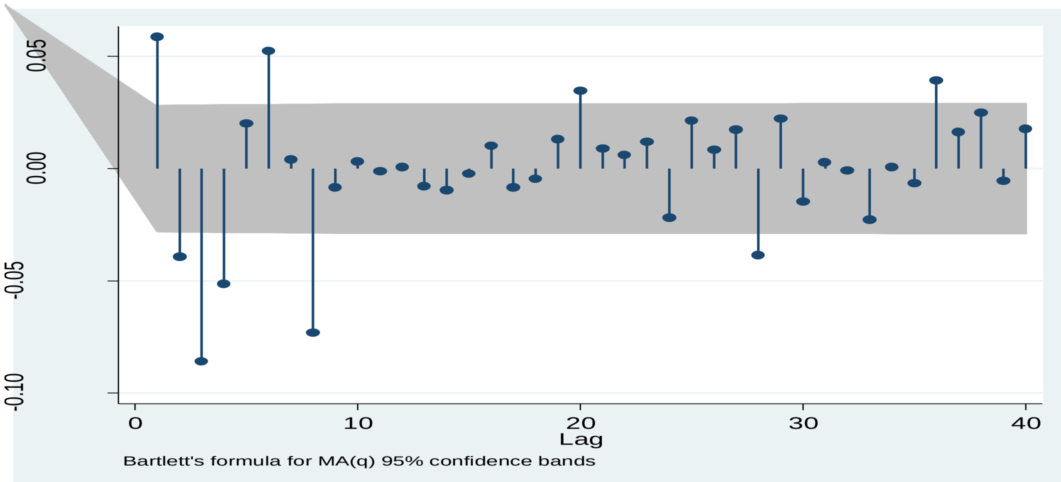


A. 2: Brazil Partial Autocorrelation Analysis

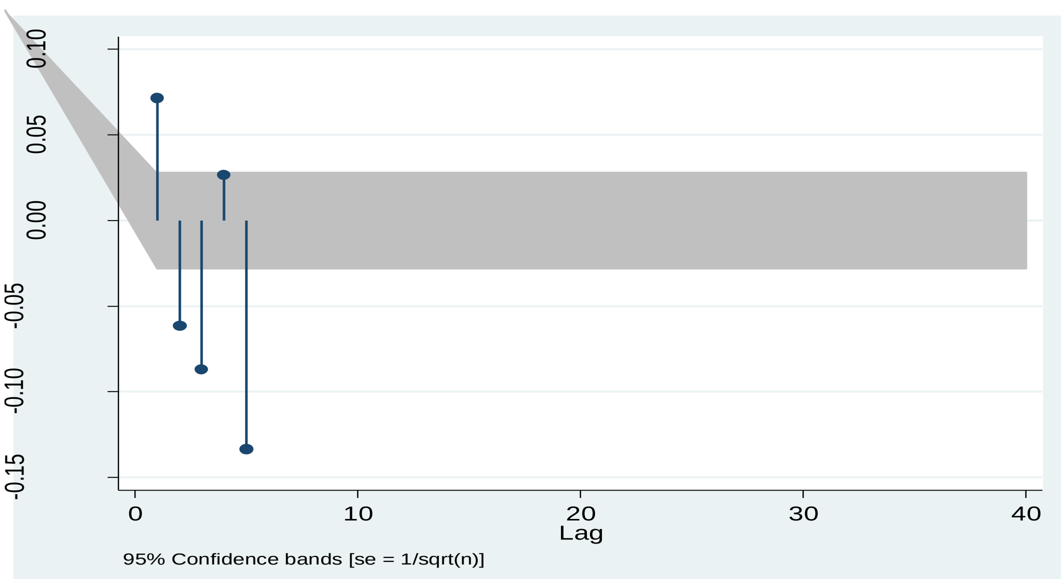


Source: Researcher Compilation

A. 3: Russia Autocorrelation Analysis

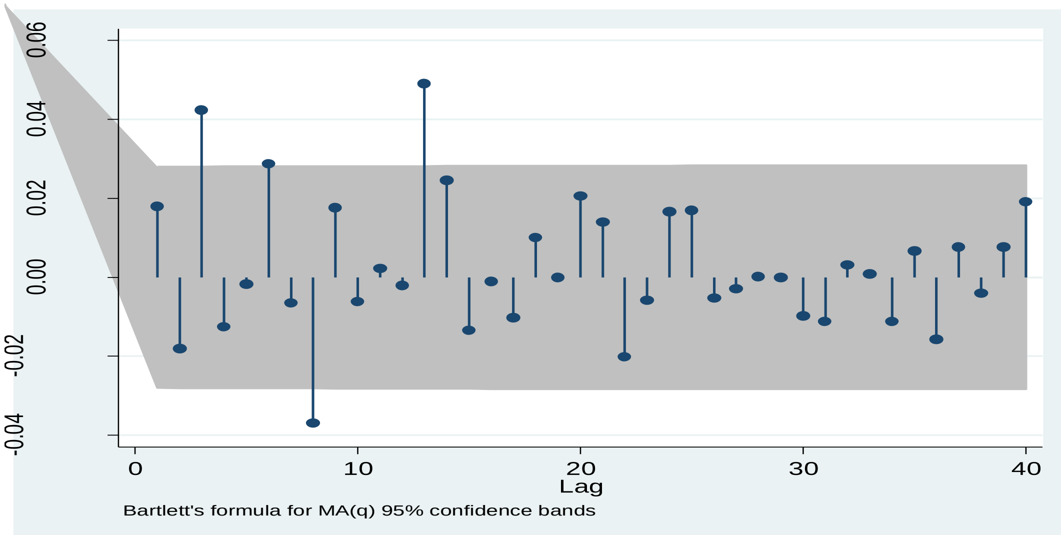


A. 4: Russia Partial Autocorrelation Analysis

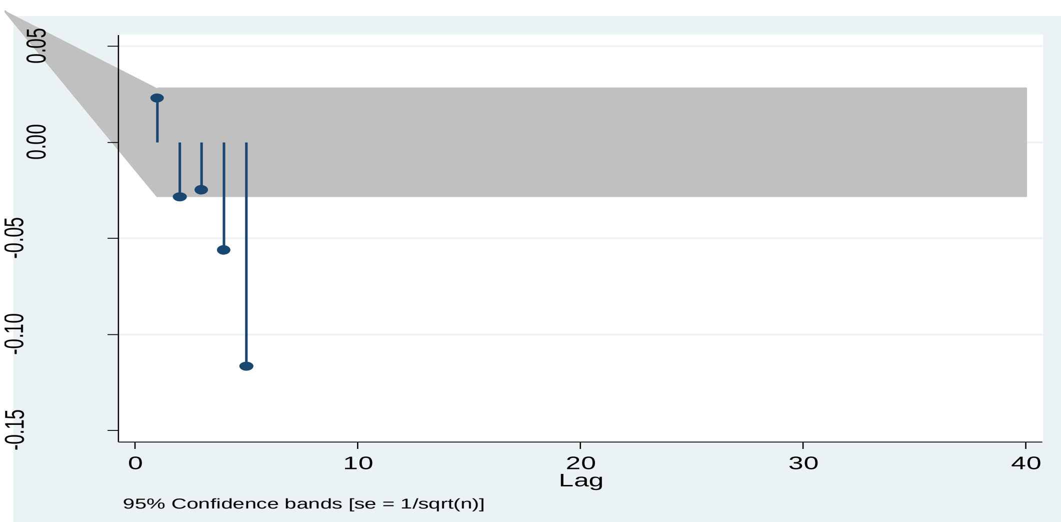


Source: Researcher Compilation

A. 5: India Autocorrelation Graph

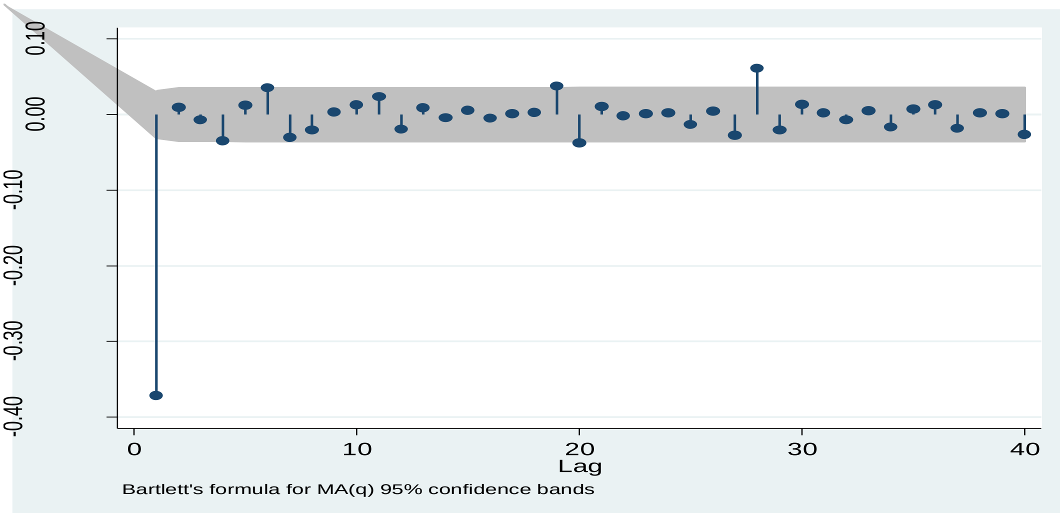


A. 6: India Partial Autocorrelation Graph

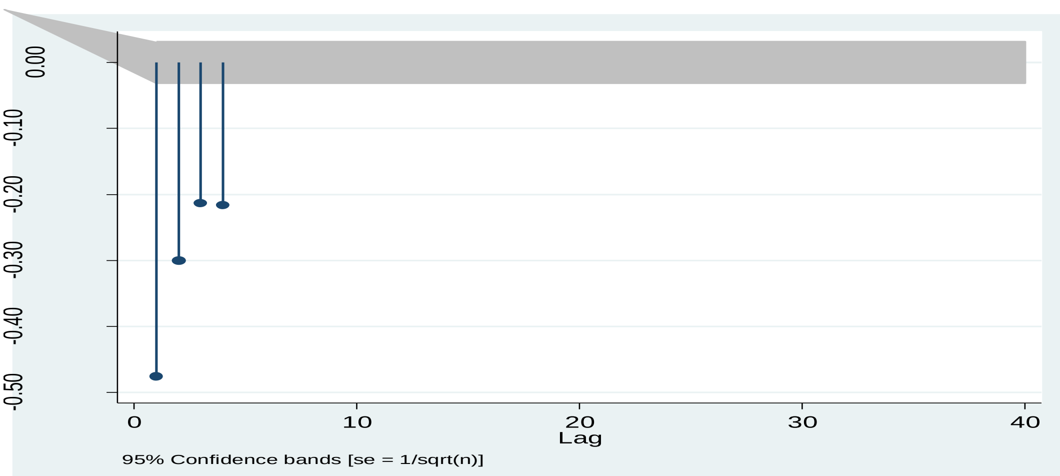


Source: Researcher Compilation

A. 7: China Autocorrelation Graph

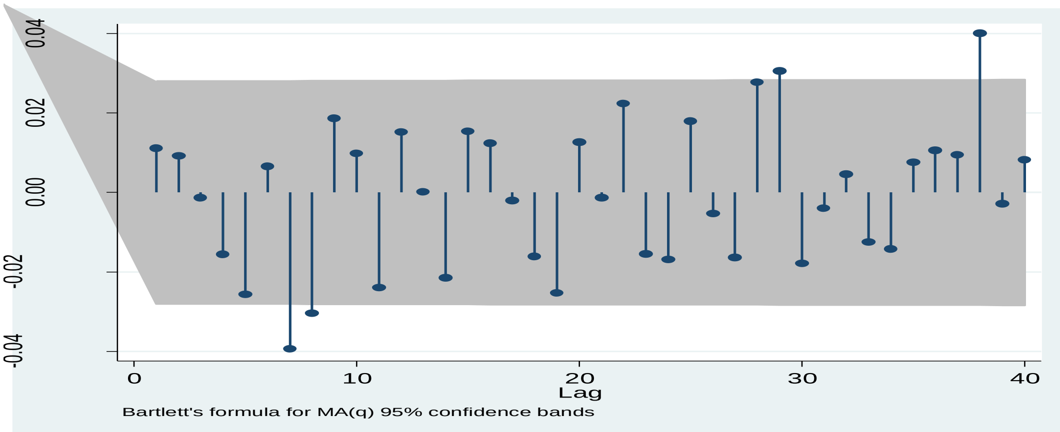


A. 8: China Partial Autocorrelation Graph



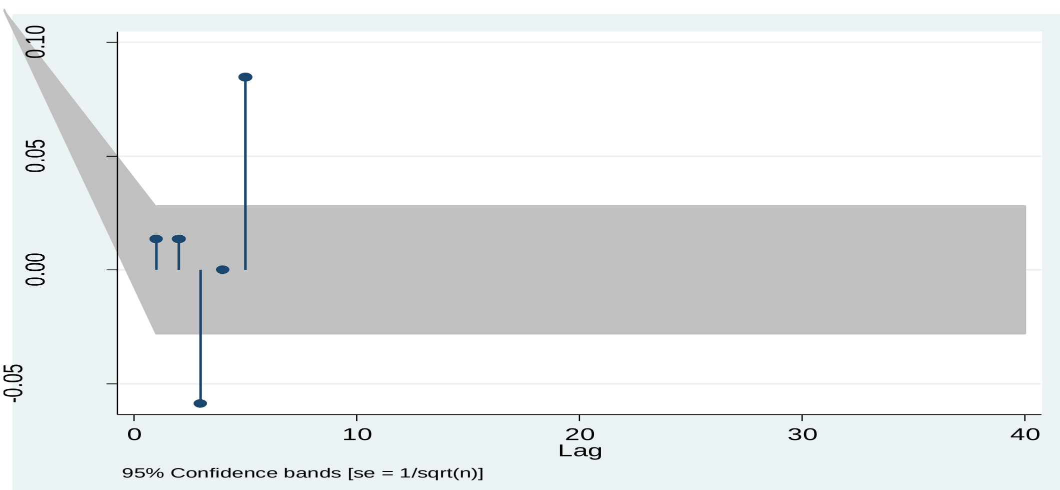
Source: Researcher Compilation

A. 9: South Africa Autocorrelation Graph



Source: Researcher Compilation

A. 10: South Africa Partial Autocorrelation Graph



Source: Researcher Compilation

APPENDIX B – FIGARCH-CHUNG Serial Correlation Test Results

B. 1: APPENDIX B. – FIGARCH – Chung Serial Correlation Test Results for Squared Standardised Residuals

Country	Box/Pierce Statistic	Decision
Brazil	Q-Statistics on Squared Standardised Residuals --> P-values adjusted by 1 degree(s) of freedom Q(5) = 3.76926 [0.4381331] Q(10) = 5.80758 [0.7590117] Q(20) = 7.89012 [0.9877427] Q(50) = 21.3401 [0.9998029] H0: No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)] ---------------	*The results show that the residuals are uncorrelated. Thus, for the estimated FIGARCH (1,d, 1) model it can be assumed that errors are Independent and Identically distributed (i.i.d).*
Russia	Q-Statistics on Squared Standardised Residuals --> P-values adjusted by 2 degree(s) of freedom Q(5) = 0.704907 [0.8720492] Q(10) = 36.7044 [0.0000130]** Q(20) = 37.7601 [0.0041665]** Q(50) = 71.9776 [0.0141149]* H0: No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)] ---------------	*The results are mixed as they show that for only Q (5) are uncorrelated while results for Q (10), (20) and Q (50) they are correlated. This may be evidence of the long memory feature of conditional volatility.*
India	Q-Statistics on Squared Standardised Residuals --> P-values adjusted by 1 degree(s) of freedom Q(5) = 2.36390 [0.6691601] Q(10) = 3.26130 [0.9530283] Q(20) = 17.4389 [0.5601565] Q(50) = 45.7314 [0.6064313] H0: No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)] ---------------	*The results show that the residuals are uncorrelated. Thus, for the estimated FIGARCH (1,d, 1) model it can be assumed that errors are Independent and Identically distributed (i.i.d).*
China	Q-Statistics on Squared Standardised Residuals --> P-values adjusted by 2 degree(s) of freedom Q(5) = 5.69563 [0.1273949] Q(10) = 8.37923 [0.3973288] Q(20) = 14.4943 [0.6963459] Q(50) = 52.6247 [0.2997137] H0: No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)] ---------------	*The results show that the residuals are uncorrelated. Thus, for the estimated FIGARCH (1,d, 1) model it can be assumed that errors are Independent and Identically distributed (i.i.d).*
South Africa	Q-Statistics on Squared Standardised Residuals	*The results show that the squared standardised residuals are correlated.*

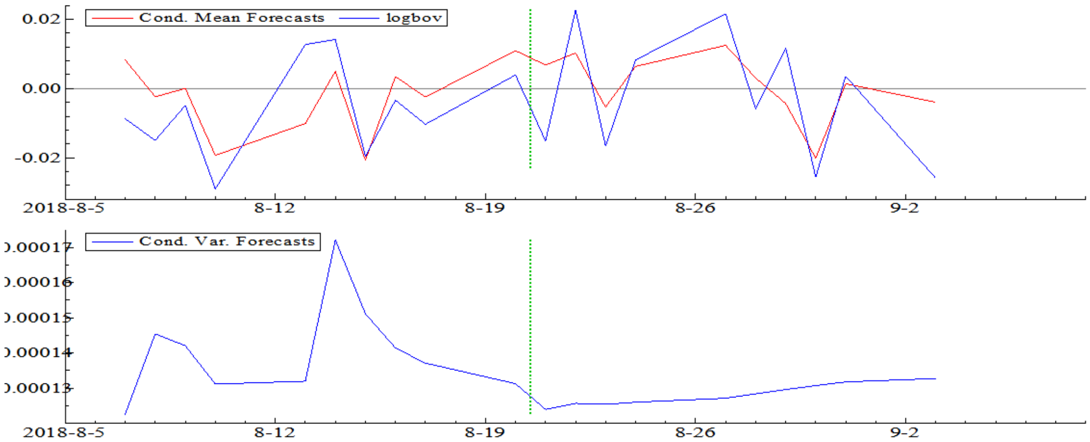
	--> P-values adjusted by 1 degree(s) of freedom Q(5) = 10.5636 [0.0319325]* Q(10) = 22.6150 [0.0071213]** Q(20) = 35.4418 [0.0123499]* Q(50) = 83.9481 [0.0013897]** H0: No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)] ---------------	*Thus, for the estimated FIGARCH (1,d, 0) model it can be assumed that errors are autocorrelation. This may be evidence of volatility persistence and long-range dependence in the conditional variance dynamics for the South African Stock Market.*

[…] indicates probability value

Source: Researcher Calculations

APPENDIX C - FIGARCH – BBM FORECAST GRAPHS

C. 1: BRAZIL - BOVESPA Forecast Graphs – FIGARCH – BBM



Source: Researcher Compilation

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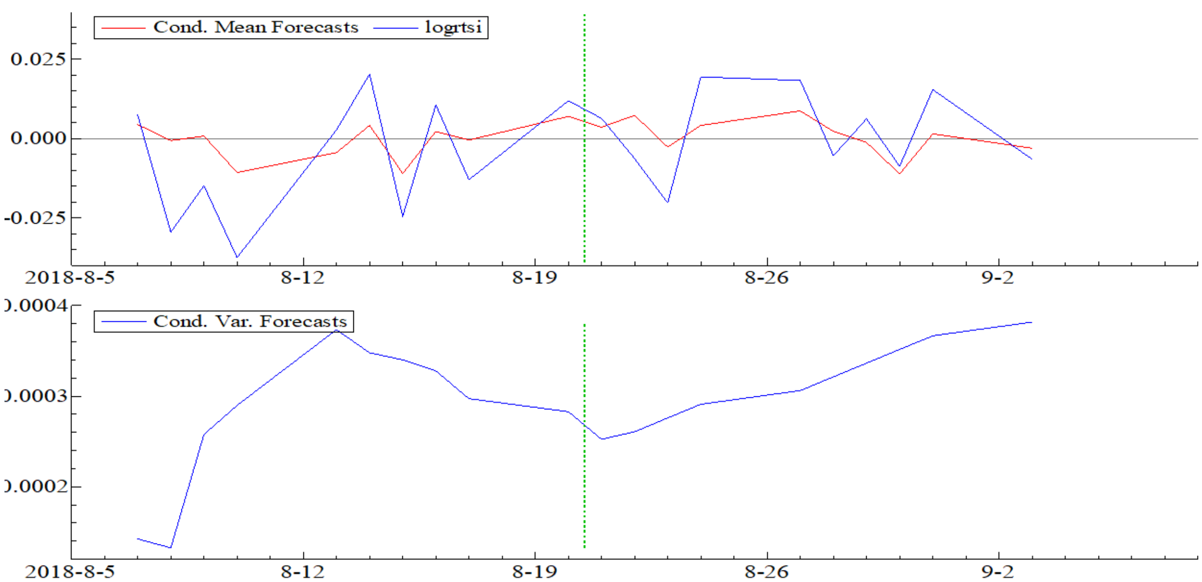
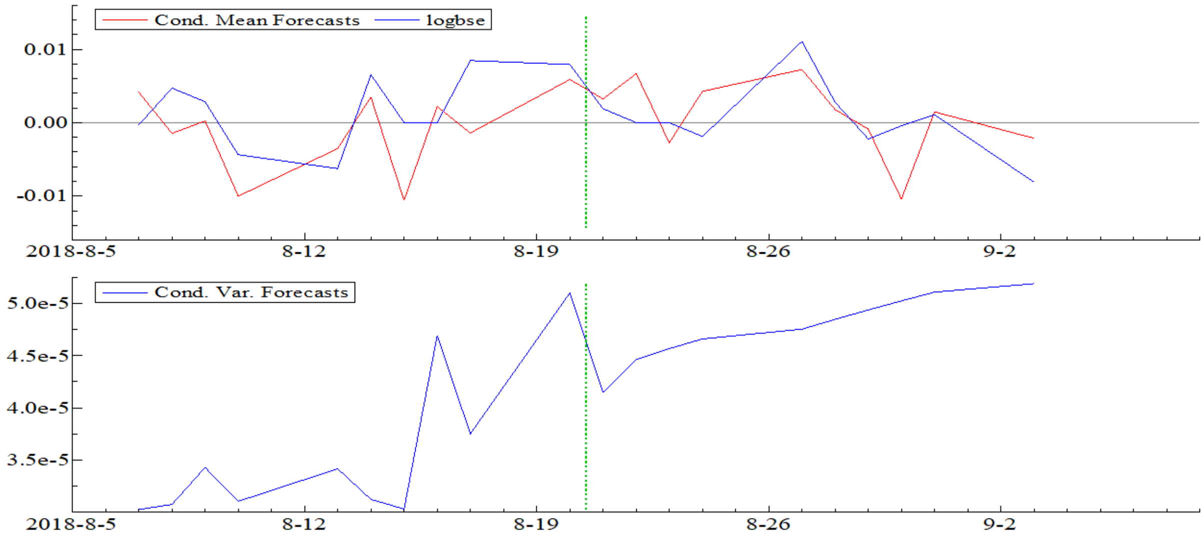
C. 2. RUSSIA - RTSI Forecast Graphs – FIGARCH – BBM



Source: Researcher Compilation

C. 3: INDIA – BSE - Forecast Graphs – FIGARCH – BBM



Source: Researcher Compilation

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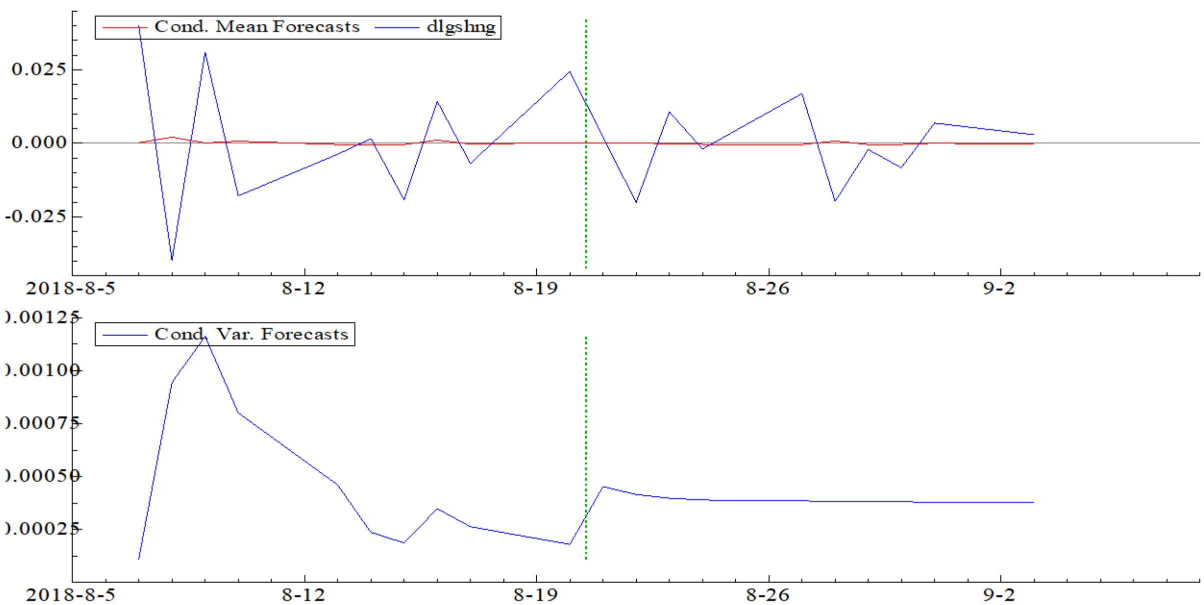
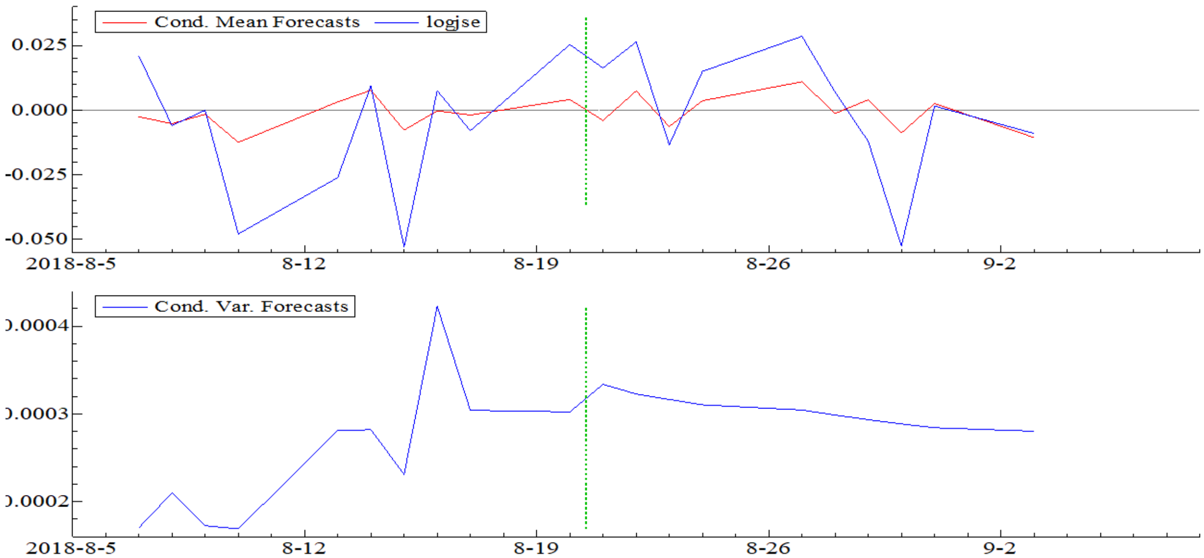
C. 4: CHINA – SHANGHAI - Forecast Graphs – FIGARCH – BBM



Source: Researcher Compilation

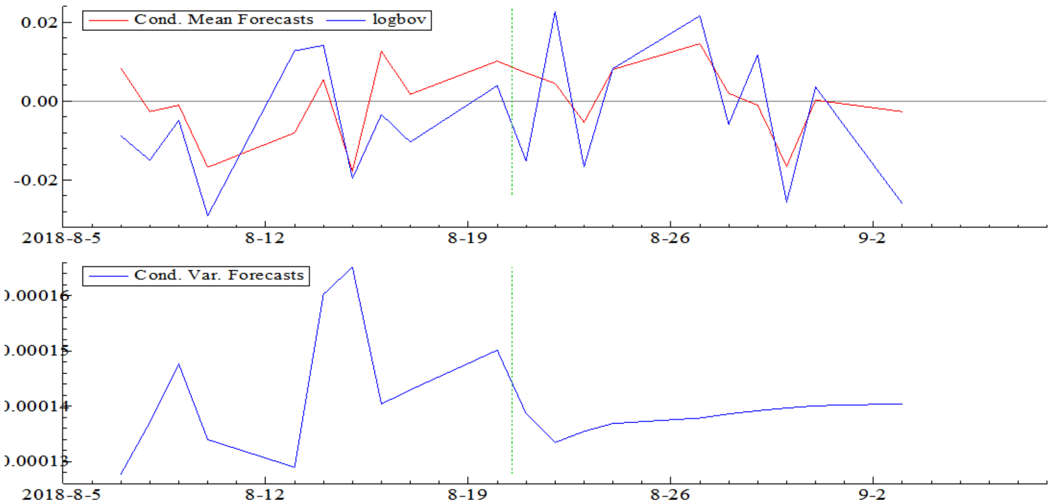
C. 5: SOUTH AFRICA – JSE - Forecast Graphs – FIGARCH – BBM



Source: Researcher Compilation

APPENDIX D – FIGARCH – CHUNG FORECAST GRAPHS

D. 1: Bovespa Conditional Mean and Variance Forecasts – FIGARCH - Chung



Source: Researcher Compilation

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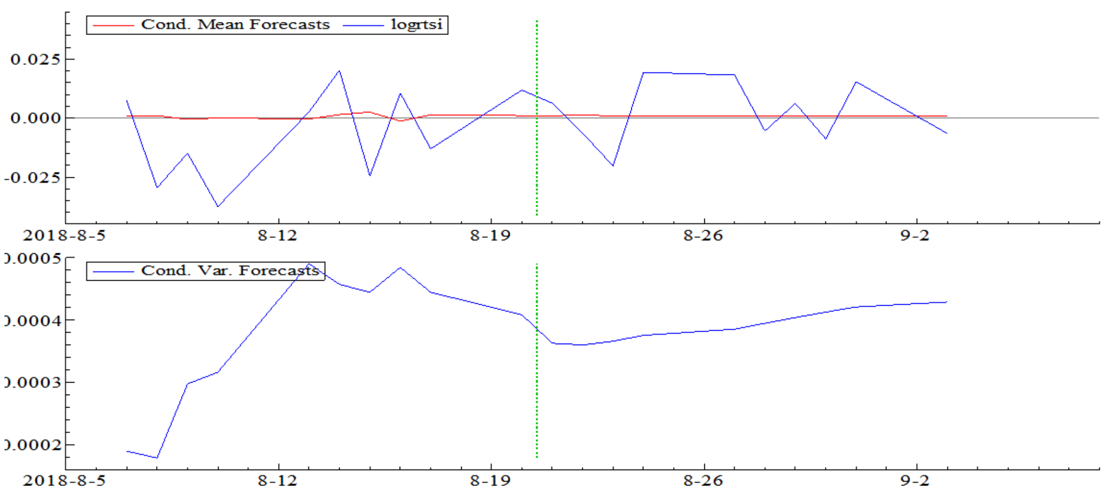
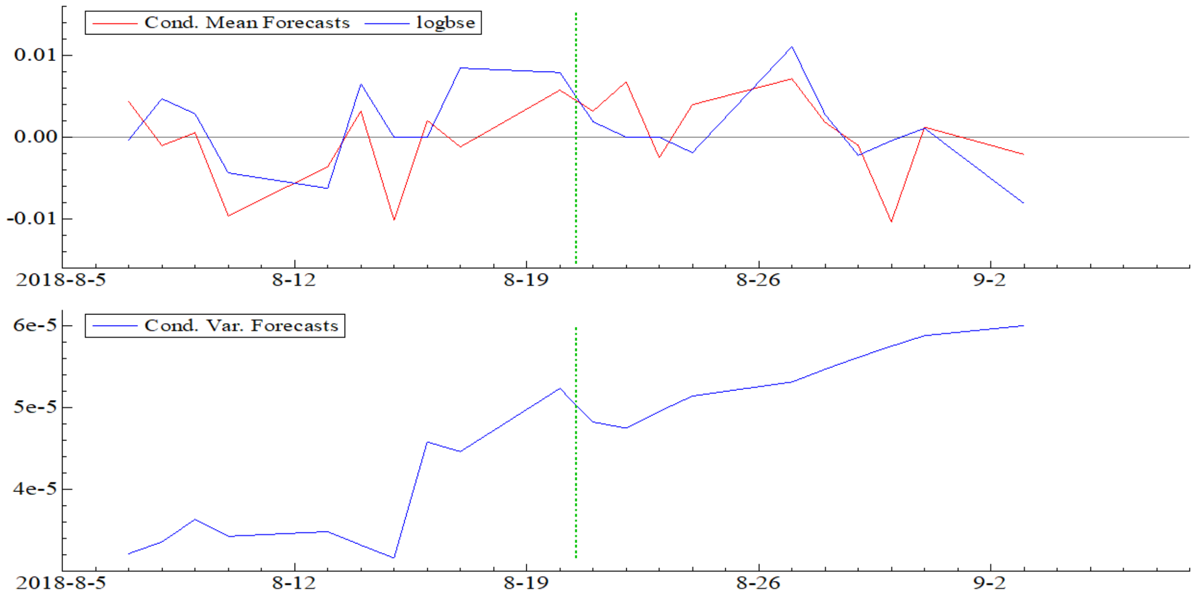
D. 2: RTSI Conditional Mean and Variance Forecasts – FIGARCH - Chung



Source: Researcher Compilation

D. 3 INDIA - BSE - Conditional Mean and Variance Forecasts – FIGARCH - Chung



Source: Researcher Compilation

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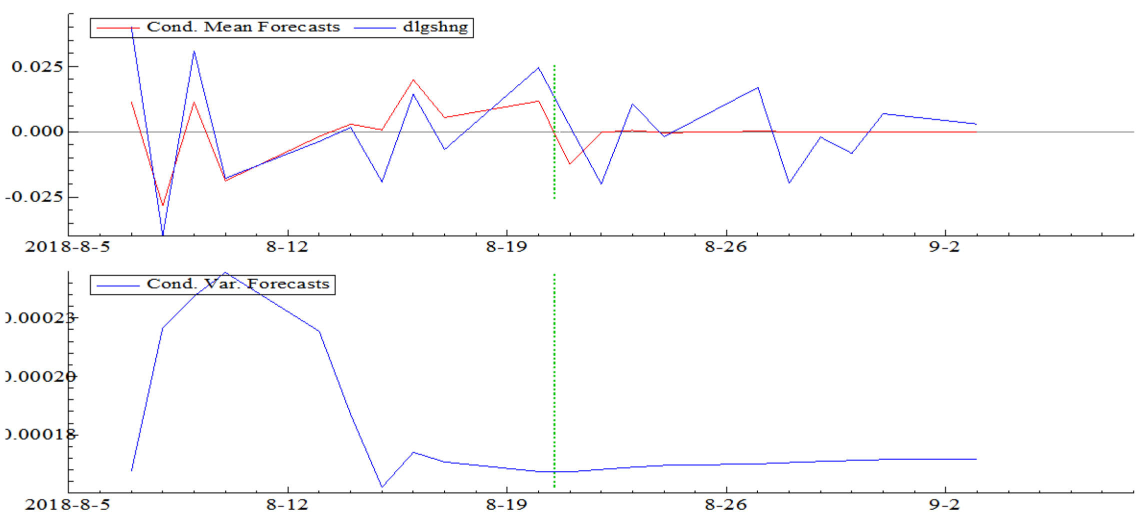
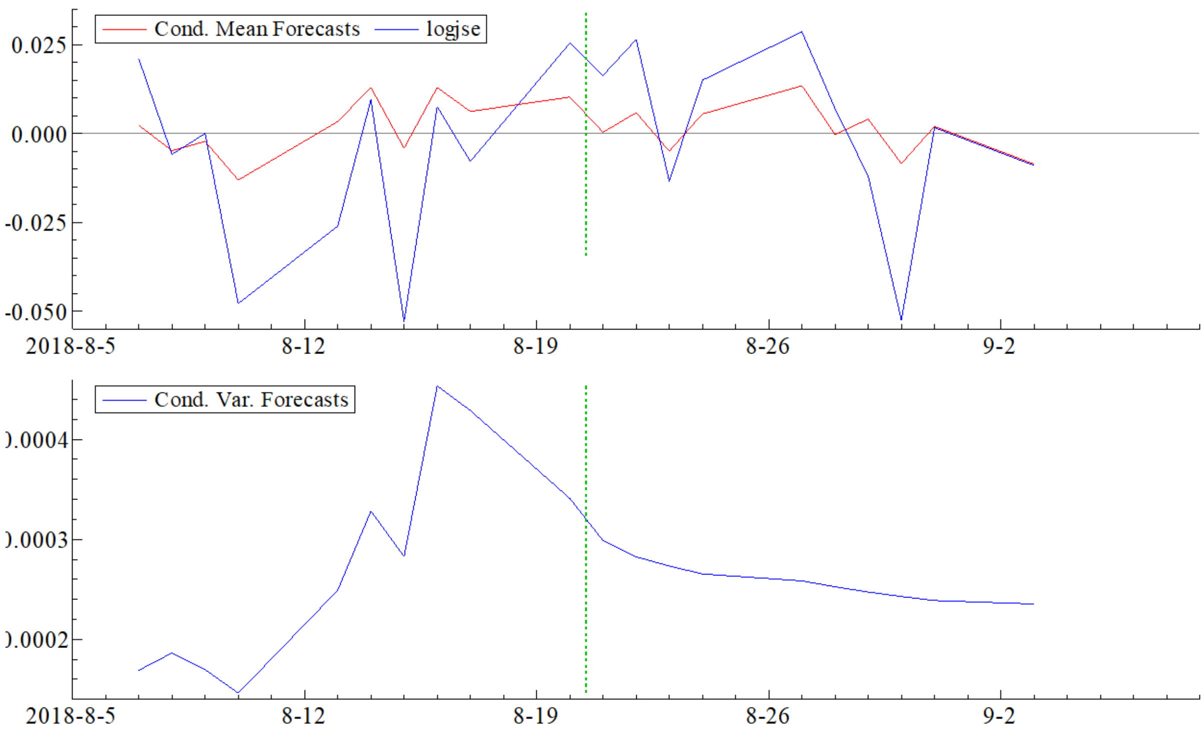
D. 4: SHANGHAI - Conditional Mean and Variance Forecasts – FIGARCH - Chung



Source: Researcher Compilation

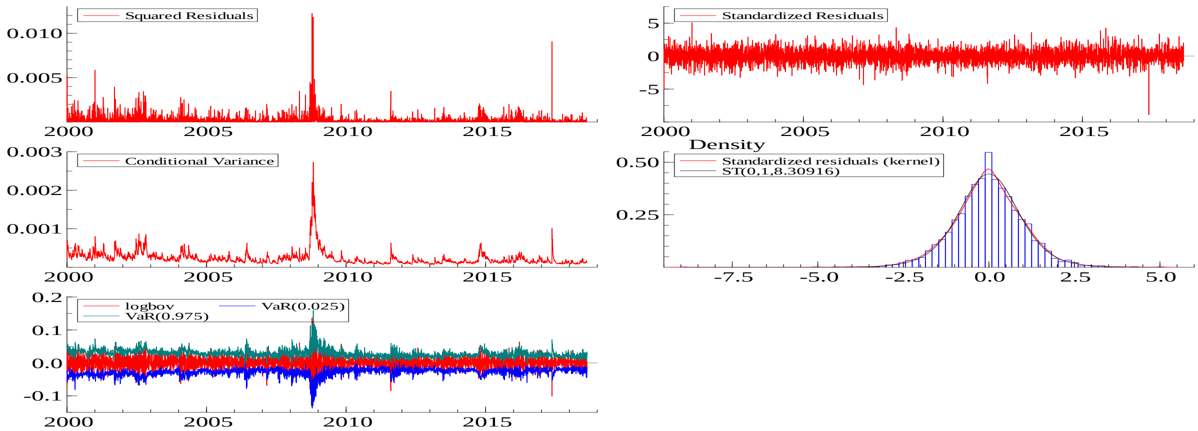
D. 5: JSE - Conditional Mean and Variance Forecasts – FIGARCH - Chung



Source: Researcher Compilation

APPENDIX E: FIGARCH – BBM GENERAL GRAPHS

E. 1: Brazil – Bovespa – General Graphs – FIGARCH - BBM



Source: Researcher Compilation

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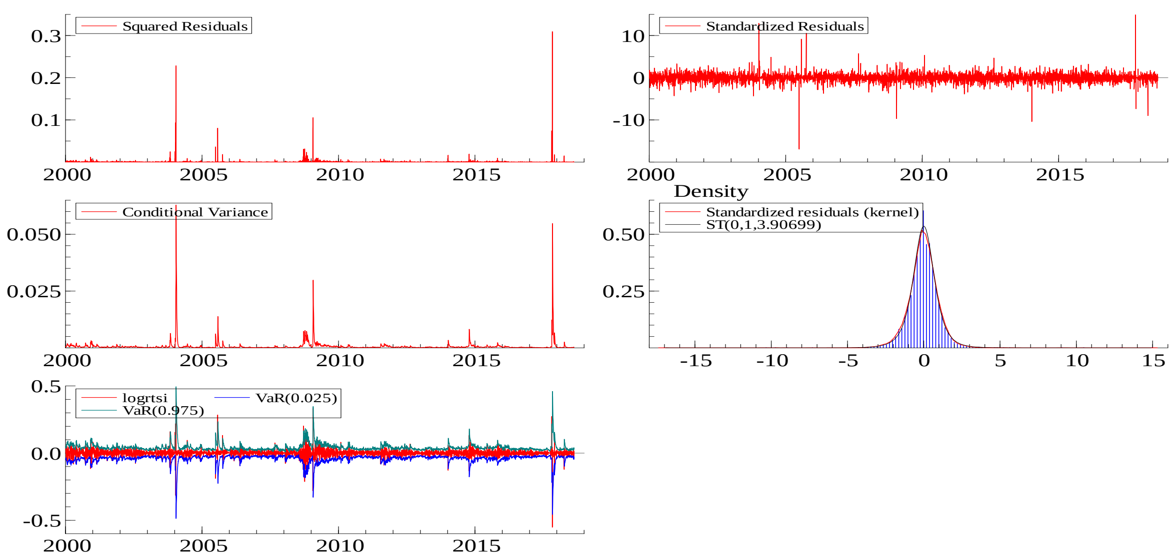
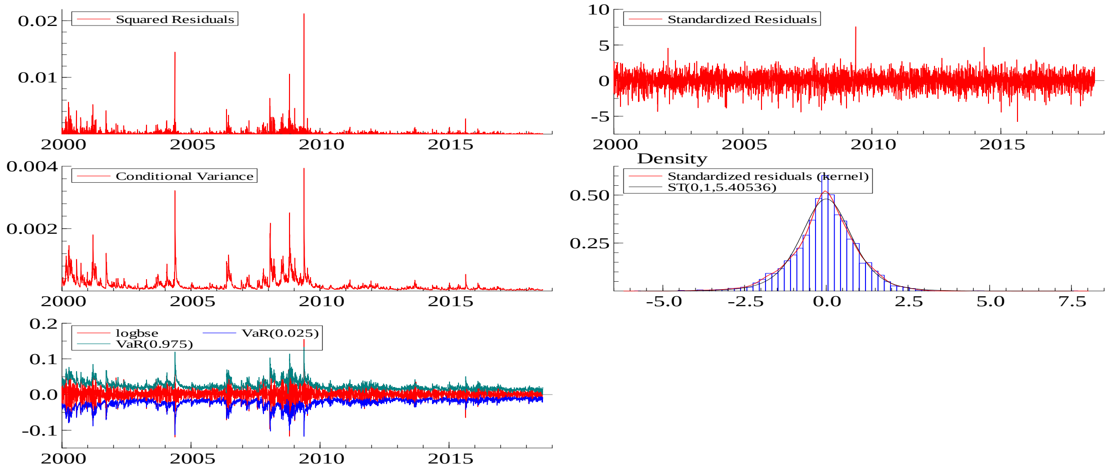
E. 2 RUSSIA – RTSI – General Graphs – FIGARCH - BBM



Source: Researcher Compilation

E. 3: INDIA – BSE – General Graphs – FIGARCH-BBM



Source: Researcher Compilation

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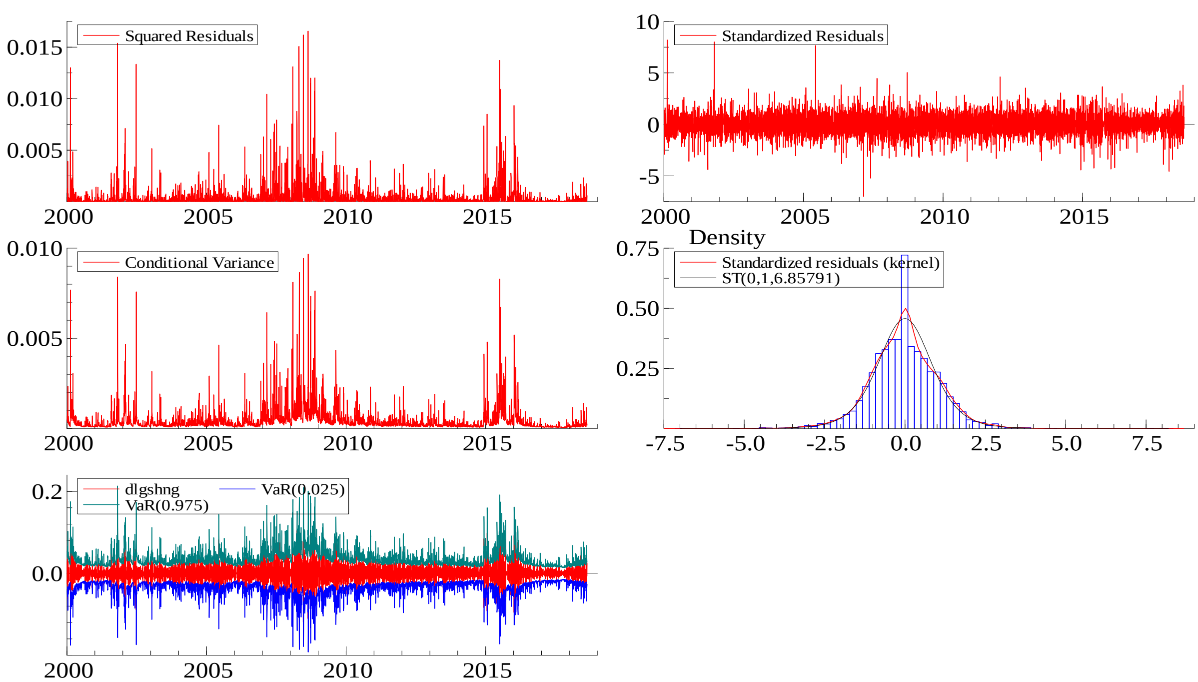
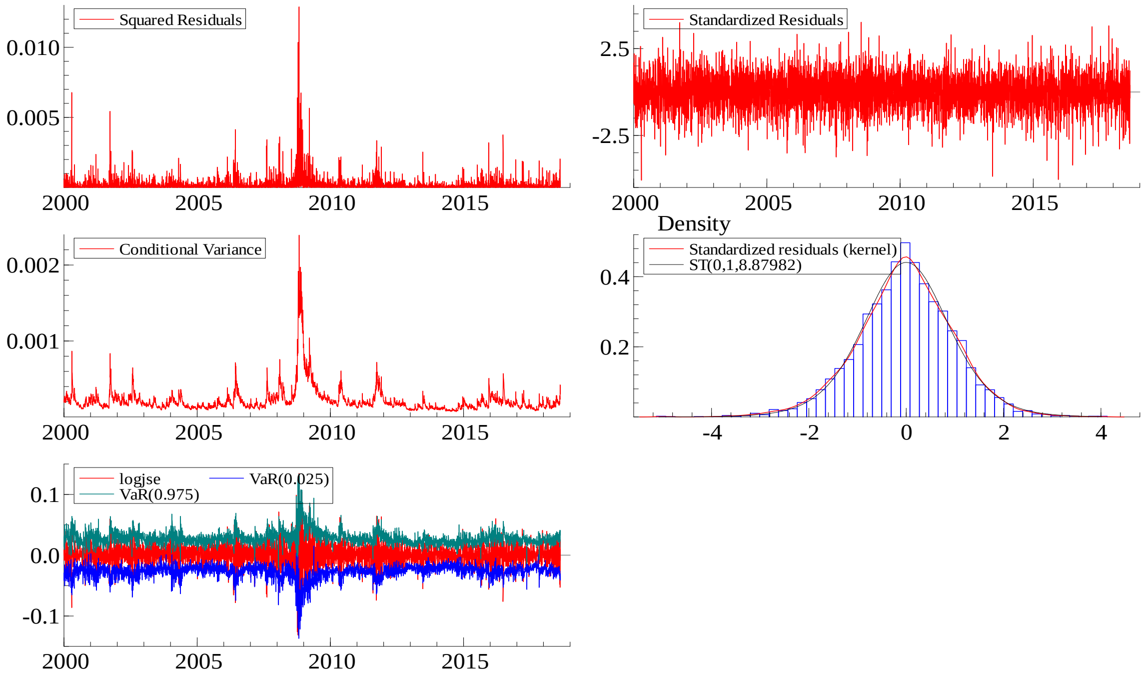
E. 4: CHINA – Shanghai – General Graphs – FIGARCH-BBM



Source: Researcher Compilation

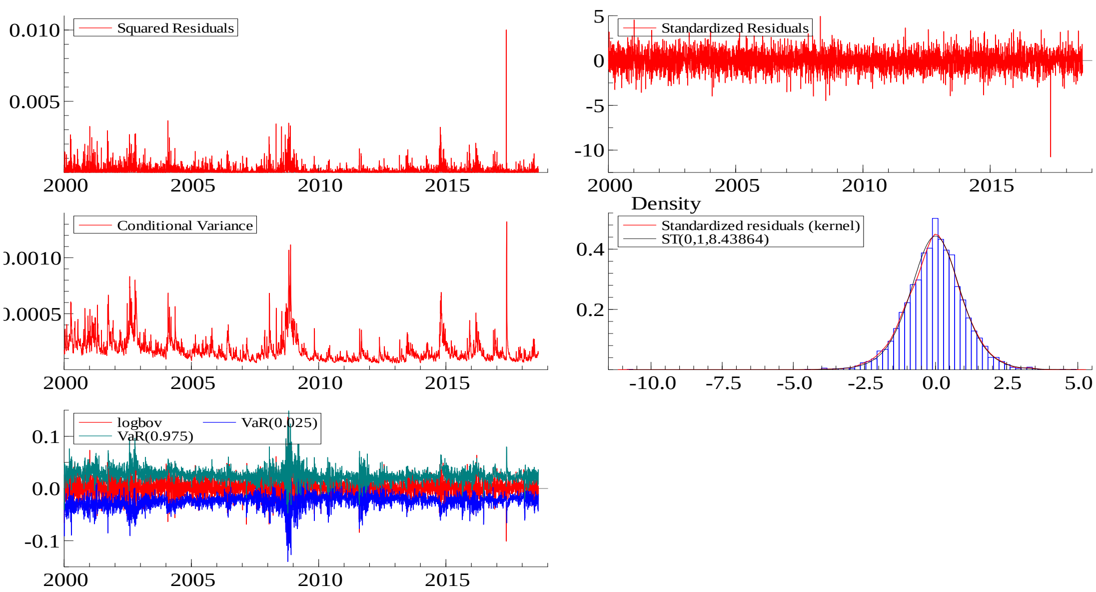
E. 5: SOUTH AFRICA – JSE – General Graphs – FIGARCH – BBM



Source: Researcher Compilation

APPENDIX F – FIGARCH – CHUNG GENERAL GRAPHS

F. 1: Brazil – General Graphs – FIGARCH – Chung



Source: Researcher Compilation

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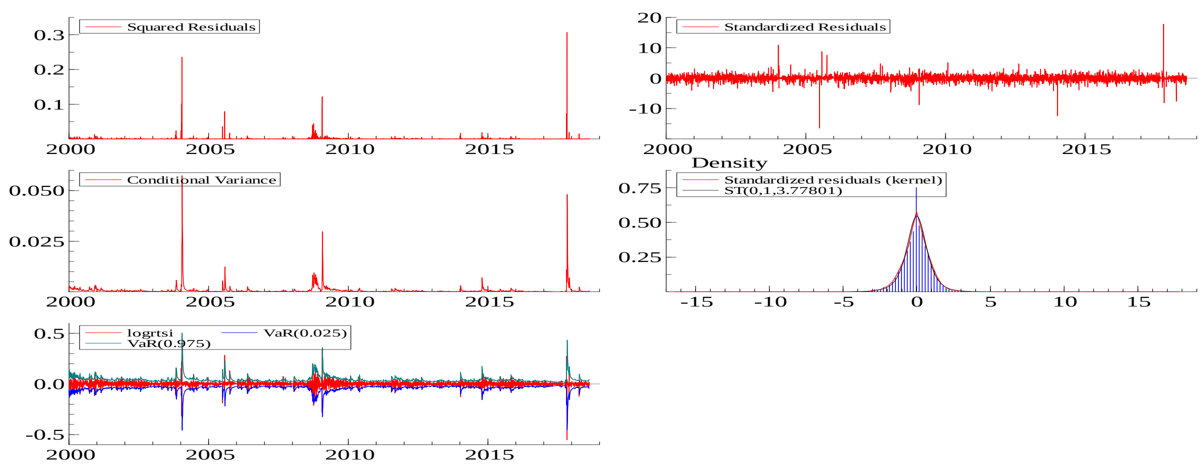
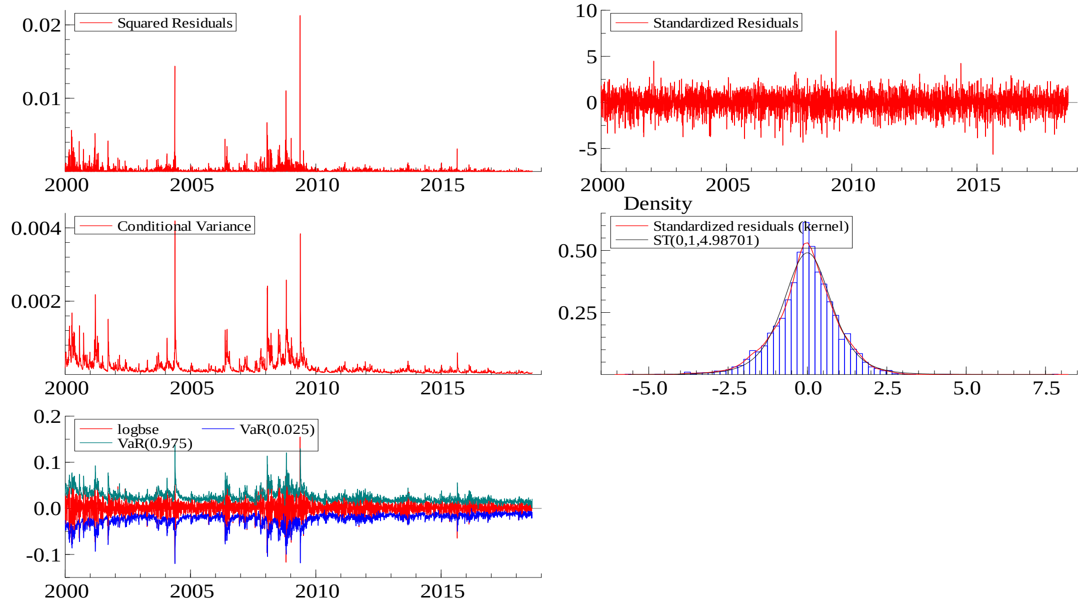
F. 2 Russia General Graphs – FIGARCH - Chung



Source: Researcher Compilation

F. 3: INDIA – General Graphs – FIGARCH - Chung



Source: Researcher Calculations

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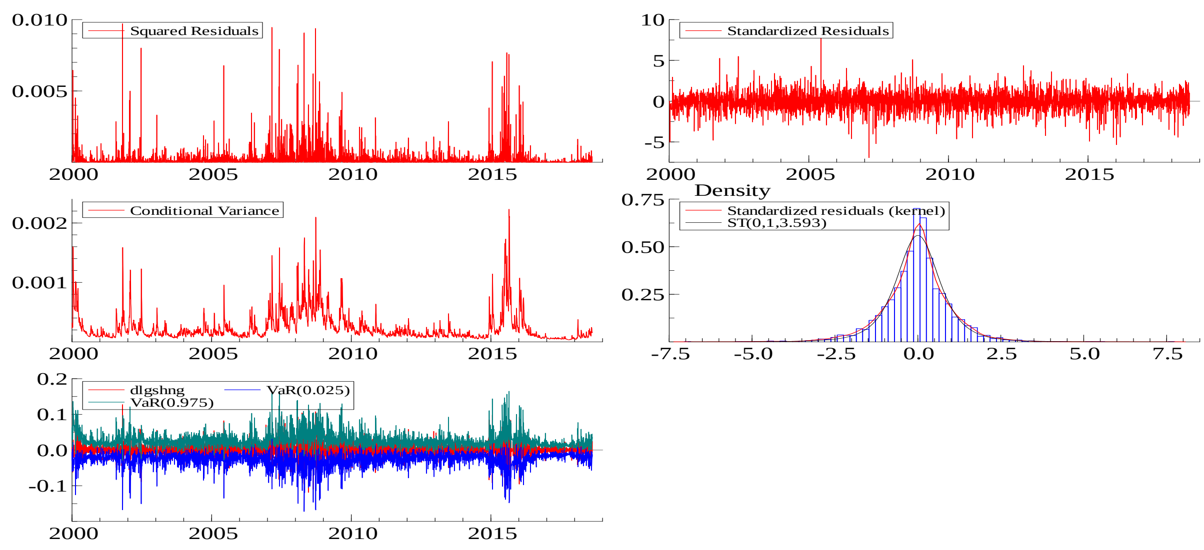
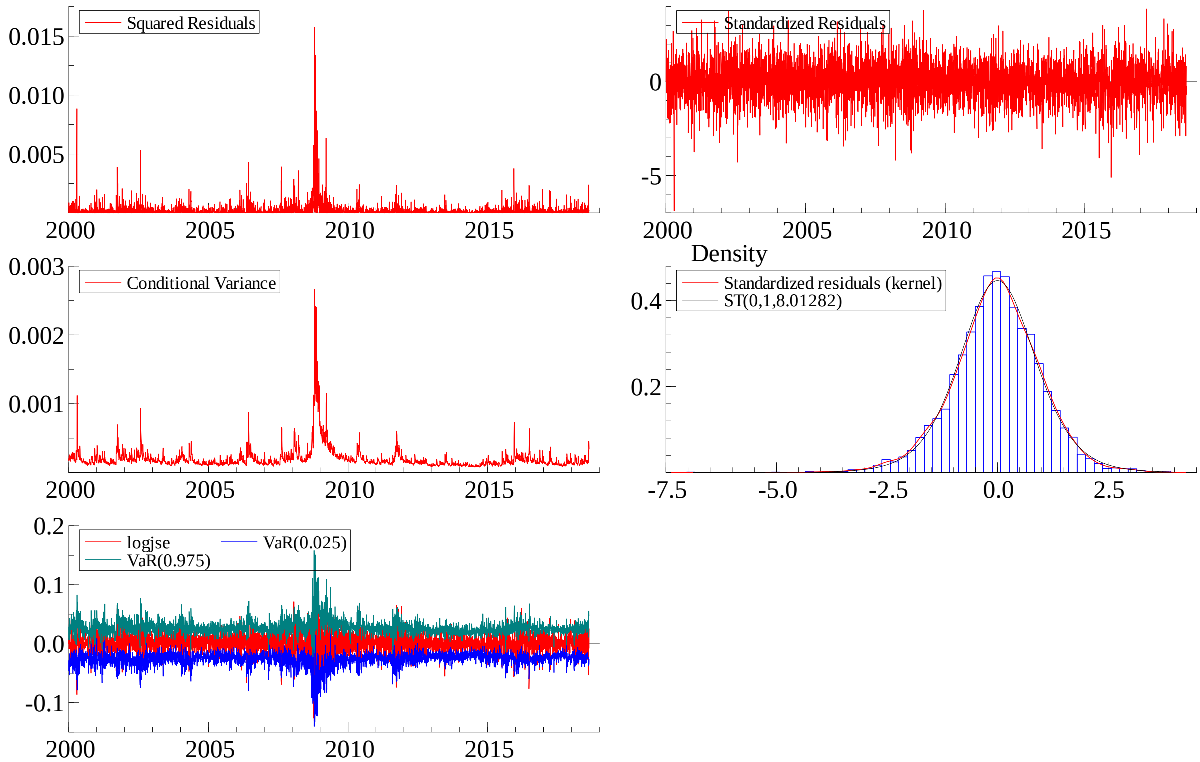
F. 4: CHINA – General Graphs – FIGARCH - Chung



Source: Researcher Compilation

F. 5: SOUTH AFRICA General Graphs – FIGARCH – Chung



Source: Researcher Compilation

APPENDIX G – R- CODE FOR ESTIMATED MODELS

G. 1: DDC- GARCH R- Software CODE Used for the BRICS

```
DCC GARCH CODE

library("XLConnect")

wb1<- loadWorkbook(file.choose(), create = T)

wb1

read_wb1<- readWorksheet(wb1, 1)

head(read_wb1)

brics<- simplify2array(read_wb1)

head(brics)


library(parallel)

library(rugarch)

library(rmgarch)

library("tseries")

library("zoo")

library("forecast")

library("FinTS")

library("vars")

library("MTS")

data(brics)

V<-varxfit(brics, 4, constant = TRUE)

show(V)

uspec.n = multispec(replicate(5, ugarchspec(mean.model =
list(armaOrder = c(1,1)))))

dcc.11mn = dccspec(uspec.n, VAR = TRUE, lag = 4, lag.max = 12,
dccOrder = c(1, 1), distribution = 'mvnorm')

fit.2.11mn = dccfit(dcc.11mn, data = brics[1:4881, 1:5])

fit.2.11mn

plot(fit.2.11mn)
```

```
resid = residuals(fit.2.11mn)/sd(residuals(fit.2.11mn))
Box.test(resid[,1],lag=1,type="Ljung-Box")
Box.test(resid[,2],lag=1,type="Ljung-Box")
Box.test(resid[,3],lag=1,type="Ljung-Box")
Box.test(resid[,4],lag=1,type="Ljung-Box")
Box.test(resid[,5],lag=1,type="Ljung-Box")
Box.test(resid[,6],lag=1,type="Ljung-Box")
```

G. 2 BRICS – R Software Code – Markov Regime Switching (MRS) – GARCH

G2. (i) – Brazil – MRS – GARCH – assuming a normal distribution

```
Code: for Brazil
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbBr<- simplify2array(read_wb1)

library(MSGARCH)
data("wbBr", package = "MSGARCH")
ms2.garch.n<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.n, data = wbBr)
summary(fit.ml)
```

==

G2. (ii) – Brazil – MRS – GARCH – assuming a skewed GED distribution

```
Code: for Brazil
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbBr<- simplify2array(read_wb1)

library(MSGARCH)
data("wbBr", package = "MSGARCH")
ms2.garch.sged<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.sged, data = wbBr)
summary(fit.ml)
```

G2. (iii) Russia – MRS – GARCH – assuming a normal distribution

```
Code: for Russia
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbRU<- simplify2array(read_wb1)

library(MSGARCH)
data("wbRU", package = "MSGARCH")
ms2.garch.n<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.n, data = wbRU)
summary(fit.ml)
```

==

G2. (iv) Russia - MRS – GARCH – assuming a skewed GED distribution

```
Code: for Russia
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbRU<- simplify2array(read_wb1)

library(MSGARCH)
data("wbRU", package = "MSGARCH")
ms2.garch.sged<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.sged, data = wbRU)
summary(fit.ml)
```

G2. (v) India – MRS – GARCH – assuming a normal distribution

```
Code: for INDIA
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbIN<- simplify2array(read_wb1)

library(MSGARCH)
data("wbIN", package = "MSGARCH")
ms2.garch.n<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.n, data = wbIN)
summary(fit.ml)
================================================================
```

G2. (vi) India – MRS – GARCH – Assuming a skewed GED distribution

```
Code: for INDIA
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbIN<- simplify2array(read_wb1)

library(MSGARCH)
data("wbIN", package = "MSGARCH")
ms2.garch.sged<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.sged, data = wbIN)
summary(fit.ml)
```

G2. (vii) China – MRS – GARCH Assuming a normal distribution

```
Code: for CHINA
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbCH<- simplify2array(read_wb1)

library(MSGARCH)
data("wbCH", package = "MSGARCH")
ms2.garch.n<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.n, data = wbCH)
summary(fit.ml)
================================================================
```

G2. (viii) China – MRS – GARCH Assuming a skewed GED distribution

```
Code: for CHINA
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbCH<- simplify2array(read_wb1)

library(MSGARCH)
data("wbCH", package = "MSGARCH")
ms2.garch.sged<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.sged, data = wbCH)
summary(fit.ml)
```

G2. (ix) South Africa – MRS – GARCH Assuming a normal distribution

```
Code: for South Africa
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbSA<- simplify2array(read_wb1)

library(MSGARCH)
data("wbSA", package = "MSGARCH")
ms2.garch.n<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.n, data = wbSA)
summary(fit.ml)
```

==

G2. (x) SOUTH AFRICA: MRS – GARCH Assuming A Student t-distribution

```
Code: for South Africa
library("XLConnect")
wb1<- loadWorkbook(file.choose(), create = T)
wb1
read_wb1<- readWorksheet(wb1, 2)
head(read_wb1)
wbSA<- simplify2array(read_wb1)

library(MSGARCH)
data("wbSA", package = "MSGARCH")
ms2.garch.t<- CreateSpec()
fit.ml<- FitML(spec = ms2.garch.t, data = wbSA)
summary(fit.ml)
```

NB: For South Africa with the exception of the Gaussian distribution, the best fitting error distribution for the MRS – GARCH model was the Student t hence the above code.

H. 1 - APPENDIX H – Links of data obtained from indexmundi.com and investing.com websites

https://www.indexmundi.com/commodities/?commodity=agricultural-raw-materials-price-index

https://www.indexmundi.com/commodities/?commodity=commodity-price-index

https://www.indexmundi.com/commodities/?commodity=food-price-index

https://www.indexmundi.com/commodities/?commodity=agricultural-raw-materials-price-index

https://www.indexmundi.com/commodities/?commodity=energy-price-index

https://www.indexmundi.com/commodities/?commodity=industrial-inputs-price-index

https://www.indexmundi.com/commodities/?commodity=metals-price-index

https://www.indexmundi.com/commodities/?commodity=petroleum-price-index

https://www.investing.com/indices/Shanghai-composite

https://www.investing.com/indices/sensex

https://www.investing.com/indices/bovespa

https://www.investing.com/indices/dj-composite-average

https://www.investing.com/indices/us-30-historical-data

https://www.investing.com/indices/ftse-jse-all-share-components

http://www.econstats.com/commsp/commsp_m2.htm

https://www.chinainternetwatch.com/

APPENDIX I – VAR Lag Selection Criteria

I. 1 VAR Lag Order Selection Criteria for Raw Daily Data

Endogenous variables: BOVESPA BSEINDEX JSEINDEX RTSI SHANGINDEX DOWJONES USCORN CRUDEOIL GOLDAUX
Exogenous variables: C
Sample: 1/03/2000 9/03/2018
Included observations: 4874

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-339642.3	NA	2.73e+49	139.3727	139.3847	139.3769
1	-288453.7	102167.2	2.13e+40	118.4012	118.5211	118.4433
2	-287343.1	2212.661	1.40e+40	117.9787	118.2065	118.0586
3	-286852.4	975.6959	1.18e+40	117.8106	118.1462*	117.9284
4	-286554.1	592.1784	1.08e+40	117.7214	118.1649	117.8771
5	-286225.2	651.4850	9.76e+39	117.6197	118.1711	117.8132
6	-285990.1	464.9681	9.16e+39	117.5565	118.2157	117.7878
7	-285793.4	388.2556	8.73e+39	117.5090	118.2761	117.7782*
8	-285656.8	269.1414*	8.54e+39*	117.4862*	118.3612	117.7932

*** indicates lag order selected by the criterion**
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SIC: Schwarz information criterion
HQIC: Hannan-Quinn information criterion

Optimum Lag chosen is 3 according SIC as shown on the Table

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I. 2 VAR Lag Order Selection Criteria for Log-Return Data

VAR Lag Order Selection Criteria
Endogenous variables: LOGBOV LOGRTSI LOGBSE LOGSHANG LOGJSE LOGDOW LOGCORN LOGCRUDE LOGGOLD
Exogenous variables: C
Sample: 1/03/2000 9/03/2018
Included observations: 4870

Lag	LogL	LR	FPE	AIC	SC	HQ
1	128759.5	1354.160	9.10e-35	-52.84167	-52.72171*	-52.79957*
2	128880.7	241.5728	8.95e-35	-52.85820	-52.63029	-52.77821
3	128962.2	161.9424	8.95e-35*	-52.85838*	-52.52251	-52.74051
4	129011.8	98.53084	9.06e-35	-52.84550	-52.40167	-52.68974
5	129086.2	147.3308	9.09e-35	-52.84278	-52.29099	-52.64913
6	129150.5	127.3090	9.15e-35	-52.83595	-52.17621	-52.60441
7	129232.9	162.6239	9.14e-35	-52.83653	-52.06882	-52.56710
8	129293.6	119.4193	9.22e-35	-52.82816	-51.95249	-52.52084
9	129352.1	115.1497	9.31e-35	-52.81894	-51.83532	-52.47374
10	129422.6	138.3214	9.35e-35	-52.81462	-51.72304	-52.43153

11	129487.9	127.8838	9.41e-35	-52.80816	-51.60862	-52.38718
12	129557.6	136.3276*	9.45e-35	-52.80353	-51.49603	-52.34466

*** indicates lag order selected by the criterion**
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SIC: Schwarz information criterion
HQIC: Hannan-Quinn information criterion

Optimum Lag chosen is 1 according Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HQIC) as shown on the Table

==

I. 3 VAR Lag Order Selection Criteria for Monthly Data

VAR Lag Order Selection Criteria
Endogenous variables: BOV BRZY BSE INDIAPTI RTSI RUSSIAPTI SSEC CHRETAIL JSEFT SAMANUF
Exogenous variables: C
Sample: 1990M01 2018M10
Included observations: 338

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-19969.64	NA	1.04e+39	118.2227	118.3358	118.2678
1	-16070.88	7543.756	1.81e+29	95.74484	96.98903	96.24070
2	-15692.92	708.9447	3.49e+28	94.10014	96.47540*	95.04678*
3	-15533.10	290.3238	2.46e+28	93.74617	97.25252	95.14360
4	-15428.19	184.3819	2.41e+28*	93.71707*	98.35450	95.56528
5	-15344.34	142.3913	2.68e+28	93.81265	99.58115	96.11165
6	-15274.39	114.6420	3.25e+28	93.99050	100.8901	96.74028
7	-15190.81	132.0567*	3.67e+28	94.08762	102.1183	97.28818
8	-15111.97	119.8970	4.29e+28	94.21281	103.3745	97.86415

*** indicates lag order selected by the criterion**
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SIC: Schwarz information criterion
HQIC: Hannan-Quinn information criterion

Optimum Lag chosen is 1 according Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HQIC) as shown on the Table