The impact of oil price shocks on stock markets: An analysis of the BRICS countries

by

Reeza Seedat 473565

MCOM (FINANCE)

in the

SCHOOL OF ECONOMIC AND BUSINESS SCIENCES

at the

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Supervisor: Ayesha Sayed

Date of submission:

SCHOOL OF ECONOMIC AND BUSINESS SCIENCES

Declaration Regarding Plagiarism

I (full names & surname):	
Student number:	

Declare the following:

1. I understand what plagiarism entails and am aware of the University's policy in this regard.
2. I declare that this assignment is my own, original work. Where someone else's work was used (whether from a printed source, the Internet or any other source) due acknowledgement was given and reference was made according to departmental requirements.
3. I did not copy and paste any information directly from an electronic source (e.g., a web page, electronic journal article or CD ROM) into this document.
4. I did not make use of another student's previous work and submitted it as my own.
5. I did not allow and will not allow anyone to copy my work with the intention of presenting it as his/her own work.

Signature　　　　　　　　　　　　　　　　Date

____________________________　　　____________________________

Abstract

This paper investigates the link between oil price shocks and share market returns in Brazil, Russia, India, China and South Africa collectively called the BRICS countries. Monthly data was analysed for the period February 1998 to December 2017. Granger causality tests were run to test uni-directional causality from oil prices to stock returns. It was found that oil prices granger cause share returns for all the BRICS countries. A Vector Auto Regressive (VAR) model was employed with Impulse Response Functions (IRFs) and variance decompositions computed in order to aid the analysis. Significant positive relationships were found between oil prices shocks and share market returns for Brazil and Russia while India, China and South Africa initially experienced positive shocks that become negative over time. The status on whether a country is a net oil importer or net oil exporter played an important role in determining the contribution of oil price shocks to fluctuations in share market returns. The findings of this study could assist investors in better understanding and predicting the performance of share markets by examining the link between share market returns and oil prices. It can also assist regulators to increase investor confidence in share markets by protecting their interests against uncertainty, the risk associated with the oil market and minimizing share markets dependency on oil prices.

Acknowledgements

I would like to thank my parents for their unwavering support throughout this long journey. You saw the finish line at times when I couldn’t. I would like to thank my friends Ullah and Sheldon who were often with me in the trenches providing moral support. To my supervisor Ayesha, I would like to thank you for your patience and guidance. I could not have done this without you.

Definition of Terms and Abbreviations

BRICS: Refers to the collective of Brazil, Russia, India, China and South Africa

BSE Sensex: An index listed on the Bombay stock exchange.

CPI: The Consumer Price Index measures the changes in the prices paid by consumers for a basket of goods and services.

GCC: The Cooperation Council for the Arab States of the Gulf, made up of Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, the United Arab Emirates and Yemen.

GDP: The Gross Domestic Product measures the national income and output for a country's economy. The GDP is equal to the total expenditures for all final goods and services produced within the country in a stipulated period of time.

GNP: The Gross National Product is a measure of a countries finished goods and services

Industrial Production: Industrial production measures the output of businesses integrated in the industrial sector of the economy.

IBOVESPA: An index listed on the Sao Paulo stock exchange

JSE All Share Index: An index listed on the Johannesburg Stock Exchange

Kurtosis: measures the peak or flatness of the distribution of the series.

MOEX: Index listed on the Moscow stock exchange

OPEC: The Organization of the Petroleum Exporting Countries made up of Algeria, Angola, Congo, Ecuador, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, United Arab Emirates, Venezuela

Shanghai Composite Index: An index listed on the Shanghai stock exchange

Skewness: is a measure of asymmetry of the distribution of the series around its mean.

US: United States

VAR: Vector autoregressive models are multivariate time-series models that employ both lagged independent as well as dependent variables in explaining time-series data.

Variance Decomposition: Also known as the forecast error variance decomposition: allows one to decompose the variation in a forecasted variable due to a shock in another variable.

Table of Contents

List of figures

List of tables

1. INTRODUCTION

For more than a hundred years, oil has been the lifeblood of the world economy. Today, oil accounts for a third of the world's energy supply and about 2.5% of the world's Gross Domestic Product (GDP) (Carlyle, 2013). The reality is that there are no viable replacements for oil in the foreseeable future.

Five of the world's most important emerging economies, Brazil, Russia, India, China and South Africa, known collectively as BRICS, are playing an increasingly critical role in the global economy. Its combined economic weight in 2015 equaled roughly that of the G-7 countries in PPP (Purchasing Power Parity) terms (Reddy, 2018). Furthermore, BRICS also accounted for an impressive 56% of the growth of global Gross National Product (GNP) during 2017-2018 and is expected to account for more than half of global economic growth up until 2030 (Reddy, 2018). This contribution could be higher if investment rates within BRICS countries increase (Reddy, 2018).

These five countries differ substantially regarding oil as a commodity. Russia and Brazil are both net oil exporters with Russia ranked as the second largest exporter in the world while Brazil is placed nineteenth on the list of exporters. The Russian Stock Market is also largely dominated by oil and gas companies, with 60% of the total market capitalization coming from these industries (Bouoiyour and Selmi, 2016; Workman, 2018).

China, India and South Africa are all net oil importers. Oil is a crucial form of energy for China and India, both highly industrialized economies. They are the second and third largest consumers of oil respectively (EIA, 2018). Oil companies make up more than 16% of the Shanghai Composite Index while they represent 1.4% of the Bombay Stock Exchange. Although less dependent on oil than India and China, South Africa ranks thirtieth in the consumption of oil globally. In South Africa, oil and gas companies comprise approximately 4% of the total share market capitalization (EIA, 2018; Bouoiyour and Selmi, 2016).

The BRICS countries consume 25% of the world's oil reserves. They are also forecasted to contribute in excess of 40% of the world's share market capitalization by 2030 when the Chinese economy is anticipated to overtake that of the United States (US) (Bouoiyour and Selmi, 2016).

Fluctuations in oil prices is not a new phenomenon. This is evident from the 1970s and 1980s when a catastrophe of political events in the Middle East disrupted the secure and certain supply of oil. This had a severe effect on the global price of oil. Fluctuations in the price of oil have noteworthy impacts on economic growth and welfare around the world (Rentschler, 2013). The need for oil has significantly increased with the industrialization of emerging economies such as India and China. This has made oil one of the most traded commodities in the world (Novac, 2019).

One of the first to study the correlation between changes in oil prices and macro-economic variables was Hamilton (1983). His findings suggested that in the US after World War II, recessions were followed by a substantial increase in oil prices. Hamilton's research spurred a plethora of studies analyzing the effect of oil price fluctuations on the macro economy.

Apart from affecting macroeconomic variables, shocks to oil prices also impinge on the performance of a company through its operational costs and revenues. This has a direct influence on the market value of a company (Aye, 2015). Jones and Kaul (1996) studied the impact of oil price shocks and share returns. This was followed by the seminal work by Sadorsky (1999) who looked at the linear and asymmetric relationship between oil prices and US stock returns. Pre-eminent in the examination of the impact of oil price shocks on emerging markets was Magyereh (2004).

While a vast amount of research has been conducted on oil price shocks and the macro-economy, relatively few studies have looked at the impact of oil price shocks on share market returns. This study aims to provide insight into the effect of changes in oil prices on the price of shares of listed companies in the BRICS countries. It will investigate the short-run linear relationship between oil price shocks and share market returns. This study will employ an unrestricted Vector Auto

Regression (VAR) in order to analyze these aspects. Monthly data will be used for the period February 1998 to December 2017. The unrestricted VAR model will use three variables namely: real industry production, real oil prices and real stock returns, however the study will focus on the relationship between real oil prices and real share returns.

1.1. Objectives and problem statement

While there has been a plethora of studies investigating the impact of oil price shocks on the macro-economy, research regarding the relationship between oil prices and share market returns in emerging markets is limited at best. Sadorsky (1999) and Park and Ratti (2008) looked at the impact of oil prices on share market returns in developed economies. However their studies did not consider the economic downturn during the financial crisis of 2008. Furthermore, while there are a limited amount of studies that looked at the impact of oil prices and share market returns in the BRICS countries, none of these studies have made use of the proposed methodology over the selected time horizon.

The objective of this study is to contribute to the limited body of knowledge regarding the impact of oil price shocks on share returns in the BRICS countries within the context of linear price changes.

The analysis of this study is based on the following hypothesis:

> $H_{1,0}$: *Oil price shocks do not have an impact on share market returns in the BRICS countries.*
>
> $H_{1,A}$: *Oil price shocks have an impact on share market returns in the BRICS countries.*

1.2. Importance and benefits of the proposed study

This study will attempt to investigate the general impact of oil price shocks on share markets in the BRICS countries more closely. This is important to study for several reasons.

First, research by Sadorsky (1999) found that movements in oil prices are a critical factor in explaining movements in share returns in developed countries. Globalisation has resulted in an increased amount of capital flow and international investment into emerging markets (Bhar and Nikolova, 2009). With all five BRICS countries classed as emerging markets and highly dependent on oil, either through exports (Brazil and Russia) or imports (India, China and South Africa), it is imperative for global portfolio investors to determine the impact that oil price shocks would have on their share markets as results may vary significantly in comparison to developed markets. Furthermore, it will assist firms and investors who are sensitive to changes in oil prices to make better informed decisions relating to oil price risk hedging. It could also assist financial analysts, portfolio managers, pension fund managers and other market participants who need a detailed understanding of the volatility of assets (Talukdar and Sunyaeva, 2011).

Secondly, several studies have shown that the effect of oil price shocks is largely dependent on whether a country is a net oil importer or net oil exporter. With three of the BRICS countries being net oil importers (India, China and South Africa) it is vital to investigate how oil price changes affect their returns in comparison to the two net oil exporting countries (Brazil and Russia).

Finally, with South Africa only joining the BRIC community in December 2010, there is a limited amount of research analysing the effect of oil price shocks on share prices for all five countries. Furthermore, to the author's knowledge, no research has been conducted using the proposed methodology over the selected time horizon. The selected time horizon is critical for two reasons. First, it includes a period of extreme economic volatility being the financial crisis of 2008. This anomaly will allow us to better examine the relationship between oil prices and stock market returns. Secondly, this period also includes a number of peaks and troughs with oil prices peaking in 2007 and reaching record lows in the beginning of 2016. The large variance in oil price over the sample period will provide us with a much clearer understanding of the relationship between oil prices and share market returns.

1.3. Applied methodology

An empirical analysis will be conducted in order to address the problem statement. Consonant with existing literature, an unrestricted Vector Autoregression model (VAR) will be used. In order to assist with the analysis of results, recourse will be had to a Granger Causality Test, Impulse Response Functions (IRFs) and Variance Decomposition (Guliman, 2015). The methodology will be considered in further detail in section 4.

1.4. Delimitations

When studying the impact of oil price shocks on share returns, the analysis will be confined to the BRICS countries. The reason for circumscribing the ambit is the dearth of studies on the relationship between oil price shocks and share price returns in emerging economies when compared to developed economies. It also allows for a comparison between net oil importing countries (India, China, and South Africa) and net oil exporting countries (Brazil and Russia). The BRICS countries also play an important strategic role in global trade with a large contribution to global GDP as well as a large influence on global GDP growth. Furthermore, there are several different benchmarks for crude oil for various regions of the world. The three most common benchmarks are Brent Blend, West Texas Intermediate (WTI) and Organization of the Petroleum Exporting Countries (OPEC) Basket. This study will rely on the Brent Blend because it remains the major benchmark for other crude oils in Europe and Africa as well as being the most commonly used standard for crude oil futures contracts (Mayer, 2017). Finally, the study will be benchmarked against seminal literature such as Sadorsky (1999), Park and Ratti (2008), Le and Chang (2011), who made use of similar models.

This study aims to examine the impact of short run dynamics of oil price shocks on the share market returns of five emerging economies of Brazil, Russia, India, China and South Africa using a non-structural VAR. The study will make use of share/equity indices instead of analyzing specific companies or industries. Analyzing equity/share indices is in line with previous literature authored by Sadorsky (1999), Bashar and Sadorsky (2006), Park and Ratti (2008) and Guliman (2015).

In line with previous studies, industrial production index has been included as it is considered an indicator of economic activity, however the focus of the analysis is on oil prices and share market returns.

Monetary policies are determined by central banks who use interest rates as a tool to control inflation. This has an impact on stock returns (Talukdar and Sunyaeva, 2011). While previous studies have used Three-month Treasury bill rates as a proxy for short-term interest rates, this study will not include short-term interest rates as a variable since these rates were not available for the period under review. Furthermore, the study will not conduct an analysis, as done by Kilian (2009) separating oil shocks into supply and demand shocks and the effect shocks may have on share markets as documented by Kilian (2009) because this would fall outside the purview of this study.

1.5. Structure of the study

Section one provides background to the study, adumbrates on the importance of the study as well as the objectives and problem statement. What follows in section two is a review of the pertinent literature. The next two sections will answer the hypothesis with section three giving further insight into the data and section four will discuss the methodology used. An empirical analysis is conducted in section five. Finally, the conclusion is presented in section six together with the possibilities for future research.

2. LITERATURE REVIEW

This section will first look at the theory regarding oil prices and stock markets. It then refers to the literature covering oil price shocks and its effect on share market returns on the basis of empirical evidence. Studies on the effects of oil prices on developed markets, emerging markets, net oil importers and net oil exporters will be discussed.

2.1. Theory

2.1.1. Definition of oil price shocks

There have been a number of definitions of oil price shocks that have emerged since the seminal literature by Hamilton (1983). There are two different schools of thought with regards to the literature which will be discussed below.

The focus of the first school of thought is on the reaction of output to fluctuations in oil prices. Hamilton (1983) was amongst the first to examine the effect of the changes in the price of oil on domestic economies. He found that a significant rise in oil prices were the cause of most of the recessions in the US. Hamilton used a linear to explain an oil price shock. This description has been widely accepted and used in the literature looking at both oil price shocks on share returns and the impact on the economy.

An extension to Hamilton's research was conducted by Mork (1989), who found a lesser correlations between oil prices and output. Furthermore, Mork noted that if increases and decreases in oil prices were categorized as discrete/independent variables, then a statistically significant relationship was found. This led him to define an asymmetric that separates oil price shocks into increases in oil prices and decreases in oil prices.

Lee, Ni and Ratti (1995) have argued that a shock to oil prices are more likely to have an impact in an environment where oil prices have been stable, as opposed to an environment where oil prices are constantly fluctuating. They postulate that during periods where oil prices are highly volatile, little information is contained in the current oil price with regards to future oil prices. The authors use a Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) (1,1) model to define a scaled specification of oil price shock. The model is given by:

$$op_t = \alpha + \sum_{i=0}^{p} \alpha_i op_{t-1} + \cdots \sum_{i=0}^{q} \beta_i Z_{t-1} + \epsilon_t$$

$$\varepsilon_t | I_{t-1} \sim N(0, h_t), h_t = \gamma_0 + \gamma_0 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1}$$

Op_t is the first log difference in real oil price, with ε_t being an error term, and $\{Z_{t-1} ; I \geq 1\}$ denotes an appropriately chosen vector contained in information set I_{t-1}. Notations p and q refer to the optimally selected lags. The scaled oil price (SOP) is then given by (Park and Ratti, 2008):

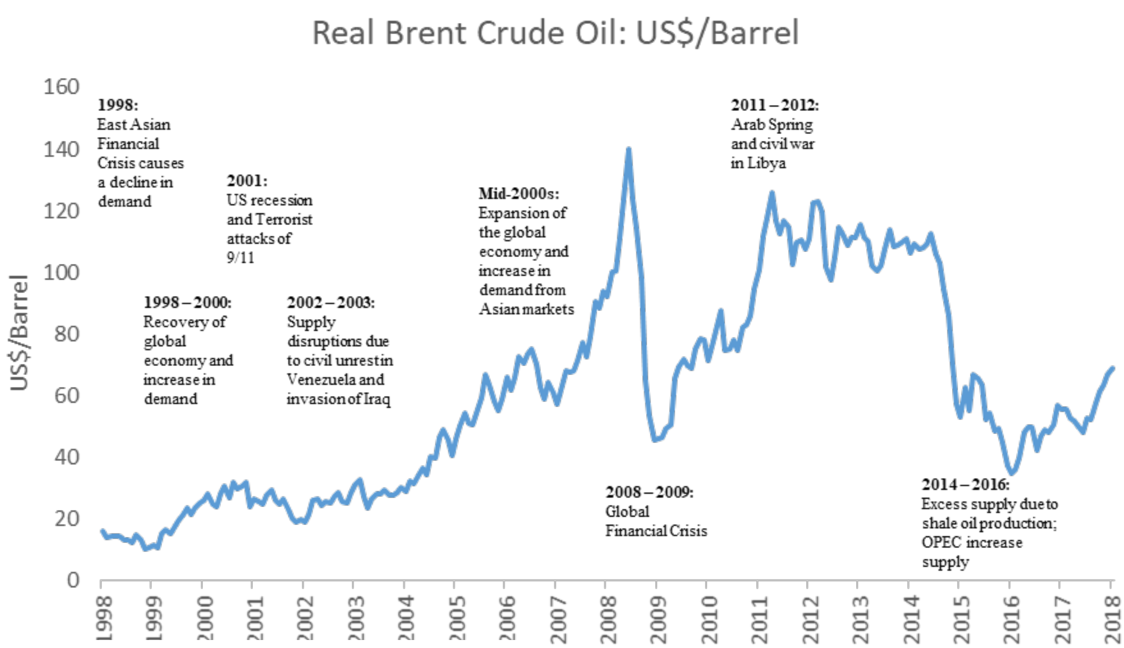
$$SOP_t = \acute{\varepsilon}/\sqrt{\hat{h}_t}$$

The focal point of the second school of thought looks at what the true "shock" movements in price is and separates shocks into demand and supply shocks (Gosh, Varvares and Morley, 2009).

This study will employ Hamilton's (1983) linear specification.

2.1.2. The history of oil prices

Figure 1: Brent crude oil prices between 1998-2018



Source: S&P Capital IQ

Between 1948 and 1970 oil prices ranged between \$2.50 and \$3.00 per barrel. On an inflation adjusted basis, that's around \$17 to \$19 per barrel. The United States (US) was one of the world's most dominant oil producers and even regulated oil prices. In 1960, OPEC was formed by Iran, Iraq, Kuwait, Saudi Arabia and Venezuela who wanted more control over oil prices. Oil price shocks were first observed in 1973 at the time of the Yom Kippur war when OPEC halted exports to the United States in retaliation to their involvement in the war. The analysis of oil prices in this study will focus around the sample period of 1998 -2018.

During the 1990s oil prices hit an all-time low of \$11 a barrel in December of 1998. Two years earlier it was trading at \$25 a barrel. The large decline in oil prices was due to a fall in demand caused by the East Asian Financial crisis of mid-1997. This was followed by recessions in other countries such as Argentina, Brazil and Russia (Baumeister and Kilian, 2016).

Between 1999 and 2000 oil prices began to recover. This was driven by multiple factors such as higher demand for oil because of a recovery in the global economy as well as a reduction in oil production (Baumeister and Kilian, 2016). However, oil prices fell again when the US was gripped by a recession in March of 2001 and the attacks on the Twin Towers in September 2001 (Christensen, 2011).

Between December 2002 and January 2003 there were major supply disruptions because of the civil unrest in Venezuela. This was followed by the invasion of Iraq which lead to the disruption of the production of oil in Iraq between April to July 2003. However, the loss in production from Venezuela and Iraq did not appear to have a major impact on oil prices as it was offset by an increase in production elsewhere (Baumeister and Kilian, 2016).

One of the largest increases in oil prices occurred between 2003 and 2008. Oil prices surged from around $30 a barrel to $140 a barrel. Baumeister and Kilian (2016) contend that the escalation in oil prices was not caused by a disruption in the supply of oil but rather by individually small increases in the demand for oil over this period. This was driven by an expansion in the global economy as well as a large increase in demand from emerging Asian markets.

The global financial crisis of 2008 saw the largest decrease of oil prices in modern history. Oil prices plummeted to $45 a barrel. The decrease in in prices was caused not by the disruptions in the production of oil but rather by a fall in demand for industrial commodities such as crude oil. However, in 2009 prices began to steadily climb as oil-producing countries began to reduce their output. By 2010, as the global economy began to recover, the oil prices started its upward climb. Prices further increased in 2011 in the wake of the Arab Spring uprisings with the civil war in Libya disrupting output and sending prices to a new high in March 2012.

Oil prices stabilized around $100 per barrel in 2013. But, by the end of 2014 oil prices had nearly halved, falling below $50 in the beginning of 2015. The fall in prices were caused by excess supply because of the shale oil production in the US. OPEC increased supply to force out shale oil producers, sending oil prices plummeting to around $34 a barrel in January 2016. Oil prices however stabilised once OPEC agreed to reduce output and have closed at $69 a barrel by the end of January 2018.

From a country stand point, the variability in oil prices will have varying impacts on the BRICS countries. Canuto (2017) discusses the impact of the decline in oil prices between 2014 – 2016.

Canuto (2017) states that a 10% decrease in oil prices is expected to increase GDP growth in oil-importing countries between 0.1% – 0.05%, depending on the share of oil imports in GDP. China is a net oil importer and growth as a result of decreasing oil prices was estimated to be in the range of 0.1% – 0.2% as oil makes up 18% of energy consumption. With an oil import bill of 7.5% of GDP, India, who is a net oil importer had also gained from the oil price evolution as falling prices had assisted to reduce inflation. Similarly, with South Africa also being a net oil importer, they had also benefited from a lower oil price by having a corresponding impact on inflation.

Oil and gas make up more than 70% of Russia's exports and the decline in oil prices contributed to the Russian financial crisis of 2014 -2015 (Canuto, 2017). Brazil faced similar implications, as Petrobas, the Brazilian state owned oil company contributed to approximately 13% of the Brazilian Government revenue (De Hollanda & Nogueira, 2015).

2.1.3. The relationship between movements in oil prices and stock markets

In order to better understand how share market returns are affected by oil prices it is important to theoretically understand the transmission mechanisms by which oil prices can alter the behaviour of stock markets. These mechanisms can be separated into four channels.

2.1.3.1. Stock valuation channel

Through the stock valuation channel, oil prices influence stock markets directly. In order to gain a better understanding into this we need to look at two equations.

Stock returns ($R_{j,t}$) can be defined as the first log-difference:

$$R_{j,t} = \log({}^{P_{j,t}}/_{P_{j,t-1}}) \tag{A}$$

Where the stock price of firm *j* at time *t* is given by $P_{i,t}$

Looking at the equation B, as suggested by economic theory, current stock prices are reflected in the discounted future cash flows of a stock (Huang, Masulis and Stoll, 1996). This is given by:

$$P_{j,t} = \sum_{n}^{N} t + 1 \left(\frac{E(CF_n)}{(1 + E(r))^n} \right), \qquad \text{(B)}$$

Where the discount rate is given by r and CF_n represents the cash flow at time period n and while the expectation operator is denoted by E(.).

Both of the above equations illustrate how stock returns can be impacted by factors that influence the discount rate and/or the expected cash flows. The status on whether a firm is an oil-producer or an oil-user will impact how its future cash flows will be affected by changes in oil prices. Oil is a critical production factor for an oil consuming firm and a rise in oil prices will increase the costs of production. This will consequently reduce profits and as a result, future cash flows will decrease. Conversely, for an oil-producer, an increase in prices of oil will result in greater profit margins which will in turn enhance expected cash flows.

2.1.3.2. Monetary channel

Changes in oil prices affect the expected discount rates of future cash flows (Equation B above). Mohanty and Nandha (2011) posit that the discount rate is partially composed of expected inflation and expected real interest rates. Therefore the second transmission channel by which stock returns are impacted by oil price changes are through inflation and interest rates.

As previously mentioned, an increase in oil prices lead to higher production costs. Consumers are burdened with these costs which lead to an increase in retail prices and therefore an increase in inflation. In response to higher inflationary pressures it is expected that the central bank will increase short-term interest rates. This increase is expected to impact stock markets in two ways. Commercial borrowing rates will increase for any future investments made by the firm due to the increase in short-term interest rates. This raises the cost of borrowing for firms. This in turn will lead to fewer positive net present value (NPV) projects and consequently lower cash flows. Therefore, stock prices decrease either due to an increase in discount rates or lower cash flows.

2.1.3.3. Output channel

Fluctuations in oil prices have an impact on aggregate output. An increase in oil prices is expected to have a production cost as well as income effect. This will affect the aggregate output. The income effect will be looked at in this section since the production cost was discussed in section 2.1.3.1.

With an increase in oil prices, households tend to experience lower discretionary income. This is as a result of changing retail prices (due to an increase in production costs) as well as an increase in the price of fuel and heating oils (Bernake, 2006; Edelstein and Kilian, 2009). This causes consumption to decrease which depresses aggregate output and leads to a decrease in labour demand. Based on equations (A) and (B), such developments lead to stock markets responding negatively. In particular it is found that firms have lower cash flows when there is a decrease in aggregate demand. This, in turn, leads to lower stock prices.

Degiannakis, Filis and Arora (2018) note that these effects do not hold for all economies and are dependent on whether an economy is a net-importer or a net-exporter of oil. The above holds for a net-oil importer. Negative production cost effects will still be experienced by a net oil exporter. The exporter will, however, experience an increase in revenue due to a positive income-effect. Deginnakis *et al.* (2018) further go on to state that this leads to an increase in aggregate demand and therefore a higher output. However, it should be noted that for the change in aggregate demand to be positive, the positive income effect must be greater than the negative production cost effect. If this holds true, there will be a positive response from stock markets to the increase in output since this will increase the expected cash flows of firms operating in net-exporting countries.

2.1.3.4. Fiscal channel

Net oil-exporting countries are the focus of the fiscal channel as they use their revenue from oil to finance social and physical infrastructure (Ayadi 2005;. Farzanegan 2011). An increase in oil prices tends to transfer wealth from a net oil-importer to a net oil-exporter which allows for an increase in government expenditure (Dohner, 1980). Based on the assumption that government expenditure and consumption are considered compliments, then the former will lead to an increase in household consumption. In this case, there can be an expected increase in cash flows of private firms, leading to a growth in their profitability. This will result in an increase in stock prices.

Conversely, the opposite would be observed if government spending and consumption are considered substitutes. This is as a result of the crowding-out effect. Private capital will be driven out of the economy due to the substitution effect and stock markets will respond negatively.

The above four channels either impact a firm's discount rate or its cash flows. In both instances, when examining the channels of transmission, we find that an increase in oil prices depress stock market returns the transmission channels suggest that an increase in oil prices lead to lower stock market returns. However, these effects are only valid for net oil-importing countries. The opposite is valid for net oil-exporting countries as stock prices respond positively to increases in oil prices.

2.2. Empirical evidence

2.2.1. Developed Economies

Jones and Kaul (1996) were amongst the first to test the impact of oil price shocks on the international share markets. The authors used a standard cash-flow dividend valuation model to test whether international share markets are rational or if they overreact to new information. They used quarterly data for four countries (US, Canada, Japan and the United Kingdom) over varying time periods, the longest being for the US (1947-1991). The findings of the authors suggest that the US and Canadian share markets are rational in that the reaction of their share prices to oil shocks significantly affect their current and future cash flows. Conversely, the results for Japan and the United Kingdom were not as strong.

Sadorsky (1999) studied the impact of oil price shocks on share market returns. Monthly data was used over a 50-year period (1947 – 1996) on a US share exchange (S&P 500). He applied an unrestricted VAR model and included monthly oil prices, share returns, short-term interest rate and industrial production. The results were significant and found that oil price shocks negatively affected share returns. Furthermore, Sadorsky also examined the asymmetric impact of oil prices and found that increases in oil prices had a greater impact on share returns than decreases in oil prices would have. He extended his study to Canadian share markets by using a multifactor arbitrage pricing theory approach. He found that Canadian markets are sensitive to interest rate and oil price risk.

The volatility spill-over from oil prices to share markets within an asymmetric BEKK model was investigated by Ågren (2006). Weekly data was used over a 16-year period (1989-2005) on the aggregate share markets of Sweden, the UK, the US, Japan and Norway. Except for Sweden, strong evidence was found of volatility spill-overs for all share markets.

Anoruo and Mustafa (2007) examined the relationship between oil and share market returns in the US. Daily data was used over a 13-year period (1993-2006). The authors applied a cointegration analysis and modified VECM to examine the long run relationship and the dynamics between oil prices and market indices. Their results suggest that oil and share market returns are cointegrated and causality runs from share market to oil market but not vice versa.

Park and Ratti (2008) analyzed the impact of oil price shocks on the share market returns of the US and 13 European countries. Monthly data was used over a 20-year period (1986-2005). The authors looked at linear and non-linear oil price shocks and found that oil prices volatility had a negative impact on share market returns for the US and all 13 European countries.

The effects of oil-market shocks on share markets for of the G-7 (United Kingdom and the US, Canada, Japan, Germany, France and Italy) and Australia was explored by Apergis and Miller (2009). They used monthly data over a 26-year period (1981-2007) and computed three different structural shocks for the oil market that captured oil supply shocks, global aggregate-demand shocks and idiosyncratic demand shocks. The authors employed a VAR model and found that three structural shocks contribute significantly in explaining share market returns in most countries.

Malik and Ewing (2009) inspected the volatility transmission between oil prices and three equity sector returns, being the consumer services, healthcare and technology industries in the US. Weekly data was used over a 15-year period (1992-2008) and the results from the bivariate GARCH models reveal the existence of a negative relationship between sector index returns and oil price volatility.

An analysis of the effect of oil price on real share returns in the G-7 nations and Norway was performed by Christensen (2011). The author applied an unrestricted VAR model to monthly data over a 24-year period (1986-2010). Oil price shocks were differentiated into the three categories of linear, asymmetric and non-linear. The findings of the author suggest that there is no notable evidence that linear oil price shocks impact real stock returns. In respect of asymmetric price shocks, increases in oil price had a greater impact on the net oil exporting countries while the converse is true in Canada and Japan where decreases in oil prices have a more powerful effect. Finally, when looking at non-linear shocks it was found that the stock reruns of all countries were impacted.

Le and Cheng (2011) examined the reaction of share markets to volatility in oil prices in Japan, Malaysia, Korea and Singapore. The authors applied the generalized impulse response and variance decomposition analysis to monthly data over a 25-year period (1986-2011). The authors found varying results across the four countries. The share markets of Japan responded positively while the converse was found in Malaysia where share markets responded negatively to shocks in oil prices. However, the results in South Korea and Singapore were unclear.

The extent of volatility transferal between oil and share markets in the US as well as Europe at a sector-level was considered by El Hedi Arouri, Jouini and Nguyen (2011). They applied a generalized VAR-GARCH modelling approach to weekly data over a 11-year period between 1998 and 2009. The authors found that there was a significant interaction between share markets and oil though the transmission of volatility is much more evident from oil to share than from shares to oil in Europe.

Using the Brent spot oil price, Fayyad and Daly (2011) looked at the relationship between oil prices and share markets in the US, United Kingdom (UK) and Kuwait, Qatar, Oman, United Arab Emirates (UAE) and Bahrain (the Gulf Cooperation Council (GCC) countries). The authors applied a VAR analysis, making use of impulse response and variance decomposition techniques to examine daily data over a 5-year period (2005-2010). Their findings suggest that there is a significant inter-relationship between GCC markets. The authors also found that oil prices do have an impact on GCC, UK and USA share markets but to varying degrees.

Talukdar and Sunyaeva (2011) looked at the relationship between oil prices and share markets of 11 Organisation for Economic Co-operation and Development (OECD) countries over a 25-year period (1986-2010). They separated countries into net oil importers and net oil exporters and applied a VAR analysis. They found that stock markets of net oil importers respond negatively to oil price shocks while net oil exporters respond positively to oil price shocks.

Ramos and Veiga (2014) interrogated 43 international share markets of developed and emerging economies over a 20-year period (1988 – 2009). They looked to examine whether oil price volatility has an impact on international share market returns and whether the impact of changes in oil prices is asymmetric. Using monthly data, the authors conducted a panel analysis and used International Arbitrage Pricing Theory to examine the impact of global factors on the share market. The authors found contrasting results between developed and emerging economies. With regards to developed markets it was found that spikes in oil prices depress share markets whereas decreases in oil prices do not necessarily increase share market returns. Furthermore, volatility in oil prices were found to have a negative impact on share market returns. However, these effects do not apply to emerging markets which are not sensitive to fluctuations in oil prices.

The question of whether oil price shocks have an impact on share market returns was asked by Dhaoui and Khraief (2014). The authors used monthly data over a 22-year period (January 1991 - September 2013) for eight developed countries. An EGARCH-M model was applied to specify the macroeconomic variables effect on both returns and volatility of share market returns. Findings by Dhaoui and Khraief suggest that share market returns and oil prices are negatively correlated while changes in oil prices increase the volatility of returns. The authors note that the results are intuitive since an increase in oil prices lead to an economic crisis as it creates significant cost-push inflation and unemployment. Consequently, an increase in oil prices act as an inflation tax which increases risk as well as uncertainty. This further affects share prices and reduces wealth.

2.2.2. Emerging Economies

Recent studies have included emerging markets in their analysis between the relationship between oil prices and share returns. Maghyereh (2004) investigated the relationships between oil and share market prices in twenty-two emerging markets using daily data over a 6-year period (1998 – 2004). He carried out a VAR analysis and found that unlike developed economies, oil price shocks have no impact on share market returns in emerging economies.

Basher and Sadorsky (2006) considered the impact of oil price changes on share market returns for twenty-one emerging markets using daily returns over a 12-year period (1992-2005). The authors applied a multi-factor model based on the international capital asset pricing model and found strong evidence that oil price volatility plays a significant role in pricing emerging market share returns.

Khan (2010) studied the relationship between crude oil prices and share market returns as well as volatility-spillover for the BRICS countries. Using cointegration and VECM he analysed daily data over a 7-year period (2003-2010). He found that oil prices and share market returns are cointegrated in all of the BRICS countries and there is a significant bidirectional long-run relationship between oil prices and share market returns. Khan could not find a short-run relationship between oil prices and share market returns in any of the BRIC countries except Russia. Furthermore, with regards to volatility-spillover, Khan concluded that the relationship is significant and bidirectional in all the BRIC countries.

The interaction between oil prices and share returns for three BRICS countries (Russia, India and China) was examined by Fang (2010). Fang used monthly data over an 8-year period (2001-2008) making use of a SVAR model. The author found that for Russia, demand shocks had a notable positive influence on Russian share returns. However, for China, the global supply and demand shocks have no remarkable bearing on Chinese share returns.

El Hedi Arouri, lahiani and Nguyen (2011) studied the correlation between returns and the transmission of volatility in oil and share markets in the GCC Countries. The authors used daily data over a 6-year period (2005-2010). The VAR-GARCH model allowed the authors to analyze the spillover effects in conditional volatilities as well as returns. The authors' results suggest that in most cases there are spillovers between oil and share markets.

Ono (2011) enquired into the impact of oil prices on real share returns for the BRICS countries. The author applied a multivariate VAR model using monthly data over a 12-year period (1999-2010). The author found that real share returns responded positively to some of the oil price indicators used, with statistical significance for China, India and Russia. However, no statistically remarkable response was observed in Brazil. Furthermore, the author looked at the asymmetric effects of oil price shocks and found that statistically significant asymmetric effects were observed in India only.

The relationship between oil price volatility and share price returns in Tunisia, was examined by Hamma, Jarboui and Ghorbel (2013) using sector data. Using a bivariate GARCH model, they analysed weekly data a 6-year period between 2006-2012. The authors found evidence of significant shock and volatility spillovers across oil and Tunisian sector share markets. The intensity of shocks did, however, vary across sectors.

El Hedi and Julien (2013) examined the short-run relationship between share markets in the GCC region and oil prices. The authors used weekly OPEC oil prices over a 3-year period (2005-2008). The authors tested both the linear and non-linear relationship between shares and oil prices by performing a regression analysis. El Hedi and Julien's findings suggest that there is a significant relationship between the two variables in Qatar, Oman and UAE and therefore, share prices react positively to oil price increases. However, for Bahrain, Kuwait and Saudi Arabia they found that changes in oil prices have no impact on share market returns.

The impact of oil price volatility on the Malaysian share market (Kuala Lumpur Composite Index (KLCI)) was probed by Janor, Housseinidoust and Rahim (2013). Monthly data was used over a

25-year period (1986-2011) and the authors used GARCH and EGARCH models to test for volatility and asymmetric effects. The authors found that oil price shocks intensified the volatility of the KLCI. The authors also found evidence of the existence of asymmetric effects with negative shocks resulting in increased volatility when compared to positive shocks of the same magnitude.

Fatima and Bashir (2014) researched the effects of volatility in international oil prices on share markets of emerging economies (Pakistan and China). The authors also tested whether oil price shocks have an asymmetric impact on share markets. Monthly data was used over a 15-year period (1999 – 2013). The authors applied a cointegration analysis along with VECM. Furthermore, the authors called on an OLS regression to determine the immediate effects. The results show that fluctuations in international oil prices have very little impact on share markets. The first reason for this is due to markets not being developed. The lack of knowledge of investors renders the market inefficient and this restricts the market from capturing the fluctuation in oil prices. The other major reason is that both countries are oil importing. Changes in oil price have a negative impact on oil importing countries. The intensity of this relationship is, however, so low that it is not captured in some studies.

Guliman (2015) considered the relationship between the inflation-adjusted Philippine Share Exchange prices and real oil prices in Philippine Peso. He used monthly data over an 18-year period (1996-2014) and applied a VAR model. Guliman also adopted a Granger Causality test to determine whether oil prices and the PSEI share prices Granger-cause each other. The results of his study indicate that there is no significant relationship between oil prices and the PSEI share prices and they do not Granger-cause each other.

The effect of oil price uncertainty on share returns in South Africa was surveyed by Aye (2015). The author used weekly data over a 19-year period (1995-2014) and applied a bivariate GARCH-in-mean model. Analysis was done using oil prices in both US Dollars (USD) as well as in Rands. The results when the oil prices were expressed in USD conclude that uncertainty around oil prices had a negative but marginally significant effect on share returns. When Aye looked at the oil prices in Rands, the author found that the effect is still negative at a 5% level.

Bouoiyour and Selmi (2016) surveyed the relationship between share returns and real oil prices over a 13-year period (1998-2015) by using a frequency domain causality test. The authors found that fluctuating components of oil prices exert a significant influence on share prices for all BRICS countries.

The studies discussed above show a variance between net oil-importing countries and net-exporting countries. However, Filis, Degiannakis and Floros. (2011) investigated the time-varying correlation between share market prices and oil prices for both net oil-importers as well as net oil-exporters. Using monthly data, the authors looked at three importing countries (US, Germany and Netherlands) as well as three exporting countries (Canada, Mexico and Brazil) over a 22-year period (1987 – 2009). The authors employed a DCC-GARCH-GJR approach and found that time-varying correlation of oil and share prices do not differ for net oil-exporting and net oil-importing countries. However, the correlation increased positively in response to demand side shocks, while supply side shocks did not impact the relationship between the two markets.

Aydoğan, Tunç, and Yelkenci (2017) also inspected the impact of oil price volatility on share market returns for ten net oil-importing and ten net oil-exporting countries. The authors used daily data over an 11-year period. Aydoğan, Tunç, and Yelkenci applied a VAR analysis and found that, depending on whether the country is a net oil-importer or net oil-exporter, the correlation between the volatilities of share market and oil price returns varies.

3. SAMPLING AND DATA COLLECTION

This study aims to analyse the effect of oil price shocks on the share market returns of the BRICS countries. While BRICS was founded in 2006, with South Africa being included in 2010, these countries were chosen as they are all classed as emerging markets and there is a limited amount of research that has been conducted on the BRICS countries. BRICS is also emerging as the new global transactional hub within the developed and emerging economic system. The BRICS countries as a collective have also stood out in terms of its growing contribution to the world economy as well as the rising importance of the economic relations between these countries. It also allows us to determine the impact of oil price shocks on share markets of countries that are both net-oil importers and net oil-exporters.

Monthly data for the period February 1998 to December 2017 will be used in this study. The use of monthly data is consistent with previous studies such as, among others, Sadorsky (1999), Apergis and Miller (2009) and Fang (2010). The reason for choosing this time period is that it is a post-liberalisation period for all the BRICS countries. This period also captures both large increases as well as decreases in oil prices and includes a period of extreme economic volatility. Furthermore, the time period is constrained by the availability of data, for example, the Russian MOEX was only launched in September 1997.

Consonant with previous literature such as Sadorsky (1999) and Park and Ratti (2008) this paper will use a VAR model. The model will contain three variables: real stock return, real industry production and real oil prices. Industry production will be used as a measure of economic activity and will be garnered from Bloomberg. Oil prices refer to Brent crude oil and will be sought from S&P Capital IQ. CPI data will also be taken from S&P Capital IQ. Nominal Share price data will be taken from Bloomberg and the effect of inflation will be removed from each country. Real share returns will be calculated according to equation 1 below.

The following share indices will be used:

- Brazil, Ibovespa (IBOV) – The IBOVESPA Index is listed on the Bolsa de Valores, Mercadorias & Futuros de São Paulo Share Exchange (BM&FBOVESPA). The index started in January 1968 and is denominated in Brazilian Reals. It is made up of 50 of the largest companies on the exchange based on trading volume and market cap. The index accounts for approximately 70% of the market cap of companies listed on the exchange (S&P Capital IQ, 2018).

- Russia, MOEX (MCX) – The MOEX is to be found on the Moscow Share Exchange. Prior to December 2017, the Russian MOEX index was known as the MICEX index. The index was launched in September 1997 and is characterised in Russian Rubbles. It is a capitalisation-weighted composite index based on the 50 most liquid shares on the Russian share exchange ("Moscow Exchange - Indices," n.d.).

- India, BSE Sensex (BSESN) – The BSE Sensex is listed on the Bombay Share Exchange. It was launched in 1986 and is determined in Indian Rupees. It is made up of 30 constituents that are selected based on market cap, liquidity, industry representation and trading frequency. ("India SENSEX Share Market Index," 2018)

- China, Shanghai Composite Index (SHSEC) – The Shanghai Composite Index is listed on the Shanghai Share Exchange. It was launched in 1991 and is denominated in Chinese Renminbi. The index is made up of all shares listed on the Shanghai Share Exchange (S&P Capital IQ, 2017).

- South Africa, JSE All Share Index (JALSH) – The JSE All Share Index is listed on the Johannesburg Share Exchange. It is denominated in South African Rands. The All Share Index is made up of approximately 300 of the largest listed companies and makes up close to 100% of the market cap and liquidity of the market ("Introduction to the JSE All Share Index," 2017).

The returns on the indexes are then computed by equation (1):

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) - \ln\left(\frac{CPI_t}{CPI_{t-1}}\right) \qquad (1)$$

where, R_t represents return at time *t*, and P_t and P_{t-1} represent the value at the current period and previous period respectively and CPI_t and CPI_{t-1} represent the consumer price index at the current period and previous period respectively, this gives us share market returns in real terms.

Oil prices will be obtained from S&P Capital IQ. The three main benchmarks for international oil prices are Brent, WTI and OPEC Basket. This study will make use of Brent spot prices to represent the international crude market. As previously discussed, Brent remains the major benchmark for other crude oils in Europe and Africa. It is also the most commonly used standard for crude oil futures contracts (Mayer, 2017). Furthermore, as reported by Chang and Wong (2003), oil prices fluctuate in the same direction and therefore the choice of an international oil benchmark will not have a significant impact on the study. It is vital to convert international oil prices into national oil prices because factors such as exchange rate fluctuations, price-controls and varying tax rates influence oil prices and must be taken into consideration. The world oil prices will be obtained directly from S&P Capital IQ, which provides Brent oil prices in the currencies of the respective countries. The national real oil price (ROP) can then be calculated by using world oil prices and deflating it by the CPI of each of the countries by using the following equation:

$$ROP = World\ Oil\ Price * (1 - \ln\left(\frac{CPI_t}{CPI_{t-1}}\right)) \quad (2)$$

Consonant with previous studies such as Sadorsky (1999), oil price shocks will be measured by Hamilton's (1983) linear specification given by:

$$\Delta ROP_t = \ln(ROP_t) - \ln(ROP_{t-1}) \quad (3)$$

Industrial production will also be measured using the linear specification and the notations used in the study are:

BRR: Real share returns Brazil
RRR: Real share returns Russia
IRR: Real share returns India
CRR: Real share returns China
SRR: Real share returns South Africa
BRIP: Real industry production Brazil
RRIP: Real industry production Russia
IRIP: Real industry production India
CRIP: Real industry production China
SRIP: Real industry production South Africa
BROP: Real oil prices Brazil
RROP: Real oil prices Russia
IROP: Real oil prices India

CROP: Real oil prices China

SROP: Real oil prices South Africa

4. ECONOMETRIC METHODOLOGY

The purpose of this paper is to determine whether oil prices impact share market returns. The research method that is employed in this study will be conducted in a time-series setting. A VAR framework will be adopted to examine the relationship between oil prices and share market returns.

4.1. Time series

Through time series analysis, we are able to gain a better understanding of the underlying forces that lead to a specific trend in our data series. It also assists in monitoring and forecasting data points by finding the appropriate models to fit the data. For this reason, the use of time series data is common in empirical financial and economic studies (Adhikari, 2013).

This study will make use of a multivariate time series analysis given that we are looking at more than one variable that is real oil prices, real share market returns and real industry production.

4.1.1. Stationarity in time series

Stationarity is a vital component in time series analysis. If a series is not stationary, then we are unable to forecast the data, rendering the series futile (Granger and Newbold, 1974). A series is considered non-stationary if it contains a deterministic or stochastic trend. If the time series y_t is non-stationary it may result in spurious regressions (Granger and Newbold, 1974). A Spurious regression is a regression of an integrated series on another unrelated integrated series which tends to indicate an apparently significant relationship. Therefore, the t-statistics will be unreliable and may spuriously indicate a significant relationship even when this is not the case. Spurious regressions can be identified due to their very high correlations, very low estimated coefficient standard error and Durbin Watson statistic close to 0 (Granger and Newbold, 1974).

4.1.2. Unit root tests

We use unit root tests to determine stationarity in a time series. There are many tests that exist, in part, because no single test stands out as having more power over the others. The majority of data series in finance and economics contain a stochastic trend. By construction, trend models are highly likely to exhibit serial correlation. In the presence of serial correlation, the preferred test to use is the Augmented Dickey Fuller (ADF) test. According to Dicky and Fuller (1979) by adding lags (by augmenting) one can control for serial correlation. This study will make use of the ADF to test the stationarity of variables in the data series, it will test the null hypothesis that a time series y_t is stationary in the first difference I(1) against the alternative that it is a trend stationary process (I(0)). The ADF statistic used in the ADF test is a negative number, and the rejection of the hypothesis that there is a unit root is stronger the more negative the number is (Deviant, 2017; Moffatt, 2003; Zivot and Wang, 2013).

Therefore, the null hypothesis for each of the variables is that the series contains a unit root, against the alternative that the series is stationary:
H_0: $\alpha = 0$;
$H_{A:}$ $\alpha < 0$

The ADF is based on the linear regression that assumes a normal distribution. Transforming the data using a log-transformation converts an exponential trend possibly present in the data into a linear trend. It is, therefore, common to take the logs of the data before applying the ADF test (Wang, 2006). This study will therefore test for stationarity of real stock returns, real oil prices, real industrial production at their log levels.

One pertinent issue with regards to implementing the ADF test is the specification of the truncation lag values of *p*. The remaining serial correlation in the errors will bias the test towards rejecting the null hypothesis if *p* is too small. Conversely, the power of the test will suffer if *p* is too large (Wang, 2006). The lag length selection for the ADF test will automatic, based on the Schwartz criterion.

4.1.3. Granger Causality

Wiener (1956) posited that if the prediction of one-time series is improved by including the knowledge of a second time series, then the latter is said to have a causal influence on the first. This idea was later formalized by Granger (1969) in the context of linear regression models (Guo, Ladroue, and Feng, 2010).

In the Granger-sense, x is a cause of y if it is helpful in forecasting y. In this context "helpful" means that x is able to increase the accuracy of the prediction of y with respect to a forecast, considering only past values of y (Foresti, 2007).

Granger causality measures whether one event occurs before another event and helps predict it. However, it does not by itself indicate causality in the more general use of the term (Sørensen, 2005).

Therefore, when given two time-series data sets (x and y) Granger-causality attempts to determine how much of the current y can be explained by past values of y and subsequently to determine whether adding lagged values of x can improve the explanation. Therefore if there are two models that predict y,τ and π, where τ gives us only the past values of y, and π gives us both the past values of y and x. The models are represented below where p is the number of lags in the time series:

$$Let\ \tau = \ y_t \ = \mu + A_t y_{t-1} + \cdots A_p y_{t-p} + \epsilon_t \qquad (4)$$

$$\text{And } \pi = \ y_t \ = \mu + A_t y_{t-1} + \cdots A_p y_{t-p} + \alpha_1 x_{t-1} + \cdots + \alpha_p x_{t-p} + \epsilon_t \qquad (5)$$

It should be noted that when choosing a lag length for the test, it is recommended that a greater number of lags be selected rather than fewer lags. This is due to the fact that theory is embedded in terms of relevance of all past information. The lag length should be chosen based on beliefs about the longest time over which one of the variables could predict the others.

Once a lag length is chosen, we can then compare the residual sums of squared errors and use a test to ascertain whether the nested model (τ) is sufficient in explaining the future values of y or if the full model (π) is superior. The following null and alternate hypotheses can then be tested based on statistics from the F-test, t-test or Wald test:

H_0: $\alpha_i = 0$ for each i of the element [1,p]
H_1: $\alpha_i \neq 0$ for at least 1 i of the element [1,p]

Based on the above hypothesis we are trying to deduce whether we can say that statistically, x provides more information about future values of y than past values of y alone. Based on this postulation it is clear that we are not trying to prove actual causation. As stated by Diebold (2001) the Granger-causality test is only a test for predictive causality and looks to show that the two values are related by some phenomenon (Sørensen, 2005).

4.1.4. Vector autoregression (VAR)

4.1.4.1. Framework of the VAR model

The unrestricted VAR used in this study was posited by Sims (1980) and is regarded as one of the most successful, flexible, and easy to use models for multivariate time series analysis. The reason for choosing a VAR model over univariate time series models and elaborate theory-based simultaneous equation models, is that VAR often provides superior forecasts to the other models. The forecasts from VAR models provide flexibility as they can be made conditional on the potential future paths of specified variables in the model. Historically, the application of VAR models has facilitated the description of the dynamic behavior of economic and financial time series and for forecasting espoused by Hamilton (1994), Tsay (2005) and Campbell, Lo and MacKinlay (2012).

An unrestricted VAR model treats all variables as jointly endogenous, therefore each variable is expressed as a linear combination of its own lagged values and the lagged values of all the other variables in the system (Baltagi, 2003).

A VAR(p) model, where p represents the number of lags where we are given a set of J time series variables, can be represented by:

$$y_t = \mu + A_t y_{t-1} + \cdots + A_p y_{t=p} + \epsilon_t \tag{6}$$

Where $y_t = (y_{1t} \dots y_{Jt})$ can be described as a column vector of observations of the past values of all the variables in the model, A_i are the J x J matrices of the coefficients, and $\epsilon_t = (\epsilon_{1t}, \dots, \epsilon_{jt})$ is a column vector of unobservable error terms (Baltagi, 2003).

4.1.4.2. Lag length selection

The first step in specifying a VAR model is selecting the appropriate lag length. It is critical to select the appropriate lag length, as demonstrated by Braun and Mittnik (1993) who postulate that when VAR models are estimated, and their lag lengths are different from their true lag lengths, they will be inconsistent. They also found inconsistencies in the impulse response functions as well as variance decompositions derived from the estimations. Lütkepohl (1993) found that choosing a higher order lag length than the true lag length will lead to an increase in the mean-square forecast errors of the VAR. On the other hand, he found that choosing a lower order lag length generates autocorrelated errors (Ozcicek and Douglas McMillin, 1999).

The first step is to select a maximum lag length "m" for VAR model. Since the data is monthly, the maximum lag length will be m = 12. The model will be run in levels 12 times, using lag orders 1,2,3,4 … 12. The information criteria will then be used, as suggested by Verbeek (2014). The Akaike information criterion (AIC) and Bayesian information criteria (BIC) will be estimated for the VAR model for each lag length. The AIC was chosen on the basis of research by Kilian (2011) that it compares more favorably than Schwarz Information Criterion and HannanÐQuinn Criterion. The lag length is selected by choosing the appropriate lag length that minimizes the AIC for the VAR model.

4.1.4.3. Impulse response analysis

The parameters contained in a VAR model often make it difficult to interpret relationship between the variables contained in the model. An impulse response function has been proposed as a tool to examine the interactions between these variables (Lütkepohl, 2010).

Simply put, an impulse response refers to the reaction of any system in response to some external change (Lu and Xin, 2010).

We can write the model as a vector moving average (VMA) if y_t is I(0):

$$y_t = \emptyset_o \varepsilon_t + \emptyset_1 \varepsilon_{t-1} + \emptyset_2 \varepsilon_{t-1} + \ldots, \tag{7}$$

Where $\emptyset_o = I_J$ and $\emptyset_s$ is given by:

$$\emptyset_s = \sum_{K=0}^{s} \emptyset_{s-j} A_j,\ \ s = 1,2\ldots \tag{8}$$

The (i,k)'th elements of the matrices $\emptyset_s$ reveal the anticipated response of $y_{t,t+s}$ to a unit change in y_{kt} assuming that all the past values of y_t are held constant. A one unit innovation ε_{it} will have an impact on the y_{it} given $\{y_{t-1}, y_{t-2}, \ldots\}$. The impulse responses of the components of y_t with respect to the ε_t innovations is represented by the elements of $\emptyset_s$.

One major issue with impulse response functions is that they are interpreted on the assumption that all other shocks are held constant. This is unrealistic. One solution to this problem as proposed by Baltagi (2003) is to transform the data into orthogonal innovations. This can be done by employing the Cholesky decomposition. The orthogonal shocks can then be described by $\mu_t = P^{-1}\varepsilon_t$. From the equation above the stationary case is given by:

$$y_t = \varphi_0 \mu_t + \varphi_1 \mu_{t-1} + \cdots, \tag{9}$$

Where $\varphi_i = \emptyset_i P(i = 0,1,2, \ldots)$, and $\varphi_i = P$ is a power triangular. Therefore a shock in the first variables will have an instantaneous impact on the other variables, while a shock in the second variables will not have an instantaneous impact on y_{1t} but rather to the remaining variables (Balatagi, 2003).

4.1.4.4. Variance decomposition

The variance decomposition is another tool which assists us in interpreting the VAR model. It assesses the importance of different shocks by determining the proportion of variance that each structural shock contributes to the total variance of each variable (Bjørnland, 2006).

The forecast error variance decomposition can be calculated by starting with a VAR equation. T is given as the forecast origin and the h-step ahead forecast is given by:

$$y_{T+h|T} = A_1 y_{T+h-1|T} + \cdots A_p y_{T+h-p|T} \tag{10}$$

Assuming h > 1. The corresponding forecast errors is:

$$y_{T+h} - y_{T+h|T} = \varepsilon_{T+h} + \emptyset_1 \varepsilon_{T+h-1} + \cdots + \emptyset_{h-1} \varepsilon_{T+1} \tag{11}$$

In order to determine the orthogonal innovations$\mu_t = (\mu_{1t}, \dots, \mu_{Jt}) = P^{-1}\varepsilon_t$, where P is a lower triangular matrix giving $PP = \Sigma_\varepsilon$ the variance decomposition is utilised

$$y_{T+h} - y_{T+h|T} = \varphi_0 \mu_{T+h} + \varphi_1 \mu_{T+h-1} \dots + \emptyset_{h-1} \mu_{T+1} \tag{12}$$

The $(i,k)th$ element of φ_n is then denoted by $\varphi_{ik,n}$,. and is founded on the supposition that the μ_{jt} are contemporaneous and uncorrelated. this further leads to the forecast error variance:

$$\sigma_j^2(h) = \Sigma(\varphi_{j1,n}^2 + \cdots + \varphi_{jJ,n}^2) = \sum_{k=1}^{j} (\varphi_{jk,0}^2 + \cdots + \varphi_{jk,h-1}^2) \tag{13}$$

The term $(\varphi_{jk,0}^2 + \cdots + \varphi_{jk,h-1}^2)$ gives the contribution of the variable k to the h-step forecast variance of variable j. and μ_{it} can be interpreted as shocks in variable i. We can then divide the above equation by $\sigma_j^2(h)$

$$w_{jk}(h) = \varphi_{jk,o}^2 + \cdots + \varphi_{jk,h-1}^2 / \sigma_j^2(h) \tag{14}$$

The contribution of variable j to the h-step forecast error variance of variable k is given in a percentage form. It is important to note that the variance decomposition is impacted by the way the residuals are ordered (Baltagi, 2003).

5. Empirical Analysis

The following section will look at the descriptive statistics as well as conduct an investigation into the time series data by employing the methodology discussed in the previous section. The results obtained will then be discussed in an attempt to explain the reasons behind the results produced

5.1. Descriptive statistics

The descriptive statistics results of all three sets of variables for each of the countries are given in table 1.

When looking at the Real Industrial Production, Brazil has the highest mean value of 0.008701 while South Africa has the lowest value of -0.302620. The highest standard deviation can be found in China. When looking at skewness, a distribution is considered highly skewed if is greater than 1 or less than -1, moderately skewed if its skewness is between -1 and -0.5 or between 0.5 and 1 and approximately symmetric if its skewness is between -0.5 and 0.5. The distribution for China and South Africa are highly skewed since they are both less than -1, while India is moderately skewed and Brazil and Russia are considered approximately symmetric. Kurtosis measures the relative peakedness as well as the outliers present in the distribution. When measuring kurtosis, any value greater than three tells us that we have a leptokurtic distribution while any value less than three tells us that we have a platykurtic distribution. Since all Kurtosis values are greater than three, the distribution is leptokurtic. The Jarque-Bera rejects the null hypothesis that the data is normally distributed at the 1% level of significance for all five countries.

When looking at the Real Share Returns Russia has the highest mean returns with a value of 0.020577 while India has the lowest return value of -1.679123. The highest standard deviation can be found in China. The distribution for Russia and South Africa are highly skewed while India is moderately skewed and Brazil and China are approximately symmetric. The distribution for all five countries are leptokurtic The Jarque-Bera rejects the null hypothesis that the data is normally distributed for all countries at the 1% level of significance, apart from Brazil when we fail to reject the null hypothesis at all levels of significance.

When looking at Real Oil Prices Brazil has the highest mean value of 0.011372 while China has the lowest value of -1.424785. The highest standard deviation can be found in China. The distribution for India and South Africa is moderately skewed while the distribution for Brazil, Russia and China are approximately symmetric. The distribution for all five countries are leptokurtic. The Jarque-Bera rejects the null hypothesis that the data is normally distributed for all five countries at the 1% level of significance.

The correlation matrix is presented in Table 2. Negative correlations can be found between Real Oil Prices and Real Share Returns for all five countries. It would be expected that oil prices and share returns are negatively correlated for India, China and South Africa since they are all net oil importers, while the opposite would be expected for Brazil and Russia who are both oil exporters. However Real Share Returns for both Russia and Brazil have negative correlations with Real Oil Prices. Industrial production which is a proxy for economic activity is expected to be positively correlated with the returns for all five countries.

Table 1: Descriptive statistics

	BRR	RRR	IRR	CRR	SRR	BRIP	RRIP	IRIP	CRIP	SRIP	BROP	RROP	IROP	CROP	SROP
Mean	0.011763	0.020577	0.010764	-0.007158	0.016344	0.008701	0.001048	0.004834	0.001066	0.003714	0.011372	0.010861	0.010945	0.010543	0.009826
Median	0.004036	0.021641	0.023542	0.004466	0.006435	0.000000	0.003388	0.004708	0.020921	0.010638	0.014785	0.002692	0.018782	0.010276	0.017560
Maximum	0.351095	0.557889	0.774693	1.725655	2.075779	0.186792	0.125622	0.100252	0.160037	0.130508	0.662231	0.573757	0.575246	1.688634	0.623798
Minimum	-0.401611	-1.448972	-1.679123	-1.591883	-0.553600	-0.134550	-0.119242	-0.054657	-0.275572	-0.302620	-0.529100	-0.487453	-0.852686	-1.424785	-1.049475
Std. Dev.	0.122177	0.179608	0.217990	0.347370	0.205169	0.062546	0.022874	0.019189	0.089213	0.066892	0.138472	0.123898	0.232171	0.411665	0.194896
Skewness	-0.049546	-3.149539	-1.605598	-0.409608	4.428658	0.401930	-0.384979	0.899470	-1.237101	-1.611550	-0.090031	0.071395	-0.367620	-0.064545	-0.570542
Kurtosis	3.571695	27.61964	18.00329	9.427230	45.94270	3.774772	10.59098	7.153571	4.416455	7.752704	5.713897	6.675472	3.805953	5.074154	7.300812
Jarque-Bera	3.352512	6431.141	2344.296	418.0548	19145.17	12.41268	579.7321	204.0297	80.94157	328.3917	73.66834	134.7311	11.85181	43.00786	197.1656
Probability	0.187073	0.000000	0.000000	0.000000	0.000000	0.002017	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.002669	0.000000	0.000000
Obs	239	239	239	239	239	239	239	239	239	239	239	239	239	239	239

Table 2: Correlation matrix

Probability	BRR	RRR	IRR	CRR	SRR	BRIP	RRIP	IRIP	CRIP	SRIP	BROP	RROP	IROP	CROP	SROP
BRR	1.000000														
RRR	0.330590	1.000000													
IRR	0.094788	0.021862	1.000000												
CRR	-0.013315	0.109917	-0.131746	1.000000											
SRR	0.233455	0.142807	0.209469	-0.040577	1.000000										
BRIP	-0.034348	0.037385	-0.030383	0.048223	-0.013303	1.000000									
RRIP	0.098439	0.025920	0.076016	-0.126530	0.079701	0.081163	1.000000								
IRIP	0.077687	0.065926	0.077072	0.001636	0.012553	0.016430	0.170984	1.000000							
CRIP	-0.013789	-0.005810	-0.024437	0.023297	0.027478	0.141518	0.235545	0.108941	1.000000						
SRIP	0.037530	0.029273	0.011834	-0.008044	0.017975	-0.269791	-0.131602	-0.015674	0.049684	1.000000					
BROP	-0.208671	0.099327	0.026485	0.054849	0.117768	-0.002671	-0.051996	-0.086012	-0.107001	0.003408	1.000000				
RROP	-0.057839	-0.026120	0.108514	-0.004017	0.081878	0.016514	-0.007635	-0.108260	-0.109698	0.008071	0.597618	1.000000			
IROP	-0.028950	0.105123	-0.396499	0.102850	-0.017077	-0.047732	0.054094	-0.105781	-0.043270	0.045509	0.428346	0.351262	1.000000		
CROP	0.153888	0.030637	0.095768	-0.526198	0.041008	-0.148916	-0.078997	-0.015324	-0.073642	0.016075	0.096342	0.105262	0.006250	1.000000	
SROP	-0.079596	0.048806	-0.086275	0.127112	-0.417966	0.012495	-0.157472	-0.104299	-0.059859	0.011124	0.330231	0.378669	0.271811	0.025972	1.000000

This is the case for four of the BRICS countries with Russia being the exception.

5.2. Time series analysis

5.2.1. Unit root tests

This study will make use of the ADF to test the stationarity of variables in the data series, it will test the null hypothesis has a time series y_t is stationary in the first difference I (1) against the alternative that it is a trend stationary process I (0). In order to choose the optimal lag length, the Schwartz information criterion will be used. E-views software will be employed to conduct the ADF test.

$$H_0: Series\ has\ a\ Unit\ Root \leq 0.05$$
$$H_1: Series\ has\ not\ a\ Unit\ Root > 0.05$$

The null and alternative hypothesis are given above and the ADF result can be seen from table 3 and table 4.

Table 3 summarizes the results from the ADF test with an intercept as well as with an intercept and a trend for Real Share Returns. The MacKinnon (1996) one-sided p-values are also included. All p-values are less than 0.5 and we therefore reject the null hypothesis of a unit root in favour of the alternative. Real Share Returns for all five BRICS countries are stationary according to the ADF.

Table 4 summarizes the results from the ADF test with an intercept as well as with an intercept and a trend for Real Oil Prices. All p-values are less than 0.5 and we therefore reject the null hypothesis of a unit root in favour of the alternative. Real Oil Prices for all five BRICS countries are stationary according to the ADF.

The results for Real Industrial Production are included in the appendices. It is also found that Real Industrial Production for all five BRICS countries are stationary according to the ADF.

Table 3: ADF Tests – Levels, Unit Root Tests on Real Monthly Data: BRR, RRR, IRR, CRR SRR										
Null Hypothesis: Variable has a unit root										
	Without Trend					**With Trend**				
Variable:	**BRR**	**RRR**	**IRR**	**CRR**	**SRR**	**BRR**	**RRR**	**IRR**	**CRR**	**SRR**
ADF test statistics:	-11.39038	-10.11095	-12.24358	-15.92845	-5.051058	-11.40379	-10.09283	-12.22183	-15.94416	-5.042826
Test critical values:										
1% level	-3.457747	-3.457747	-3.457747	-3.457747	-3.457747	-3.997083	-3.997083	-3.997083	-3.997083	-3.997083
5% level	-2.873492	-2.873492	-2.873492	-2.873492	-2.873492	-3.428819	-3.428819	-3.428819	-3.428819	-3.428819
10% level	-2.573215	-2.573215	-2.573215	-2.573215	-2.573215	-3.137851	-3.137851	-3.137851	-3.137851	-3.137851
p-values	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0002*** **

Reported are the probability values associated with the null hypothesis of the absence of a unit root in Augmented Dickey-Fuller tests.
Monthly real data over the period: February 1998 – December 2017
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

Table 4: ADF Tests - Levels on Real Monthly Data: BROP, RROP, IROP, CROP SROP										
Null Hypothesis: Variable has a unit root										
	Without Trend					**With Trend**				
Variable:	**BROP**	**RROP**	**IROP**	**CROP**	**SROP**	**BROP**	**RROP**	**IROP**	**CROP**	**SROP**
ADF test statistics:	-11.81281	-17.29250	-15.90339	-16.90721	-14.83583	-10.45961	-17.30658	-15.91927	-16.96347	-7.588934
Test critical values:										
1% level	-3.457747	-3.457747	-3.457747	-3.457747	-3.457747	-3.997083	-3.997083	-3.997083	-3.997083	-3.997083
5% level	-2.873492	-2.873492	-2.873492	-2.873492	-2.873492	-3.428819	-3.428819	-3.428819	-3.428819	-3.428819
10% level	-2.573215	-2.573215	-2.573215	-2.573215	-2.573215	-3.137851	-3.137851	-3.137851	-3.137851	-3.137851
p-values	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **

Reported are the probability values associated with the null hypothesis of the absence of a unit root in Augmented Dickey-Fuller tests.
Monthly real data over the period: February 1998 – December 2017
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

In summary, the ADF test revealed that all series in the study are I(0) processes and therefore all variables are stationary.

5.2.2. Granger Causality

Oil prices have been shown to impact share market returns, while industrial production is used as a proxy of changes in economic activity and is therefore expected to impact share market returns.

Several hypotheses about the relationship between share market returns and oil prices, as well as share market returns and industrial production are formulated:

1. Unidirectional Granger-causality from ROP to RSR. In this case, real oil prices increase the prediction of stock prices, but not vice versa
2. Unidirectional Granger-causality from RIP to RSR. In this case, real industrial production increases the prediction of stock prices, but not vice versa

Granger-causality tests are conducted on the following regressions, using 1 to 6 lags, l. Where RSR are the real stock returns for each country, ROP are the real oil prices for each country and RIP are the real industrial production for each country.

$$RSR \ = \mu + A_t RSR_{t-1} + \cdots A_p RSR_{t-p} + \alpha_1 ROP_{t-1} + \cdots + \alpha_p ROP_{t-p} + \epsilon_t \qquad (15)$$

$$RSR \ = \mu + A_t RSR_{t-1} + \cdots A_p RSR_{t-p} + \alpha_1 RIP_{t-1} + \cdots + \alpha_p RIP_{t-p} + \epsilon_t \qquad (16)$$

The null hypothesis are as follows: real oil prices do not Granger-cause real stock returns (1) and real industrial production does not Granger-cause real stock returns (2). F-tests are conducted with the joint hypothesis that $\alpha_1$through α_6 are zero.

Table 5 below summarizes the pairwise Granger-causality tests. In each of the 6 lags we reject the null hypothesis that real oil prices do not Granger real share returns in all of the BRICS countries. Unidirectional causality exists between real share returns and real oil prices. Oil prices are therefore able to increase the accuracy of the prediction of share market returns with respect to a forecast. Previous studies that also looked at causality between share market returns and oil prices in the BRICS countries had found contrasting results. Khan (2010) looked at Brazil, Russia, India and China and found a short-run relationship for Russia and China, while no short-run relationship was found for Brazil and India. Conversely, Bouoiyour and Selmi (2016) had found a significant short-run relationship for all five BRICS countries.

Table 6 below summarizes the pairwise Granger-causality tests. In each of the 6 lags we fail to reject the null hypothesis that real industrial production does Granger real share returns in all of the BRICS countries. Unidirectional causality does not exist between real share returns and real industrial production. Industrial production is therefore unable to increase the accuracy of the prediction of share market returns with respect to a forecast.

With regards to industrial production, the finding contradicts much of the previous literature by Fama (1990) and Geske and Roll (1983) who had found that industrial production, which has been used as a proxy for economic activity had a significant and causal relationship with the stock market.

5.2.3. VAR Analysis

This section will analyze the impact of oil price shocks on real stock returns using an unrestricted VAR model. The unrestricted VAR has been used in previous studies such as Sadorsky (1999), Maghyereh (2004) and Park and Ratti (2008).

One pertinent issue with an unrestricted VAR is whether it can be used in the instance that the variables in the VAR are cointegrated. The use of a VECM or cointegrating VAR in the presence of cointegrated variables, I(1), is supported by a body of literature. The VECM model is expected to produce results in the impulse response analysis and variance decomposition that more accurately reflect the relationship between the variables than the standard unrestricted VAR. This is due to the fact that cointegrating vectors bind the long run behavior of the variable

Table 5: Pairwise Granger-causality tests on real monthly: BRR, BROP, RRR, RROP, IRR, IROP, CRR, CROP, SRR, SROP										
No. of lags	1. From BRR to BROP	2. From BROP to BRR	3. From RRR to RROP	4. From RROP to RRR	5. From IRR to IROP	6. From IROP to IRR	7. From CRR to CROP	8. From CROP to CRR	9. From SRR to SROP	10. From SROP to SRR
1.	0.9653	**0.0000*****	0.5686	**0.0000*****	**0.0000*****	**0.0000*****	**0.0000*****	**0.0000*****	**0.0000*****	**0.0000*****
2.	0.2326	**0.0000*****	0.3048	**0.0000*****	**0.0044*****	**0.0000*****	**0.0000*****	**0.0000*****	**0.0000*****	**0.0000*****
3.	0.4085	**0.0000*****	**0.0216****	**0.0000*****	**0.0047*****	**0.0000*****	**0.0000*****	**0.0000*****	**0.0056*****	**0.0000*****
4.	0.4426	**0.0004*****	**0.0363****	**0.0000*****	0.0659*	**0.0000*****	**0.0000*****	**0.0000*****	**0.0144****	**0.0000*****
5.	0.0945*	**0.0009*****	**0.0148****	**0.0000*****	0.1190	**0.0000*****	**0.0000*****	**0.0000*****	**0.0138****	**0.0000*****
6.	0.1301	**0.0029*****	**0.0927***	**0.0000*****	0.2429	**0.0000*****	**0.0000*****	**0.0000*****	**0.0001****	**0.0000*****

The Granger causality tests are conducted using real monthly data for six lags.
Reported are the probability values of the null hypothesis of no Granger causality being present.
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

Table 6: Pairwise Granger-causality tests: BRR, BRIP, RRR, RRIP, IRR, IRIP, CRR, CRIP, SRR, SRIP										
No. of lags	1. From BRR to BRIP	2. From BRIP to BRR	3. From RRR to RRIP	4. From RRIP to RRR	5. From IRR to IRIP	6. From IRIP to IRR	7. From CRR to CRIP	8. From CRIP to CRR	9. From SRR to SRIP	10. From SRIP to SRR
1.	0.7536	0.1655	**0.0358****	0.1915	0.8271	0.1230	0.4679	0.0996*	0.4867	0.3082
2.	0.6453	0.3759	**0.0018*****	0.1231	0.9647	0.1876	0.9558	0.1905	0.3689	0.5903
3.	0.8090	0.5902	**0.0073*****	0.5220	0.9954	0.3307	0.6666	0.2882	0.5794	0.7701
4.	0.7475	0.8014	**0.0165****	0.5015	0.6551	0.5238	0.7329	0.3823	0.6449	0.8484
5.	0.8252	0.8833	**0.0146****	0.6825	0.6515	0.4778	0.6165	0.4703	0.7333	0.9445
6.	0.8472	0.9125	**0.0174****	0.7696	0.7587	0.5038	0.7419	0.5876	0.8318	0.9521

The Granger causality tests are conducted using real monthly data for six lags.
Reported are the probability values of the null hypothesis of no Granger causality being present.
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

Conversely, it has been argued by Naka and Tufte (1997) that in the short run, unrestricted VARs perform better than a cointegrating VAR. Further evidence by Engle and Yoo (1987), Clements and Hendry (1995) and Hoffman and Rasche (1996) has underlined the supremacy of an unrestricted VAR over a restricted VECM in the short run. On studying the performance of unrestricted VARs and VECMs for impulse response analysis over the short-run, Naka and Tufte (1997) found that the performance of the two models is nearly identical.

Based on the above exposition cointegration will be ignored and an unrestricted VAR model will be employed.

$$y_t = \mu + A_t y_{t-1} + \cdots + A_p y_{t=p} + \epsilon_t$$

The VAR model used in this study will contain three variables being the real oil price (ROP), the Real Industrial Production (RIP) and Real Stock Returns (RSR). y_t will then be given by y_t = [ROP, RIP, RSR]. A_p is a 3x3 matrix of unknown coefficients. p denotes how many lags will be used. The ϵ_t is the vector of innovations to the disturbances (ϵ^{ROP}, ϵ^{RIP}, ϵ^{RSR}) where $E(\epsilon_t \epsilon_t) = \sum$. We can interpret the disturbances ϵ^{ROP}, ϵ^{RIP}, ϵ^{RSR} as shocks to real oil price, real industrial production and real stock return respectively, however the analysis of this study will focus on the shock to ϵ^{ROP}.

There will be one equation for each dependent variable and each variable depends on is own lags and lags of other variables in the system.

$$\begin{aligned} ROP_t = \mu_{20} + \beta_{21} ROP_{t-1} + \cdots + \beta_p \mathrm{ROP}_{t-p} + \gamma_{21} RIP_{t-1} + \cdots + \gamma_p \mathrm{RIP}_{t-p} \\ + \delta_{21} RSR_{t-1} + \cdots + \delta_p RSR_{t-p} + \epsilon_t^{ROP} \end{aligned} \tag{17}$$

$$\begin{aligned} RIP_t = \mu_{30} + \beta_{31} \mathrm{ROP}_{t-1} + \cdots + \beta_p \mathrm{ROP}_{t-p} + \gamma_{31} \mathrm{RIP}_{t-1} + \cdots + \gamma_p \mathrm{RIP}_{t-p} \\ + \delta_{31} RSR_{t-1} + \cdots + \delta_p RSR_{t-p} + \epsilon_t^{RIP} \end{aligned} \tag{18}$$

$$\begin{aligned} RSR_t = \mu_{30} + \beta_{41} \mathrm{ROP}_{t-1} + \cdots + \beta_p \mathrm{ROP}_{t-p} + \gamma_{41} \mathrm{RIP}_{t-1} + \cdots + \gamma_p \mathrm{RIP}_{t-p} \\ + \delta_{41} RSR_{t-1} + \cdots + \delta_p RSR_{t-p} + \epsilon_t^{RSR} \end{aligned} \tag{19}$$

The variables will follow the same ordering as previous studies such as Sadorsky (1999) and Park and Ratti (2008). Real stock returns will be positioned at the end of the ordering and separate VAR models will be run for each of the five countries.

5.2.3.1. VAR estimation

As previously discussed, the first step in specifying a VAR model is selecting the appropriate lag length. In choosing the lag order of the VAR for the variables RSR, ROP, RIP a VAR is estimated 12 times using lag orders 12, 11, 10 ... 2, 1 for each of the BRICS countries. The Akaike information criteria can then be used for model selection such as determining the lowest value of the VAR. The lower the value of the AIC, the more accurate the model. Table 6 below provides the results from the AIC for each of the BRICS countries.

When comparing the AIC for the different lag orders, it is clear that a lag order of 12 is favorable for all BRICS countries except for India, where a lag order of 3 is preferred.

Table 7: Vector Auto Regression estimates using AIC

No. of lags	**Brazil**	**Russia**	**India**	**China**	**South Africa**
0.	-5.443780	-7.402570	-5.542151	-0.520343	-3.477272
1.	-5.745276	-7.789544	-6.164772	-1.086169	-4.351246
2.	-5.708223	-7.865047	-6.209657	-1.359291	-4.460275
3.	-5.665325	-7.866498	**-6.222098***	-1.369284	-4.494776
4.	-5.674756	-7.851454	-6.185397	-1.317517	-4.488909
5.	-5.610898	-7.893310	-6.136511	-1.324514	-4.514649
6.	-5.678477	-7.851099	-6.101048	-1.293925	-4.524391
7.	-5.669569	-7.855097	-6.051404	-1.342737	-4.486166
8.	-5.661743	-7.808848	-6.001688	-1.362985	-4.552503
9.	-5.685079	-7.816900	-5.961423	-1.369005	-4.492476
10.	-5.697452	-7.879172	-5.956895	-1.885244	-4.610729
11.	-6.590006	-7.988130	-6.099859	-2.264421	-5.239289
12.	**-9.028743***	**-8.003574***	-6.131158	**-2.625927***	**-5.843324***

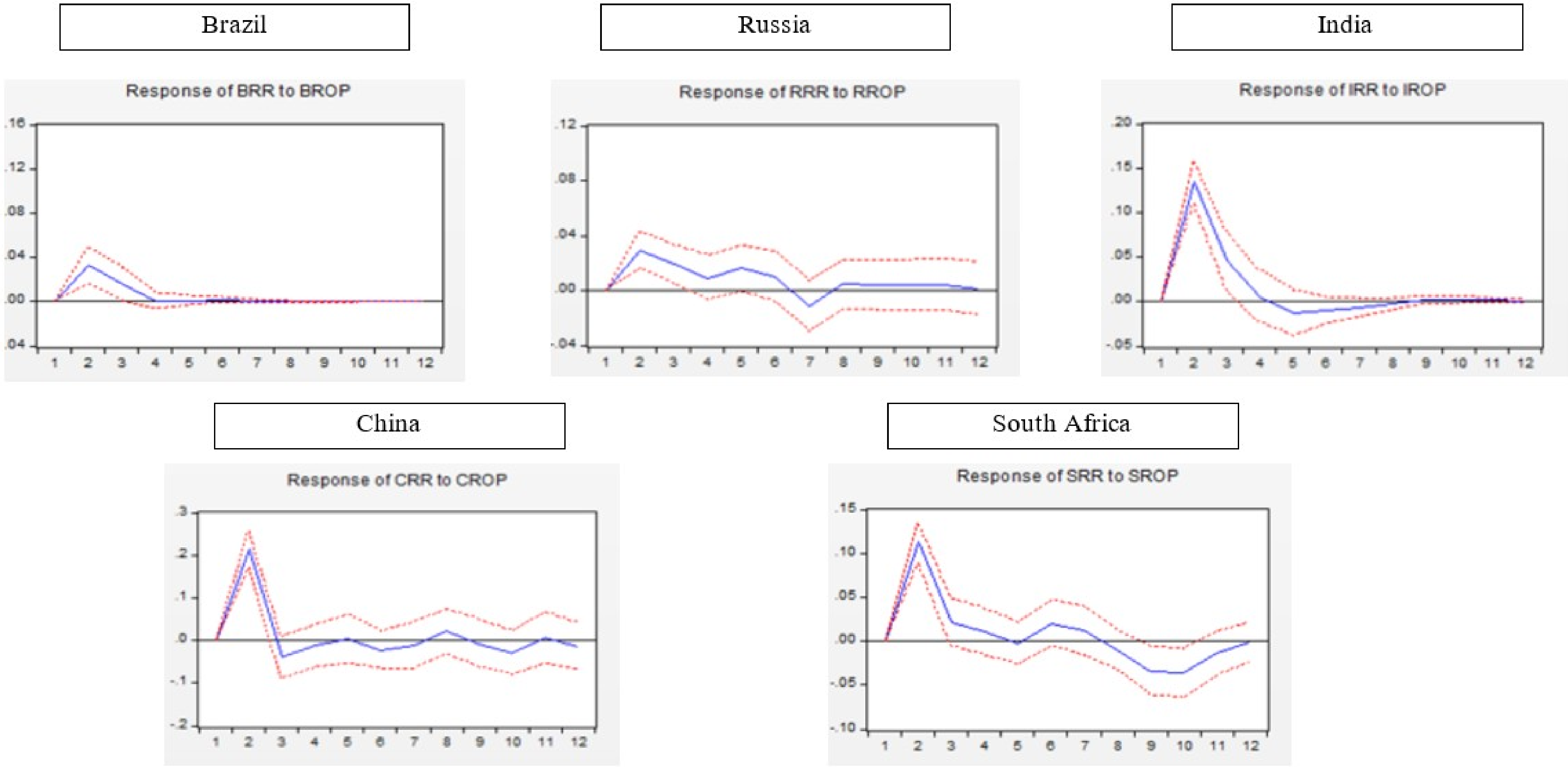
5.2.3.2. Impulse Response Functions

This section looks to analyze the results from the impulse response to determine the impact of real oil price shocks on real stock returns. Brazil, Russia, china and South Africa were all VAR(12) models while India was a VAR(3) model.

Figure 1 below presents the impulse response of real stock returns resulting from a one standard deviation shock to real oil prices disturbances. Monte Carlo constructed 95% confidence intervals are constructed to assess the statistical significance of the impulse response function. Looking at Brazil when the impulse is real stock returns, a positive shock to real oil prices can be seen in the first month with the response dissipating around the third month with the results being significant until month three. Looking at Russia, a positive shock to real oil prices can be seen within the first month, while a negative decrease is seen around the seventh month and then reverts to zero around month eight, however the results are only significant until month three and become insignificant thereafter. In India, a positive shock to real oil prices can be seen in the first month, and remains positive until month four, when a negative decrease is seen, with the response dissipating close to zero shortly after that. The results for India are significant until month three and then become insignificant. China sees a positive shock to real oil prices in the first month and then a negative decrease is seen close to the third month with the response hovering close to zero from month four onwards, however the results are only significant in month one and month two. South Africa sees a positive shock to real oil prices within the first month and then a negative decrease around month 7 and finally dissipating towards zero in month 12. The results for South Africa are significant for months one and two and then month's eight to ten.

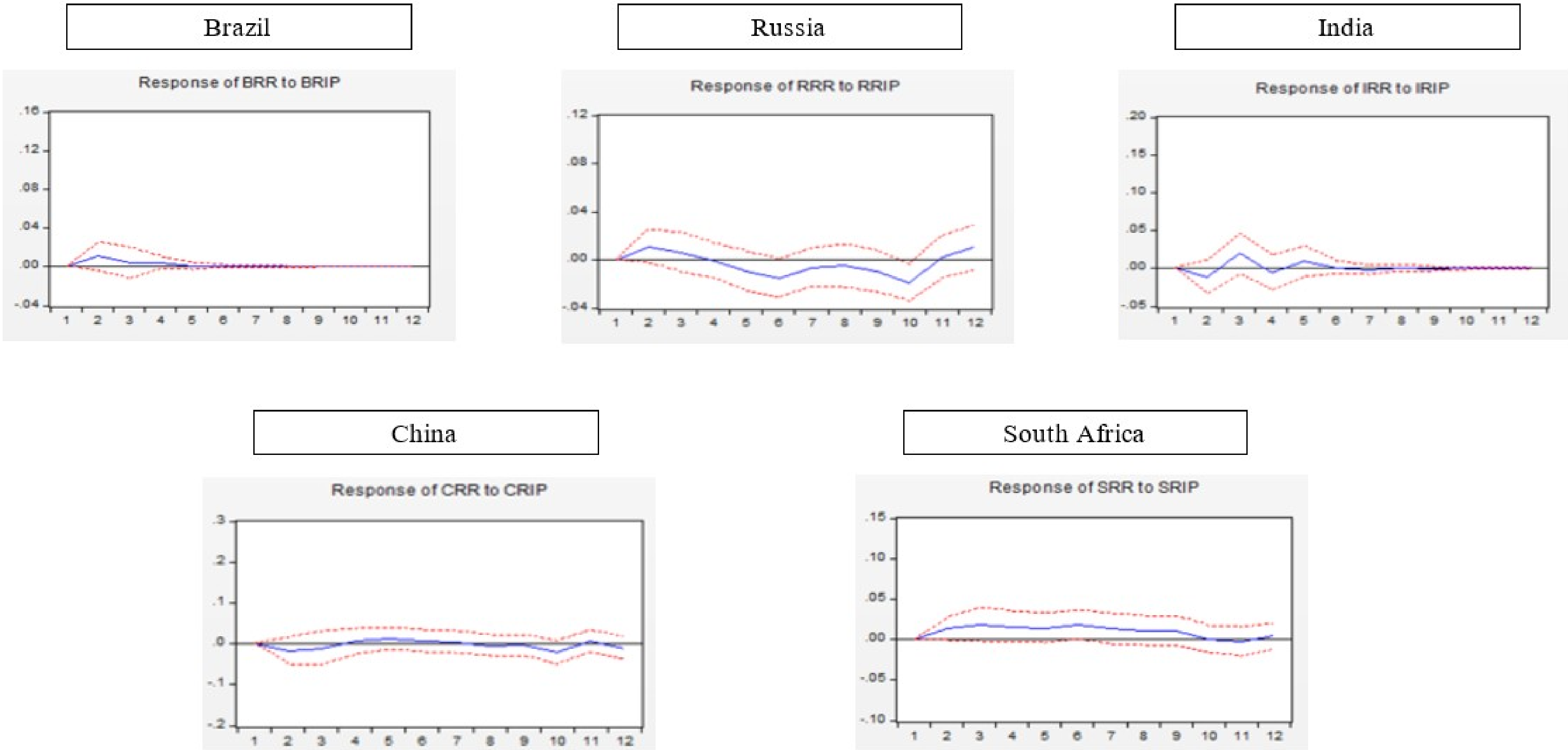
Figure 2 below presents the impulse response of real stock returns resulting from a one standard deviation shock to real industrial production disturbances. Looking at Brazil when the impulse is real stock returns, a positive shock to real industrial production can be seen within the second month as it dissipates towards zero in month 3. Looking at Russia a positive shock can be seen in month two, while a negative decrease is seen around the fifth month and then a further negative decrease in month ten and then becomes positive in the twelfth month. In India a negative shock can be seen in month two and then a positive increase can be seen in the third month before dissipating towards zero in month six. In China, a positive shock can be seen in month one and remains consistently positive till the tenth month when it dissipates to zero. In South Africa a negative shock can be seen in month two but dissipates towards zero in month four. The results for all five countries were found to be insignificant.

Figure 2: Orthogonalized impulse response function of real stock returns to linear real oil price shocks in VAR (ROP, RIP, RSR)



Note: The figure shows the response of real stock returns to a Cholesky one standard deviation oil price shock. The model is fixed to see the response in a period of 12 months. The two outer lines are Monte Carlo constructed 95% confidence bounds

Figure 3: Orthogonalized impulse response function of real stock returns to industrial production in VAR (ROP, RIP, RSR)



Note: The figure shows the response of real stock returns to a Cholesky one standard deviation industrial production shock. The model is fixed to see the response in a period of 12 months. The two outer lines are Monte Carlo constructed 95% confidence bounds

5.2.3.3. Variance Decomposition

Table 8 gives us the results of a VAR model (ROP, RIP, RSR). It looks at the forecast error variance decomposition of real stock returns due to real oil prices and real industrial production shocks after 12 months. Each number in the table gives the percentage of how much of the unanticipated changes of real stock returns are due to oil price shocks and how much are due to industrial production shocks.

When looking at Brazil 8.57% of the variability of stock returns is due to oil price shocks while 0.92% is due to industrial production. In Russia, 11.86% of the variability of stock returns is due to oil price shocks while 7.29% is due to industrial production. India has the largest variability in stock returns due to oil price shocks of 41.07% while industrial production only contributes 1.28%. For China 37.83% of the variability of stock returns is due to oil price shocks while 1.00% is due to industrial production. Finally, in South Africa 38.97% of the variability of stock returns is due to oil price shocks while 3.96% is due to industrial production.

Table 8: Variance Decomposition of forecast error variance in real stock returns due to real oil price (ROP) and real industrial production (RIP) after 12 months with Monte Carlo constructed SEs shown in parenthesis

Country/Variable	RIP	ROP
Brazil	0.922310	8.572812
	(1.54039)	(3.39317)
Russia	7.294156	11.86344
	(3.86956)	(4.90310)
India	1.283089	41.06922
	(1.45240)	(4.94082)
China	1.005835	37.83408
	(1.46185)	(4.53983)
South Africa	3.963783	38.96576
	(3.86715)	(6.36427)

6. Conclusion

While there has been a plethora of studies investigating the relationship between oil price shocks and the macro-economy, research regarding the relationship between oil prices and share market returns in emerging markets is lacking. This study investigated the impact of oil price shocks on the five emerging economies of Brazil, Russia, India, China and South Africa, collectively known as BRICS.

Granger-causality tests were employed in order to test the predictive ability of real oil prices in forecasting real share market returns. Results from the Granger-causality test indicated that causality does exist between oil prices and share market returns for all five BRICS countries. The tests found a statistically significant unidirectional causal relationship between oil prices and share market returns. Oil prices are therefore able to increase the accuracy of the prediction of share market returns with respect to a forecast.

In order to examine the short-run dynamics among variables, VAR models were estimated and impulse response functions and variance decompositions were computed.

The findings from the impulse response function indicate a significant positive relationship between linear oil price shocks and share market returns for the BRICS countries. The relationship becomes insignificant at month three for all BRICS countries except China, where the relationship becomes insignificant in the second month. It is also worth noting that South Africa experiences a significant negative response from month eight to month ten.

These results are not consonant with the studies of Sadorsky (1999), Park and Ratti (2008), Malik and Ewing (2009) and Ramos and Veiga (2014), who found a negative relationship between oil price shocks and share market returns in different countries.

This variance in readings can be attributed to a number of factors. This study reviewed the data for the period February 1998 to December 2017, while the four studies did not use data post 2009. In fact, Sadorsky (1999) only looked at data until 1996 while Park and Ratti (2008) examined data until 2005. Both these studies did not consider the financial crisis of 2008 that can be considered a financial anomaly. Furthermore, while Malik and Ewing (2009) and Ramos and Veiga (2014) may have factored the 2008 economic meltdown in their studies, they did not take cognizance of the significant decrease in oil prices between the years 2014 and 2016.

While Sadorsky (1999) and Park and Ratti (2008) both conducted a VAR analysis the models used by Malik and Ewing (2009) and Ramos and Veiga (2014) differed. Malik and Ewing (2009) used a bivariate GARCH model and Ramos and Veiga (2014) employed the International Arbitrage Pricing Theory model.

Sadorsky (1999) and Malik and Ewing (2009) only looked at developed economies when research by Asteriou, Dimitras, and Lendewig (2013) shows that the oil price shocks impact developed and emerging economies differently.

Park and Ratti (2008) and Talukdar and Sunyaeva (2011) found that the effect of oil price shocks on a country is dependent on whether it is a net oil exporter or a net oil importer. They noted that oil price shocks negatively affected net oil importers whereas the converse was true for net oil exporters.

The results of this study correlated with the findings of Park and Ratti (2008) and Talukdar and Sunyaeva (2011) for Brazil and Russia who are both net oil exporters. But for India, China and South Africa who are net oil importers, the results did not correspond. Similar unexpected results were found by Cong, Wei, Jiao, and Fan (2008) in examining the Hong Kong Stock Exchange (HKEX). When the authors separated oil shocks into supply shocks, global demand shocks and oil specific demand shocks, they found that the HKEX responded positively to all three shocks. They posit that the rapid growth of the Chinese economy may be the reason the positive sentiment effect outweighs the negative precautionary demand effect. Since Hong Kong has a close to perfect capital mobility, investor sentiment creates the expectation that the economy will still perform well without a decrease in capital flow even during periods where oil prices are high. The same would hold for India which is the fastest growing economy in the world.

When looking at the variance decomposition of real stock returns for the period under review, it seems to be significantly higher than the results obtained by Sadorsky (1999) and Park and Ratti (2008). Wang, Wu and Yang (2012), found similar results to this study. The findings of this study suggest that when looking at net oil importing countries, a larger portion of variability of stock returns are because of oil price shocks when compared to net oil exporting countries. The reason may be that China and India, as the second and third largest importers of oil respectively, are heavily reliant on oil to fuel their economic growth. As a result, companies within these economies are highly sensitive to variability in oil prices and would be impacted through their expected cash flows as illustrated in equation b in section 2.1.3.1. This in turn would influence the share market returns of these companies making them much more vulnerable to shocks in oil prices.

Findings that oil price shocks impact share market returns are important to regulators and investors for several reasons. It could assist investors in better understanding and predicting the performance of share markets by examining the link between oil prices and share market returns. Furthermore, these findings can assist firms and investors who are sensitive to changes in oil prices to make better informed decisions relating to oil price risk hedging. They could use these findings to construct their portfolios so as to diversify their investments which would allow investors to adequately manage the portfolio risks. Risk can be mitigated by allocating investments between oil importing and exporting countries each of which would react differently to changes in oil prices. Finally, regulators can use this information to increase investor confidence in share markets by protecting the interest of the investor against uncertainty and risk inherent in the oil market. This would allow them to minimize the share markets dependency on oil prices.

The findings of this study also offer a platform for future research. Firstly, future studies could look to investigate the long-run relationship between share market returns and oil prices by conducting a cointegration analysis to determine whether the finding are consistent over the long-run by making use of a Vector Error Correction Model. Secondly, the link between oil prices and share market returns can be expected to differ between sectors. For this reason, a cross-sector analysis could be beneficial in determining the extent to which particular sectors are impacted by oil price shocks. Thirdly, while the financial crisis of 2008 was included in the sample period, further studies could benefit from exploring the impact of this crisis with the inclusion of a structural break. Finally, future research could use the data set of this study and separate oil shocks into supply and demand shocks as done by Kilian (2009) in order to determine the extent that the source of the shock impacts share market returns.

Another interesting point of research would be looking at how the findings of this paper may change over time as countries try to move towards renewable energy sources such as solar, wind and hydropower. Even though emerging markets do not rely much on green energy, this could change rapidly because the cost of renewable energy is decreasing at an exponential rate. Furthermore, as the effects of global warming become more apparent, countries are under increasing pressure to reduce carbon emissions. China has implemented an Air Pollution Action Plan in order to address the high levels of pollution because of carbon emissions (World Economic Forum, 2019). Plans such as these could decrease the reliance of developed economies on fuel and impact the way the share markets of these countries react to shocks in oil prices.

7. Reference list

Adhikari, R. (2013). *An Introductory Study on Time Series Modeling and Forecasting* (Doctoral dissertation). Retrieved from https://arxiv.org/ftp/arxiv/papers/1302/1302.6613.pdf

Ågren, M. (2006). Does Oil Price Uncertainty Transmit to Stock Markets? *Department of Economics, Uppsala University,* Working Paper.

Anoruo, E., and Mustafa, M. (2007). An empirical investigation into the relation of oil to stock market prices. *North American Journal of Finance and Banking Research*.

Apergis, N., and Miller, S. M. (2009). Do structural oil-market shocks affect stock prices? *Energy Economics*, *31*(4), 569-575.

Asteriou, D., Dimitras, A., & Lendewig, A. (2013). The Influence of Oil Prices on Stock Market Returns: Empirical Evidence from Oil Exporting and Oil Importing Countries. *International Journal of Business and Management*, *8*(18). doi:10.5539/ijbm.v8n18p101

Ayadi, O. F. (2005). Oil price fluctuations and the Nigerian economy. *OPEC Review*, *29*(3), 199-217. doi:10.1111/j.0277-0180.2005.00151.x

Aye, G. (2015). Does oil price uncertainty matter for stock returns in South Africa? *Investment Management and Financial Innovations*, *12*(1), 173-188.

Aydoğan, B., Tunç, G., and Yelkenci, T. (2017). The impact of oil price volatility on net-oil exporter and importer countries' stock markets. *Eurasian Economic Review*, *7*(2), 231-253. doi:10.1007/s40822-017-0065-1

Baltagi, B. H. (2003). *A Companion to Theoretical Econometrics*. Hoboken, NJ: John Wiley & Sons.

Basher, S. A., and Sadorsky, P. (2006). Oil price risk and emerging stock markets. *Global Finance Journal*, *17*, 224-251.

Baumeister, C., and Kilian, L. (2016). Forty Years of Oil Price Fluctuations: Why the Price of Oil May Still Surprise Us. *SSRN Electronic Journal*. doi:10.2139/ssrn.2714319

Bernake, B.S. (2006). Energy and the Economy. Speech to the Economic Club of Chicago, June, 15.

Bhar, R., and Nikolova, B. (2009). Oil Prices and Equity Returns in the BRIC Countries. *World Economy*, *32*(7), 1036-1054. doi:10.1111/j.1467-9701.2009.01194.x

Bjornland, H. C. (2006). PhD course: structural VAR models. Retrieved from http://home.bi.no/a0310125/Lecture%201a%20Motivation.pdf

Bouoiyour, J., and Selmi, R. (2016). How differently Does Oil Price Influence BRICS Stock Markets? *Journal of Economic Integration*, *31*(3), 547-568. Retrieved from https://www.jstor.org/stable/43868320

Braun, P. A., and Mittnik, S. (1993). Misspecifications in vector autoregressions and their effects on impulse responses and variance decompositions. *Journal of Econometrics*, *59*(3), 319-341. doi:10.1016/0304-4076(93)90029-5

Canuto, O. (2017, December 6). BRICS Apart as Oil Prices Plunge. Retrieved from https://www.huffpost.com/entry/brics-apart-as-oil-prices_b_6815590

Carlyle, R. (2013). What Are The Top Five Facts Everyone Should Know About Oil Exploration? Retrieved from http://www.forbes.com/sites/quora/2013/04/03/what-are-the-top-five-facts- everyone-should-know-about-oil-exploration/

Campbell, J. Y., Lo, A. W., and MacKinlay, A. C. (2012). *The Econometrics of Financial Markets*. Princeton, NJ: Princeton University Press.

Chang, Youngho and Fong Wong, Joon. (2003). Oil price fluctuation and Singapore economy. Energy Policy. 31. 1151-1165. 10.1016/S0301-4215(02)00212-4.

Christensen, J. I. (2011). Oil Price Shocks and Stock Returns: Empirical Evidence for the G-7 and Norway

Clements, M., and Hendry, D. (n.d.). Forecasting in cointegrated systems. *Forecasting economic time series*, 119-156. doi:10.1017/cbo9780511599286.008

Cong, R. G., Wei, Y. M., Jiao, J. L., & Fan, Y. (2008). Relationship Between Oil Price Shocks and Stock Market: An Empirical Analysis from China. *Energy Policy*, *36*(9). Retrieved from https://doi.org/10.1016/j.enpol.2008.06.006

De Hollanda, L. R., & Nogueira, R. (2015). *The Implications of the Recent Oil Price Drop on the Brazilian Economy*. Retrieved from International Association for Energy Economics website: http://www.fgv.br/fgvenergia/paper_rafael_e_lavinia/files/assets/common/downloads/paper_rafael_e_lavinia_0.pdf

Degiannakis, S., Filis, G., and Arora, V. (2018). Oil Prices and Stock Markets: A Review of the Theory and Empirical Evidence. *The Energy Journal*, *39*(5). doi:10.5547/01956574.39.5.sdeg

Deviant, S. (2017). Unit Root: Simple Definition, Unit Root Tests. Retrieved from http://www.statisticshowto.com/unit-root/

Dhaoui, A., and Khraief, N. (2014). Empirical Linkage between Oil Price and Stock Market Returns and Volatility: Evidence from International Developed Markets*, Kiel Institute for the World Economy*, Economics Discussion Papers.

Dickey, D. and Fuller W. (1979). "Distribution of the Estimators for Autoregressive Time Series with a Unit Root" *Journal of the American Statistical Association,* 74: 427-431.

Diebold, F. X., and Kilian, L. (2001). Measuring predictability: theory and macroeconomic applications. *Journal of Applied Econometrics*, *16*(6), 657-669. doi:10.1002/jae.619

Dohner, R. S. (1980). Energy prices, economic activity, and inflation : a survey of issues and results. *Energy prices, inflation, and economic activity. Cambridge/Mass*.

Econometrics with R. (2017, March 19). An Introduction to Vector Autoregression (VAR). Retrieved from https://econometricswithr.wordpress.com/time-series/an-introduction-to-vector-autoregression-var/

Edelstein, P., and Kilian, L. (2009). How sensitive are consumer expenditures to retail energy prices? *Journal of Monetary Economics*, *56*(6), 766-779. doi:10.1016/j.jmoneco.2009.06.001

EIA (Economic Intelligence Agency). (2018). What countries are the top producers and consumers of oil? - FAQ - U.S. Energy Information Administration (EIA). Retrieved from https://www.eia.gov/tools/faqs/faq.php?id=709&t=6

El Hedi Arouri, M., Jouini, J. and Nguyen, D. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International Money and Finance*, 30(7), pp.1387-1405.

Engle, R. F., and Yoo, B. S. (1987). Forecasting and testing in co-integrated systems. *Journal of Econometrics*, *35*(1), 143-159. doi:10.1016/0304-4076(87)90085-6

Fama, E. F. (1990). Stock Returns, Expected Returns, and Real Activity. *The Journal of Finance*, *45*(4), 1089. doi:10.2307/2328716

Fang, C. R. (2010). The Impact of Oil Price Shocks on the Three Bric Countries' Stock Prices. *Open Access Library Journal*, *3*(12). Retrieved from https://www.scirp.org/(S(vtj3fa45qm1ean45vvffcz55))/reference/ReferencesPapers.aspx?ReferenceID=1930029

Farzanegan, M. R. (2011). Oil revenue shocks and government spending behavior in Iran. *Energy Economics*, *33*(6), 1055-1069. doi:10.1016/j.eneco.2011.05.005

Fatima, Tajalli and Bashir, Adnan. (2014). Oil Price and Stock Market Fluctuations: Emerging Markets (A Comparative Study of Pakistan and China). International Review of Management and Business Research. 3. 1958.

Fayyad, A. and Daly, K. (2011) The Impact of Oil Price Shocks on Stock Market Returns: Comparing GCC Countries with the UK and USA. Emerging Markets Review, 12, 61-78. https://doi.org/10.1016/j.ememar.2010.12.001

Filis, G., Degiannakis, S., and Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, *20*(3), 152-164.

Foresti, P. (2007). Testing for Granger causality between stock prices and economic growth. *Munich Personal RePEc Archive*. Retrieved from https://mpra.ub.uni-muenchen.de/2962/1/MPRA_paper_2962.pdf

Geske, R., & Roll, R. (1983). The Fiscal and Monetary Linkage Between Stock Returns and Inflation. *The Journal of Finance*, *38*(1), 1. doi:10.2307/2327635

Ghosh, N., Varvares, C., and Morley, J. (2009). The Effects of Oil Price Shocks on Output. *Business Economics*, *44*(4), 220-228. doi:10.1057/be.2009.33

Granger, C. W. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, *37*(3), 424. doi:10.2307/1912791

Granger, C., and Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111-120. doi:10.1016/0304-4076(74)90034-7

Guliman, S. D. (2015). Oil Prices and Stock Market: A Philippine Perspective. *Business and Economic Research*, *5*(2), 122. doi:10.5296/ber.v5i2.7941

Guo, S., Ladroue, C., and Feng, J. (2010). Granger Causality: Theory and Applications. In *Frontiers in Computational and Systems Biology. Computational Biology* (15th ed., pp. 83-111). Retrieved from https://doi.org/101007/978-1-84996-196-7_5

Guo, H., and Kliesen, K. (2006). Oil Price Volatility and U.S. Macroeconomic Activity. *Federal Reserve Bank of St. Louis Review, 87*(6), 669-683.

Hamilton, J. D. (1983). Oil and the Macroeconomy since World War II. *Journal of Political Economy*, *91*(2), 228-248. doi:10.1086/261140

Hamilton, J. (1988). A Neoclassical Model of Unemployment and the Business Cycle. *Journal of Political Economy, 96*(3), 593-593.

Hamilton, J. D. (1994). *Time Series Analysis*. Taylor & Francis US.

Hamilton, J. D. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics*, *38*(2), 215-220.

Hamma, W., Jarboui, A., and Ghorbel, A. (2014). Effect of Oil Price Volatility on Tunisian Stock Market at Sector-level and Effectiveness of Hedging Strategy. *Procedia Economics and Finance*, *13*, 109-127. doi:10.1016/s2212-5671(14)00434-1

Hoffman, D. L., and Rasche, R. H. (1996). Assessing forecast performance in a cointegrated system. *Journal of Applied Econometrics*, *11*(5), 495-517. doi:10.1002/(sici)1099-1255(199609)11:5<495::aid-jae407>3.0.co;2-d

Huang, R., Masulis, R., and Stoll, H. (1998). Energy shocks and financial markets. *Journal of Futures Markets, 16*(1), 1-27.

India SENSEX Stock Market Index. (2018). Retrieved from https://tradingeconomics.com/india/stock-market

Introduction to the JSE All Share Index. (2017, December 26). Retrieved from https://www.sashares.co.za/jse-all-share-index/

Janor, H., Abdul-Rahman, A., Housseinidoust, E., and Rahim, R. (2013). Oil Price Fluctuations and Firm Performance in an Emerging Market: Assessing Volatility and Asymmetric Effect. *JOEBM Journal of Economics, Business and Management, 1*(4), 385-390.

Jones, C. M., and Kaul, G. (1996). Oil and the Stock Markets. *The Journal of Finance*, *51*(2), 463-491.

Khan, S. (2010). Crude Oil Price Shocks to Emerging Markets: Evaluating the BRICs Case. *SSRN Electronic Journal*. doi:10.2139/ssrn.1617762

Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review*, *99*(3), 1053-1069. doi:10.1257/aer.99.3.1053

Kilian, L. (2001). Impulse response analysis in vector autoregressions with unknown lag order. *Journal of Forecasting*, *20*(3), 161-179. doi:10.1002/1099-131x(200104)20:3<161::aid-for770>3.0.co;2-x

Le, T. H. and Chang, Y. (2011). *The impact of oil price fluctuations on stock markets in developed and emerging economies* (Master's thesis, Nanyang Technological University). Retrieved from https://mpra.ub.uni-muenchen.de/31753/1/MPRA_paper_31753.pdf

Lee, K., Ni, S., and Ratti, R. A. (1995). Oil Shocks and the Macroeconomy: The Role of Price Variability. *The Energy Journal*, *16*(4). doi:10.5547/issn0195-6574-ej-vol16-no4-2

Lee, Y. H., and Chiou, J. S. (2011). Oil sensitivity and its asymmetric impact on the stock market. *Fuel and Energy Abstracts*, *36*(1), 168-174.

Lu, C., and Xin, Z. (2010). *Impulse-Response function Analysis: An application to macroeconomic data of China* (Master's thesis, Hoskolan Dalarna, China). Retrieved from http://www.statistics.du.se/essays/D10_Xinzhou_lucao.pdf

Lütkepohl, H. (1993). Introduction. *Introduction to Multiple Time Series Analysis*, 1-6. doi:10.1007/978-3-642-61695-2_1

Lütkepohl, H. (2010). Impulse response function. In *Macroeconometrics and Time Series Analysis. The New Palgrave Economics Collection* (pp. 145-150). London: Palgrave Macmillan.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, *11*(6), 601-618. doi:10.1002/(sici)1099-1255(199611)11:6<601::aid-jae417>3.0.co;2-t

Maghyereh, A. (2004). Oil Price Shocks and Emerging Stock Markets: A Generalized VAR Approach. *International Journal of Applied Econometrics and Quantitative Studies*, *1*(2), 27-40.

Malik, F., and Ewing, B. T. (2009). Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis*, *18*(3), 95-100.

Mayer, I.L. (2017). Crude Oil Guide: Brent Vs. WTI, What's The Difference?. Cannon Trading. Retrieved 8 December 2017, from https://www.cannontrading.com/tools/support-resistance-levels/crude-oil-guide-brent-vs-wti-whats-the-difference/

Moscow Exchange - Indices. (n.d.). Retrieved from http://www.moex.com/en/index/RTSI

Moffatt, M. (2003, November 26). How Statisticians Use the Augmented Dickey-Fuller Test. Retrieved from https://www.thoughtco.com/the-augmented-dickey-fuller-test-1145985

Mohanty, S. K., and Nandha, M. (2011). Oil Risk Exposure: The Case of the U.S. Oil and Gas Sector. *Financial Review*, *46*(1), 165-191. doi:10.1111/j.1540-6288.2010.00295.x

Mork, K. A. (1989). Oil and the Macroeconomy When Prices Go Up and Down: An Extension of Hamilton's Results. *Journal of Political Economy*, *97*(3), 740-744. doi:10.1086/261625

Naka, A., and Tufte, D. (1997). Examining impulse response functions in cointegrated systems. *Applied Economics*, *29*(12), 1593-1603. doi:10.1080/00036849700000035

Novac, A. G. (2019). Which is the Most Traded Commodity in the World?. Retrieved from https://www.orbex.com/blog/en/2019/01/the-most-traded-commodity-in-the-world

Ono, S. (2011). Oil Price Shocks and Stock Markets in BRICS. *The European Journal of Comparative Economics*, *8*(1), 29-45.

Ozcicek, O., and McMillin, W. (1999). Lag length selection in vector autoregressive models: symmetric and asymmetric lags. *Applied Economics*, *31*(4), 517-524. doi:10.1080/000368499324237

Park, J., and Ratti, R. A. (2008). Oil price shocks and stock markets in the U.S. and 13 European countries. *Energy Economics*, *30*(5), 2587-2608.

Ramos, S. B., and Veiga, H. (2013). Oil price asymmetric effects: Answering the puzzle in international stock markets. *Energy Economics*, *38*, 136-145. doi:10.1016/j.eneco.2013.03.011

Reddy, S. G. (2018). The Role of Brics in the World Economy and International Development. Retrieved December 14, 2018, from https://reddytoread.files.wordpress.com/2017/09/brics-2017.pdf

Rentschler, J. (2013). Oil Price volatility – its risk on economic growth and development. Retrieved from http://blogs.worldbank.org/developmenttalk/oil- price-volatility-its-risk-economic- growth-and-development

S&P Capital IQ. (2017). Shanghai Stock Exchange Composite Index. Retrieved December 25, 2017, from https://www.capitaliq.com/CIQDotNet/company.aspx?companyId=20246487

S&P Capital IQ. (2018). Brazil IBOVESPA Index (IBOV). Retrieved from https://www.capitaliq.com/CIQDotNet/company.aspx?companyId=32199944

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics, 21*(5), 449-469.

Sørensen, Michael. (2005) Comment: A Selective Overview of Nonparametric Methods in Financial Econometrics. Statist. Sci. 20 (2005), no. 4, 344--346. doi:10.1214/088342305000000449. https://projecteuclid.org/euclid.ss/1137076649

Talukdar, K. H. and Sunyaeva A. (2011). *Oil price shocks and stock market returns: Evidence from 11 member countries of Organization of Economic Cooperation and Development (OECD)* (Master's thesis, Lunds Universitet, Lund, Sweden).

Tsay, R. S. (2005). Analysis of Financial Time Series. Hoboken, NJ: John Wiley & Sons.

Verbeek, Marno. (2014). *A Guide to Modern Econometrics. Applied Econometrics*. 8. 125-132.

Wang, Y., Wu, C., & Yang, L. (2012). *Oil Price Shocks and Stock Market Returns: Evidence from Oil-Importing and Oil-Exporting Countries*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2189575

Wang, W. (2006). *Stochasticity, nonlinearity and forecasting of streamflow processes*. Amsterdam: IOS Press.

Wiener, Norbert. Nonlinear Prediction and Dynamics. Proceedings of the Third Berkeley Symposium on Mathematical Statistics and Probability, Volume 3: Contributions to Astronomy and Physics, 247--252, University of California Press, Berkeley, Calif., 1956. https://projecteuclid.org/euclid.bsmsp/1200502197

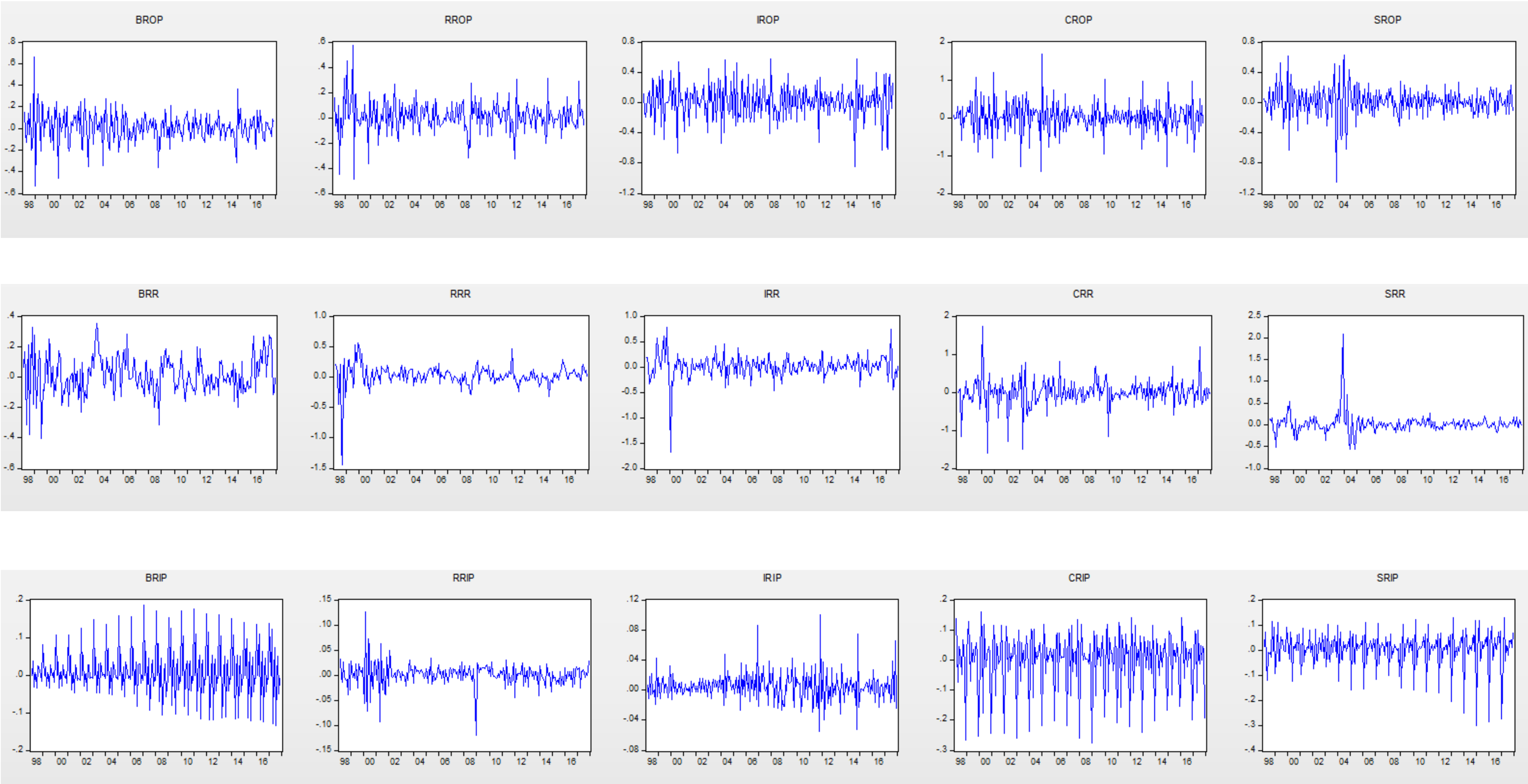
World Economic Forum. (2019). *Fostering Effective Energy Transition 2019*. Retrieved from World Economic Forum website: http://www3.weforum.org/docs/WEF_Fostering_Effective_Energy_Transition_2019.pdf

Workman, D. (2018). Crude Oil Exports by Country. Retrieved from http://www.worldstopexports.com/worlds-top-oil-exports-country/

Zivot, E., & Wang, J. (2013). *Modeling Financial Time Series with S-PLUS*. Berlin, Germany: Springer Science & Business Media.

8. Appendices

Appendix 1 – Plotted data

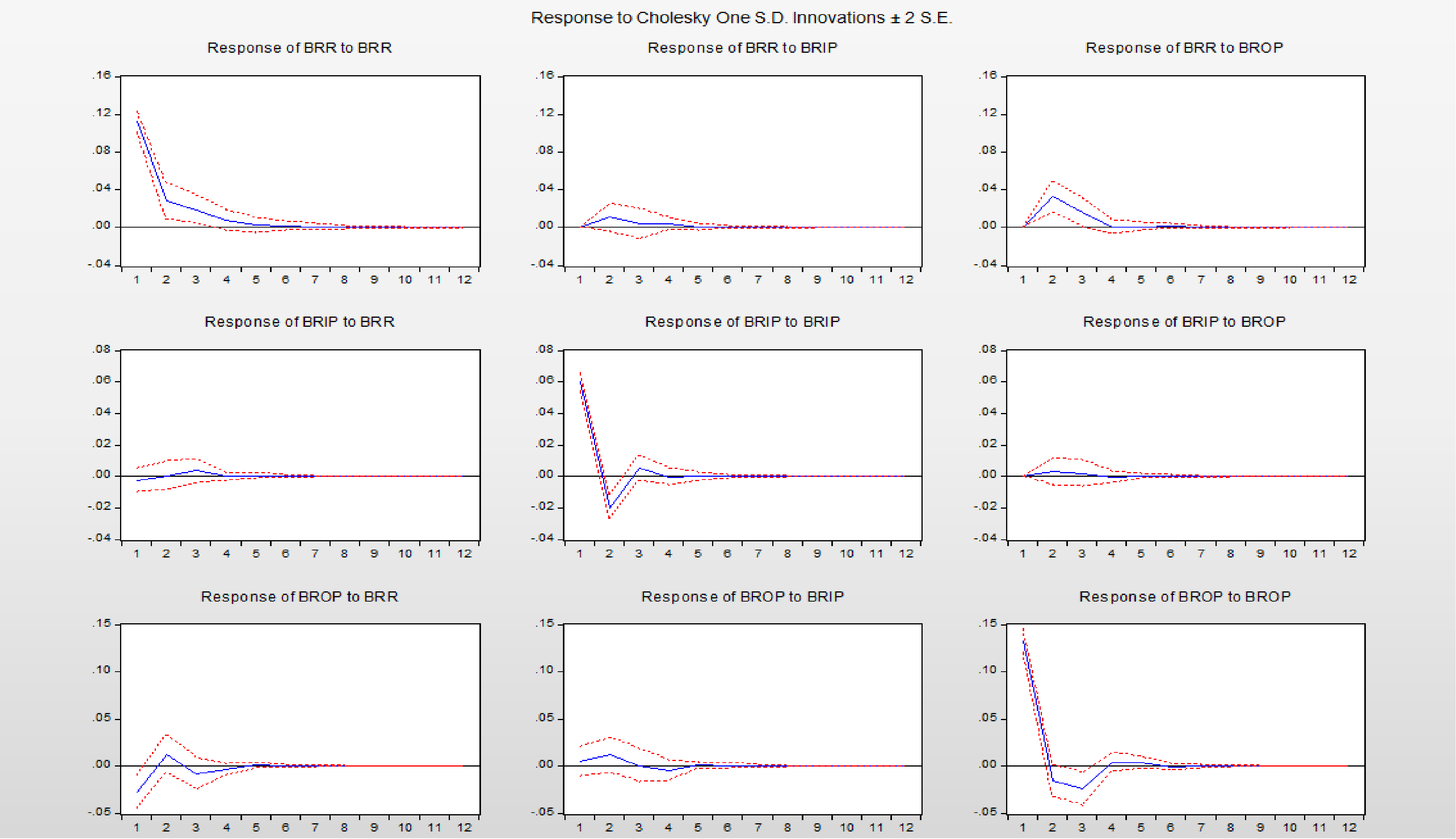


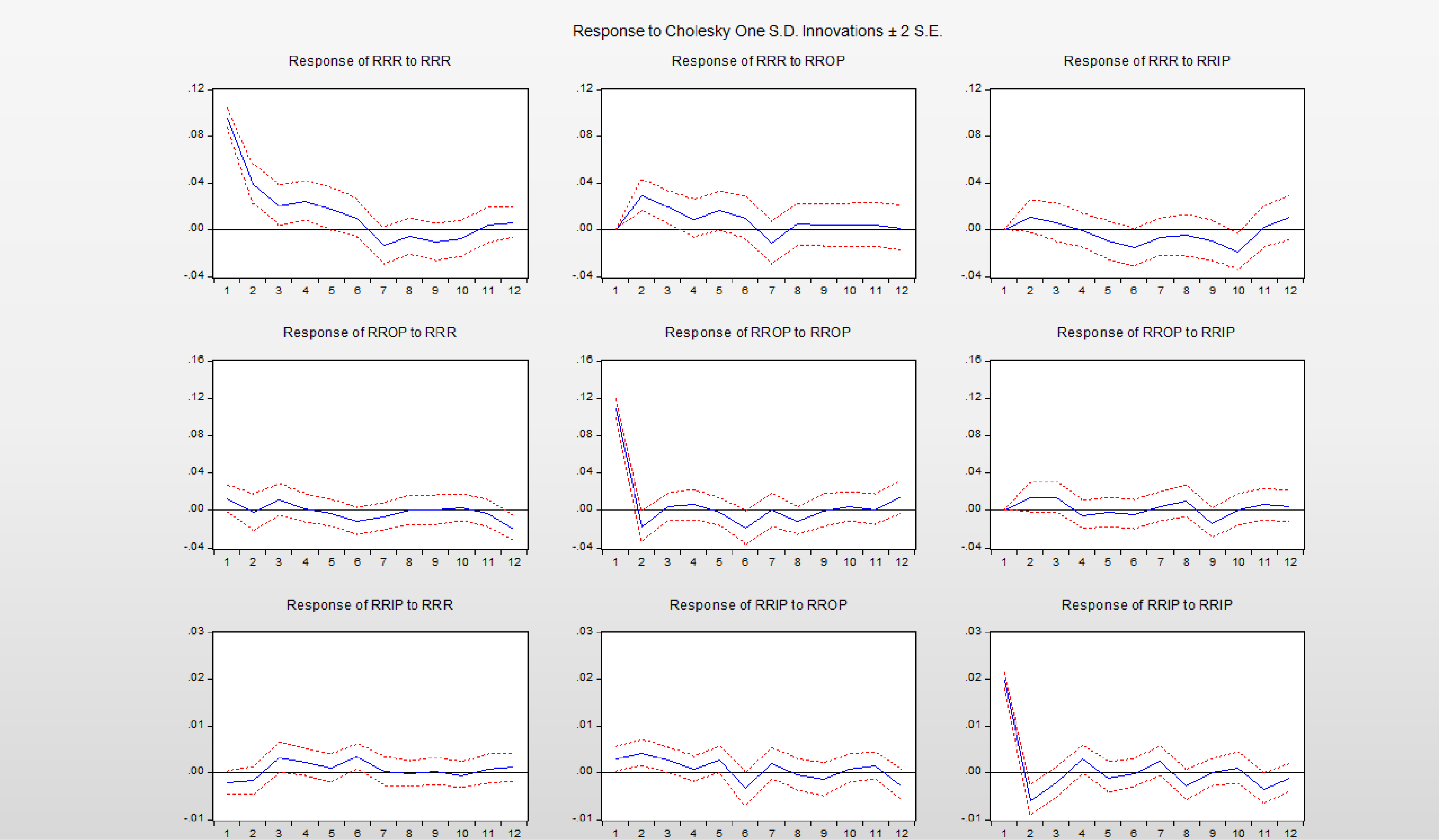
Appendix 2 – Unit root test, industrial production

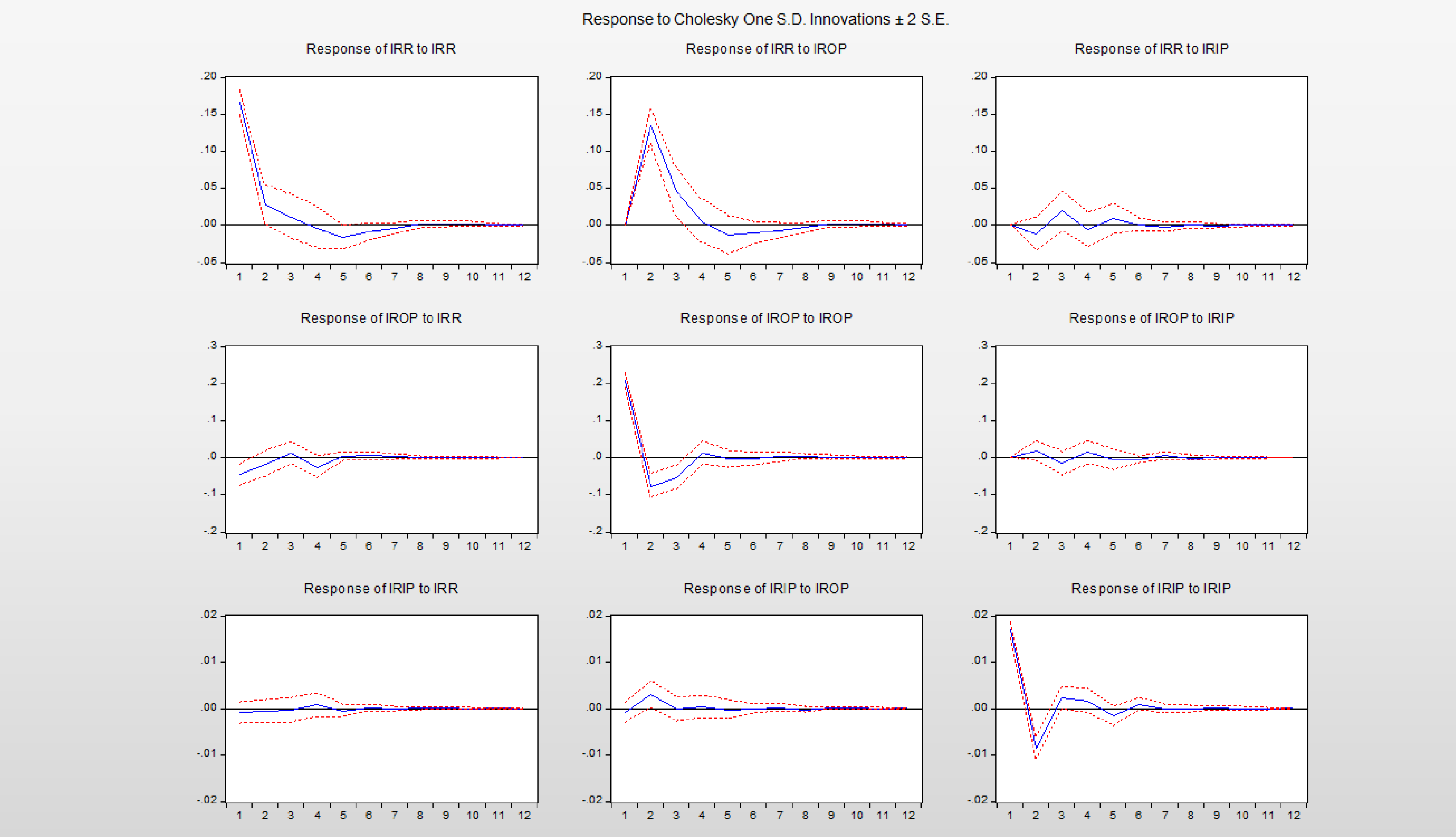
Table 3.3 – Unit Root Tests on Real Monthly Data: BRIP, RRIP, IRIP, CRIP SRIP										
ADF Tests - Levels										
Null Hypothesis: Variable has a unit root										
	Without Trend					**With Trend**				
Variable:	**BRIP**	**RRIP**	**IRIP**	**CRIP**	**SRIP**	**BRIP**	**RRIP**	**IRIP**	**CRIP**	**SRIP**
ADF test statistics:	-1.691105	-8.492900	-15.04523	-3.454683	-3.817807	-2.250376	-8.562795	-15.09909	-3.521035	-4.408756
Test critical values:										
1% level	-3.457747	-3.457747	-3.457747	-3.457747	-3.457747	-3.997083	-3.997083	-3.997083	-3.997083	-3.997083
5% level	-2.873492	-2.873492	-2.873492	-2.873492	-2.873492	-3.428819	-3.428819	-3.428819	-3.428819	-3.428819
10% level	-2.573215	-2.573215	-2.573215	-2.573215	-2.573215	-3.137851	-3.137851	-3.137851	-3.137851	-3.137851
p-values	0.4344	**0.0000*** **	**0.0000*** **	**0.0101** **	**0.0032*** **	0.4590	**0.0000*** **	**0.0000*** **	**0.0395** **	**0.0026*** **

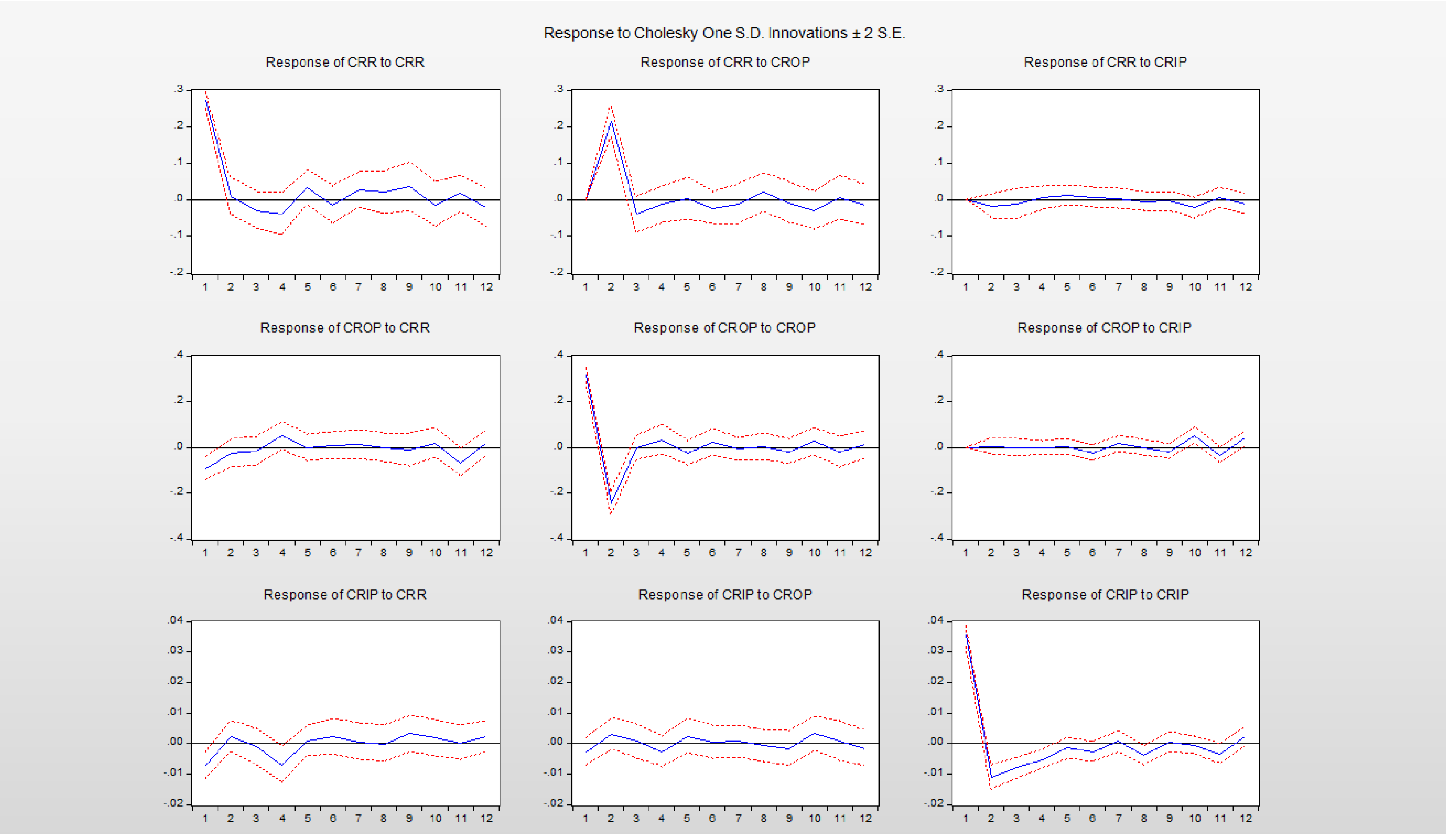
Reported are the probability values associated with the null hypothesis of the absence of a unit root in Augmented Dickey-Fuller tests.
Monthly real data over the period: February 1998 – December 2017
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

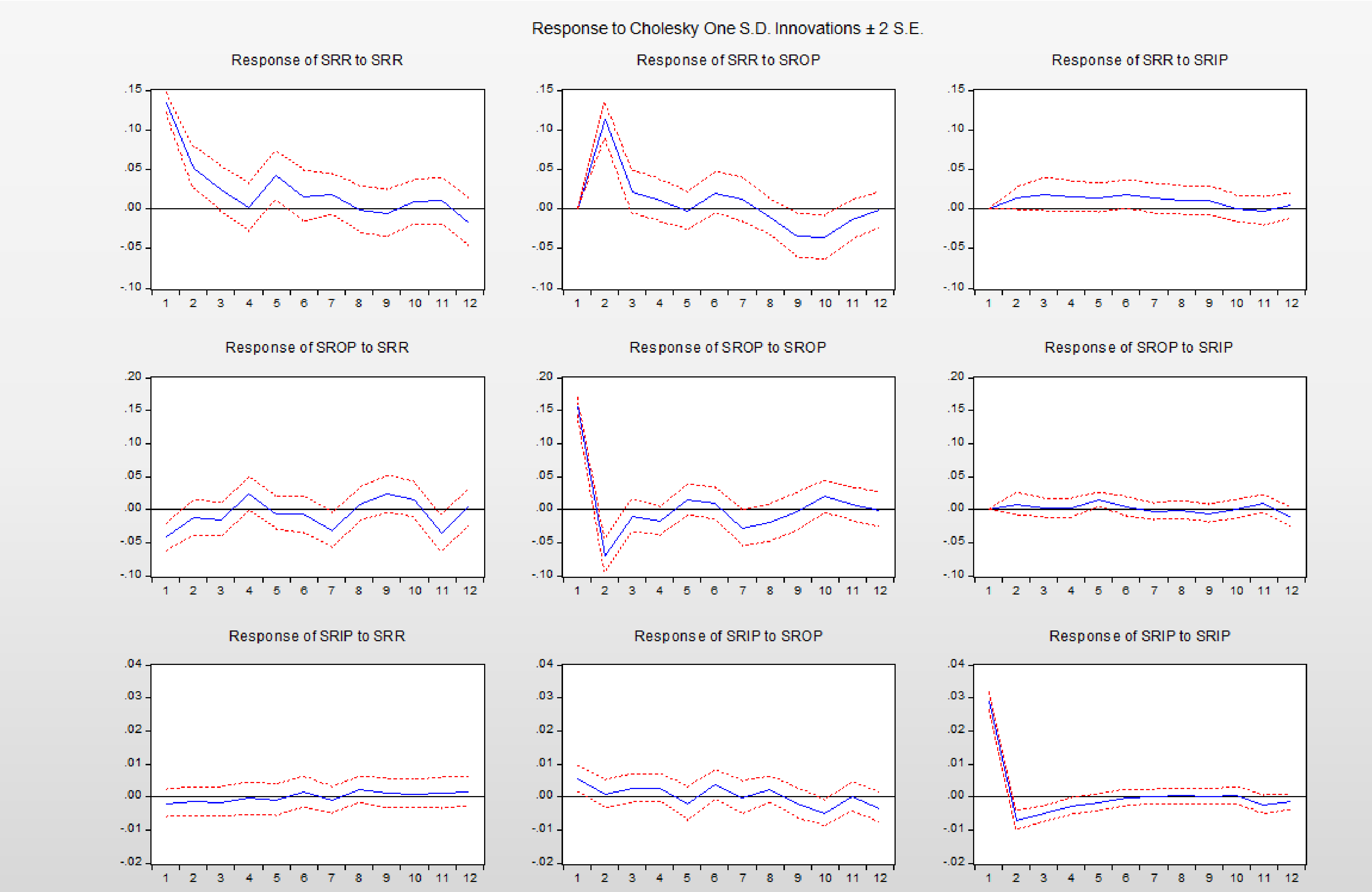
Appendix 3 – Impulse Response Function (IRF)




Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of RRR to RRR
Response of RRR to RROP
Response of RRR to RRIP
Response of RROP to RRR
Response of RROP to RROP
Response of RROP to RRIP
Response of RRIP to RRR
Response of RRIP to RROP
Response of RRIP to RRIP


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of IRR to IRR
Response of IRR to IROP
Response of IRR to IRIP
Response of IROP to IRR
Response of IROP to IROP
Response of IROP to IRIP
Response of IRIP to IRR
Response of IRIP to IROP
Response of IRIP to IRIP


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of CRR to CRR
Response of CRR to CROP
Response of CRR to CRIP
Response of CROP to CRR
Response of CROP to CROP
Response of CROP to CRIP
Response of CRIP to CRR
Response of CRIP to CROP
Response of CRIP to CRIP
.3
.2
.1
.0
-.1
-.2
.4
-.4
.04
.03
.02
.01
.00
-.01
-.02
1 2 3 4 5 6 7 8 9 10 11 12


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of SRR to SRR
Response of SRR to SROP
Response of SRR to SRIP
Response of SROP to SRR
Response of SROP to SROP
Response of SROP to SRIP
Response of SRIP to SRR
Response of SRIP to SROP
Response of SRIP to SRIP

Appendix 4 – Variance decomposition

Variance Decomposition of **BRR**: Period	S.E.	BRR	BRIP	BROP
1	0.112524	100.0000	0.000000	0.000000
		(0.00000)	(0.00000)	(0.00000)
2	0.121013	91.87984	0.796108	7.324057
		(3.36357)	(1.24549)	(3.00132)
3	0.123448	90.55658	0.844293	8.599123
		(3.78865)	(1.43013)	(3.39150)
4	0.123718	90.51439	0.922077	8.563530
		(3.88160)	(1.51836)	(3.38276)
5	0.123743	90.51511	0.921887	8.563000
		(3.89425)	(1.53462)	(3.38578)
6	0.123757	90.50580	0.921904	8.572296
		(3.90003)	(1.53780)	(3.39178)
7	0.123759	90.50490	0.922280	8.572820
		(3.90184)	(1.53968)	(3.39284)
8	0.123759	90.50490	0.922310	8.572789
		(3.90223)	(1.54014)	(3.39302)
9	0.123759	90.50489	0.922309	8.572803
		(3.90239)	(1.54030)	(3.39312)
10	0.123759	90.50488	0.922310	8.572812
		(3.90244)	(1.54036)	(3.39316)
11	0.123759	90.50488	0.922310	8.572812
		(3.90245)	(1.54038)	(3.39317)
12	0.123759	90.50488	0.922310	8.572812
		(3.90246)	(1.54039)	(3.39317)

Variance Decomposition of **RRR**:

Period	S.E.	RRR	RROP	RRIP
1	0.095885	100.0000	0.000000	0.000000
		(0.00000)	(0.00000)	(0.00000)
2	0.108064	91.65479	7.309451	1.035761
		(3.17513)	(2.99337)	(1.41717)
3	0.111640	89.06398	9.708381	1.227640
		(4.18811)	(3.83632)	(1.63221)
4	0.114609	89.00378	9.826461	1.169761
		(4.51942)	(4.21145)	(1.67671)
5	0.117389	87.02735	11.21185	1.760792
		(5.07201)	(4.89337)	(1.93437)
6	0.119199	85.00307	11.51783	3.479103
		(5.50046)	(5.30891)	(2.35043)
7	0.120752	84.17122	12.16119	3.667595
		(5.30158)	(4.94993)	(2.63554)
8	0.121095	83.94300	12.23144	3.825565
		(5.43761)	(5.01190)	(2.74478)
9	0.122056	83.42467	12.14385	4.431482
		(5.61803)	(4.96345)	(3.09350)
10	0.123827	81.45288	11.87582	6.671302
		(5.80813)	(4.87796)	(3.75808)
11	0.123962	81.34964	11.96570	6.684658
		(5.82453)	(4.88517)	(3.79734)
12	0.124546	80.84240	11.86344	7.294156
		(5.83624)	(4.90310)	(3.86956)

Variance Decomposition of **IRR**:

Period	S.E.	IRR	IROP	IRIP
1	0.165920	100.0000	0.000000	0.000000
		(0.00000)	(0.00000)	(0.00000)
2	0.215687	60.78218	38.93243	0.285390
		(4.88609)	(4.89194)	(0.62789)
3	0.221473	57.89721	41.05765	1.045136
		(5.03715)	(4.93329)	(1.12234)
4	0.221635	57.83595	41.05400	1.110046
		(5.01895)	(4.88626)	(1.30453)
5	0.222847	57.78077	40.94837	1.270868
		(5.00912)	(4.87671)	(1.40393)
6	0.223260	57.71586	41.01549	1.268644
		(5.03297)	(4.90224)	(1.42719)
7	0.223426	57.65960	41.05984	1.280563
		(5.04772)	(4.92733)	(1.43891)
8	0.223452	57.65238	41.06648	1.281132
		(5.04922)	(4.93285)	(1.44362)
9	0.223466	57.65098	41.06595	1.283069
		(5.04794)	(4.93288)	(1.45055)
10	0.223477	57.64941	41.06752	1.283067
		(5.05051)	(4.93607)	(1.45206)
11	0.223481	57.64784	41.06907	1.283091
		(5.05375)	(4.93997)	(1.45234)
12	0.223482	57.64769	41.06922	1.283089
		(5.05442)	(4.94082)	(1.45240)

Variance Decomposition of **CRR**:

Period	S.E.	CRR	CROP	CRIP
1	0.271522	100.0000	0.000000	0.000000
		(0.00000)	(0.00000)	(0.00000)
2	0.346680	61.41180	38.31906	0.269135
		(4.86003)	(4.88575)	(0.62579)
3	0.350286	60.81938	38.81873	0.361891
		(4.70940)	(4.63180)	(1.01362)
4	0.352749	61.20607	38.41637	0.377559
		(4.57286)	(4.45743)	(1.00814)
5	0.354586	61.48926	38.02993	0.480813
		(4.62961)	(4.50520)	(1.04094)
6	0.355732	61.28897	38.19197	0.519066
		(4.50406)	(4.32740)	(1.04351)
7	0.356950	61.41892	38.06114	0.519936
		(4.46995)	(4.29032)	(1.05149)
8	0.358144	61.32659	38.13791	0.535499
		(4.64171)	(4.50084)	(1.06838)
9	0.360192	61.70601	37.75109	0.542899
		(4.63300)	(4.51838)	(1.11359)
10	0.362256	61.15009	37.97753	0.872378
		(4.65422)	(4.51729)	(1.41082)
11	0.362772	61.19304	37.90933	0.897634
		(4.68910)	(4.52856)	(1.40075)
12	0.363898	61.16009	37.83408	1.005835
		(4.69025)	(4.53983)	(1.46185)

Variance Decomposition of **SRR**: Period	S.E.	SRR	SROP	SRIP
1	0.134811	100.0000	0.000000	0.000000
		(0.00000)	(0.00000)	(0.00000)
2	0.183796	61.83591	37.65181	0.512280
		(5.70436)	(5.76589)	(0.60953)
3	0.187432	61.09642	37.46153	1.442052
		(5.98545)	(6.05134)	(1.45612)
4	0.188380	60.48614	37.37502	2.138843
		(6.15643)	(6.10803)	(2.18069)
5	0.193517	62.01443	35.44946	2.536108
		(6.14431)	(6.00733)	(2.53868)
6	0.195993	61.07744	35.62707	3.295487
		(6.24491)	(6.02754)	(2.92063)
7	0.197627	60.91483	35.41299	3.672186
		(6.36397)	(6.15113)	(3.25483)
8	0.198203	60.56367	35.47694	3.959396
		(6.44172)	(6.13272)	(3.62204)
9	0.201428	58.72292	37.18110	4.095981
		(6.34680)	(6.10880)	(3.91704)
10	0.204844	56.95541	39.08402	3.960568
		(6.35636)	(6.38249)	(3.88695)
11	0.205612	56.78977	39.25892	3.951307
		(6.39753)	(6.41295)	(3.84805)
12	0.206401	57.07046	38.96576	3.963783
		(6.35467)	(6.36427)	(3.86715)

Appendix 5 – VAR estimates

VAR Lag Order Selection Criteria
Endogenous variables: **BRR BRIP BROP**
Exogenous variables: C
Sample: 1998M02 2017M12
Included observations: 227

Lag	LogL	LR	FPE	AIC	SC	HQ
0	620.8691	NA	8.68e-07	-5.443780	-5.398517	-5.425516
1	664.0888	84.91641	6.42e-07	-5.745276	-5.564222	-5.672218
2	668.8833	9.293259	6.66e-07	-5.708223	-5.391377	-5.580371
3	673.0144	7.898110	6.95e-07	-5.665325	-5.212688	-5.482679
4	683.0848	18.98746	6.89e-07	-5.674756	-5.086329	-5.437317
5	684.8369	3.257121	7.35e-07	-5.610898	-4.886679	-5.318665
6	701.5071	30.54993	6.87e-07	-5.678477	-4.818468	-5.331451
7	709.4961	14.42935	6.94e-07	-5.669569	-4.673768	-5.267749
8	717.6078	14.43676	7.00e-07	-5.661743	-4.530151	-5.205129
9	729.2564	20.42354	6.84e-07	-5.685079	-4.417696	-5.173671
10	739.6608	17.96705	6.77e-07	-5.697452	-4.294279	-5.131251
11	849.9657	187.5669	2.78e-07	-6.590006	-5.051042	-5.969011
12	1135.762	478.4260*	2.43e-08*	-9.028743*	-7.353987*	-8.352954*

* 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
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: **RRR RROP RRIP**
Exogenous variables: C
Sample: 1998M02 2017M12
Included observations: 227

Lag	LogL	LR	FPE	AIC	SC	HQ
0	843.1917	NA	1.22e-07	-7.402570	-7.357306	-7.384305
1	896.1133	103.9781	8.31e-08	-7.789544	-7.608490*	-7.716486
2	913.6828	34.05547	7.71e-08	-7.865047	-7.548201	-7.737195*
3	922.8475	17.52200	7.70e-08	-7.866498	-7.413862	-7.683853
4	930.1400	13.74973	7.81e-08	-7.851454	-7.263026	-7.614015
5	943.8907	25.56298	7.50e-08	-7.893310	-7.169092	-7.601078
6	948.0997	7.713314	7.82e-08	-7.851099	-6.991089	-7.504072
7	957.5536	17.07527	7.80e-08	-7.855097	-6.859297	-7.453277
8	961.3042	6.675190	8.17e-08	-7.808848	-6.677256	-7.352234
9	971.2182	17.38218	8.12e-08	-7.816900	-6.549518	-7.305493
10	987.2861	27.74718	7.64e-08	-7.879172	-6.475999	-7.312971
11	1008.653	36.33277	6.86e-08	-7.988130	-6.449166	-7.367135
12	1019.406	18.00045*	6.77e-08*	-8.003574*	-6.328819	-7.327786

* 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
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: **IRR IROP IRIP**
Exogenous variables: C
Sample: 1998M02 2017M12
Included observations: 227

Lag	LogL	LR	FPE	AIC	SC	HQ
0	632.0342	NA	7.86e-07	-5.542151	-5.496888	-5.523887
1	711.7016	156.5272	4.22e-07	-6.164772	-5.983717*	-6.091714*
2	725.7961	27.31973	4.03e-07	-6.209657	-5.892812	-6.081806
3	736.2081	19.90659	3.99e-07*	-6.222098*	-5.769461	-6.039452
4	741.0426	9.115264	4.13e-07	-6.185397	-5.596970	-5.947958
5	744.4940	6.416212	4.34e-07	-6.136511	-5.412292	-5.844278
6	749.4690	9.117185	4.50e-07	-6.101048	-5.241039	-5.754022
7	752.8343	6.078452	4.73e-07	-6.051404	-5.055604	-5.649584
8	756.1916	5.974961	4.98e-07	-6.001688	-4.870096	-5.545074
9	760.6215	7.767040	5.19e-07	-5.961423	-4.694041	-5.450016
10	769.1076	14.65432	5.22e-07	-5.956895	-4.553721	-5.390694
11	794.3340	42.89600	4.53e-07	-6.099859	-4.560894	-5.478864
12	806.8865	21.01304*	4.40e-07	-6.131158	-4.456403	-5.455370

* 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
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: **CRR CROP CRIP**
Exogenous variables: C
Sample: 1998M02 2017M12
Included observations: 227

Lag	LogL	LR	FPE	AIC	SC	HQ
0	62.05892	NA	0.000119	-0.520343	-0.475079	-0.502078
1	135.2802	143.8621	6.77e-05	-1.086169	-0.905115	-1.013111
2	175.2795	77.53170	5.16e-05	-1.359291	-1.042445*	-1.231439
3	185.4138	19.37562	5.10e-05	-1.369284	-0.916648	-1.186639
4	188.5382	5.890879	5.38e-05	-1.317517	-0.729089	-1.080078
5	198.3324	18.20774	5.34e-05	-1.324514	-0.600296	-1.032281
6	203.8605	10.13088	5.51e-05	-1.293925	-0.433916	-0.946899
7	218.4007	26.26192	5.25e-05	-1.342737	-0.346937	-0.940917
8	229.6987	20.10762	5.15e-05	-1.362985	-0.231393	-0.906371
9	239.3821	16.97778	5.12e-05	-1.369005	-0.101623	-0.857598
10	306.9752	116.7248	3.06e-05	-1.885244	-0.482071	-1.319043
11	359.0118	88.48507	2.10e-05	-2.264421	-0.725457	-1.643426
12	409.0427	83.75217*	1.47e-05*	-2.625927*	-0.951172	-1.950139*

* 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
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Lag Order Selection Criteria
Endogenous variables: **SRR SROP SRIP**
Exogenous variables: C
Sample: 1998M02 2017M12
Included observations: 227

Lag	LogL	LR	FPE	AIC	SC	HQ
0	397.6703	NA	6.20e-06	-3.477272	-3.432008	-3.459007
1	505.8664	212.5791	2.59e-06	-4.351246	-4.170191*	-4.278188
2	527.2412	41.43132	2.32e-06	-4.460275	-4.143429	-4.332423
3	540.1571	24.69384	2.24e-06	-4.494776	-4.042140	-4.312131
4	548.4911	15.71347	2.26e-06	-4.488909	-3.900481	-4.251470
5	560.4127	22.16258	2.20e-06	-4.514649	-3.790431	-4.222417
6	570.5183	18.51954	2.18e-06	-4.524391	-3.664381	-4.177364
7	575.1798	8.419493	2.26e-06	-4.486166	-3.490366	-4.084346
8	591.7091	29.41777	2.12e-06	-4.552503	-3.420912	-4.095890
9	593.8961	3.834345	2.26e-06	-4.492476	-3.225094	-3.981069
10	616.3177	38.71936	2.01e-06	-4.610729	-3.207556	-4.044528
11	696.6593	136.6161	1.07e-06	-5.239289	-3.700325	-4.618294
12	774.2173	129.8328*	5.87e-07*	-5.843324*	-4.168569	-5.167536*

* 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
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion