THE CREDIT CHANNEL OF MONETARY POLICY TRANSMISSION IN THE SELECTED EMERGING MARKETS

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DECLARATION

I declare that this dissertation is the product of my own effort. I have, to the best of my knowledge and belief, acknowledged all the resources of information in line with normal academic conventions. I further certify that the dissertation is original, and has not been submitted before at this, or in any other, university for the award of any degree for the purpose of obtaining a degree.

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Lwazi Senzo Ntshangase   Date: 28 January 2019

ABSTRACT

The credit channel has been investigated extensively in developed countries yet few studies have been conducted in emerging, developing and in less developed countries. This research employs a panel VAR model and five country-specific-VAR models to determine the effectiveness of the credit channel in the selected inflation targeting emerging markets (Brazil, Chile, Mexico, Russia and South Africa), that have implicitly or explicitly embraced the inflation targeting monetary policy framework, over the period 2000Q1-2016Q4. The balance sheet channel is not investigated due to a lack of data in the available database. The study adopted the traditional bank lending channel theory by Bernanke and Blinder (1988), according to which monetary policy rate shocks are propagated to economic variables through credit. The control variables in the models include gross domestic product, bank loans to the private sector, monetary policy rate, money supply, consumer price index and the nominal exchange rate. IRF are generated from the panel VAR model as averages, and compared to the IRF generated from each VAR model. Overall, the bank lending channel and interest rate channel were found to be according to theory and effective with a 1.5 period lag in the selected emerging markets. It is advisable for the five emerging countries to continue to develop innovations for greater efficiency in the conducting of monetary policy; this will further assist the more inelastic variables to become more responsive. The bank lending channel was found to be more effective in Brazil and Russia and the magnitudes of the decline of bank loans are quite similar for both countries, where, after the third period, the decline is about o.2% for a 1% initial shock to interest rates. However, the bank lending channel in South Africa, Chile and Mexico was found to be ineffective, perhaps due to the high indebtedness of consumers, perhaps arising out of financialization reasons. In the South African context, the authorities ought to revisit the National Credit Act to assess why bank loan issues are inelastic to monetary policy tightening.The causality patterns suggests that all variables Granger cause each other.

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LIST OF ABBREVIATIONS AND ACRONYMS

3SLS -	Three-Stage Least Squares
5SEE -	Five South East European
ADF -	Augmented-Dickey Fuller test
AIC -	Akaike Information Criterion
BCB -	Central Bank of Brazil
BVAR -	Bayesian Vector Autoregressive
CBC -	Central Bank of Chile
CMN -	National Monetary Council
COPOM -	Brazil Monetary Policy Committee
ECB -	European Central Bank
FAVAR -	Factor-Augmented Vector Autoregressive
FPE -	Final Prediction Error
GDP -	Gross Domestic Product
GMM -	General Moments of Methods
HQC -	Hannan-Quinn Information Criterion
IFS -	International Financial Statistics
IMF -	International Monetary Fund
IPS -	Im, Pesaran-Shin
IRF -	Impulse Response Function
IS -	Investment-Savings
IT -	Inflation Targeting
LLC -	Levin, Lin and Chu
MPC -	Monetary Policy Committee
OLS -	Ordinary Least Squares

PC -	Philips Curve
PP -	Philips-Perron
PVAR -	Panel Vector Autoregressive
PVAR -	Panel Vector Autoregressive Model
PVECM -	Panel Vector Error Correction Model
RBNZ -	Reserve Bank of New Zealand
SARB -	South African Reserve Bank
SBIC -	Schwarz Bayesian Information Criterion
TR -	Taylor Rule
TVAR -	Threshold Vector Autoregressive
UK -	United Kingdom
USA -	United States of America
VAR -	Vector Autoregressive Model
VECM -	Vector Error Correction Model

CHAPTER 1: INTRODUCTION

1.1 Background

The process through which monetary policy shocks are initiated, amplified and transmitted through real economic variables, especially via the credit channel, has always been a key topic in monetary economics. The credit channel of monetary policy transmission was first examined by Bernanke and Blinder (1988) in the United States. In their paper, Bernanke and Blinder propounded a model which demonstrated how monetary policy shocks are transmitted to economic variables through credit, which is also referred to as the “credit view”. The credit channel is an extension of the “money view”, which would arise when money and bonds are perfect substitutes. Recent empirical literature that has examined the credit channel include the authors Shkokani (2016), Matousek and Solomon, (2018), and, Ippolito, Ozdagli and Perez-Orive (2018). Bernanke and Gertler (1995) defined the credit channel as the process by which monetary policy shocks influence economic activity and prices through credit.

New Zealand began setting inflation targets in the 1980s, however, in February 1990 the Reserve Bank of New Zealand (RBNZ) Act came into effect, making it the first country to formally adopt inflation targeting. Since then, many developed and emerging market economies began adopting the Inflation Targeting Monetary Policy Framework (ITMPF). In February 2000, South Africa officially adopted ITMPF. Chile was the second country after New Zealand to adopt the inflation targeting regime in the world. Mexico and Brazil adopted the inflation targeting regime in 2001, and 1999, respectively, while Russia has moved towards the fully-fledged inflation targeting regime since 2006. Output and price volatility have since dampened.

Under the inflation targeting regime, monetary policy accountability and transparency have improved over the years. Consistency in fiscal monetary policy and constant communication with the public enhance prudent monetary policy. Since adoption, an inflation targeting regime has proved to be a success in these selected emerging markets (Korhonen & Nuutilainen, 2017). South Africa, together with Chile, Mexico, Brazil and Russia, has tended to respond in a similar fashion to international shocks, for example, when the dollar strengthens, or when investor sentiment turns in favour of, or against, emerging markets as a group. Moreover, for these mentioned countries, sufficiently large time data are available on the IMF database. Additionally, there are few studies that have investigated the bank lending channel in emerging markets, both individually and as a group, during the inflation targeting regime. Hence, this study has endeavored to apply a VAR (Vector Autoregresssion) model for each country, which is estimated to observe how economic variables respond to monetary policy shocks during the period. Furthermore, the study has estimated the novel panel VAR model to assess the average response of these countries as a group.

The central bank of each selected emerging market utilizes the short-term interest rate to control prices and economic activity. The main objective of inflation targeting is to maintain a stable price level, which in turn reduces exchange rate volatility, induces low stable policy interest rates and thus sustains economic growth. Most studies have shown that prices and economic activity are responsive to the monetary policy rate (Krainer, 2014; Vithessonthi *et al*., 2017).

Monetary policy operates through numerous channels: the interest rate channel, the assets price, the exchange rate and the credit channel (Khundrakpam, 2013). The present study examines the importance of the credit channel in selected emerging markets (Brazil, Chile, Mexico, South Africa, and Russia) for the period 2000 to 2016.

The credit channel consists of two subtopics: the balance sheet channel and the bank lending channel. The credit channel is one mechanism that amplifies the transmission of monetary policy because of credit market frictions such as asymmetric information (Mora, 2014). The bank lending channel is the process through which restrictive monetary policy rate influence bank loans supply by draining their reserve requirement, due to imperfect substitute (Bernanke & Gertler, 1995). Hence, banks reduce the supply of loans due, resulting in a decline of capital formation and to low economic output. The two main conditions for the bank lending channel is that firms and household must be dependent on bank loans for credit and also there must also be an imperfect substitute for bank loans (Bernanke & Gertler, 1995). According to an empirical literature review of the credit channel, there are three characteristics of banks that influence the bank loans responsiveness to monetary shocks: bank liquidity, asset size and bank capitalization (Cantero-Saiz *et al*., 2014; Ciccarelli *et al*., 2015; Kashyap & Stein, 2000).

The balance sheet channel is the responsiveness of the statement of financial position (liabilities or deposits and assets or loans) of borrowers to monetary policy innovations (Özlü & Yalçın, 2012; Ciccarelli *et al*., 2015; Kashyap & Stein, 2000). Restrictive monetary policy directly weakens the financial position of borrowers by decreasing their net cash flow because of the high-interest rate expenses and also, by decreasing borrower's collateral values due to a reduction of assets prices (Shkokani, 2016). Monetary policy rate operates through both the balance sheet channel and the bank lending channel since banks are both lenders and borrowers at the same time (Shkokani, 2016). An empirical literature review on the credit channel has found bank lending to be the most effective channel in the transmission of monetary policy, relative to the balance sheet channel (Matousek & Solomon, 2017; Heryán & Tzeremes, 2016; Vithessonthi *et al*., 2017; Ciccarelli *et al*., 2015).

There is limited literature on the credit channel in the selected emerging markets and in less developed countries. Extensive work on the responsiveness of bank loan supply on monetary policy decisions has been conducted in European countries and the United States of America (Dajcman, 2016; Creel, 2016; Heryan & Tzeremes, 2016; Vera, 2012; Bernanke & Gertler, 1995; Kashyap & Stein, 2001). Also, there are few papers that have ascertained the credit channel in emerging countries that have adopted the inflation targeting regime. The study of the credit channel of monetary policy transmission was popularized by Bernanke and Blinder (1988), who found the presence of the bank lending channel in the USA. Recent studies that have examined the credit channel of monetary policy transmission include Shkokani (2016) and Mtousek and Solomon (2018).

Kashyap and Stein (2001) made a significant contribution to the traditional bank lending channel. They employed microdata of firms' balance sheets to investigate the existence of the bank lending channel in the USA. The paper included firm characteristics such as size, liquidity, and capitalization. Firm features were found to influence monetary policy propagation in the USA. Small, less liquid firms with limited capital, are more vulnerable to monetary policy shocks, as they are unable to substitute bank loans. A large listed firm seems to be less responsive to monetary policy as they can obtain capital from other sources. In another study, Rey (2015) employed panel data of banks for the period 1996-2001 in the USA. The study found bank characteristics to be effective in the propagation of monetary policy transmission.

This study attempts to fill the gap in the literature by assessing the impact of tightening monetary policy shocks on credit channel in the selected emerging market economies, with the control variables being bank loans, money supply (M2), exchange rate, output, inflation, and the policy lending rates. This study makes an important contribution to the understanding of the impact of banking lending channels on growth, monetary policy, exchange rates, especially since the 2008 global credit 'crunch' and the ensuing quantitative easing, followed by its reversal in the form of tapering, has given rise to a series of monetary policy shocks which has had debilitating effects on emerging market economies.

The credit channel has been investigated extensively in developed countries, yet there are limited studies that have been conducted in the selected emerging, developing and less developed countries. Apergis and Christou (2015) investigated the credit channel of monetary policy transmission in the United Kingdom through the Quantile Regression Method (QRM) and the Generalized Method of Moments (GMM). The study found the operation of the bank lending to be weak as the short-term interest rate approached zero. Mwabutwa *et al*. (2016) conducted a similar study in Malawi using a Bayesian Time-Varying Vector Autoregressive and found the bank lending channel to be operational with a long lag.

The majority of the papers that have estimated the bank lending channel have employed a reduced VAR model (Fan & Jianzhou, 2011; Ekomane & Benjamin, 2016; Jacobsen, 2016; Abuka, 2015; Mengesha & Holmes, 2013; Bernanke & Gertler, 1995). According to Bernanke and Gertler (1995), the impulse response is suitable for estimating monetary policy shocks. However, the VAR model is criticized for wasting the degree of freedom with short sample data. The present study estimates a panel VAR and five VAR models for each selected country. A panel VAR model is superior relative to a VAR model since it does not waste the degrees of freedom. In addition, in one model, one can examine the shocks of monetary policy to other economic variables of different emerging countries.

The credit channel is vital in emerging countries since it determines the level of credit to firms and households, subsequently resulting in a capital formation increase in demand and consumption. Firms in the selected emerging countries seem to have little substitute for bank loans. Brazil and South Africa was downgraded in September 2015 and in November 2017 respectively, which resulted to reduction in foreign direct investment. Since the recession of 2007-2009, emerging markets experience tightening monetary policy with high-interest rate and out of target inflation rate. The adverse effect of high short-term interest rate is the high cost of credit, hence low investment, and economic growth. One of the objectives of the paper is to investigate the bank lending channel in an environment with high short-term interest rate and the effective and magnitude of the lag.

Emerging markets are characterized by high inflation rates and low economic growth, despite the objections of inflation targeting framework being to stabilize general price level and economic growth. Also, the main course of a high inflation rate is the quantitative easing practice by developed countries with a low-interest rate. The quantitative easing resulted in emerging countries with a large volume of currencies, which they could not manage. In contrast, developed countries face an obstacle of low inflation and interest rate approaching zero. The bank lending channel seems to be less effective in markets with low-interest rate and in economies with interest rate approaching zero.

There are numerous factors that could weaken the operation of the bank lending channel. The existence of the nonbank intermediaries violates the condition of no substitute to bank loans. In the context of the selected emerging markets, firms and household depend on bank loans for credit, hence the bank lending channel is effective. However, in developed countries, firms and household have access to other forms of credit, and as such the bank lending channel is less effective. The ability of banks to adjust their holdings of securities, rather than loans, in response to a decline in reserves, may cause the bank lending channel to be ineffective. The commercial banks in emerging markets are still in the development phase, hence such conditions may not apply. Another threat to the operation of bank lending is the bank's ability to raise funds with a non-reserves form of financing. Lastly, the existence of risk-based capital requirements is a treat to the operation of the bank lending channel.

1.2 The problem statement

There seems to be inconclusive evidence on the existence of the bank lending channel in emerging markets. Simpasa *et al*. (2014) and Favero *et al*. (1999) did not find the existence of the bank lending channel in Zambia and Germany, respectively. On the other side, there are numerous studies that have found the existence of the bank lending channel in emerging markets (Gambacorta & Marques-Ibanez, 2011; Ekomane & Benjamin, 2016; Caporale *et al*., 2016; Obafemi & Ifere, 2015; Ogbulu & Torbira, 2012). The present study employs the panel Vector Autoregressive Model (PVAR), unlike most recent studies that have investigated the bank lending channel of monetary policy in emerging and developed countries which utilized the Vector Autoregressive Model (VAR). The panel VAR model is one of the few advanced models that do not wastefully consume more degrees of freedom such as the VAR model. Also, in one study the researcher analyzed the impulse response of monetary policy shocks to other economic variables in different countries with unique characteristics. Khundrakpam (2013) employed the VAR and the Rolling Regression in India to investigate the bank lending channel of monetary policy transmission. The study found the result to be consistent with the theory of the bank lending channel.

Most papers have found the importance of the bank lending channel in transmitting monetary policy in emerging markets, however, there seem to be differences in evidence on the effectiveness and the magnitude of the lag of monetary policy transmission. Catão and Pagan (2009) identified monetary transmission to operate with a shorter lag in Brazil and Chile, compared to developed countries. Monetary policy transmission operated with a shorter timeframe of less than five quarters. Salachas *et al*. (2017) investigated the credit lending channel of monetary policy transmission for the pre and post financial crisis of 2007-2009. The bank lending channel was effective in the transmission of monetary policy during the pre and post financial period. Also, the unconventional monetary policy which was applied after the recession was effective in inducing bank balance sheet. There are numerous studies that have investigated the importance of the credit channel in developed countries, however, there are relatively few studies that have been conducted in emerging countries and in less developed countries (Mahathanaseth & Tauer, 2018).

1.3 Objectives of the study

The aim of this study is to assess the impact of monetary shocks on credit channel for a selection of emerging market economies, with the control variables being exchange rate, output, inflation, and the policy lending rates. The objectives of the study are as follows:

i. To determine the effect of monetary policy interest rate shocks on bank loans supply in the selected emerging markets.
ii. To investigate the effect of monetary policy interest rate shocks on national output in the selected emerging markets.
iii. To identify the effect of the monetary policy interest rate shocks to the inflation rate in the selected emerging markets.

1.4 The hypothesis of the study

The hypothesis of the study is as follows:

(i) H_0 : Monetary policy interest rate shocks have a negative effect on the supply of bank loans in the selected emerging markets

(ii) H_0 : Monetary policy interest rate shocks have a significant effect on national output in the selected emerging markets

(iii) H_0 : Monetary policy interest rate shocks have a significant effect on the inflation rate in the selected emerging markets

1.5 The significance of the Study

The credit channel of monetary policy transmission affects bank loan supply using the central bank policy rate, due to imperfect competition. Tightening monetary policy reduces bank loans supply by draining the required reserves and deposits. The understanding of the timing and duration of how the central bank interest rate induces credit, and hence economic variables, is important to policymakers. It is also vital for the central bank to be able to manage effectively the access and level of credit in an economy. Proper management and access to credit will enhance investment, aggregate demand, and economic growth. Bank credit in the selected emerging markets is the main source of credit, because of the tough economic conditions they are experiencing. Most of the selected countries have low economic growth and they are in a recession. There are limited studies that have investigated the effect of the credit channel in emerging markets yet; there are many studies that have been conducted in developed countries. This study will employ a recent, advance econometric model to analyze the impulse response of monetary shocks in emerging markets with the high-interest rate.

1.6 Organization of the study

This dissertation consists of five chapters. Chapter one is divided into four major subtopics: the background, the problem statement, objectives, hypotheses and the significance of the theses. The main purpose of this chapter is to discuss the background of the credit channel in emerging markets. The topic of the credit channel of monetary policy was first analyzed in the early 1990s by (Bernanke and Blinder (1988). Even though recent studies have been conducted in developed countries there seem to be a lack of literature review on emerging markets. The paper will attempt to contribute to the existing literature by employing a panel VAR model, which treats all variables as an endogenous variable and add a cross-sectional characteristic.

Chapter two details the literature review of the theses. In addition, it discusses the different channels of monetary policy transmission mechanism and the monetary framework in the selected emerging markets. The main theories that are considered include the credit channel theory of Bernanke and Gertler (1995). Other theories of monetary policy to be considered by the study involve the bank loss function, the Taylor rule, and the IS-LM model. The monetary policy rule employed in the selected emerging markets is discussed.

The empirical literature review is also discussed in the chapter. The empirical literature is divided into two major subtopics: empirical literature from developed countries, and empirical literature from emerging, developing and less developed markets. Most of the studies on the credit channel of monetary policy seem to be in line with the theory of traditional credit channel by (Bernanke and Blinder (1988). Other forms of credit will also be analyzed and the inflation targeting framework will also be discussed.

Chapter three of the study reviews the methodology and data techniques. The panel VAR model is estimated the over the period 2000Q1-2016Q4. The control variables include bank loans, nominal effective exchange rate, output, money supply, and inflation rate. Also, a Granger Causality is estimated to examine the direction of causality among variables. In addition, five VAR models are estimated for each country as robustness checks and to compare the impulse response with the panel VAR model. Panel unit roots are tested through the Lm, Pesaran, and Shin Tests (2003) and panel tests of cointegration are tested through the Pedroni tests. The lags are selected through the Akaike Information Criterion, the Schwarz's Information Criterion, and the Hannan-Quinn Criterion.

Chapter four examines the empirical results of the panel VAR model and the results for the five VAR models. Most studies that have estimated the credit channel have utilized the Vector Autoregressive model, whereas no study has utilized the panel VAR to investigate the bank lending channel in the selected emerging markets.

Chapter five discusses the policy recommendation and summary of the dissertation.

CHAPTER 2: THEORETICAL FRAMEWORK

2.1. Introduction

The chapter reviews both the theories and the channels of monetary policy transmission in the selected emerging markets. According to literature, there are five credit channels of monetary policy transmission: the credit channel, the interest rate channel, the exchange rate channel, the asset price channel and the wealth channel (Mishkin, 1996; Nwosa & Saibu, 2015). The credit channel consists of two subsections: the bank lending channel and the balance sheet channel (Matousek & Solomon, 2018). This study applies the traditional bank lending channel theory by Bernanke and Blinder (1988) to estimate a panel VAR and five VAR models for the selected emerging markets. The bank lending channel theory is an extension of the IS-LM model, according to which monetary policy shocks are amplified to economic variables through credit (Mishkin, 2001).

2.2. Theoretical framework

There are numerous theories that discuss the credit channel of monetary policy transmission. Most papers follow the theory of credit channel (Bernanke, 1993, Bernanke & Blinder, 1988, Bernanke *et al*., 1995). According to their findings, contractionary monetary policy induces bank lending through the reduction of banks' required reserves, hence, in response, banks increase the lending interest rate which decreases the supply of loans. There are five channels of monetary policy: the interest rate channel, the credit channel, the asset price channel, the wealth channel and the exchange rate channel. The credit channel consists of two main channels: the balance sheet channel and the bank lending channel. Chapter 2 will begin by discussing the IS-LM model, followed by the Taylor rule, and the bank loss function. Lastly, the different channels of monetary policy will also be reviewed.

2.2.1. The IS-LM Model

The IS-LM model, introduced by Hicks (1980), is assumed to be an appropriate mechanism for analyzing how monetary policy is amplified to national income and output. The IS-LM model is defined as the interaction in the goods market and in the money market for a particular level of money supply, taxes, government spending and the price level (Mankiw, 2014). The IS curve determines the equilibrium in the goods markets, whereas the LM represents the equilibrium in the money market. The IS curve represents the combinations of interest rate that are consistent with equilibrium in the commodity market. The IS curve may also be explained as a curve that determines how national output varies with different interest rate level. A rise in interest rate induces a fall in investment and consumption and hence, a fall in aggregate output. The IS equation may be specified as follows:

$$Y_t - Y_t^* = -c(r_{t-1} - r^*) \tag{1}$$

Where r_{t-1} is the real interest rate; r^* is the equilibrium real interest rate; and c is a parameter that relates how output responds to the interest rate shocks. Contractionary monetary policy raises interest rates which leads to a fall in investment and hence, output. The IS equation is used in the derivation of the money rule. The LM model shows the relationship between interest rate and the levels of income that arises in the market for money balance. The IS-LM model represents interest rate and money to economic output by combining the elements of the liquidity preference and those of the Keynesian cross. The Keynesian cross is a model that determines how aggregate income is ascertained by government spending and by household consumption.

The theory of liquidity preference gives the background of how the LM model is explained. It explains how interest rates influence the demand and supply for money. The LM curve relates the positive relationship income and the level of interest rate that arises in equilibrium in money balance. Mankiw (2014) disputed that money supply is not ascertained by interest rates, but higher interest rates make the cost of holding money more expensive and hence decrease the demand for money.

The IS-LM model may be defined as a mechanism through which the monetary policy transmission operates through changes in the interest rates (Meltzer, 1995, Mankiw, 2014). They argued that contractionary monetary policy increases the short-term interest rate, and hence a decline in investment, consumption, price level and in national income. Bernanke and Blinder (1988) used the IS-LM model to derive variables to be used in the estimation of a VAR model for the credit channel of monetary policy transmission in Botswana. The variables selected were: aggregate economic activity, inflation rate, central bank policy interest rate, the exchange rate, and money supply. The present study will employ similar variables except for the money supply. Most recent studies have utilized the IS-LM model as a basis for the traditional bank lending channel (Mahathanaseth & Tauer, 2018, Anwar & Nguyen, 2018; Afrin, 2017).

2.2.2. The Taylor Rule

The major objective of the monetary policy is to manage low unemployment, price stability, and sustainable economic activity. The Taylor Rule was propounded by John B. Taylor in 1993. Kasaï and Naraidoo (2013) defined the TR as a mechanism through which the central bank of a nation determines the short-term interest rate to induce prices and economic growth. The TR may be represented by the following function:

$$r^n = \pi_t + r^* + \beta_\pi(\pi_t - \pi^*) + \beta_y(Y_t - Y_t^*) \tag{2}$$

Where: r^n is the nominal interest rate; π is the current inflation rate; r^e is the equilibrium real interest rate; $(\pi - \pi^*)$ is the inflation gap; π^* is the target inflation rate; $(Y_t - Y_t^*)$ is output gap; Y_t^* is potential output; and β_π and β_y are positive parameters that represent the relative weights the central places to inflation and output respectively to achieve its objectives. The central bank raises the nominal interest rate in response to positive deviations of inflation from its target and economic activity from its potential level.

The Taylor rule consists of the following criticisms: (1) the rule does not consider the impact of exchange rate adjustment. This is a disadvantage since small open economies do not operate in isolation; their nominal interest rate is affected by external factors; (2) the Taylor rule is a backward-looking approach, whereas monetary policy is a forward-looking rule. In the determination of the nominal interest rate policymakers adjust interest rate relative to expected inflation changes; and lastly (3) it is challenging to measure the output gap. A modified version of the Taylor rule consists of the smoothing of an interest rate. Also, the most recent estimation of the Taylor rule includes other variables, such as the exchange rate, and it is also estimated in a forward-looking approach.

2.2.3. The Central Bank Loss Function

Monetary policymakers utilize the short-term interest rate to induce inflation rate and national output. Most emerging markets adopted Inflation targeting framework during the early 1990s. Under inflation targeting, monetary policy uses the short-term interest rate to influence economic variables. The central bank of each country sets the short-term interest rate that minimizes the central bank's loss function. The bank loss function is defined as the trade-off between price stability and the stability in the real economy. The bank's loss function may be written as:

$$L = (Y_t - Y_t^*)^2 + (\pi_{t+1} - \pi^*)^2 \quad (3)$$

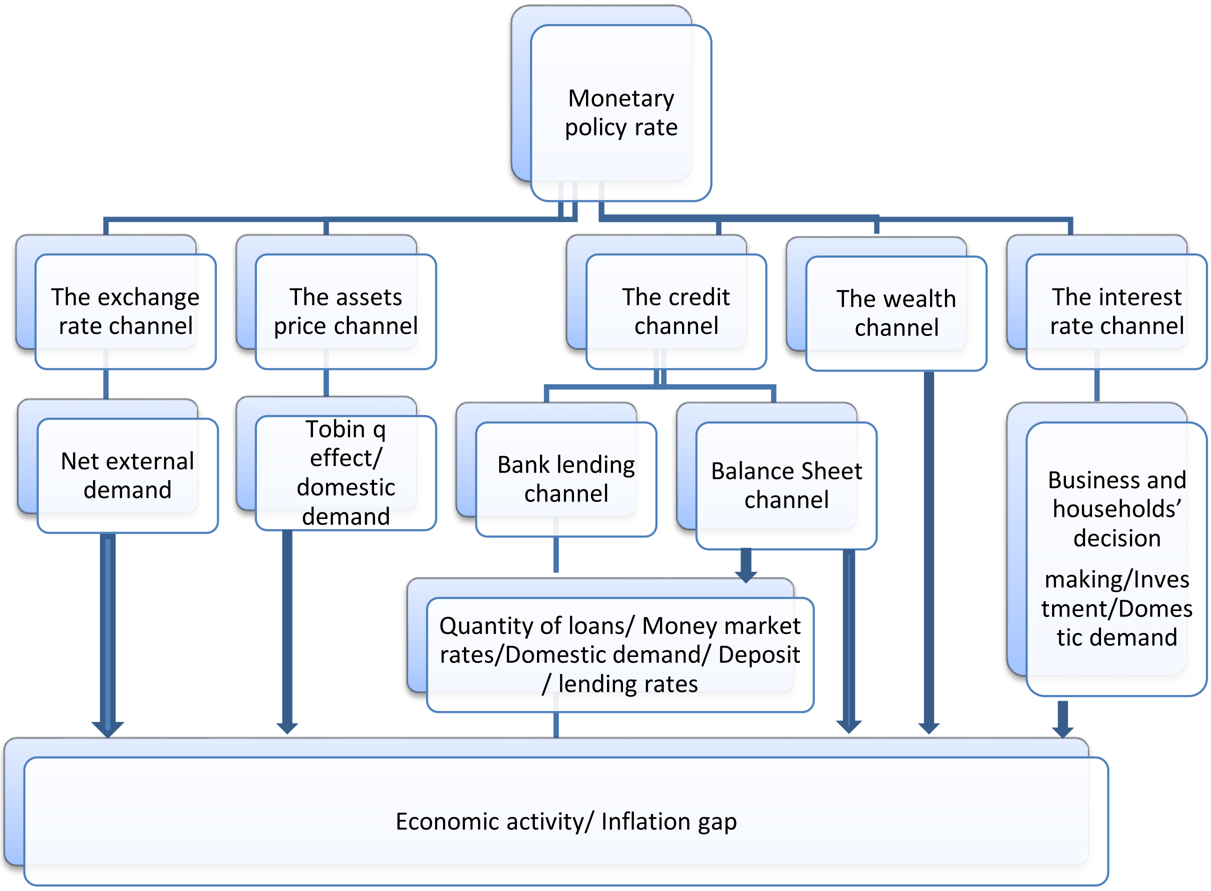
The bank loss function assumes that the central bank attempts to reduce the deviation of output (Y_t) from its potential output (Y_t^*) and it also minimizes the difference between current inflation (π_{t+1}) and the target inflation rate(π^*). The central bank raises the interest rate to restore positive deviation of inflation to its target. However, the central bank decreases the nominal interest rate when output is less than its potential output. A large deviation of inflation from its target rate is not preferred by the central bank. Also, large differences between output and potential output are equally less preferable by the central bank (Kasaï & Naraidoo, 2013).

Through the process of minimizing, the central bank affects the bank loss function indirectly when it employs monetary policy tightening to restore inflation to its target. The tightening monetary process drains the required reserve by banks, hence minimizing the supply of loans by banks (Bernanke & Gentler, 1995).

2.4. Channels of Monetary Policy Transmission Mechanism

The monetary policy transmission mechanism affects the economy through numerous channels such as the interest rate channel, the asset price channel, the credit channel, the wealth channel and the exchange rate channel (Mishkin, 2001). The channels explain theoretically how monetary policy rate affect the general price level and economic activity. The effectiveness of the various channels of monetary policy is different in numerous countries, due to the structure of the economy and the level of development of financial markets (Munyengwa, 2012). It is important for policymakers to understand the different channels of monetary policy transmission so that it will be effective to its objective of stabilizing inflation and maintaining a stable output.

In most empirical literature, the interest rate channel is most effective in the propagation of monetary policy relative to other channels (Chong *et al*., 2006, Wulandari, 2012, Brissimis *et al*., 2014, Krainer, 2014). The credit channel is divided into two subsections: the bank lending channel and the balance sheet channel. The bank lending channel was propounded by Bernanke and Blinder (1988) and it is defined as the amplification of monetary policy through bank loans to other economic variables (Matousek & Solomon, 2018). Figure 2.1 below depicts the hierarchical structure of the monetary policy transmission mechanism. The upper face illustrates the monetary policy interest rate, followed by the different channels of monetary policy transmission.



Source: Petursson (2001)

Figure 2.1: The channels of monetary policy transmission mechanism

2.4.1. The Interest Rate Channel

The interest rate channel is referred mostly in literature as the main effective mechanism of transmission of a monetary policy decision to economic variables. Borio and Gambacorta (2017) argued that tightening monetary policy will cause an increase in the interest rate. Hence, rising interest rates lead to high cost of capital. It also causes a reduction in investment, consumption, followed by a decline in aggregate demand and inflation. Mishkin (1995) and Mies and Tapia (2003) argued similarly concerning the interest rate channel. They advocated that a restrictive monetary policy increase the nominal policy rate. In response to an increase in nominal interest rate, the real interest rate will be induced to rise because of an imperfect alteration mechanism in the economy. They argued that investment and consumption will fall, due to the high cost of capital. As a result, aggregate output and inflation decline.

The IS-LM model assumes that changes in financial assets, which are bonds and money, affect the long-term interest rate, which in turn can influence prices and aggregate output (Nwosa Philip & Saibu Olufemi, 2015). Even though most literature found the interest rate to be the most effective channel in emerging and developed countries, Shah (2011) however found the exchange rate to be the most effective channel in India. In addition, a rise in interest rate may influence the economy in another form. It may act as a catalyst for more savings. The opportunity cost of holding money relative to saving is high when the interest rate increases. This implies consumption and aggregate demand will fall and subsequently inflation.

Wulandari (2012) investigated the importance of the interest rate channel in the propagation of monetary policy in Indonesia. The study employed the Structural VAR model consisting of the lending interest rate, loans, real GDP, consumer price index, deposit rate, and consumer price index as a proxy of inflation. The interest rate was found not to explain the variation in output level. However, the monetary policy rate was found to explain 87% of the variation in the inflation rate. The results confirm the effectiveness of the interest rate channel in Indonesia. There seem to be consensus in the results on the effectiveness of the interest rate channel. Munyengwa (2012) and Bernanke and Blinder (1995) also found the interest rate to propagate monetary transmission to other economic variables.

2.4.2. The Exchange Rate Channel

The exchange rate channel is derived from the interest rate channel in the transmission of monetary impulses to inflation and output. In recent years, most economies have adopted the floating exchange rate. The floating exchange rate is preferable to the flexible exchange rate because it enables policymakers to pursue other objectives. However, advocates of fixed exchange rate have argued that a fixed exchange rate is one way to manage policy makers and to stabilize general price level and money supply. Countries operating under the fixed exchange rate set their domestic currency at a determined level and the central bank sells and purchases the domestic currency for foreign currency at a predetermined price. In contrast, an exchange rate that the central bank allows to fluctuate, in response to changing economic condition, is a floating exchange rate.

The Mundell-Fleming model of a small open economy assumes that monetary policy expansion is effective through the exchange rate channel. Expansionary monetary policy (an increase in money supply) shifts the LM curve to the right, lowering the exchange rate and raising income. The depreciation of the domestic currency value increases the cost of goods relative to foreign goods. According to Mishkin (2001), there are two primary mechanisms of the exchange rate channel; exchange rate effects on net exports and exchange rate effects on the balance sheets. This channel operates well as the country pursues a floating exchange rate regime and imposes minimum trade restriction. Expansionary monetary policy causes a fall in domestic interest rate, hence the opportunity cost of investing in domestic currency increases. Subsequently, the domestic currency depreciates making domestic goods cheaper relative to foreign goods. This causes an increase in net exports and aggregate demand.

The concept of interest rate parity assumes spread in yields, between two countries, should be compensated by the currencies movements, so that no excess returns are possible. Adjustment of the exchange rate is transmitted via the interest rate parity condition, since the domestic interest rate on bonds must equal the interest rate obtained from foreign bonds, plus the expected rate of appreciation or depreciation of the exchange rate. Taylor (1995) argued that interest rate parity is vital for the exchange rate channel, since capital inflows are induced by a higher rate of returns, until the expected rate of returns are equalized between countries, if the interest rate parity condition does not hold. Munyengwa (2012) employed the VAR model to investigate the monetary policy transmission mechanism in Botswana for the period 1995 to 2009. The empirical results found the exchange rate channel and the credit channel to be more effective. However, Nagayasu (2007) examined the exchange rate channel in Japan. The study determined the pass-through effect of the exchange rate via monetary policy to output. The study found the exchange rate channel to be effective in Japan.

2.4.3. The asset price channel

According to Mishkin (2001), monetary policy transmission affects economic variables through stock market prices, real estate prices and exchange rates. The Tobin's q-theory explains how the monetary policy affects the economy through equity prices (Tobin, 1969). The theory focuses on how firms make investment decisions in the stock market. Mishkin (2001) defined the Tobin q theory as a ratio of the market value of firms to the replacement cost of capital, which assumes a higher q-ratio implies that the market value of a firm is higher relative to its replacement cost of capital. New property, plant and equipment will be less expensive relative to market value of business firms. In response, firms issue equity to buy more investment goods, hence investment rises, and output also rises. Restrictive monetary policy influences the economy through equity prices by reducing the money supply.

In addition, monetary policy is also propagated through equity prices via the wealth effects on consumption. Munyengwa (2012) assumed that consumption is ascertained by financial wealth and other resources. Also, common stocks are the largest constituents of financial wealth, and a contractionary monetary policy will reduce stock prices, hence reducing the value of financial wealth.

According to Mishkin (1995:6), restrictive monetary policy transmission affects economic variables through equity prices by reducing the money supply. A reduction in the money supply will reduce cash at hand by household. Hence, households will use their income to increase their purchase in the stock market, in order to earn interest. Subsequently, the demand for equities decreases and prices decline. Lower equity prices cause a lower q-ratio, leading to low investment and lower output and aggregate demand.

Mishkin (2001) argued that firms do not finance investment only through bonds but by issuing equities. The increase in stock prices enables firms to finance investment at a lower price because issued shares are sold at a higher price. Therefore, expansionary monetary policy induces a rise in stock prices and a decline in the cost of capital. Mishkin (2001) stated that real estate prices are another form of asset prices that play an important role in the transmission of monetary transmission. Tightening monetary policy, which increases the interest rate, also increases the cost of financing houses and so lowers their prices. With a lower price of housing relative to its construction cost, construction firms are demotivated to build housing and thus housing expenditure will fall and so aggregate demand will fall.

Zhang and Huang (2017) investigated the asset price channel of monetary policy transmission in China for data spanning from 2000M2 to 2015M5. The study employed an Ordinary Leased Squares model with money supply (M2), narrow money (M1), consumer price index, and real-estate investment, the one-year treasury bond yield to maturity and ten-year treasury bond yield to maturity. The empirical results found the asset price channel to be effective in the short run but invalid in the long term. In addition, a VAR model was estimated to determine the effectiveness of bond yields in propagating monetary policy to inflation and output using data spanning from 2002M2 to 2015M5. The asset price channel was found to be effective in propagating monetary policy.

2.4.4. The credit channel

The credit channel of monetary policy transmission consists of two subsections: the bank lending channel and the balance sheet channel. The credit channel is the process through which monetary policy affects economic variables through credit (Bernanke and Gertler, 1995). According to Kashyap and Stein (1994), there are three assets upon which monetary policy can be propagated: through (i) money, (ii) publicly issued bonds and (iii) intermediated loans. There are three main conditions through which the credit channel operates: (i) the central bank use the short-term interest rate to influence prices and national income; (ii) the central bank must be able to induce economic variables via the reserve requirements and (iii) lastly, there must be an imperfect substitute of bank loans and publicly issued bonds. In emerging countries with more reliance on credit on banks, the credit channel seems to be more effective.

According to Kashyap and Stein (1994), the bank lending channel is derived from the money view (IS-LM framework) of monetary transmission. In the money view of monetary policy transmission, a decline in reserves, constrains the banking sector's ability to issue demand deposits. Hence, the banking sector must hold fewer bonds and the consumers must hold more money and fewer bonds. As a result, consumers will have less money in real terms and the equilibrium will require an increase in the real interest rate. The monetary policy will ultimately have a significant impact on economic activity and investment. The money view of the credit channel is perceived to be weak as the decline in bank reserves will have minimal effect on the interest rate on publicly held bonds (Kashyap and Stein (1994).

The money view of the bank lending channel was modified by Bernanke and Blinder (1988), which included the supply of bank loans and bonds as important assets. According to this approach, tightening monetary policy can only have a real effect on the propagation of monetary policy if the decline in bank reserves influences them to decrease their supply of bank loans. Hence, the cost of loans will rise more than the cost of bonds and the firms that depend on bank lending will be induced to reduce their investment. As a result, aggregate demand and output will decline. The balance sheet channel can be defined as the ability of monetary policy to influence the assets or liabilities of banks which will lead to changes in investment and aggregate demand (Mishkin, 2001).

2.4.4.1. The bank lending channel

The traditional bank lending channel was propounded by (Bernanke and Blinder (1988) who explained how monetary policy shocks induce changes in bank loans supply due to the imperfect substitutability of bank credit. Tightening monetary policy drain banks required reserves and deposits, with consequently a fall in investment, consumption and finally a decline in inflation and national output. There are three main requirements the bank lending channel must meet for it to function effectively: (i) the must be no perfect substitute for intermediated bank loans and open-market bonds for firms on the liability side of their balance sheets. Simply stated, firms must depend on commercial banks for credit; (ii) there must be imperfect price adjustment that prevents monetary policy innovation from being neutral. When prices alter frictionless, a deviation in nominal reserves will be met with an equal adjustment in prices, and both firms and banks balance sheets will remain the same in real terms. (iii) the central bank must be able to affect the supply of bank loans by altering the number of their reserves through changes in the policy rate. That is banks must not be able to completely protect its lending activities from shocks to reserves, either by paring its net holdings of bonds, and finally.

Bernanke (1986) found that shocks of credit shift aggregate out. In another study, Bernanke and Blinder (1990) found monetary policy shocks to be propagated through money supply and credit (bank loans) to other macroeconomic variables. In the following paper, Bernanke and Blinder (1992) found bank loans to contract in response to an increase in the Federal Reserve rate. The decline in the loans led to a decline in investment and aggregate output. There seems to be a consensus in the effectiveness of the bank lending channel, as Bernanke and Gertler (1995) employed a VAR model, and observed the presence of the bank lending channel. There appears to be solid empirical literature that shows that restrictive monetary policy reduces the loan supply and aggregate output (Romer & Romer, 1990). They observed that loans adjust gradually following a shift in the monetary policy rate.

Kashyap and Stein (2000) made a huge contribution to the traditional theory of Bernanke and Blinder (1988) by employing microdata to examine the bank lending channel of monetary policy transmission. That study categorized banks and firms according to their size, liquidity, and capital. Small firms with less liquidity and capital seem to respond more to tightening monetary policy transmission since they have limited substitute for bank credit. In contrast, large firms seem to be less responsive to monetary shocks as they could acquire finance from nonbank intermediaries, public debt and commercial paper (Gertler & Hubbard, 1988). In a similar study, Gertler and Gilchrist (1994) examined the impact of the monetary policy on small and large manufacturing firms. Small firms were found to be distorted by tightening monetary policy shock, whereas large firms were able to substitute bank loans by public debt and commercial paper.

In a panel data approach, Khosravi (2015) found less liquid banks to amplify monetary policy more than more liquid banks in European countries. However, bank size and capitalization seem not to influence monetary policy transmission. In a similar study, Ono (2015) employed the General Method of Moment's framework in Russia to investigate the credit channel for data spanning from 2005 to 2012. More liquid and capitalized banks were found to influence the propagation of monetary policy. Small banks were found to be more responsive to monetary policy transmission. There seem to be mixed results on the response of banks to monetary policy shocks according to their size, liquidity, and capitalization. Mbowe (2016) found bank characteristics (which are size, liquidity, and capitalization) did not influence the propagation of monetary shocks. In addition, large, internationally active banks seem to be less affected by changes in the policy rate if they obtain a significant fraction of their funding from foreign affiliates, which are less likely to change the markup they require (Disyatat, 2011).

In a recent work, Disyatat (2011) provided an important contribution to the theory of traditional bank lending. He argued that the bank lending channel is influenced by demand for loans, rather than its supply. According to Disyatat (2011), bank reserves are not affected by changes in the policy rate, since banks keep more reserve than the requirement to cushion against unexpected shocks. Hence, the requirement of the traditional bank lending does not hold if bank reserves are more than required. Most of the studies on the bank lending channel have been conducted in advanced economies, yet a few have been conducted in emerging and less developed countries. The current study will follow the traditional bank lending channel by Bernanke and Blinder (1988) in the selected emerging markets.

2.4.4.2. The balance sheet channel

The balance sheet channel assumes that interest rate charge to a borrower is determined by the borrower's financial position. A borrower with less liquid assets and less profitable security to safeguard the loan is charged more. Changes in the borrower's financial position influence the status of debtor's balance sheet. Hence, changes in financial position of debtors are translated into their investment and spending decision. Apergis and Alevizopoulou (2012) argued that monetary policy shocks may influence the balance sheet indirectly or directly. For example, an indebted householder is further impoverished by a contractionary monetary policy. The cost of financing the debt will rise automatically due to the rise in the monetary policy rate, and consequently a fall in the borrower's consumption patterns. Aggregate demand will fall causing low inflation. Contractionary monetary policy indirectly influences consumers, by increasing the opportunity cost of purchasing goods relative to saving.

According to Mishkin (2001), asymmetric information obstacle in credit markets provides a transmission channel that operates through stock prices. The balance sheet channel operates through the effect of stock prices on firms balance sheets. Moral hazard and adverse selection are worsened by lower net worth in lending to firms. It is a high risk for banks to lend to firms with lower net worth since they do not have sufficient collateral for the loans. A decrease in net worth causes a rise in the adverse selection and moral hazard obstacle, and hence causes a decline to firms lending. The lower net worth of firms increases the probability of borrowers to default on their payment hence decreases the lending and investment spending. Tightening monetary policy decrease stock prices and firms net worth, leading to an increase in moral hazard and adverse selection effect and leading to a contraction in lending. Lower lending then leads to lower investment spending and aggregate spending (Mishkin, 2001).

In addition, the balance sheet channel operates through consumer household wealth effects. Tightening monetary policy decreases stock prices and the value of household wealth, and thus decreases the lifetime resources of consumers and leads to a decrease in consumption (Mishkin, 2001). Cohen-Cole and Martinez-Garcia (2009) employed the DSGE model in Chile to investigate the balance sheet channel and found it to be effective. Restrictive monetary policy weakens banks reserve, hence reducing credit and investment. Bougheas *et al*. (2006) examined the presence of the balance sheet channel in the United Kingdom. The paper investigates the impact of tightening monetary policy on a firm’s access to external sources of finance in the United Kingdom using microdata of 15000 UK firms during the 1990s. The balance sheet was found to be effective and firms’ characteristics (size, capitalization and liquidity) influence the propagation of monetary policy transmission. In a similar study, Angelopoulou and Gibson (2009) used a panel of UK manufacturing firms to examine the presence of the balance sheet channel. The empirical literature indicates the existence of the balance sheet channel.

2.5. Conclusion of the chapter

The chapter reviewed the theoretical framework and the channels of monetary policy transmission. The study follows the traditional bank lending channel of Bernanke and Blinder (1988). According to the theory, tightening monetary policy shocks drain banks reserve, which constrains them in the supplying of loans. The bank lending channel operate effectively when small firms and consumers depend on banks for credit. The theory was derived from the IS-LM model, according to which monetary impulse are transmitted into economic variable through money supply. The bank lending channel has proven that credit plays a significant role in propagating monetary policy shocks to economic variables. The credit channel has been investigated extensively in USA through the traditional bank lending channel of monetary policy transmission. Kashyap and Stein (2001) in USA made a vital contribution to the body of knowledge by determining the importance of bank characteristics (size, liquidity and capitalization) in transmitting monetary policy. The interest rate channel is the main effective channel in the transmission of monetary policy (Afrin, 2017, Rey, 2016). The chapter has also reviewed the Tailor rule and the bank loss function as additional theories of monetary policy, since the policy rate and the inflation rate are included in all the estimated models.

Chapter 3: Empirical literature review and monetary regime

3.1. Introduction

The chapter reviews the empirical literature and the monetary regime in the selected emerging markets. Most of the studies on the credit channel of monetary policy transmission has been conducted in the US and in other developed countries (Bernanke and Gertler, 1995). However, few studies on emerging, developing and less developed countries have investigated the credit channel of monetary policy transmission (Matousek & Solomon, 2017, Nguyen, 2018). Most studies on the credit channel of monetary policy use macrodata (Apergis & Alevizopoulou, 2012; Heryan & Tzeremes, 2017). Kashyap and Stein (2001) made a significant contribution to the theory of traditional bank lending by utilizing microdata in the USA. His results showed the importance of bank characteristics in amplifying monetary impulse through credit.

3.2. Empirical literature review

There are various studies that have been conducted in developed and European countries, whereas there is a lack of literature in emerging and less developed countries. Most of the studies conducted in emerging markets employed macro- and microdata. The bank lending channel of monetary policy transmission, according to Bernanke and Blinder, (1988) theory presumes a negative response of bank loans supply to monetary policy shocks. The bank lending channel seems to be more responsive to monetary policy transmission in emerging markets relative to developed countries. The main reason is the ability of banks in developed countries to react to changes in reserves by adjusting their holdings of securities, rather than loans. Furthermore, commercial banks in developed countries keep more reserves than required and there is an existence of nonbank intermediaries who are sensitive to monetary policy shocks (Mishkin, 2001). The chapter review studies from developed countries, followed by studies from emerging markets and lastly reviews the monetary policy in the selected emerging markets (South Africa, Brazil, Chile, Mexico, and Russia).

3.2.1. Studies from developed countries

The study of the bank lending channel of monetary policy was first conducted in the United States in the 1990s and followed by several studies from European countries. Dajcman (2016) investigated the credit channel of monetary policy transmission in Slovenia for European countries. The paper employed quarterly data, spanning from 2008 to 2014, to estimate two regressions using the Vector Auto Regression (VAR) model. The result found the interest rate channel and the bank lending channel to be effective in European countries. In an alternative study, Gertler and Gilchrist (1994) used microdata from manufacturing firms in the USA. The empirical literature confirmed Kashyap and Stein (2000) results, according to which firm's characteristics influence monetary policy transmission. Small and less liquid firms are more responsive to monetary policy transmission.

In a similar study, Vera (2012) employed the VAR model to demonstrate the decline of bank loans in response to monetary policy innovation. The paper used alternative orderings of variables to show that the bank lending was weak in the United States. These results are due to the changes in the financial sector; banks have increased in size and they tend to keep more reserves than stipulated to safeguard their business. The bank lending in developed countries is less effective compared to emerging markets. Creel *et al*. (2016) employed the VAR to examine the pass-through effect of the European Central Bank (ECB) monetary policy on interest rates and bank loans during the financial crisis of 2007-2009. The interest rate and bank lending channel were found to be effective, however, the unconventional policies were not effective. Also, Florio (2006) investigated the propagation of monetary policy in Italy for the period 1982-1998. The paper employed a two-step OLS procedure and the results suggest the importance of the bank lending channel.

Apergis and Christou (2015) utilized the GMM model to ascertain the monetary propagation in the United Kingdom. The result suggests that the numerous channels (interest rate channel, bank lending channel and balance sheet channel) of monetary policy transmission are effective, however, they are weak. Apergis and Alevizopoulou (2012) also employed the GMM to investigate the importance of the credit channel in monetary policy transmission in EU for the period 2000-2009. He estimated two models on the bank lending channel and on the interest rate channel. Both channels were found to be vital in monetary policy transmission.

Heryan and Tzeremes (2017) employed the generalized method of moments to investigate the importance of bank lending in European countries for the period 1999 to 2012. For the estimation of the bank lending channel, banks were categorized according to size, liquidity, and capitalization. The main objective of their study was to analyze the effect of monetary policy rate and monetary aggregate on the bank lending channel. The findings of the paper confirmed the results of Kashyap and Stein (2000): less liquid banks are more responsive to monetary policy shocks.

Matousek and Sarantis (2009) employed panel data to investigate the effect of monetary policy innovation on bank lending channel in Eastern Central European countries (Hungary, Lithuania, Slovakia, Lativia, Estonia and the Slovak Republic) for the period 1994 to 2003. Banks were categorized according to size, capital strength, ownership structure, and liquidity. The paper found the presence of the bank lending channel in most countries. However, the liquidity and the size of the banks also influence the level of responsiveness of banks to monetary policy shocks. Less liquid and smaller banks seem to be more responsive to changes in the monetary policy rate.

Vithessonthi *et al*. (2017) employed the panel OLS regression and the panel quantile regression to examine the monetary policy transmission mechanism and the bank lending channel for the period 1990 to 2013. The countries selected in that paper were Germany, Thailand, and Switzerland. The empirical results revealed a negative response of bank loans to monetary policy innovations. Also, the supply of bank loans was found to determine investment relative to bank lending rate.

Hendricks and Kempa (2009) used the Markov-switching model to examine the credit channel of monetary policy transmission in the United States economic history consisting of monthly data over the period 1920M1 to 2005M12. The study utilized the default premium as the difference between yields on BAA-and AAA-rated corporate bond portfolios as an indicator of the credit channel. The empirical result identified two regimes through which the bank lending channel is active and passive. The credit channel is more responsive to monetary shocks during a recession in the USA. This was evident during the credit crunch episode of 1990 to 1991 and 2000 to 2003.

Senbet (2016) employed the Factor-Augmented Vector Autoregressive (FAVAR) Model to analyze the channels of monetary policy transmission in the United States of

America. The study estimated two regressions for the interest rate channel and for the credit channel. The study used monthly data for the period 1970 to 2014. The model of estimation included more than 150 variables, since it did not waste the degrees of freedom and it provided a more reliable impulse response. The study found the bank lending channel to be effective in the USA.

Black and Rosen (2007) investigated the balance sheet channel and the bank lending channel of monetary policy transmission in the USA. Their study used public debt as a baseline for firm demand to separately examine bank loan supply to small and large firms. The sample size of the data are from 1982Q3 to 2006Q1 and the data are obtained from the Survey of Terms of Business Lending. Two empirical specifications are based on the proportion of commitment loans to spot loans and by focusing on the quantities of commitment loans and spot loans. The identification of spot lending and commitment lending centered on a comparison by loan size and loan maturity. The Logit Analysis and Baseline Model were employed to estimate the regressions. The estimated model consists of the federal policy rate, short maturity, the firm size, and bank loans. The empirical evidence suggests small firms be more responsive to interest rate policy shock.

Another study in Germany employed a Vector Autoregressive model to investigate the response of bank loans to monetary policy shock (Eickmeier *et al*., 2009). The control variable for the study was real GDP, GDP deflator, inflation rate, real loans to the private sector and the three-month money market rate over the period 1985Q1 to 2005Q3. The German financial system is characterized by close borrower-lender relationships. However, small banks and small firms seem to be more volatile to monetary policy shocks. The main results of this analysis were that with the exception of the response to the supply shock in Germany, the response of loans to the three macroeconomic shocks is rather weak and, in most cases, insignificant.

A similar study conducted in developed economies (France, Germany, Japan, UK, and the USA) found the bank lending channel to be effective in Japan and Greece. However, it was found to be ineffective in the UK and the USA (Brissimis & Delis, 2009). The study analyzed the bank lending channel through the identification of the loan supply function and examined the impact of bank characteristics. The characteristics of banks include bank size, liquidity, and capitalization. The study test for appropriate restrictions that are valid when perfect substitutability exists between loans and bond in bank portfolios. The study used the GMM Model to estimate the regression over the period 1996 to 2003.

In a subsequent study, Brissimis *et al*. (2014) employed panel data to examine the bank market power and monetary policy transmission in the United States and Euro-area. The study used bank year level data obtained from a bank scope over the period 1997 to 2010. He used bank characteristics such as liquidity, size, and capitalization to examine the bank lending channel. The control variables included in the model were bank loans, the monetary policy interest rate, and bank characteristics. The empirical result found the bank lending channel to be effective in the European area and to be ineffective in the USA. This may be a result of low monetary policy interest rate and the substitutability of bank loans in the USA.

There seem to be mixed evidence on the bank lending channel in the USA and in the European countries. Banks that have less liquidity, and are small and less capitalized are worsened by tightening monetary policy. In contrast, firms and borrowers that are bank-dependent for loan supply also amplify monetary policy transmission. The empirical evidence indicates that bank loans' response to monetary policy shocks is effective in an international context, especially in countries where firms and banks have less direct access to financial markets (Peek & Rosengren, 2013).

Hülsewig *et al*. (2004) used macro data to identify loan supply effects of monetary policy transmission in Germany. The study used the Vector Error Correction Model to analyze the impulse response of monetary policy shocks to another economic variable. The VECM is an appropriate model to test the long and short run relationship between monetary policy shocks and economic variables. The control variables in the model are GDP, inflation rate, bank loans, money supply, and monetary policy interest rate. The evidence suggests the credit channel and the interest rate channel to be operative.

Rey (2015) examined the bank lending channel of monetary policy transmission in the United States. The analysis utilized panel data for the period 1996-2001. The results show that small banks with less liquidity are worsened by tightening monetary policy. The increase in monetary policy rate reduces their ability to supply loans. Also, Favero *et al*. (1999) analyzed the response of bank loans to monetary policy shocks for a selection of four European countries (Germany, Italy, Spain, and France) for the period

1991 to 1992. The empirical result did not found the importance of bank lending in the large European countries in 1992. The study assumed banks in developed countries are less responsive to monetary policy shocks since they use their access required reserves to insulate loans from monetary policy shocks.

Kandrac (2012) employed the Generalized Method of Moments (GMM) in the United States to examine the balance sheet and bank lending channel of monetary policy transmission for the period 1993Q2 and 2008Q4. The data were extracted from the Call Report. The GMM Model included the following variables: inflation rate, GDP growth, the bank lending rate, bank liabilities and bank assets (loans). The empirical results revealed the presence of the balance sheet channel. Smaller banks are more responsive to monetary shocks compared to large banks.

Kumamoto and Zhuo (2017) employed the Vector Autoregressive Model to examine the bank lending channel of monetary policy transmission in Japan, during the quantitative easing from 2000 to 2012. The study employed four models on city bank loans, on regional bank loans, on all firm's bank loans, and on small medium enterprise loans. The results found the regional bank loans to be more responsive to monetary policy shocks than the city bank loans, following a quantitative easing.

There seem to be a consensus in the empirical literature on the role of bank characteristics on monetary policy transmission. Kishan and Opiela (2000) employed quarterly data, spanning from 1980Q1 to 1995Q4, to investigate the credit channel and the bank lending channel in the USA. The empirical literature revealed the existence of the credit and the bank lending channel in monetary policy transmission. Bank characteristics, such as bank size, capitalization, and liquidity, influence the transmission of monetary policy transmission. Small, less capitalized banks and less liquid banks are more responsive to monetary policy shocks in the USA. In another study, Kishan and Opiela (2006) examined the bank lending channel in the USA in the pre-Basel and the post-Basel periods. The study also found the existence of the bank lending channel and less capitalized banks to be more responsive in monetary policy shocks.

In another study, in the USA Nilsen (2002) used the VAR model to examine the bank lending channel of monetary policy transmission. He also observed small banks with less liquidity and less capitalization to be more responsive to monetary policy shocks.

In the UK, Mateut, Bougheas and Mizen (2006) employed the VAR model to examine the bank lending channel of monetary policy transmission in the UK with panel data of manufacturing firms spanning from 1990-1992, during a tightening monetary policy cycle, and 1993-1999, when it was loose. The endogenous variables in the model also included bank characteristics such as size, capitalization, and liquidity. The empirical literature confirms the effectiveness of bank features in the transmission of monetary policy transmission. Moreover, the bank lending channel was found to be effective to restrictive monetary policy shocks.

3.2.2. Studies from emerging markets

There is a lack of studies in emerging markets that have investigated the effectiveness of bank lending in monetary policy transmission. Walia and Raju (2014) employed the VAR model to investigate the monetary policy transmission in India. Their study found the bank lending channel to be vital and effective in the monetary policy transmission process. These results are in aligned with the theory, as in emerging markets there is an imperfect substitution of credit by banks in other sectors. Rahman and Ahmed (2014) also ascertained the monetary policy transmission in Bangladesh for the period 1999 to 2013. The analysis confirmed the existence of the exchange rate channel and credit channel to be more effective. The asset price channel and the interest rate works but are less effective.

Özlü and Yalçın (2012) employed microdata over the period 1996-2008 to examine the trade credit channel of monetary policy transmission in Turkey. Tightening monetary policy constrained banks’ credit availability to small firms because of imperfect substitution. Credit offered to small firms was found to be inelastic during a monetary policy tightening in emerging markets. Rey (2015) examined the bank lending channel of monetary policy transmission in the United States. The analysis utilized a panel data for the period 1996-2001. The results show that small banks with less liquidity are worsened by tightening monetary policy. The increase in monetary policy rate reduces their ability to supply loans.

Rashid and Rahman (2015) examined monetary policy transmission in Bangladesh for the period 1998Q1 to 2013Q1. The exchange rate channel and the credit channel were found to be strong and effective in the transmission of monetary policy. However, the interest rate channel of monetary policy seems to be weak. Collectively, the monetary policy transmission influence output and inflation. Ifeakachukwu and Olufemi (2012) employed the VAR model to examine monetary policy transmission in Nigeria. Also, in this analysis, the bank lending seems to be strong in the transmission of monetary policy.

Tabak *et al*. (2016) examined the monetary transmission mechanism in Brazil for BRICS (Brazil, Russia, India, China, and South Africa) countries. The study employed panel data and GMM Models and microdata over the period 2000-2012. The empirical results suggest that growth in loans as a result of the monetary expansion is non-linear and inverted U-shaped. Fernald *et al*. (2014) also ascertained the effectiveness of monetary policy in China for the period 2000 to 2013. The result suggests that monetary policy transmission in China operated in the same manner as in Europe and the United States. Shocks in interest rate led to changes in economic activity and in prices, also, it led to changes in other monetary policy in other countries.

There seems to be consensus on the importance of the bank lending of monetary policy transmission in most of the literature. Gupta *et al*. (2010) investigated the bank lending channel in South Africa for the period 2000Q1-2004Q4. The study showed the importance of bank lending in monetary policy propagation. Mallick and Sousa (2012) employed the Bayesian Vector Autoregressive Model (BVAR) to examine monetary policy transmission. The result showed the effectiveness of bank lending in the transmission of monetary policy. Also, the monetary transmission was found to be successful in stabilizing prices and output gap in the short run.

Ibarra (2016) employed the VAR approach to examine the importance of the bank lending channel of monetary policy propagation in Mexico over the period 2004-2013. The empirical results were aligned with the theory, restrictive monetary policy constraint banks reserves and hence, bank loan supply declined. The results confirm the dependency of other sectors of the economy for credit from banks because of imperfect substitution. Also, expansionary monetary policy induces a rise in credit, investment subsequently a rise in output.

Bauer and Neely (2014) examined the response of the bank lending from monetary policy innovations. Their result confirmed the findings of Kashyap and Stein (2000), where banks with less liquidity are worsened by restrictive monetary policy in their supply of loans. However, banks with liquid balance sheets operate normally during a monetary policy tightening cycle. In contrast, Zulkhibri (2013) investigated the credit channel of monetary policy transmission in emerging countries over the period 1997-2005. The paper employed micro data, through the panel data approach. The result suggested the bank lending operates through the money multiplier and less liquid banks.

Bhoi *et al*. (2017) employed the VAR Model to examine the importance of the channels of monetary policy transmission in India for the period 1996-1997. Output responds with a lag of three quarters to contractionary monetary policy shocks, whereas inflation responds with a lag of four quarters. The asset price channel, the credit channel and the interest rate channel are important in monetary policy transmission, with the later as a dominant propagation.

Munyengwa (2012) employed the VAR Model to investigate the different channels of monetary policy transmission in Botswana for the period 1995-2009. The empirical findings found the monetary policy to be more effective through the interest rate channel, followed by the credit channel and the exchange rate. Monetary policy influenced other economic indicators with one period lag that lasted for seven months. Disyatat (2011) examined the bank lending channel in South Africa. He argued that expectation of interest rate, not only the prevailing interest rates, affect bank loan supply. Also, shifts in the willingness, the terms on which banks are prepared to lend, determine the bank lending channel. The status of the balance sheet of banks are also important.

Matousek and Solomon (2017) utilized the Generalised Method of Moments (GMM) and the Bias Corrected Fixed Effects two-step estimator to examine the bank lending channel in Nigeria for the period 2002 to 2008. The paper's main objective was to examine the effect of monetary tightening innovations on bank loans supply, according to capital strength, bank size, and liquidity. The findings of the research showed that less capitalized and less liquid banks are more responsive to monetary policy shocks.

Most emerging markets' economic variables are influenced by external monetary shocks, especially from the United States of America. Mora (2012) examined the responsiveness of bank loans to monetary policy in a partially dollarized country (Mexico). The study estimated two models using the panel regression, one for the growth in bank deposits, and the second one for the growth in bank loans. In the study, bank deposits are constrained by restrictive monetary policy in Mexico. The responsiveness of small banks to monetary innovations was found to be high relative to bigger banks, similar to Kashyap and Stein (2000). The results of the bank loans' model suggest that a currency lending channel exists.

Simpasa *et al*. (2014) employed bank-level data in Zambia to investigate the bank lending channel of monetary policy transmission for the period 1998Q1 to 2011Q4. The study employed the Arellano and Bond (1991) linear dynamic GMM panel data estimation technique. The estimated model included bank-specific characteristics, such as size, capital ratio, and liquidity ratio. Other variables included in the model are bank loans, the exchange rate, the inflation rate, and economic activity. The bank lending was found to be ineffective in Zambia. The variables were statistically insignificant, and the signs of coefficient were not consistent with the theory.

In another study, Simpasa *et al*. (2014) used the VAR model to ascertain the bank lending channel in South Africa for the period 1987Q1 to 2004Q4. The endogenous variables in the model were loans, deposits, economic activity, and the repo rate, all extracted from the South African Reserve Bank. The empirical results suggest that loans in South Africa are demand driven and not supply driven. The results support the revised bank lending channel theory by Disyatat (2011), which states that bank loans are demand driven. The supply of loans is determined by consumer demand, rather than changes in the monetary policy rate.

Mengesha and Holmes (2013) used the Vector Autoregressive to investigate the monetary policy transmission in Eritrea for the period 1996Q1 to 2008Q4. The endogenous variables included in the model are consumer price index, domestic credit, the exchange rate, and the gross domestic product. The empirical result found the interest rate channel, the exchange rate channel and the credit channel to be effective in Eritrea.

Abuka (2015) used loan-level data to empirically analyze the bank lending channel in Uganda for the period 2010Q1 to 2014Q4. The study estimated a model based on the traditional bank lending channel theory by (Bernanke and Blinder, 1988). The bank lending channel and balance sheet channel was found to be effective in Uganda. Less capitalized banks were found to be more responsive to monetary policy shocks, relative to more capitalized banks.

Said (2013) empirically used the Static Model to analyze the bank lending channel under regulatory constraint under a monopolistic structure in Malaysian. Also, the study employed the GMM to examine the impact of average rates charged and paid by commercial banks to changes in monetary policy and the Basel regulatory constraint for the period 1999 to 2007. The bank lending channel was found to be effective, whereas the balance sheet channel was found to be ineffective in Malaysian.

De Mello and Pisu (2010) employed the Vector Error Correction Model (VECM) approach to analyze the effectiveness of the bank lending channel in Brazil. The study used monthly data for the period 1995M12 to 2008M6. The endogenous variables included in the VECM are inflation rate, inter-bank deposits certificate rate, the pre-set lending rate, economic activity, and bank capital. The theses estimated two equations: the loan supply equation and the loan demand equation. The study found the presence of bank lending in Brazil. The monetary policy rate restored equilibrium in the supply of loans in the short run. However, the monetary policy rate did not restore equilibrium in the demand for bank loans.

Olivero *et al*. (2011) used annual bank-level data to investigate the effect of consolidation of banks to the bank lending channel of monetary policy transmission in eighteen Asian and Latin economies for the period 1996 to 2006. The panel data technique was utilized and it consists of the unconsolidated balance sheet and income statement for a sum of 936 commercial banks. The monetary policy rate interacted with the banking concentration indicator in order to model the impact of the consolidation on the bank lending channel. According to the empirical result of the study, banks concentration weakens the bank lending channel of monetary policy transmission. The result of the study is consistent with other empirical literature. Karakuş (2014) also employed bank-level data to examine the impact of banks consolidation in Turkey over the period 2006 to 2012. A sample of fourteen banks was used in the panel data approach. The empirical result was consistent with those of (Olivero *et al*., (2011).

Halvorsen and Jacobsen (2016) employed a linear and nonlinear VAR to empirically investigate the revised bank lending channel of monetary policy transmission in Norway. The study followed Disyatat’s (2011) revised theory of the credit channel for a monthly frequency of data over the period of 1993 to 2008. The variables included in the VAR are banks equity ratio, real economic activity, consumer price index, banks retail depository funding ratio and the central bank's policy rate. The empirical result found the traditional bank lending channel to be ineffective, since monetary policy shocks did not amplify the response to bank loans through the required reserves. However, according to the result, the bank lending channel is determined by the demand for bank loans (Disyatat, 2011).

Hsieh (2015) also investigated the bank lending channel of monetary policy transmission in Greece. The empirical analyses used quarterly data over the period from 2001 to 2013. The researcher utilized the EGARCH Model to estimate a reduced form equation derived from the demand and supply of bank loans. The demand for bank loans equation consists of the lending rate, the interest rate on bonds and economic activity. The supply for bank loans equation include the bank deposits, the policy rate, the foreign interest rate, the exchange rate, the lending rate and the interest rate on bonds. The reduced equation of the EGARCH consists of output, bank deposits, and the policy rate, interest rate on bonds, the foreign interest rate and the exchange rate. The bank lending channel of monetary policy transmission was found to be effective in Greece.

Hsing (2013) used the Three-Stage Least Squares (3SLS) to investigate the bank lending channel in Australia. The empirical work used quarterly data over a period from 2007 to 2012. The study estimated two models: the demand and supply of bank loans. The demand function consists of following explanatory variables: the interest rate on loans, the interest rate on bonds and real economic activity and the dependent variable was the demand for bank loans. The equation for the supply of bank loans was included, using bank deposits, cost of borrowings, the world interest rate, the exchange rate, interest rate on bonds, and the interest rate on loans as explanatory variables. The results found the bank lending channel to be effective in Australia.

Fotopoulos *et al*. (2011) employed the Vector Autoregressive Model to empirically test the effectiveness of the bank lending channel of monetary policy transmission in five South East European economics (5SEE), namely FYROM, Romania, Bulgaria, Albania and Romania. The study employed annual data over a period of 2000 to 2009. The VAR Model was also employed to test the response of bank loans to monetary policy shocks in Greece since it was a comparative study. The VAR Model included four endogenous variables, namely real gross domestic product per capita, the inflation rate, the monetary policy rate and the ratio of the total credit supply. The empirical results found the bank lending channel to be effective in the five Eastern European economies. However, Greek banks were less responsive to a monetary shock; it adjusted bank loans to one standard deviation of monetary policy shock less compared the 5SEE countries.

Burgstaller (2010) examined the bank lending channel of monetary policy transmission in Austria. The Balanced Panel Data Model was used to estimate the regression over the period from 1998 to 2005. The variables included in the estimated, dynamic, one-step GMM Model were the growth rate of loans, the monetary policy, bank characteristic, and real economic activity. The bank lending channel for monetary policy transmission was found to be effective in Austria.

Coelho *et al*. (2010) investigated the bank lending channel in Brazil over the period 2000M1 to 2006M12. The study utilized high-frequency bank-level data to isolate supply shocks driven by the short-term interest rate. Variables included in the model were daily bank-level data on interest rate and quantity. The empirical results of the study found the bank lending channel to be effective in Brazil. Credit volume and interest rate respond strongly to monetary policy shocks. The study also examined the impact of monetary policy shocks to bank structures. Unlike in other studies, large banks were found to be more responsive to monetary shocks, relative to small banks.

Gumata *et al*. (2013) utilized the Large Bayesian Vector Autoregressive Model to analyse the importance of monetary policy transmission in South Africa for the period 1990Q1 to 2012Q2. The LBVAR Model enables the researcher to estimate large cross-sectional models without compromising the degree of freedom. The model leads to the better identification of the monetary policy rate shock. The numerous channels investigated in the article included the interest rate channel, the exchange rate channel, the bank lending channel and the expectations channel. As in most papers, the study found the interest rate channel, followed by the exchange rate, and lastly by the credit channel, to be the most effective of monetary policy transmission in South Africa respectively.

Ekomane and Benjamin (2016) employed the Vector Autoregressive Model and the Granger causality test to investigate the importance of the credit channel in the CEMAC Zone (the Republic of the Congo, Chad, Gabon, Cameroon, Equatorial Guinea and the Central African Republic) over the period of 1960 to 2012. The control variables are the money supply, the domestic credit, the private sector's credit, total investment, and nominal Gross Domestic Product. The study found the bank lending channel to be effective in the CEMAC Zone.

Gomez-Gonzalez *et al*. (2016) used monthly data for the period 1996M4 to 2014M8 to investigate the response of bank loans to monetary policy transmission in Colombia. The study analysed the impact of financial structure on the bank lending channel. It employed panel data from 51 banks in the financial sector of Colombia. The study found the bank’s loans supply to be responsive to monetary policy shocks. However, the magnitude of the bank lending channel’s response to monetary shocks is determined by financial structure. The report also found an asymmetric effect depending on the monetary policy stance.

Caporale *et al*. (2016) also analysed the bank lending channel of monetary policy transmission in a dual banking system in Malaysia, a country with a dual banking system, including both Islamic and conventional banks. The study employed the two-regime Threshold Vector Autoregressive (TVAR) Model since monetary policy is designed differently during economic contraction and expansion phases, thus a nonlinear specification was more appropriate. The empirical evidence reveals the conventional credit to be more responsive to monetary shocks, compared to the Islamic credit.

Khosravi (2015) found the evidence of the bank lending channel in the European Union’s ten new member states. The study employed a VAR Model with control variables, such bank characteristic (liquidity, and capitalization), bank loans, the policy rate, and consumer price index. The bank’s liquidity was found to be an important characteristic in the transmission of monetary policy, whereas bank size and capital were found to be ineffective. The study employed a panel data with data retrieved from a large number of banks from the European Union's countries from 2004 to 2013. Also, there was an indication of the importance of bank liquidity and risk from 2008 to 2010.

Budha (2013) examined the bank lending channel of monetary policy transmission in Nepal for the period 2003 to 2012. The study used the Arellano-Bond General Method of Moments Model. The endogenous variables included in the model are bank loans, real GDP, the inflation rate, the monetary policy, and bank-specific characteristics. The estimated loan supply equation consists of microdata from 25 commercial banks and macrodata. Two bank loan supply equations were estimated based on government bank loans and for the private banks. The bank loan supply model for state owned banks were found to be more responsive to monetary policy shocks than the loans from privately own banks.

Mbowe (2016) employed the Dynamic Panel Data Model, for the period 2001 to 2011, to examine the response of credit to monetary policy rate shocks in Tanzania. The study analysed the distributional effects of the monetary policy on banks with different balance sheet characteristics and ownership structures. The estimated regression was according to Bernanke and Blinder's theory of the credit channel. According to this theory, economic variables are influenced by the monetary policy rate through credit. The study also estimated a model which followed Kashyap and Stein (2000) theory. This model also included bank characteristics, which are size, liquidity, capitalization, and profitability. The empirical result found small banks to be consistent with theory more responsive to monetary policy shocks, whereas large banks to be less responsive to monetary policy rate shocks. However, banks' liquidity were found to be statistically insignificant, which is inconsistent with most empirical literature.

Ono (2015) employed the General Method of Moments to investigate the bank lending channel of monetary policy transmission. The study used annual bank-level data from Russian domestic banks for the period from 2005 to 2012. Variables in the model included economic activity, consumer price index, size, liquidity, capitalization, and loans. More liquidity and capitalized banks were found to be less responsive to monetary shocks in Russia, which is consistent with the theory and empirical literature.

Obafemi and Ifere (2015) used the Factor Augmented Vector Autoregressive Model to investigate the credit channel of monetary policy transmission in Nigeria. The regression model estimated 53 variables spanning the quarterly period of 1970Q01 to 2013Q04. The FAVAR Model involves a two-step technique using principal component analysis. The interest rate and credit channel were found to be effective in Nigeria. The exchange rate channel and money channel was also found to be effective. However, the stock channel was found to be insignificant.

In contrast, Ogbulu and Torbira (2012) also examined the monetary policy transmission mechanism in Nigeria. The study employed the Error Correction Model, the Granger-causality method and the Cointegration test to estimate the long-run and short-run relationship of the bank lending channel of monetary policy transmission. The Log-linear Model included bank assets, money supply, gross domestic product, and the minimum rediscount rate. The empirical literature indicated the presence of the bank lending channel and balance sheet channel in monetary policy transmission.

In Pakistan, Janjua and Rashid (2014) examined the impact of monetary policy on banks' balance sheets. The study employed the panel data framework for the period from 2006 to 2012 and the frequency was annual. Banks were categorized according to size and liquidity. Variables included in the model were loan supply, economic activity, inflation, the lending rate, size, liquidity, capital, credit risk, profitability and debt to equity ratio. The empirical literature supports the theory, as small banks seem to be more responsive to monetary policy shocks relative to big banks. Big banks are able to obtain finance from the external markets and usually keep more reserves than required.

Caldas Montes and Cabral Machado (2013) employed the General Method of Moments, the Vector Autoregressive and the Ordinary Least Squares models to investigate the response of bank loans to monetary policy shocks in Brazil. The study adopted the Bernanke and Blinder (1988) theoretical framework, using annual data spanning from 2003 to 2010. The evidence found the bank lending to be effective and in accordance with the Bernanke and Blinder model. Less liquid and smaller banks are more responsive to monetary policy shocks.

Sun *et al*. (2010) employed the VAR and VECM models to analyse the bank loans and the effects of monetary policy in China. The VAR Model consists of monthly aggregate bank data over the period of 1996 to 2006. The control variables included in both models are bank loans, the growth rate of M2, inflation rate, gross domestic product, and total deposits. The study found the interest rate channel, the asset price channel and the bank lending channel to be effective in China. The VECM examined the long-run relationship between the monetary policy and the macro-variables.

Fan and Jianzhou (2011) also investigated the impact of monetary policy transmission mechanism in China over the period 1996M1 to 2009M12, under endogenous structural breaks. The study used the VAR Model with the quasi-maximum likelihood procedure. The main equations estimated were for the credit channel, the exchange rate channel, the interest rate channel and the asset price channel. Each model contained one structural break, however the structural breaks were different. The credit channel was found to be effective before and after the structural break of March 2001. Output responded with a positive shock to monetary policy rate shock. The interest rate channel and the exchange rate channel were also important in monetary transmission in China. The asset price channel was found to be the less effective channel.

Aleem (2010) employed the VAR Model to investigate the monetary transmission mechanism in India. The paper used quarterly data from 1996 to 2007, to analyse the bank lending channel, the asset price channel and the exchange rate channel of monetary policy transmission. The bank loans have a negative response of 0.57% to a one standard deviation shock of monetary policy tightening and the GDP declined by 0.27% to a one standard deviation shock of the policy rate. The empirical result reflected the presence of the bank lending channel, assets price channel and the exchange rate channel.

Akinci *et al*. (2013) investigated the monetary policy transmission mechanism in Turkey over the period from 1991 to 2007. The paper employed the pooled-OLS models and the control variables included bank characteristics (liquidity and capital), economic activity, bank loans, and the interest rate. The bank lending channel was found to be effective and bank characteristics affect the bank lending channel. Less liquid firms and less capitalized firms are more effective in propagating monetary policy transmission. A tightening monetary policy causes a decline in output and bank loans. Bank efficiency did not influence the bank lending channel.

Shokr *et al*. (2014) examined the importance of the bank loans’ response to monetary policy mechanism in Egypt using macro-level bank data and the GMM approach. The study utilized a sample of 32 commercial banks for the period from 1998 to 2011. The main variables included in the estimated model include bank characteristics (size, liquidity, and capital), output and inflation. The empirical results support the relevance of the bank lending channel in Egypt in amplifying monetary policy transmission. Also, bank liquidity, size, and capital play a role in propagating monetary policy shocks.

Afrin (2017) employed a structural VAR to investigated monetary policy transmission in Bangladesh for the period 2003-2014. The study employed domestic and foreign variables, which include oil prices, foreign price, nominal interest rate, money supply

(M2), nominal effective exchange rate, and credit to the private sector by banks, the consumer price index and output. The ordering of variables was adopted from Bhattacharya *et al*. (2007) which is as follows: $Y^d = (neer, i, m, cr, y, p)$. The ordering means nominal effective exchange rate affects other economic variables but it is not contemporaneously influenced by them. The paper found the bank lending channel to be less effective in transmitting monetary policy and the exchange rate channel was also found to be less effective. The conclusion by the researcher supported the use the flexible exchange rate policy by Bangladesh.

Alfaro *et al*. (2004) employed both the panel data (GMM) and the VAR Model to examine the existence of the bank lending channel in Chile for the period 1990-2002. The panel data are used to test the impact of bank characteristics (liquidity, size, and capitalization) and the response of bank loan supply to tightening monetary policy shocks. The study employed micro data obtained from banks' financial statements and listed firms or enterprises. In addition, the study employed macroeconomic data from secondary data sources. The control variables in the VAR Model are real GDP, consumer price index, bank loans, the real exchange rate, the policy rate, and bank characteristic. Small, less liquid banks seem to be worsened by monetary policy shocks. The bank lending channel was found to be effective and bank characteristics influence monetary policy shocks.

Farinha and Marques (2001) employed the SVAR model to examine the credit channel of monetary policy transmission mechanism in Portugal, consisting of micro bank data spanning 1990-1997. The control variables in the model include bank loans, inflation rate, short-term interest rate, bank-specific features (size, capitalisation, and liquidity) and total deposits. The study found the presence of the bank lending channel in Portugal. Moreover, the bank characteristics affect monetary policy shocks, small banks, with less liquidity and less capitalization are worsen by tightening monetary policy shocks.

Dabla-Norris and Floerkemeier (2006) employed the VAR Model to estimate the transmission of monetary policy transmission in Armenia. The study found the exchange rate channel to be more responsive to monetary policy shocks, relative to the interest rate channel and bank lending channel. The lending interest rate does not amplify monetary policy shocks in Armenia. Using a similar framework Son, Smith and

Pyun (2009) examined monetary policy transmission in Korea over the period 1998-2003 and 1999-1996. The control variables were the industrial production index, consumer price index, short-term interest rate, money aggregate, oil prices in terms of US dollars and the nominal exchange rate. The interest rate channel, the credit channel and the exchange rate seem to be existent in both periods. From most of the empirical literature, the credit channel seems to be effective in most emerging markets.

3.3. Overview of the monetary policy framework

This section reviews the monetary policy framework in Brazil, Chile, Mexico, South Africa, and Russia respectively for the period 2000 to 2018. Most emerging markets have adopted the popular inflation targeting framework at the end of the 1990s. Chile was one of the first countries to adopt the inflation targeting regime after New Zealand in 1991. However, other authors have argued that Chile adopted the inflation targeting framework in 1999 (Schaechter, Stone, & Zelmer, 2000). Brazil, Mexico, and South Africa also adopted the inflation targeting regime in the year 1999, 2001 and 2000 respectively. Other industrial and developing countries that have adopted the inflation regime include Canada, the UK, Australia, Israel, Poland, Colombia, and Switzerland. Russia seems to be the only country in the study that has not adopted the inflation targeting framework. This is interesting as it enables the researcher to ascertain the response of bank loans to monetary policy shocks both in an inflation targeting country and in a non-inflation targeting country.

3.3.1. Monetary policy framework in Chile

The inflation targeting regime was first and formally adopted by the reserve bank of New Zealand in 1989. Chile was the second country in the world to adopt the inflation targeting in 1991. The Central Bank of Chile (CBC) first announced the target of inflation in September 1990 to be in the range of 15-20% for the following year. The CBC was given full autonomy and a legal mandate from the government to aim at currency stability and normal functioning of domestic and external payments. The current target range for inflation is 2%-4%. The CBC has been able to reduce inflation from 27% in 1991 to less than 4% over the years. The main objective of the inflation targeting framework is to maintain price stability, sustainable economic growth, and low unemployment and to protect the domestic currency. Some authors argue that

Chile formally adopted the inflation targeting framework in 1999 when it adopted mandatory features (Schaechter, Stone, & Zelmer, 2000).

There seems to be consensus on the main features of inflation targeting. The main features comprise of (i) an explicit quantitative target for the rate increase in the general price level; (ii) stabilizing of inflation rate must be the dominance objective relative to other nominal targets; (iii) monetary policy must dominate fiscal policy; (iv) independence of the central bank; and (v) monetary transparency and credibility in the conduct of monetary policy and the obtainment of the target. The central bank of Chile minimizes both inflation volatility and output volatility as empirical literature by monetary policy (Schmidt-Hebbel *et al*., 2002).

In the period 1984-1999, the CBC pursued a partially fixed exchange rate target and accompanied by the reduction of the inflation rate. The CBC's main objective was to steer inflation to a one single digit similar to its main trading partners. The CBC used to announce a specified target of inflation for each year, which was usually fixed. In contrast, in 1995, the target rate was reduced from 9 to 8%. The inflation target announcement by the CBC was accompanied by explicit proclamations that lower inflation was beneficial due to inflation inertia and that rapid convergence was uncertain and was harmful to sustainable to economic growth and may jeopardize the disinflation approach. The framework lacked important features before 1999, such as transparency and open and frequent communication of decisions with the nation, markets and the media (Schmidt-Hebbel *et al*., 2002; Cespedes *et al*., 2006).

Most authors consider the year 1999 as the formal period of adoption of the inflation targeting regime by CBC (Valdes, 2007; Schmidt-Hebbel *et al*., 2002). During this period, the CBC introduced all the characteristics of inflation targeting which include: the free-floating exchange rate mechanism; the complete opening of the capital account; the deepening of the foreign exchange derivatives forward markets; use of the short-term interest rate as an instrument instead of the CPI-indexed real interest rate; and the transparency in conducting of monetary policy. The CBC supported its decision on fully-fledged inflation targeting on the grounds that inflation was at its lowest level and the exchange rate was less volatile to shocks and the importance of a long time for monetary policy to influence inflation to avoid output volatility.

According to Roger (2010), the inflation rate target was set at 2-4% target in September 1999 and after 2007, it was changed to 3%, with a tolerance band of plus or minus 1% till to the presence. In addition, the CBC stipulated the target horizon of 12-24 months as the period within which inflation will stabilize back to its target. Inflation hovered around 2.8% from 2001 to 2007, upon which during 73% of the period it was within the target range, and 10% of the period it was more than 4% and 17% of the period it was less than 2% (Valdes, 2007).

The monetary policy and inflation target regime have matured and improved over the years to the same level as in advance economies from September 1999. The improvement in the operation of CBC includes: transparency in disclosure of minutes of monetary policy meetings with a lag of three weeks; publishing of forecasts, together with analyses of transmission mechanism; and the announcement of monetary policy meeting dates in a lag of six months. In addition, the fiscal policy of Chile supported the inflation target system, as it adopted consistent fiscal policy and transparency.

The CBC observed the formation of inflationary expectations via numerous sources that include breakeven inflation; economic analyses by approximately 40 economists and steering of monthly expectation surveys where households, the private sector, and economists are interviewed. The expectations indicators are vital since it assists in monitoring and analysing the economic outlook and monetary policy and ensure the credibility of the CBC. For inflation targeting to operate well, it is important for investors to have confidence in the credibility of the CBC and political stability is crucial (Valdes, 2005; Kaseeram, 2012).

Over the years, the CBC has been successful in its objective of stabilizing inflation rate and reducing output volatility. Recent statistics show that inflation had remained below its target of 3% from 1999-2006. During the credit crunch period of 2007-2008, the inflation rate was above the target at 4, 4% and 8, 7%. After the credit crunch in 2009-2013, the interest rate was below the target. However, during the year 2014-2015, the inflation was above the target by 1%, and in the following years, it stabilized below the target rate. Inflation targeting regime has proven to be a success in Chile as it has converged to the target and credibility to agents has improved significantly. In addition, the consistency, and transparency of the CBC improved the monetary policy operations.

3.3.2. Monetary policy framework of South Africa

This subsection reviews the monetary policy reforms that have been undertaken before and during the inflation targeting framework period in South Africa, especially in the period of the year 2000-2016. The popular inflation targeting in South Africa was adopted in the year 2000 and the target rate of the CPIX was set at 3-6%. There have been different types of monetary policy frameworks, since the 1960s. During 1960-1981, the South African Reserve bank (SARB) pursued a liquid asset ratio-based regime with quantitative management on credit and interest rate. A series of the mixed mechanism during the transition was introduced in 1981-1985, which included the cash reserves-based regime with pre-announced monetary targets during 1985-1998, as recommended by the de Kock Commission Reports (1978, 1985). The regime targeted money supply, inducing market interest rates via overnight rates and through the market operations. Nonetheless, the regime was criticized since the interest rate was irresponsive to liquidity shocks in the economy, since accommodation was freely available, hence money contraction in the money market did not influence the short-term interest rate.

Since 1976-1989, the policymakers were concerned with stabilizing output volatility with an aim of stimulating the economy, which resulted in negative interest rates and a rise in inflation (Aron & Muelbauer, 2007; Brito & Bystedt, 2010). The SARB was involved in a tightening monetary policy cycle since 1989, when Chris Stalls was appointed as the SARB governor. In his reign as governor, the interest rate stabilized and inflation was on a downward trend, which has become the custom for the reserve bank in recent times. According to Friedman (1963), price stability is always and everywhere a monetary phenomenon. This reflects the importance of central bank ability to manage inflation and maintain sustainable economic growth. According to Romer (2006), the restrictive monetary policy stance from 1989 and by global economies from the 1990s is a “conservative window dressing” and is the result of the decline in the average inflation rate.

The daily tenders of liquidity through repurchase transactions, plus pre-announced M3 targets, and informal targets for core inflation, were introduced in 1998-1999. In this system, the repo rate replaced the bank rate and was determined by the SARB as to the liquidity it makes available. Over the years, the regime went under modification.

Nonetheless, after 2001, the main refinancing operations is the weekly seven-day repurchase auction that is determined with the private banks, as the repo rate being ascertained by the Monetary Policy Committee (MPC). The SARB lends funds to commercial banks against worthy collateral, which consist of liquid assets in terms of the prudential liquid asset prerequisite (Aron & Muellbauer, 2005). In addition, this regime is improved by a minimal lending facility, where in situations of unpredictable liquidity shortages, banks borrow for a few days at punitive rates, relative to the repo rate. This regime is designed to enable underlying liquidity circumstances in the market to reveal the short-term market interest rates. Furthermore, it allows the SARB superior discretion regarding liquidity provision as a replacement for automatically providing it, and as a result of its interest rate policy is made transparent (Kaseeram, 2012).

The main objective in the adoption of the inflation targeting in 2000, is to maintain a low rate in the growth of the total consumer price index, excluding the mortgage interest cost, within the range of 3-6% annually. The SARB pursues low inflation rate, protects the value of the domestic currency and maintains sustainable economic growth. The national treasury sets the target range in consultation with the SARB, which was previously determined by the minister of finance. The target range was a change in 3-5% for 2004 and 2005 but in 2006 it was restored to its initial range. The 3% width is not extremely wide to reinforce divergent inflationary expectations and enables the constrained variability in the inflation rate (Kaseeram, 2012).

The Monetary Policy Committee (MPC) consists of seven members and is responsible for the determination of the repo rate after careful consideration of the domestic and international economic outlook. More attention is dedicated to the inflation forecast than before and a fan chart is utilized to ascertain the risks inherent in the forecast. Meetings are held on even months of the year but provision is made for unscheduled meetings. Over the years, there have been clear benefits in the adoption of the inflation targeting; the inflation and output volatility has to dampen; there is a significant improvement of monetary policy credibility to agents; there are transparency and accountability in monetary policy; and the SARB forecasting performance has improved over the years and compares well with credible agencies. The inflation rate was within the target range in 2000-2001, and it was above the target range in 2002 at 9%. During the year 2003-2007, it was within the target range but it was off target in 2008 and 2009 at 10% and 7%, respectively, during the credit crunch. In the year 2010-2017, the inflation target was within the target.

3.3.3. Monetary policy framework of Brazil

There have been several reforms in the monetary policy framework of Brazil since the Real Plan in 1994. The Real Plan stabilization policy included using the exchange rate as a nominal anchor, introducing financial liberalization and trade and freeing the capital accounts. Under the Real Plan, Brazil pursued a fixed exchange rate and a free trade policy. The exchange rate was the price anchor used in the 1990s, accompanied by high interest rates, which was used as a catalyst to attract short-term foreign direct capital inflows, in order to maintain a surplus in the balance of payment. As a result, the currency appreciated as more than anticipated capital flows were received and the current account surplus increased. The global recession of 1997-1998, and the South East Asian and Russian crises, led to the capital outflow, budget deficit and depreciation of the domestic currency and slump of the economy. The failure of the fixed exchange rate regime prompted Brazil to shift to the floating exchange rate regime.

Since June 1999, Brazil adopted the inflation targeting regime to reduce the inflation pressure that resulted from the exchange rate depreciation. The Central Bank of Brazil (BCB) also adopted the floating exchange rate regime in January 1999. The BCB engaged in a tightening monetary policy cycle to accommodate the currency depreciation shock and to curb the inflation rate. As a result, the inflation rate declined significantly to a single figure and the exchange rate appreciated immediately (Serrano & Summa, 2012). The BCB utilized the short-term interest rate to keep the inflation low, within the target range. The inflation target of Brazil is adapted from the Swedish and British Inflation targeting framework (Schmidt-Hebbel *et al*., 2002). The National Monetary Council (CMN) determines the inflation target, as proposed by the finance minister. The president of Brazil is responsible for the appointment of the BCB governor, the minister of finance and planning, and three directors all of whom are members of the CMN. The CMN determines the inflation targets annually and the range of tolerance for the next two years (Kaseeram, 2012)

The Central Bank of Brazil Monetary Policy Committee (COPOM) utilizes the short-term interest rates to steer the inflation toward the target range. The targets are based on headline consumer price index and the target range is 4.5%. When the inflation target is out of the target band, the BCB governor is expected to explain the causes and the measures and time frame on how to steer the inflation index within the target band in an open letter. The Selic, which is the policy instrument, is set by the COPOM between its general meetings. The BCB governor has the authority to change the policy instrument to steer inflation index towards the target in response to inflationary shocks in the economy between the COPOM meetings. The BCB releases minutes of the COPOM meeting on its website and to the public media after eight days (Schmidt-Hebbel & Werner, 2002)

The inflation targeting framework has proved to be beneficial to the Brazil economy, despite fiscal and political uncertainty. The inflation volatility and output volatility has decreased significantly. Since the inflation targeting monetary policy has improved significantly, it enhanced credibility, accountability, and transparency. The inflation target rate in Brazil is 2.5%-6.5% and the inflation targeting framework was officially adopted in June 1999 (Roger & Stone, 2005). The average level of real inflation rate has declined significantly from 600%, before adoption, to 6% average rate during the inflation targeting regime, which was a remarkable experience in such a short period (Maumela, 2010). Nonetheless, the mean, absolute deviation is higher at 1.9%, relative to developed markets with inflation targeting; it seems on par with the rates experienced by other emerging markets. During the inflation target period, inflation was at its highest at 14.8% in 2003 and at its lowest at 3.4% in 2017.

3.3.4. Monetary policy framework in Mexico

Monetary policy has evolved in Mexico over the years; before 1994 it pursued the fixed exchange rate framework. In terms of the fixed exchange rate, the central bank is constrained by the exchange rate; it pegs the domestic currency to a foreign currency such as the USA dollar. In 1995, Mexico experienced a recession, which impacted negatively on the credibility and accountability of the monetary institution. Hence, it made it impossible for the central bank of Mexico to establish monetary policy as the nominal anchor of the economy. The financial crises led the Mexican bank to move towards fully-fledged inflation targeting, in order to improve financial stability and reducing the inflation rate. On December 19, 1994, the Central Bank of Mexico adopted the floating exchange rate regime as it failed to protect its domestic currency.

Mexico pursued a mixed framework of money and inflation targeting in January 1995 (Maumela, 2010).

A fully fledged inflation targeting regime in Mexico was adopted in January 2001 (Hu, 2006; Ramos-Francia & Garcia, 2005). There were numerous benefits from the inflation targeting regime in Mexico. The inflation rate has been reduced from two digits to a single digit since its adoption. Credibility, transparency, and accountability of monetary policy have been improved significantly. The objective of the Bank of Mexico has shifted from an exchange rate targeting to an inflation targeting. The short-term interest rate is used as the main instrument of monetary policy and it is announced by the board of the bank of Mexico. The volatility of the headline CPI and the output gap has declined significantly. Moreover, inflation expectations have converged to the target. In addition, the fiscal policy side in Mexico is sustainable and consistent. The independence of the Bank of Mexico is maintained and vital for the effectiveness of the Bank of Mexico. The banks forecasting performance compares well with reputable agencies.

The average inflation declined significantly since the adoption of the inflation rate by 38.4% and reached the lowest rate of 4% by the end of 2005 (Maumela, 2010). The inflation rate in 2000-2001 was within the upper and lower target band. However, in 200, the inflation rate was above the target band by 3%, and at the end of 2003, it stabilized below the target range. In 2004, the inflation rate declined to reach its minimum at -0.7%, and it remained within the target band until the end of 2007. Like South Africa, Chile, and Brazil, the inflation rate was above the target bank 10% and 7%, during the financial crisis in 2008-2009, respectively. Since 2009, the inflation rate has been within the target band. The experience of Mexico demonstrates the effectiveness of the inflation targeting system with a combination of a floating exchange rate in reducing inflation and maintaining a sustainable economic growth.

3.3.5. Monetary policy framework in Russia

The Russian economy is one of the few economies that has not fully adopted a full-fledged inflation targeting framework. Yudaeva (2018) argued that the main reason for Russia not fully adopting the inflation targeting regime is a political one, with uncertainty fiscal policy dominating and a constrained monetary policy. Hence, the central bank is directly exposed to political pressure and must make resolutions driven by goals other than inflation control. Thus, the budget rule in 2017 enhances the Bank of Russia’s effectiveness in maintaining inflation targets and cutting long-term interest rates. Russia is not a fully-fledged inflation targeter, since the central bank independence is not enshrined in the constitution and there is a lack of transparency in in its work.

The current study examines the credit channel of monetary policy transmission for quarterly data spanning 2000-2016. During this period, the Bank of Russia pursued several monetary policies, such as the fixed exchange rate regime, although it has subsequently moved towards a fully-fledged inflation targeting regime. The fixed exchange rate regime has been the main framework until November 2014. However, the Bank of Russia is always prepared to intervene in the foreign exchange market to reduce undue shocks or volatility. The Bank of Russia widens the allowed fluctuation band around the central parity of its exchange rate basket. In addition, the exchange rate targeted was not allowed to adjust to reflect underlying market pressures, especially after 2008 (Korhonen & Nuutilainen, 2017).

Since 1998, the problem Russia has faced is high global oil prices improving fiscal balance but generating serious problems for monetary and exchange rate policies. As a result, the Bank of Russia has had to intervene in the foreign exchange rate, which increases the money supply and inflation. Similarly, the domestic currency would have appreciated if the Bank did not intervene in the foreign exchange market. Thus, there is a contradiction between the policy objectives of stabilizing the exchange rate or inflation, as there seem to be a high inflation rate and an appreciation of the domestic currency. To resolve this contradiction, the Bank had to pursue both the inflation target and exchange rate target objectives (Granville & Mallick, 2006).

The Bank of Russia first announced the reduction of the general price level as its objectives in the 2007 monetary policy guidelines (Bank of Russia, 2006). The 2006 annual target for inflation rate was set at 8.5%, but it had to be revised up to 9%, and for the subsequent year (2007) it was 6.5-8%, according to the federal budget. In 2008, during the financial crisis, the inflation target was revised from 4.5-6% to 7%. The appreciation of the domestic currency is one of the instruments utilized to contain inflation, nonetheless, it proves to be ineffective. Russia's economy has been hindered by many obstacles, such as economic sanctions by the United Nations and the civil war in the Ukraine. Hence, there have been many inflationary pressures and policy uncertainty as consequences of the civil wars.

The move towards fully-fledged inflation targeting has significantly benefited the Russian economy in numerous ways. The inflation and output volatility since 2006 has been dampened significantly. Since 2006, a large deviation of the actual inflation from the target inflation rate has been experienced in 2008 and 2015, respectively. Russia's inflation rate has been within the target band since 2006, except in 2008 during the global financial crises. During 2008, the inflation rate was 3% above the revised inflation target. However, during 2009-2016 periods, the inflation rate has been within the target band. Inflation targeting regime in emerging markets have been significantly successful in reducing the inflation rate and maintaining a sustainable economic growth. For inflation targeting regime to operate successfully, fiscal policy must be sustainable.

3.4. The conclusion of the chapter

There is an apparent consensus in empirical literature with the existence of the bank lending channel in emerging markets (Tabak *et al*., 2016; Ibarra, 2016; Matousek & Solomon, 2017; Anwar & Nguyen 2018). However, there are other studies which have not found the existence of the bank lending channel (Simpasa *et al*., 2014). The chapter reviewed the monetary policy framework in the selected emerging markets. South Africa, Brazil, Chile, and Mexico use the inflation targeting regime to reduce the price level and maintain a sustainable economic growth. Russia is the only country that has not fully adopted the inflation targeting regime. After the year 2000, Russia has moved towards the fully-fledged inflation targeting regime. Emerging markets that have fully adopted the inflation targeting regime have been able to reduce the CPI and output volatility. They have been able to curb the CPI within the upper and lower target band, except during the credit crunch of 2007-2008. In addition, the selected emerging markets have been hindered by fiscal policy, corruption and political uncertainty in recent years.

CHAPTER 4: METHODOLOGY AND DATA

4.1. Introduction

This chapter analyzes the methodology, data and its sources, lag length selection approach, panel unit root test, impulse response function, the variance decomposition and lastly, the diagnostic tests. For analytical purpose of the response of bank loans to monetary policy rate shocks, the study adopted the Panel Vector Autoregressive Model utilized by (Seleteng and Motelle (2016). A panel VAR Model consists of endogenous and interdependent variables, both in a static and in a dynamic manner, while in some relevant cases, exogenous variables could be included and it adds a cross sectional heterogeneity to the framework (Canova & Cicarrelli, 2013).

The contribution of the study to the available literature is through the employment of the PVAR Model to investigate the credit channel of monetary policy transmission in emerging markets. Unlike in developed countries, few studies have employed the PVAR Model to analyze the impulse response of the bank lending to monetary policy rate innovations in emerging countries. Most studies that have been conducted in emerging and developed countries to investigate the credit channel have used the VAR Model (Obafemi & Ifere, 2015, Ciccarelli *et al*., 2015). The VAR Model treats all variables as endogenous and interdependent both in a static and dynamic manner (Ramey and Shapiro, 1998). The PVAR model is one of the latest models, which combines both the characteristics of panel data and the Vector Autoregressive model.

PVAR model is appropriate to analyze credit shocks of monetary policy transmission since, (i) it captures both dynamic and static interdependencies, (ii) easily incorporates time variations in the coefficients and in the variance of the shocks, (iii) treats the links across units in an unrestricted fashion, and (iv) accounts for cross sectional dynamic heterogeneities (Canova & Cicarrelli, 2013). The model consists of five variables: gross domestic product, inflation rate, nominal effective exchange rate, interest rates and bank loans. Economic activity is represented by gross domestic product, exchange rate represents external shocks, interest rate represents interest rate policy rate, bank loans represent credit supply by banks and inflation rate represents domestic prices. During the selected period of 2008-2016, emerging markets experienced high-interest rate volatility and rising inflation relative to developed countries. The main cause of high-interest rate in emerging countries was the recession of 2007-2011 and the quantitative easing practiced by the United States and other developed countries.

4.2. Data and sources

The analysis employs macrodata obtained from secondary data sources. Data are retrieved from the International financial Statistics (IFS), compiled by the International Monetary Fund, from Quandl founded by Nasdaq and from Bank of International Settlement (BIS). The consumer price index (CPI), the lending interest rate (R), the money supply (M2), gross domestic product (GDP) and the nominal effective exchange rate (NEER) for the selected emerging countries is obtained from the IFS. Bank loans are retrieved from the Bank of International Settlement (BIS) and the exchange rate is obtained from Quandl. The M2 and the GDP is in domestic currency and in millions. Hence, both the M2 and GDP are multiplied by the exchange rate (the domestic currency per US dollar), in order to convert it into a common currency for all the countries. The formula for money supply in US dollars may be written as follows: $M2 = M * EXR$. Where:M is money supply in domestic currency, EXR is the exchange rate and $M2$ is money supply in US dollars. The frequency of the time series data is quarterly for the period 2000 to 2016. A sample size of 340 is adequate for estimation purposes since it does not compromise the degree of freedom. Variables that are in level form and in index are log transformed in order to interpret them as elasticity and to minimize heteroskedasticity, as shown in the Table 4.1 below:

Table 4.1: Summary of data sources, measurement and expected signs

Variables	Measurement	Sources	Expected Sign
L	Percentage	BIS	–
R	Percentage	IFS	–
LogCPI	Index	IFS	$+/-$
LogM2	US dollars	IFS/FED	$+$
LogGDP	US dollars	IFS	–
LogNEER	Index	IFS	$-/+$

Source: Generated by author

4.3. Panel unit roots

The following section details the numerous panel unit root tests that are employed in the study. The three panel unit root tests that are considered are those from Levin and Lin (1992, 1993); Levin, Lin and Chu (2002); Im, Pesaran and Shin (1997); Maddala and Wu (1999) and Choi (2001). Non-stationary panel data may result in biased standard errors, however, the point estimation of the value of parameters are consistent. The main advantage of utilizing panel unit root tests is that they are more effective relative to the standard time-series unit root tests in finite samples (Campbell and Perron 1991). Panel unit root tests are more effective than standard time series unit roots, since the total variation across countries adds more information to the variation across time, resulting in more precise parameter estimates (Taylor & Sarno, 1998). The study begins by analyzing the tests of Levin and Lin (1992, 1993), followed by Im, Pesaran and Shin (1997) and lastly Maddala and Wu (1999) and Choi (2001).

4.3.1. The Levin and Lin tests

The Levin and Lin (1992, 1993) and Levin, Lin and Chu (2002) tests, are an extension of the Dickey Fuller test, which allows for heterogeneity of individual deterministic effects (a constant and/or linear time trend) and heterogeneous auto-correlation structure of the errors assuming homogeneous AR (1) parameters. It presumes that both N and T tend to infinity, but that T rises more rapidly, such that N divided by T approaches zero. The equation of the Levin and Lin may be specified as follows:

$$\Delta Y_{i,t} = \alpha_i + \varphi Y_{i,t-1} + \sum_{k=1}^{n} \emptyset_k \Delta Y_{i,t-k} + \delta_{i,t} + \theta_t + U_{it} \tag{4}$$

This framework consists of both the unit-specific time trends and the unit-specific fixed effects. The LL test consists of pooling the t-statistic of the estimator to estimate the null hypothesis, that every individual time series is non-stationary against the alternative hypothesis, that every individual time series does not contain a unit root. Hence, LL assumes consistent autoregressive coefficients for all individuals. By imposing a cross-equation restriction on the first-order partial serial correlation coefficients under the null hypothesis, this LL test has a much higher power than performing a separate unit root test for each individual (Barbieri, 2006). However, since the LL was bypassed by the IPS (for several reasons discussed later) was not chosen to present results from the LL tests in this thesis.

4.3.2. The Im, Pesaran and Shin (IPS) tests

The Im, Pesaran and Shin (1997) is an alternative testing method which utilizes a standardized t-bar test measurement, based on the augmented Dickey-Fuller test statistics, averaged across the panels, while it considers the case of serially uncorrelated and correlated errors. The IPS test can be specified as follows:

$$\Delta Y_{i,t} = \alpha_i + \varphi_i Y_{i,t-1} + \sum_{k=1}^{n} \emptyset_k \Delta Y_{i,t-k} + \delta_{it} + U_{it} \tag{5}$$

Unlike the LL, the IPS allows heterogeneity on the coefficient of $Y_{i,t-1}$ under the alternative hypothesis. The test does not assume that all individual time series units converge towards the equilibrium value at the same rate, making it a much less tightening test than the LL test. Both the LL and IPS have a similar null hypothesis of all series containing a unit root; the LLC offered a homogenous alternative of all series being stationary. Since IPS allows for φ_i to contrast across groups, the alternative hypothesis is that some of the series are stationary. Thus, the study employs IPS rather than LL, since the variables are of a mixed order. In addition, the alternative hypothesis under IPS is accommodative, since a fraction of the series, is assumed not to contain a unit root. Specifically, for consistency purposes, the assumption is that, under the alternative hypothesis, the fraction of series which are stationary are non-zero.

The IPS is more relevant to the study since the balance PVAR has the same T for all cross-sections to compute the t-test statistic. IPS is appropriate for a data-set in this study, with a limited number of cross-sectional units over a comparatively long period of time. Moreover, it is suitable for this dynamic heterogeneous panel data since it allows for heterogeneity across countries such as individual-specific effects and unique patterns of residual serial correlations

IPS's (1999) simulations show that, when the disturbances in the dynamic panel are auto-correlated, the LL test tends to over-reject the null hypothesis, as N is allowed to increase, and that the size and power of the IPS test are efficient, given that T and N are sufficiently large. It is also vital not to under-estimate the order of the underlying ADF regressions: if an enormous lag order has been selected for the underlying ADF estimate, then the finite sample characteristics of the t-bar test is significant and generally more effective relative to the LL test. In addition, the power of the t-bar test is much more favourably affected by a rise in T than by an equivalent rise in N. Conversely, it must be considered that the LL test is dependent on pooled regressions, while IPS test considers a combination of different independent tests and does not pool the data as the LL test does. Therefore, when making power comparisons, the worse performances of LL test may be because this test has to use a panel estimation method which is invalid if there is no necessity for pooling.

Special care needs to be exercised when interpreting the results of the IPS panel unit root test. Due to the heterogeneous nature of the alternative hypothesis, rejection of the null hypothesis does not necessarily imply that the unit root null is rejected for all i, but only that the null hypothesis is rejected for N1<N members of the group such that as $N \to \infty$, $N1/N \to \delta$. Moreover, the test does not provide any guidance as to the magnitude of δ, or the identity of the particular panel members which the null hypothesis is rejected.

4.3.3. The Fisher-type tests

Maddala and Wu (1999), and Choi (2001) consider the drawbacks of both the IPS and LL tests and offer different method for performing unit root tests on panel data. They suggest using non parametric Fisher-type tests which approach panel-data unit root testing from a meta-analysis perspective. More specifically, these tests conduct unit-root tests for each time series individually, and then combine the p-values from these tests to produce an overall test. Both IPS and Fisher tests combine information based on individual unit root tests, and allow for a heterogonous alternative hypothesis, where ρi can vary across countries. The MW test is flexible since it can be estimated with unbalanced panels. The Fisher test statistics takes the following form:

$$\pi = -2\sum_{i=l}^{N} \ln \pi_i \qquad (6)$$

Where π_i is the probability limit value from regular DF or ADF unit root tests for each cross-sectional i.The null hypothesis and alternative hypothesis is:

H_o : pi =1 for all i.

H_a : pi <1 for at least one i for finite N

The null means that every time series contains a unit root in the panel data set, whereas the alternative implies that at least a fraction of the time series is stationary. The Fisher test allows for the scenario that some time series are stationary, whereas the others are non-stationary.

The Fisher and IPS test are directly comparable because both tests are a combination of different independent tests and both seek to verify the same hypothesis. The main difference between the two tests is that the Fisher test is conducted by combining the significance levels of the different tests, whereas the IPS test is conducted by combining the test statistics. Furthermore, the Fisher test is a non-parametric test, whereas the IPS test is a parametric test. The distribution of the t-bar statistic used in IPS requires the mean and variance of the t-statistics used. Even though IPS have provided directly implementable critical values (for different lag lengths and sample sizes), these are only valid if the ADF test is used for the individual regressions. In comparison, the Fisher test has the advantage of being compatible with the use of any unit root test, and even if the ADF test is chosen, a different lag length for each sample can be separately determined. Lastly, in the IPS test, the length of the time series must be the same for all samples a balanced panel is required, while Fisher imposes no such restriction of the sample sizes for different samples.

The Fisher test is an exact test while the IPS test is an asymptotic test, however this does not lead to a great difference in finite sample results: the adjustment terms in the IPS test and the p-values in the Fisher test are all derived from simulations. However, the asymptotic validity of the IPS test depends on a number of observations, while for the Fisher test it depends on a time frame. Since the dataset in this study is considerably larger in T than in N, the Fisher test may be more appropriate.

Maddala and Wu (1999) conducted simulations (not size-corrected) to compare their Fisher test, LLC test and IPS test and to show that the Fisher test has the highest power in all cases. In fact, the relative advantage grows stronger with the number of stationary processes included. Thus, if only part of the panel in this study is stationary, the Fisher test is the most likely to point it out. Therefore, while both tests offer alternative hypotheses, which allow for a mixture of stationary and non-stationary series in the group, the Fisher test is strictly preferred because it has the highest power in distinguishing the null and the alternative.

While both tests can take care of heteroscedasticity and serial correlation of the error terms, when there is cross-sectional dependence neither can handle this problem well. The Monte Carlo evidence suggests that the problem is more severe with the IPS test, than the Fisher test. Specifically, when T is large but N is not very large (such as in this study's case), the size distortion is smallest with the Fisher test. Choi's simulations (2001) found that, in terms of size-adjusted power, the Fisher test is superior to the t-bar.

4.4. Lag length determination

The main objective of selecting a lag-length is to determine the best-fitting model (Munyengwa, 2012). Unlike the VAR model, the panel VAR does not waste the degrees of freedom. Careful consideration is taken when selecting the appropriate lag length, since less or more lags may result in an adverse effect in the model results. The lag-length selection that was considered for the purpose of this study were: there Swartz Information Criterion (SIC), the Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQC) and the Bayesian Information Criterion (BIC). Other lag-length selection criterion that were considered in other studies include the Sequential Modified test statistic (LR) and the Final Prediction Error (FPE) (Enders, 2004).

According to Liew (2004), the AIC and FPE are superior, relative to other criteria for data sample, with less than sixty observations (small sample size). They also minimize the chance of under estimation, while maximizing the probability of recovering the appropriate lag length. In addition, they impose a penalty if a large number of variables are included as a catalyst to the performance of the model. The efficiency of criterion accelerates as sample size increases. In addition, the HQC is more suitable for large sample sizes with more than (120 observations) (Liew, 2004). Hence, the HQC and BIC are employed in this study, as the number of observations is 340.

The criterion utilizes the following formulas:

$$AIC = \ln|\Sigma| + \frac{2pk^2}{T-p} \quad \text{And} \quad SIC = \ln|\Sigma| + \frac{pk^2\ln(T-p)}{T-p} \qquad (7)$$

An obstacle arises when the lag lengths selected by the various criteria are not the same. In that circumstance, the procedure of determining the lag-length when estimating the PVAR model is to select the minimum lag length among the estimated criteria (Enders, 2004:69). For example, it is possible that three approaches determine one lag, one select three lags and the last select four lags, and the suggested lag to be selected is one.

4.5. The panel cointegration tests

The requirements of the panel VAR Model are that regressors must be stationary or integrated, and no cointegration is detected. Hence, regressors must be differenced until covariance stationary is realized and estimate the panel VAR model using log-transformed data. However, if regressors are of mixed order I(1) and I(0), the Panel Vector Error Correction (PVECM) model is appropriate for estimation purpose. The determination of cointegration is important to prevent the estimation of spurious regression. According to literature, there are two methods for the panel cointegration tests: residual based, and maximum likelihood based. McCoskey and Kao (1998), Kao (1999), and Pedroni (1995, 1997, 1999) propounded the residual based panel cointegration test statistics. Additionally, the maximum likelihood based panel cointegration test statistics was introduced by Larsson and Lyhagen (1999), Larsson *et al.* (2001), and Groen and Kleibergen (2003).

McCoskey and Kao (1998) derived a panel cointegration test for the null of cointegration, which is an extension of the LM test and the locally best unbiased invariant test for MA root. Kao (1999) considered the spurious regression for the panel data and propounded the DF and ADF type tests. He proposed four different DF type test statistics, and used the sequential limit theory of Philips and Moon (1999), to derive the asymptotic distributions of these statistics. The study considers properties of the residual based panel cointegration tests of Pedroni (1999) and the maximum likelihood based panel cointegration rank test of Larsson *et al*. (2001) for testing panel cointegration.

4.5.1. The Pedroni tests

The Pedroni test for panel cointegration was proposed by Pedroni (1997, 1999, 2000) and allows for heterogeneity. Unlike the Kao tests, the Pedroni test assumes trends of the cross sections, and the null hypothesis contains no cointegration. The Pedroni's test is superior to the Kao test since it allows for a multiple variable, for a cointegration vector to vary across numerous sections of the panel. In addition, it allows for heterogeneity in the disturbance term across cross sectional units. The Pedroni test is specified as follows:

$$Y_{it} = a_i + \delta_{it} + \sum_{m=1}^{M} \beta_{mi} X_{mi,t} + u_{i,t} \tag{8}$$

Where T is the number of observations over time, i is the number of individual members in the panel and M denotes the endogenous variables. The slope coefficient $\beta_{1i}, \dots, \beta_{mi,}$ and the member specific intercept a_i can fluctuate or vary across each cross section. The δ_{it} is a deterministic time trend specific to an individual to another, enabling the cointegrating vectors to be heterogeneous across members of the cross section.

There are seven methods of cointegration statistics for the Pedroni test, which capture the within and between effects in the panel. The tests are divided into two categories. The first group consists of four tests based on pooling along the within dimension. The four tests are similar to the Koa tests and involve calculating the average test statistics for cointegration in the individual time series across the numerous sections.

The cointegration statistics are derived through a process of five steps. It begins by computing the residuals $u_{it}^{\wedge}$ from the panel equation (8) above. The estimation process includes all appropriate time trends or common time dummies and fixed effects. The second step computation of residuals is from the following regression:

$$\Delta Y_{it} = a_i \Delta X_{it} + a_{2it} \Delta X_{2it} + a_{mi} \Delta X_{mi,t} + u_{i,t} \quad (9)$$

For $t = 1,2, \dots, T; i = 1,2, \dots, N;\ m = 1,2, \dots, M$

Where: Y_i is the endogenous variable and X_{mi} is the regressors, T refers to the number of observations over time, N represents the individual countries in the panel, and M is the number of regressors in the model. The slope coefficient is represented by a_i and $u_{i,t}$ refers to the deviations from the modelled long-run correlation. The $u_{i,t}$ does not contain a unit root, when the series included in the regression are cointegrated. The third step is to compute the long-run variance ($L_{lli}^{\wedge 2}$):

$$\hat{L}_{lli}^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{u}_{it}^2 + \frac{2}{T}\sum_{s=1}^{K}(1 - \frac{S}{K_i + 1}) \sum_{t=s+1}^{T} \hat{u}_{it}\hat{u}_{it-s} \quad (10)$$

Where u_{it} is the residual computed from the error of the cointegration equation (10), K and S are lag lengths and T is the number of observations over a period of time (Newey & West, 1987; Pedroni, 1999).

After computing the long run variance, the following step is to obtain residuals of the ADF test for $\hat{\varepsilon}_{it}(\hat{u}_{it})$ and compute the residuals variances below:

$$\hat{S}_i^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{u}_{it}^2 \quad and \quad \check{S}_{NT}^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{S}_i^2 \quad (11)$$

Where $\hat{S}_i^2$ refers to the contemporaneous variance and $\hat{u}_{it}^2$ refers to the long-run variance of the residual $\hat{u}_{it}$; and $\check{S}_{NT}^2$ refers to the contemporaneous panel variance estimator. Last, but not least, is to obtain group-t and panel-t statistics. These statistics are asymptotically normally distributed.

4.5.2. Kao tests

Koa (1999) proposed DF and ADF type tests for cointegration in panel data. The Koa test consists of four DF-type tests: the DF_p test, DF_t test, DF_p^* test, and the DF_p^* test. Both the DF_p test and DF_t test refers to a strongly exogenous relationship between the errors and the regressors, whereas, the DF_p^* and the DF_t^* tests refers to the endogenous relationship between errors and regressors. In addition, Kao (1999) propounded the ADF test which can be estimated in the regression below:

$$u_{i,t} = \rho\mu_{i,t-1} + \sum_{j=1}^{n} \emptyset_j \Delta\mu_{i,t-1} + v_{it} \tag{12}$$

The null hypothesis of the DF tests and ADF type tests is that of no cointegration in the cross sectional data. The ADF test statistics is computed by the following equation:

$$ADF = \frac{t_{ADF} + \sqrt{6N_{\sigma^v}}/(2_{\hat{\sigma}ov)}}{\sqrt{\hat{\sigma}_{ov}^2/(2\hat{\sigma}_{ov)}^2 + 3\hat{\sigma}_v^2/(10\hat{\sigma}_{ov}^2)}} \tag{13}$$

Where t_{ADF} is the ADF statistics of equation (13), and both the DF tests and the ADF tests follow the standard normal distribution. Kao's test imposes homogeneous cointegrating vectors and AR coefficients, but it does not allow for multiple exogenous variables in the cointegrating vector. Another drawback is that it does not address the issue of identifying the cointegrating vectors and the cases where more than one cointegrating vector exists.

4.6. Granger causality test

Granger (1969) propounded the causality test which is utilized to determine the direction of causality among variables respectively in the five selected emerging countries. When two variables, X and Y, are cointegrated, that may imply variable X only affects variable Y, or both X and Y affect each other. The first shows a unidirectional relationship and the second show a bidirectional relationship. The null hypothesis of the test is that there is no causality relationship from Y to X, for at least one cross sectional unit, and the alternative hypothesis is that there is causality relationship between regressors in the panel. The popular Granger causality test is specified as follows:

$$\Delta Y_t = \sum_{i=1}^{n} \delta_i \, \Delta Y_{t-1} + \sum_{j=1}^{n} \alpha_j \Delta \, X_{t-j} + \varepsilon_t \tag{14}$$

$$\Delta X_t = \sum_{i=1}^{n} {}_{\sigma_i \Delta X_{t-1}} + \sum_{j-1}^{n} \beta_j \, \Delta Y_{t-j} + \varepsilon_{2t} \tag{15}$$

Equation (14) indicates that the present value of ΔY is related to the past values of itself and the past values of ΔX. Whereas, the equation shows that ΔX is related to the past values of itself and that of ΔY. The null hypothesis in equation (14) is $\alpha_j = 0$ which postulates "ΔX does not Granger cause ΔY". While the null hypothesis in equation (15) is $\beta_j = 0$, hence ΔX does not Granger cause ΔY. The F-statistics is critical in the acceptance and rejection of the null hypothesis.

4.7. Model specification

This section discusses the model that is employed for analysing the impact of a one standard deviation shock of monetary policy rate to other economic variables in the selected emerging markets. The study adopts the PVAR framework by Seleteng and Motelle (2016), which controls for heterogeneity and endogeneity in a cross sectional approach. The PVAR model is an extension of the VAR framework, which treats all the variables in the system as endogenous, with a cross-sectional, which allows for unobserved heterogeneity (Love & Zicchino, 2006).

The PVAR model was developed by Holtz-Eakin *et al*. (1988). It combines both the panel data framework and the VAR model. The PVAR model is suitable for ascertaining the response of bank loans to monetary policy shocks since, (i) it captures both dynamic and static interdependencies, (ii) easily incorporates time variations in the coefficients and in the variance of the shocks, (iii) treats the links across units in an unrestricted fashion, and (iv) accounts for cross sectional dynamic heterogeneities (Canova & Cicarrelli, 2013). Dynamic interdependency refers to when one country's lagged variables affect another country's variables, or it refers to links across countries through PVAR coefficients. In equation (16), the endogenous variables for each country depend on the lags of the endogenous variables for every country.

Static interdependency occurs when the correlations between the disturbance term in two countries PVARs are non-zero y). Static interdependence is modelled through the error covariance matrix. If Σ_{jk} = 0, then there is no static interdependence between countries j and k. Cross section heterogeneities occurs when two countries have PVARs with different coefficients (Canova & Ciccerelli, 2013).

Most studies used the VAR model to ascertain the response of bank loans to monetary policy shocks (Bhoi *et al*., 2017,Ibarra, 2016, Ifeakachukwu & Olufemi, 2012, Walia & Raju, 2014). However, there are no studies that have use the PVAR framework to analyse the effect of monetary shocks to credit in the selected emerging markets. This study contributes to the existing empirical literature through the use of the PVAR in analysing the credit channel of monetary policy transmission in emerging economies.

As a result of the limitation of data in emerging countries, employing a VAR model is not suitable since it comprises the degree of freedom (Seleteng & Motelle, 2016). However, a PVAR also suffers from the same limitations of lack of theoretical background as the VAR model. Following the work of (Dajcman (2013), the control variables used in this analysis include: bank loans (CR), monetary policy rate (r), the nominal exchange rate (E), inflation rate (π), and gross domestic product (Y).

The dissertation presents the following simultaneous equation that will be estimated in the reduced PVAR model:

$$Z_{it} = \Psi_0 + \Psi_1 Z_{i,t-1} + \Psi_2 Z_{i,t-2} + \cdots + \Psi_p Z_{i,t-p} + \varepsilon_{it} \tag{16}$$

Where Z_{it} represents a (5$\times$ 1) vector of system variables (Cr, R, π, and M2), Ψ_0 is a (5$\times$ 1) vector of constants, $\Psi_{1,2,\ldots,s}$ is a (5$\times$ 5) matrix of coefficient estimates, ε is a (5$\times$ 1) vector of the white noise error term, whereas i is a cross-sectional identifier and s is the maximum lag length of each variable selected in accordance with the Schwarz Bayesian Criterion (SBC) and the Akaike Information Criterion (SBC). The emerging countries used in the model are Brazil (1), Chile (2), Russia (3) and South Africa (4).

In the PVAR framework, in order to make sure that the underlying structure is equal for all the countries in the panel, some constraints (16) on parameters need to be imposed. Yet, in practice, such constraints are likely to be violated; one way to overcome this problem is to allow for individual heterogeneity in all the variables by introducing fixed effects, denoted by f_{it} in (16). However, the fixed effects are correlated with the regressors due to the lags of the dependent variable, therefore, forward mean-differencing are used, also known as the Helmert procedure (Arellano & Bover, 1995). The Helmert procedure removes the mean of all future observations available for each country and time in order to preserve the orthogonality between transformed variables and lagged independent variables (Love & Zicchino, 2006).

Even so, the differencing might result in a simultaneity problem due to the correlation between regressors and the differenced error term. Moreover, heteroscedasticity may also exist due to the maintenance of heterogeneous errors with different countries in the panel. Accordingly, after eliminating fixed effects by differencing, the panel GMM was applied, where lagged regressors were used as instruments in order to estimate coefficients more consistently. Thus, the equation in (16) becomes:

$$Z_{it} = \Psi_0 + \Psi_1 Z_{i,t-1} + \Psi_2 Z_{i,t-2} + \cdots + \Psi_p Z_{i,t-p} + f_i + \varepsilon_{it} \quad (17)$$

4.8. Impulse response function

The impulse-response functions (IRFs) describes the reaction of one variable in the system to the innovations in another variable in the system, holding all other shocks at zero. Impulse response functions (IRFs) are computed to evaluate the effect of monetary policy rate shocks on other economic variables, especially inflation rate and bank loans. The IRFs may be defined as the instantaneous effect of a one-standard deviation innovation shock on the endogenous variables from the another variable. IRFs are constructed from the estimated VAR coefficients, and their standard errors, and may be plotted to visually represent the behaviour of the variables of interest to the various shocks. According to Bernanke and Blind (1988), impulse responses are suitable for analyzing monetary policy transmission through impulse response shocks. Unlike most studies that have used the VAR model, the current study used PVAR, which also produces impulse response and adds a cross sectional dimension. The current study is superior to previous studies since impulse response of different emerging countries are analyzed in one study.

Nevertheless, the variance-covariance matrix of the disturbance term is improbable to be diagonal, and consequently, in order to control the innovations to one of the VAR errors, it is essential to decompose the residuals in such a way that they become orthogonal. The Cholesky decomposition of the variance-covariance matrix of residuals is used in the PVAR (Love & Zicchino 2006; Zuniga 2011). The convention is to adopt a particular ordering and allocate any correlation between the residuals of any two elements to the variable that comes first in the ordering. Therefore, the assumption is that the variables at the beginning of the ordering contemporaneously affects the variables that follow them, as well as with a lag, while the latter variables affect the former only with a lag.

4.9. Variable ordering in PVAR

The selection and ordering of regressors in a panel VAR model is of paramount importance in accordance with most literature reviews of applied econometrics (Belingher, 2015; Seleteng, 2016). Alternative orderings of variables may result in biased coefficients, and may also change the explanatory power of variables. It has been argued that the importance of a given variable, in terms of extent to which its innovations influence other variables, may depend critically on the arbitrary ordering that is chosen (Porter & Offenbacher, 1983). This study's analysis assumes that the shocks of monetary policy interest rate (R) run to money supply (M2), then to the general price level (INF), to output (GDP) and to bank loans (L). The choice of ordering is based on the premise that the announcement of the repo rate changes by the SARB evokes commercial banks' movements in lending rates within 24 hours, within the CMA. This means that it is assumed that this rate does not respond to any other variables within the current period, but that all other variables potentially respond to it. The nominal effective exchange rate has been included since most emerging markets are volatile to external shocks, especially from developed countries.

4.10 The VAR models

The study also estimates the VAR model for specific countries included in the panel VAR model. The VAR model per specific country is estimated in order to compare the impulse response of the control variables to monetary policy rate shock among the countries. The impulse response of the VAR for each country is also compared to the average impulse response computed from the PVAR model. A VAR model is a system of equations where each endogenous variable is regressed with its own lag (Gujarati, 2004). VAR model is suitable for analyzing monetary policy shocks, however, like most models, a VAR model has its advantages and disadvantages. Its main disadvantage is that it wastes the degrees of freedom and it lacks a theoretical background (Asterio & Hall, 2007). The discussion on the VAR model includes the analyses of the unit root test, the lag selection criterion, model specification and the diagnostics tests.

4.10.1 Unit root tests

The statistical procedure utilized to ascertain the stationary of a series is referred to as a unit root test. It is important to test for stationarity in time series data, since non-stationary data may result in spurious regression. Stationary time series is determined by a constant mean, autocovariance and variance over time (Gujarati, 2004:382). Non-stationary time series, however, tends to have a variance that varies over time and has a time dependent mean. This mean that variables may tend to move along in the long-run yet there is no relationship (Gujarati, 2004:797). Generally, time series data are assumed to be stationary, however, due to structural breaks it may become non-stationary. Estimation of a model with non-stationary variables violates the asymptotic analysis assumption, hence hypothesis testing about a regression is not appropriate, since $t - ratios$ do not follow a t-distribution. Furthermore, regressing non-stationary time series may also result in an unstable VAR model, in bias variance decomposition and also to overestimated standard errors for impulse response (Munyengwa, 2012).

For the purpose of this study, the Augmented Dickey-Fuller test (ADF) is employed as the main test for unit root and the Philips-Perron test (PP) is employed as a robustness check. Another unit root test acknowledged by the literature review includes the KPSS test. The ADF test was propounded by Dickey and Fuller (1979, 1981) and it is developed from the Dickey Fuller test by adding the lags. The ADF test equation can be specified as follows:

$$\Delta x_t = \alpha_0 + \beta_t + \delta x_{t-1} + \sum \gamma_i \Delta x_{t-1} + \varepsilon_t \tag{19}$$

Where $\Delta x_{t-0} = (Y_{t-0} - Y_{t-1})$, $\Delta x_{t-1} = (Y_{t-1} - Y_{t-2})$, ε_t is the error term and δ is the coefficient used to test the null hypothesis of no stationarity. The ADF equation assumes that variable X is stationary if δ is negative and significantly different from zero.

The ADF is more suitable for the VAR model since it uses more lags compared to the DF test. The ADF test utilizes three equations: the intercept, the trend, and intercept and no intercept. However, the present study employs the trend and intercept since most time series data consist of trend and intercept. Unlike the DF test, the ADF test is superior since it tackles the autocorrelation problem. The test is conducted in STATA by using the Dickey Fuller Command, and in Eviews using the ADF under the unit root test. The lag length selection method is determined by the AIC and the SBC is used as the alternative lag length selection approach.

The Phillips-Perron test is also considered for unit root tests for the purpose of this study. The PP is an extension of the ADF and DF test and was developed by Philips and Perron (1988). The PP test corrects for any serial correlation and heteroskedasticity in the errors $+\varepsilon_t$ non-parametrically by modifying the Dickey Fuller test statistics. Phillips and Perron’s test statistics can be viewed as Dickey–Fuller statistics that have been made robust to serial correlation by using the Newey–West (1987) heteroscedasticity and autocorrelation-consistent covariance matrix estimator. The PP test merit to the ADF test is that there is no need to postulate a lag length during the estimation process. Unlike the ADF test, the PP test is robust to general forms of heteroscedasticity. The PP test also uses three methods: the trend and constant, no trend and the constant. However, for the purpose of this study, the trend and intercept is employed.

4.10.2 Lag selection criteria

The main objective of selecting a lag-length is to determine the best-fitting model (Ogbulu and Torbira, 2012). Careful consideration is taken when selecting an appropriate lag length because it may result in a bias coefficient and spurious model. For the VAR model, the lag-length selection that is considered for the purpose of this study are the Swartz Information Criterion (SIC) and the Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQC) and the Bayesian Information Criterion (BIC). Other lag-length selection criteria that are considered by the literature review include the Sequential Modified test statistic (LR) and the Final Prediction Error (FPE) (Enders, 2004).

According to Liew (2004), the AIC and FPE are superior, relative to other criteria, for a data sample with less than sixty observations (small sample size). They also minimize the chance of under estimation, while maximizing the probability of recovering the appropriate lag length. In addition, they impose a penalty if a large number of variables are included as a catalyst to the performance of the model. The efficiency of the criterions accelerates as the sample size increases. Additionally, the HQC is more suitable for a large sample size with more than (120 observations) (Liew, 2004). Hence, the HQC and BIC are employed in this study as the number of observation is 340.

The AIC and the SIC utilizes the following formulas:

$$AIC = \ln|\Sigma| + \frac{2pk^2}{T-p} \text{ And } SIC = \ln|\Sigma| + \frac{pk^2 \ln(T-p)}{T-p} \quad (20)$$

An obstacle arises when the lag lengths selected by the various criteria are not the same. In that circumstance, the procedure of determining the lag-length when estimating the PVAR model is to select the minimum lag length among the estimated criteria (Enders, 2004:69). For example, it is possible that three approaches select one lag, one selects three lags and the last selects four lags, and the suggested lag to be selected is one.

4.10.3 Cointegration test

When two or more time series data are linked to form an equilibrium relationship over the long run period, they are referred as correlated. It is common practice in time series data analysis to determine if there is a long run relation among variables. The obstacle of spurious regression resulting from nonstationary variables is the main reason for a cointegration test. When all series in the regression model share the same stochastic trend, they are said to be cointegrated and may produce significant and robust results. The cointegration obstacle arises when a combination of I(1) are integrated with order zero. In contrast, Asteriou and Hall (2015) argued that regressing two series of different order I(1) and I(0) respectively may result in significant and robust results. This enables the researcher to select the appropriate model between the VAR and VECM. Cointegration necessitates that variables be integrated with the same order (Enders, 2004). Cointegrated variables have a long run relationship; they move along over time and they have a tendency to adjust to equilibrium (Enders, 2004). If variables are not cointegrated, a VAR model is estimated and when they are cointegrated, a VECM system is estimated. In the present study, only a VAR system is estimated, since inflation targeting regime was only adopted in the year 2000.

4.10.3.1 The Johansen cointegration test

The Johansen cointegration test is an extension of the Engel Granger method, and was propounded by Johansen and Juselius (1990) and Johansen (1988). The popular

Johansen test (1988) is suitable for testing cointegration in a multivariate regression system and is incorporated in numerous econometric software. The Johansen test is based on the relationship between the rank of matrix and its characteristics' roots. The Johansen test begins by determining the order of integration of each variable through unit root testing (Enders, 2010). Subsequently, the VAR lag length must be determine by utilizing the appropriate lag selection criterion. The AIC and the FPE is more suitable for time series with less than 140 observations, as is the case in this study.

Johanson (1988) propounded the maximum eigenvalue and the trace likelihood ratio tests to determine the significance of the canonical correlations. The test statistics are specified as follows:

$$\delta_{trace}(r) = -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\delta}_i\right) \tag{21}$$

$$\delta_{max}(r, r+1) = -T \sum_{i=r+1}^{n} -T \ \ln\left(1 - \hat{\delta}_{i+1}\right) \tag{22}$$

Where δ is the projected value for the ith ordered eigenvalue, from the long-run coefficient matrix, and T represents the number of observations. The δ_{trace} statistics examine the null hypothesis that the number of cointegrating vectors is less or equal to r against the null hypothesis, whereas the δ_{max} statistics tests the null hypothesis that the number of cointegrating vectors is r against an alternative of $r + 1$ cointegrating vectors. The more the difference between the eigenvalues are from zero, the more negative is $\ln\left(1 - \hat{\delta}_i\right)$ and $\ln\left(1 - \hat{\delta}_{i+1}\right)$ and the larger the δ_{max} and the δ_{trace} statistics, respectively. The trace test is preferable since it can be attuned for degrees of freedom and it is more robust to excess kurtosis and skewness.

10.4.3.2 Model specification

In line with previous studies on the credit channel of monetary policy transmission, a reduced VAR model for each country in the estimated panel VAR model above was estimated. The VAR model consists of six variables: bank loans to the private sector, output, inflation rate, money supply, monetary policy rate and the nominal effective exchange rate. The nominal effective exchange rate is for external shocks, as emerging markets are influence by shocks from developed countries. The inflation rate represents the price level, gross domestic product represents the output gap and the lending interest rate represents the monetary policy rate. The benchmark VAR model for this study is specified below:

$$X_t = \alpha + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots\cdots + \beta_q X_{t-k} + \mu_t \tag{23}$$

Where: $X_t = [L \quad GDP \quad INF \quad M2 \quad R \quad NEER\,]$

Where X_t is a $k \times 1$ dimensional Vector of the endogenous variables, α is a $k \times 1$ dimensional vector of constant and $\beta_1 \ldots\ldots \beta_q$ are $k \times k$ dimensional autoregressive coefficient matrices and μ_t is k-dimensional vector of the stochastic error term nominally distributed with the following properties:

$E(\mu_t) = 0$

$E(\mu_t \mu_t') = \Omega$

$E(\mu_i \mu_j') = 0, if\ i \neq j$

Equation (2) above can be represented by the matrix below:

$$\begin{bmatrix} X_t \\ X_{t-1} \\ \vdots \\ . \\ X_{t-k+1} \end{bmatrix} = \begin{bmatrix} \alpha \\ 0 \\ \vdots \\ . \\ 0 \end{bmatrix} + \begin{bmatrix} \beta_1 \beta_2 \cdot & \cdot & \cdot & \beta_{q-1} & \beta_q \\ 1 \quad 0 \cdot & \cdot & \cdot & 0 & 0 \\ \vdots \quad \vdots \quad \vdots & \vdots & \vdots & \vdots & \vdots \\ . \quad . \quad . & . & . & . & . \\ 0 \quad 0 \cdot & \cdot & \cdot & 1 & 0 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ X_{t-2} \\ \vdots \\ . \\ X_{t-k} \end{bmatrix} + \begin{bmatrix} \mu_t \\ 0 \\ \vdots \\ . \\ 0 \end{bmatrix} \tag{24}$$

Equation (3) can be simplified as follows

$$X_t = \alpha + \sum_{i-1}^{k} \tau_i X_{t-k} + \mu_t \tag{25}$$

$i = 1, 2, 3, \cdots\cdots\cdots k$

4.10.3.3 Impulse-response functions

As in the panel VAR model impulse-response functions (IRFs), which describe the reaction of one variable in the system to the innovations in another variable in the system, holding all other shocks at zero will be computed from the five VAR models. Impulse response functions (IRFs) are computed to evaluate the effect of monetary policy rate shocks on other economic variables of especially inflation rate and bank loans. The IRFs may be defined as the instantaneous effect of a one-standard deviation innovation shock to the endogenous variables from another variable. IRFs are constructed from the estimated VAR coefficients and their standard errors and may be plotted to visually represent the behaviour of the variables of interest to the various shocks. According to Bernanke and Blind (1988), impulse responses are suitable for analyzing monetary policy transmission through impulse response shocks. The current study is superior to previous studies since the impulse responses of the selected emerging countries are analyzed in one study and compared to those computed from the panel VAR model.

Nevertheless, the variance-covariance matrix of the disturbance term is improbable to be diagonal; consequently, in order to control the innovations to one of the VAR errors, it is essential to decompose the residuals in such a way that they become orthogonal. The Cholesky decomposition of the variance-covariance matrix of residuals is used in the VAR method (Love & Zicchino, 2006). The convention is to adopt a particular ordering and allocate any correlation between the residuals of any two elements to the variable that comes first in the ordering. Therefore, the assumption is that the variables at the beginning of the ordering contemporaneously affect variables that follow them, as well as with a lag, while the latter variables affect the former only with a lag.

4.10.3.4 Variance decomposition analysis

The variance decomposition is crucial in econometrics modeling in interpretation of the multivariate time series model. The variance decomposition measures the proportion of variation explained by each variable in the endogenous variable in a VAR system. It is developed under the assumption that the forecast error variance of each endogenous variable in the model could be affected by its own shocks and those of other variables included in the model. In this study's context, the response and magnitude of bank loans and other economic variables to shocks in the bank lending interest rate was to be determined.

4.10.4 Diagnostic test

The diagnostic tests that are considered for the VAR model include the lag structure, coefficient diagnostics and residual diagnostics. In econometric modeling, residual diagnostics are vital since regression models try to reduce errors (or residuals). Residual diagnostics ascertain whether the disturbance terms are independently and identically distributed. In other words, they must be 'white noise' (Shrestha & Bhatta, 2017). The Lagrange multiplier test, heteroskedasticity and correlogram test are the main tests utilized for residual diagnostics. The diagnostic checks used in the study include normality, autocorrelation, heteroskedasticity and stability tests. Diagnostic tests are vital to check the robustness of estimated coefficients and stability of the model. The presence of heteroskedasticity and serial correlation violates the classical assumptions of the OLS, and may result in spurious models and invalidates the statistical of parameter estimates. A robustness check is vital to confirm the validity and reliability of estimated result with different estimation techniques.

4.10.4.1 Normality test

Normality assumption is required in order to conduct single or joint hypothesis about model parameters (Gujarati, 2011). The Jarque and Bera (1981) test for normality is employed. This test formalizes the idea of joint hypothesis by testing if the coefficient of kurtosis and coefficient of skewness are jointly zero. It is a weighted average of the squared sample moments corresponding to skewness and excess kurtosis. Skewness is the extent to which the distribution is asymmetric, that is, one side of the distribution is not a mirror image of the other (Stewart, 2005). It is estimated by the coefficient of skewness:

$$S = \frac{\sum(Y_i - Y)^3/n - 1}{S^3} \tag{26}$$

Where denominator S is the standard deviation. In contrast, kurtosis refers to the peakedness of the distribution. It is estimated by the coefficient of kurtosis:

$$K = \frac{\sum(Y_i - Y)^3/n - 1}{S^3} \tag{27}$$

The Jarque Bera test can be specified as follows:

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \tag{28}$$

Where n=sample size, s=skewness coefficient, and k=kurtosis. For a normally distributed variable, s=0, and k=3.

Under the null hypothesis of a normally distributed error, the residuals are normally distributed and the JB statistic has a Chi-square distribution with two degrees of freedom (Verbeek, 2004). The histogram should be bell-shaped and the Bera-Jarque should not be significant, i.e. the p-value should be larger than 0.05.

4.10.4.2 Heteroskedasticity

The presence of heteroskedasticity in a regression framework results in underestimation of standard errors, underestimation of variances, hence resulting in biased and overestimated τ and F-statistics. The Breusch-Pegan test was utilized to test for the presence of heteroskedasticity for the purpose of this study.

4.11 Conclusion of the chapter

This chapter analyzed the steps and justification of the estimation of the panel VAR model and the VAR model. The panel VAR model is estimated for Mexico, South Africa, Chile, Brazil and Russia. The control variables included in the model are bank loans, gross domestic product, inflation rate, money supply, the monetary policy rate and the nominal effective exchange rate. The summary of the steps followed when estimating the panel VAR is depicted in Table 4.1 above. Both the panel VAR model and the VAR models employ quarterly data spanning from the year 2000 to 2015. Eviews 10 and STATA 14 software are used for estimation of models. Five VAR models are estimated for each country as robustness checks and for comparison purpose. The VAR models employs the same data as in the panel VAR model. The VAR models are estimated using level data since differenced data waste the degree of freedom.

CHAPTER 5: EMPIRICAL RESULTS DISCUSSIONS (PVAR)

5.1 Introduction

This chapter discusses and interprets the empirical results of the analytical model presented in the previous chapter. The chapter begins by discussing the data properties and summary statistics. It is followed by presenting formal and informal panel unit roots tests. The chapter continues to present the lag length selection criteria and ascertain the PVAR model results. The Granger causality results to ascertain the direction of causality among variables are discussed. The results of the cointegration tests to determine whether a long run relationship among variables exists are presented. Also, the impulse responses of other economic variables to the monetary policy rate shocks are analyzed. Moreover, the variance decomposition is computed from the estimated model. Lastly, the diagnostic checks are discussed and the summary of the chapter is given.

5.2 Descriptive statistics of the variables

It is vital to commence the empirical results discussion by analyzing the properties of the time series data to be applied in the econometric models. The data consist of 340 observations from five emerging markets, of quarterly data spanning from 2000 to 2016. The estimation of the numerous summary statistics, like the median, mean, probability, skewness, Jarque-Bera and kurtosis tests, are presented in Table 5.1 below. The mean for bank loans, lending interest rate, inflation rate, money supply and nominal effective exchange rate in Table 5.1 are 55.405, 9.09, 1.29, 18.128 and 4.597, respectively. The probability for all the variables is less than 10%, which indicates that the variables may not be normally distributed. Non-normality is a result of the structural break in the data. The main cause of the structural break in data was caused by the global recession of 2007-2008. Also, most of the emerging markets were hindered by credit rating agencies as most were downgraded to junk status due to corruption, poor policies and political uncertainty. Kurtosis measures the degree of flatness of asymmetry distribution compared with a normal distribution of the same variance. The Kurtosis of bank loans and money supply is 2.2 and 2.1, which is close to 3. Whereas the kurtosis for the lending interest rate, inflation rate, and the nominal exchange rate is above 3, which indicates non-normality statistics (Gujarati, 2004).

Table 5.1: Descriptive statistics of the variables

	L	LOGGDP	INF	LOGM2	R	LOGNEER
Mean	44.43676	16.55875	1.531474	21.00841	17.62391	4.556858
Median	50.75000	15.41958	1.400673	19.64655	10.50000	4.583274
Maximum	82.20000	24.12446	8.106784	28.32417	72.40000	5.020698
Minimum	8.500000	9.605544	-2.440315	14.85835	3.303333	3.989415
Std. Dev.	22.51535	4.442936	1.220565	4.201118	16.38597	0.207365
Skewness	-0.194797	0.200561	1.531178	0.355677	1.626273	-0.562295
Kurtosis	1.609895	1.884444	7.726986	1.678131	4.349145	3.247335
Jarque-Bera	29.52583	19.90931	449.4009	31.92262	175.6559	18.78329
Probability	0.000000	0.000048	0.000000	0.000000	0.000000	0.000083
Sum	15108.50	5629.975	520.7012	7142.859	5992.129	1549.332
Sum Sq. Dev.	171853.0	6691.753	505.0353	5983.143	91021.50	14.57708
Observations	340	340	340	340	340	340

Source: Estimated by the researcher

The skewness of bank loans, money supply, and the nominal exchange rate is 0 or less which is accepted by literature (Gujarati, 2004). The study could have used a dummy variable for the structural break, however, due to the nature of the model, it does not accommodate it as an exogenous variable and the results are robust and the signs of the coefficient are according to theory. The Jarque-Bera test of normality is an asymptotic test, based on the OLS residuals. It is a test of the joint hypothesis that skewness and kurtosis are 0 and 3 respectively (Gujarati, 2004). The JB test follows the Chi-square distribution with 2 degrees of freedom with the null hypothesis that the residuals are normally distributed. If the JB statistic is greater than the value of the Chi-square of 5.99 at 5 percent level, we reject the null hypothesis that the residuals are normally distributed.

5.3 Correlation matrix

The correlation matrix is a measure of the direction and strength of the linear relationship among variables. The correlation matrix represented in Table 5.2 indicates that the variables are not correlated, as the coefficient of the variables is less than 70%. There seem to be a positive correlation between L and LogGDP, and LogM2 and R respectively. The variables do not have multicollinearity; the results are robust and statistically significant. Multicollinearity results in the wide confidence of the intervals and in small statistics. There is a negative correlation between LogGDP and INF, R and LogNEER. Overall, the variables are not highly correlated and they don't suffer from multicollinearity.

Table 5.2: The correlation matrix

	L	LogGDP	INF	LogM2	R	LogNEER
L	1.0000					
LogGDP	0.6324	1.0000				
INF	-0.1931	0.0079	1.0000			
LogM2	0.2535	0.3003	-0.0916	1.0000		
R	-0.0459	-0.2213	0.1861	0.6682	1.0000	
LogNEER	-0.3337	-0.1371	-0.0458	-0.4561	-0.4172	1.0000

Source: Estimated by the researcher

5.4 Panel unit root tests

The chapter will proceed to discuss the forma l and informal panel unit roots test of the panel data. According to the literature review, it is vital to test for stationarity and determine the order of integration in cross-sectional data before the estimation of a regression. As stated in the previous chapter, most time series data are nonstationary at levels, and stationary at first difference. Employing non-stationary data in estimating a PVAR model may result in a spurious and an unstable PVAR model. In estimating a PVAR model, the variables must be I(1) at the level form and I(0) at first difference. However, an obstacle arises when the variables are of mix order; some scholars advocate that a PVAR can be estimated in level form as long as the regression satisfies all diagnostic test.

The present study begins by graphically inspecting the data for panel unit roots. Figure 5.1(a) in the Appendix A depicts the graphical plots of the data in levels. According to the plots in Figure 5.1(a) Appendix A bank loans (L), gross domestic product (LogGDP) and money supply (LogM2) seem to be non-stationary and downward trend. The nominal effective exchange rate (NEER) is non-stationary and downward sloping at levels. However, the lending interest rate (R) and the inflation rate (INF) seem to be stationary at levels. However, when the variables are plotted at the first difference, they are all stationary (see Figure 5.1(b) in Appendix A). Formal panel unit roots are conducted to confirm the graphical unit root test in the preceding section.

5.4.1 Formal panel unit roots tests

The Fisher type test, the Pesaran and Shin test and the Levin, Lin and Chu tests are the main tests that are considered by literature for panel unit root test. The Fisher-Type test is employed as the main test for panel unit root test, while the Pesaran and Shin and the Levin and Lin Chu are used as robustness check tests. All the variables exhibit a trend and are tested for stationarity by employing an intercept and a time trend (Wang *et al*., 2005). The Fisher-type test is superior to other panel unit root tests since it allows for heterogeneity and it is suitable for both balanced and unbalanced panels. The Fisher test is more suitable since the time period is larger than the number of countries in the panel data. Also, it does not put a restriction on the sample size of the panel. The Pesaran and Shin test operates effectively for a balanced panel, hence it is appropriate for the present study to be used as a confirmation test.

The bank loans (L) is non-stationary at levels for all the panel unit root tests (ADF-Fisher-type test; PP-Fisher-type test; Im, Pesaran and Shin and Levin and Lin and Chu). Also, it is stationary at first difference and statistically significant at one percent level for the intercept and trend. The lending interest rate (R) and the inflation rate (INF) are stationary at levels for all tests and statistically significant at one percent level. The money supply (LogM2), nominal effective exchange rate (LogNEER), and the gross domestic product (LogGDP) are non-stationary at levels for most of the tests, except for LogGDP, which is stationary with the PP-Fisher type test and statistically significant at four percent. However, all non-stationary variables are stationary at first difference.

The variables are of mix integration order of I(1) and I(0) which means the panel VAR can be estimated in levels if it satisfies all the diagnostic tests (Sims, 1980; Sims, Stock & Watson, 1990). Their justification is that differencing variables decrease the degree of freedom, hence resulting in biased results. However, some authors have argued that estimating a panel VAR model in levels may result in biased coefficients and an unstable model.

Table 5.3: Summary of panel unit root tests

Variables	Tests	Statistics		Conclusion and order of integration
		Levels	First difference	
L	ADF-Fisher Type test PP-Fisher Type test Im Pesaran and Shin Levin, Lin, and Chu	14.616 14.616 -2.660^{**} -7.638^{*}	72.145^{*} 115.145^{*}	Non-stationary I(1)
R	ADF-Fisher Type test PP-Fisher Type test Im Pesaran and Shin Levin, Lin, and Chu	33.928^{*} 20.879^{**} -3.739^{*} -3.018^{*}	33.928^{*} 20.879^{**} -3.739^{*} -3.018^{*}	Stationary I(0)
INF	ADF-Fisher Type test PP-Fisher Type test Im Pesaran and Shin Levin, Lin, and Chu	46.275 99.358 -5.222 -3168	46.275^{*} 99.358^{*} -5.222^{*} -3.168^{*}	Stationary I(0)
LogM2	ADF-Fisher Type test PP-Fisher Type test Im Pesaran and Shin Levin, Lin, and Chu	10.507 11.618 -0.470 -0.382	157.674^{*} 156.408^{*} -16.642^{*} -18.310^{*}	Non-Stationary I(1)
LogNEER	ADF-Fisher Type test PP-Fisher Type test Im Pesaran and Shin Levin, Lin, and Chu	12.556 8.377 -0.848 -0.321	134.995^{*} 131.691^{*} -13.821^{*} -14.564^{*}	Non-Stationary I(1)
LogGDP	ADF-Fisher Type test PP-Fisher Type test Im Pesaran and Shin Levin, Lin, and Chu	8.722 18.881^{**} -0.130 0.714	134.995^{*} 131.691^{*} -13.821^{*} -11.411^{*}	Non-stationary I(1)
Note: *, ** and *** denotes the statistical significance at 1%,5% and 10% levels respectively. While the optimal lag length was automatically determined.				

Source: Author’s own calculations

Table 5.3 above shows the summary of the panel unit root tests. The first column represents variables tested for unit roots; the second column represents the tests employed; the third and fourth column represents the t-statistics in levels and in first differenced with their probabilities; and lastly, the fifth column represents the conclusion and order of integration of data. A panel VAR is estimated through the use of stationary variables.

5.5 The lag length selection criteria

The lag length is determined by estimating the panel VAR model with an optimal lag length, reducing the number of lags until the appropriate lag length is obtained (Asteriou & Hall, 2007). A panel VAR model can be estimated in levels if it passes the entire diagnostic test and the appropriate lag length is selected (Charemza & Deadman, 1992). The values of the Bayesian Information criteria, Akaike Information criteria and Hannan-Quinn Information criterion, and their respective autocorrelation, heteroskedasticity and normality diagnostics, are analyzed and the model that minimizes AIC and SBC, and passes all diagnostic checks, is selected as the one with the optimal lag length. According to the Bayesian Information criteria, the Akaike Information criteria and the Hannan-Quinn Information criterion, by Andrews and Lu (2001), the selected minimum lag is one. All the three lag length selection criteria (MBIC, MAIC, and MQIC) suggest that a first order panel VAR is preferred.

The Akaike Information criteria is preferred by most researchers as it imposes a penalty when a large number of variables are regressed, and hence, it is more applicable as a panel. VAR is a system of equations which consumes a large degree of freedom. The PVAR model employs similar specification of the instrument as the GMM framework. The first column in Table 5.4 Appendix A shows the lag length, the third shows the Hansen's J statistic, the fourth shows Hansen's J probability and the last column shows the three selection criteria. The BIC is minimum at first lag by -627.252; the AIC is minimum at first lag by -91.52711 and the HQIC is minimum at first lag by -305.8058. Hence, a first order panel VAR is estimated as suggested by all the lag selection criterion.

5.6 The stability test

Before computing impulse response function and variance decomposition, it is important to determine the stability of the model. Stability refers to an invertible panel VAR that has an infinite-order vector moving-average representation, providing sound results of impulse response functions and forecast-error variance decompositions (Abrigo & Love, 2015). A panel VAR model is stable when all moduli of companion matrix are strictly less than one (Hamilton, 1994; Lutkepohl, 2005). An unstable panel VAR model results in biased impulse response and variance decomposition. Figure 5.2 in Appendix A shows the results of the stability of the estimated panel VAR. The panel VAR model satisfies the stability condition, as all the eigenvalues lie inside the unit circle. Hence, the impulse response and variance decomposition will be significant and robust. The modulus in Table 5.5 Appendix A are all less than one, and hence satisfy the stability of the panel VAR model. Eigen values greater than one implies that one of the variables consist of a unit root and it will lie along the circle or outside the circle (Johnston & Dinardo, 1997).

5.7 The panel VAR-Granger causality test

The Granger causality test is computed from the panel VAR model to analyze the direction of causality among the regressed variables. These tests inspect whether or not the null hypothesis of non-causality between the dependent and independent variable is significant at a given probability, against the alternative hypothesis, stating the presence of a causal relationship. The rejection, and the lack thereof, of the hypotheses are based on the Chi-square X^2 test of the Wald criterion. Notably, the rejection of the null hypothesis means that there is evidence of causality. In this study, the null hypothesis is not accepted when the probability value of X^2 is less than 10 percent.

The Ganger causality test results are shown in Table 5.6 Appendix A. Collectively, and individually, the variables (DlogGDP, INF, DlogM2, R and DlogNEER) Granger cause DL and are statistically significant at 1 percent level, except for R, which is statistically significant at a 5 percent level. Hence, the null hypothesis of the excluded variable does not and Granger-cause DL is rejected. With regards to DlogGDP, collectively, and individually, the all variables Granger cause it (DlogGDP) and are statistically significant at 1 percent, except for DL who does not Granger cause any of the other variables but is Granger caused by them all. However, R is statistically significant at 5 percent and there seems to be a unidirectional causality between DL and DlogGDP.

Collectively, the variables Granger cause INF and are statistically significant at 1 percent level. However, DL and DlogNEER do not Granger cause INF. Hence, there is a unidirectional causality between INF and DL, and between DlogNEER and INF. Moreover, collectively, the variables granger cause DlogM2 and are statistically significant at 1 percent level. Unlike, in most literature review, R does not Granger cause DlogM2 and is statistically insignificant. This may be due to the fact that money supply in emerging markets is determined by other factors such as aggregate demand. Also, the DL does not Granger cause DlogM2, which implies there is a unidirectional causality between the two variables. Collectively, and individually, the variables granger cause R and are statistically significant at 1 percent level except for DL. Hence, there seem to be a unidirectional causality from R to DL, which is according to Bernanke's traditional theory of the bank lending channel. Collectively, the variables granger cause DlogNEER and are statistically significant at 1 percent except for R and DL.

5.8 Panel VAR model estimation

The study estimates a panel VAR model comprising of stationary variables DL, DLogGDP, INF, DLogM2, R and DLogNEER for a period of 2000Q1 to 2016Q4. The lag order of one is utilized, as suggested by the lag selection criterion. The ordering of variables follows that of Munyengwa (2012), where DL, DLogGDP, INF, DLogM2, R and DLogNEER are regressed in a panel VAR model. According to literature, a VAR may be estimated in levels form if it satisfies all diagnostic tests (Charemza & Deadman’s, 1992). However, anti-advocates of the level form VAR model criticize it for producing an unstable model and bias impulse response function and forecast-error variance decomposition (Gujarati, 2004). The level form panel VAR model is rejected since it failed the diagnostic test of stability. The study continues to estimate a panel VAR model comprising of I(0) variables and it passes the diagnostic tests. The coefficients and signs of variables conform to theory and are statistically significant. The panel VAR model is shown in Table 5.7.

5.9 Impulse response of the bank lending channel

The study's main objective is to utilize the impulse response function to analyze monetary policy rate shocks to other economic variables through bank loans. According to Bernanke and Blinder (1988), the impulse response is the most effective method of analyzing monetary policy shocks' transmission. However, the present study also adds the cross-sectional element to the VAR model. The impulse response is computed from the panel VAR model and will enable the researcher to accept or reject the null hypothesis of the existent of the bank lending channel in the selected emerging markets. The bank lending impulse response function is shown in Figure 5.3 below. The first column shows the impulse response of other economic variables to the nominal effective exchange rate, one standard deviation unanticipated shock; the second column shows the response of economic variables to the policy interest rate, one standard deviation shock; the third column shows the response of economic variables to one standard deviation shock of the price level; the fourth column shows the response of economic variables to one standard deviation shock of gross domestic product and the last column shows the response of economic variables to one standard deviation shock of bank loans

5.9.1 Response to monetary policy interest rate shocks

The researcher began by examining the response of macroeconomic variables to one standard deviation shock of monetary policy interest rate. There is an immediate decrease of the nominal effective exchange rate to one standard deviation shock of the monetary policy rate in the second column, first row panel. This could be due to the persistence (inertia) of the effects of the depreciation, which is reversed in periods to come where expectations are reassessed. In keeping with this perspective, after one period, the exchange rate begins to appreciate, which is consistent with a rise in the short term. Increase of the policy rates will cause capital inflows because foreign investors will want to take advantage of a higher interest rate differential, hence the exchange rate appreciates. After two lags, the nominal effective exchange rate retraces back to the equilibrium position. In contrast, Munyengwa (2012) found the nominal effective exchange rate to respond to tightening monetary policy shocks with one period lag.

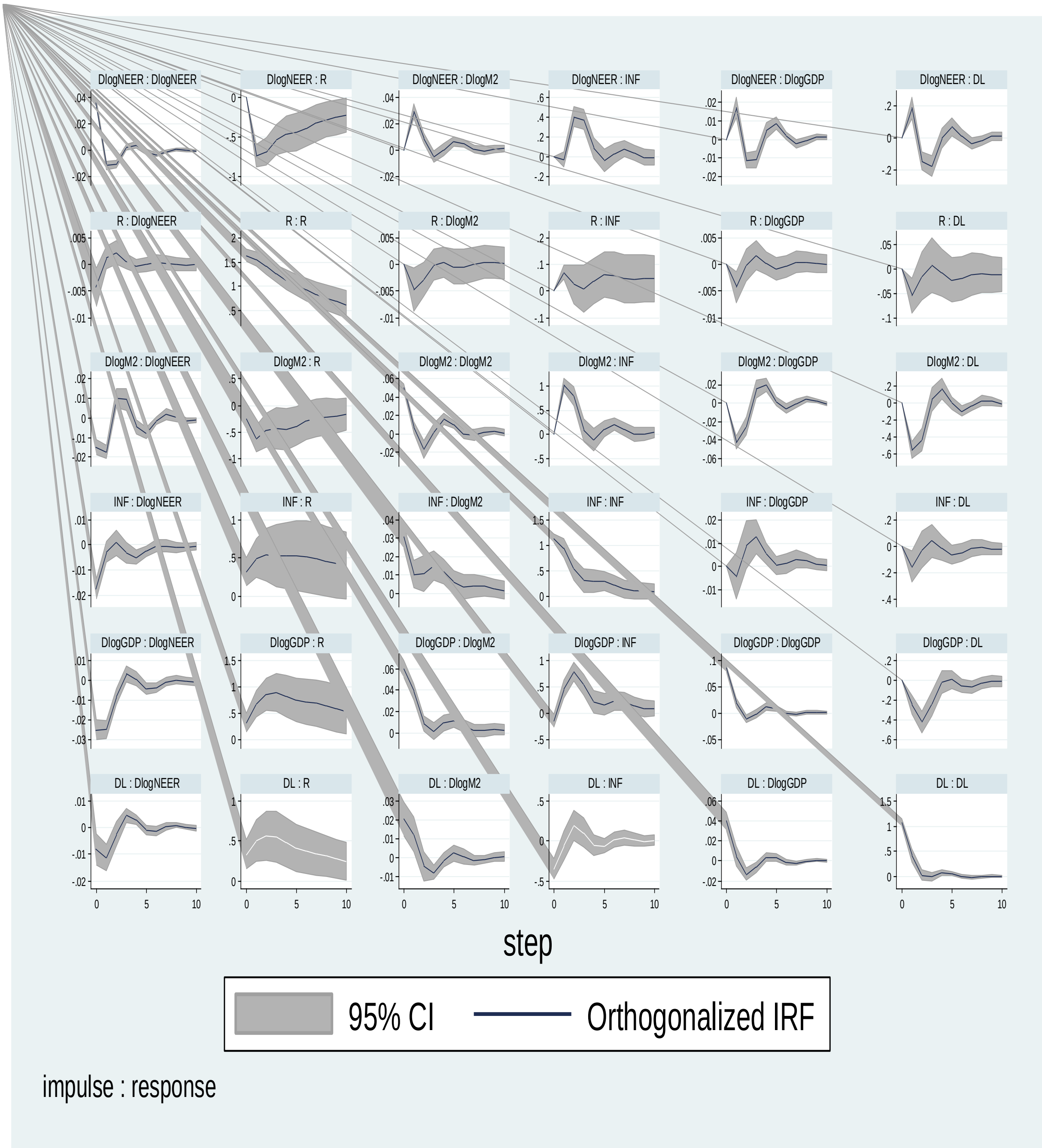


Figure 5.3: Impulse response function panel VAR model

Source: Estimated by the researcher

There is a sudden decrease in money supply in response to a tightening monetary policy shock. The response rate, although inelastic, is relatively large at a 0.6%-0.7% fall to a 1% shock in interest rate. An increase in the policy interest rate induces an increase in other related interest rates, hence, it increases the opportunity cost of holding money, relative to keeping it in the banks. The immediate decline in money supply, in response to a positive monetary policy shock, is according to theory. After two quarters, the money supply retraces back to its equilibrium point. The increase in money supply after two quarters is stimulated by the increase in saving, which is a catalyst for capital formation. This induces foreign direct investment, due to higher returns in emerging markets, resulting in higher aggregate demand and output. The demand for money increases in response to the increase in aggregate demand and output at the end of the second quarter.

The impulse response of the money supply to the policy rate is in consensus with Afrin (2017). Afrin (2017) employed a Bayesian Structural VAR model to examined monetary policy transmission, in Bangladesh, over the period 2003 to 2014. He also examined a sharply negative response of money supply to the policy rate which reaches its minimum over two quarters. The money supply increases sharply after the end of the second quarter to reach its maximum in the fourth quarter. Subsequently, it stabilizes to its equilibrium after the seventh quarter. The results are consistent with theory. In contrast to this study's results, the money supply responds with a lag of two quarters to monetary policy shocks. In the second quarter, money supply declines sharply in response to tightening monetary policy and reaches its minimum in the third quarter. It stabilizes to its equilibrium after the fourth quarter. The money supply is consistent with theory, however, the magnitude of the lag of response to monetary policy shock must be investigated.

The inflation rate responds with a lag to monetary policy shocks. After a one standard deviation shock, the inflation rate increase is highly elastic, with about 3%-4% rise in inflation immediately to a 1% shock, and reaches its maximum at the second lag. The response of the inflation rate to monetary policy rate is consistent with contemporary theory. The increase in the price level to monetary policy shocks is an indication of the price puzzle. The contractual obligation of consumers to service a debt after a monetary policy rate shock may be the cause for inflated prices (Rashid and Rahman, (2015). On the other side, an increase in the policy interest rate increases the opportunity cost of access to credit, hence increasing the general price level. However, the inflation rate declines after the second quarter. There seems to be a consensus in the empirical literature, as Mallick and Sousa (2012) also found inflation rates to respond with a lag to monetary policy transmission in BRICS countries.

A one standard deviation shock of monetary policy rate induces national output to decline with a lag. An increase in monetary policy causes an increase in national output which reaches its maximum after two lags. The sudden increase in national output is not consistent with theory due to the negative response of investment to the high interest rate, however due to inertia in an expanding economy, GDP continues on an upward momentum until expectations are revised after the policy shock has been registered by economic agents. At the beginning of the third quarter, gross domestic product declines gradually towards the equilibrium. In contrast to this study, Mallick and Sousa (2012) observed a sharp decline in GDP in response to monetary policy shocks. At the end of the fourth quarter, GDP stabilizes towards the equilibrium. Bernanke and Gertler (1995) observed a sharp decline in GDP after four months in response to monetary policy rate shocks in the USA. The results suggest GDP responds with a lag to monetary policy shocks both in emerging and in developed countries.

A one standard deviation shock of the policy interest rate causes a sharp decline in the interest rate. The results are consistent with theory, as tightening monetary policy induces a fall in inflation which invokes an easing in monetary policy. Heryan and Tzeremes (2017) also observed a fall in the interest rate in response to the monetary policy shocks. The interest rate declined to reach its minimum in the fourth quarter and retraced to its equilibrium at the end of the sixth quarter.

The null hypothesis that the monetary policy rate does not decrease bank loans supply is rejected and the alternative hypothesis is accepted. A one standard deviation shock of monetary policy shock induces an increase in bank loan supply. As expected after the second quarter, bank loans decline which implies they respond with a one period lag to monetary policy shock. The results are consistent with Bernanke and Blinder’s (1988) theory of the bank lending channel. According to the theory, tightening monetary policy causes a decline in monetary policy by draining banks reserves, which takes a while to be accomplished, hence the evidence of the lag effects. Heryan and Tzeremes (2017) also observed a decline in bank loans in response to monetary policy shocks in Botswana. The monetary policy in Botswana responds with a one period lag. The bank lending channel responds with a lag to monetary policy shock in Mexico (Ibarra, 2016). Mallick and Sousa (2012) found the bank loans to response with a lag to monetary policy in BRICS countries.

In contrast to this study's findings, the presence of the bank lending channel in Germany, France, Italy, and Spain was not found (Favero *et al*., 1999). The main justification may be due to the low interest rate in developed countries. Simpasa *et al*. (2014) employed a VAR model in Zambia and did not find the presence of the bank lending channel. Ground and Ludi (2006) also did not find the presence of a monetary policy in South Africa. Both South Africa and Zambia have adopted the inflation targeting framework and did not find bank loans to respond to monetary policy shocks.

5.9.2 Response to nominal effective exchange rate shocks

The study continues to discuss the nominal effective exchange rate shocks to other economic variables in emerging economies in Figure 5.3, column one. A one standard deviation shock of the nominal effective exchange rate causes a sharp increase to the policy interest rate above the equilibrium. At the end of the second quarter, the policy rate stabilizes to the equilibrium. The response of the policy interest rate to the appreciation of the exchange rate is in line with theory. The appreciation of the exchange rate induces a decline in the policy rate and money supply. However, the increase in money supply occurs at the end of the first quarter. At the fourth quarter money supply decrease and increases at the end of the sixth quarter. Hence, money supply responds with a lag to the policy rate and the nominal effective exchange rate. An appreciation of the exchange rate also causes a rise in the general price level, GDP and to bank loans supply. The summary response in of economic variables can be presented as follows: $\uparrow NEER \rightarrow R \downarrow \rightarrow M \uparrow \rightarrow GDP \uparrow \rightarrow L \uparrow$. Where $\uparrow NEER$ is the appreciation of the nominal effective exchange rate, $R \downarrow$ is the fall of the interest rate, $M \uparrow$ is the increase of money supply, $GDP \uparrow$ is the increase of the gross domestic product and $L \uparrow$ is the increase of the loan supply. The findings show that monetary policy transmission affects economic variables.

5.9.3 Response to money supply shocks

This section discusses the response of economic variables to the money supply, as illustrated in Figure 5.3, column 3. A one standard deviation shock of the money supply causes a sharp decline in the policy interest rate, however, the response is quite small, a 0.005% decline for a 1% shock. At the end of the second quarter, money supply stabilizes towards its equilibrium. The increase in interest rate may be motivated by a rise in consumer savings which shifts inwards the supply curve for money. Hence, the response of the policy rate is according to theory. A one standard deviation shock of monetary policy causes a sharp decline in the inflation rate and it rises after the fourth quarter and declines after the sixth quarter. The response of the inflation rate is against the theory, as an increase in the money supply must increase aggregate demand, output and the general price level. The decline in inflation may be influenced by the high rate of unemployment and a high rate of indebtedness of consumers. GDP and bank loans supply respond with a two-period lag to money supply shocks

5.9.4 Response to shocks of the inflation rate

A one standard deviation shock of inflation rate induces depreciation in the domestic currency with a two period lag. General price increases induce an appreciation to the exchange rate after a one period lag. However, after two quarters, the exchange rate depreciates until it reaches its equilibrium. A one standard deviation shock of inflation rate induces an immediate appreciation of the exchange, which is according to theory. After two lags, the exchange rate depreciates to its equilibrium. A one standard deviation shock of inflation rate induces a sharp increase in money supply and it decreases after two period lags. Economic activity responds with a two period lag to a one standard deviation shock of the inflation rate. The response of economic activity conforms to theory, as investors will attempt to increase supply as prices hike. In the process, decreasing aggregate demand economic activity. Bank loans respond with a three period lag to the inflation rate, which may be caused by long-term contractual loans.

5.9.5 Response to GDP shocks

The exchange rate appreciates in response to a one standard deviation shock of GDP, however, after a one period lag, it depreciates to reach its minimum at three quarters. The policy interest rate declines below its equilibrium in response to a one standard deviation shock of GDP and it increases after two lags. Money supply responds with a two period lag to a one standard deviation shock, whereas the inflation rate declines immediately. It responds to a one standard deviation shock of GDP. After a one period lag, the inflation rate increases sharply to reach its maximum at the fourth lag and after the fourth lag, it declines towards the equilibrium. Bank loan supply declines below its equilibrium in response to a one standard deviation shock and increases after the third quarter to reach its equilibrium. Bank loans seem to have a negative response to GDP shocks because of the high rate of indebtedness of households, hence, during an economic boom, banks are reluctant to increase bank loan supply.

5.9.6 Response to loan shocks

The exchange rate appreciates in response to a one standard deviation shock of bank loans supply. After the first period, lag bank loans depreciate below the equilibrium until the third period lag and retraces its equilibrium at the sixth quarter. A one standard deviation shock of bank loans induces a decrease in the policy interest rate. In contrast to theory, a one standard deviation shock of bank loans causes a sharp decrease to money supply and a decline in DlogGDP. However, a one standard deviation shock of bank loan induces a sharp decline in the inflation rate, but it increases after the third period lag. The impulse of DL leads to a sharp decline to DL. The shock of DL induces the monetary policy to increase the interest rate, hence increasing the cost of borrowing money and draining the required reserves. In response, commercial banks increase the bank lending interest rate which decreases bank loan supply. The DL shock is according to theory and expectation.

5.10 The forecast-error variance decomposition

According to the forecast error variance decomposition in Table 5.8 (a) Appendix A, 13% of the variation in bank loans supply is explained by GDP. The inflation rate explains only one percent of the variation in bank loans supply and money supply explains 23% of the variation in bank loans supply. The policy interest rate seems to have minimum impact on bank loans supply in emerging markets, explaining less than 1% of the variation. The minimum influence of the policy rate to bank loans in emerging markets may be a result of banks keeping more reserves than expected. Also, it may reflect more substitute bank loans. In addition, the nominal effective exchange rate has a minimum influence on bank loans supply, explaining only 4% of the variation in bank loan supply. Most of the variation in bank loans supply is explained by its lag. At lag, 75% of the variation in bank loans supply is explained by its lag. With the addition in the number of lags, the variation explained by the lags of the bank loans supply decreases gradually until it becomes 58% at lag five. Money supply and GDP seems to explain most of the variation in bank loans supply relative to other variables.

A complete table of forecast-error variance decomposition is showed at the appendix. Table 5.8(b), Appendix A shows that most of the variation in DlogGDP is mostly explained by its impulse, money supply, and bank loans respectively. DlogGDP accounts for 58% of the variation in the fifth period and 100% of the variation in the first period. In the selected emerging markets, DlogM2 explains 26% of the variation in DlogGDP at the fifth period, whereas DL explains 13% of the variation in DlogGDP. As the number of years are added, the impulse explanatory power in DlogGDP decreases, while it increases in DlogM2. Similar to the variance decomposition of DL, inflation rate, the policy interest rate, and the nominal effective exchange rate do not explain the variation in DlogGDP. The inflation rate, the policy interest rate, and the nominal effective exchange rate explain 2%, 0.2%, and 4%, respectively, of the variation in DlogGDP.

Table 5.8(c) Appendix A shows the variance decomposition of the inflation rate. Similar, to the variance decomposition of DL and DlogGDP, the variation in INF is mostly explained by its own impulse, DlogGDP, and DlogM2. In the first period, the variation in INF is explained by 90% of its impulse and by 8% of the DL. As the number of periods increases, the variation in INF is explained by its own impulse and DL decreases from 8% to 3% and from 90% to 44% in the fifth period respectively. The variation explained by DlogGDP in INF increases from 1% in the first period to 20% in the fifth period. As expected, and according to economic theory, DlogGDP explains a significant variation in INF. DL and DLogNEER only explain 3% and 5% of the variation in INF, which is in contradiction to economic theory. Also, the policy interest rate does not explain the variation in the inflation rate in the selected emerging markets. The reason may be due to the fact that some of the countries, like South Africa and Brazil, use the inflation rate targeting framework, while countries like Russia does not employ the inflation targeting framework. Moreover, countries like Chile seem to have a low interest rate, as in developing countries, and in such situations, the inflation targeting framework is ineffective.

Table 5.8(d) Appendix A represents the variance decomposition shocks of DlogM2 to other economic variables. The variation in DlogM2 is mostly explained by the variance decomposition of DlogGDP, INF, and DlogM2 respectively. In the first period, DlogGDP explains the most variation at 47%, followed by DlogM2 at 34% and by INF at 12%. The monetary policy interest rate and DLogNEER does not explain the variation in DlogM2. Both DLogNEER and R explain 0.2% of the variation in DlogM2. DL and DLogNEER do not explain a significant variation, only 6% and 8% respectively in the fifth period. However, the variance decomposition of R does not play a significant effect in DlogM2, it only explains 0.2% of the variation. The findings are in line with theory and other empirical literature as the variation in DlogM2 is mostly explained by DlogGDP in the selected emerging markets.

In Table 5.8(e) Appendix A the variation in R is explained by its lag, which explains 87% of the variation in R in the first period. The variation explained by R is that R decreases as the number of periods is increased. DlogGDP explains a significant variation in R of 15%. Other variables do not play a significant effect in explaining the variation in R. DL, INF and DLogNEER only explain 7%, 7%, and 8%, respectively. In Table 5.8(f) Appendix A the variation in DLogNEER is significantly explained by its variance decomposition. There is a 50% variation in DLogNEER, which is explained by its variance decomposition during the first period. DlogGDP and INF explain 24 % and 12%, respectively, during the first period. As the number of periods increases, the variation explained by DlogGDP and DlogM2 increases to 31% and 17%, respectively, in DLogNEER. DL and R do not play a significant impact in DLogNEER in the selected emerging markets. Both DL and R only explain 5% and 0% of the variation in DLogNEER.

5.11 The cointegration test

The variables in the panel VAR are of mixed order in the level form I(1) and I(0), respectively, and stationary at first difference. Prior to the estimation of the model the I(1) variables were first difference to be I(0). The requirements of the panel VAR model are that the variables must be non-stationary at the level form and stationary at first difference. Hence, they were tested for cointegration to examine if they had a long run relationship. If the variables contain a cointegration, a panel VECM must be estimated to ascertain the long run and short run relationship. The variables were tested for cointegration and the results of the Pedroni tests are shown in Table 5.9 Appendix A. The null hypothesis is that there is no cointegration and the alternative hypothesis is that there is cointegration. The panel v-statistic, panel rho-statistics, panel PP-statistic, and the Panel ADF-statistic's probability is individually above 5%. Hence, the null hypothesis of no cointegration is accepted as all the probability is above 5%. This means there is no long-run relationship among the variables and only a panel VAR has been estimated.

5.12 Conclusion of the chapter

The chapter discussed pre-estimation results which are data descriptive statistics, formal and informal unit roots results. According to the descriptive statistics, the variables seems to be not normally distributed. In addition, all the variables are I(1) at levels, and I(0) at first difference, except for the inflation rate and the monetary policy rate. Cuthberson (2002:436) argued that a VAR regime must be specified in levels, as VAR in differences may results in spurious models and loss of degrees of freedom. However, in the current study, the panel VAR is estimated at first difference since it does not waste the degrees of freedom. The estimation technique of the panel VAR is according to Abrigo and Love (2015), where the only diagnostic performed is the stability tests. The model is stable, thus all modulus are less than one. All the control variables are coefficients and are statistically significant with expected signs. The null hypothesis of a negative impact of the monetary policy interest rate on bank loans supply is accepted. Hence, the bank lending channel operates with a lag in the selected emerging and credit plays a role in the transmission of monetary policy in the selected emerging markets. In addition, monetary policy interest rates influence GDP and INF, with a one period lag. Thus, monetary policy rate in the selected emerging markets affect macroeconomic variables. The Granger causality test was also estimated to determine the direction of causality among variables. All the variables Granger cause each other.

CHAPTER 6: THE VAR FRAMEWORK

6.1. Introduction

The chapter reviews the empirical results for the VAR models for each individual country as a robustness test and for comparison purposes. The panel VAR computes average impulse response for the selected emerging markets. It is vital to understand the behaviour of each country's bank lending channel relative to another countries bank lending channel. The assumption is that the selected countries economic variables are influenced by the monetary policy rate impulse in the same approach. The bank lending channel of monetary policy transmission is effective in the selected emerging markets, according to the panel VAR regime. This section begins by discussing the VAR model for Mexico (model 2), followed by South Africa (model 3), and thereafter by Chile (model 4), Brazil (model 5) and finally Russia (model 6). The impulse response for each country are compared.

6.2 The Mexico VAR model (model 2)

This section reviews the empirical results for model 2. Notably the impulse response for the five models (model 2 to model 6) are computed as tables and discussed collectively for comparative purpose. Similar variables as in the panel VAR model are employed.

6.2.1 Descriptive statistics

This section discusses the data features employed in the estimation of model 2. The data consists of 68 observations, of quarterly data spanning from the year 2000 to 2016. The variables included in the model include bank loans supply to the private sector (L), the logarithm of gross domestic product (LGDP), inflation rate (INF), the logarithm of money supply (LM2), lending interest rate (R) and the logarithm of the nominal effective exchange rate (LNEER). This section analyses the mean, median, variance, kurtosis, Jarque-Bera, skewness and probability of the data. The Jarque-Bera and skewness tests are good measures of normality, and to confirm normality they must be 3, 0 and above a 10% significance level, respectively. The kurtosis coefficient measures the thickness of the distribution tails and it must be three if the data are normally distributed.

Table 6.1 below represents the summary of the descriptive statistics model 2. The variables used to estimate the model 2 are normally distributed as the mean and the median is more or less the same. The skewness is less or close to zero for all the variables, excluding R. All the variables, L, LGDP, INF, LM2, and LNEER, are skewed to the left, whereas R is skewed to the right. Also, the probability seems to be according to expectation for normally distributed data, as it is above 10% for all the variables, except for R. The minimum and maximum are almost identical, hence the variables are stable in the period of the study distributed as the variation is marginalized. The kurtosis for a normal distribution is three and it measures the thickness of the distribution.

Table 6.1: Descriptive statistics

	L	LGDP	INF	LM2	R	LNEER
Mean	13.22794	7.979246	1.088333	15.52130	7.283535	4.690330
Median	14.10000	8.007110	1.192663	15.53884	6.953333	4.747674
Maximum	19.30000	8.561489	3.113081	16.34130	18.14667	5.020698
Minimum	8.500000	7.375971	-0.334199	14.56034	3.303333	4.220608
Std. Dev.	3.152343	0.345884	0.725462	0.518846	3.587425	0.191963
Skewness	-0.018273	-0.121366	-0.042757	-0.182370	1.491592	-0.246387
Kurtosis	1.819833	1.784491	2.729931	1.835333	5.034440	2.601217
Jarque-Bera	3.950036	4.353078	0.227376	4.220210	36.94193	1.138588
Probability	0.138759	0.113433	0.892537	0.121225	0.000000	0.565925
Sum	899.5000	542.5888	74.00661	1055.448	495.2804	318.9424
Sq . Dev.	665.7969	8.015594	35.26177	18.03645	862.2642	2.468937
Observations	68	68	68	68	68	68

Source: Estimated by the researcher

6.2.2 Correlation matrix

This is a measure of the direction and strength of the linear relationship among variables. This section discusses the correlation matrix for model 2. The correlation matrix represented in Table 6.2.1 Appendix B indicates that the variables are not correlated, as the coefficient of the variables is less than 80%. The variables do not have multicollinearity; the results are robust and statistically significant. Multicollinearity results in the wide confidence of the intervals and in small statistics. It becomes difficult to reject the null hypothesis of any study when multicollinearity is present in the data under study. There is a negative correlation between LGDP, INF, LM2, R, and LNEER. Overall the variables are not highly correlated and they don't suffer from multicollinearity.

6.2.3 Stationarity tests

The testing of stationarity in time series is vital to determine the order of integration. Estimating a time series in the presence of a unit root may result in spurious regression. Variables in the presence of unit root may tend to move along in the long-run, while there is no relationship among them. As stated in the previous chapter, most time series data are nonstationary at levels and stationary at first difference. Employing non-stationary data in estimating a VAR model may result in a spurious and unstable model. In estimating a VAR model the variables must be I(1) at the level form and I(0) at first difference. However, an obstacle arises when the variables are of mix order. Some scholars advocate that a VAR can be estimated in level form as long as the regression satisfies all diagnostic test.

For the purpose of this study, the stationarity test will be tested by the ADF and the PP will be employed as a robustness test. This section discusses the unit root tests for Model 2. The ADF test and the PP test investigate the null hypothesis that states the variables have a unit root. When the tau statistic value is greater than the corresponding Mackinnon (1996) critical value, the alternative hypothesis is accepted and the null hypothesis is rejected. However, when the tau statistic value is lesser than the Mackinnon (1996) critical value, the null hypothesis is accepted. The summary of unit root test results for model 2 variables is represented by Table 6.2.2 below.

Table 6.2.2: Unit root tests

ADF Test					PP Test			
	Levels		1st Difference		Levels		1st Difference	
	t-value	Lag	t-value	Lag	t-value	Lag	t-value	Lag
L	-3.032	4	-2.313^{**}	3	-3.988^{**}	4	-5.432^{**}	2
LGDP	-2.912	1	-5.178^{**}	0	-2.203	1	-4.999^{**}	4
INF	-2.989	10	-5.411^{**}	6	-10.214^{*}	22		
LM2	-2.231	0	-4.524^{**}	8	-1.900	36	-18.211^{*}	36
R	-3.041	2	-6.960^{**}	1	-2.558	5	-4.468^{**}	15
LNEER	-1.946	0	-7.404^{**}	0	-2.257	3	-7.404^{**}	0
Note: *, **, *** represent 10%, 1% and 5% level of significance, significance. The number of lags in the ADF test is determined by AIC and SIC, while the PP test is determined by Bartlett Kernel.								

Source: Generated by the researcher

Table 6.2.2 above indicates that both the ADF and PP test shows that all the variables are nonstationary at the level form, and stationary at first difference, except for L and INF. The null hypothesis that variables contain a unit root is accepted and the alternative is rejected. All the nonstationary variables both in the ADF and PP test are stationary upon first difference. L and INF are stationary at level form, according to the PP test, hence they are I(0). Since the ADF test is the main test for the study, the null hypothesis is rejected for both L and INF, so the variables are treated as I(1) variables.

6.2.4 Lag length selection

This section discusses the selection of the lag length criteria for Model 2. As discussed in chapter three, it is vital to select the appropriate lag order for the VAR model before estimating and computing impulse response function and variance decomposition. An incorrect lag selection of a VAR model results in biased impulse response and variance decomposition. The Akaike Information criteria is preferred by most researchers as it imposes a penalty when a large number of variables are regressed.

The lag length selection criteria are determined by the Swartz information criteria, the Akaike information criteria, the FPE, and the HQ tests.

The optimal lag length selected for the model 2 is selected from an estimated VAR model in level form. The unrestricted VAR is estimated using an optimal lag length, decreasing the lag length until the appropriate optimal lag length is selected, which produces a VAR model that is robust and conforms to theory (Asteriou & Hall, 2007). According to Charemza and Deadman (1992), an unrestricted VAR model may be estimated in levels form for a short sample size data if the model passes all diagnostic tests. According to Table 6.2.3 Appendix B, the lag length selected is 2 and it is according to the Schwarz information criterion (SIC), the final prediction error (FPE) and the Hannan-Quinn information criteria (HQ). Most of the lags have agreed on lag two, which include the FPE, which is suitable for a small sample size (Liew, 2004).

6.2.5 Stability of the VAR

The stability of the VAR model is one of the requirements that must be satisfied before the impulse response and variance decomposition are estimated. An unstable VAR model may result in biased impulse response function and variance decomposition. The study employs the Autoregressive test to examine the stability of the VAR process and the modulus companion. A VAR model is stable when all moduli of companion matrix are strictly less than one (Hamilton, 1994; Lutkepohl, 2005). When one of the modulus is more than one, or one of the roots lies outside the unit circle, the model is unstable and produces biased impulse response function. The VAR model satisfies the stability condition as all the modulus are less than one, as shown in Table 6.2.4 Appendix B. In addition, the eigenvalues lie inside the unit circle, as shown in Figure 6.1 Appendix B, and hence, the VAR model is stable and will produce unbiased impulse response function and variance decomposition.

6.2.6 VAR model estimation

The purpose of the study is to investigate the short run relationship in the bank lending channel. The VAR model of each country is estimated to compare the shocks of monetary policy to economic through impulse response in each country. The ordering of variables in each country is according to the panel VAR model as L-LGDP-INF-M2-R-LNEER. However, in Chile, the LNEER was omitted in the model because it was insignificant and the overall model was not stable with its inclusion. In addition, the INF or LCPI is used alternatively as a proxy for the general price level in all the five models. The VAR model results is shown in Table 6.2.5 in Appendix B.

6.2.7 Forecast error variance decomposition

In Table 6.2.7(a) Appendix B, the variation in L for the case of Mexico is mostly explained by its lag in the first period. Other variables seem not to have any effect in L. However, as the number of lags increases the variation explained by its lag decreases from 100% to 43% in the tenth period. The variation explained by LNEER, R, and LGDP in L increases from 0% to 35%, 7%, 6% and 5%, respectively. In Mexico, the bank lending channel seems to be effective as R affects L. The variation in LGDP seems to be mostly explained by its lag and the LNEER, as displayed in Table 6.2.7(b) Appendix B. R, INF, and L explains 8%, 3% and 4% of the variation in LGDP in the tenth period. Hence, the monetary policy rate does affect economic activity in Mexico. In contrast to theory, LM2 does not explain the variation in LGDP in Mexico.

The variation in INF is mostly explained by its lag and L as displayed in Table 6.2.7(c) Appendix B. LGDP, R, LM2, and LNEER explain 5%, 4%, 3%, and 1%, respectively, of the variation in INF, and hence, the monetary policy stance does affect the INF in Mexico. Table 6.2.7(d) Appendix B shows that the variation in LM2 is mostly explained by its lag: the LNEER, 62%, and 27%, respectively. The R, LGDP, L, and INF explain 3%, 5%, 1%, and 2%, respectively, of the variation in LM2. The lag of R, L, and LM2 explains most of the variation in R, 48%, 15%, and 16%, respectively, as shown by Table 6.2.7(e) Appendix B. LNEER, and INF LGDP also explain a significant portion of the variation of 10%, 5%, and 6%, respectively. In Table 6.2.7(f) Appendix B, as in the case of South Africa, the variation in LNEER is mostly explained by LGDP, explaining 72% of the variation. The lag of LNEER and R also explains a significant variation of 10% and 9% in LNEER. The L and INF explain 5% and 3% of the variation in LNEER. LM2 does not explain the variation in LNEER.

6.2.8 Model 2 diagnostic tests results

All the diagnostics tests which included normality, residual serial correlation and the VAR residual heteroskedasticity tests were performed to determine the reliability and robustness of the VAR model. As displayed in Table 6.2.7 Appendix B, at the given lag length, the VAR model contains residuals that are not normally distributed and homoscedastic. However, the null hypothesis of no serial autocorrelation was accepted as the probability is above 5%. Thus, autocorrelation is not an obstacle in the model (Vespignani, 2010).

6.2.9 Cointegration test results

The cointegration results are displayed in Table 6.2.8 Appendix B. The Johansen cointegration indicates the presence of a long run relationship among variables at five percent significant level. Both the trace statistics and the maximum eigenvalue statistics indicate the presence of two cointegrating relationship at the 0.05 percent significance level, which indicates the rejection of the null hypothesis of no cointegration. However, since the study attempts to examine the short run impact of the bank lending channel, the VECM is not estimated in the present study as all the characteristic roots lie inside the unit circle.

6.3 The South African VAR model (model 3)

This section reviews the empirical results for model 3. This section begins by discussing descriptive statistics, correlation matrix, stationarity, and lag selection criterion, stability of the VAR, variance decomposition and impulse response.

6.3.1 Descriptive statistics

In Table 6.3.1 below, the descriptive statistics for a VAR model of South Africa shows that the mean and the median is identical, hence the variables have a normal distribution. The coefficient of the probability of the variables is above 10%, hence it satisfies a normal distribution. However, as in the case of Mexico, the R is not normal a distribution as its coefficient is less than 5%. The Jarque-Bera must be three in order to satisfy a normal distribution. The variables are normally distributed as the Jarque-Bera and the skewness of the variables is three and 0, respectively. Two of the variables have negative coefficient L and LNEER are skewed to the left. LGDP, INF, LM2, and R skewed to the right.

Table 6.3.1: Descriptive statistics

	L	LGDP	INF	LM2	R	LNEER
Mean	63.66765	15.34557	1.439607	16.14667	11.59681	4.541381
Median	65.85000	15.36434	1.420458	16.24560	10.66667	4.562247
Maximum	75.70000	16.60576	3.917263	17.44889	17.00000	4.931401
Minimum	50.80000	14.16733	-1.196302	14.85835	8.500000	3.989414
Std. Dev.	7.159889	0.651092	0.892009	0.697869	2.520834	0.238048
Skewness	-0.235827	0.350589	0.250177	0.168216	0.543104	-0.464288
Kurtosis	1.853127	2.150492	3.656502	2.092154	2.030952	2.352451
Jarque-Bera	4.357027	3.437721	1.930488	2.655887	6.003558	3.631120
Probability	0.113210	0.179270	0.380890	0.265022	0.049699	0.162747
Sum	4329.400	1043.499	97.89325	1097.974	788.5833	308.8139
Sq. Dev.	3434.689	28.40271	53.31052	32.63044	425.7585	3.796694
Observations	68	68	68	68	68	68

Source: Estimated by the researcher

6.3.2 Correlation matrix

It is important to measure the level of correlation among variables' prior estimation of a model. In Table 6.3.2 Appendix C, the correlation matrix for the South African VAR model shows that the LGDP, L, INF, LM2, and R have a positive correlation and there is no multicollinearity among the variables as the correlation is less than 80%. In addition, INF, L, and LGDP have a negative correlation of less than 80%, which is an indication of no multicollinearity among the variables. There is a negative moderate correlation between LNEER and R and between LM2 and LNEER of 0.46% for both variables. For the rest of the other variables, there is a weak correlation which is less than 0.40%.

6.3.3 Stationarity tests

Table 6.3.3 below shows the unit root tests for the South African VAR model variables. All the variables (L, LGDP, INF, LM2, R, and LNEER) under the ADF tests, which is the main test, are nonstationary at the level form and stationary at first difference. The trend and intercept are employed as most time series data consist of a trend and an intercept. According to the PP test in Table 6.3.3, variables L, LGDP, LM2, R, and LNEER are nonstationary at the level form and stationary at first difference, except for INF. Since the ADF test is the main test, the null hypothesis of the presence of a unit root in the variables is accepted and the alternative hypothesis of no unit root test is rejected.

Table 6.3.3: Unit root tests

ADF Test					**PP Test**			
	Levels		**1st Difference**		**Levels**		**1st Difference**	
	t-value	Lag	t-value	Lag	t-value	Lag	t-value	Lag
L	-2.619	7	-6.400^{**}	1	-0.960	4	-6.404^{**}	2
LGDP	-1.921	0	-7.252^{**}	0	-2.184	3	-7.228^{**}	2
INF	-2.935	8	-3.816^{***}	10	-4.927^{**}	1		
LM2	-2.193	0	-3.831^{***}	2	-2.446	3	-6.985^{**}	2
R	-1.941	2	-4.678^{**}	1	-2.264	4	-3.796^{**}	4
LNEER	-2.411	0	-6.085^{**}	0	-2.241	4	-6.035^{**}	2

Note: *, **, *** represent 10%, 1% and 5% level of significance, significance. The number of lags in the ADF test is determined by AIC and SIC, while the PP test is determined by Bartlett Kernel.

Source: Generated by the researcher

6.3.4 Lag length selection

The lag length selection criteria for the model 3 is depicted in Table 6.3.4 in Appendix C and the lag suggested by the numerous selection criteria is two and one. The SIC and the HQ suggest one lag, while FPE and the LR suggest two lags and the AIC suggests 6 lags. The lag length selection criteria that is applied for the model is one which is determined by the SIC and the HQ. The lag has been selected because it produces a robust VAR model which conforms to the diagnostic test.

6.3.5 Stability of the VAR

The stability of the VAR model is one of the requirements that must be satisfied before the impulse response and variance decomposition are estimated. An unstable VAR model may result in biased impulse response function and variance decomposition. The study employs the Autoregressive test to examine the stability of the VAR process and the modulus companion. A VAR model is stable when all moduli of companion matrix are strictly less than one (Hamilton, 1994; Lutkepohl, 2005). When one of the modulus is more than one, or one, of the roots lies outside the unit circle, the model is unstable and produce biased impulse response function. The VAR model satisfies the stability condition as all the modulus are less than one, as shown in Table 6.3.5 Appendix C. Moreover, the eigenvalues lie inside the unit circle, as shown in Figure 6.2 Appendix C. Hence, the VAR model is stable and will produce unbiased impulse response function and variance decomposition.

6.3.6 VAR model estimation

The purpose of the study is to investigate the short run relationship in the bank lending channel. The VAR model of each country is estimated to compare the shocks of monetary policy to economic variables through impulse response in each country. The ordering of variables in each VAR model is similar to the ordering of variables in the panel VAR model, L-LGDP-INF-M2-R-LNEER. However, in Chile, the LNEER was omitted in the model because it was insignificant and the overall model was not stable with its inclusion. In addition, the INF or LCPI is used alternatively as a proxy for the general price level in all the five models. The VAR model results are shown in Table 6.3.6 Appendix C.

6.3.7 Forecast error variance decomposition

In Table 6.3.7(a) Appendix C, the variation in bank loans supply for model 3 is mostly explained by its lag in the first period. As the number of lags increases, the variation explained by its lag decreases from 100% to 30% in the tenth period. LM2 and LNEER explain a significant portion of the variation in L. The LM2 and LNEER explain 24% and 40% of the variation in L, respectively, in the tenth period. Both LGDP and R explain a minimum variation in L of 1.8% and 1.7%, respectively. INF seems not to explain the variation in L. The variation in LGDP is mostly explained by its lag as indicated by Table 6.3.7(b) Appendix C. LNEER, LM2, R, and INF explain 11%, 6%, 3%, and 3%, respectively, of the variation in LGDP. However, L seems not to have an impact in LGDP explaining 0% of the variation in LGDP.

Table 6.3.7(c) Appendix C shows that the variation in INF is mostly explained by its lag. In the fifth period, the lag of INF, LNEER, L, and LGDP explain 85%, 10%, 3% and 1% of the variation in INF, respectively. In contrast to the theory, LM2 does not have an impact on INF. LGDP seems to explain a significant variation of 87% in LM2 in the first period. L and the lag of LM2 explain 6% and 7% of the variation in LM2, respectively. As the number of periods increases, the variation explained by R and LNEER in the LM2 increase from 0% to 2% and 21%, respectively, in the tenth period. The variation in R in the first period is explained mainly by its lag, INF and the LM2. The results are consistent with theory, as South Africa has adopted the inflation targeting regime, where inflation changes induce a change in the policy interest rate. In Table 6.3.7(d) Appendix C, 87% of the variation is explained by LGDP. While in Table 6.3.7(e) Appendix C the variation in R is mostly explained by its lag and INF.

The variation in LNEER is mostly explained by its lag and LGDP during the first period. In the first period, LGDP and its lag explain a significant portion variation of 60% and 27%, respectively, of LNEER as shown in Table 6.3.7(f) Appendix C. INF and L explain 6% and 3% of the variation in LNEER, whereas R seems not to have an impact on LNEER. As the number of lags is increased, the variation explained by its lag decrease to 9% in the tenth lag, while the variation explained by R increase to 1%. In addition, the variation explained by LGDP increase by 9%, whereas the variation explains by L decrease to 2%. The results are consistent with other empirical literature who found LGDP to explain the most variation in LNEER (Munyengwa, 2013).

6.3.8 Model 3 diagnostic tests results

The diagnostics tests, which included normality, serial correlation and heteroskedasticity, were performed to determine the reliability and robustness of the VAR model. As displayed in Table 6.3.8 Appendix C, at the given lag length, the VAR model contains residuals that are normally distributed and homoscedastic, moreover the model also passed the LM autocorrelation test. Hence, the coefficients, impulse response and variance decomposition are not biased.

6.3.9 Cointegration test results

The cointegration result is displayed in Table 6.3.9 Appendix C. The Johansen cointegration indicates the presence of a long run relationship among variables at five percent significant level. The trace test indicates two cointegration eigenvalue tests at 0.05 percent significance level, which indicates the rejection of the hypothesis of no cointegration. However, since the study attempts to examine the short run impact of the bank lending channel the VECM is not estimated in the present study.

6.4 The Russian VAR model (model 4)

This section reviews the empirical results for model 4.

6.4.1 Descriptive statistics

The descriptive statistics for Russia are represented in Table 6.4.1 below. The mean and the median are identical, hence the variables conform to a normal distribution. The probability of the coefficient data for a normal is above 10%. Most of the coefficient of the probability of variables in Table 6.4.1 are less than 10%, except for L, hence they are not normally distributed. The main reason is that Russia has been in a recession and has been hindered by trade sanctions. Also, Russia's economy has not been doing well because of civil wars with Check Republic. The coefficient of the Jarque-Bera test for L, LGDP and LM2 are 4, 5 and 6, respectively, hence they are all normally distributed, as they are close to three. However, other variables INF, R, and LNEER are not normally distributed since the Jarque-Bera test is above three. The skewness for L, LGDP, and LM2 is 0, hence it is normally distributed and the other variables are not normally distributed.

Table 6.4.1: Descriptive statistics

	L	LGDP	INF	LM2	R	LNEER
Mean	32.61176	4.325564	2.677749	16.01467	12.82314	4.602835
Median	35.80000	4.441081	2.199467	16.37439	11.55000	4.667150
Maximum	55.50000	5.177763	8.106784	17.46403	31.70000	4.791659
Minimum	11.50000	3.156520	0.122812	13.55207	8.000000	4.017383
Std. Dev.	13.45905	0.624489	1.600907	1.168434	4.130296	0.186987
Skewness	0.026701	-0.297514	1.082331	-0.560690	2.083938	-1.793183
Kurtosis	1.774468	1.800389	3.908013	2.000008	8.884730	5.197356
Jarque-Bera	4.263547	5.080520	15.61238	6.396185	147.3368	50.12276
Probability	0.118627	0.078846	0.000407	0.040840	0.000000	0.000000
Sum	2217.600	294.1383	182.0870	1088.998	871.9733	312.9928
Sum Sq. Dev.	12136.79	26.12906	171.7145	91.47092	1142.976	2.342607
Observations	68	68	68	68	68	68

Source: Generated by the researcher

6.4.2 Correlation matrix

In Table 6.4.2 Appendix D, the correlation matrix for the Russian VAR model shows that there is a negative moderate correlation of 40% between LM2 and INF. Additionally, there is a positive moderate relationship between R and L of 48%. Among other variables, there is a weak correlation among the variables which is less than 40%. There is no multicollinearity among the variables so the coefficients estimates are not compromised. As there is no multicollinearity among the variables, that implies the variables are appropriately selected and the regression coefficients remain unbiased and standard errors maintain their validity.

6.4.3 Stationary unit roots

In Table 6.4.3 below, both the ADF and the PP tests agree that the variables L, LGDP, LM2 and LNEER for the Russian model are nonstationary at the level form and stationary at first difference. Hence, the variables are of I(1) and are suitable for the estimation of a VAR model. However, variables R and INF are nonstationary at the level and stationary at first difference under the ADF test, whereas under the PP tests, they are stationary at the level form. This implies variable R and INF are I(1) under the ADF test and are I(0) under the PP test. Since the ADF test is the main test both variables R and INF are treated as I(1) in the current study.

Table 6.4.3: Unit root tests

ADF Test					**PP Test**			
	Levels		**1st Difference**		**Levels**		**1st Difference**	
	t-value	Lag	t-value	Lag	t-value	Lag	t-value	Lag
L	-1.800	0	-6.800^{**}	0	-2.111	3	-6.754^{**}	2
LGDP	-0.867	0	-9.055^{**}	0	-0.236	9	-9.828^{**}	8
INF	-2.178	7	-5.383^{***}	6	-5.330^{**}	4		
LM2	-0.645	9	-3.470^{***}	1	-1.021	9	-10.505^{*}	1
R	-2.194	1	-4.780^{**}	4	-4.971^{**}	3		
LNEER	-1.985	0	-9.102^{**}	0	-1.918	1	-9.134^{**}	2
Note: *, **, *** represent 10%, 1% and 5% level of significance, significance. The number of lags in the ADF test is determined by AIC and SIC, while the PP test is determined by Bartlett Kernel.								

Source: Generated by the researcher

6.4.4 Lag length selection

The Akaike Information criteria is preferred by most researchers as it imposes a penalty when a large number of variables are regressed. The lag length selection criteria are determined by the Swartz information criteria, the Akaike information criteria, the FPE, and the HQ tests. In Table 6.4.4 Appendix D which shows the lag selection criteria of the Russian VAR model, the lag is selected according to the LR, FPE, AIC and the HQ. The lag length selected is two, as suggested by all selection criterions, except for the SIC. The selection is good as it is selected by the FPE and the AIC , as they are suitable for small sample size data less than 60 observation (Liew, 2004).

6.4.5 Stability of the VAR

The stability of the VAR model is one of the requirements that must be satisfied before the impulse response and variance decomposition are estimated. An unstable VAR model may result in a biased impulse response function and variance decomposition. The study employs the Autoregressive test to examine the stability of the VAR process and the modulus companion. A VAR model is stable when all moduli of companion matrix are strictly less than one (Hamilton, 1994; Lutkepohl, 2005). When one of the modulus is more than one, or one of the roots lies outside the unit circle, the model is unstable and produce biased impulse response function. The VAR model satisfies the stability condition as all the modulus are less than one as shown in Table 6.4.5 Appendix D. Moreover, the eigenvalues lie inside the unit circle hence, the VAR model is stable and will produce unbiased impulse response function and variance decomposition.

6.4.6 VAR model estimation

The purpose of the study is to investigate the short run relationship in the bank lending channel. The VAR model of each country is estimated to compare the shocks of monetary policy rate to other economic variables through impulse response in each country. The ordering of variables in each country is according to the panel VAR model as L-LGDP-INF-M2-R-LNEER. However, in Chile, the LNEER was omitted in the model because it was insignificant and the overall model was not stable with its inclusion. In addition, the INF or LCPI is used alternatively as a proxy for the general price level in all the five models. The VAR model result is shown in Table 4.4.6 Appendix D.

6.4.7 Forecast error variance decomposition

The variation in L in the case of Russia is explained by its lag as shown in Table 6.4.7(a) Appendix D. As the number of lags is increased, the variations explained by its lag decrease from 100% to 62% in the tenth period. LNEER, LM2, INF, R, and LGDP explain only 26%, 4%, 3%, 1% and 4% of the variation in L in the ten periods. The variation in LGDP as shown in Table 6.4.7(b) Appendix D is mostly explained by its lag and L. In the tenth period, LNEER, LM2, R, and INF explain 9%, 16%, 7%, and 4%, respectively, of the variation in LGDP. The variation in INF is mostly explained by its lag and LM2. In the tenth period, the variation explains by R, L, LNEER, and LGDP is 6%, 23%, 4%, and 3%, respectively, in INF as shown in Table 6.4.7(c) Appendix D. The variation in R is mostly explained by its lag and L in the first period. The variation explain by LNEER, LM2, INF and LGDP in R increases from 0%, 1%, 6%, and 0% to 7%, 22%, 11%, and 2%, respectively, in the ten period as shown in Table 6.4.7(e) Appendix D. The variation in LNEER Table 6.4.7(f) Appendix D is significantly explained by its lag, LM2, L, and INF. The R and LGDP seem not to explain the variation in LNEER. In Table 6.4.7(d) Appendix D, the variation in M2 is mostly explained by its lag and L.

6.4.8 Diagnostic tests results

All the diagnostics tests, which included normality, serial correlation and heteroskedasticity, were performed to determine the reliability and robustness of the VAR model. As displayed in Table 6.4.8 Appendix D, at the given lag length, the VAR model contains residuals that are normally distributed and homoscedastic, however, the model also passed the LM autocorrelation test, hence, the coefficients, impulse response and variance decomposition are not biased.

6.4.9 Cointegration test results

The cointegration result is displayed in Table 6.4.9 Appendix D. The Johansen cointegration indicates the presence of a long run relationship among variables at five percent significant level. The trace test indicates two cointegration eigenvalue tests at 0.05 percent significance level, which indicates the rejection of the hypothesis of no cointegration. However, since the study attempts to examine the short run impact of the bank lending channel the VECM is not estimated in the present study.

6.5 The Brazil VAR model (model 5)

This section reviews the empirical results for model 5.

6.5.1 Descriptive statistics

The descriptive statistics for model 5 are represented in Table 6.5.1 below. The probability coefficient for the LGDP, R, INF, and LNEER are less than 10%, hence they are normally distributed. However, L and an LM2 probability is 0.02% and 0.002%, respectively, and they are not normally distributed. The skewness of L, LGDP, and LM2, respectively, is positive and less than zero, hence, they have a right tail and are normally distributed. The skewness for R, INF, and LNEER is negative and less than zero. The right and left tail are equal for all the variables, hence they are normally distributed. The mean and the median are identical, hence the variables are normally distributed. The kurtosis coefficient for LGDP, LM2, and R is three, hence the variables are normally distributed. The kurtosis for other variables (L, INF, and LNEER) is less than three, then the distribution is flat relative to normally distributed.

Table 6.5.1: Descriptive statistics

	L	LGDP	LM2	R	INF	LNEER
Mean	44.99853	14.35293	27.43698	48.06520	4.501758	4.382741
Median	43.45000	14.22513	27.35557	48.01667	4.510050	4.410027
Maximum	66.80000	15.61647	28.32230	72.40000	5.030023	4.654092
Minimum	28.30000	13.08912	26.87702	26.23333	3.939925	4.018521
Std. Dev.	14.31861	0.600942	0.341037	10.77358	0.302713	0.182098
Skewness	0.270617	0.317055	0.999562	-0.030449	-0.133899	-0.421880
Kurtosis	1.429537	2.769624	3.539290	2.605208	2.126847	2.047381
Jarque-Bera	7.817981	1.289647	12.14745	0.452114	2.363316	4.588334
Probability	0.020061	0.524755	0.002303	0.797673	0.306770	0.100845
Sum	3059.900	975.9991	1865.714	3268.433	306.1195	298.0264
Sum Sq. Dev.	13736.51	24.19578	7.792534	7776.693	6.139546	2.221700
Observations	68	68	68	68	68	68

Source: Estimated by the researcher

6.5.2 Correlation matrix

In Table 6.5.2 Appendix E, the matrix correlation for the Brazil VAR model shows that there is a strong positive correlation between LM2 and LGDP of 93%, hence there is no multicollinearity among the variables, since the significant level is 5%. Multicollinearity causes the confidence intervals of the coefficients to become very wide and the statistics to be very small (Gujarati, 2004). Advocates of multicollinearity have argued that it does not lead to unbiased of standard errors and to miss-specified the regression coefficients (Dougherty, 2001). There is no multicollinearity among the variables, hence the regression coefficient is not biased.

6.5.3 Stationarity tests

In Table 6.5.3, the variables for model 5 are non-stationary at the level form and stationary at first difference in both the ADF test and PP test. The variables are suitable for estimation of a VAR model as all of them are I(1) variables. The null hypothesis that variables contain a unit root is accepted and the alternative hypothesis that variables do not contain a unit root is rejected.

Table 6.5.3: Unit root tests

ADF Test					**PP Test**			
	Levels		**1st Difference**		**Levels**		**1st Difference**	
	t-value	Lag	t-value	Lag	t-value	Lag	t-value	Lag
L	-1.610	8	-3.842^{***}	6	-1.527	5	-6.790^{**}	4
LGDP	-2.118	0	-5.587^{**}	2	-2.172	5	-7.034^{**}	16
LCPI	-2.785	3	-3.490^{***}	2	-1.801	3	-4.630^{***}	10
LM2	-1.448	0	-6.756^{**}	0	-1.554	3	-6.641^{**}	9
R	-2.423	1	-4.513^{**}	0	-1.385	3	-4.367^{**}	4
LNEER	-2.451	1	-5.768^{**}	0	-1.884	6	-5.426^{**}	24
Note: *, **, *** represent 10%, 1% and 5% level of significance, significance. The number of lags in the ADF test is determined by AIC and SIC, while the PP test is determined by Bartlett Kernel.								

Source: Generated by the researcher

6.5.4 Lag length selection

The lag length selected in Table 6.5.4 Appendix E is lag two as suggested by all selection criterions. There is unanimous agreement by the selection criterion on lag two. The lag will be appropriate as it is supported by the FPE and the AIC which are suitable for small sample size and it imposes a penalty when a large number of variables are regressed (Liew, 2004).

6.5.5 Stability of the VAR

The stability of the VAR model is one of the requirements that must be satisfied before the impulse response and variance decomposition are estimated. An unstable VAR model may result in biased impulse response function and variance decomposition. The study employs the Autoregressive test to examine the stability of the VAR process and the modulus companion. A VAR model is stable when all moduli of companion matrix are strictly less than one (Hamilton, 1994; Lutkepohl, 2005). When one of the modulus is more than one, or one of the roots lies outside the unit circle, the model is unstable and produce biased impulse response function. The VAR model satisfies the stability condition as all the modulus are less than one, as shown in Table 6.5.5 Appendix E. Moreover, the eigenvalues lie inside the unit circle as shown in Figure 6.3 Appendix E, hence the VAR model is stable and will produce unbiased impulse response function and variance decomposition.

6.5.6 VAR model estimation

The purpose of the study is to investigate the short run relationship in the bank lending channel. The VAR model of each country is estimated to compare the shocks of monetary policy to economic through impulse response in each country. The ordering of variables in each country is according to the panel VAR model above as L-LGDP-INF-M2-R-LNEER. However, in Chile, the LNEER was omitted in the model because it was insignificant and the overall model was not stable with its inclusion. In addition, the INF or INF is used alternatively as a proxy for the general price level in all the five models. The VAR model results is shown in Table 6.5.6 Appendix E.

6.5.7 Forecast error variance decomposition

In Table 6.5.7(a) Appendix E, the variation in L in Brazil is explained by its lag. As the number of lags increases the variation explained by its lag decreases to 24% in the tenth period. Whereas the variations explained by LGDP, LM2 and LNEER increase from 0% to 62%, 11%, and 1%, respectively. R and INF seem not to affect L in Brazil according to the variance decomposition. The variation in LGDP in Table 6.5.7(b) Appendix E is explained by its lag and L in Brazil in the first period. The lag of LGDP, L, LM2, and LNEER explains 81%, 8%, 5%, and 5%, respectively, in LGDP. R and INF do not explain the variation in LGDP. The variation in R is explained by its lag in the first period as shown in Table 6.5.7(c) Appendix E. In the tenth period, the variation in R is significantly explained by its lag, LM2 and LGDP, 29%, 22%, and 41%, respectively, as shown in Table 6.5.7(d) Appendix E. The variation in INF, as shown in Table 6.5.7(e) Appendix E is significantly explained by its lag and R in the first period. LGDP explain 5% of the variation in INF. There seems to be a consensus among Brazil, Mexico, and South Africa as the variation in LNEER is explained by its lag and LGDP as shown in Table 6.5.7(f) Appendix (E). Only 1% of the variation in LNEER is explained by L.

6.5.8 Diagnostic tests results

All the diagnostics' tests, which included normality, serial correlation and heteroskedasticity, were performed to determine the reliability and robustness of the VAR model. As displayed in Table 6.5.8 Appendix E, at the given lag length the VAR model, contains residuals that are normally distributed and homoscedastic, however, the model also passed the LM autocorrelation test. Hence, the coefficients, impulse response and variance decomposition are not biased.

6.5.9 Cointegration test results

The cointegration result is displayed in Table 6.5.9 Appendix E. The Johansen cointegration indicates the presence of a long run relationship among variables at five percent significant level. The trace test indicates two cointegration eigenvalue tests at 5 percent significance level, which indicates the rejection of the null hypothesis of no cointegration. However, since the study attempts to examine the short run impact of the bank lending channel, the VECM is not estimated in the present study.

6.2. The Chile VAR model (Model 6)

This section reviews the empirical results for model 6.

6.6.1 Descriptive statistics

The descriptive statistics for the VAR for Chile are represented in Table 6.6.1 below. The majority of the variables LGDP, R and LM2 are normally distributed as the coefficient of their probability is above 10%. The skewness of coefficient of the variables is zero for all the variables, hence they conform to normality. Variables L, LGDP, and LM2 have a positive skewness, hence they are skewed to the left, Whereas R and INF are having a negative skewness, and hence it is skewed to the right. The Jarque-Bera statistics for LGDP, LM2, and R, are less than three, hence it conforms to a normality distribution. The variables are normally distributed as the mean and median are identical. The kurtosis coefficient of the variables is well below three, hence the results indicate a platykurtic distribution of the series.

Table 6.6.1: Descriptive statisticts

	L	LGDP	LM2	R	INF
Mean	67.67794	23.25720	23.95195	4.002647	0.809263
Median	66.25000	23.23313	23.96746	4.250000	0.834067
Maximum	82.20000	24.12359	25.00761	8.250000	3.519023
Minimum	58.10000	22.38418	22.98597	0.500000	-2.440315
Std. Dev.	7.954438	0.434439	0.544019	1.639565	0.836054
Skewness	0.423012	0.208029	0.331980	-0.136245	-0.147761
Kurtosis	1.760708	2.424808	2.111591	3.006722	6.744554
Jarque-Bera	6.379535	1.427857	3.485323	0.210505	39.97554
Probability	0.041181	0.489716	0.175054	0.900097	0.000000
Sum	4602.100	1581.489	1628.733	272.1800	55.02987
Sum Sq. Dev.	4239.297	12.64542	19.82911	180.1075	46.83211
Observations	68	68	68	68	68

Source: Estimated by the researcher

6.6.2 Matrix correlation

In Table 6.6.2 Appendix F, the matrix correlation for the Chile VAR model shows that LM2 and LGDP have a very strong positive correlation at 0.82%. However, since the significant level is 10%, there is no multicollinearity among the variables. According to Gujarati (2004), multicollinearity may cause biased standard errors and coefficients. In contrast, Dougherty (2001) argued that multicollinearity leads to biased regression coefficients and standard errors, but that does not imply the model has been misspecified and the regression coefficients are valid. Also, there is a positive strong correlation between L and LM2 of 0.68%. In addition, there is a moderate correlation between L and LGDP and between R and INF. In most of the variables, there is a weak correlation. Overall, there is no multicollinearity among the variable, hence the regression coefficients will be unbiased and robust.

6.6.3 Stationary tests

In Table 6.6.3, the variables for the Chile VAR model are of mix order I(1) and I(0) both the ADF test and the PP test. Variables L, LGDP and LM2 are nonstationary at the level form and stationary at first difference in both the ADF and PP tests. The INF is stationary in levels form for both tests 1%, hence it is an I(0) variable. The R and LNEER are stationary at 10% level under the ADF test in level form. However, under the PP test, both the R and the LNEER are nonstationary at the level form and stationary at first difference. The conclusion on the R and LNEER is that both variables are I(1) since 10% is a higher risk. The variables are of mix order I(1) and I(0) in level form.

Table 6.6.3: Unit root tests

	ADF Test				**PP Test**			
	Levels		**1st Difference**		**Levels**		**1st Difference**	
	t-value	Lag	t-value	Lag	t-value	Lag	t-value	Lag
L	-2.417	2	-5.692^{**}	0	-2.072	4	-5.790^{**}	3
LGDP	-1.565	3	-6.817^{**}	2	-0.352	66	-11.919^{*}	13
INF	-4.200^{**}	4			-4.917^{**}	9		
LM2	-2.282	0	-8.336^{**}	0	-2.330	1	-8.554^{**}	7
R	-3.678^{**}	3	-3.887^{**}	4	-2.708	2	-4.088^{**}	8
LNEER	-3.585^{**}	1	-6.734^{**}	0	-2.876	5	-6.637^{**}	14

Note: *, **, *** represent 10%, 1% and 5% level of significance, significance. The number of lags in the ADF test is determined by AIC and SIC, while the PP test is determined by Bartlett Kernel.

Source: Generated by the researcher

6.6.4 VAR Lag order (p) selection

The lag length selection criterion of model 6 is represented by Table 6.6.4 Appendix F. The applied lag in the model is lag one as suggested by the SIC and the HQ. Lag one is the minimum lag selected by two criteria, when the optimal lag six is employed. The FPE and LR suggested the lag four, while the AIC suggested lag six.

6.6.5 Stability of the VAR

The stability of the VAR model is one of the requirements that must be satisfied before the impulse response and variance decomposition are estimated. An unstable VAR model may result in biased impulse response function and variance decomposition. The study employs the Autoregressive test to examine the stability of the VAR process and the modulus companion. A VAR model is stable when all moduli of companion matrix are strictly less than one (Hamilton, 1994; Lutkepohl, 2005). When one of the modulus is more than one, or one of the roots lies outside the unit circle, the model is unstable and produce biased impulse response function. The VAR model satisfies the stability condition as all the modulus are less than one as shown in Table 6.6.5. Moreover, the eigenvalues lie inside the unit circle as shown in Figure 6.4 Appendix F. Hence the VAR model is stable and will produce unbiased impulse response function and variance decomposition.

6.6.6 VAR model estimation

The purpose of the study is to investigate the short run relationship in the bank lending channel. The VAR model of each country is estimated to compare the shocks of monetary policy to economic through impulse response in each country. The ordering of variables in each country is according to the panel VAR model, as L-LGDP-INF-M2-R-LNEER. However, in model 6, the LNEER was omitted in the model because it was insignificant and the overall model was not stable with its inclusion. In addition, the INF is utilized as a proxy for the general price level in all the five models. The VAR model results are shown in Table 6.6.6 in Appendix F.

6.6.7 The forecast-error variance decomposition

In Table 6.6.7(a) Appendix F, the variation in L in the case of Chile is explained by its lag in the first period. As the number of lags is increased, the variation explained by the lag of L in L decreases from 100% to 58%, in the tenth period. The variation explained by LM2, INF, and R is 28%, 10% and 3% in L in the tenth period. In contrast to theory, LGDP does not explain the variation in L. The variation in LGDP is explained by its lag and L in the first period as shown in Table 6.6.7(b) Appendix F. The variation explained by LM2, L, INF and R in the tenth period is 22%, 45%, 1%, and 2%, respectively, in LGDP. In Table 6.6.7(c) Appendix F, the variation in LM2 is mostly explained by L, LGDP and its lag, 49%, 30%, and 20%, respectively. The INF explains only 4% of the variation in LM2 in period ten. The variations explain by INF and LGDP in period ten is 21% and 2%, respectively, as shown in Table 6.6.7(e) Appendix F. The variation in INF is significantly explained by its lag and L. LM2, LGDP and R only explain 4%, 2% and 1% of the variation in INF. Lastly the variation in R is mostly explained by its lag and L, as shown in Table 6.6.7(d) Appendix F.

6.6.8 Diagnostic tests results

All the diagnostics tests which included normality, serial correlation and heteroskedasticity, were performed to determine the reliability and robustness of the VAR model. As displayed in Table 6.6.8 Appendix F, at the given lag length, the VAR model contains residuals that are normally distributed and homoscedastic, however, the model also passed the LM autocorrelation test. Hence the coefficients, impulse response and variance decomposition are not biased.

6.6.9 Cointegration test results

The cointegration result is displayed in Table 6.6.9 Appendix F. The Johansen cointegration indicates the presence of a long run relationship among variables at five percent significant level. The trace test indicates two cointegration eigenvalue tests at 0.05 percent significance level, which indicates the rejection of the hypothesis of no cointegration. However, since the study attempts to examine the short run impact of the bank lending channel the VECM is not estimated in the present study.

6.7 The impulse response function

The impulse response function is computed from the five VAR models (model 2 - model 6). In the present study, the impulse response is computed as a table from each model. The purpose of this section is also to compare the response of the economic variables to monetary policy shocks in the selected emerging markets. This section begins by examining the response of bank loans to one standard deviation shock of the monetary policy interest rate in each countries model. The impulse response of the bank loans of Brazil, Chile, Mexico, Russia, and South Africa are represented by L_BR, L_CH, L_M, L_R, and L_SA, respectively, represented in Figure 6.5(a). The bank loans in Brazil and Russia declines immediately in response to the monetary policy interest rate shock, which supports the theory of the bank lending channel by Bernanke and Blinder (1988). L_BR at the end of the third period at its minimum retraces back to its equilibrium until the 8 periods. After the 8 periods at its maximum, L_BR declines below the equilibrium. The L_R reaches its minimum during the second period and increases until it reaches the equilibrium during the fourth period. The response of the L_BR is consistent with those of de Mello and Pisu (2010) who found a negative response of bank loans to monetary policy interest rate shocks. Juurikkala *et al*. (2011) also found the bank loans to be negatively responsive to monetary policy shocks. Notice the magnitudes of the decline are quite similar for both countries where after the third period the decline is about o.2% for a 1% initial shock to interest rates.

In contrast to the bank lending channel theory by Bernanke and Blinder (1988), L_SA increase in response to a one standard deviation shock of monetary policy. The result indicates the lack of the presence of the bank lending channel in South Africa, which implies bank loans are not responsive to interest rate shocks and takes longer than 10 periods before the interest channel takes effect. This behaviour explains the high levels of indebtedness among most household in South African context. The response of L_SA to a one standard deviation shock of monetary policy is inconsistent with the empirical results by Ludi and Ground (2006), who found a negative response of bank loans to monetary policy shocks. Both the L_CH and L_M also are not immediately responsive to interest rate shocks, it is only after five periods have past that there is a decline in bank loans issued to the public, similar to South Africa, where there is no return to equilibrium even after ten periods. Furthermore, although Chile and Mexico appear to exhibit similar patterns their magnitudes are entirely different, the upsurge in the Mexican loans are quite subdued at 5 period, the response is 0.05% to a 1% shock, while for Chile it is about 0.28%. Alfaro *et al*. (2006) also found the bank lending to be effective with a lag in Chile. The L_BR and L_R are more responsive to monetary shocks than in Mexico, Chile, and South Africa.

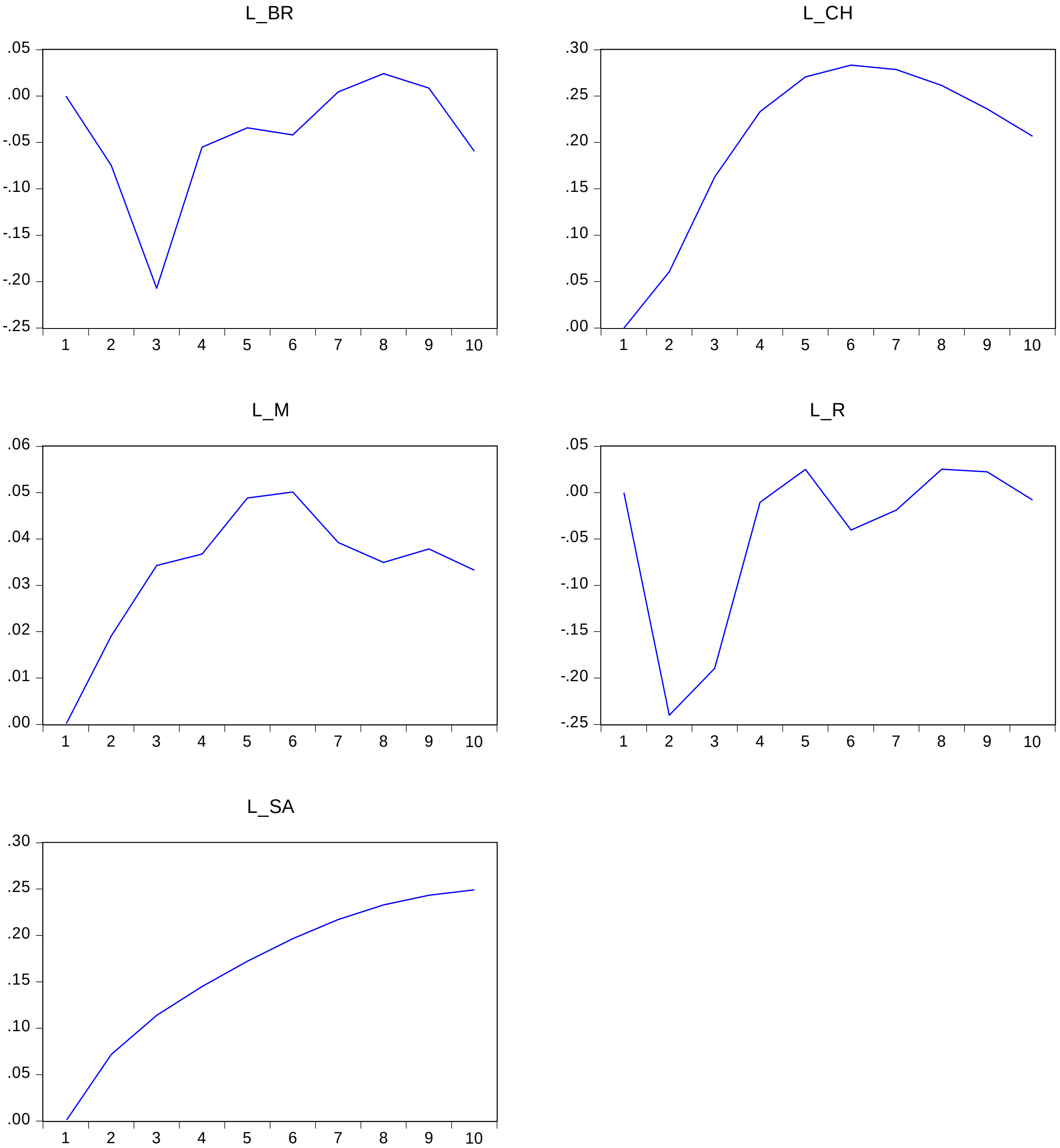


Figure 6.5(a): Response of bank loans to interest rate shocks

Source: Generated by the researcher

In Figure 6.5(b) below, the LGDP_BR, LGDP_CH, LGDP_M, LGDP_R, and LGDP_SA in the respective countries (Brazil, Chile, Mexico, Russia, and South Africa) decline in response to a one standard deviation shock of monetary policy transmission. The magnitude of the decline after 2 periods in ascending order is Mexico (0.004%), Russia (0.005), South Africa (0.004), Brazil (0.2%) and Chile (0.011). All the declines are relatively small to a 1% shock, and apart from South Africa and Russia, all the other economies retrace and hover around their respective equilibrium levels.

Both the LGDP_BR and LGDP_M, at the end of the 1.5 periods, retrace back to an equilibrium position and reach their maximum above the equilibrium position during the sixth period. The successive increase in both LGDP_BR and LGDP_M may be induced by high aggregate demand and low inflation rate. Both LGDP_BR and LGDP_M, after the sixth period, decline below the equilibrium point until they reach a low at the 10 periods. The LGDP_CH in response to a one standard deviation shock declines and reaches its minimum in the second period and increases during the third period towards the equilibrium point.

The LGDP_R declines in response to a one standard deviation shock of monetary policy rate and reach its minimum at the end of the 4.5 periods and increases towards the equilibrium until the 5.5 periods. However, LGDP_R remains below the equilibrium point at 0.006. The LGDP_SA, in response to a one standard deviation shock of monetary, declines steady until it reaches its minimum at the 10 periods. The response of the gross domestic product in the respective countries to a one standard deviation shock of monetary policy rate is according to theory and expectation. Hence, the findings are consistent with the theory of the bank lending channel by Bernanke and Blinder (1988). Fan and Jianzhou (2011) employed the VAR model to investigate the presence of the bank lending channel in China. The study found LGDP to have a negative relationship with the monetary policy interest rate. Another study that was carried in a volatile emerging market (Turkey) found the LGDP to have a negative response to tightening monetary policy transmission shocks (Akinci *et al.,* 2013). The study employed the Pooled OLS model which also found the bank lending channel to be effective in Turkey.

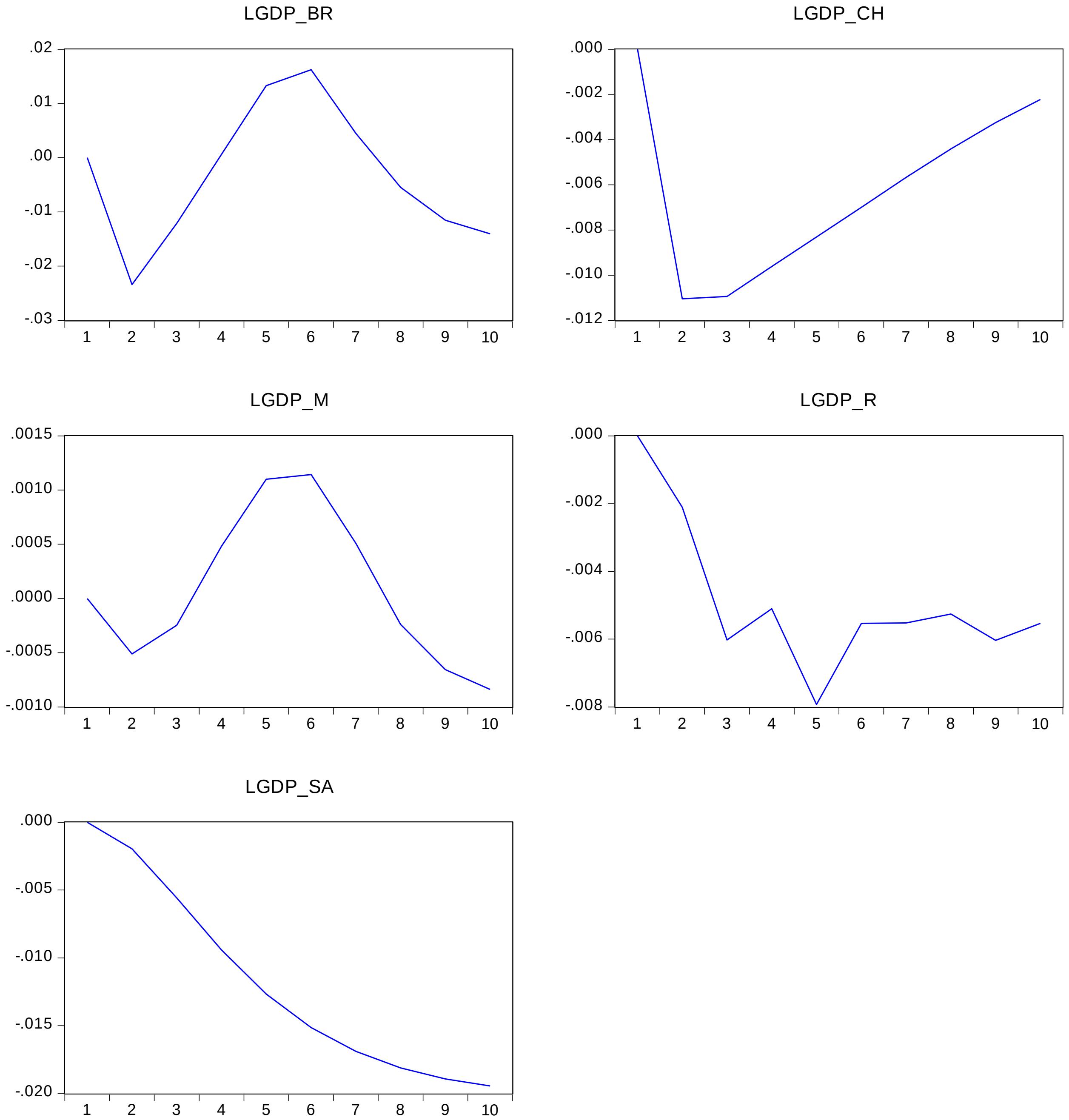


Figure 6.5(b): Response of LGDP to interest rate shocks

Source: Generated by the researcher

In Figure 6.5(c) below, there seem to be mixed results of the response of INF to a one standard deviation shock of monetary policy rate in the select emerging markets. South Africa and Chile exhibit similar results, where there is an immediate decline in inflation, while the effect is deeper for Chile, 0.08% compared which is 0.03% after 1.5 periods to a 1% shock. Thereafter, Chile equilibrates to marginally below the initial equilibrium and South Africa above to marginally above. In the cases of Mexico, Brazil and Russia, the immediate responses are marginally increases in inflation but over time the inflation hovers around the initial equilibrium in a staccato fashion.

The INF_CH declines immediately in response to a one standard deviation shock of monetary policy and reach its minimum at 1 period. After the first period, the INF_CH increases but remains below the equilibrium level. The INF_SA declines in response to a one standard deviation shock of monetary policy rate and reaches its minimum at 1.5 periods. Subsequently, the INF_SA increases to 0.2 above the equilibrium. The response of the inflation rate to restrictive monetary transmission shocks in Chile and South Africa is robust and according to the theory of Bernanke and Blinder (1988).

The INF_BR, INF_M, and INF_R respond with a lag to a one standard deviation shock of monetary policy interest rate. In response to a one standard deviation shock of the monetary policy interest rate, the INF_BR increases slightly above the equilibrium at 0.002, which is an indication of the price puzzle. The contractual obligation of consumers to service a debt after a monetary policy shock may be the cause for inflated prices (Munyengwa, 2013). In addition, an increase in the monetary policy interest rate increases the opportunity cost of access to credit, hence increasing the general price level. Subsequently, the INF_BR declines to reach the minimum of 0.003 at the 1.5 periods. At the end of 1.5 periods, the INF_BR retrace towards the equilibrium. The results are in consensus with the results of the panel VAR model above and Mallick and Sousa (2012).

The INF_M and INF_R also respond with a lag to monetary policy interest rate shocks. The INF_M increases sharply in response to a one standard deviation shock of monetary policy rate and reach the maximum at 0.8 at the 1 period. As it has been alluded to, the increase of the INF_M may be due to a price puzzle. That is the contractual obligation of consumers to service a debt after a monetary policy shock and may be the cause of inflated prices (Munyengwa, 2013). After the first period, the INF_M declines to reach its minimum at 3.5 periods below the equilibrium position and increase thereafter. The INF_R also increases in response to a one standard deviation shock of the monetary policy rate. However, it also declines below the equilibrium position after the first period. In the selected emerging markets, the inflation rate responds with a lag to monetary policy rate shocks, except for the case of South Africa and Chile.

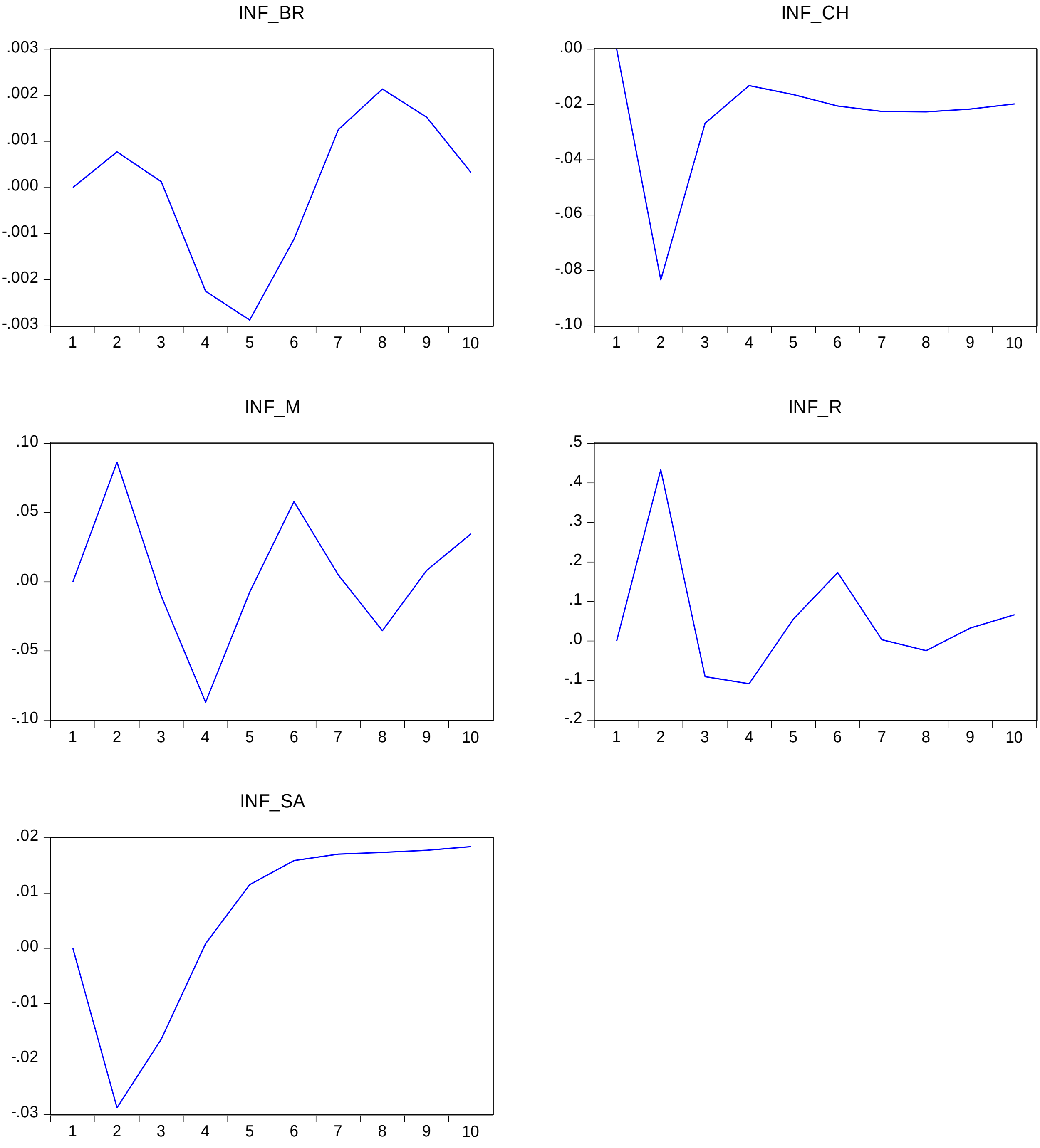


Figure 6.5(c): Response of INF to R shocks

Source: Generated by the researcher

The impulse response of LM2_BR, LM2_CH, LM2_M, LM2_R, and LM2_SA to the monetary policy interest rate, represented in Figure 6.5(d) below, shows a decline. There seems to be a consensus in the response of LM2 to monetary policy interest rate shocks for all the respective countries. There is a negative response of the LM2 to a one standard deviation shock of monetary policy transmission in the respective countries. The response of the LM2 to a one standard deviation shock in the selected emerging markets is according to theory and expectations. In response to a one standard deviation shock of monetary policy, the LM2_BR declines immediately until it reaches the minimum of 0.2 at the end of the first period. However, after the first period, the LM2_BR increases above the equilibrium and declines after the fifth period below the equilibrium. On the other hand, the LM2_CH declines immediately in response to a one standard deviation shock of monetary policy interest rate. At the end of the second period, the LM_CH increases above the equilibrium level.

The LM2_M and LM2_R decline immediately in response to a one standard deviation shock of monetary policy interest rate. The LM2_R declines below the equilibrium level and reach its minimum at the end of the first period. Subsequently, it increases but remains below the equilibrium level. In addition, the LM2_M, in response to a one standard deviation shock of monetary policy interest rate, declines immediately to reach its minimum at the end of the third period. However, it increases and reaches the equilibrium at the end of the sixth period. The LM2_SA does not respond immediately to monetary policy interest rate shock, but declines after two periods.

The response of the LM2 to the monetary policy interest rate for the respective countries is consistent with theory and other empirical literature. The decline in money supply is induced by the decline in inflation rate (Mankiw, 2002). The decline in the money supply is expected as the opportunity cost of holding money increases due to a hike in interest rate. Munyengwa (2013) also observed a negative response of money supply to a monetary policy interest rate. Other scholars who found a negative response of monetary policy interest rate include Ekomane and Benjamin (2016), Caporale *et al*. (2016), Anwar and Nguyen (2018) and Bhoi *et al*. (2017).

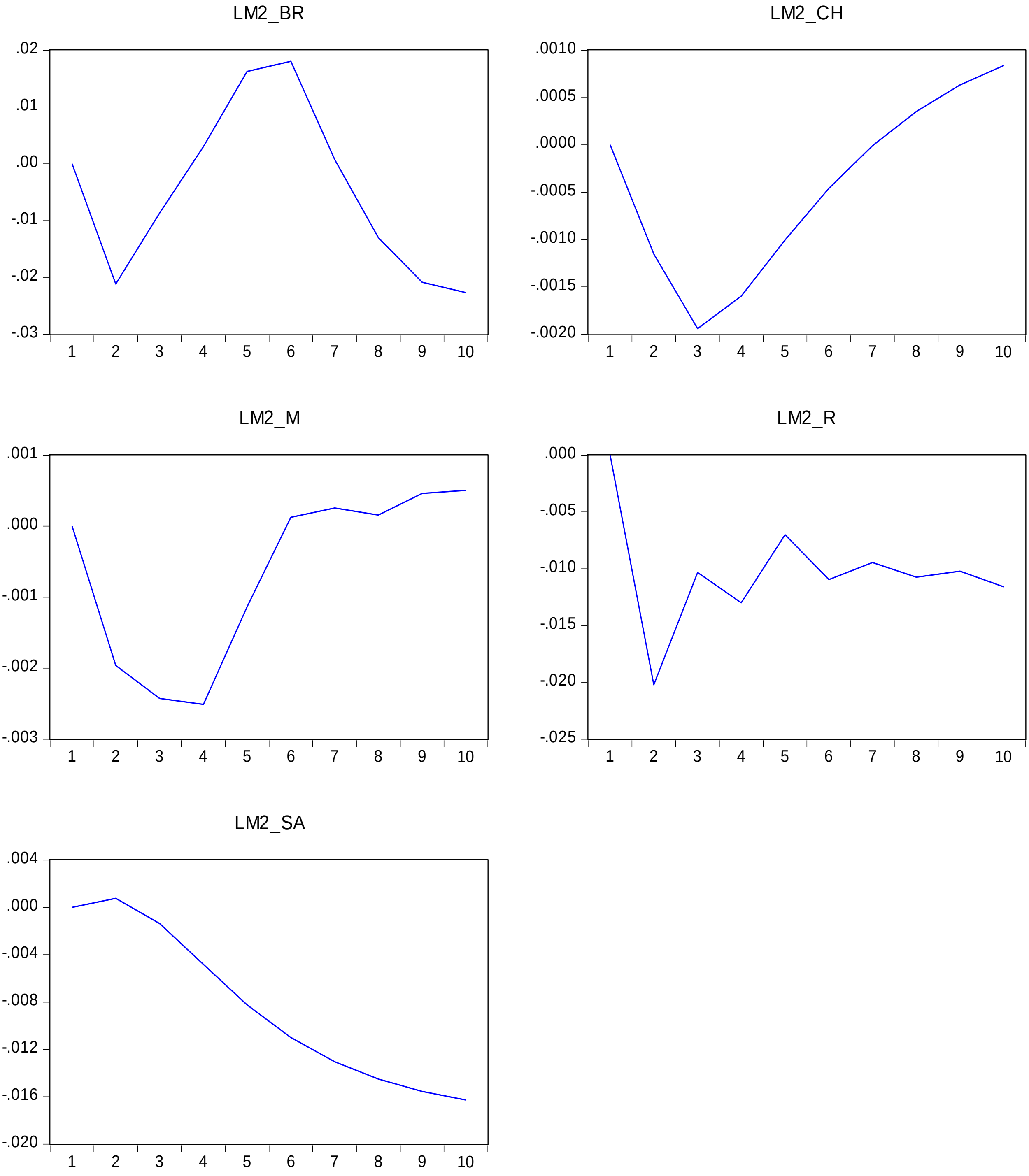


Figure 6.5(d): Response of LM2 to R shocks

Source: Generated by the researcher

In Figure 6.5(e) below, the LNEER_BR, LNEER_M, and LNEER_SA seem to appreciate in response to a monetary policy shock. The increase in monetary policy interest rate increases the opportunity cost of holding money. As the monetary policy interest rate increases, there is a demand for domestic currency, leading to an increase in foreign direct investment and finally an increase in the value of the domestic currency. The LNEER_BR seems to increase sluggishly in response to the monetary policy shock and rises rapidly after the first period. The slow rise of the LNEER_BR may be between the periods of an announcement of a hike in the policy rate and the effective date. However, after the second period, the LNEER_BR depreciates below the equilibrium level and appreciates after the sixth period above the equilibrium. The response of the LNEER_BR is robust and according to theory.

The LNEER_M and the LNEER_SA seem to respond with a one period lag to monetary policy interest rate shock. Both the LNEER_SA and the LNEER_M are flat before the one period lag and increase after one period. After the one period, the LNEER_M appreciates above the equilibrium until it reaches its maximum at 0.006. After the fourth lag, it depreciates steadily and remains above the equilibrium. Also, the LNEER_SA appreciates after the one period and remains above the equilibrium. The appreciation of the nominal effective exchange rate in South Africa and Mexico is consistent with theory and other empirical literature. Munyengwa (2013) also found the nominal effective exchange rate to respond with a one period lag to monetary policy interest rate shocks.

In contrast to the response of nominal effective exchange rate to monetary policy rate shocks, there is depreciation in the nominal effective exchange rate for the case of Russia. The LNEER_R declines below the equilibrium to until the first period. Subsequently, the LNEER_R appreciates above the equilibrium. The delay in response of LNEER_R may be due to the sanctions and lower investor confidence in Russia. Moreover, Russia is the only emerging country that does not employ the inflation targeting framework. Overall, the LNEER in the selected emerging markets seems to respond with one lag to a one standard deviation shock of the policy interest rate. This is an indication of the existence of the bank lending channel in the selected countries.

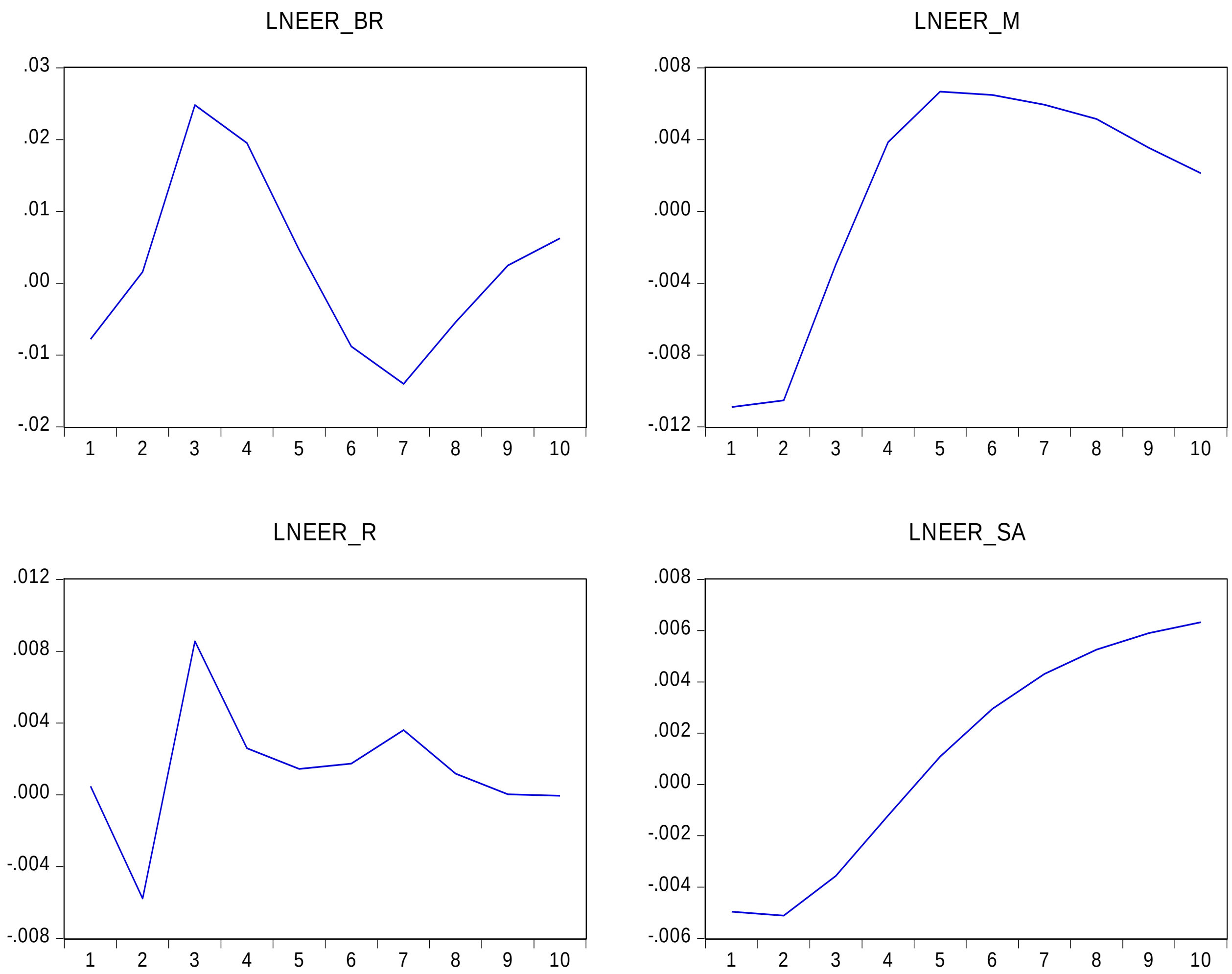


Figure 6.5(e): Response of LNEER to R shocks

Source: Generated by the researcher

There seems to be a consensus in the response of the interest rate to monetary policy rate in Figure 6.5(f) below. A one standard deviation shock of the policy interest rate causes a sharp decline to the R_CH, R_SA, and R_R. The results are consistent with theory, as tightening monetary policy induces a fall in inflation, which invokes an easing in monetary policy. Munyengwa (2013) also observed a fall in the interest rate in response to the monetary policy shocks. In the case of Brazil and Mexico, the interest rate seems to respond with a one period lag to a one standard deviation shock of the monetary policy rate. The R_M declines in response to a monetary policy shock after the one period lag to below the equilibrium level. Also, the R_BR declines after the first period lag in response to positive monetary shocks below the equilibrium level.

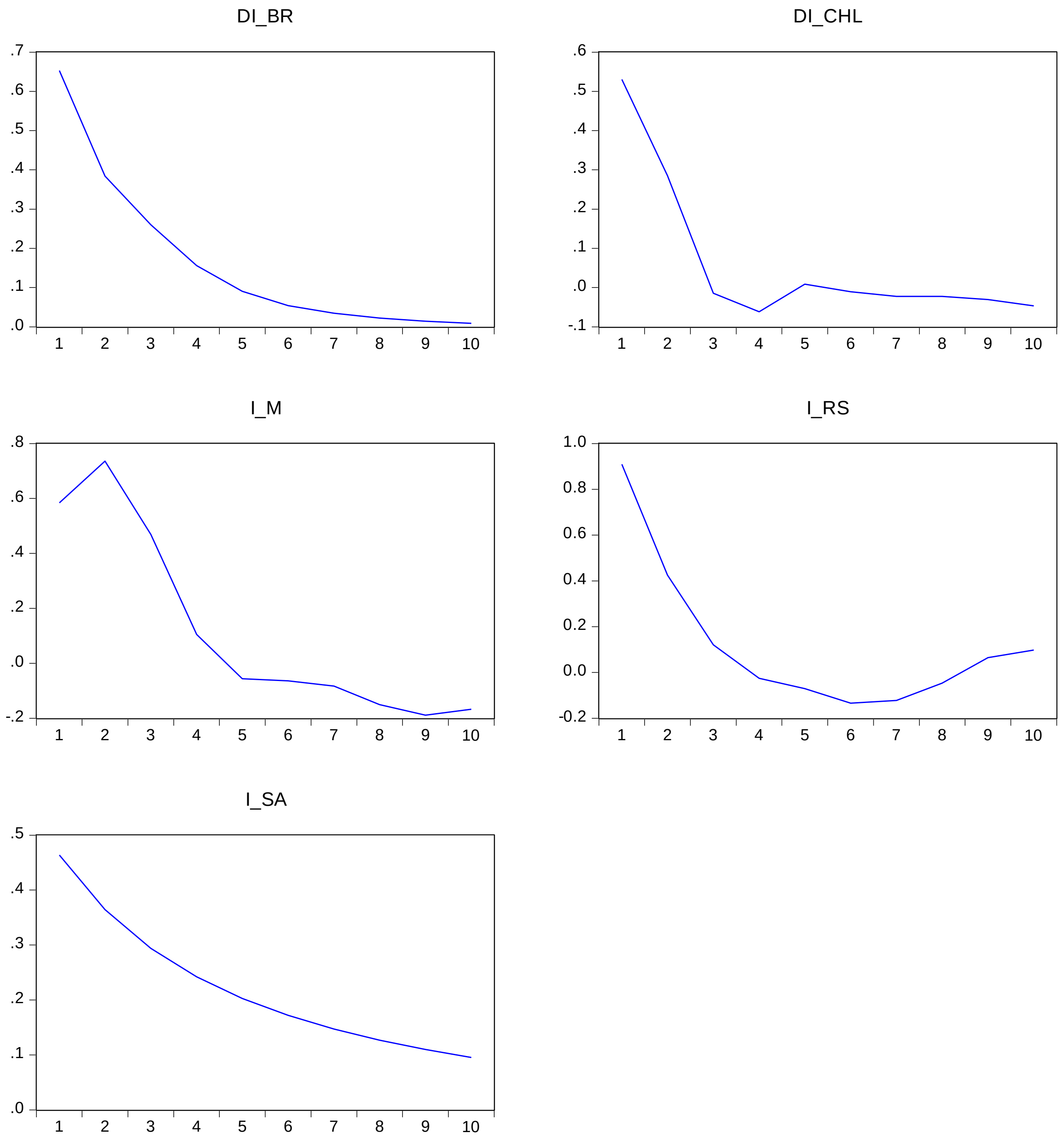


Figure 6.5(f): Response of R to R shocks

Source: Generated by the researcher

6.8 The conclusion of the chapter

The chapter discussed the empirical results of the panel VAR model and the five VAR models for the selected emerging markets. The empirical result of the panel VAR model, which is estimated according to Abrigo and Love (2015), through STATA 14, seems to conform to theory and to the diagnostic test. The coefficients of the variables are significant and robust. With regards to the model, the only diagnostic tests is the stability test. According to the panel VAR model, the bank lending interest rate affects inflation with a one period lag. This may be due to the prize puzzle and contractual obligation by consumers to service their debt. Hence, the null hypothesis of a negative impact of monetary policy to the inflation rate is accepted. Moreover, there seem to be the presence of the bank lending channel in the selected emerging markets. However, monetary policy rate affect bank loan supply with a two period lag. There seem to be consensus with the results of the single VAR model for each country. The VAR models also show the presence of the bank lending channel in the selected countries. Bank loans respond with a lag in Chile, Mexico and South Africa to monetary policy shocks. While bank loans in Russia and Brazil respond immediately to monetary policy shocks, both in the panel VAR and in the VAR models for the selected emerging countries, M2 responds negatively and immediately to monetary policy shocks. There is a contraction in output in response to monetary policy shocks. The findings are robust and according to theory.

CHAPTER 7: THE CONCLUSION AND POLICY RECOMMENDATION

7.1. Conclusion

This chapter will review the credit channel of monetary policy transmission in five selected emerging markets. The credit channel is the process through which monetary policy shocks are propagated to economic variables through credit (Bernanke & Blinder, 1995). The credit channel consists of two subtopics: the bank lending channel and the balance sheet channel. The balance sheet channel is the process through which monetary policy is propagated to economic variables by altering the financial position of banks (Cohen-Cole & Garcia, 2013). In contrast, the bank lending channel is defined as the process through which tightening monetary policy shocks are propagated to economic variables by draining banks' reserve requirement. Hence, banks are constrained on the supply of bank loans to the private sector. Consequently, aggregate demand and output declines (Bernanke & Blinder (1988). Due to data constraints, the balance sheet is not estimated in the study.

The bank lending channel operates effectively when firms depend on bank loans for credit. In addition, there must be an imperfect substitution between bonds and bank loans. According to Kashyap and Stein (2001), the bank lending channel is more effective in small, less liquid and less capitalized banks or firms. This is caused by the fact that less liquid and small banks have limited access to external funding. The study followed estimation, through the VAR approach, the impact of monetary policy rate shocks to economic variables in the selected emerging markets according to the traditional bank lending channel of Bernanke and Blinder (1988). Most studies have found the bank lending channel to be effective in emerging markets (Mahathanaseth & Tauer, 2018; Dajcman, 2016; Creel *et al*., 2016). Wu *et al*. (2011) argued that immature financial markets in emerging markets strengthen the bank lending channel of monetary transmission. In contrast, Sanfilippo-Azofra *et al*. (2018) found the bank lending channel to be more effective in a country with developed financial markets.

In the study, the panel VAR model has been adopted for estimation purpose, since it is appropriate for transmission of monetary policy shocks. In addition, it is considered as superior to the popular VAR model, which wastes the degree of freedom for short sample data (Abrigo & Love, 2015). The panel VAR is estimated over the period 2000-

2016, during which the selected emerging markets adopted the inflation targeting regime. During this period, most emerging countries were successful in dampening inflation and output volatility. The current study has been investigated extensively in developed countries, yet little has been done in emerging and less developed countries. Also, five VAR models for each country were estimated for comparison purposes. The control variables included in the panel VAR and VAR models are bank loan supply (L), gross domestic product (GDP) , inflation rate (INF), money supply (M2), the bank lending interest rate (R) and the nominal effective exchange rate.

The panel VAR model was estimated using stationary variables and the first order lag length was selected. The model is stable and all the control variables are statistically significant. The estimation of the panel VAR model follows that of Abrigo and Love (2015). Unfortunately, the panel VAR algorithm programmed into STATA 14 software provides no diagnostic tests in order to confirm the robustness of the model, hence the study was confined to the student t statistics and the unit circle tests to confirm validity. The bank lending channel operates with a two period lag according to the IRF results generated by the panel VAR model results. Hence the bank lending channel is according to Bernanke and Blinder's traditional theory and statistically significant. The first null hypothesis of a negative impact of the monetary policy rate to bank loans supply is accepted. M2 responds negatively to a one standard innovation shock of monetary policy interest rate which is consistent with theory and other empirical literature (Munyengwa, 2012). The inflation rate in the selected emerging market responds with a lag to monetary policy shocks, in the selected emerging markets. Thus, the second null hypothesis of a negative impact of tightening monetary policy rate is accepted. LGDP also responds negatively with a lag to monetary policy rate shocks. The third null hypothesis of a negative impact of monetary policy rate to LGDP is accepted. Monetary policy rate does affect economic variables in emerging markets.

A panel VAR-Granger causality Wald test was also estimated to determine the direction of causality among variables. The monetary policy interest rate Granger causes all variables, except for money supply and nominal effective exchange rate. All the variables Granger causes bank loan supply. However, R is statistically significant at 5 percent and there seems to be a unidirectional causality between DL and DlogGDP. Collectively, the variables Granger cause INF and are statistically significant at 1 percent level. However, DL and DlogNEER do not Granger cause INF.

Hence, there is a unidirectional causality between INF and DL, and between DlogNEER and INF.

A VAR model for each country (Mexico, South Africa, Russia, Brazil and Chile) was estimated as a robustness check and for comparison purpose. Each model consists of the same variables and time frame (200-2016) as in the panel VAR model. Data in level form were utilized to estimate each VAR model. All the VAR models are stable and do not violate the assumptions of the OLS. There seem to be a unanimous negative response of the bank loans to a monetary policy rate shock in all the VAR models. However, for the case of South Africa, bank loans responds positively to monetary policy rate shock, which is in consensus with Ludi and Ground's (2006) empirical results. This result is consistent with the high indebtedness of South African householders and reflects the South African banks' preference to lend at high short term rates to householders than to firms at a lower rate over a longer term in the interest of securing higher profit margins.

The bank lending channel seems to be more effective in Brazil relative to other selected emerging markets. The VAR results are in line with the panel VAR results, where bank loans respond with a lag to monetary policy rate shocks. Monetary policy has a negative impact to output level as expected in all the selected emerging markets. The inflation rate responds negatively with a 1.5 period lag to tightening monetary policy in all the countries. However, in Chile and South Africa, inflation rate responds immediate and negatively to monetary policy rate shock. Money supply declines in response to the monetary policy rate in all the countries. In addition nominal effective exchange rate appreciates in response to the tightening of monetary policy. The VAR and panel VAR results suggest that monetary policy in the selected emerging markets does influence economic variables.

7.2. Policy recommendations

Overall, both the bank lending and interest rate channels appear to work consistently with economic theory, thus implying the monetary policy actions are predictable and since all five economies adopted inflation targeting over the period under investigation, it is advisable for them to continue to develop innovations for greater efficiency in the conducting of monetary policy. This will further assist the more inelastic variables to become more responsive. Furthermore, the successful outcomes that these five emerging economies have attained calls of other emerging economies who have not as yet adopted IT to follow suit.

In the South African context, the bank lending channel is ineffective perhaps due to financialization reasons, and the authorities ought to revisit the National Credit Act to assess why bank loan issues are inelastic to monetary policy tightening.

7.3. Limitations of the study and future research directions

The study could not assess the robustness of the PVAR model due to the absence of diagnostic test features in the STATA 14 software. Future studies ought to make use of alternative software that possess these features.

Due to the lack of data on the available databases, the balance sheet channel of monetary policy could not be investigated. Perhaps future research could start constructing balance sheet time series data by focusing on a small open economy like South Africa, which has about four dominant banks whose balance sheets are available in the public domain.

In regard to the bank lending channel, South Africa has behaved contrary to its other emerging market counterparts, and this has to be investigated further as to why this difference exists. This study proposed that perhaps the financialization motives of banks are a contributing role, but this needs to be investigated further.

Unlike the present study, which considered only five emerging economies, future studies must consider investigating the credit channel through the panel VAR or panel VECM, in at least ten small open markets, in order to have a clear impact or effectiveness of the bank lending channel and balance sheet channel in propagating monetary policy impulse to other macroeconomic variables.

Furthermore, future studies ought to consider employing the panel VECM to investigate the long and short run effectiveness of the credit channel in emerging markets, when the variables are cointegrated, which this study neglected to do due to uncertain/mixed results having been achieved regarding the cointegration of the variables.

In addition, for the context of South Africa, bank level data from the five big banks and also for the small banks may also be employed to determine the impact of bank characteristic (size, capitalization and liquidity) in propagating monetary policy transmission by estimating a panel VAR or panel VECM model for the two class of banks.

REFERENCES

Abrigo, M.R. and Love, I. (2015). *Estimation of Panel Vector Autoregresssion in Stata: A package of programs*. Manuscript, available on: http://paneldataconference2015.ceu.hu/Program.Michael-Arigo.pdf [Accessed 10 September 2018].

Abuka, C. (2015). *Monetary Policy in a Developing Country: Loan Applications and Real Effects*. International Monetary Fund. Navarra Center for International Development, University of Navarra.

Afrin, S. (2017). Monetary policy transmission in Bangladesh: Exploring the lending channel. *Journal of Asian Economics*, Vol. 49:60-80.

Alfaro, R., Franken, H., Garcia, C. and Jara, A., (2004). The bank lending channel in Chile. *Banking Market Structure and Monetary Policy*. Pp.121-145.

Akinci, D. A., Matousek, R., Radić, N. and Stewart, C. (2013). Monetary policy and the banking sector in Turkey. *Journal of International Financial Markets, Institutions and Money,* Vol. 27: 269-285.

Aleem, A. (2010). Transmission mechanism of monetary policy in India. *Journal of Asian Economics,* Vol. 21: 186-197.

Andrews, D.W. and Lu, B., (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*, Vol. *101*(1): 123-164.

Angelopoulou, E. and Gibson, H.D. (2009). The balance sheet channel of monetary policy transmission: evidence from the United Kingdom. *Journal of Economica*, Vol. *76*(304): 675-703.

Anwar, S. and Nguyen, L.P. (2018). Channels of monetary policy transmission in Vietnam. *Journal of Policy Modelling*, Vol. 40: 709-729

Apergis, N. and Alevizopoulou, E. (2012). The bank lending channel and monetary policy rules: Evidence from European banks. *International Advances in Economic Research,* Vol. 18: 1-14.

Apergis, N. and Christou, C. (2015). The behaviour of the bank lending channel when interest rates approach the zero lower bound: Evidence from quantile regressions. *Economic Modelling,* Vol. 49: 296-307.

Aron, J. and Muellbauer, J. (2005). Monetary policy, macro-stability and growth. *World Economics*, Vol. *6(*4): 123-147.

Aron, J. and Muellbauer, J. (2007). Review of monetary policy in South Africa since 1994. *Journal of African Economies*, Vol. *16(5*): 705-744.

Asteriou, D. and Hall, S.G., (2007). Applied econometrics: A modern approach using eviews and microfit (Revised edition). New York: Palgrave Macmillan.

Asteriou, D. and Hall, S.G. (2015). *Applied econometrics*. Macmillan International Higher Education: New York.

Auel, M. C. and De Mendonça, H. F. (2011). Macroeconomic relevance of credit channels: Evidence from an emerging economy under inflation targeting. *Economic Modelling,* Vol. 28: 965-979.

Bauer, M. D. and Neely, C. J. (2014). International channels of the Fed's unconventional monetary policy. *Journal of International Money and Finance, Vol.* 44: 24-46.

Berg, J., van Rixtel, A., Ferrando, A., De Bondt, G. and Scopel, S. (2005). The bank lending survey for the euro area. ECB Occasional Paper, No.23, European Central Bank (ECB), Frankfurt a.M. Available from: http://hdl.handle.net/10419/154476. [Accessed 10^{th} September 2018].

Bernanke, B. S. (1993). How important is the credit channel in the transmission of monetary policy?: A comment. In *Carnegie-Rochester Conference Series on Public Policy*, Vol. 39: 47-52.North-Holland.

Bernanke, B.S. and Blinder, A.S. (1988). Is it money or credit, or both, or neither. *American Economic Review*, Vol. *78*(2): 435-439.

Bernanke, B. (1990). The federal funds rate and the channels of monetary transmission (No. w3487). National Bureau of Economic Research. Princeton University.

Bernanke, B.S. and Gertler, M., (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic Perspectives*, Vol. *9(*4): 27-48.

Bernanke, B.S. (1986). *Alternative explanations of the money-income correlation*. Research Memorandum, Princeton University.

Bhattacharya, R., Patnaik, I. and Shah, A. (2011). Monetary policy transmission in an emerging market setting. International Monetary Fund. National Institute of Public Finance and Policy, New Delhi.

Bhoi, B. K., Mitra, A. K., Singh, J. B. and Sivaramakrishnan, G. (2017). Effectiveness of alternative channels of monetary policy transmission: some evidence for India. *Macroeconomics and Finance in Emerging Market Economies,* Vol. 10: 19-38.

Black, L. K. and Rosen, R. K. (2007). How the credit channel works: differentiating the bank lending channel and the balance sheet channel. Working Paper, Federal Reserve Bank of Chicago.Chicago IL.

Borio, C. and Gambacorta, L. (2017). Monetary policy and bank lending in a low interest rate environment: diminishing effectiveness? *Journal of Macroeconomics*, Vol. 54: 217-231.

Bougheas, S., Mizen, P. and Yalcin, C. (2006). Access to external finance: Theory and evidence on the impact of monetary policy and firm-specific characteristics. *Journal of Banking and Finance*, Vol. *30(*1): 199-227.

Brissimis, S. N. and Delis, M. D. (2009). Identification of a loan supply function: A cross-country test for the existence of a bank lending channel. *Journal of International Financial Markets, Institutions and Money,* Vol. 19: 321-335.

Brissimis, S. N., Iosifidi, M. and Delis, M. D. (2014). Bank market power and monetary policy transmission. *MPRA*, No. 49206

Brito, R.D. and Bystedt, B. (2010). Inflation targeting in emerging economies: Panel evidence. *Journal of Development Economics*, Vol. *91(* 2): 198-210.

Budha, B. B. (2013). The Bank Lending Channel of Monetary Policy in Nepal: Evidence from Bank Level Data. *NRB Economic Review,* Vol. 25: 43-65.

Burgstaller, J. (2010). Bank lending and monetary policy transmission in Austria. *Jahrbücher für Nationalökonomie und Statistik.* Vol. 230: 163-185.

Caldas Montes, G. and Cabral Machado, C. (2013). Credibility and the credit channel transmission of monetary policy theoretical model and econometric analysis for Brazil. *Journal of Economic Studies,* Vol. 40: 469-492.

Campbell, J.Y. and Perron, P. (1991). Pitfalls and opportunities: what macroeconomists should know about unit roots? *NBER Macroeconomics Annual*, Vol. *6*: 141-201.

Canova, F. and Ciccarelli, M. (2013). Panel Vector Autoregressive Models: A Survey. In *VAR Models in Macroeconomics–New Developments and Applications: Essays in Honour of Christopher A. Sims*. Emerald Group Publishing Limited, pp. 205-246.

Cantero-Saiz, M., Sanfilippo-Azofra, S., Torre-Olmo, B. and López-Gutiérrez, C. (2014). Sovereign risk and the bank lending channel in Europe. *Journal of International Money and Finance,* Vol. 47: 1-20.

Caporale, G. M., Nazif, A., Çatik, M. H. H., Ali, F. M. and Tajik, M. (2016). *The Bank Lending Channel in a Dual Banking System: Evidence from Malaysia.German Institute for Economic Research*. DIW Discussion Papers, No. 1557,Deutsches Institut Fur Wirtschaftsforschung (DIW), Berlin.

Catão, L. & Pagan, A. (2009). The credit channel and monetary transmission in Brazil and Chile: a structured VAR approach. *The 2009 Annual Conference of the Central Bank of Chile.* Santiago:105-144.

Céspedes, L.F., Goldfajn, I., Lowe, P. and Valdés, R. (2006). Policy Responses to external shocks: the experiences of Australia, Brazil and Chile. *External Vulnerability and Preventive Policies*, Vol. *10*: 109-70.

Charemza, W.W. Deadman, F.D. (1992). New Direction in Econometric Practice: General to specific modelling, Cointegration and Vector Auto Regression. Edward EI gar, Aldershot.

Ciccarelli, M., Maddaloni, A. and Peydró, J.L. (2015). Trusting the bankers: A new look at the credit channel of monetary policy. *Review of Economic Dynamics,* Vol. 18: 979-1002.

Coelho, C. A., De Mello, J. M., Garcia, M. G. and Galindo, A. J. (2010). Identifying the Bank Lending Channel in Brazil through Data Frequency. *Economía,* Vol. 10: 47-79.

Creel, J., Hubert, P. and Labondance, F. (2016). *The Intertwining of Bank Credit and Bank Instability*. (No. 14). OFCE Working Paper. Paris, France.

Dabla-Norris, M.E. and Floerkemeier, H. (2006). *Transmission mechanisms of monetary policy in Armenia: evidence from VAR analysis*. International Monetary Fund: 6-248.

Dajcman, S. (2013). Asymmetric correlation of sovereign bond yield dynamics in the eurozone. *Panoeconomicus,* Vol. 60: 775-789.

Dajcman, S. (2016). The Bank Lending Channel of Monetary Policy and its Macroeconomic Effects: Evidence from a Sample of Selected Euro Area Countries. *Engineering Economics,* Vol. 27: 124-133.

De Kock Commission. (1985). The Monetary System and Monetary Policy in South Africa. Final Report of the Commission of Inquiry into the Monetary System and Monetary Policy in South Africa. Commission chaired by G.P.C. de Kock, RP70/1984. Pretoria: Government Printer.

De Kock, G. (1998). Inflation under Scrutiny. *South African Reserve Bank Quarterly Bulletin*, Vol. 168: 21 – 25.

De Mello, L. and Pisu, M. (2010). The bank lending channel of monetary transmission in Brazil: A VECM approach. *The Quarterly Review of Economics and Finance,* Vol. 50: 50-60.

Disyatat, P. (2011). The bank lending channel revisited. *Journal of Money, Credit and Banking,* Vol. 43: 711-734.

Eickmeier, S., Hofmann, B. and Worms, A. (2009). Macroeconomic fluctuations and bank lending: evidence for Germany and the euro area. *German Economic Review,* Vol. 10: 193-223.

Ekomane, J. L. and Benjamin, Y. (2016). The Measurement of Credit Channel in the CEMAC Zone. *Journal of Economics and Political Economy,* Vol. 3: 744.

Enders, W. (2004). Applied Econometric Time Series, Wiley Series in Probability and Statistics*,* Vol. 46, 264.

Fan, Y. and Jianzhou, T. (2011). Studying on the monetary transmission mechanism in China in the presence of structural changes. *China Finance Review International,* Vol. 1: 334-357.

Farinha, L. and Robalo Marques, C., (2001). The bank lending channel of monetary policy: identification and estimation using Portuguese micro bank data (No. 102). *ECB Working Paper*. Frankfurt.

Favero, C. A., Giavazzi, F. and Flabbi, L. (1999). *The transmission mechanism of monetary policy in Europe: evidence from banks' balance sheets*. National Bureau of Economic Research. University of Bocconi: Milan.

Fernald, J. G., Spiegel, M. M. and Swanson, E. T. (2014). Monetary policy effectiveness in China: Evidence from a FAVAR model. *Journal of International Money and Finance,* Vol. 49: 83-103.

Fotopoulos, S. V., Papapanagos, H. V. and Siokis, F. M. (2011). Into the Bank Lending Channel of SEE: Greek Banks' Buffering Effects. *World Academy of Science, Engineering and Technology, International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering,* Vol. 5(11):1755-1762.

Ramos-Francia, M. and Torres, A. (2005). Reducing inflation through inflation targeting: the Mexican experience. In Monetary policy and macroeconomic stabilization in Latin America (pp. 1-29). Springer, Berlin, Heidelberg

Friedman, M., and Meiselman, D. (1963). The Relative Stability of Monetary Velocity and the Investment Multiplier in the United States, 1897-1958. In *Stabilization Policies, a Series of Research Studies Prepared for the Commission on Money and Credit*. Englewood Cliffs, NJ: Prentice-Hall. Pp165-268.

Gertler, M. and Gilchrist, S. (1994). Monetary policy, business cycles, and the behaviour of small manufacturing firms. *The Quarterly Journal of Economics*, Vol. *109(*2): 309-340.

Gertler, M. and Hubbard, R.G. (1988). Financial factors in business fluctuations, *Financial Market Volatility* (Federal Reserve Bank of Kansas City, Kansas City).

Gomez-Gonzalez, J. E., Kutan, A. M., Ojeda-Joya, J. N. and Ortiz, M. C. (2016). Bank Lending Channel of Transmission of Monetary Policy: Does the Financial Structure of Banks Matter? *Borradores de Economia*; No. 953.

Granville, B. and Mallick, S. (2006). Does inflation or currency depreciation drive monetary policy in Russia? *Research in International Business and Finance*, Vol. *20(*2): 163-179.

Gregorio, J.D., Tokman, A. and Valdés, R. (2005). *Flexible exchange rate with inflation targeting in Chile: Experience and issues*. Inter-American Development Bank, New York Avenue: Washington.

Groen, J.J.J. and Kleibergen, F. (2003). Likelihood-based cointegration analysis in panels of vector error-correction models. *Journal of Business and Economic Statistics*, Vol. *21(*2): 295-318.

Gujarati, D. N. (2009). *Basic econometrics*. New York: Tata McGraw-Hill Education.

Gumata, N., Kabundi, A. and Ndou, E. (2013). Important channels of transmission monetary policy shock in South Africa. *South African Reserve Bank Working Paper WP/2013/06.* Pretoria: South African Reserve Bank.

Gupta, R., Jurgilas, M. and Kabundi, A. (2010). The effect of monetary policy on real house price growth in South Africa: A factor-augmented vector autoregression (FAVAR) approach. *Economic modelling*, Vol. 27: 315-323.

Halvorsen, J. I. and Jacobsen, D. H. (2016). The bank-lending channel empirically revisited. *Journal of Financial Stability*, Vol. 27: 95-105.

Hamilton, J.D. (1994). *Time series analysis* (Vol. 2, pp. 690-696). Princeton, NJ: Princeton University Press.

Havranek, T. and Rusnak, M. (2012). *Transmission lags of monetary policy: A meta-analysis*. *International Journal of Central Banking*, Vol. 9: 39-75.

Hendricks, T. W. and Kempa, B. (2009). The credit channel in US economic history. *Journal of policy modeling*, Vol. 31: 58-68.

Heryán, T. and Tzeremes, P. G. (2017). The bank lending channel of monetary policy in EU countries during the global financial crisis. *Economic Modelling*, Vol. 67: 10-22.

Hsieh, W. J. (2015). Bank Lending and Monetary Policy Transmission in Greece and Policy Implications. *International Journal of Applied Economics*, Vol. 12: 71-79.

Hsing, Y. (2013). Test of the Bank Lending Channel: The Case of Australia. *Economics Bulletin*, Vol. 33: 2575-2582.

Hülsewig, O., Winker, P. and Worms, A. (2004). Bank Lending and Monetary Policy Transmission: A VECM Analysis for Germany/Bankkredite und geldpolitische Transmission: Eine VECM Analyse für Deutschland. *Jahrbücher für Nationalökonomie und statistik*, Vol. 224: 511-529.

Hu, Y., (2006). The choice of inflation targeting—an empirical investigation. *International Economics and Economic Policy,* Vol. *3(*1): 27-42.

Ibarra, R. (2016). How important is the credit channel in the transmission of monetary policy in Mexico? *Applied Economics*, Vol. 48: 3462-3484.

Ifeakachukwu, N. P. and Olufemi, S. M. (2012). The monetary transmission mechanism in Nigeria: A sectoral output analysis. *International Journal of Economics and Finance*, Vol. 4: 204.

Janjua, P. Z. and Rashid, A. (2014). Impact of Monetary Policy on Bank'Balance Sheet in Pakistan. *International Journal of Economics and Finance*, Vol. 6: 187.

Jarque, C.M. and Bera, A.K. (1981). Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte Carlo evidence. *Economics Letters*, Vol. *7(*4): 313-318.

Johansen, S. and Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and statistics*, Vol. *52(*2):169-210.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, Vol. *12(*2-3): 231-254.

Johnston, J. and DiNardo, J. (1997). *Econometric Methods 4th Edition* McGraw-Hill: New York.

Kandrac, J. (2012). Monetary policy and bank lending to small firms. *Journal of Macroeconomics*, Vol. 34: 741-748.

Kao, C., (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of econometrics,* Vol. *90(*1):1-44.

Karakuş, F. (2014). *Concentration in Banking and Lending Channel of Monetary Policy: Evidence from Turkey.* İstanbul Bilgi University, Istanbul.

Kasaï, N. and Naraidoo, R. (2013). The opportunistic approach to monetary policy and financial market conditions. *Applied Economics*, Vol. 45: 2537-2545.

Kaseeram, I. (2012). *Essays on the impact of inflation targeting in South Africa.* (Doctoral dissertation). University of Zululand, Kwazulu-Natal.

Kashyap, A.K. and Stein, J.C. (1994). Monetary policy and bank lending. In *Monetary policy* (pp. 221-261). Chicago: The University of Chicago Press.

Kashyap, A. K. and Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*: 407-428.

Khosravi, T. (2015). The bank lending channel: An empirical analysis of EU accession countries from 2004-2013. MPRA Working Paper (No. 66795) University of Sussex, Brighton, United Kingdom.

Khundrakpam, J. K. (2013). Credit Channel of Monetary Policy Transmission in India: How Effective and Long Is the Lag?. *IUP Journal of Applied Economics,* Vol. 12(26).

Kishan, R.P. and Opiela, T.P. (2000). Bank size, bank capital, and the bank lending channel. *Journal of Money, Credit and Banking*: 121-141.

Kishan, R.P. and Opiela, T.P. (2006). Bank capital and loan asymmetry in the transmission of monetary policy. *Journal of Banking & Finance*, Vol. *30(*1): 259-285.

Korhonen, I. and Nuutilainen, R. (2017). Breaking monetary policy rules in Russia. *Russian Journal of Economics*, Vol. *3(*4): 366-378.

Krainer, R.E. (2014). Monetary policy and bank lending in the euro area: is there a stock market channel or an interest rate channel? *Journal of International Money and Finance*, Vol. *49*: 283-298.

Kumamoto, M. and Zhuo, J. (2017). Bank Lending Channel in Transmission of Monetary Policy in Japan, 2000–2012: The Sign Restrictions VAR Approach. *Applied Economics and Finance*, Vol. 4: 87-100.

Larsson, R. and Lyhagen, J. (1999). Likelihood-based inference in multivariate panel cointegration models. *Stockholm School of Economics Working Paper Series in Economics and Finance*, No. *331*.

Larsson, R., Lyhagen, J. and Löthgren, M. (2001). Likelihood-based cointegration tests in heterogeneous panels. *The Econometrics Journal*, Vol. *4(*1):109-142.

Levin, A. and Lin, C.F. (1992). Unit root tests in panel data: asymptotic and finite-sample properties. University of California, *San Diego.*

Levin, A. and Lin, C.F. (1993). Unit root tests in panel data: new results. *Economics Working Paper Series*. University of California, San Diego.

Levin, A., Lin, C.F. and Chu, C.S.J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, Vol. *108(*1): 1-24.

Im, K.S., Pesaran, M.H. and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, Vol. *115(*1): 53-74.

Love, I. and Zicchino, L. (2006). Financial development and dynamic investment behaviour: Evidence from panel VAR. *The Quarterly Review of Economics and Finance*, Vol. *46(*2): 190-210.

Ludi, K.L. and Ground, M. (2006). Investigating the bank-lending channel in South Africa: A VAR approach. *University of Pretoria Department of Economics Working Paper*, No. *2006-04*. Pretoria, South Africa.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science and Business Media, Berlin.

Maddala, G.S. and Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and statistics*, Vol. *61(*S1):631-652.

McCoskey, S. and Kao, C. (1998). A residual-based test of the null of cointegration in panel data. *Econometric reviews*, Vol. *17(*1): 57-84.

Mallick, S. K. and Sousa, R. M. (2012). Real effects of monetary policy in large emerging economies. *Macroeconomic Dynamics*, Vol. 16: 190-212.

Mankiw, N. G. (2014). *Principles of macroeconomics*. 8th ed. Worth Publishers/Palgrave Macmillan: New York.

Mateut, S., Bougheas, S. and Mizen, P. (2006). Trade credit, bank lending and monetary policy transmission. *European Economic Review*, Vol. *50(*3): 603-629.

Matousek, R. and Sarantis, N. (2009). The bank lending channel and monetary transmission in Central and Eastern European countries. *Journal of Comparative Economics*, Vol. *37(*2): 321-334.

Matousek, R. and Solomon, H. (2018). Bank Lending Channel and Monetary Policy in Nigeria. *Research in International Business and Finance*, Vol. 45: 467-474.

Maumela, P.K. (2010). *Is inflation targeting an appropriate framework for monetary policy? Experience from the inflation targeting countries.* Doctoral dissertation. University of Pretoria, Pretoria.

Mbowe, W. E. (2016). The Bank Lending Channel of Monetary Policy Transmission: A Dynamic Bank-level Panel Data Analysis on Tanzania. *Applied Economics and Finance*, Vol. 4: 169-190.

Meltzer, A. H. (1995). Monetary, credit and (other) transmission processes: a monetarist perspective. *The Journal of Economic Perspectives*, Vol. 9: 49-72.

Mengesha, L. G. and Holmes, M. J. (2013). Monetary policy and its transmission mechanisms in Eritrea. *Journal of Policy Modeling*, Vol. 35: 766-780.

Mies, V. and Tapia, M. (2003). *Monetary policy and transmission mechanisms in Chile: Has the effect of monetary policy changed in time? Why?* [online]. Available from: http:/www.cemla.org/old/pdf/redviii/chile_mies_tapia.pdf. [Accessed 10th September 2018]

Mishkin, F.S. (1995). Symposium on the monetary transmission mechanism. *Journal of Economic perspectives*, Vol. *9(*4):3-10.

Mishkin, F.S. (1996). *The channels of monetary transmission: lessons for monetary policy.* [online]. Available from: http://www.nber.org/papers/w5464.pdf. [Accessed 10^{th} September 2018]

Mishkin, F.S. (2001). *The transmission mechanism and the role of asset prices in monetary policy*. Available from: http://www.nber.org/papers/w8617.pdf. [Accessed 10^{th} September 2018].

Munyengwa, T. (2012). *Monetary policy transmission mechanism in Botswana: how does the Central Bank policy rate affect the economy?* University of the Western Cape, Potchefstroom.

Nagayasu, J. (2007). Empirical analysis of the exchange rate channel in Japan. *Journal of International Money and Finance*, Vol. *26(*6): 887-904.

Newey, W.K. and West, K.D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*,777-787.

Nwosa Philip, I. and Saibu Olufemi, M. (2015). Monetary Transmission Mechanism in Nigeria. *Contemporary Legal and Economic Issues III*, 353.

Obafemi, F. N. and Ifere, E. O. (2015). Monetary policy transmission mechanism in Nigeria: A FAVAR approach. *International Journal of Economics and Finance,* Vol. 7: 229.

Ogbulu, O. M. and Torbira, L. L. (2012). Monetary policy and the transmission mechanism: evidence from Nigeria. *International Journal of Economics and Finance,* Vol. 4: 122.

Olivero, M. P., Li, Y. and Jeon, B. N. (2011). Consolidation in banking and the lending channel of monetary transmission: Evidence from Asia and Latin America". *Journal of International Money and Finance,* Vol. 30: 1034-1054.

Ono, S. (2015). Bank Lending Channel in Monetary Policy Transmission: Evidence from Russia. *International Journal of Economics and Finance,* Vol. 7: 1.

Özlü, P. and Yalçin, C. (2012). The Trade Credit Channel of Monetary Policy Transmission: Evidence from Nonfinancial Manufacturing Firms in Turkey. *Emerging Markets Finance and Trade*, Vol. 48: 102-117.

Özşuca, E. A. (2012). *Banks and Monetary Policy Transmission Mechanism: An empirical Analysis for Turkey.* Middle East Technical University, Ankara.

Peek, J. and Rosengren, E. S. (2013). The role of banks in the transmission of monetary policy. *Public Policy Discussion Papers, Federal Reserve Bank of Boston*. Available from: http://www.bostonfed.org/economic/ppdp/index.htm. [Accessed 10^{th} September 2018].

Pedroni, P. (1995). Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis. *Indiana University Working Papers in Economics*, No. 95-013

Pedroni, P. (1997). Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis, New Results. *Indiana University Working Paper in Economics*. Available from: http://www.web.williams.edu/Economics/wp/pedronipanelcointegration.pdf [Accessed 10^{th} September 2018].

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory*, Vol. *20(*3): 597-625.

Rahman, A. A. and Ahmed, T. (2014). Monetary Policy Transmission In Low Income Countries: Do Traditional Channels Work In Bangladesh? *Journal of Academic Research in Economics*, Vol. 6.

Rashid, S. and Rahman, A. A. (2015). The Effectiveness of the Channels of Monetary Policy Transmission of Bangladesh: A Path Analysis Approach. *Journal of Academic Research in Economics,* Vol.7(2).

Rey, H. (2015). International credit channel and monetary policy autonomy. *IMF Economic Policy Review*.No.122-152.

Romer, C.D., Romer, D.H., Goldfeld, S.M. and Friedman, B.M. (1990). New evidence on the monetary transmission mechanism. *Brookings Papers on Economic Activity*, Vol.*1990*(1): 149-213.

Romer, D. (2006). *Advanced Macroeconomics*. McGraw Hill, Irwin: New York.

Schaechter, A., Stone, M.R. and Zelmer, M. (2000). *Practical Issues in the Adoption of Inflation Targeting by Emerging Market Countries*. IMF Working Paper, Mimeo

Schmidt-Hebbel, K., Werner, A., Haussmann, R. and Chang, R. (2002). Inflation targeting in Brazil, Chile, and Mexico: Performance, Credibility, and the exchange rate. *Economica*, Vol. *2(*2): 31-89.

Salachas, E. N., Laopodis, N. T. and Kouretas, G. P. (2017). The bank-lending channel and monetary policy during pre-and post-2007 crisis. *Journal of International Financial Markets, Institutions and Money*, Vol. 47: 176-187.

Seleteng, M. and Motelle, S. (2016). Sources of economic growth in the southern african development community: its likely impact on povery and employment. *Review of Economic and Business Studies*, Vol. 9(2): 211-249.

Senbet, D. (2016). Measuring the Channels of Monetary Policy Transmission: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *Journal of Central Banking Theory and Practice,* Vol. 5: 5-40.

Seob Son, Y., Smith, W.T. and Soo Pyun, C. (2009). The monetary transmission mechanism of a small open economy with sweeping financial reforms: The case of Korea. *Multinational Business Review*, Vol. *17(*4): 1-20.

Serrano, F. and Summa, R. (2012). Macroeconomic policy, growth and income distribution in the Brazilian economy in the 2000s. *Investigation Económica*, 55-92.

Shah, R. B. I. P. A. (2011). *Monetary policy transmission in an emerging market setting*. Working Paper, No.78. Available on: http://www.nipfp-dea-program/index.html. [Accessed 10^{th} September 2018].

Shkokani, H. M. K. (2016). *Bank characteristics and the credit channel of monetary policy transmission in the European Economic and Monetary Union. Is there new evidence?* (Doctoral dissertation). University of Texas, Texas.

Shokr, M. A., Karim, Z. A., Jusoh, M. and Zaidi, M. A. S. (2014). The bank lending channel of monetary policy? The panel evidence from Egypt. *Gadjah Mada International Journal of Business,* Vol. 16: 255-274.

Shrestha, M.B. and Bhatta, G.R. (2018). Selecting appropriate methodological framework for time series data analysis. *The Journal of Finance and Data Science*, Vol. *4(*2): 71-89.

Simpasa, A. M., Nandwa, B. and Nabassaga, T. (2014). *Bank Lending Channel of Monetary Policy Transmission in Zambia: Evidence from Bank-Level Data*. Working Paper Series, No. 211 African Development Bank, Tunis, Tunisia. Available from: http://www.afdb.org/en/ [Accessed 10th September 2018].

Sims, C.A., Stock, J.H. and Watson, M.W. (1990). Inference in linear time series models with some unit roots. *Econometrica: Journal of the Econometric Society*, 113-144.

Sims, C.A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*,1-48.

Sun, L., Ford, J. L. and Dickinson, D. G. (2010). Bank loans and the effects of monetary policy in China: VAR/VECM approach. *China Economic Review,* Vol. 21: 65-97.

Tabak, B. M., Moreira, T. B. S., Fazio, D. M., Cavalcanti, A. L. C. and De Moura Cunha, G. H. (2016). Monetary Expansion and the Banking Lending Channel. *PloS one,* 11, e0164338.

Valdés, R.O. (2007). February. Inflation Targeting in Chile: Experience and Issues. In *Presentation at the Monetary Policy in Emerging Markets seminar*, organized by the OECD/Bank of England, Paris, February (Vol. 28).

Vera, D. (2012). How responsive are banks to monetary policy? *Applied Economics,* Vol. 44: 2335-2346.

Vithessonthi, C., Schwaninger, M. and Müller, M. O. (2017). Monetary policy, bank lending and corporate investment. *International Review of Financial Analysis*, Vol. 50: 129-142.

Walia, S. V. and Raju, G. R. (2014). Monetary Policy Transmission in India: A Post-Reform Analysis. *IUP Journal of Applied Economics*, Vol. 13: 7.

Wulandari, R. (2012). Do credit channel and interest rate channel play important role in monetary transmission mechanism in Indonesia? A Structural Vector Autoregression Model. *Procedia-Social and Behavioural Sciences*, Vol. *65*: 557-563.

Yudaeva, K. (2018). Frontiers of Monetary Policy: Global Trends and Russian Inflation Targeting Practicies. *Russian Journal of Money and Finance*, Vol. *77*(2): 95-100.

Zulkhibri, M. (2013). Bank-characteristics, lending channel and monetary policy in emerging markets: bank-level evidence from Malaysia. *Applied Financial Economics,* Vol. 23: 347-362.

Appendices

Appendix A: Model 1 estimation results (PVAR)

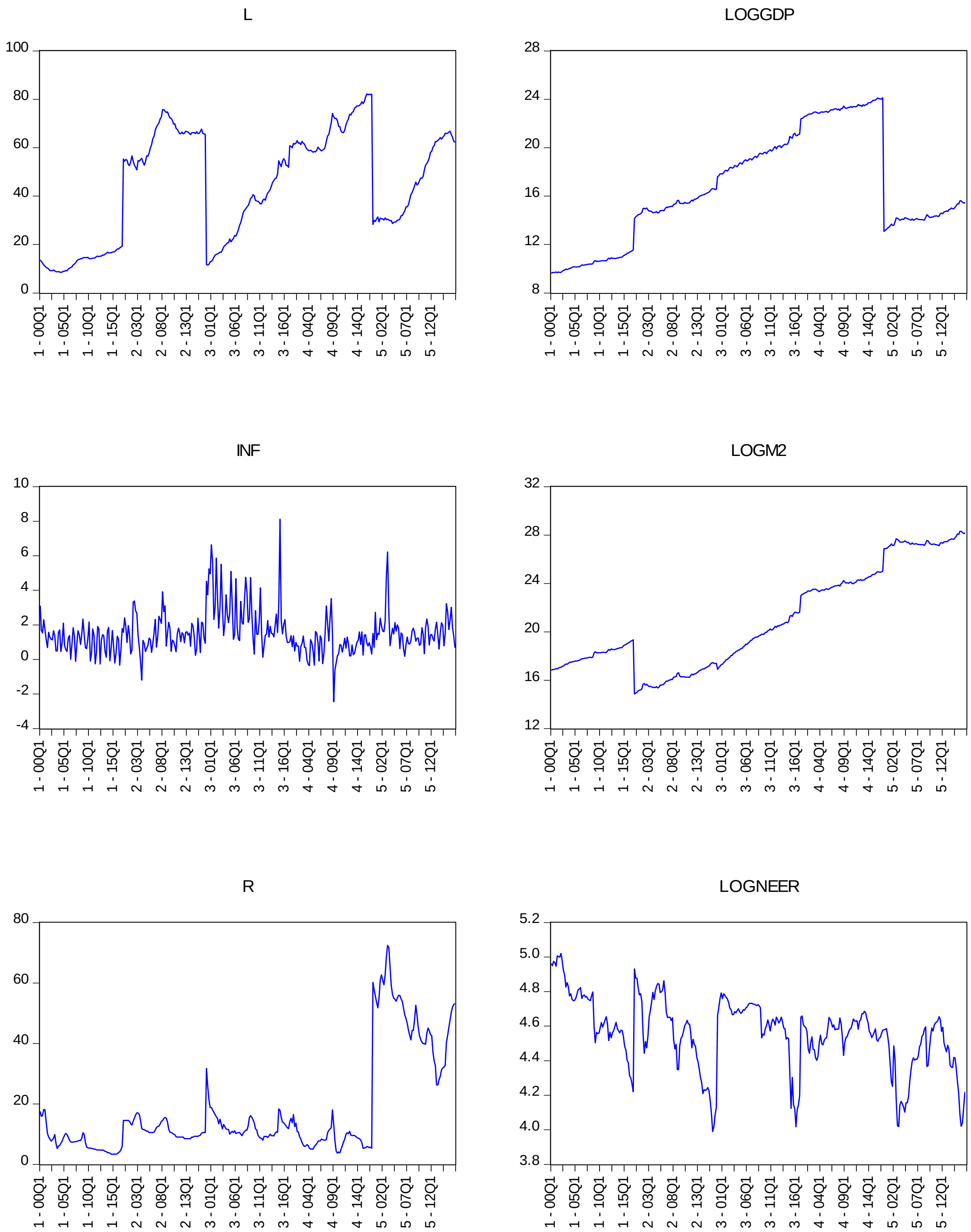


Figure 5.1(a): Graphical unit roots tests at level form

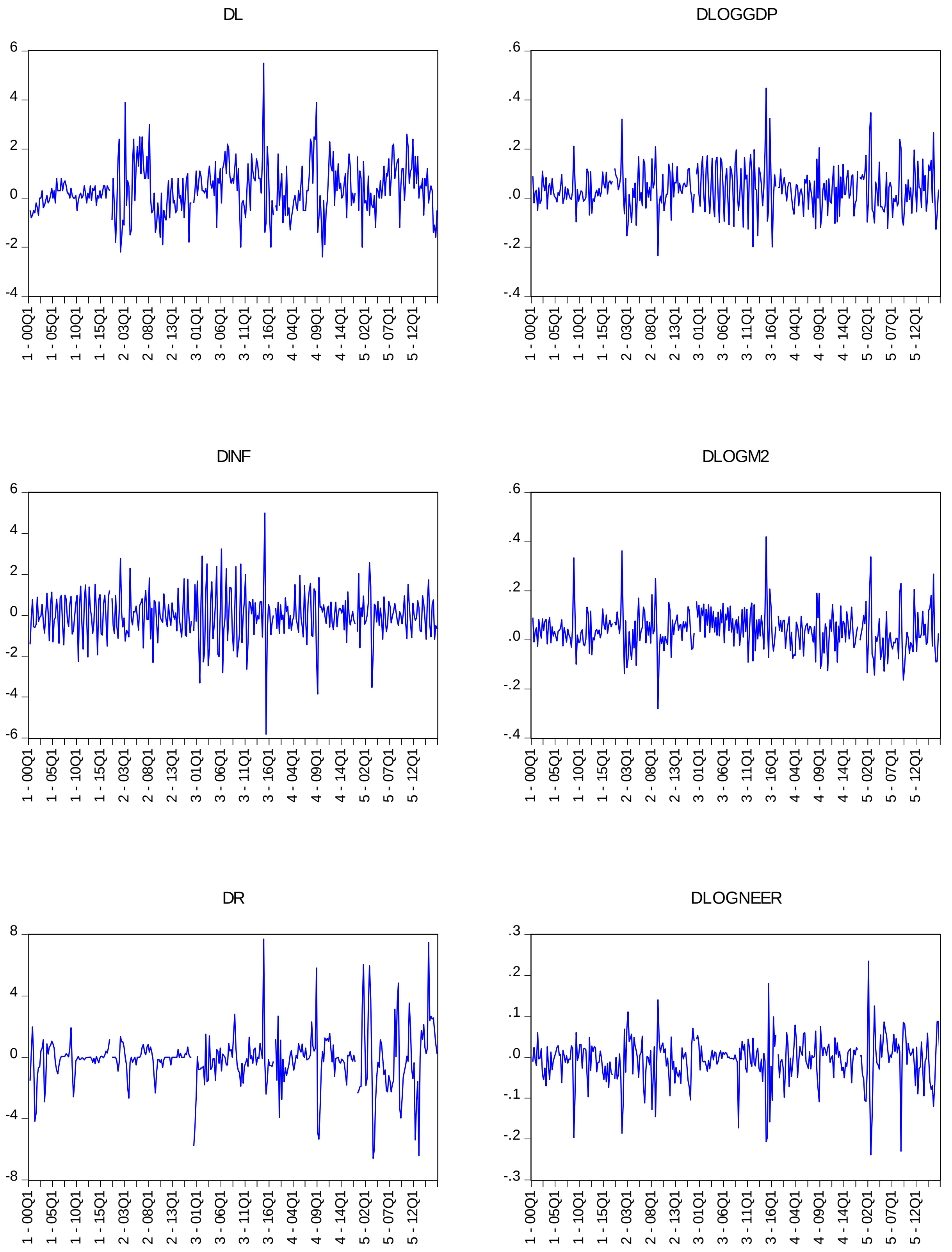


Figure 5.1(b): Graphical unit roots after first difference

Source: Estimated by the author

Table 5.4: Lag length selection criterion

Selection order criteria

Sample: 7 - 67

No. of obs = 305

No. of panels = 5

Ave. no. of T = 61.000

lag	CD	J	pvalue	MBIC	MAIC	MQIC
1	.9908869	197.6847	.0020095	-626.0402	-90.31531	-304.594
2	.9962032	148.3998	.0060397	-469.3938	-67.60015	-228.3092
3	.9977034	113.5553	.0013002	-298.3072	-30.44472	-137.5841
4	.999584	47.99211	.0872482	-157.9391	-24.00789	-77.57757

Table 5.5: Eigenvalue stability condition

Eigenvalue stability condition

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.9088892	0	.9088892
.748334	0	.748334
.1373552	-.6691372	.6830894
.1373552	.6691372	.6830894
.4840706	0	.4840706
.1790841	0	.1790841

All the eigenvalues lie inside the unit circle. pVAR satisfies stability condition.

Figure 5.2: Roots of the companion matrix

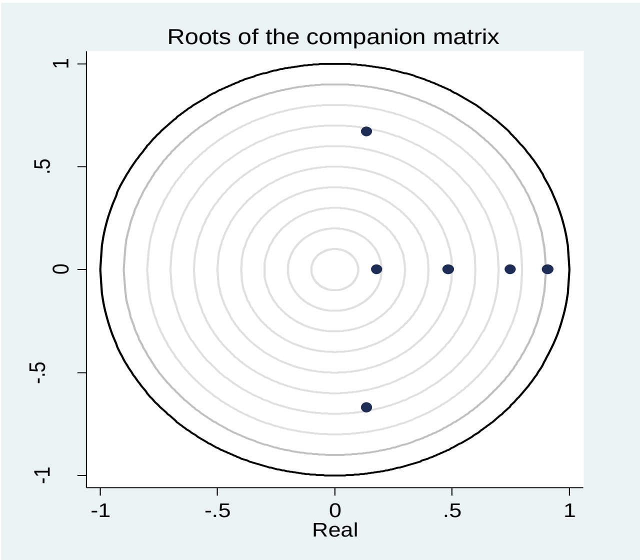


Table 5.6: Granger causality test

panel VAR-Granger causality Wald test

Ho: Excluded variable does not Granger-cause Equation variable

Ha: Excluded variable Granger-causes Equation variable

Equation\Excluded		chi2	df	Prob > chi2
DL				
	DlogGDP	55.620	1	0.000
	INF	23.713	1	0.000
	DlogM2	107.757	1	0.000
	R	4.525	1	0.033
	DlogNEER	34.264	1	0.000
	ALL	208.495	5	0.000
DlogGDP				
	DL	1.225	1	0.268
	INF	38.132	1	0.000
	DlogM2	84.931	1	0.000
	R	4.640	1	0.031
	DlogNEER	34.849	1	0.000
	ALL	193.809	5	0.000
INF				
	DL	1.194	1	0.275
	DlogGDP	109.563	1	0.000
	DlogM2	309.433	1	0.000
	R	23.385	1	0.000
	DlogNEER	0.363	1	0.547
	ALL	400.848	5	0.000
DlogM2				
	DL	0.398	1	0.528
	DlogGDP	50.951	1	0.000
	INF	12.130	1	0.000
	R	1.392	1	0.238
	DlogNEER	141.140	1	0.000
	ALL	177.669	5	0.000
R				
	DL	0.763	1	0.382
	DlogGDP	39.621	1	0.000
	INF	11.740	1	0.001
	DlogM2	74.406	1	0.000
	DlogNEER	126.050	1	0.000
	ALL	184.011	5	0.000
DlogNEER				
	DL	0.073	1	0.787
	DlogGDP	5.990	1	0.014
	INF	5.530	1	0.019
	DlogM2	121.383	1	0.000
	R	0.004	1	0.948
	ALL	279.861	5	0.000

Table 5.7: The panel VAR model

```
Panel vector autoregresssion
GMM Estimation
Final GMM Criterion Q(b) =      .628
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                   No. of obs      =       325
                                                   No. of panels   =         5
                                                   Ave. no. of T   =    65.000
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
DL           |
          DL |
         L1. |   .4728148   .0515567     9.17   0.000     .3717655    .5738641
     DlogGDP |
         L1. |   5.605197   .7515772     7.46   0.000     4.132133    7.078261
         INF |
         L1. |   .2048523   .0420673     4.87   0.000     .1224019    .2873026
      DlogM2 |
         L1. |  -9.461448   .9114537   -10.38   0.000    -11.24786   -7.675032
           R |
         L1. |  -.0201245   .0094607    -2.13   0.033    -.0386671   -.0015819
    DlogNEER |
         L1. |   5.192635   .8870914     5.85   0.000     3.453967    6.931302
-------------+----------------------------------------------------------------
DlogGDP      |
          DL |
         L1. |  -.0042643    .003853    -1.11   0.268     -.011816    .0032874
     DlogGDP |
         L1. |   .9073734   .0771819    11.76   0.000     .7560996    1.058647
         INF |
         L1. |   .0232467   .0037646     6.18   0.000     .0158682    .0306252
      DlogM2 |
         L1. |  -.7124503   .0773074    -9.22   0.000      -.86397   -.5609305
           R |
         L1. |  -.0013681   .0006351    -2.15   0.031    -.0026129   -.0001233
    DlogNEER |
         L1. |   .4774483   .0808781     5.90   0.000     .3189301    .6359664
-------------+----------------------------------------------------------------
INF          |
          DL |
         L1. |  -.0510617   .0467298    -1.09   0.275    -.1426504     .040527
     DlogGDP |
         L1. |  -8.565206   .8182885   -10.47   0.000    -10.16902    -6.96139
         INF |
         L1. |   .2683336   .0482762     5.56   0.000     .1737141    .3629532
      DlogM2 |
         L1. |   20.10406    1.14288    17.59   0.000     17.86406    22.34407
           R |
```

```
         L1. |   .0409277   .0084634     4.84   0.000     .0243397    .0575156
    DlogNEER |
         L1. |  -.7090091   1.176833    -0.60   0.547    -3.015559    1.597541
-------------+----------------------------------------------------------------
DlogM2       |
          DL |
         L1. |  -.0021959   .0034801    -0.63   0.528    -.0090167    .0046249
     DlogGDP |
         L1. |   .4504065      .0631     7.14   0.000     .3267327    .5740803
         INF |
         L1. |    .011982   .0034404     3.48   0.000      .005239     .018725
      DlogM2 |
         L1. |   .3728034   .0647176     5.76   0.000     .2459591    .4996476
           R |
         L1. |  -.0007639   .0006474    -1.18   0.238    -.0020328     .000505
    DlogNEER |
         L1. |   .8213144   .0691328    11.88   0.000     .6858167    .9568121
-------------+----------------------------------------------------------------
R            |
          DL |
         L1. |   .0617114   .0706617     0.87   0.382     -.076783    .2002057
     DlogGDP |
         L1. |   8.870553    1.40925     6.29   0.000     6.108474    11.63263
         INF |
         L1. |   .2483393   .0724781     3.43   0.001     .1062848    .3903938
      DlogM2 |
         L1. |  -14.19258   1.645347    -8.63   0.000     -17.4174   -10.96776
           R |
         L1. |   .8943902   .0175823    50.87   0.000     .8599295    .9288509
    DlogNEER |
         L1. |  -20.71092   1.844712   -11.23   0.000    -24.32649   -17.09535
-------------+----------------------------------------------------------------
DlogNEER     |
          DL |
         L1. |  -.0004526   .0016737    -0.27   0.787    -.0037331    .0028278
     DlogGDP |
         L1. |  -.0714429   .0291918    -2.45   0.014    -.1286577   -.0142281
         INF |
         L1. |   .0041872   .0017806     2.35   0.019     .0006974    .0076771
      DlogM2 |
         L1. |  -.4370779   .0396716   -11.02   0.000    -.5148328   -.3593229
           R |
         L1. |  -.0000263   .0004017    -0.07   0.948    -.0008136    .0007611
    DlogNEER |
         L1. |   -.320627   .0460469    -6.96   0.000    -.4108774   -.2303767
------------------------------------------------------------------------------
Instruments : l(1/5).(DL DlogGDP INF DlogM2 R DlogNEER)
```

Table 5.8(a): Summary of forecast-error variance decomposition of DL

Response variable and Forecast horizon	Impulse variable					
	DL	DlogGDP	INF	DlogM2	R	DlogNEER
DL						
0	0	0	0	0	0	0
1	1	0	0	0	0	0
2	.754825	.0356048	.0137919	.1737615	.0017277	.0202891
3	.6171248	.1128137	.0116071	.2308993	.0015213	.0260336
4	.5921502	.1332859	.0119675	.2224731	.0014825	.0386409
5	.5849221	.1312523	.0118326	.2324795	.0014855	.0380281
6	.5830801	.1305495	.0133898	.2311108	.0017019	.0401678
7	.5791701	.1309852	.0142283	.2337772	.0018543	.0399849
8	.577339	.1325447	.0142634	.2336044	.0018981	.0403505
9	.5768118	.1327816	.0142748	.2337483	.0019323	.0404511
10	.576552	.132724	.0143926	.2338561	.0019923	.0404829

Table 5.8(b): Summary of forecast-error variance decomposition of DlogGDP

	Impulse variable					
DlogGDP	DL	DlogGDP	INF	DlogM2	R	DlogNEER
0	0	0	0	0	0	0
1	.1804893	.8195106	0	0	0	0
2	.1408246	.6615964	.0023141	.1688128	.0015907	.0248614
3	.1415166	.6079178	.0076166	.2082852	.0014367	.0332272
4	.1389716	.5830098	.01891	.2159093	.0015948	.0416045
5	.1339463	.5681334	.0201589	.2350125	.0015309	.0412182
6	.1332249	.5670962	.0199173	.23231	.0015628	.0458887
7	.1328025	.5649154	.0198979	.2348952	.0015643	.0459247
8	.1329458	.5641418	.0204327	.2346111	.0015757	.0462929
9	.1327085	.5632914	.0207977	.2353608	.0015895	.0462521
10	.1326087	.5631305	.0208291	.2354918	.0015896	.0463502

Table 5.8(c): Summary of forecast-error variance decomposition of INF

INF	DL	DlogGDP	INF	DlogM2	R	DlogNEER
			Impulse variable			
0	0	0	0	0	0	0
1	.0844423	.0142829	.9012747	0	0	0
2	.0342142	.0656866	.6105638	.2878539	.001451	.0002306
3	.0312371	.1626778	.4645659	.3098499	.0011413	.030528
4	.0305271	.1965515	.438113	.2825903	.0010688	.0511494
5	.0301815	.1989663	.4406141	.2780846	.0013678	.0507858
6	.030033	.1990892	.4449839	.2737543	.0021164	.0500232
7	.0294029	.2029664	.442054	.27387	.0027477	.0489589
8	.0293449	.2077878	.4390265	.2714628	.0031649	.0492133
9	.0292401	.2097095	.4383372	.2699713	.0035609	.0491811
10	.0291428	.2102685	.4384723	.2690842	.0040061	.0490261

Table 5.8(d): Summary of forecast-error variance decomposition of DlogM2

DlogM2	DL	DlogGDP	INF	DlogM2	R	DlogNEER
			Impulse variable			
0	0	0	0	0	0	0
1	.0589607	.4744457	.1260695	.3405242	0	0
2	.0592414	.4962102	.103152	.2553678	.0021358	.0838927
3	.057612	.4735973	.1069679	.2730145	.0026881	.0861203
4	.0616661	.4607768	.1229821	.2656344	.0026175	.0863231
5	.0592592	.4484001	.1293855	.2776334	.0025368	.082785
6	.0582493	.4477877	.1286348	.2785923	.0024745	.0842613
7	.057922	.4483059	.1286541	.2768859	.0024674	.0857648
8	.0579784	.4477732	.1294823	.2766761	.0024681	.085622
9	.057943	.4472288	.1303325	.2765025	.0024929	.0855003
10	.0578279	.4470415	.1305764	.2766871	.0025092	.0853578

Table 5.8(e): Summary of forecast-error variance decomposition of R

R	Impulse variable DL	DlogGDP	INF	DlogM2	R	DlogNEER
0	0	0	0	0	0	0
1	.0347932	.0337258	.034773	.0204258	.8762822	0
2	.0497747	.0764235	.0492783	.0615266	.6904929	.072504
3	.0611609	.1128013	.0591586	.0587343	.6213005	.0868445
4	.0682263	.1392802	.0651512	.0584332	.5837929	.0851162
5	.0705451	.1539086	.0706285	.0610832	.5606872	.0831474
6	.0707819	.1628518	.0765484	.0616908	.5455583	.0825689
7	.0708267	.1706964	.0820213	.0601401	.5345577	.0817577
8	.0710021	.1780309	.0863952	.0583742	.5258757	.0803217
9	.0710593	.1840356	.0898744	.0571579	.5190014	.0788714
10	.0709319	.1886061	.0928268	.0562779	.5136085	.0777489

Table 5.8(f): Summary of forecast-error variance decomposition of DlogNEER

DlogNEER	Impulse variable DL	DlogGDP	INF	DlogM2	R	DlogNEER
0	0	0	0	0	0	0
1	.0274951	.2474972	.1238332	.0884232	.0073257	.5054255
2	.0531343	.3365569	.0864361	.140459	.0054129	.3780008
3	.0507869	.3277456	.0801494	.1583644	.006181	.3767727
4	.0539289	.3188697	.0796444	.1773103	.0060255	.3642212
5	.0550385	.3138712	.0842415	.1787239	.0059613	.3621637
6	.0541412	.3115574	.0841407	.1891001	.0058412	.3552193
7	.0541957	.3126701	.0836143	.1883505	.0058405	.355329
8	.0541276	.3122644	.0835183	.1892091	.0058469	.3550337
9	.0542643	.3120905	.0837279	.1891659	.0058434	.3549082
10	.0542318	.3119005	.0838846	.1894896	.0058413	.3546522

Table 5.9: Pedroni cointegration tests

Pedroni Residual Cointegration Test
Series: L I LOGGDP INF LOGM$ LOGNEER
Date: 04/17/18 Time: 23:21
Sample: 2000Q1 2016Q4
Included observations: 340
Cross-sections included: 5
Null Hypothesis: No cointegration
Trend assumption: Deterministic intercept and trend
Automatic lag length selection based on SIC with a max lag of 10
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	-0.933875	0.8248	-0.623764	0.7336
Panel rho-Statistic	0.460992	0.6776	0.499421	0.6913
Panel PP-Statistic	-0.621603	0.2671	-0.633807	0.2631
Panel ADF-Statistic	0.488694	0.6875	0.565232	0.7140

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	0.796764	0.7872
Group PP-Statistic	-0.545126	0.2928
Group ADF-Statistic	1.065111	0.8566

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
1	0.771	0.329431	0.333611	6.00	67
2	0.674	3.300182	2.925777	4.00	67
3	0.352	2.120861	2.418001	4.00	67
4	0.729	4.339685	4.339685	0.00	67
5	0.703	0.883258	1.047088	2.00	67

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
1	0.771	0.329431	0	10	67
2	0.674	3.300182	0	10	67
3	0.522	1.314077	4	10	63
4	0.729	4.339685	0	10	67
5	0.703	0.883258	0	10	67

Appendix B: Model 2 estimation results

Table 6.2.1: Correlation matrix for Mexico model variable

	L	LGDP	INF	LM	R	LOGNEER
L	1.000000	0.097388	-0.156856	0.215062	0.241752	-0.316474
LGDP	0.097388	1.000000	-0.237262	-0.025696	0.020266	-0.000150
INF	-0.156856	-0.237262	1.000000	0.154389	0.234379	0.063016
LM	0.215062	-0.025696	0.154389	1.000000	0.262054	-0.464367
R	0.241752	0.020266	0.234379	0.262054	1.000000	-0.385288
LOGNEER	-0.316474	-0.000150	0.063016	-0.464367	-0.385288	1.000000

Source: Generated by the researcher

Table 6.2.3: Lag selection criteria Mexico VAR model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-90.04119	NA	8.10e-07	3.001287	3.203683	3.081021
1	375.3007	828.8902	1.21e-12	-10.41565	-8.998878	-9.857509
2	459.2302	133.7627*	2.79e-13*	-11.91344*	-9.282305*	-10.87691*
3	492.0973	46.21933	3.32e-13	-11.81554	-7.970029	-10.30060
4	522.2441	36.74139	4.65e-13	-11.63263	-6.572745	-9.639284

* 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

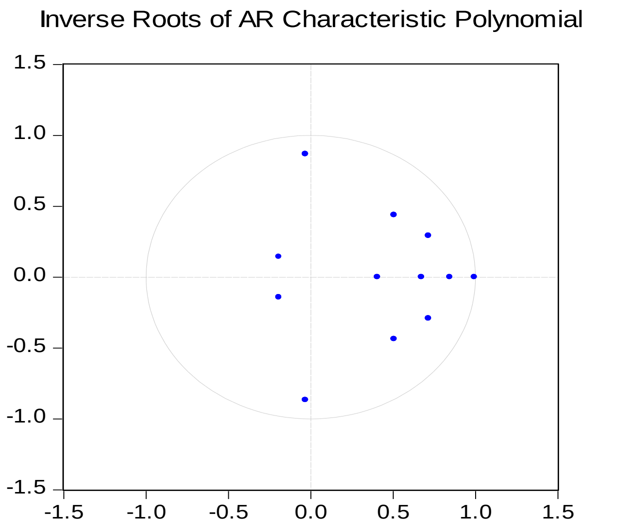
Table 6.2.5: VAR estimation results

Table 6.2.4: AR root table

Roots of Characteristic Polynomial
Endogenous variables: L LGDP INF LM2 R LNEER
Exogenous variables: C
Lag specification: 1 2
Date: 08/15/18 Time: 20:40

Root	Modulus
0.994756	0.994756
-0.031861 - 0.867890i	0.868475
-0.031861 + 0.867890i	0.868475
0.846204	0.846204
0.714947 - 0.291175i	0.771966
0.714947 + 0.291175i	0.771966
0.673171	0.673171
0.506467 - 0.438076i	0.669641
0.506467 + 0.438076i	0.669641
0.405559	0.405559
-0.192978 - 0.142463i	0.239867
-0.192978 + 0.142463i	0.239867

Figure 6.1: AR root table



Vector Autoregression Estimates
Date: 09/10/18 Time: 14:58
Sample (adjusted): 2000Q3 2016Q4
Included observations: 66 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	L	LGDP	INF	LM2	R	LNEER
L(-1)	0.981601	-0.021421	0.559991	-0.010433	0.972794	0.002337
	(0.12845)	(0.02611)	(0.22752)	(0.00880)	(0.39923)	(0.02142)
	[7.64194]	[-0.82038]	[2.46132]	[-1.18621]	[2.43671]	[0.10909]
L(-2)	-0.133997	0.023059	-0.265899	0.008400	-0.585219	-0.005529
	(0.11371)	(0.02312)	(0.20142)	(0.00779)	(0.35343)	(0.01896)
	[-1.17836]	[0.99753]	[-1.32013]	[1.07878]	[-1.65582]	[-0.29157]
LGDP(-1)	0.880507	1.407486	-1.655487	0.184235	9.290898	-0.520606
	(1.22905)	(0.24984)	(2.17696)	(0.08416)	(3.81993)	(0.20496)
	[0.71641]	[5.63357]	[-0.76046]	[2.18918]	[2.43222]	[-2.54001]
LGDP(-2)	1.090963	-0.063527	-2.601482	-0.099766	-5.877291	0.223227
	(1.28978)	(0.26219)	(2.28454)	(0.08832)	(4.00869)	(0.21509)
	[0.84585]	[-0.24230]	[-1.13874]	[-1.12965]	[-1.46614]	[1.03783]
INF(-1)	-0.104619	0.000585	-0.197335	-0.002436	0.026337	0.000813
	(0.05230)	(0.01063)	(0.09264)	(0.00358)	(0.16256)	(0.00872)
	[-2.00025]	[0.05502]	[-2.13009]	[-0.68007]	[0.16201]	[0.09319]

INF(-2)	-0.045712	-0.005243	-0.731517	-0.009088	-0.111025	0.005764
	(0.04928)	(0.01002)	(0.08729)	(0.00337)	(0.15318)	(0.00822)
	[-0.92754]	[-0.52338]	[-8.37995]	[-2.69309]	[-0.72482]	[0.70133]
LM(-1)	-4.779170	0.582435	2.357244	0.860617	0.808819	-0.374486
	(2.07444)	(0.42169)	(3.67437)	(0.14204)	(6.44744)	(0.34594)
	[-2.30383]	[1.38119]	[0.64154]	[6.05880]	[0.12545]	[-1.08250]
LM2(-2)	5.164397	-0.784327	-2.082216	0.109684	-8.061275	0.564027
	(2.09531)	(0.42593)	(3.71133)	(0.14347)	(6.51230)	(0.34942)
	[2.46474]	[-1.84144]	[-0.56104]	[0.76449]	[-1.23785]	[1.61416]
R(-1)	0.050723	0.002376	0.149142	8.09E-05	1.306986	0.000460
	(0.03464)	(0.00704)	(0.06135)	(0.00237)	(0.10765)	(0.00578)
	[1.46450]	[0.33749]	[2.43109]	[0.03410]	[12.1413]	[0.07959]
R(-2)	-0.003617	-0.010214	-0.149285	0.002041	-0.696262	0.005514
	(0.03453)	(0.00702)	(0.06115)	(0.00236)	(0.10731)	(0.00576)
	[-0.10478]	[-1.45531]	[-2.44118]	[0.86334]	[-6.48861]	[0.95763]
LNEER(-1)	1.417215	0.972230	-2.911220	0.252195	17.76745	0.299976
	(1.53983)	(0.31301)	(2.72743)	(0.10544)	(4.78585)	(0.25679)
	[0.92037]	[3.10602]	[-1.06738]	[2.39190]	[3.71250]	[1.16818]
LNEER(-2)	1.600760	-0.506620	-1.004448	-0.137066	-16.85186	0.293217
	(1.56728)	(0.31859)	(2.77605)	(0.10732)	(4.87116)	(0.26137)
	[1.02136]	[-1.59018]	[-0.36183]	[-1.27721]	[-3.45952]	[1.12186]
C	-38.71332	-2.595734	56.72555	-0.910928	70.08731	2.076238
	(8.84014)	(1.79701)	(15.6582)	(0.60531)	(27.4755)	(1.47422)
	[-4.37927]	[-1.44447]	[3.62275]	[-1.50489]	[2.55090]	[1.40836]
R-squared	0.995707	0.992824	0.707947	0.999173	0.959317	0.965790
Adj. R-squared	0.994735	0.991199	0.641822	0.998986	0.950106	0.958045
Sum sq. resids	2.857514	0.118079	8.965031	0.013398	27.60331	0.079469
S.E. equation	0.232197	0.047201	0.411280	0.015899	0.721677	0.038722
F-statistic	1024.420	611.0525	10.70616	5338.417	104.1474	124.6889
Log likelihood	9.960244	115.1100	-27.77128	186.9267	-64.88322	128.1775
Akaike AIC	0.092114	-3.094242	1.235493	-5.270507	2.360097	-3.490227
Schwarz SC	0.523409	-2.662946	1.666789	-4.839211	2.791393	-3.058932
Mean dependent	13.22424	10.49120	1.048550	15.54984	6.998289	4.682267
S.D. dependent	3.200099	0.503136	0.687208	0.499342	3.230871	0.189046

Table 6.2.6(a): Summary of forecast-error variance decomposition of L

L

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.232197	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.332416	90.96209	0.264037	2.910099	4.445153	0.896417	0.522203
3	0.404363	82.80778	1.181216	4.080605	5.547702	2.820743	3.561952
4	0.463150	73.17780	2.778033	3.144824	6.320831	4.888934	9.689576
5	0.522288	64.57903	3.976788	2.486729	6.233614	7.084197	15.63964
6	0.579082	57.14479	4.895516	2.652269	6.175838	8.273508	20.85808
7	0.624606	51.28479	5.691719	2.859141	6.389524	8.338817	25.43601
8	0.657106	47.49421	5.965725	2.679398	6.528475	8.088424	29.24377
9	0.682843	44.88729	5.835144	2.598201	6.446510	7.822176	32.41067
10	0.706064	42.52415	5.620688	2.829484	6.280407	7.486547	35.25873

Table 6.2.6(b): Summary of forecast-error variance decomposition of LGDP

LGDP

Period	S,E	L	LGDP	INF	LM2	R	LNEER
1	0.047201	8.044007	91.95599	0.000000	0.000000	0.000000	0.000000
2	0.061405	5.778529	86.26120	0.056753	0.690546	0.010816	7.202154
3	0.071165	4.305064	78.68609	1.063773	0.521885	0.318926	15.10426
4	0.079789	3.626423	73.00181	2.131324	0.532936	1.638350	19.06916
5	0.088113	3.388542	69.27108	2.359739	0.552521	3.600001	20.82812
6	0.095989	3.288547	66.62454	2.474476	0.503851	5.208126	21.90046
7	0.103261	3.320638	64.02222	2.850926	0.450733	6.282905	23.07258
8	0.109739	3.546652	61.45451	3.120727	0.408931	7.009395	24.45979
9	0.115362	3.797146	59.38195	3.126384	0.372107	7.420692	25.90172
10	0.120309	3.920322	57.73974	3.118171	0.342325	7.541468	27.33797

Table 6.2.6(c): Summary of forecast-error variance decomposition of INF

INF

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.411280	0.537689	0.770198	98.69211	0.000000	0.000000	0.000000
2	0.470686	15.99301	1.763306	75.59767	1.116688	4.430269	1.099056
3	0.576586	12.11015	2.008678	80.58757	1.318737	3.133040	0.841824
4	0.601873	13.68914	4.111231	74.25580	2.682801	4.472838	0.788191
5	0.647822	11.81655	3.663001	76.90399	2.340142	3.989127	1.287188
6	0.662710	13.75066	3.909561	73.94077	2.547346	4.476091	1.375567
7	0.688471	12.78676	4.200215	74.88095	2.469597	4.217895	1.444586
8	0.697814	13.24537	5.025215	73.35450	2.669861	4.268301	1.436746
9	0.710924	12.78288	4.842766	74.14590	2.599485	4.128636	1.500340
10	0.716787	13.38886	4.779442	73.25579	2.628136	4.457476	1.490302

Table 6.2.6(d): Summary of forecast-error variance decomposition of LM2

LM2

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.015899	7.921005	6.641176	6.236531	79.20129	0.000000	0.000000
2	0.020417	5.152813	7.422672	4.161175	78.87214	0.007809	4.383388
3	0.024363	3.619383	5.766969	3.209396	78.95780	0.145086	8.301366
4	0.027637	3.019528	4.741260	2.572684	77.15669	0.330144	12.17969
5	0.030969	2.427766	4.183062	3.009081	74.59573	0.955063	14.82930
6	0.034094	2.075600	3.967195	2.634711	71.91536	2.026376	17.38076
7	0.036802	1.828173	3.741628	2.275081	69.02329	2.758223	20.37361
8	0.039117	1.620045	3.679219	2.037657	66.48411	2.997752	23.18122
9	0.041308	1.466435	4.011572	1.938320	64.19863	3.053181	25.33187
10	0.043425	1.365444	4.617944	1.753972	61.94949	3.017659	27.29550

Table 6.2.6(e): Summary of forecast-error variance decomposition of R

R

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.721677	7.449876	1.823707	10.15040	0.383905	80.19211	0.000000
2	1.234476	13.84054	0.672312	6.974516	0.138560	72.42270	5.951371
3	1.541617	16.14022	1.502657	4.514504	1.721386	66.32651	9.794723
4	1.689047	17.86431	1.568444	4.157006	5.355446	60.21517	10.83963
5	1.760216	18.44246	1.555312	4.073526	9.524913	55.57872	10.82506
6	1.821043	18.03452	2.612349	4.054977	12.44993	52.48065	10.36757
7	1.888131	16.93454	4.145395	4.585214	14.09778	50.39669	9.840385
8	1.952145	15.86383	5.220186	5.179756	15.03864	49.20361	9.493980
9	2.000934	15.30421	5.920165	5.246560	15.54993	48.58064	9.398501
10	2.033567	15.00931	6.413369	5.225957	15.80680	48.01764	9.526920

Table 6.2.6(f): Summary of forecast-error variance decomposition of LNEER

LNEER

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.038722	8.087484	70.48458	1.467635	0.742860	0.056772	19.16067
2	0.053970	8.577906	77.94322	0.962629	1.736127	0.029239	10.75088
3	0.060741	7.281068	80.88756	1.192652	1.445005	0.368276	8.825438
4	0.066054	6.162888	80.63348	1.880287	1.276953	1.883650	8.162747
5	0.071285	5.491825	79.51179	1.888153	1.216557	4.198767	7.692907
6	0.076253	5.042053	78.36543	1.870841	1.127715	6.090279	7.503684
7	0.080671	4.819078	76.69979	2.230419	1.061345	7.390551	7.798814
8	0.084443	4.913117	74.64639	2.537177	1.036092	8.365097	8.502131
9	0.087572	5.115203	72.95239	2.546155	1.014872	9.004981	9.366401
10	0.090200	5.198752	71.66898	2.550406	0.985378	9.286860	10.30962

Table 6.2.7: Diagnostic tests

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Date: 09/10/18 Time: 14:59

Sample: 2000Q1 2016Q4

Included observations: 66

Lags	LM-Stat	Prob
1	36.09106	0.4644
2	50.08424	0.1595
3	25.11230	0.9132
4	51.83506	0.0425

Probs from chi-square with 36 df.

VAR Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)

Null Hypothesis: residuals are multivariate normal

Date: 09/10/18 Time: 15:00

Sample: 2000Q1 2016Q4

Included observations: 66

Component	Skewness	Chi-sq	Df	Prob.
1	-0.467107	2.400082	1	0.1213
2	0.431749	2.050475	1	0.1522
3	0.150370	0.248723	1	0.6180
4	0.060602	0.040399	1	0.8407
5	-0.574535	3.630993	1	0.0567
6	0.132674	0.193627	1	0.6599
Joint		8.564300	6	0.1996
Component	Kurtosis	Chi-sq	Df	Prob.
1	3.072490	0.014451	1	0.9043
2	2.884652	0.036589	1	0.8483
3	3.215196	0.127351	1	0.7212

4	2.984215	0.000685	1	0.9791
5	6.350255	30.86658	1	0.0000
6	2.948206	0.007377	1	0.9316
Joint		31.05303	6	0.0000

Component	Jarque-Bera	df	Prob.
1	2.414533	2	0.2990
2	2.087064	2	0.3522
3	0.376074	2	0.8286
4	0.041084	2	0.9797
5	34.49757	2	0.0000
6	0.201005	2	0.9044
Joint	39.61733	12	0.0001

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)

Date: 09/10/18 Time: 15:01

Sample: 2000Q1 2016Q4

Included observations: 66

Joint test:

Chi-sq	Df	Prob.
561.3541	504	0.0390

Table 6.2.8: Cointegration test results

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.842357	214.8562	95.75366	0.0000
At most 1 *	0.562373	92.92626	69.81889	0.0003
At most 2	0.333878	38.38458	47.85613	0.2855
At most 3	0.107074	11.56997	29.79707	0.9457
At most 4	0.059624	4.095369	15.49471	0.8957
At most 5	0.000575	0.037964	3.841466	0.8455

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.842357	121.9300	40.07757	0.0000
At most 1 *	0.562373	54.54168	33.87687	0.0001
At most 2	0.333878	26.81461	27.58434	0.0625
At most 3	0.107074	7.474600	21.13162	0.9328
At most 4	0.059624	4.057404	14.26460	0.8532
At most 5	0.000575	0.037964	3.841466	0.8455

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Appendix C Model 3 estimation results

Table 6.3.2: Correlation matrix

	L	LGDP	INF	LM2	R	LNEER
L	1.000000	0.092950	-0.025282	0.241355	0.155397	-0.160368
LGDP	0.092950	1.000000	0.105424	0.749218	0.250425	-0.789105
INF	-0.025282	0.105424	1.000000	0.067670	0.569218	-0.335467
LM2	0.241355	0.749218	0.067670	1.000000	0.328214	-0.797953
R	0.155397	0.250425	0.569218	0.328214	1.000000	-0.463447
LNEER	-0.160368	-0.789105	-0.335467	-0.797953	-0.463447	1.000000

Table 6.3.4: Lag selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-213.1264	NA	4.73e-05	7.068592	7.274444	7.149415
1	157.5712	657.6892	9.74e-10	-3.728104	-2.287142*	-3.162346*
2	206.1916	76.85153*	6.69e-10*	-4.135212	-1.459140	-3.084519
3	233.4592	37.82279	9.65e-10	-3.853522	0.057661	-2.317893
4	271.2623	45.11982	1.08e-09	-3.911686	1.234607	-1.891122
5	317.3808	46.11856	1.05e-09	-4.238091	2.143312	-1.732591
6	356.3013	31.38747	1.58e-09	-4.332300*	3.284214	-1.341865

Note: * 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

Table 6.3.5(a) AR root table	***Figure 6.2 AR root***

Roots of Characteristic Polynomial

Endogenous variables: L LGDP INF LM2 R LNEER

Exogenous variables: C

Lag specification: 1 1

Date: 08/15/18   Time: 20:38

Root	Modulus
0.990103	0.990103
0.949433	0.949433
0.853733 - 0.107453i	0.860468
0.853733 + 0.107453i	0.860468
0.388808 - 0.325006i	0.506755
0.388808 + 0.325006i	0.506755

Inverse Roots of AR Characteristic Polynomial

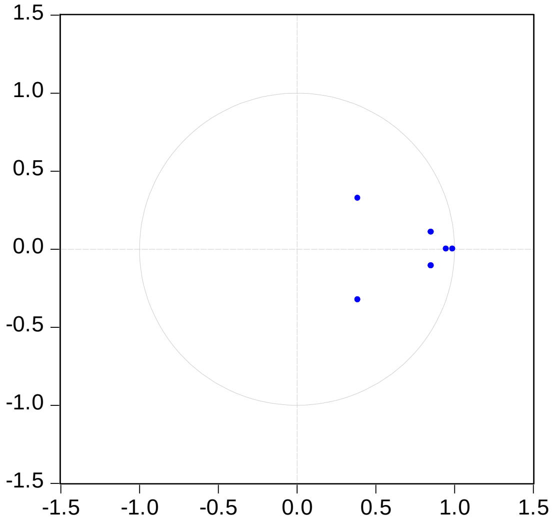


Table 6.3.6: VAR estimation results

South Africa VAR

Vector Autoregression Estimates

Date: 09/10/18   Time: 14:44

Sample (adjusted): 2000Q2 2016Q4

Included observations: 67 after adjustments

Standard errors in ( ) & t-statistics in [ ]

	L	LGDP	INF	LM2	R	LNEER
L(-1)	0.789234	0.004087	0.046724	0.005716	0.003594	-0.004843
	(0.05716)	(0.00435)	(0.04005)	(0.00442)	(0.03023)	(0.00284)
	[13.8082]	[0.94046]	[1.16676]	[1.29369]	[0.11889]	[-1.70452]
LGDP(-1)	-5.101291	1.597056	-3.691806	0.981235	-0.340867	-0.653074
	(4.51337)	(0.34316)	(3.16219)	(0.34888)	(2.38692)	(0.22437)
	[-1.13026]	[4.65393]	[-1.16748]	[2.81256]	[-0.14281]	[-2.91068]
INF(-1)	0.264765	0.012063	0.332750	0.003148	0.399521	-0.000143

	(0.18626)	(0.01416)	(0.13050)	(0.01440)	(0.09851)	(0.00926)
	[1.42146]	[0.85181]	[2.54979]	[0.21868]	[4.05579]	[-0.01546]
LM2(-1)	11.22457	-0.460495	0.797837	0.260738	-0.766220	0.513645
	(4.23657)	(0.32212)	(2.96825)	(0.32748)	(2.24053)	(0.21061)
	[2.64945]	[-1.42959]	[0.26879]	[0.79620]	[-0.34198]	[2.43883]
R(-1)	0.337634	0.000129	-0.142016	0.009115	0.812487	-0.004635
	(0.12503)	(0.00951)	(0.08760)	(0.00966)	(0.06612)	(0.00622)
	[2.70046]	[0.01354]	[-1.62121]	[0.94312]	[12.2877]	[-0.74566]
LNEER(-1)	14.55837	0.406416	-6.400295	0.629160	-2.206511	0.632352
	(3.65071)	(0.27757)	(2.55778)	(0.28219)	(1.93070)	(0.18149)
	[3.98782]	[1.46418]	[-2.50228]	[2.22954]	[-1.14286]	[3.48429]
C	-159.7828	-3.815966	72.45584	-6.414301	28.92744	3.748075
	(41.8514)	(3.18207)	(29.3222)	(3.23504)	(22.1334)	(2.08055)
	[-3.81786]	[-1.19921]	[2.47102]	[-1.98276]	[1.30696]	[1.80148]
R-squared	0.977654	0.983903	0.307661	0.985487	0.949610	0.948999
Adj. R-squared	0.975419	0.982293	0.238427	0.984036	0.944571	0.943899
Sum sq. resids	75.16519	0.434525	36.89697	0.449114	21.02287	0.185760
S.E. equation	1.119265	0.085100	0.784187	0.086517	0.591930	0.055642
F-statistic	437.4979	611.2234	4.443797	679.0429	188.4525	186.0759
Log likelihood	-98.92123	73.71059	-75.08401	72.60434	-56.23964	102.1788
Akaike AIC	3.161828	-1.991361	2.450269	-1.958338	1.887751	-2.841159
Schwarz SC	3.392169	-1.761020	2.680610	-1.727997	2.118092	-2.610818
Mean dependent	63.79254	15.36315	1.437659	16.16590	11.55348	4.535560
S.D. dependent	7.138910	0.639528	0.898595	0.684746	2.514214	0.234918

Determinant resid covariance (dof adj.)	4.66E-10
Determinant resid covariance	2.41E-10
Log likelihood	171.5422
Akaike information criterion	-3.866931
Schwarz criterion	-2.484885

Table 6.3.7(a): Summary of forecast-error variance decomposition of L

L

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	1.119265	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	1.561576	90.22088	0.320026	0.275285	1.665987	0.211110	7.306708
3	1.967247	76.55127	0.828842	0.468378	5.342348	0.467808	16.34135
4	2.366300	64.32315	1.299154	0.432817	9.681813	0.698078	23.56499
5	2.755351	54.60227	1.635947	0.333062	13.70568	0.905358	28.81768
6	3.127528	47.11364	1.831217	0.258791	17.05987	1.098166	32.63832
7	3.476874	41.37613	1.912221	0.215268	19.73942	1.278882	35.47807
8	3.799266	36.96662	1.912810	0.188054	21.85710	1.446691	37.62873
9	4.092504	33.55607	1.862141	0.167650	23.53546	1.600419	39.27826
10	4.356043	30.89776	1.782194	0.150574	24.87409	1.739526	40.55586

Table 6.3.7(b): Summary of forecast-error variance decomposition of LGDP

LGDP

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.085100	0.863969	99.13603	0.000000	0.000000	0.000000	0.000000
2	0.119590	0.535176	96.86717	0.155405	1.444428	0.026924	0.970899
3	0.145293	0.375935	93.98609	0.463399	2.925673	0.165382	2.083518
4	0.165380	0.295634	91.65685	0.557016	4.030648	0.451676	3.008179
5	0.181527	0.250982	89.72088	0.479110	4.821258	0.862374	3.865400
6	0.195075	0.222886	87.78773	0.456232	5.372254	1.349028	4.811872
7	0.206997	0.201888	85.62112	0.641273	5.720662	1.864417	5.950635
8	0.217931	0.183883	83.15302	1.075093	5.889322	2.372763	7.325920
9	0.228280	0.167851	80.41213	1.733535	5.903749	2.850132	8.932601
10	0.238297	0.154144	77.46839	2.568450	5.795610	3.281812	10.73159

Table 6.3.7(c): Summary of forecast-error variance decomposition of INF

INF

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.784187	0.063918	1.171645	98.76444	0.000000	0.000000	0.000000
2	0.866845	0.845546	1.137778	93.01635	0.307010	0.110425	4.582893
3	0.894031	1.969219	1.102228	88.11552	0.347848	0.137494	8.327696
4	0.905760	2.803836	1.080576	85.86175	0.340981	0.134047	9.778811
5	0.910765	3.349245	1.069129	84.94946	0.353066	0.148570	10.13053
6	0.913702	3.726970	1.063728	84.51933	0.354125	0.177735	10.15811
7	0.916215	4.019155	1.066661	84.23257	0.356240	0.211273	10.11410
8	0.918617	4.264830	1.080809	83.96069	0.386668	0.245732	10.06127
9	0.920968	4.477829	1.105992	83.66200	0.457513	0.281535	10.01513
10	0.923315	4.661816	1.139510	83.33114	0.566719	0.319694	9.981119

Table 6.3.7(d): Summary of forecast-error variance decomposition of LM2

LM2

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.086517	5.825223	86.64144	0.073714	7.459626	0.000000	0.000000
2	0.119233	4.600600	88.92466	0.161809	3.968102	0.004115	2.340717
3	0.144521	3.634404	87.60660	0.154541	2.945198	0.011742	5.647513
4	0.165120	3.028458	85.54824	0.249280	2.638736	0.094124	8.441159
5	0.182009	2.660402	83.61805	0.240753	2.512631	0.281893	10.68627
6	0.196293	2.419470	81.69019	0.217520	2.428928	0.556221	12.68767
7	0.208974	2.237635	79.52760	0.340514	2.345611	0.880386	14.66825
8	0.220748	2.080380	77.04181	0.681295	2.246561	1.220765	16.72919
9	0.232033	1.933720	74.27029	1.229507	2.128085	1.553528	18.88487
10	0.243059	1.793922	71.30617	1.940342	1.994561	1.863961	21.10104

Table 6.3.7(e): Summary of forecast-error variance decomposition of R

R

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.591930	2.414792	5.617217	30.34982	9.698353	51.91982	0.000000
2	0.951409	1.504732	4.752855	52.80931	6.264782	34.21615	0.452168
3	1.218627	1.502015	4.276838	60.14481	5.003078	26.54130	2.531962
4	1.413152	1.805023	3.978147	61.75421	4.246280	22.63952	5.576815
5	1.559729	2.194909	3.740992	61.39918	3.664813	20.32934	8.670773
6	1.675011	2.575425	3.522287	60.55048	3.217636	18.79294	11.34123
7	1.768612	2.917262	3.311150	59.70450	2.889350	17.68562	13.49212
8	1.845977	3.221025	3.110755	58.97846	2.652603	16.84849	15.18866
9	1.910415	3.495054	2.929155	58.37022	2.479066	16.20118	16.52532
10	1.964238	3.746421	2.774332	57.85483	2.347446	15.69695	17.58003

Table 6.3.7(f): Summary of forecast-error variance decomposition of LNEER

LNEER

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.055642	2.571824	60.46076	6.602270	2.416253	0.795685	27.15321
2	0.073699	2.112762	66.92861	6.357461	1.999546	0.935292	21.66633
3	0.087162	1.687082	68.79433	7.914225	3.523799	0.835541	17.24502
4	0.097928	1.419676	68.80544	9.553299	5.124161	0.677179	14.42024
5	0.106236	1.276761	68.60696	10.40205	6.431405	0.585951	12.69687
6	0.112472	1.211763	68.61699	10.50614	7.493698	0.591570	11.57984
7	0.117138	1.189052	68.78970	10.19940	8.366750	0.680802	10.77429
8	0.120690	1.185034	69.00061	9.756831	9.066143	0.831245	10.16013
9	0.123482	1.186054	69.14679	9.334617	9.591141	1.022634	9.718766
10	0.125780	1.185128	69.15544	9.006153	9.944111	1.238456	9.470713

Table 6.3.8: Diagnostic tests

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Date: 09/10/18 Time: 14:50

Sample: 2000Q1 2016Q4

Included observations: 67

Lags	LM-Stat	Prob
1	79.00768	0.0000
2	37.20379	0.4134
3	31.01911	0.7043
4	47.38981	0.0970
5	27.84701	0.8326
6	32.29662	0.6454

Probs from chi-square with 36 df.

VAR Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)

Null Hypothesis: residuals are multivariate normal

Date: 09/10/18 Time: 14:51

Sample: 2000Q1 2016Q4

Included observations: 67

Component	Skewness	Chi-sq	Df	Prob.
1	0.621889	4.318663	1	0.0377
2	0.115686	0.149445	1	0.6991
3	0.272235	0.827584	1	0.3630
4	-0.050852	0.028876	1	0.8651
5	-0.332438	1.234082	1	0.2666
6	-0.117524	0.154233	1	0.6945
Joint		6.712882	6	0.3482

Component	Kurtosis	Chi-sq	Df	Prob.
1	3.255891	0.182799	1	0.6690
2	3.905614	2.289548	1	0.1302
3	3.615254	1.056749	1	0.3040
4	2.987836	0.000413	1	0.9838
5	3.690277	1.330178	1	0.2488
6	2.605020	0.435526	1	0.5093
Joint		5.295213	6	0.5065

Component	Jarque-Bera	df	Prob.
1	4.501462	2	0.1053
2	2.438993	2	0.2954
3	1.884333	2	0.3898
4	0.029289	2	0.9855
5	2.564260	2	0.2774
6	0.589759	2	0.7446
Joint	12.00810	12	0.4450

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)

Date: 09/10/18   Time: 14:52

Sample: 2000Q1 2016Q4

Included observations: 67

Joint test:

Chi-sq	df	Prob.
259.3800	252	0.3612

Table 6.3.9: Cointegration tests

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.495686	117.4978	95.75366	0.0007
At most 1 *	0.375483	72.31707	69.81889	0.0312
At most 2	0.328492	41.24585	47.85613	0.1810
At most 3	0.147396	14.96272	29.79707	0.7825
At most 4	0.057795	4.438346	15.49471	0.8652
At most 5	0.007686	0.509229	3.841466	0.4755

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.495686	45.18076	40.07757	0.0122
At most 1	0.375483	31.07122	33.87687	0.1043
At most 2	0.328492	26.28313	27.58434	0.0726
At most 3	0.147396	10.52437	21.13162	0.6944
At most 4	0.057795	3.929117	14.26460	0.8667
At most 5	0.007686	0.509229	3.841466	0.4755

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Appendix D: Model 4 estimation results (Russia)

Table 6.4.2: Correlation matrix

	L	LRGDP	INF	R	LM	LNEER
L	1.000000	-0.176003	-0.207356	0.482335	0.163126	-0.399985
LRGDP	-0.176003	1.000000	0.216916	-0.060699	-0.181606	-0.090398
INF	-0.207356	0.216916	1.000000	0.169113	-0.407651	-0.365707
R	0.482335	-0.060699	0.169113	1.000000	-0.184854	-0.330592
LM	0.163126	-0.181606	-0.407651	-0.184854	1.000000	0.244304
LNEER	-0.399985	-0.090398	-0.365707	-0.330592	0.244304	1.000000

Table 6.4.4: Lag selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-333.1099	NA	0.001169	10.27606	10.47512	10.35471
1	98.50896	771.6822	7.30e-09	-1.712393	-0.318976*	-1.161788
2	166.5660	109.3037*	2.84e-09*	-2.683818*	-0.096044	-1.661266*

Note: * 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

Table 6.4.5: AR root table	***Figure 6.3: AR root table***

Roots of Characteristic Polynomial
Endogenous variables: L LGDP INF LM2 R LNEER
Exogenous variables: C
Lag specification: 1 2
Date: 08/15/18   Time: 21:28

Root	Modulus
0.985825	0.985825
0.953761 - 0.133771i	0.963096
0.953761 + 0.133771i	0.963096
0.822773	0.822773
0.003183 - 0.746081i	0.746088
0.003183 + 0.746081i	0.746088
-0.669082	0.669082
0.542059	0.542059
0.258471 - 0.316729i	0.408809
0.258471 + 0.316729i	0.408809
-0.272611	0.272611
0.194900	0.194900

Inverse Roots of AR Characteristic Polynomial

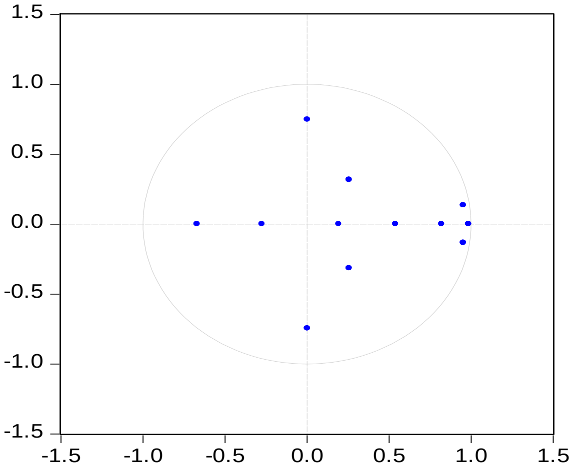


Table 6.4.6: VAR model estimation results

Vector Autoregression Estimates
Date: 09/11/18   Time: 13:34
Sample (adjusted): 2000Q3 2016Q4
Included observations: 66 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	L	LGDP	INF	LM2	R	LNEER
L(-1)	1.458222	-0.005122	0.332381	0.040282	0.637730	-0.030281
	(0.19113)	(0.00551)	(0.20331)	(0.01484)	(0.23881)	(0.00893)
	[7.62941]	[-0.92957]	[1.63488]	[2.71476]	[2.67046]	[-3.39101]
L(-2)	-0.539066	0.008483	-0.198044	-0.031205	-0.220537	0.022028
	(0.18510)	(0.00534)	(0.19689)	(0.01437)	(0.23127)	(0.00865)
	[-2.91230]	[1.58987]	[-1.00586]	[-2.17159]	[-0.95358]	[2.54725]
LGDP(-1)	0.792352	0.730409	-4.319801	0.433101	0.928162	0.201554
	(4.36906)	(0.12594)	(4.64735)	(0.33918)	(5.45890)	(0.20412)
	[0.18136]	[5.79950]	[-0.92952]	[1.27689]	[0.17003]	[0.98740]
LGDP(-2)	1.012859	0.089835	3.479389	0.014268	5.491105	-0.297037
	(4.53046)	(0.13060)	(4.81903)	(0.35171)	(5.66056)	(0.21167)
	[0.22357]	[0.68789]	[0.72201]	[0.04057]	[0.97006]	[-1.40334]
INF(-1)	0.058042	0.008668	0.425458	-0.003692	0.118846	-0.002744
	(0.11950)	(0.00344)	(0.12711)	(0.00928)	(0.14931)	(0.00558)
	[0.48572]	[2.51634]	[3.34719]	[-0.39798]	[0.79599]	[-0.49156]
INF(-2)	0.196879	-3.55E-05	-0.464751	0.004394	0.119738	-0.003245
	(0.10013)	(0.00289)	(0.10651)	(0.00777)	(0.12511)	(0.00468)

	[1.96614]	[-0.01230]	[-4.36333]	[0.56528]	[0.95703]	[-0.69359]
LM2(-1)	-4.830863	0.283234	6.036347	0.390730	-4.456630	0.003101
	(2.58611)	(0.07455)	(2.75084)	(0.20077)	(3.23121)	(0.12082)
	[-1.86800]	[3.79937]	[2.19437]	[1.94618]	[-1.37925]	[0.02567]
LM2(-2)	5.183665	-0.228352	-7.446889	0.251095	-3.847528	0.130566
	(2.59350)	(0.07476)	(2.75870)	(0.20134)	(3.24044)	(0.12117)
	[1.99871]	[-3.05444]	[-2.69942]	[1.24711]	[-1.18735]	[1.07755]
R(-1)	-0.108034	-0.007223	0.329903	-0.010066	0.548661	-0.009206
	(0.13212)	(0.00381)	(0.14053)	(0.01026)	(0.16508)	(0.00617)
	[-0.81770]	[-1.89652]	[2.34748]	[-0.98144]	[3.32369]	[-1.49140]
R(-2)	0.132362	0.001610	-0.224192	0.002982	-0.127988	0.012633
	(0.10068)	(0.00290)	(0.10709)	(0.00782)	(0.12579)	(0.00470)
	[1.31474]	[0.55477]	[-2.09353]	[0.38147]	[-1.01748]	[2.68585]
LNEER(-1)	4.758164	0.233778	8.965753	-0.008841	-2.725045	0.476042
	(3.33637)	(0.09617)	(3.54888)	(0.25901)	(4.16861)	(0.15588)
	[1.42615]	[2.43076]	[2.52636]	[-0.03413]	[-0.65371]	[3.05396]
LNEER(-2)	-2.332475	-0.151712	-9.313904	-0.348519	-3.933133	0.609526
	(3.60728)	(0.10398)	(3.83704)	(0.28004)	(4.50709)	(0.16853)
	[-0.64660]	[-1.45899]	[-2.42737]	[-1.24452]	[-0.87265]	[3.61665]
C	-23.58101	-0.710139	29.40537	6.556405	157.4853	-2.347987
	(41.9623)	(1.20961)	(44.6351)	(3.25766)	(52.4295)	(1.96049)
	[-0.56196]	[-0.58708]	[0.65880]	[2.01261]	[3.00375]	[-1.19765]
R-squared	0.995808	0.998330	0.681235	0.997284	0.877584	0.955868
Adj. R-squared	0.994859	0.997952	0.609062	0.996669	0.849867	0.945876
Sum sq. resids	47.06251	0.039107	53.24876	0.283640	73.46985	0.102728
S.E. equation	0.942323	0.027164	1.002344	0.073155	1.177380	0.044026
F-statistic	1049.204	2640.737	9.438905	1621.520	31.66250	95.66153
Log likelihood	-82.49007	151.5770	-86.56550	86.19027	-97.18821	119.7058
Akaike AIC	2.893639	-4.199303	3.017136	-2.217887	3.339037	-3.233509
Schwarz SC	3.324934	-3.768008	3.448432	-1.786591	3.770332	-2.802213
Mean dependent	33.24848	4.360296	2.633665	19.57469	12.33899	4.600346
S.D. dependent	13.14243	0.600270	1.603109	1.267453	3.038637	0.189239

Determinant resid covariance (dof adj.)	1.31E-09
Determinant resid covariance	3.51E-10
Log likelihood	156.5064
Akaike information criterion	-2.378982
Schwarz criterion	0.208792

Table 6.4.7(a) Summary of forecast-error variance decomposition of L

L

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.942323	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	1.397774	91.71847	0.056269	0.053832	6.712314	0.365665	1.093450
3	1.646113	87.00016	0.455874	1.169025	8.083718	0.321870	2.969357
4	1.888399	82.44246	0.669186	2.504116	6.411268	0.797931	7.175039
5	2.066102	79.33213	0.962176	2.249126	5.568240	1.230339	10.65799
6	2.171485	76.05718	1.394547	2.086998	5.319121	1.353023	13.78913
7	2.242482	72.48522	2.012366	2.023427	5.072074	1.408112	16.99880
8	2.308232	68.74855	2.657846	1.990007	4.789372	1.474741	20.33948
9	2.371195	65.18145	3.264032	2.191687	4.566272	1.474787	23.32177
10	2.433290	61.96182	3.807463	2.732586	4.382128	1.413401	25.70261

Table 6.4.7(b) Summary of forecast-error variance decomposition of LGDP

LGDP

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.027164	5.369180	94.63082	0.000000	0.000000	0.000000	0.000000
2	0.038168	5.601547	80.12941	0.642105	7.733775	2.353091	3.540073
3	0.045939	5.893304	77.59313	0.554179	7.271819	4.440008	4.247562
4	0.051054	5.434482	73.77757	1.156077	8.425612	5.519752	5.686510
5	0.055344	5.751979	70.33689	2.306275	8.695237	6.747817	6.161801
6	0.058920	5.833495	67.10618	2.790166	10.13653	7.178657	6.954965
7	0.061994	5.530923	64.41670	3.040818	12.01117	7.238248	7.762139
8	0.064716	5.144030	62.02632	3.455183	13.70412	7.246496	8.423849
9	0.067165	4.825742	60.03498	3.904729	15.06987	7.323446	8.841236
10	0.069427	4.544842	58.31265	4.169876	16.45849	7.360579	9.153567

Table 6.4.7(c) Summary of forecast-error variance decomposition of INF

INF

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	1.002344	0.228346	6.344862	93.42679	0.000000	0.000000	0.000000
2	1.336598	23.65733	3.584707	60.64650	2.315991	5.549609	4.245859
3	1.436481	23.76115	3.111394	56.49588	7.915405	4.921407	3.794765
4	1.481000	23.24420	2.933930	54.01640	11.03730	5.095789	3.672376
5	1.499632	23.03373	2.905221	54.40514	10.78213	5.104422	3.769355
6	1.519969	22.96860	2.828582	53.61258	10.55888	5.668484	4.362868
7	1.528397	22.85137	2.801254	53.32089	10.90053	5.648696	4.477263
8	1.538687	22.83390	2.764767	52.92500	11.41397	5.585303	4.477057
9	1.544070	23.07892	2.745935	52.55857	11.41564	5.563465	4.637467
10	1.547992	23.05228	2.738908	52.29334	11.35996	5.628056	4.927459

Table 6.4.7(d) Summary of forecast-error variance decomposition of LM2

LM2

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.073155	43.58154	0.004042	0.013973	56.40045	0.000000	0.000000
2	0.090870	55.34018	1.452583	0.536584	41.69573	0.974024	0.000893
3	0.101878	56.47139	3.727768	0.487464	36.71787	2.551591	0.043913
4	0.114104	56.35254	5.659151	1.482569	34.02423	2.341969	0.139547
5	0.125729	57.04622	7.272014	1.780906	31.57772	2.066851	0.256292
6	0.134436	57.42738	8.970064	1.662975	29.56636	2.062374	0.310850
7	0.141298	56.77406	10.83427	1.623857	28.21796	2.183211	0.366650
8	0.147743	55.71540	12.55389	1.701376	27.31379	2.211614	0.503932
9	0.153739	54.74099	14.07480	1.711900	26.55728	2.214821	0.700211
10	0.158907	53.78894	15.49258	1.644968	25.89268	2.269561	0.911276

Table 6.4.7(e) Summary of forecast-error variance decomposition of R

R

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	1.177380	36.64500	0.042031	5.588183	0.740269	56.98452	0.000000
2	1.556300	49.10881	0.092842	7.106137	1.234478	42.16843	0.289304
3	1.805282	47.85418	1.055515	10.00919	8.393650	32.30995	0.377518
4	1.989939	45.86807	1.599010	12.82682	12.29614	27.01753	0.392428
5	2.121034	44.62816	1.793118	13.43025	15.10078	24.20908	0.838606
6	2.204715	43.23497	1.815812	12.90097	17.74910	22.71990	1.579255
7	2.260729	41.55335	1.796309	12.36544	19.84158	21.86066	2.582662
8	2.303884	40.04334	1.753837	11.92846	20.96504	21.34883	3.960491
9	2.342611	38.75189	1.700382	11.54572	21.48633	20.95477	5.560902
10	2.381568	37.73136	1.645290	11.31056	21.67175	20.50516	7.135874

Table 6.4.7(f) Summary of forecast-error variance decomposition of LNEER

LNEER

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.044026	25.24750	0.017815	8.979687	16.77051	0.301084	48.68340
2	0.067934	57.68587	0.461397	6.639064	8.935679	1.197945	25.08005
3	0.082637	58.93415	0.549098	8.030676	6.739206	1.238480	24.50839
4	0.095022	61.33643	0.536347	11.46328	5.169199	0.936955	20.55779
5	0.105890	63.01730	0.669208	13.55092	4.313074	0.767282	17.68222
6	0.114166	64.98773	0.746468	13.90105	3.958832	0.686986	15.71893
7	0.119956	65.80988	0.895453	14.07620	4.022994	0.628182	14.56730
8	0.124332	66.18742	1.050205	14.44547	4.051825	0.606158	13.65892
9	0.127785	66.43636	1.207600	14.72028	4.080145	0.612340	12.94328
10	0.130321	66.63518	1.353861	14.76885	4.172979	0.623327	12.44581

Table 6.4.8: Diagnostic tests

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Date: 09/11/18 Time: 13:43

Sample: 2000Q1 2016Q4

Included observations: 66

Lags	LM-Stat	Prob
1	56.91953	0.0146
2	54.41422	0.0251
3	46.39847	0.1149
4	41.51394	0.2429
5	48.52347	0.0794
6	43.06798	0.1945

Probs from chi-square with 36 df.

VAR Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)

Null Hypothesis: residuals are multivariate normal

Date: 09/11/18 Time: 13:44

Sample: 2000Q1 2016Q4

Included observations: 66

Component	Skewness	Chi-sq	Df	Prob.
1	2.000246	44.01084	1	0.0000
2	-0.205628	0.465110	1	0.4952
3	0.055869	0.034335	1	0.8530
4	0.319964	1.126145	1	0.2886
5	-0.025658	0.007241	1	0.9322
6	-0.564228	3.501888	1	0.0613
Joint		49.14555	6	0.0000

Component	Kurtosis	Chi-sq	Df	Prob.
1	13.00836	275.4598	1	0.0000
2	3.578978	0.921844	1	0.3370

3	2.900860	0.027029	1	0.8694
4	3.400217	0.440477	1	0.5069
5	3.474655	0.619567	1	0.4312
6	3.279843	0.215359	1	0.6426
Joint		277.6841	6	0.0000

Component	Jarque-Bera	df	Prob.
1	319.4707	2	0.0000
2	1.386954	2	0.4998
3	0.061364	2	0.9698
4	1.566622	2	0.4569
5	0.626809	2	0.7310
6	3.717247	2	0.1559
Joint	326.8297	12	0.0000

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)

Date: 09/11/18 Time: 13:47

Sample: 2000Q1 2016Q4

Included observations: 66

Joint test:

Chi-sq	Df	Prob.
554.6992	504	0.0585

Table 6.4.9: Cointegration tests

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.705535	166.6145	95.75366	0.0000
At most 1 *	0.457157	85.92326	69.81889	0.0015
At most 2	0.296939	45.60150	47.85613	0.0802
At most 3	0.143319	22.34894	29.79707	0.2795
At most 4	0.129536	12.13941	15.49471	0.1504
At most 5	0.044195	2.983293	3.841466	0.0841

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.705535	80.69121	40.07757	0.0000
At most 1 *	0.457157	40.32176	33.87687	0.0074
At most 2	0.296939	23.25256	27.58434	0.1630
At most 3	0.143319	10.20953	21.13162	0.7247
At most 4	0.129536	9.156120	14.26460	0.2734
At most 5	0.044195	2.983293	3.841466	0.0841

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Appendix E: Model 4 estimation results

Table 6.5.2: Correlation matrix

	L	LGDP	INF	LM2	R	LNEER
L	1.000000	0.877920	-0.018035	0.924096	-0.777444	0.104611
LGDP	0.877920	1.000000	0.101912	0.990600	-0.551566	-0.311132
INF	-0.018035	0.101912	1.000000	0.071195	0.345465	-0.477557
LM2	0.924096	0.990600	0.071195	1.000000	-0.615877	-0.200564
R	-0.777444	-0.551566	0.345465	-0.615877	1.000000	-0.463636
LNEER	0.104611	-0.311132	-0.477557	-0.200564	-0.463636	1.000000

Table 6.5.4: Lag selection criteria Brazil VAR model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-373.3089	NA	0.004719	11.67104	11.87176	11.75024
1	29.40538	718.6901	5.97e-08	0.387527	1.792516	0.941885
2	105.6528	121.9958*	1.78e-08*	-0.850855*	1.758410*	0.178668*

* 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

Table 6.5.5(a) AR root table

Roots of Characteristic Polynomial
Endogenous variables: L LGDP INF LM2 R LNEER
Exogenous variables: C
Lag specification: 1 2
Date: 11/21/18 Time: 19:13

Root	Modulus
0.986489	0.986489
0.934904 - 0.116042i	0.942079
0.934904 + 0.116042i	0.942079
0.688466 - 0.228806i	0.725492
0.688466 + 0.228806i	0.725492
0.283271 - 0.587812i	0.652507
0.283271 + 0.587812i	0.652507
0.049638 - 0.567301i	0.569468
0.049638 + 0.567301i	0.569468
0.327276 - 0.172072i	0.369754
0.327276 + 0.172072i	0.369754
-0.361567	0.361567

No root lies outside the unit circle.
VAR satisfies the stability condition.

Figure 6.3: AR root table

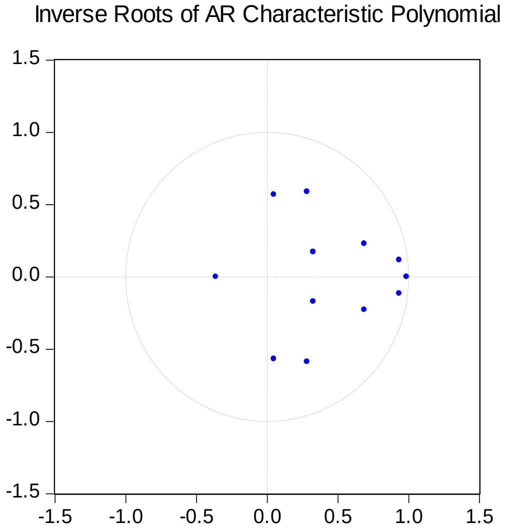


Table 6.5.6: VAR model estimation results

Vector Autoregression Estimates

Date: 11/21/18 Time: 19:11

Sample (adjusted): 2000Q3 2016Q3

Included observations: 65 after adjustments

Standard errors in ( ) & t-statistics in [ ]

	L	LGDP	INF	LM2	R	LNEER
L(-1)	0.619592	-0.051412	0.150493	-0.046007	-0.420643	0.029656
	(0.12519)	(0.01478)	(0.12369)	(0.01561)	(0.40239)	(0.00901)
	[4.94908]	[-3.47849]	[1.21668]	[-2.94664]	[-1.04535]	[3.29055]
L(-2)	0.233858	0.055976	-0.099092	0.051501	0.415942	-0.029801
	(0.11778)	(0.01390)	(0.11636)	(0.01469)	(0.37856)	(0.00848)
	[1.98557]	[4.02576]	[-0.85156]	[3.50618]	[1.09875]	[-3.51487]
LGDP(-1)	6.583337	1.541834	-0.373376	0.730371	9.137298	-0.716914
	(3.51911)	(0.41545)	(3.47687)	(0.43888)	(11.3110)	(0.25333)
	[1.87074]	[3.71120]	[-0.10739]	[1.66417]	[0.80782]	[-2.82995]
LGDP(-2)	-2.008716	0.177509	-0.127717	0.325105	0.352248	0.143148
	(3.37553)	(0.39850)	(3.33502)	(0.42097)	(10.8495)	(0.24300)
	[-0.59508]	[0.44544]	[-0.03830]	[0.77227]	[0.03247]	[0.58910]
INF(-1)	-0.001636	-0.008285	0.383248	-0.013355	0.723127	-0.011429
	(0.13773)	(0.01626)	(0.13608)	(0.01718)	(0.44270)	(0.00992)
	[-0.01188]	[-0.50954]	[2.81630]	[-0.77749]	[1.63344]	[-1.15265]
INF(-2)	0.378791	0.042546	-0.368936	0.036313	-0.585806	-0.010594
	(0.13526)	(0.01597)	(0.13364)	(0.01687)	(0.43476)	(0.00974)
	[2.80039]	[2.66435]	[-2.76066]	[2.15264]	[-1.34742]	[-1.08798]
LM2(-1)	-5.617245	-0.278359	0.546015	0.644779	1.416000	0.097593
	(3.43421)	(0.40543)	(3.39300)	(0.42829)	(11.0381)	(0.24722)
	[-1.63567]	[-0.68657]	[0.16092]	[1.50547]	[0.12828]	[0.39476]
LM2(-2)	4.431917	-0.334832	-0.976603	-0.520003	-9.264518	0.316011
	(3.19906)	(0.37767)	(3.16067)	(0.39897)	(10.2823)	(0.23029)
	[1.38538]	[-0.88657]	[-0.30899]	[-1.30338]	[-0.90101]	[1.37222]

R(-1)	-0.022973	-0.002892	0.059048	0.000195	1.348299	0.002124
	(0.04422)	(0.00522)	(0.04369)	(0.00551)	(0.14213)	(0.00318)
	[-0.51951]	[-0.55404]	[1.35153]	[0.03531]	[9.48630]	[0.66714]
R(-2)	-0.025187	0.003789	-0.035200	0.001744	-0.455554	-0.003274
	(0.04201)	(0.00496)	(0.04150)	(0.00524)	(0.13502)	(0.00302)
	[-0.59957]	[0.76398]	[-0.84810]	[0.33295]	[-3.37387]	[-1.08258]
LNEER(-1)	4.031599	0.586033	-4.975685	0.719503	4.087334	0.654281
	(1.84048)	(0.21728)	(1.81839)	(0.22953)	(5.91561)	(0.13249)
	[2.19052]	[2.69712]	[-2.73631]	[3.13465]	[0.69094]	[4.93829]
LNEER(-2)	4.446985	-0.007402	2.460786	-0.004994	-2.827336	-0.098359
	(2.02048)	(0.23853)	(1.99623)	(0.25198)	(6.49417)	(0.14545)
	[2.20095]	[-0.03103]	[1.23271]	[-0.01982]	[-0.43537]	[-0.67624]
C	-76.66232	-4.221238	22.54245	-5.913435	-23.03244	4.282474
	(20.3029)	(2.39689)	(20.0592)	(2.53204)	(65.2569)	(1.46155)
	[-3.77593]	[-1.76113]	[1.12379]	[-2.33544]	[-0.35295]	[2.93009]
R-squared	0.998017	0.982040	0.556436	0.988140	0.964667	0.937267
Adj. R-squared	0.997560	0.977895	0.454075	0.985403	0.956513	0.922790
Sum sq. resids	25.64293	0.357395	25.03113	0.398835	264.9138	0.132887
S.E. equation	0.702234	0.082903	0.693807	0.087578	2.257099	0.050552
F-statistic	2181.281	236.9411	5.436016	361.0322	118.3082	64.74227
Log likelihood	-62.00212	76.87628	-61.21733	73.31083	-137.8941	109.0300
Akaike AIC	2.307758	-1.965424	2.283610	-1.855718	4.642894	-2.954770
Schwarz SC	2.742635	-1.530547	2.718488	-1.420840	5.077772	-2.519892
Mean dependent	45.22154	14.37306	1.673951	14.51754	47.65051	4.379105
S.D. dependent	14.21574	0.557608	0.939014	0.724869	10.82356	0.181929

Determinant resid covariance (dof adj.)	5.95E-09
Determinant resid covariance	1.56E-09
Log likelihood	105.6528
Akaike information criterion	-0.850855
Schwarz criterion	1.758410

Forecast error variance decomposition

Table 6.5.7(a): Summary of forecast-error variance decomposition of L

L

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.702234	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.864121	93.20085	0.619430	0.151019	2.358994	0.330981	3.338729
3	1.133096	76.78641	5.452431	1.080938	1.912833	2.463265	12.30413
4	1.441748	65.74046	14.79700	0.742575	1.223180	3.734396	13.76239
5	1.732476	58.11190	20.85045	0.940549	0.985382	5.105091	14.00663
6	2.036682	49.77899	24.84039	2.315564	1.548539	6.833657	14.68286
7	2.383487	41.75030	27.83627	4.085789	2.812833	8.308431	15.20638
8	2.756653	35.24102	29.86058	5.896549	4.454455	9.226296	15.32110
9	3.136542	30.13286	30.72522	7.718857	6.332961	9.738879	15.35123
10	3.518646	25.99331	30.69712	9.488941	8.338982	9.977587	15.50406

Table 6.5.7(b): Summary of forecast-error variance decomposition of LGDP

LGDP

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.082903	0.563777	99.43622	0.000000	0.000000	0.000000	0.000000
2	0.123197	4.951132	90.29515	0.828358	0.187759	0.266898	3.470705
3	0.139181	4.136725	84.36324	0.969709	0.956559	0.420247	9.153519
4	0.147257	4.075257	79.77862	2.240528	3.210998	0.411137	10.28346
5	0.155801	4.155645	76.53401	3.609404	5.440736	0.535345	9.724863
6	0.163923	3.962984	74.84691	4.515057	6.869982	0.548177	9.256894
7	0.170083	3.938056	73.15248	5.198188	7.974900	0.514938	9.221435
8	0.174497	4.256936	71.11158	5.751185	9.074851	0.489429	9.316019
9	0.177914	4.852574	69.06921	6.164592	10.05771	0.480720	9.375193
10	0.180610	5.582805	67.27331	6.420997	10.76098	0.515945	9.445962

Table 6.5.7(c): Summary of forecast-error variance decomposition of INF

INF

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.693807	1.205485	2.068817	96.72570	0.000000	0.000000	0.000000
2	0.852676	2.475714	10.53441	79.76653	0.002121	1.998303	5.222923
3	0.933257	3.098117	22.19778	66.70133	0.169200	2.976905	4.856671
4	0.957216	4.070230	22.52510	63.59630	0.889011	3.006665	5.912691
5	0.977459	4.056509	22.84509	61.55890	2.430180	3.044842	6.064479
6	1.002230	4.611263	22.45258	59.83509	3.769954	3.173262	6.157855
7	1.014381	4.594230	22.03454	59.02599	4.310558	3.180796	6.853884
8	1.019900	4.558136	22.21328	58.55973	4.481990	3.149032	7.037824
9	1.021726	4.542494	22.15953	58.42891	4.641931	3.167835	7.059292
10	1.024172	4.557687	22.11866	58.23141	4.842022	3.169333	7.080889

Table 6.5.7(d): Summary of forecast-error variance decomposition of LM2

LM2

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.087578	0.800739	90.46117	0.061661	8.676428	0.000000	0.000000
2	0.133306	2.816840	85.48343	1.346756	5.882681	0.001974	4.468320
3	0.153239	2.250070	78.70881	1.027402	4.581607	0.015830	13.41628
4	0.162250	2.614382	73.26414	1.235212	4.460216	0.413163	18.01289
5	0.169497	3.527832	69.55869	1.777012	4.938727	0.935374	19.26237
6	0.175659	4.006489	67.64286	2.134597	5.259098	1.086488	19.87047
7	0.180446	4.425984	66.04422	2.280003	5.422198	1.041713	20.78588
8	0.184043	5.108452	64.16116	2.305032	5.565394	1.021580	21.83838
9	0.187112	6.075674	62.18001	2.268973	5.656241	1.093291	22.72582
10	0.190054	7.174119	60.26995	2.202912	5.625733	1.297943	23.42934

Table 6.5.7(e): Summary of forecast-error variance decomposition of R

R

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	2.257099	0.281887	15.54543	10.71280	0.496454	72.96343	0.000000
2	4.269444	0.633688	26.72787	14.66123	0.529881	57.30675	0.140577
3	5.785074	1.139277	32.01338	13.50679	0.316793	52.75726	0.266498
4	6.782589	1.538070	33.86155	12.34175	0.415241	51.40097	0.442417
5	7.406153	1.687066	33.56253	12.13523	1.269290	50.84678	0.499111
6	7.833260	1.647932	32.58416	12.66516	2.800513	49.85593	0.446307
7	8.171844	1.574229	31.71684	13.43516	4.571728	48.12555	0.576497
8	8.457596	1.522227	31.13248	14.11756	6.249655	46.01252	0.965558
9	8.699147	1.487170	30.63496	14.66991	7.770617	43.95250	1.484839
10	8.906217	1.447182	30.04357	15.15373	9.169700	42.12591	2.059906

Table 6.5.7(f): Summary of forecast-error variance decomposition of LNEER

LNEER

Period	S.E.	L	LGDP	INF	LM2	R	LNEER
1	0.050552	0.589615	36.86685	1.848445	0.604042	0.070787	60.02026
2	0.093175	4.133763	68.05609	1.922367	0.516929	0.139860	25.23099
3	0.114729	6.499999	72.36223	2.368321	1.646815	0.164583	16.95805
4	0.124865	6.038669	69.74735	4.510997	5.136092	0.217542	14.34935
5	0.134901	5.177295	63.77564	7.608779	9.930779	0.778559	12.72894
6	0.146056	4.416627	58.50123	10.41976	13.54554	1.388537	11.72831
7	0.156305	3.863339	55.05225	12.45664	15.85988	1.723282	11.04461
8	0.164666	3.482621	52.40952	13.94561	17.70136	1.878584	10.58230
9	0.171448	3.218344	49.95484	15.11907	19.42773	1.951634	10.32839
10	0.177154	3.045895	47.67371	16.08324	20.98465	1.968774	10.24373

Table 6.5.8: Diagnostic tests

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Date: 11/21/18   Time: 19:15
Sample: 2000Q1 2016Q3
Included observations: 65

Lags	LM-Stat	Prob
1	58.20341	0.0510
2	59.60732	0.0280
3	32.16557	0.6516

Probs from chi-square with 36 df.
VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Date: 11/21/18   Time: 19:16
Sample: 2000Q1 2016Q3
Included observations: 65

Component	Skewness	Chi-sq	Df	Prob.
1	-0.763954	6.322611	1	0.0119
2	0.866216	8.128577	1	0.0044
3	0.639960	4.436785	1	0.0352
4	0.353365	1.352722	1	0.2448
5	-0.752363	6.132210	1	0.0133
6	0.392212	1.666492	1	0.1967
Joint		28.03940	6	0.0001

Component	Kurtosis	Chi-sq	Df	Prob.
1	4.240245	4.165982	1	0.0412
2	3.573210	0.889877	1	0.3455
3	4.605793	6.983630	1	0.0082
4	3.803954	1.750509	1	0.1858
5	5.191821	13.01105	1	0.0003
6	4.158215	3.633129	1	0.0566
Joint		30.43418	6	0.0000

Component	Jarque-Bera	df	Prob.
1	10.48859	2	0.0053
2	9.018454	2	0.0110
3	11.42041	2	0.0033
4	3.103231	2	0.2119
5	19.14326	2	0.0001
6	5.299621	2	0.0707
Joint	58.47357	12	0.0000

Table 6.5.9: Cointegration tests

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.491864	122.2092	95.75366	0.0002
At most 1 *	0.411560	78.88081	69.81889	0.0079
At most 2	0.304574	44.94287	47.85613	0.0915
At most 3	0.159938	21.69614	29.79707	0.3157
At most 4	0.111756	10.54222	15.49471	0.2413
At most 5	0.045161	2.957633	3.841466	0.0855

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.491864	43.32836	40.07757	0.0208
At most 1 *	0.411560	33.93795	33.87687	0.0492
At most 2	0.304574	23.24673	27.58434	0.1632
At most 3	0.159938	11.15392	21.13162	0.6319
At most 4	0.111756	7.584590	14.26460	0.4225
At most 5	0.045161	2.957633	3.841466	0.0855

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Appendix F: Model 4 estimation results

Table 6.6.2: Correlation matrix

	L	LGDP	LM2	R	INF
L	1.000000	0.463099	0.686599	0.236608	0.407703
LGDP	0.463099	1.000000	0.822326	0.188061	0.136676
LM2	0.686599	0.8022326	1.000000	0.236263	0.328805
R	0.236608	0.188061	0.236263	1.000000	0.448382
INF	0.407703	0.136676	0.328805	0.448382	1.000000

Table 6.6.4: Lag selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-255.6969	NA	0.003089	8.409576	8.581119	8.476928
1	30.11329	516.3022	6.88e-07	-0.003654	1.025604*	0.400459*
2	63.88187	55.55477	5.27e-07	-0.286512	1.600462	0.454362
3	79.88848	23.75173	7.33e-07	0.003598	2.748287	1.081232
4	119.8449	52.84563*	4.90e-07*	-0.478869	3.123536	0.935526
5	143.1186	27.02751	5.94e-07	-0.423181	4.036939	1.327975
6	171.9831	28.86445	6.51e-07	-0.547841*	4.769995	1.540076

Note: * 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

Table 6.6.5 AR root table

Roots of Characteristic Polynomial
Endogenous variables: L LGDP LM2 INF R
Exogenous variables: C
Lag specification: 1 1
Date: 08/15/18 Time: 21:41

Root	Modulus
0.993863	0.993863
0.832123 - 0.151787i	0.845853
0.832123 + 0.151787i	0.845853
0.145820 - 0.164764i	0.220024
0.145820 + 0.164764i	0.220024

Figure 6.4: Modulus

Inverse Roots of AR Characteristic Polynomial

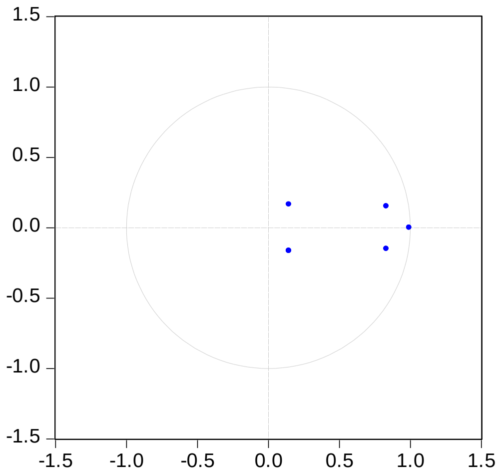


Table 6.6.6: VAR estimation results

Vector Autoregression Estimates
Date: 09/11/18 Time: 11:59
Sample (adjusted): 2000Q2 2016Q4
Included observations: 67 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	L	LGDP	LM2	R	INF
L(-1)	0.709722	-0.006821	0.000592	-0.141997	-0.147145
	(0.06440)	(0.00458)	(0.00505)	(0.09085)	(0.05455)
	[11.0209]	[-1.48823]	[0.11703]	[-1.56293]	[-2.69724]
LGDP(-1)	-10.87668	0.063892	-0.134640	-8.372899	-7.176036
	(3.10495)	(0.22098)	(0.24370)	(4.38051)	(2.63032)
	[-3.50302]	[0.28913]	[-0.55249]	[-1.91140]	[-2.72820]
LM2(-1)	12.91197	0.811068	1.091335	7.957879	7.553099
	(3.09188)	(0.22005)	(0.24267)	(4.36207)	(2.61925)
	[4.17609]	[3.68579]	[4.49719]	[1.82434]	[2.88369]
R(-1)	0.056189	-0.010207	-0.001057	0.733636	-0.076145
	(0.04967)	(0.00353)	(0.00390)	(0.07007)	(0.04208)
	[1.13130]	[-2.88743]	[-0.27108]	[10.4697]	[-1.80973]
INF(-1)	0.394179	0.006810	0.016112	0.965131	0.338900
	(0.13702)	(0.00975)	(0.01075)	(0.19331)	(0.11607)
	[2.87681]	[0.69835]	[1.49821]	[4.99268]	[2.91967]
C	-37.13947	2.911231	0.929350	15.03585	-2.897867
	(15.0322)	(1.06986)	(1.17983)	(21.2077)	(12.7344)
	[-2.47066]	[2.72113]	[0.78770]	[0.70898]	[-0.22756]
R-squared	0.988740	0.979860	0.984609	0.846465	0.276082
Adj. R-squared	0.987817	0.978209	0.983348	0.833880	0.216745
Sum sq. resids	47.19368	0.239053	0.290719	93.93440	33.86825
S.E. equation	0.879583	0.062601	0.069035	1.240930	0.745129
F-statistic	1071.286	593.5640	780.4962	67.26084	4.652748
Log likelihood	-83.32939	93.72923	87.17415	-106.3887	-72.21469
Akaike AIC	2.666549	-2.618783	-2.423109	3.354886	2.334767
Schwarz SC	2.863984	-2.421348	-2.225674	3.552321	2.532202
Mean dependent	67.78060	23.26998	23.96643	8.265942	0.806036
S.D. dependent	7.968959	0.424079	0.534981	3.044647	0.841938

Determinant resid covariance (dof adj.)	1.18E-06
Determinant resid covariance	7.37E-07
Log likelihood	-2.285382
Akaike information criterion	0.963743
Schwarz criterion	1.950919

Table 6.6.7(a): Summary of forecast-error variance decomposition of L

L

Period	S.E.	L	LGDP	LM2	R	INF
1	0.879583	100.0000	0.000000	0.000000	0.000000	0.000000
2	1.494395	85.89013	0.811159	9.927359	0.415295	2.956055
3	2.067043	77.26813	0.633046	15.64402	1.311533	5.143272
4	2.600821	71.40767	0.418859	19.27063	2.139255	6.763590
5	3.089482	67.20530	0.302826	21.82207	2.740618	7.929187
6	3.527599	64.13070	0.287657	23.71550	3.129027	8.737121
7	3.913993	61.84844	0.360474	25.16396	3.351873	9.275251
8	4.250958	60.13202	0.507373	26.29301	3.453964	9.613638
9	4.542886	58.82568	0.714976	27.18257	3.471434	9.805348
10	4.795175	57.82042	0.970481	27.88666	3.432176	9.890268

Table 6.6.7(b): Summary of forecast-error variance decomposition of LGDP

LGDP

Period	S.E.	L	LGDP	LM2	R	INF
1	0.062601	23.33513	76.66487	0.000000	0.000000	0.000000
2	0.082103	28.58641	60.03009	9.397428	1.693745	0.292322
3	0.096807	31.29841	52.63110	13.38256	2.429140	0.258785
4	0.109190	33.66356	48.08351	15.37754	2.638256	0.237140
5	0.120382	35.94532	44.40470	16.79212	2.598868	0.258986
6	0.130942	38.11265	41.12043	17.99843	2.433815	0.334676
7	0.141169	40.10535	38.12024	19.09531	2.212798	0.466304
8	0.151217	41.88008	35.38186	20.10987	1.979536	0.648648
9	0.161151	43.41708	32.90389	21.04822	1.759715	0.871088
10	0.170981	44.71764	30.68540	21.91068	1.565991	1.120298

Table 6.6.7(c): Summary of forecast-error variance decomposition of LM2

LM2

Period	S.E.	L	LGDP	LM2	R	INF
1	0.069035	49.25875	30.24386	20.49739	0.000000	0.000000
2	0.100655	51.54416	24.60600	22.76067	0.000529	1.088644
3	0.126002	52.24752	20.90174	24.93692	0.000376	1.913438
4	0.147593	52.57708	18.69337	26.30223	0.000997	2.426328
5	0.166707	52.78130	17.25188	27.17904	0.004746	2.783027
6	0.184061	52.91328	16.22180	27.79455	0.011895	3.058471
7	0.200068	52.99421	15.44110	28.25932	0.021554	3.283816
8	0.214978	53.03794	14.82837	28.62758	0.032664	3.473441
9	0.228959	53.05475	14.33717	28.92861	0.044307	3.635173
10	0.242129	53.05242	13.93799	29.17984	0.055782	3.773965

Table 6.6.7(d): Summary of forecast-error variance decomposition of R

R

Period	S.E.	L	LGDP	LM2	R	INF
1	1.240930	18.60017	1.197744	0.938425	79.26366	0.000000
2	1.862645	22.01351	1.145575	7.199815	58.23418	11.40692
3	2.284633	21.37530	1.893959	12.57589	47.59214	16.56271
4	2.527476	20.46799	2.120332	15.32628	43.38063	18.70476
5	2.657071	19.70784	2.125970	16.68692	41.71712	19.76215
6	2.720833	19.14132	2.085942	17.34023	41.10455	20.32796
7	2.748485	18.79257	2.054180	17.60606	40.93135	20.61585
8	2.758809	18.67131	2.038964	17.66149	40.90101	20.72723
9	2.763340	18.76453	2.033650	17.62255	40.85547	20.72379
10	2.768498	19.03705	2.029062	17.56766	40.71752	20.64871

Table 6.6.7(e): Summary of forecast-error variance decomposition of INF

INF

Period	S.E.	L	LGDP	LM2	R	INF
1	0.745129	16.34826	1.523650	4.247084	1.357896	76.52311
2	0.844570	13.64232	4.260541	14.21559	1.476417	66.40513
3	0.849772	13.48076	4.213518	14.99763	1.527762	65.78033
4	0.851174	13.55408	4.357537	14.96092	1.555481	65.57198
5	0.853242	13.67224	4.510955	14.90879	1.602600	65.30541
6	0.855673	13.80784	4.613330	14.88574	1.674573	65.01851
7	0.858232	13.94147	4.671790	14.89131	1.759619	64.73580
8	0.860692	14.05996	4.699300	14.91897	1.844765	64.47700
9	0.862876	14.15702	4.707086	14.95952	1.921063	64.25531
10	0.864690	14.23158	4.703914	15.00442	1.983926	64.07616

Table 6.6.8: Diagnostics tests

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Date: 09/11/18 Time: 12:04

Sample: 2000Q1 2016Q4

Included observations: 67

Lags	LM-Stat	Prob
1	42.88379	0.064
2	42.97548	0.0541
3	33.06442	0.1295
4	43.18777	0.0133
5	39.23462	0.1049
6	30.17334	0.2179

Probs from chi-square with 25 df.

VAR Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)

Null Hypothesis: residuals are multivariate normal

Date: 09/11/18 Time: 12:06

Sample: 2000Q1 2016Q4

Included observations: 67

Component	Skewness	Chi-sq	df	Prob.
1	-0.289648	0.936839	1	0.3331
2	-0.206191	0.474750	1	0.4908
3	0.274624	0.842172	1	0.3588
4	0.025097	0.007034	1	0.9332
5	-0.115180	0.148142	1	0.7003
Joint		2.408936	5	0.7901

Component	Kurtosis	Chi-sq	df	Prob.

1	3.019082	0.001016	1	0.9746
2	2.838679	0.072652	1	0.7875
3	3.153852	0.066080	1	0.7971
4	3.366089	0.374142	1	0.5408
5	3.402490	0.452244	1	0.5013
Joint		0.966134	5	0.9653

Component	Jarque-Bera	df	Prob.
1	0.937855	2	0.6257
2	0.547401	2	0.7606
3	0.908252	2	0.6350
4	0.381176	2	0.8265
5	0.600386	2	0.7407
Joint	3.375070	10	0.9712

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)

Date: 09/11/18 Time: 12:06

Sample: 2000Q1 2016Q4

Included observations: 67

Joint test:

Chi-sq	df	Prob.
194.5760	150	0.0084

Table 6.6.9: Cointegration tests

Unrestricted cointegration rank test (trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.546548	100.7276	69.81889	0.0000
At most 1 *	0.289393	49.32125	47.85613	0.0362
At most 2	0.227797	27.11495	29.79707	0.0989
At most 3	0.146622	10.31192	15.49471	0.2575
At most 4	9.18E-05	0.005969	3.841466	0.9377

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted cointegration rank test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.546548	51.40635	33.87687	0.0002
At most 1	0.289393	22.20630	27.58434	0.2100
At most 2	0.227797	16.80303	21.13162	0.1815
At most 3	0.146622	10.30595	14.26460	0.1926
At most 4	9.18E-05	0.005969	3.841466	0.9377

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values