Monetary Policy and Output Growth Forecasting in a SVAR Perspective

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Abstract

This paper presents a short-term forecasting model of monthly South African macroeconomic variables to estimate the effects of monetary policy on output growth from a Structural Vector Autoregression ($SVAR$) perspective. A set of forecasting experimentations are carried out to evaluate the out-of-sample static and dynamic forecast for the post-apartheid period. We carried out a combined forecast in order to compare the static with dynamic forecasting approach for improving output growth. The findings reveal that money supply is observed to exert a significant positive impact on output growth from about the eighth month. In addition, the dynamic forecasting is observed to have a more robust result and outperforms the static forecasting. It clearly brings out the growth patterns (increase and decrease) and can be justified and recommended to policymakers in calculating or in predicting the outcome of monetary policy actions for future development. However, in order to improve the predictive forecasting accuracy, the study recommends combined forecasting as dynamic forecasting is associated with risk and uncertainty that is central to its prediction and expected reliability.

Keywords: monetary policy, output growth forecasting, structural VARs

1. Introduction

Generally, many studies have used time series macroeconomic variables to forecast output growth using low-dimensional methods such as Generalized Method of Moments (GMM), Vector Autoregression (VAR) and Single-equation Regression among others. These low-dimensional methods omit thousands of important variables that are available to economic forecasters due to constraints in accommodating a large number of variables. They are further constrained by degree of freedoms. However, to ensure forecast accuracy and good predictive power of a model, one needs to impose adequate restrictions so that the number of estimated parameters is kept small (Stock & Watson, 2004). One way to impose such restrictions and employ a high-dimensional system is to assume that the variables have a dynamic factor structure model. Stock and Watson (2002) and Forni et al. (2003) suggest that there are potential gains from forecasting using high-dimensional dynamic factor structural models. This context furnishes this study with two objectives. First, the study aims to estimate the effects of monetary policy on output growth in South Africa using a Structural Vector Autoregression ($SVAR$) model. The second objective is to forecast the time series data used in the model and determine the predictive power and accuracy of the $SVAR$ model. After an extensive review of the literature, there is, to the best of the researchers' knowledge, no study that has estimated monetary policy and output growth in South Africa as well as those employing a $SVAR$ model.

The monetary policy linkage of the South African economy arises from the interdependence of the financial sector and the industrial sector for meeting the needs of productive input and output to boost investment. The impact of funds supplied by the financial sector increases industrial production, while the interest paid on those funds increases the money growth that the financial institution is able to supply to the economy.

However, natural rate models suggest that monetary policy will not have a significant impact on the business cycle in stimulating economic activity with respect to output and employment in the long run (see Sargent & Wallace, 1975; Barro & Gordon, 1983). Their view is that there is a limited effect of monetary policy on output growth. Ping (2004) carried out a study in China and found evidence for the existence of long run monetary neutrality in stimulating output growth and employment (monetary authority mandates is to stabilize prices). Nevertheless, it is observed that an increase in monetary growth provides incentives to monetary authorities to

pursue countercyclical policies. These in turn promote the goals of maximum employment, stable prices, and moderate long-term interest rates. This behaviour is consistent with the rational expectation that when prices are stable, belief is likely to remain that the prices of goods, services, materials and labour are undistorted by inflation and serve as strong signals and guides for the efficient allocation of resources and boosting of investments, inadvertently contributing to higher standards of living. The view that there is a monetary policy linkage to stimulating output growth further motivated us to estimate the effects of monetary policy on output growth from a *SVAR* perspective and also determine the predictive accuracy of the model.

In addition to monetary policy linkages to stimulating output growth, the pursuit of output growth and stable prices fosters savings and capital formation, which encourages households and businesses to increase their investments. Goodfriend's (1997) study provides a meticulous analysis explaining the role of quantitative monetary expansion for effective monetary policy that can have an important effect on real economic activities. An effective monetary policy system will lead to an increase in the capacity of an economy to produce goods and services, and consequently lead to qualitative changes in the economy via output growth and employment generation.

Conversely, the optimum monetary policy linkage between interest rates and money supply rules in promoting output growth and sustainable development has also become a topic of lively interest. The interest centres on the use of interest rates and money supply to stimulate the economy. Taylor (1997, p. 36) points out that deflation in Japan "made an interest rate rule unreliable, calling for greater emphasis on money supply rules". Friedman (1997), Hayashi (1998) and Meltzer (1998) provide recent reports along these lines for money supply as the optimum monetary policy rule. Woodford (2001) holds an opposing view and believes that an optimal rule will generally involve a commitment to history-dependent behaviour; in particular, a more gradual adjustment of the level of interest rates has important advantages in stimulating output growth. Orphanides and Wieland (2000) discuss along these lines how monetary policy may continue to use interest rate instruments on an operational level, if that is deemed more appropriate by the central bank, and optimal interest rates respond to inflation. However, if both rules are applied together, the process of sustainable development that the monetary authorities are aiming to achieve, especially when targeting output growth and price stability, will be fast-tracked.

2. The Instruments of Policy and Targets by Monetary Authorities

According to Mishkin (2007), all central banks pursue a different strategy in the conduct of monetary policy by aiming at a variable that falls within its tools to achieve as its goal. Having decided on the goal needed to stimulate output and price, the policy maker then selects from existing tools to achieve those goals. The central bank chooses a target known as an *intermediate target* (such as a short/long-term interest rate and monetary aggregate) that has a direct effect on the monetary policy goal (stimulating output and prices). However, if these targets are not directly affected by the central bank's tools, then it chooses another target known as the *operating target* (Mishkin, 2007). According to Mishkin, the monetary policy authorities use monetary policy tools, which may not affect monetary policy goals directly. Rather, they affect intermediate targets or the operating targets of monetary policy. The term intermediate target is used to differentiate between the monetary authorities' targets drawn from the ultimate monetary goal variables (such as the unemployment rate, inflation rate, growth rate of output, price stability, interest rates and the stability of the financial markets), and the operating variables such as the central bank's reserves and the federal fund rates', which are more responsive to policy tools.

A reserve bank employs the strategy of pursuing intermediate and operating targets because it is easier to achieve a goal by aiming at a target, than by aiming at a goal directly. Aiming directly at a goal can be disastrous if a reserve bank waits to see what the output and price level will be after a specific period (say one year) and this is not achieved. Therefore, through its operating tools, the South African Reserve Bank (SARB), for example, can stimulate output growth and achieve price stability in the country.

3. Methodology

Since this study attempts to estimate the effects of monetary policy on industrial output growth in South Africa using a *SVAR* approach, the brief description of the methodology that is used is described in this section. The *SVAR* model is a multivariate and linear representation of a vector of observable variables on its own lags. All the observable variables are assumed to be endogenous and interdependent, except for those identified as exogenous. In addition, the model is an economically interpretable simplification of the VAR model, where the structural identification (factorization) restrictions are used in line with some economic theory.

3.1 SVAR Framework

The *SVAR* in this study is estimated using six endogenous variables, namely, Industrial Output (IP), Aggregate

Output (AG), Exchange Rate (EX), Inflation Rate (IF), Interest Rate (IN) and Money Supply (MS) and two exogenous variables, namely, the global Commodity Price (COMM) and the global Oil Price (OP).

Supposing the South African economy can be denoted by the following structural equation:

$$AY_t = \alpha_0 + A_1^* Y_{t-1} + \cdots \ldots \ldots + A_p^* Y_{t-p} + B_0^* X_t + \cdots \ldots . + B_q^* X_{t-q} + B\varepsilon_t \tag{1}$$

where A is an invertible (8×8) matrix describing the contemporaneous relationship among the variables; Y_t is a (8×1) vector of endogenous variables such that $Y_t = Y_{1t}, Y_{2t}, \ldots Y_{nt}$. α_0 is a (8×1) vector of constant terms; $A_1^* - A_p^*$ is a (8×8) matrix of coefficients of lagged endogenous variables (for every $i = 1 \ldots p$); $B_0^* - B_q^*$ and $X_t \ldots X_{t-q}$ are coefficients and vectors of lagged exogenous variables, respectively, capturing external shocks; B is a (8×8) matrix whose non-zero off-diagonal elements allow for direct effects of some shocks on more than one endogenous variable in the system; and ε_{it} is a vector of white-noise structural disturbances (uncorrelated error terms).

Sharifi-Renani (2010) argues that the point of departure for a structural analysis is a reduced form model that has to be specified before the $SVAR$ analysis can be entered. Therefore, equation 1 has to be transformed into a reduced form by pre-multiplying it by an inverse of A in line with Ngalawa and Viegi (2011) as:

$$A^{-1}AY_t = A^{-1}\alpha_0 + A^{-1}A_1^* Y_{t-1} + \cdots \ldots \ldots + A^{-1}A_p^* Y_{t-p} + A^{-1}B_0^* X_t + \cdots \ldots . + A^{-1}B_q^* X_{t-q} + A^{-1}B\varepsilon_t \tag{2}$$

This gives:

$$Y_t = A^{-1}\alpha_0 + A^{-1}A_1^* Y_{t-1} + \cdots + A^{-1}A_p^* Y_{t-p} + A^{-1}B_0^* X_t + \cdots . + A^{-1}B_q^* X_{t-q} + A^{-1}B\varepsilon_t \tag{3}$$

One can denote:

$$A^{-1}\alpha_0 = \beta_0, \ A^{-1}A_1^* = A_i \ for \ every \ i = 1 \ldots . p, A^{-1}B_0^* = \alpha_i \ for \ every \ i \ldots . q \ and \ A^{-1}B\varepsilon_t = \mu_t$$

Hence, equation 3 becomes:

$$Y_t = \beta_0 + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \alpha_1 X_t + \cdots . + \alpha_q X_{t-q} + \mu_t \tag{4}$$

The variance between equations (1) and (4) is that the first is called a long form $SVAR$ that cannot be estimated directly due to the feedback inherent in the VAR process (Enders, 2004) as the endogenous variables have a contemporaneous (immediate) effect on each other in the current and past realization time path of AY_t. Equation 4 is called a reduced form $SVAR$ in which no variable has a direct contemporaneous (immediate) effect on another in the model. Additionally, the error term (μ_t) is a composite of shocks in Y_t (Enders, 2004).

Note that equation 4 can be splitting as:

$$Y_t = IP, AG, EX, IF, IN \ and \ MS \tag{4.1}$$

$$X_t = COMM \ and \ OP \tag{4.2}$$

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_{21} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_{31} & 0 & 1 & 0 & 0 & 0 & 0 & \alpha_{38} \\ \alpha_{41} & 0 & \alpha_{43} & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \alpha_{53} & \alpha_{54} & 1 & \alpha_{56} & 0 & 0 \\ \alpha_{61} & \alpha_{62} & 0 & 0 & \alpha_{65} & 1 & \alpha_{67} & 0 \\ \alpha_{71} & \alpha_{72} & \alpha_{73} & \alpha_{74} & \alpha_{75} & \alpha_{76} & 1 & 0 \\ 0 & 0 & 0 & 0 & \alpha_{85} & \alpha_{86} & 0 & 1 \end{pmatrix} \begin{pmatrix} \mu_t^{logOP} \\ \mu_t^{logCOMM} \\ \mu_t^{logIP} \\ \mu_t^{logAG} \\ \mu_t^{logIF} \\ \mu_t^{logMS} \\ \mu_t^{EX} \\ \mu_t^{IN} \end{pmatrix} = \begin{pmatrix} \varepsilon_t^{logOP} \\ \varepsilon_t^{logCOMM} \\ \varepsilon_t^{logIP} \\ \varepsilon_t^{logAG} \\ \varepsilon_t^{logIF} \\ \varepsilon_t^{logMS} \\ \varepsilon_t^{EX} \\ \varepsilon_t^{IN} \end{pmatrix} \tag{5}$$

The terms μ_t^{logOP}, $\mu_t^{logCOMM}$, μ_t^{logIP}, μ_t^{logAG}, μ_t^{logIF}, μ_t^{logMS}, μ_t^{EX} and μ_t^{IN} are residuals in the reduced form disturbances to both the domestic and foreign variables and further represent unexpected movements (given information in the system) of each variable; and ε_t^{logOP}, $\varepsilon_t^{logCOMM}$, ε_t^{logIP}, ε_t^{logAG}, ε_t^{logIF}, ε_t^{logMS}, ε_t^{EX} and ε_t^{IN} are the structural shocks associated with the respective equations.

3.2 The Identification Restrictions

The $SVAR$ methodology suggests the imposition of restrictions on the contemporaneous structural parameters

only for reasonable economic structures to be derived. The work of Buckle et al. (2007) sets the foundation for the traditional $SVAR$ that forms the hybrid approach to structural identification. The main adjustments to the Buckle et al. (2002) model contain the incorporation of identifications to which restrictions' methodology is applied. The restrictions restrict attention to rotations that produces shocks that satisfy an anticipated sign in the responses of key variables (see Dungey & Fry, 2009). The traditional restrictions are denoted by "NA" (referred as αij in equation 5) and "0" for the contemporaneous and sluggish lagged relationships, respectively. A total of 36 zero restrictions were imposed on matrix A, which makes the covariance matrix of the reduced-form residuals restricted. The matrix A is the finite-order lag polynomial matrix that clearly demonstrates how the structural restrictions are being estimated with the diagonal constrained to be "1" and the B matrix is the diagonal matrix that is orthogonal (uncorrelated). Eight by eight matrices are formed using the AB-model of Amisano and Gianini (1997, 2012) to impose short run structural restrictions on the model given as:

$$
A=\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
NA & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
NA & 0 & 1 & 0 & 0 & 0 & 0 & NA \\
NA & 0 & NA & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & NA & NA & 1 & NA & 0 & 0 \\
NA & NA & 0 & 0 & NA & 1 & NA & 0 \\
NA & NA & NA & NA & NA & NA & 1 & 0 \\
0 & 0 & 0 & 0 & NA & NA & 0 & 1
\end{bmatrix}
\quad
B=\begin{bmatrix}
NA & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & NA & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & NA & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & NA & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & NA & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & NA & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & NA & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & NA
\end{bmatrix}
\tag{6}
$$

3.3 Data and Data Sources

The model consists of eight monthly time series data spanning a period of twenty years from 1994:1 to 2013:12. The study's starting period is the post-apartheid period and the cut-off dates are dictated by data availability. The data are obtained from the South African Reserve Bank (SARB), Statistics South Africa (Stat SA), World Bank's World Development Indicators (WDI) and the Quantec Database. The Aggregate Output Production (AG) (without industrial output production (i.e., GDP minus IP)) and Industrial Output Production (IP) represent the domestic activity and characterize the goods market in the economy. M2 is the Money Supply (MS) and captures the monetary aggregate while Exchange Rates (EX) is the official Rand to Dollar exchange rate as fixed by the Reserve Bank. They both represent our policy variables. The Interest Rate (IN) is the repo rate and the Consumer Price Index (CPI) is proxied to capture the inflation rate (IF) in the economy. Both variables also serve as instrumental variables in the control of the monetary authority. Finally, the global commodity price (COMM) and global oil price (OP) are the exogenous variables that are included to capture the open economy status of the country. All variables are expressed in natural logarithms except the interest rate and the exchange rates.

4. The Forecast Variance Decomposition

Raghavan and Silvapulle (2008) define variance decomposition as a percentage of a shock to a specific variable that is related to either its own innovations or those associated with other dependent variables, at various forecasted time horizons in a model. It analyzes the relative importance of shocks in explaining variations among variables. Therefore, the variance decomposition in this study will help to determine the effects of monetary policy on industrial output growth in South Africa. The monthly variables are allowed to affect each other over a longer period of time. However, we simplified the monthly period into quarterly periods (at 3, 6, 9 and 12 months) for convenient and easy interpretation of the results as shown below:

4.1 The Variance Decomposition of Industrial Output (IP)

From the Table 1, the first result explains the proportion of fluctuations to a given variable caused by different shocks to industrial output. In the first quarter in column 2 ($LogIP$), the industrial output responds contemporaneously to its own shocks with 92.75% variation, while other variables explain the remaining 7.25%. Of this 7.25% variation to industrial output, the inflation rate explains 3.43%; the oil price capturing the external influence explains 2.50%, while the remaining variables do not significantly contribute to the industrial output growth in South Africa. However, after six months (second quarter), the aggregate output ($Logag$) contributes 9.99%, the inflation rate explains 4.48% and the oil price explains 3.60% to the 80.44% explained by industrial output to its own variation. In addition, the aggregate output, exchange rate, inflation rate, money supply, and oil price appear to be playing an important role in explaining much of the variation in the industrial output growth in the third and fourth quarters, respectively, after a 12-month period. Therefore, the total analysis shows that $LogIP$ (response to its own variation), $LogIF$ and $LogOP$ significantly respond to variations in industrial output growth for the entire periods ($Q1 - Q4$) while $LogCOMM$ and IN were insignificant for the entire periods. $LogMS$ and EX were insignificant in the first and second periods but their variations to IP turned significant in the third

and fourth quarters, respectively. Also, $LogAG$ responds insignificantly to IP in the first quarter but it responded significantly in the other periods $(Q2 - Q4)$.

Table 1. Variance decomposition of IP

Period	S.E.	LogIP	LogAG	EX	LogIF	IN	LogMS	LogCOMM	LogOP
3	0.01617	92.7474	0.45558	0.46516	3.42881	0.05952	0.19248	0.15053	2.50045
6	0.01805	80.4366	9.98462	0.56124	4.47828	0.07113	0.19860	0.67401	3.59545
9	0.01983	69.4833	19.8501	1.31750	3.72541	0.24753	1.55794	0.68595	3.13214
12	0.02131	62.7563	23.2390	2.04018	3.31618	0.49512	4.81920	0.60892	2.72504

4.2 The Variance Decomposition of Aggregate Output (AG)

Industrial output shows 55.32% in explaining the variation in aggregate output, while for aggregate output, its own shocks shows 41.65% in the first quarter. The inflation rate only shows 1.20% as other variables do not contribute significantly to the variation in aggregate output. However, money supply and interest rates contribute significantly with 3.05% and 2.09% in the second quarter. Also, in the third quarter, industrial output contributes 27.60%. The aggregate output contributes 59.18% to its own lagged value (variation), the exchange rate contributes 1.19%, interest rate contributes 2.83% and money supply contributes 7.49%, totaling 98.29%, while other variables remain insignificant to the variations in aggregate output. However, in the fourth quarter, money supply shows 13.64%, the interest rate shows a 3.40% variation, exchange rate shows 3.28%, the industrial output shows 19.80% to the significant variation in aggregate output, and the aggregate output shows 58.35% to its own variation. Consequently, the total analyses of each variable response to aggregate output shows that $LogIP$ significantly contributes to the variation in aggregate output for all quarters while $LogOP\ and\ LogCOMM$ are insignificant. $LogMS$ and IN can be summed to show 75% (Q2-Q4) variations in explaining aggregate output while EX shows 50% (Q3-Q4) variations and $LogIF$ shows 25% (only in Q1).

Table 2. Variance decomposition of AG

Period	S.E.	LogIP	LogAG	EX	LogIF	IN	LogMS	LogCOMM	LogOP
3	0.00620	55.3178	41.6485	0.47651	1.19655	0.82465	0.14525	0.10881	0.28193
6	0.00866	35.6184	57.1509	0.63971	0.83452	2.08741	3.05377	0.21764	0.39765
9	0.01104	27.6004	59.1747	1.18598	0.82142	2.83294	7.48554	0.36012	0.53896
12	0.01321	19.7960	58.3518	3.27945	0.58628	3.40139	13.6364	0.41382	0.53493

5. The $SVAR$ Forecasting of Variables

The time series data used in a model is forecasted to determine the predictive power and accuracy of the structural VAR in an econometrics model. Following the graphical approach of Harvey (1989) and Batten and Thornton (1983), the out-of-sample forecasting is employed to show the different trend types that include seasonal components, trend components and irregular components. In the forecasting process, this study is largely based on the view of Diebold and Li, (2006, p. 253) to develop a regression model using time series data from 1994:01-2010:12 to estimate the model and sample data from 2011:01-2013:12 for the ex-post (all data have been identified) static and dynamic forecasting. The "root mean-squared error" serves as the benchmark for the evaluation of the forecasting value and the actual value (see Harvey, 1989; Clarida et al., 2003). The lower the root mean-squared error (value), the smaller the error margin line (gap between the actual value and the forecasted value), hence the more satisfactory the predictive power of the model. In contrast, the greater or the bigger the value of the root mean-squared error, the wider the gap between the actual value and the forecasted value and the lesser the satisfactory power of the model. The forecasting process further presented a line graph (figure) obtained with the use of the Eviews software and by a scientific method of Pair-wise correlation coefficient matrix (pwcorr) using STATA software. This method assists the study in verifying the true movement and correlation existence between the actual variable (value) and the forecasted variable in order to substantiate and confirm the predictive power of the model for policy recommendation. The detailed results obtained from the $pwcorr$ are shown in Appendix 2 and Appendix 3, respectively.

6. Static versus Dynamic Forecasting

In this study, combined forecasting is carried out to distinguish between the static and dynamic approaches using

the root mean-squared error as the benchmark. The combined forecasting technique was first introduced by Bates and Granger in 1969 and has since been applied by many researchers with the belief that it can improve predictive accuracy (see Clemen, 1989; Armstrong, 1989).

In general, static forecasting (simulation modelling) is based on current exposures and assumes a constant balance with no new growth. It uses actual rather than forecasted values (it can only be used when actual data are available). Conversely, dynamic forecasting relies on detailed assumptions regarding changes (increases or decreases) within the economy. It uses the previously forecasted values of the lagged variable. According to Menezes et al. (2000), reviewing both methods will lead to distinct preferences. In addition, Hibon and Evgeniou (2005) argue that the advantage of combined forecasts is not that the best possible combinations perform better than the possible individual forecasts, but that it is less risky, in practice, to combine forecasts than to select individual forecasting methods. The analysis of static and dynamic forecasting in this study will offer researchers the opportunity to choose from the two forecasting methods and select the most accurate or predictive approach that would provide useful information about future events.

6.1 The Static and Dynamic Forecasting of Industrial Sector Performance (IP)

The data estimates for industrial sector performance as an endogenous variable in the regression model ranges from 1994:01 to 2010:12. Figures 1a and 1c show the out-of-sample forecasting error for static and dynamic forecasting. In Figure 1a, the forecasting horizon is from 2011:01-2013:12 as the two red lines show a 95% confidence interval between the two (± 2) standard deviation error lines. The movement of $logipf$ within the confidence interval shows that the forecasting model is satisfactory as this is further confirmed by the lower value of 0.011209 as the root-mean squared error. Figure 1b illustrates the line figure to show the movement of $logip$ and $logipf$ for the static forecasting.

There was a co-movement in the actual and the forecasted values of industrial output (IP) for the forecast period. This is further confirmed by the $pwcorr$. It shows a strong positive correlation of about 94% between the actual and the forecasted value of the industrial sector's performance. Furthermore, the dynamic forecasting figures also have a lower root mean-squared error of 0.029469 and satisfactory predictive power as shown in Figure 1c and confirmed by the line Figure 1d for the co-movements of the actual and forecasted value of the industrial sector performance (output). The $pwcorr$ equally shows that a strong positive relationship (75%) exists between $logip$ and $logipf$.
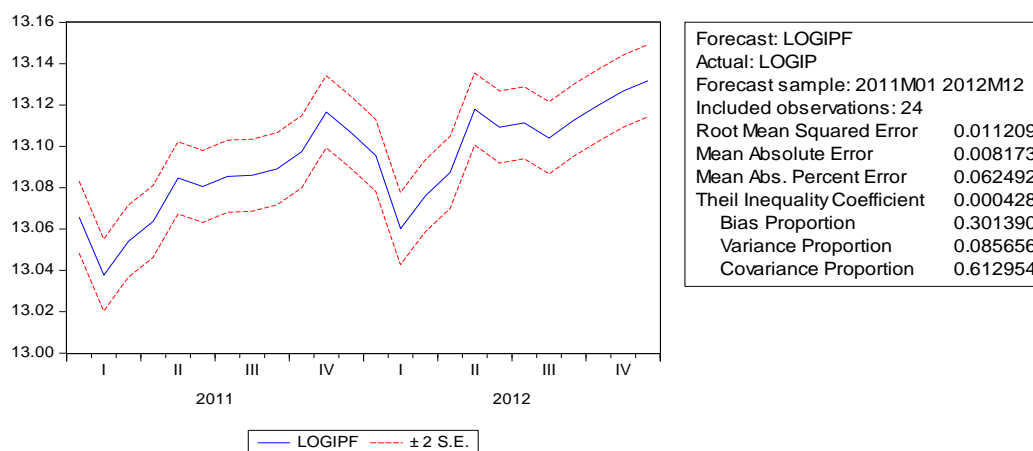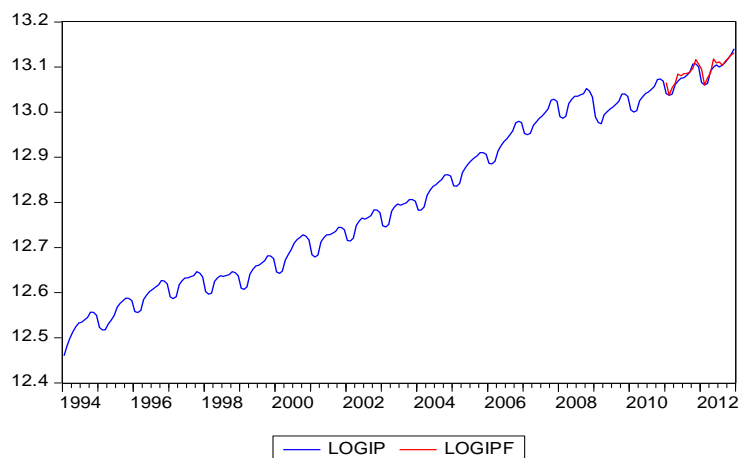

Forecast: LOGIPF	
Actual: LOGIP	
Forecast sample: 2011M01 2012M12	
Included observations: 24	
Root Mean Squared Error	0.011209
Mean Absolute Error	0.008173
Mean Abs. Percent Error	0.062492
Theil Inequality Coefficient	0.000428
Bias Proportion	0.301390
Variance Proportion	0.085656
Covariance Proportion	0.612954

Figure 1a. Static forecasting for LogIP

Figure 1b. Static line for LogIP

Forecast: LOGIPF	
Actual: LOGIP	
Forecast sample: 2011M01 2012M12	
Included observations: 24	
Root Mean Squared Error	0.029469
Mean Absolute Error	0.025689
Mean Abs. Percent Error	0.196464
Theil Inequality Coefficient	0.001125
Bias Proportion	0.620987
Variance Proportion	0.097093
Covariance Proportion	0.281920
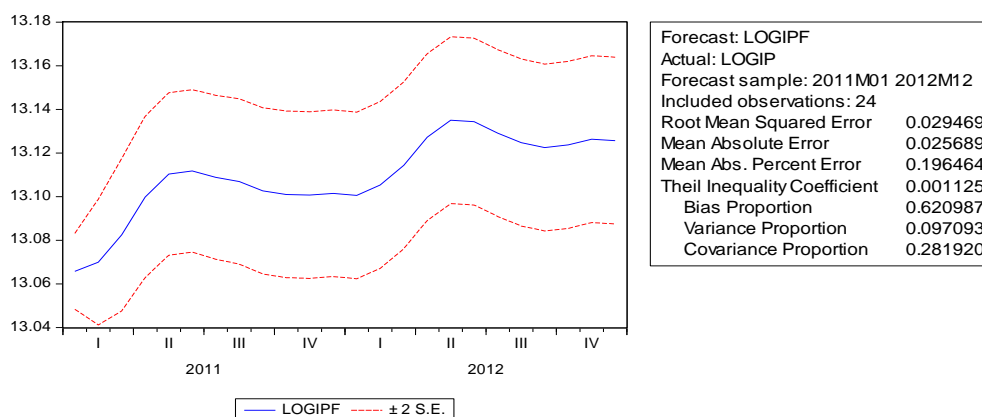
Figure 1c. Dynamic forecasting for LogIP
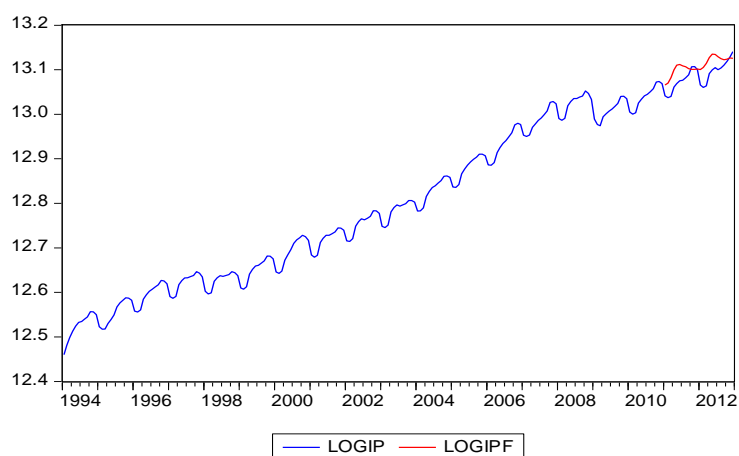
Figure 1d. Dynamic line for LogIP

6.2 The Static and Dynamic Forecasting of Aggregate Output (AG)

According to Figure 2a, the actual value of aggregate output and the forecasted value obtained from the static forecasting drifts together within the 95% confident interval. This equally shows the predictive and satisfactory power of the model, which is confirmed by the smaller value of the root-mean squared error of 0.003661. The movement is further substantiated in Figure 2b using the line and symbol figure. The $logag$ and $logagf$ move together throughout the forecasting horizon and thus further confirms the satisfactory and predictive ability of the

model utilized with a very strong positive correlation of 97% as indicated by the *pwcorr*.

On the other hand, the dynamic forecast has a root mean-squared error of 0.020323, which also indicates a satisfactory and predictive power for the model. Figures 2c and 2d show the movements of the actual and forecasted values of aggregate output and this has a strong positive correlation of 83% as shown by *pwcorr*.
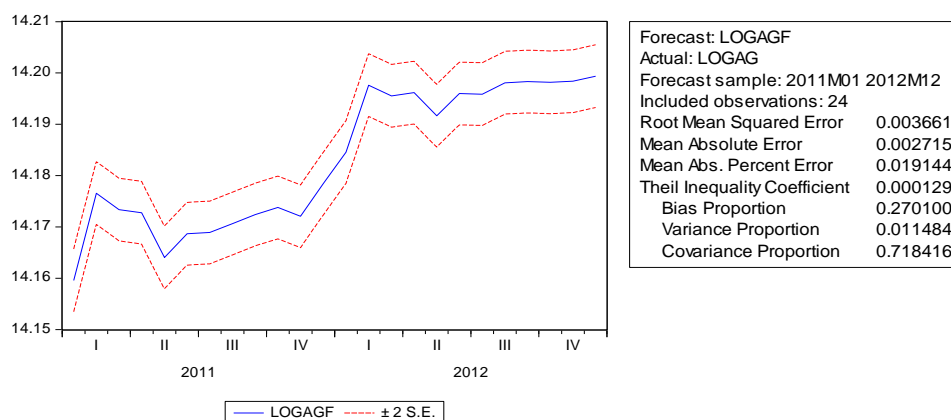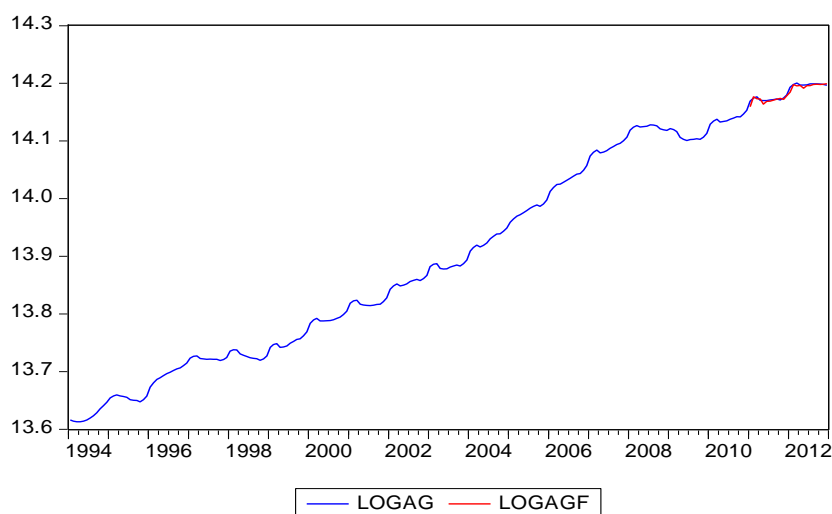

Forecast: LOGAGF	
Actual: LOGAG	
Forecast sample: 2011M01 2012M12	
Included observations: 24	
Root Mean Squared Error	0.003661
Mean Absolute Error	0.002715
Mean Abs. Percent Error	0.019144
Theil Inequality Coefficient	0.000129
Bias Proportion	0.270100
Variance Proportion	0.011484
Covariance Proportion	0.718416

Figure 2a. Static forecasting for LogAG

Figure 2b. Static line for LogAG

Forecast: LOGAGF	
Actual: LOGAG	
Forecast sample: 2011M01 2012M12	
Included observations: 24	
Root Mean Squared Error	0.020323
Mean Absolute Error	0.019001
Mean Abs. Percent Error	0.133934
Theil Inequality Coefficient	0.000717
Bias Proportion	0.874129
Variance Proportion	0.001434
Covariance Proportion	0.124437
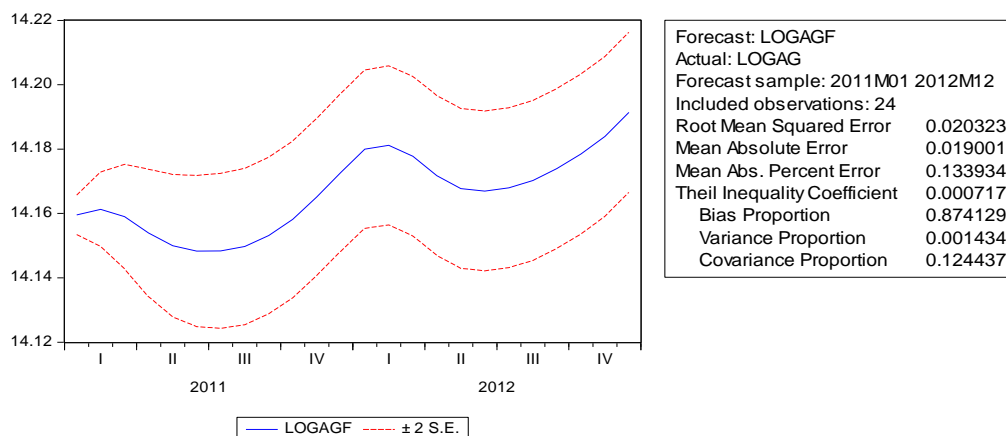
Figure 2c. Dynamic forecasting for LogAG
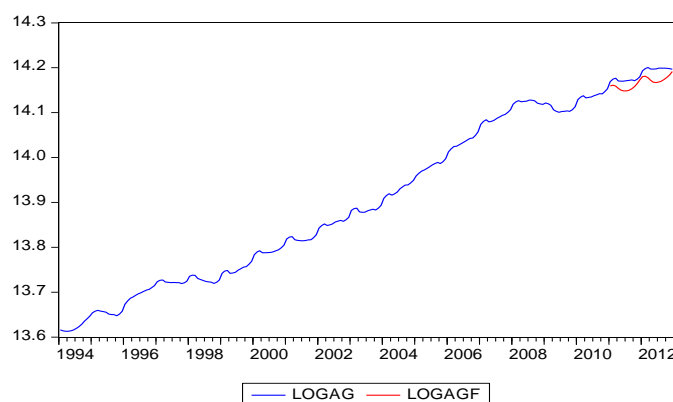
Figure 2d. Dynamic line for LogAG

6.3 The Static and Dynamic Forecasting of the Exchange Rate (EX)

The exchange rate as a policy variable also gives a good result. The predictive ability of the model is quite satisfactory with a root-mean squared error of 0.245802. Although, the value of the root-square mean is a bit higher and far from zero due to instability in the external value of the exchange rate system in the global market and the current depreciation of the external value of the Rand exchange rate. The predictive ability of the model used in this study was still satisfactory and can account for both variations in the domestic and external value of the currency (exchange rate system) as shown in Figure 3a. The satisfactory predictive power of the model is further confirmed in Figure 3b. The exchange rate and exchange rate forecast (ex and exf) move together in the same direction and the $pwcorr$ shows a 94% positive correlation between the actual value of the exchange rate and the forecasted value. However, the dynamic forecasting brought out the likely changes (increase or decrease) in the economy. The root mean-squared error was very high and far from zero (1.901262) as shown in Figure 3c. This is further confirmed in Figure 3d. The $pwcorr$ shows a strong negative correlation of 87% between ex and exf.
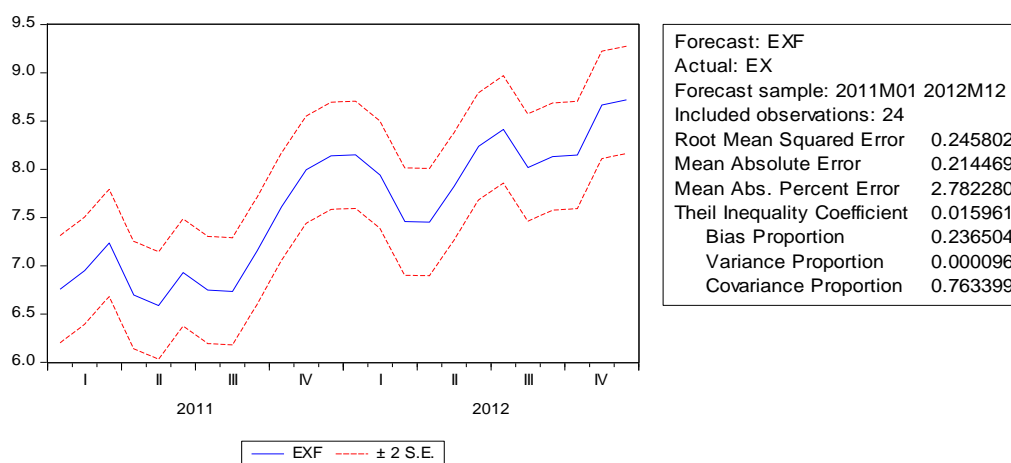
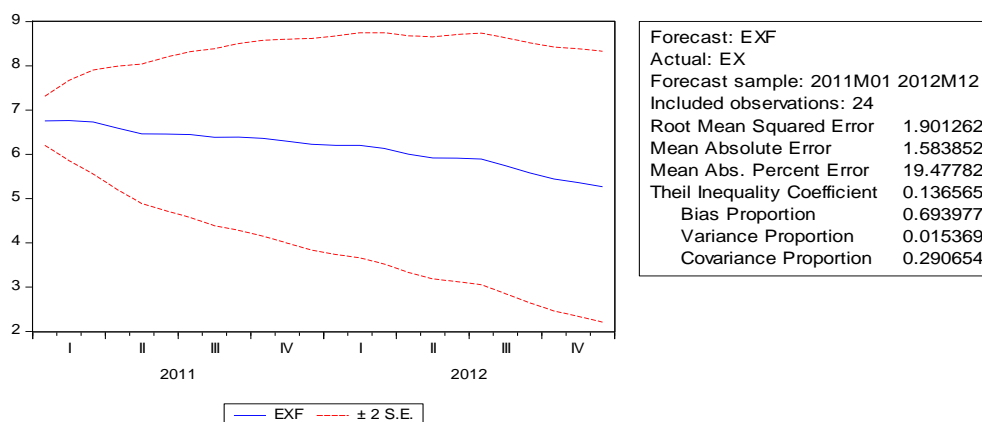Figure 3a. Static forecasting for EX
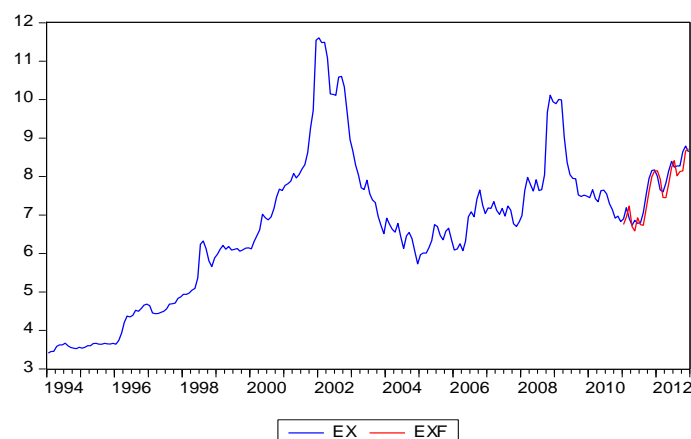
Figure 3b. Static line for EX

Forecast: EXF	
Actual: EX	
Forecast sample: 2011M01 2012M12	
Included observations: 24	
Root Mean Squared Error	1.901262
Mean Absolute Error	1.583852
Mean Abs. Percent Error	19.47782
Theil Inequality Coefficient	0.136565
Bias Proportion	0.693977
Variance Proportion	0.015369
Covariance Proportion	0.290654

Figure 3c. Dynamic forecasting for EX
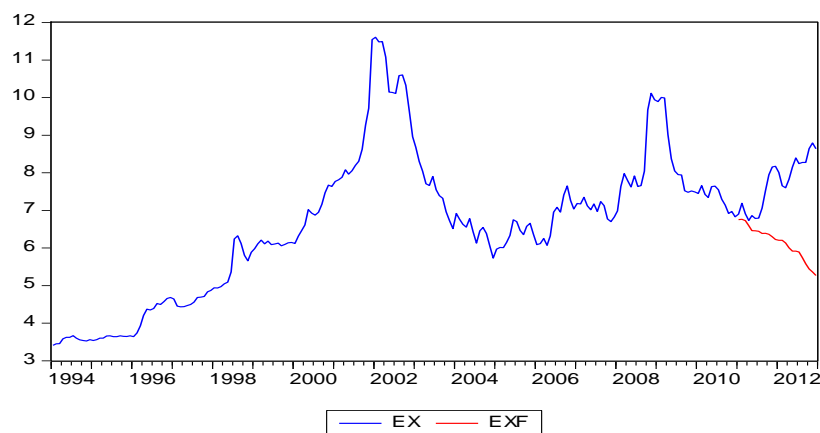
Figure 3d. Dynamic line for EX

6.4 The Static and Dynamic Forecasting of the Inflation Rate (IF)

The CPI is the proxy to capture the actual value of the $logif$ for data estimates in the $SVAR$ model. Figure 4a shows the movement of the $logiff$ along the 95% confidence interval. There is a close movement between the $logif$ and $logiff$, which indicates that there is a satisfactory forecasting ability of the model as confirmed by the lower value of the root-mean squared error of 0.004549. In addition, Figure 4b shows a clear picture to re-affirm

the predictive ability of the model and to confirm the strong positive correlation of 99%. This shows that the actual value of the inflation rate and the forecasted value move closely together. The dynamic forecasting has its root mean-squared error of 0.042398 as shown in Figure 4c. The line Figure 4d shows the co-movements between $logif$ and $logiff$ with 97% strong Pair-wise correlation coefficients $(pwcorr)$.
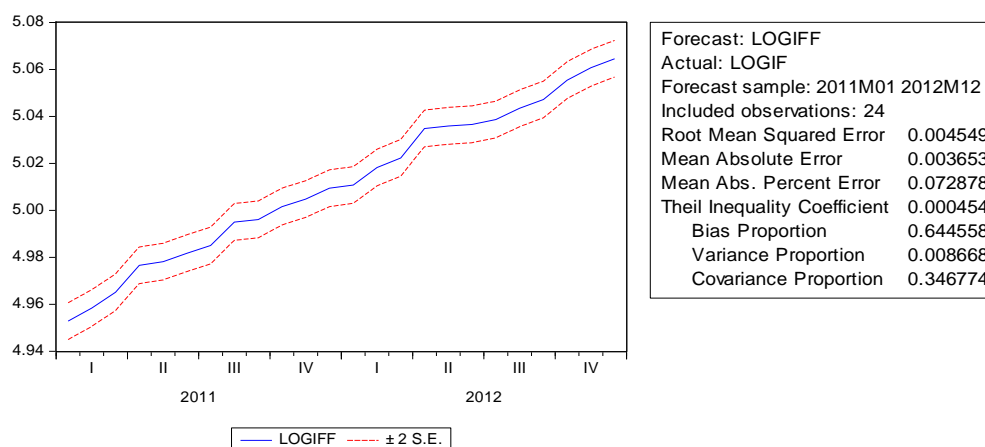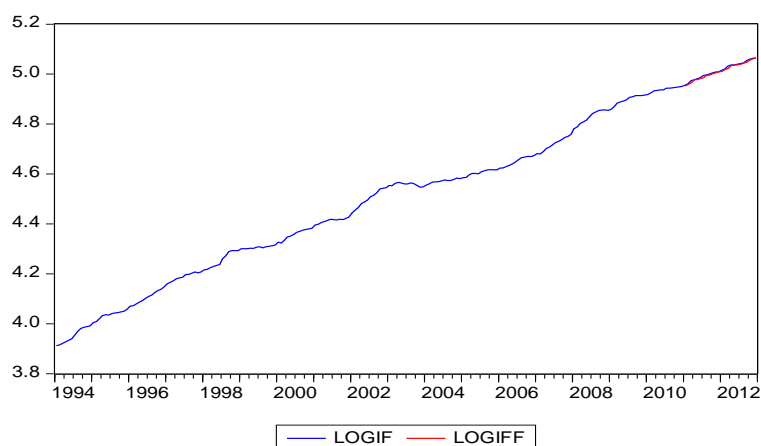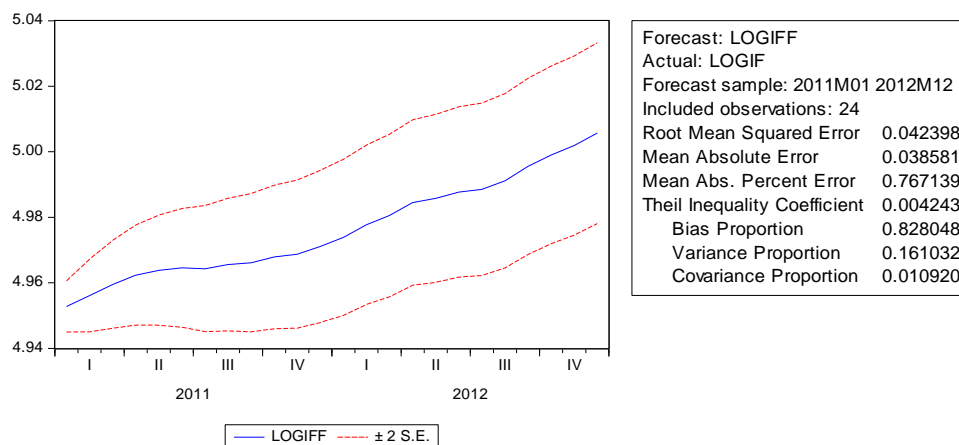

Figure 4a. Static frecasting for LogIF

Figure 4b. Static line for LogIF

Figure 4c. Dynamic forecasting for LogIF
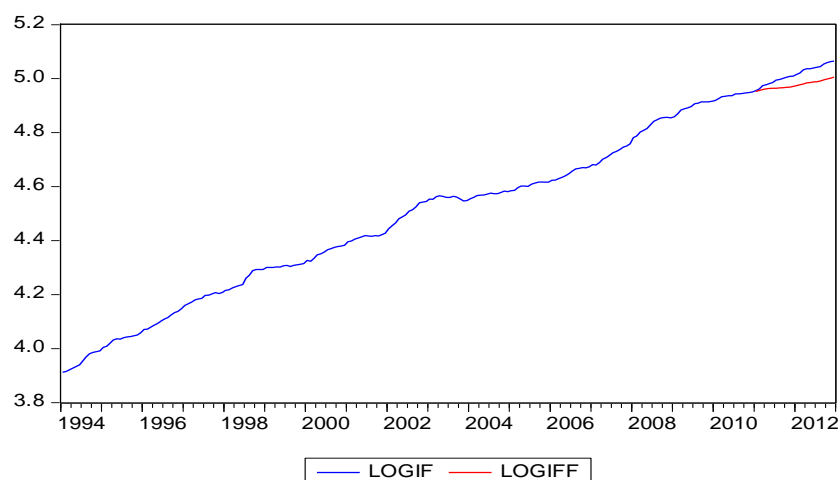
Figure 4d. Dynamic line for LogIF

6.5 The Static and Dynamic Forecasting of the Interest Rate (IN)

The frequent changes in the interest rate as a policy variable to control inflation in the economy give the root mean-squared a high value. The out-of-sample static forecasting model is nonetheless satisfactory in determining the movement of the actual and the forecasted values of the interest rate in the economy for the forecast horizon. IN and INF move together within the two standard deviation error lines as confirmed by the value of the root-mean squared error of 0.155570 as shown in Figure 5a. This means that the predictive ability of the model for the actual value and the forecasted value for the interest rate is satisfactory and can guarantee that the future rate can be set by the Reserve Bank within the economy. Figure 5b shows the co-movements of the variables and further confirms the ability of the model to predict the interest rate in the economy with a strong ($pwcorr$) positive correlation of 83%. However, the dynamic forecasting has a high root mean-squared error of 1.168728 as shown in Figure 5c and is thus capable of identifying the likely changes in the interest rate. Figure 5d shows the movement of in and inf. The $pwcorr$ shows a strong positive relationship of 84% between the actual value and the forecasted value of the interest rate in the economy.
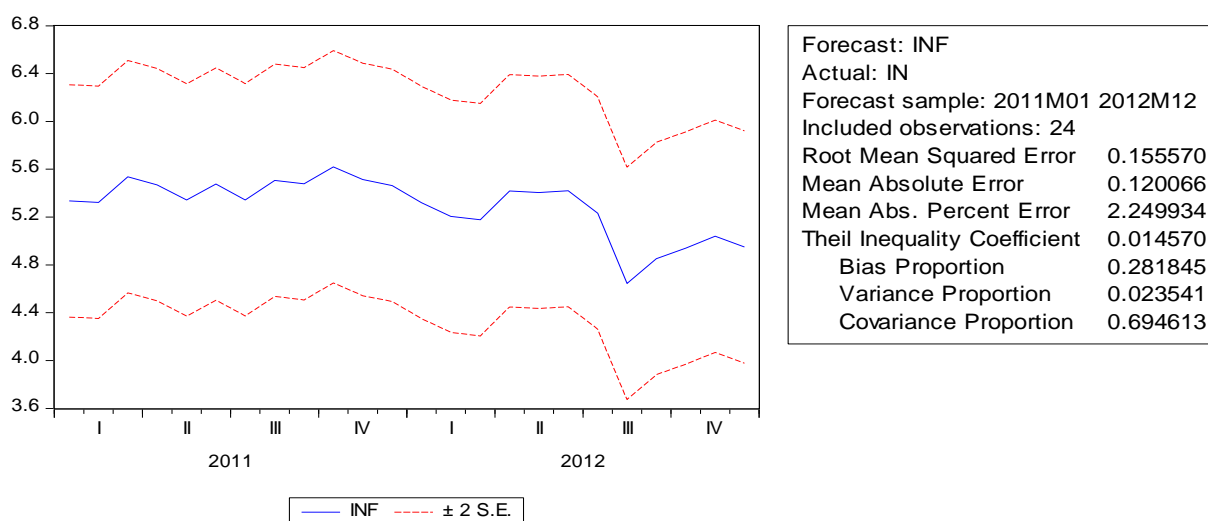

Forecast: INF	
Actual: IN	
Forecast sample: 2011M01 2012M12	
Included observations: 24	
Root Mean Squared Error	0.155570
Mean Absolute Error	0.120066
Mean Abs. Percent Error	2.249934
Theil Inequality Coefficient	0.014570
Bias Proportion	0.281845
Variance Proportion	0.023541
Covariance Proportion	0.694613

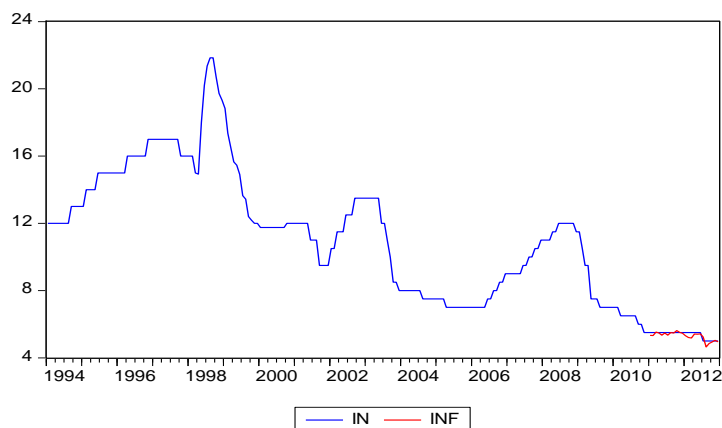Figure 5a. Static forecasting for IN
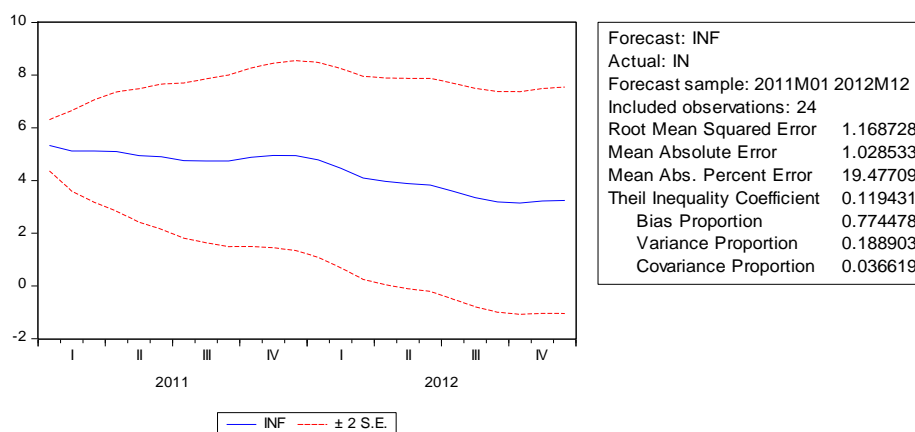
Figure 5b. Static line for IN
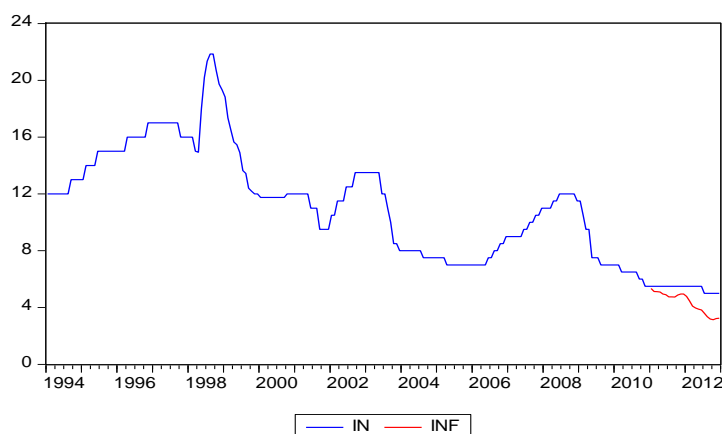

Figure 5c. Dynamic forecasting for IN

Figure 5d. Dynamic line for IN

6.6 The Static and Dynamic Forecasting of Money Supply (MS)

The forecasting power of money supply in the model is satisfactory as the actual value and predicted values move closely together. As illustrated in Figure 6a, the *logms* and *logmsf* move very close to each other along the two standard deviation error lines and this is further established by the small value of the root-mean squared error of 0.018489. Figure 6b shows the movements of *logms* and *logmsf* for the entire forecasting period with a 95%

strong positive relationship. On the other hand, the dynamic forecasting has a root mean-squared error of 0.093869 as shown in Figure 6c, hence the good predictive ability of the model. The line figure 6d shows the movements of the variables ($logms$ and $logmsf$). In addition, the $pwcorr$ shows a strong positive correlation of 95% between the actual and forecasted value of money supplies.
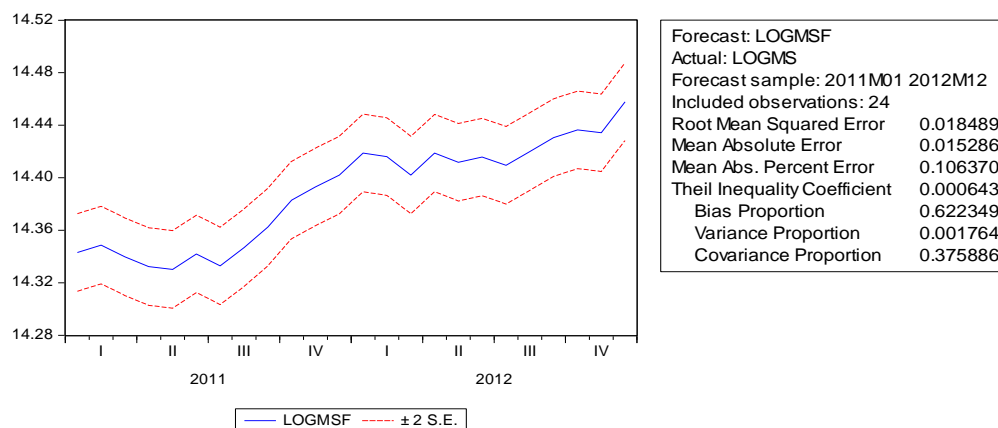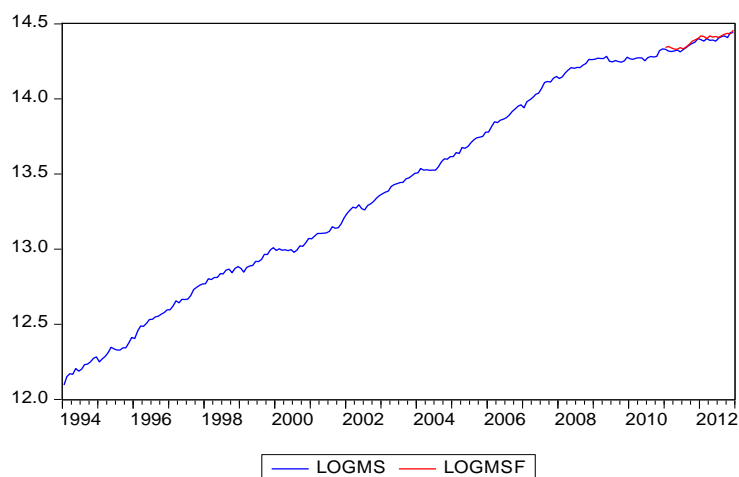

Figure 6a. Static forecasting for LogMS

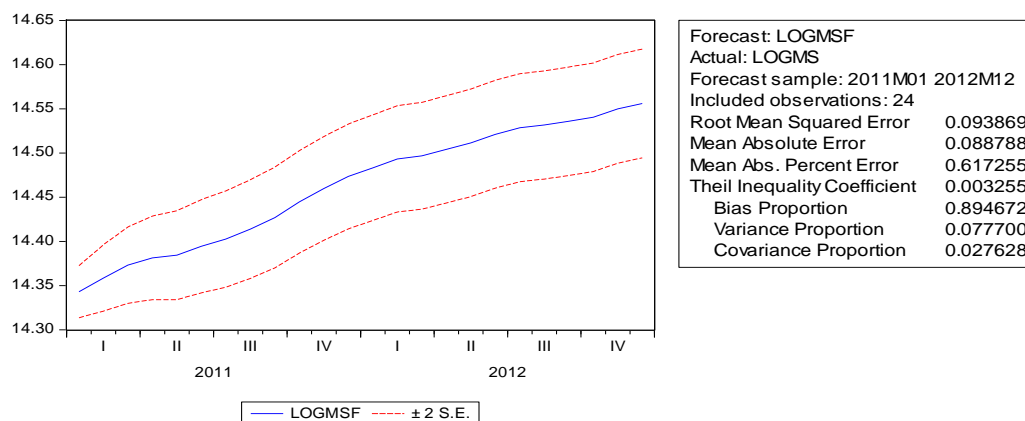Figure 6b. Static line for LogMS
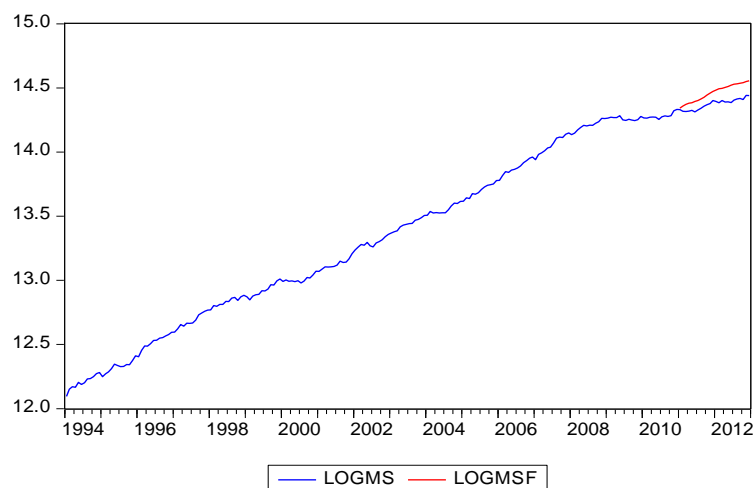

Figure 6c. Dynamic forecasting for LogMS

Figure 6d. Dynamic line for LogMS

6.7 The Static and Dynamic Forecasting of Commodity Prices (COMM)

This is the commodity price captured by South Africa's main exports and it represents an external variable that is shock responsive and that has an impact on the domestic variables. Based on the results obtained in Figure 7a, the $logcommf$ moves very closely within the two standard deviation error lines with a lower root mean-squared error of 0.010966, while Figure 7b shows the co-movements of the $logcomm$ and $logcommf$ for the whole static forecasting horizon. The benchmark for the forecasting confirms the satisfactory power of the model to predict future commodity prices. The $pwcorr$ also confirms a strong correlation of 92% between the actual value of commodity prices and the forecasted value. Furthermore, the dynamic forecasting has a root mean-squared error of 0.039149 as indicated in Figure 7c and the co-movements of $logcomm$ and $logcommf$ are shown in Figure 7d. The movements also show the satisfactory power of the model with $pwcorr$ coefficients of 51%.
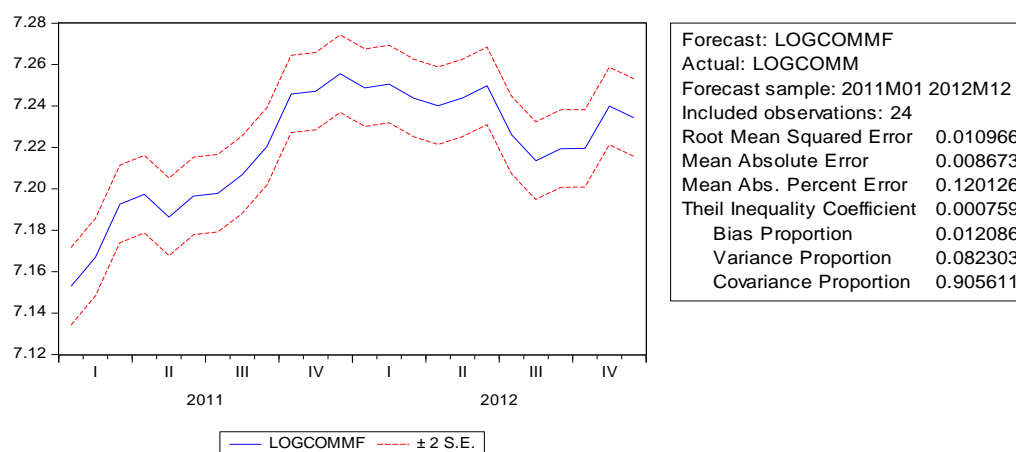

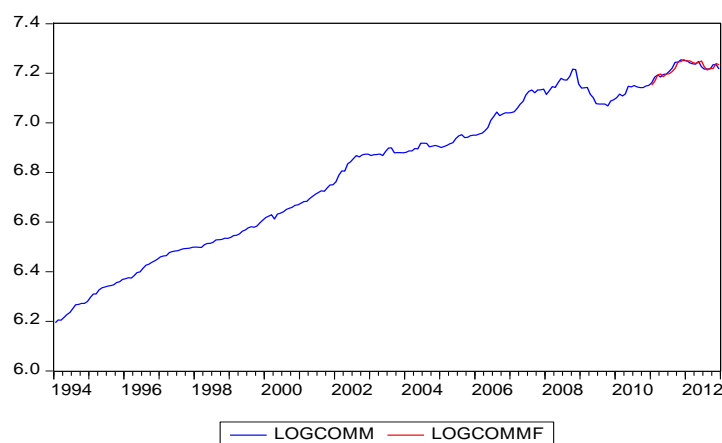Figure 7a. Static forecasting for LogCOMM
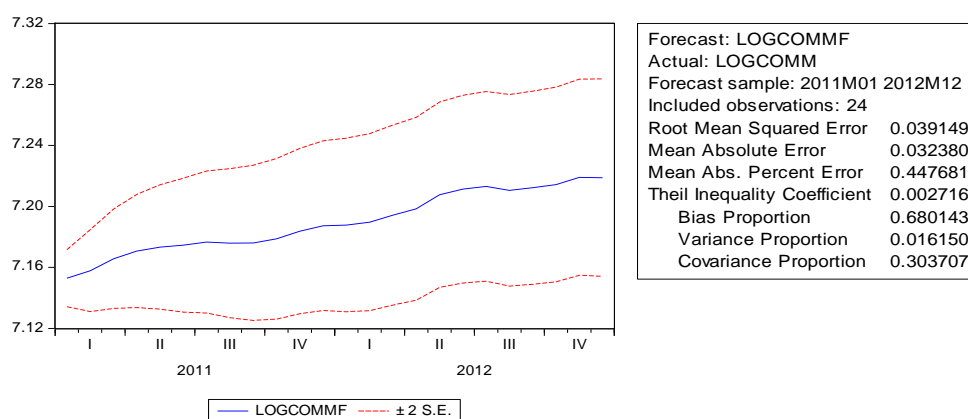
Figure 7b. Static line for LogCOMM

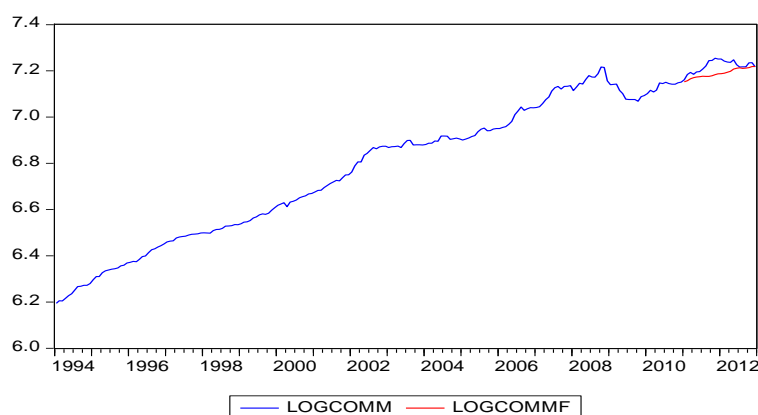Figure 7c. Dynamic forecasting for LogCOMM

Figure 7d. Dynamic line for LogCOMM

6.8 The Static and Dynamic Forecasting of Oil Prices (LogOP)

The oil price also captures the external shock from the global market that persistently affects domestic prices due to its spillover effects. An increase in the price of oil also leads to an increase in domestic prices. In the results presented, by estimating the model the figures show up-spring and down-spring movements of the actual and forecasted values. In Figure 8a, the *logopf* moves within the two standard deviation error lines within the 95% confidence interval. The low root mean-squared error of 0.052861 shows the predictive power of the model to be satisfactory. Furthermore, Figure 8b shows that *logcomm* and *logcommf* are moving closely together for the forecasting periods with a strong positive correlation of 69%. Moreover, the dynamic forecasting has a root

mean-squared error of 0.098685 as shown in Figure 8c and by the covariance of the variables in Figure 8d, the actual value of the oil price and the forecasted value drifts together. However, the *pwcorr* shows a weak negative relationship of −0.1243 between *logop* and *logopf*. This conforms to the literature, that dynamic forecasting facilitates the generation of changes (increases or decreases) within the economy and provides small forecasting improvements compared to static forecasting (see details in Schumacher & Breitung, 2008).
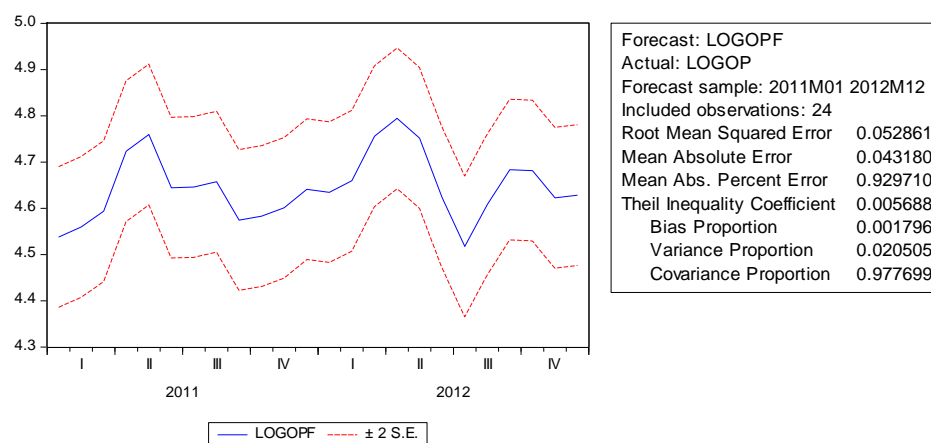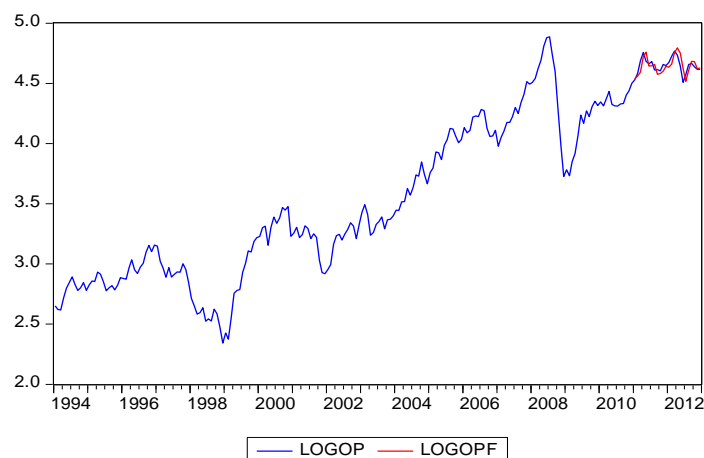
Figure 8a. Static forecasting for LogOP
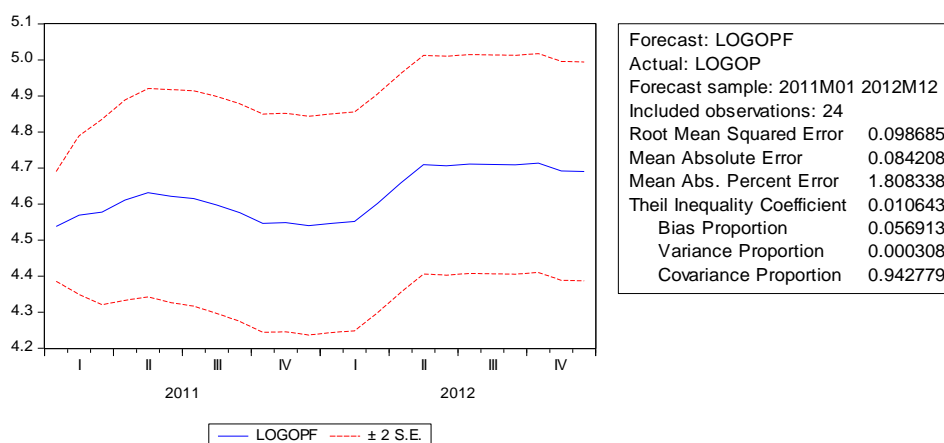
Figure 8b. Static line for LogOP

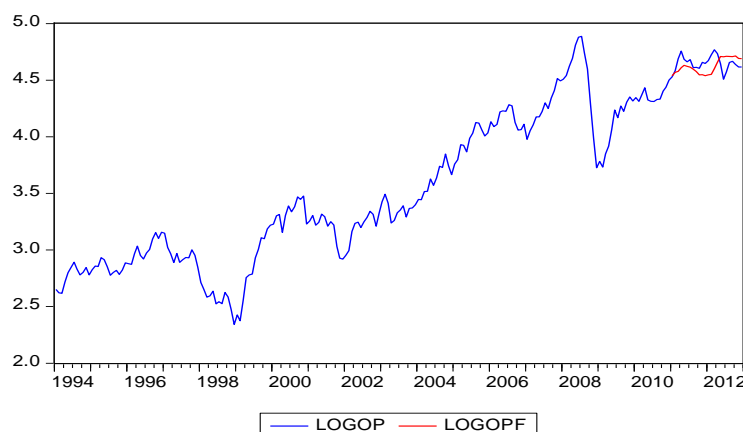Figure 8c. Dynamic forecasting for LogOP

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Figure 8d. Dynamic line for LogOP

7. Conclusions

The main aim of this study is to examine the impact of monetary policy shocks on output growth in South Africa and also forecast the predictive power of the model in assisting monetary authorities to cope with uncertainties in the future. After estimating the *SVAR* equation, the estimated model passes through structural imposition of restrictions, the variance decomposition analyses and several forecasting processes in order to forecast and predict South African data to achieve the objectives of the study.

The results from the variance decompositions of the macroeconomic variables are presented in Table 1 and Table 2. The results show that the interest rate and the commodity prices are the only variables found to be insignificant in explaining the variations in industrial output for all the months (Q1-Q4). The impacts of an unexpected change in the South African monetary policy on output (both industrial output and aggregate output) show a temporary impact of an upward and downward spring of monetary variables and global oil price shocks to the economy. The exchange rate, inflation and money are found to significantly impact output growth in the long run as well as the global oil price. The impact of interest rates to changes in industrial production remains below 1% in all periods. This may indicate that industrial producers in South Africa are not constrained by the cost of credit in their production of goods and services. Nonetheless, since oil price shock has an impact on economic activities and could negatively affect output growth, the policy recommendation suggests a continuous diversification of the economy and also that the monetary policy action should factor in the leading indicators of global prices and economic activity, taking into account the various channels, especially the exchange rate, for the forecast horizon (period).

Finally, the analysis from static and dynamic *SVAR* forecasting shows the analysis of trends in order to direct future trends and to direct policy response to stimulate output growth. Dynamic forecasting has a more robust result than static forecasting. It clearly brings out the growth patterns (increase and decrease) and can be justified and recommended to policymakers in calculating or in predicting the outcome of monetary policy actions for future development. However, the implication of the recommendation for the use of dynamic forecasting is the associated risk and uncertainty that might be central to its prediction, it's expected reliability and attributes (see Sohn, 1997), which are essential to its success and failure. Therefore, it will generally be a good practice if a combined (static and dynamic) forecasting technique is employed in order to compare and validate the degree of uncertainty attached to the model when forecasters are uncertain about the situation, uncertain about which method is most accurate, avoid large errors and draw from different sources of information in an attempt to stimulate output growth in the economy.

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Appendix 1

Results of Variance Decomposition of all the Variables

Table 1. Variance decomposition of logIP

Period	S.E.	LogIP	LogAG	EX	LogIF	IN	LogMS	LogCOMM	LogOP
1	0.008875	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.013963	96.78180	0.030355	0.244777	1.726532	0.045114	0.197805	0.036831	0.936790
3	0.016178	92.74746	0.455585	0.465166	3.428809	0.059522	0.192477	0.150533	2.500449
4	0.016785	88.39537	2.185483	0.529521	4.619696	0.060791	0.181627	0.351888	3.675628
5	0.017267	84.26276	5.692285	0.500922	4.843747	0.058531	0.173973	0.559361	3.908424
6	0.018055	80.43667	9.984623	0.561241	4.478277	0.071127	0.198603	0.674008	3.595451
7	0.018817	76.57377	14.00705	0.765910	4.125327	0.109127	0.370419	0.706871	3.341532
8	0.019370	72.76509	17.36960	1.044421	3.904242	0.170862	0.811455	0.704047	3.230283
9	0.019830	69.48337	19.85015	1.317502	3.725407	0.247533	1.557938	0.685951	3.132143
10	0.020322	66.92833	21.43946	1.554027	3.557875	0.329092	2.535319	0.659643	2.996248
11	0.020836	64.81180	22.45167	1.778640	3.422034	0.411189	3.640432	0.632243	2.851993
12	0.021319	62.75630	23.23905	2.040187	3.316175	0.495122	4.819203	0.608923	2.725039

Table 2. Variance decomposition of logAG

Period	S.E.	LogIP	LogAG	EX	LogIF	IN	LogMS	LogCOMM	LogOP
1	0.003085	77.48383	22.51617	4.88E-27	1.45E-32	1.74E-30	5.62E-28	1.05E-29	4.58E-29
2	0.005058	67.59600	30.76214	0.233060	0.788784	0.394393	0.004059	0.058007	0.163556
3	0.006198	55.31778	41.64852	0.476512	1.196554	0.824647	0.145252	0.108812	0.281926
4	0.006949	44.11716	51.60564	0.627367	1.161870	1.341528	0.756394	0.150134	0.239899
5	0.007750	38.00727	56.37699	0.654785	0.934512	1.780316	1.817465	0.183258	0.245403
6	0.008655	35.61838	57.15093	0.639709	0.834515	2.087411	3.053767	0.217635	0.397649
7	0.009528	33.59041	57.34906	0.677145	0.855914	2.339638	4.372244	0.262062	0.553527
8	0.010310	30.78635	58.17517	0.840124	0.869218	2.588930	5.832682	0.313409	0.594125
9	0.011036	27.60037	59.17467	1.185978	0.821423	2.832936	7.485542	0.360122	0.538960
10	0.011753	24.57400	59.68210	1.733694	0.737539	3.054348	9.346160	0.392526	0.479639
11	0.012476	21.94962	59.40347	2.451849	0.654584	3.244352	11.40893	0.408955	0.478249
12	0.013206	19.79598	58.35179	3.279454	0.586282	3.401386	13.63636	0.413820	0.534933

Appendix 2

Detail Results of Static Forecasting of Variables

. pwcorr logip logipf

```
         |    logip    logipf
-------------+-----------------
      logip | 1.0000
     logipf | 0.9410    1.0000
```

. pwcorr logag logagf

```
         |    logag    logagf
-------------+-----------------
      logag |1.0000
     logagf | 0.9716    1.0000
```

. pwcorr ex exf

```
         | ex        exf
-------------+-----------------
      ex |1.0000
     exf|0.9470      1.0000
```

. pwcorr logif logiff

```
         | logif        logiff
-------------+-----------------
    logif |1.0000
    logiff|0.9965      1.0000
```

. pwcorr in inf

```
         |   in       inf
-------------+-----------------
      In| 1.0000
     Inf| 0.8385    1.0000
```

. pwcorr logms logmsf

```
         |logms       logmsf
-------------+-----------------
   logms |1.0000
   logmsf |0.9591      1.0000
```

. pwcorr logcomm logcommf

```
         | logcomm logcommf
-------------+-----------------
 logcomm |1.0000
logcommf | 0.9201      1.0000
```

. pwcorr logop logopf

              | logop   logopf

-------------+------------------

       logop |1.0000

      logopf |0.6931   1.0000

Appendix 3
Detail Results of Dynamic Forecasting of Variables

. pwcorr logip logipf

              | logip   logipf

-------------+------------------

       logip | 1.0000

      logipf | 0.7509   1.0000

. pwcorr logag logagf

              | logag   logagf

-------------+------------------

       logag |1.0000

      logagf |0.8337   1.0000

. pwcorr ex exf

              | ex   exf

-------------+------------------

          ex | 1.0000

         exf |-0.8704   1.0000

. pwcorr logif logiff

              |logif   logiff

-------------+------------------

       logif |1.0000

      logiff |0.9794   1.0000

. pwcorr in inf

              | in   inf

-------------+------------------

          In|1.0000

         Inf|0.8406   1.0000

. pwcorr logms logmsf

              | logms   logmsf

-------------+------------------

       logms |1.0000

      logmsf |0.9540   1.0000

. pwcorr logcomm logcommf

```
         | logcomm logcommf
-------------+------------------
Logcomm|1.0000
logcommf|0.5171    1.0000
```

. pwcorr logop logopf

```
         |logop    logopf
-------------+------------------
   logop |1.0000
  logopf |-0.1243   1.0000
```

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