

Monetary Policy Transmission Mechanism in Kenya: A Bayesian Vector Auto-regression (BVAR) Approach¹ Benjamin Maturu² and Lydia Ndirangu

Abstract

This study revisits the enduring empirical question about how monetary policy is transmitted in Kenya. Using quarterly data to estimate a Bayesian vector autoregressive (BVAR) model with the Kalman filter while taking into account a number of analytical innovations, we obtain results that are consistent with the stylized facts regarding monetary policy transmission mechanism in small open economies. For instance, although the magnitude of direct effects of changes in the central bank rate, which is the monetary policy interest rate, on prices and real output are rather small, the effects are statistically significant and they are of the expected extent of persistence on output and prices. Besides that, these empirical results suggest that the central bank rate is an effective instrument of signalling monetary policy. Therefore the interest rate channel of monetary policy transmission was operational in Kenya during the period 2008Q1-2012Q and it is expected to be in the future, barring significant economic transformations and major domestic and external shocks, considering that the results are robust to variation in the estimation sample.

Most importantly, we find that, on average, for every 30 basis points of monetary policy tightening using the policy rate, a 1 basis point reduction in the headline consumer price index could be achieved. However, the 30 basis points of monetary policy tightening would also penalize the economy to the extent of 0.6 basis points of reduced real output. The output-price stabilization trade-off resultant from a sudden 1 standard deviation of monetary policy tightening is 10:6. Thus, the monetary policy tightening comes with a net gain in price stability. This may owe to the efficacy of the expectations channel of monetary policy transmission mechanism. The order of importance of the monetary policy transmission channels is as follows: the interest rate, the exchange rate, the money and bank credit channel. The bank credit channel is relatively more important over the short to medium term period of 2½ years. Beyond this period, the exchange rate channel overtakes the bank credit channel.

The study also shows that most of the fluctuations in the headline consumer price index are due to the headline consumer price index's own past innovations. So inflation seems to have a strong inertia component. This implies that once headline inflation sets in, it tends to entrench itself over a long period of time. Thus the need for the close monitoring of the evolution of the headline consumer price index inflation so as to take timely pre-emptive monetary policy action for effective control over inflation. Otherwise, it is a daunting task trying to control headline consumer price index inflation using monetary policy tools when such inflation has been predominantly driven by real supply shocks.

Another important finding is that the Marshall-Lerner Condition did not hold during the study period. The response of real output to an exchange rate shock implies that a depreciation of the shilling permanently exacerbates the current account deficit.

Keywords: *Monetary policy transmission mechanism, Bayesian vector auto-regression (BVAR) Model, Kalman filter, Headline consumer price index, Channels of monetary policy transmission*

JEL Classification: *E52, F42, O55*

1. Introduction

Monetary policy transmission mechanism relates to the effects of monetary policy on output and prices as well as seeking to appreciate the relative importance of the channels of monetary policy transmission mechanism continues to be a major motivation for carrying out empirical analysis of monetary policy transmission across many countries in support of effective monetary policy management. A key general finding from the numerous past monetary policy transmission mechanism studies is that monetary policy is transmitted through many channels and that policy effects on output and the prices involve varied delays. Usually, the peak effect on output precedes the effect on prices. Moreover, the effect on output is short-lived compared to the relatively more persistent and permanent effect on prices. As to the actual timing of when the policy effects befall output and prices and what the magnitude of effects involved are, the results vary across countries as well as across time for any given country. This therefore underscores the need for carrying out country-specific monetary policy transmission mechanism studies.

Empirical analysis of monetary policy transmission mechanism provides policy makers with current information regarding the relative importance of channels of monetary policy transmission as well as estimates of the magnitude and timelines of impact of an unanticipated monetary policy action on output and prices. Using the study findings, policy makers decide, as the need arises, on the appropriate amount and timing of policy action aimed to checking undesirable economic stability prospects. The appropriateness of the policy action, for instance, entails choosing suitable policy instruments in line with the empirical results which show the relative importance of the channels of monetary policy transmission mechanism. This way, the practical monetary policy management question about which policy instruments should be used and what the optimal amount of change in the instruments to check anticipated undesirable output and price instability should be is addressed. Clearly, therefore, understanding the monetary policy transmission mechanism is certainly useful to policy makers and, for this reason, virtually all established central banks have studied the monetary policy transmission mechanisms in their respective countries. In some instances, past studies are updated to take into account significant changes in economic structure as well as incorporating the influence of significant economic shocks.

Like many modern central banks, the Central Bank of Kenya (CBK) has, in the past, studied the monetary policy transmission mechanism in Kenya and, from time to time, it updates the available evidence. Examples of these studies include Cheng (2006), Maturu (2007), Maturu, Maana and Kisinguh (2010), Sichei and Njenga (2012), and Davoodi, Dixit and Pinter (2013). The evidence from these studies suggests that the money, interest rate, exchange rate and credit channels were operational during varied study periods with various strengths. Cheng (2006), for instance points that the interest rate channel was weak during in 1997-2005 because of financial sector rigidities. In their empirical analysis using monthly data covering the period 2000-2010, Davoodi, Dixit and Pinter (2013) show that the credit channel is important in complementing the money and interest rate channels.

In this study, we update the available evidence using quarterly data for the period 1997Q4-2012Q3. The use of quarterly data avoids the criticism which is sometimes levelled against empirical results derived from monthly interpolated data. The plausibility of such results is difficult to establish in the event of any inconsistencies arising in the empirical results as one would attribute such inconsistencies to the “synthetic” data or model misspecification. Of course using quarterly data glosses over the finer details of monetary policy transmission mechanism such as the precise timing of when monetary policy effects on output and prices occur.

In view of the limited degrees of freedom which would lead to over-fitting of coefficients in the unrestricted VAR, we use a Bayesian vector auto-regression (BVAR) model and therefore augment the limited observed data with a prior joint probability density function of the parameters to be estimated thereby ensuring that the model parameters are efficiently estimated. Another important analytical innovation that we have considered in this study is that we have used seasonally unadjusted data. Most studies use seasonally adjusted data to control for too much volatility in estimated impulse response functions that arise from the seasonal effects in seasonally unadjusted data. In this study, we control for seasonal effects in the seasonally unadjusted data by explicitly incorporating seasonal dummies in the estimable BVAR model. By explicitly modelling seasonality, we estimate the effect of seasonal factors on the empirical results and we also avoid the problem of non-constancy of historical seasonally adjusted data because whenever seasonally adjusted data is updated using such smoothing procedures as the Hodrick Prescott filter, past realisations for the seasonally adjusted data end up being revised with every update. It is also preferable that one models the endogenous variables in a form that is amenable to recovery of the original form of the data following simulations carried out using the estimated model. It can be challenging, however, if not impossible, to recover model forecast data in the form that corresponds to observed data when seasonally adjusted data is used in empirical analysis.

We also take into account that Kenya’s open economy is susceptible to external economic developments such as the global financial and economic crises of 2007/2008. We therefore control for the effect of trends in external economic and financial environments in the analysis.

Upon taking into account all these analytical innovations, we obtain results that are consistent with the stylized facts regarding monetary policy transmission mechanism in small open economies. Although the magnitude of direct effects of changes in the central bank rate (CBR), which is the monetary policy interest rate, on prices and real output are rather small, the effects are statistically significant and they are of the expected extent of persistence on output and prices. Besides that, these empirical results suggest that the CBR is an effective instrument of monetary policy. Therefore, the interest rate channel of monetary policy transmission mechanism was operational in Kenya during the period 2008Q1-2012Q3 and it is expected to be in the future, barring significant economic transformations and major domestic and external shocks, considering that the results are robust to variation in the estimation sample.

The other key result is that most of the fluctuations in the headline CPI are due to the headline CPI’s own past innovations, partly reflecting past policies and other determining factors. These imply that

there has been substantial inertia in the headline CPI inflation. As such, once headline inflation sets in, it tends to entrench itself over a long period of time. This therefore calls for total vigilance on the evolution of the headline CPI inflation so as to take timely pre-emptive monetary policy action for effective control over inflation. Otherwise, it must be a daunting task trying to control headline CPI inflation using monetary policy tools when the headline CPI inflation is predominantly driven by real supply shocks.

The paper is organised into 6 sections. A brief review of the literature and some background to Kenya's economy is provided in section 2. In order to put the BVAR model into perspective for the ease of appreciation of the analytical basis of the empirical results, we briefly describe the model in section 3 upon which we specify the estimable model in section 4. Empirical results and discussions are presented in section 5. Section 6 summarises the results and concludes.

2. Brief Review of the Literature

Among the studies carried out by the CBK in the recent past include Maturu (2007), Maturu, Maana and Kisinguh (2010), Misati *et al.* (2010) and Sichei and Njenga (2012). Other studies include Davoodi, Dixit and Pinter (2013) and Cheng (2006) in the IMF. A key result emanating from most of these studies is that monetary policy transmission through the interest rate channel has been weak and that monetary policy involved a transmission lag of between 1 to 2 years. The other channels of policy transmission found to have been important include the credit and the exchange rate. It is also inferred from such studies as Maturu, Maana and Kisinguh (2007) that the expectations channel of monetary policy transmission has also been important.

A one-off dependable empirical analysis of the transmission mechanism of monetary policy suffices, if and only if a country's economic structure remained unchanged and it was sufficiently insulated from being buffeted by domestic and external shocks. In reality, however, countries experience major economic transformations and can also be rocked by domestic and external shocks from time to time. It is imperative, under such circumstances, that existing evidence on monetary policy transmission mechanism be updated. Kenya continues to enjoy tremendous technological progress in the financial sector and as Misati *et al.* (2010) has shown, such innovations have had significant implications for monetary policy transmission in the country.

Technological progress in Kenya's financial sector continues with the notable innovations being adoption of electronic-banking and mobile banking. Kenya has also adopted the real time gross settlement and payments system. In terms of institutional development, deposit taking micro-finance institutions, agency banking and credit rating agencies have also been licensed in the recent past and continue to be operational. All these developments have promoted financial deepening and inclusion, whereby many hitherto unbanked residents in Kenya do enjoy access to financial services thereby enhancing monetization of Kenya's economy with huge potential for enhanced efficiency in monetary policy transmission.

There also have been changes in data compilation methods and revision of baskets of key statistics including the gross domestic product (GDP) and the CPI in recent past. These changes have potential to influence monetary policy transmission outcomes considering that they have the potential of inducing significant, though intermitted, structural breaks in data. Similar effects on the empirical analysis are expected to occur because of changes in the conduct of monetary policy including changes in the cash ratio requirements as was done, for instance, in June 2003 and on a number of other occasions thereafter. The change in 2003 caused a sudden increase in bank reserves with implication for output and price stability and the effectiveness of monetary policy in the country.

There also have been major developments in the global economic environment such as the 2007/2008 global financial and economic crises that induced significant shocks for most open economies including Kenya. Such shocks need to be taken into account in empirical analysis of monetary policy transmission. Above all, improvements continue to be witnessed in the analytical tools. Applications of such improved tools lead to improved evidence to support effective monetary policy management.

In terms of methodological considerations, it has been observed in past studies that use of quarterly data is consistent with the medium term period over which monetary policy management is focused. It is therefore common to find that most studies on monetary policy transmission, especially among industrialized countries, tend to apply quarterly data. Perhaps this is also because quarterly data is readily available for sufficiently long time spans to support this kind of analysis which is data-intensive as large degrees of freedom are necessary. Using monthly data is also useful for the avoidance of grossing over short run monetary policy transmission features. For this reason a number of studies use monthly data. It is expected that the challenge of seasonality effects is however aggravated when one uses higher frequency data such as the monthly, and this explains preference for using seasonally adjusted data in most of the past studies on monetary policy transmission mechanism.

In order to efficiently estimate a large vector autoregressive (VAR) model, for a comprehensive unified empirical analysis of the many channels of monetary policy transmission, recent studies including Davoodi, Dixit and Pinter (2013) have resorted to using Bayesian model estimation techniques. Bayesian estimation overcomes the limitation of inadequate degrees of freedom which leads to over-fitting of the VAR coefficients much to the detriment of out-of-sample forecasting based on the VAR model. Under Bayesian VAR model estimation, one augments observed data by using prior information about the parameters to be estimated so as to circumvent the challenge of inadequate degrees of freedom. The prior information, which is summarized into a prior joint probability density function of the parameters to be estimated, is combined with the observed data in line with Bayes' Theorem to yield a posterior joint probability density function of the coefficients which are then integrated out as posterior means.

3. Model Description

3.1. The Vector Auto-regression (VAR) Model

We generally follow the succinct specification of the vector auto-regression model as the bivariate VAR advanced by Racette and Raynauld (1990) and latter applied by Racette, Raynauld and Sigouin (1994) to the Canadian economy. Since the immediate purpose of the model we formulate in this study is, for the time being, not for economic forecasting, we will focus more on the domestic component of the bivariate VAR and therefore formulate a structural economic model in which we explicitly include deterministic terms as provided by (1). The reduced form of the structural model is provided by (2) under the re-parameterisation including (3).

$$AX_t = B(L)X_{t-1} + C(L)Z_{t-1} + D_t^T \Phi + u_t \quad (1)$$

$$X_t = \hat{B}(L)X_{t-1} + \hat{C}(L)Z_{t-1} + D_t^T \hat{\Phi} + e_t \quad (2)$$

Whereby, $\hat{B}(L) = A^{-1}B(L)$

$$\hat{C}(L) = A^{-1}C(L)$$

$$\hat{\Phi} = A^{-1}\Phi$$

$$e_t = A^{-1}u_t \quad (3)$$

If, for an empirically determined value of p the coefficient matrices $\hat{B}(L^{p-1})$, $\hat{C}(L^{p-1})$ and the column vector Φ are stacked row-wise, in their order, to obtain the stacked coefficient matrix \tilde{B} and if we also stacked the vectors of predetermined variables X_{t-1} , Z_{t-1} and D_t , also in their order, to form \tilde{X}_t , we can re-write (2) as provided by (4).

$$X_t = \tilde{B}\tilde{X}_t + e_t \quad (4)$$

In (1) through (4), X_t is the vector of endogenous domestic variables and Z_t is the vector of exogenous variables that may include both domestic and foreign variables. The matrix of contemporaneous coefficients in the structural model is A . Also, $B(L)$ and $C(L)$ are matrix polynomials in the lag operator L and the order of the lag polynomial, p , is to be determined empirically. The vector of deterministic terms is provided by D_t and Φ is the vector of coefficients mapping D_t into X_t . The structural shocks, which are linearly related to the regression residuals, e_t , as provided by (3) are denoted by u_t .

The immediate practical problem we seek to solve using VAR modelling is to estimate the VAR model coefficients which are succinctly provided by \tilde{B} in (4). With adequate degrees of freedom, as it is the

case with small VAR models involving few endogenous variables, amid sufficiently long data spans, and under certain simplifying assumptions, ordinary least squares suffices in estimating the reduced form VAR equations. Then one proceeds to imposing economic structure on the model by fixing values of a sufficient number of selected elements of the contemporaneous coefficients matrix while the free elements are estimated. Imposing economic structure on the model uniquely links the reduced form model to a structural model of the economy under consideration thereby paving way to recovery of the structural shocks from the reduced form regression residuals for further empirical analysis such as generating impulse response functions, variance decomposition and historical decomposition of the endogenous variables time series. An introductory discussion of this essence of the identification problem is provided by Gottschalk (2001).

Otherwise, when the degrees of freedom are inadequate, the practice is to recast the unrestricted VAR model into a Bayesian VAR form which is a state-space representation of the standard reduced form VAR augmented with prior joint probability density function and then estimated using, for instance, the Kalman filter.

Knowing that the VAR estimated in this paper is large, and considering that we use quarterly data which exacerbates the problem of limited degrees of freedom, we apply the Bayesian VAR methodology.

3.2. State-Space Representation and the Bayesian VAR

3.2.1. State-Space Representation

Under the assumption that the parameter matrix \tilde{B} is a random walk process, as it is common practice, we re-write (4) into a dynamic linear system in \tilde{B} , which is essentially the state-space representation of (4), as provided by (5) and (6). In this case, the state (or transition) equation is provided by (5) whilst (6) is the space (or measurement) equation whereby the state and measurement equation errors are denoted by v_t and ε_t , respectively.

$$\tilde{B}_t = \tilde{B}_{t-1} + v_t \quad (5)$$

$$X_t = \tilde{B}_t \tilde{X} + \varepsilon_t \quad (6)$$

$$\forall v_t, \varepsilon_t \sim \text{i.i.d.N}(0, \Sigma_s), s \in \{v_t, \varepsilon_t\}, \text{Cov}(v_t, \varepsilon_t) = 0 \text{ and } \text{Time} = t, \dots, T, \forall t < T$$

At this juncture, the immediate practical problem we need to solve is dual in nature and it involves estimating $\{\tilde{B}\}_t^T$ and choosing the optimal set of $\{\tilde{B}\}_t^T$ which we denote by $\hat{\tilde{B}}_t$. Once we have $\hat{\tilde{B}}_t$, we can generate the corresponding estimate of the measurement equations' vector of errors, ε_t , and denote the

estimate by $\hat{\varepsilon}_t$, which we apply in our further empirical analysis in generating the impulse responses, $\pi(L^p)$, of the endogenous variables X_t with respect to the estimated structural shocks, \hat{u}_t , from the moving average representation of the structural model. The moving average representation of the structural model provided by (7) in which \bar{X} is the vector of steady state values of the endogenous variables.³

$$X_t \approx \bar{X} + \pi(L^p)u_t; \quad \forall p < \infty \quad (7)$$

As already observed when the degrees of freedom are inadequate, we estimate \tilde{B}_t and e_t using the state-space representation of the reduced form VAR model and augmenting observed data with a prior joint probability density function of the state variables succinctly provided by the state vector \tilde{B}_t . We now have to use Bayesian econometric estimation which exploits Bayes' theorem and involves use of the period-by-period (or recursive) Kalman filter to obtain the posterior joint probability density function of the state vector.

3.2.2. Bayes' Theorem

Once the prior joint probability density function is fully specified, Bayes' theorem is applied to combine the prior joint probability density function with the likelihood function of the observed data into a posterior joint probability density function of the state variables. The posterior density function is essentially estimates of the mean values of the unknown coefficients, which we denote by $\{\tilde{B}_t\}_t^T$, and the mean estimates' variances, $\{\tilde{\Sigma}_t\}_t^T$.

The standard Bayes' theorem (or rule) is generally provided by (8), which is recast within the context of our BVAR model, whereby $p(\tilde{B})$ is the prior joint probability density function of the unknown coefficients, \tilde{B} , $p(X)$ is the sample probability density function of the observed data and $p(X)$ is used in this case to scale the prior, $p(\tilde{B})$, so as to obtain correctly scaled $p(\tilde{B} | X)$ in terms of units of measurement of the observed data. In (8), $p(X | \tilde{B})$ is the log likelihood function for the observed data and, most importantly, $p(\tilde{B} | X)$ is the posterior joint probability density function of the coefficients conditional on the observed data which is with respect to \tilde{B} over the estimation period to obtain the posterior mean estimates, $\{\tilde{B}_t\}_t^T$.

$$p(\tilde{B} | X) = \frac{p(X | \tilde{B})p(\tilde{B})}{p(X)} \quad (8)$$

3.2.3. Kalman Filter

We follow Estima (2012) in outlining the Kalman filter. The essential elements of the Kalman filter are the three equations which are the state vector and the state vector precision updating equations provided by (9)-(11).

$$\tilde{\Sigma}_{t|t-1} = \tilde{\Sigma}_{t-1} + M_t \quad (9)$$

$$\hat{B}_{t|t} = \tilde{B}_{t-1|t-1} + \tilde{\Sigma}_{t|t-1} \tilde{X}_t^T (\tilde{X}_t \Sigma_{t|t-1} \tilde{X}_t^T + \eta_t)^{-1} (X_t - \tilde{X}_t \tilde{B}_{t|t-1}) \quad (10)$$

$$\hat{\Sigma}_t = \tilde{\Sigma}_{t-1} - \tilde{\Sigma}_{t|t-1} \tilde{X}_t^T (\tilde{X}_t \tilde{\Sigma}_{t|t-1} \tilde{X}_t^T + \eta_t)^{-1} \tilde{X}_t \tilde{\Sigma}_{t|t-1} \quad (11)$$

Time = $t, \dots, T; \forall t < T$

Using prior information about the measurement equations' error variances which we denote by the vector, η_t ; the variances of the vector of state equations' errors, M_t , and the variance-covariance matrix of the state variables, $\tilde{\Sigma}_{t-1}$, (9) is solved for $\tilde{\Sigma}_{t|t-1}$ and the solution applied to: firstly, computing the one-period ahead forecast of the vector of endogenous variables, $\tilde{X}_t \tilde{B}_{t|t-1}$, thereby obtaining the one-period ahead vector of endogenous variables' forecast errors, $(X_t - \tilde{X}_t \tilde{B}_{t|t-1})$, which features in (10), as a prelude to getting the estimates of the state variables in period t using available information through the period, $\hat{B}_{t|t}$; and, secondly, computing these estimates' updated variance-covariance matrix according to (11).

Notice that $\hat{B}_{t|t}$ and $\hat{\Sigma}_t$, which are obtained from (10) and (11), are the posterior joint probability density function outcomes for the period t . This process of forecasting X_t to compute the forecast error, and updating the state vector estimates, $\hat{B}_{t|t}$, as well as the variance-covariance matrix, $\hat{\Sigma}_t$, using the Kalman filter is repeated period-by-period for all periods in the estimation sample. During the Kalman filter recursive estimation process, the current period estimates of $\hat{B}_{t|t}$ and $\hat{\Sigma}_t$ are used as initial values in forecasting the subsequent period values of the endogenous variables vector X_t , forming the basis for computing the forecast errors of X_t , as well as being used in updating $\hat{B}_{t|t}$ and $\hat{\Sigma}_t$ to $\hat{B}_{t+1|t+1}$ and $\hat{\Sigma}_{t+1}$, respectively.

According to (10), the current period's estimate of the state variable(s) using information available through the current period, $\hat{B}_{t|t}$, is computed as the preceding period estimates of the state variables, $\hat{B}_{t-1|t-1}$, adjusted for the one period ahead forecast error of the endogenous variables based on $\hat{B}_{t-1|t-1}$,

which is $(X_t - \tilde{X}_t \tilde{B}_{t|t-1})$ in (10). This correction for the forecast error, which is akin to the backward looking *coefficient of adjustment* in standard vector error correction modeling, is a fraction of the Kalman gain factor provided by $\Sigma_{t|t-1} \tilde{X}_t^T (\tilde{X}_t \Sigma_{t|t-1} \tilde{X}_t^T + \eta_t)^{-1}$ in (10). Because the variance vector of the measurement equation errors, η_t , applies in the Kalman gain factor, it should be known a priori in order for (10) and (11) to be determinate. Otherwise, the Kalman filtering process stalls and the whole empirical analysis collapses.

Having updated the state vector in line with (10), so that $\hat{B}_{t|t}$ is superior to $\tilde{B}_{t-1|t-1}$ in the sense that $\hat{B}_{t|t}$ is relatively more converged on the true population value than $\tilde{B}_{t-1|t-1}$, then logically the covariance of $\hat{B}_{t|t}$ ought to be smaller than that of $\tilde{B}_{t-1|t-1}$ so that $\hat{\Sigma}_t < \tilde{\Sigma}_{t-1}$ in line with the subtractive term in (11). And once the Kalman filter has worked its way through the estimation sample, $t+s, \dots, T-1; \forall s \geq 1$, we shall have generated, among other results, $\left\{ \hat{B} \right\}_{t+s}^{T-1}$ and $\left\{ \hat{\Sigma} \right\}_{t+s}^{T-1}$ and the next step is for us to optimize an objective function in choosing the optimal estimate of \hat{B}_t and its corresponding variance-covariance matrix, $\hat{\Sigma}_t$.

It is common to use the log likelihood function of an observation drawn from the observed data, X_t , for this purpose. The idea being that we choose the state vector estimate which minimizes the out-of-sample forecast errors of the endogenous variables thereby, invariably, maximizing the log likelihood function's value. Assuming therefore, as we have, that X_t is a multi-normal in its distribution, it can be shown that the negative of its pseudo log likelihood function is as provided by (12). The pseudo log likelihood differs from the true underlying log likelihood to the extent that constants in the true log likelihood are dropped out to obtain the pseudo log likelihood. Dropping out the constants does not make any difference in the outcome of the optimization problem regardless of whether the pseudo log likelihood or the true underlying log likelihood function is applied. Enders (2003) provides a useful reference as to the derivation and application in empirical analysis of a pseudo log likelihood function.

The whole idea is that we choose \hat{B}_t from $\left\{ \hat{B} \right\}_{t+s}^{T-1}$ which minimizes the sum of squared forecast errors, $(X_t - \tilde{X}_t \tilde{B}_{t|t-1})^2$, or, equivalently, choosing \hat{B}_t which maximize $\Lambda_{t|t}$ as provided by (12).

$$\Lambda_{t|t} = \log(\hat{\sigma}^2) + \frac{(X_t - \tilde{X}_t \hat{B}_{t|t-1})^2}{\hat{\sigma}^2} \quad (12)$$

Whereby,

$\tilde{X}_t, \hat{\tilde{B}}_{t|t-1}$ is the one period ahead forecast value of X_t (simply the expected value of X_t); and

$\hat{\sigma}^2$ is the standard error of X_t , which is computed as provided by (13) in line with Estima (2012).

$$\hat{\sigma}^2 = \eta_t + X_t (\tilde{\Sigma}_{t-1} + M_t) \tilde{X}_t^T \quad (13)$$

The optimization problem is therefore provided by (14).

$$\underset{\hat{\tilde{B}}_{t|t} = \tilde{B}_{t|t}}{\text{Max}} \quad \Lambda_{t|t} = \left(\log(\hat{\sigma}^2) + \frac{(X_t - \tilde{X}_t \hat{\tilde{B}}_{t|t-1})^2}{\hat{\sigma}^2} \right) \quad (14)$$

At the practical level of solving for $\hat{\tilde{B}}_t$, we set up the program executing the Kalman filter in such a manner that for each period of updated state vector, the program computes the pseudo log likelihood value so that in the whole, we do also have $\{\Lambda\}_{t+s}^{T-1}$. Our solution to (14) is then determined by evaluating $\{\Lambda\}_{t+s}^{T-1}$ to choose the $\hat{\tilde{B}}$ that corresponds to the largest value of $\Lambda_{t|t}$ as stated in (15).

$$\hat{\tilde{B}}_t = \{\tilde{B}\}_{t+s}^{T-1} \Big|_{\text{Max}\{\Lambda\}_{t+s}^{T-1}} \quad (15)$$

3.3. Prior Joint Probability Density Function

In order to start-off the Kalman filter algorithm, we must provide the starting values of the state variables which are also referred to as the prior means and which we denote by $\tilde{B}_{0|0}$. We must also provide initial values of the elements of the variance-covariance matrix of the prior means, Σ_0 , as well as the covariances of the vector of measurement equations' errors, η_t , and the covariances of the vector of state equations' errors, M_t .

Under the received wisdom, assigning prior means and prior means' covariances, should follow standard priors provided by, among others, Doan, Litterman and Sims (1984), which are collectively referred to as the Minnesota prior, or extensions of the Minnesota prior such as those provided by, for instance, Sims (1992) or by Racette, Raynauld and Sigouin (1994). A key feature of these priors is the assumption that modelled variables, just like most economic variables, are adequately represented by random walk with drift processes.

It is further assumed, in assigning the priors, that more recent information as represented by relatively shorter lags attaching to the endogenous variables' lagged terms, is relatively more useful in predicting

the one period ahead forecasted values of the endogenous variables than distant past information which is technically represented in long lagged terms of the endogenous variables. It is also assumed that own lagged terms are more informative than corresponding cross-variable lagged terms.

Using the assumptions, the process of assigning prior means and prior variances to the parameters in the BVAR can be generalized and therefore simplified by indexation of groups of prior means and prior variances to a relatively smaller number of other parameters conventionally called hyper-parameters. This way, an otherwise onerous task of having to assign specific prior means and prior variances to each of the Unrestricted VAR coefficients is circumvented. Essentially, the hyper-parameters are indicative of the strength of belief one has about the true population means falling within close neighbourhood of the assigned prior means.

The Minnesota prior, which we use in our analysis considering that it provides good results in spite of its simplicity, and as presented and discussed in Doan, Litterman and Sims (1984), assigns prior means and corresponding prior variances according to (16) and (17), respectively. In this case, each of the elements of the variance-covariance matrix denoted by $\tilde{b}_{i,j,l}$ and therefore identified with the j^{th} variable in the i^{th} equation of the system and situated at the l^{th} order lag of the j^{th} variable, is assigned a different value in line with (17).

For simplicity purposes, however, priors of the elements of the variance-covariance matrix can be assigned under the assumption that the variance-covariance matrix is not only symmetrical but also one in which we have a constant value assigned to all of the off-principal diagonal elements. In this case, one assigns the prior variance-covariance matrix according to (18). In spite of its simplicity, the symmetric variance-covariance prior, when combined with appropriately chosen values for the hyper-parameters, namely, decay factor, tightness of the prior means relative to others i.e. the value of w , has the potential to yield plausible results.

$$Mean[\tilde{b}_{i,j,l}] = \begin{cases} 1.0 & \text{if } i = j \\ 0.0 & \text{Otherwise} \end{cases} \quad (16)$$

$$Var[\tilde{b}_{i,j,l}]_{General} = \varphi_1 \cdot \varphi_2(l) \cdot \varphi_3(i, j) \cdot \varphi_4(s_i, s_j) \quad (17)$$

$$Var[\tilde{b}_{i,j,l}]_{symmetric} = \begin{cases} 1.0 & \text{if } i = j \\ w & \text{Otherwise} \end{cases} \quad (18)$$

Notice that in (16), (17) and (18),

$Mean[\tilde{b}_{i,j,l}]$ Represents the prior mean of the coefficient attaching to j^{th} variable's l^{th} order lagged term in the i^{th} variable's equation of the BVAR. It follows from (16) that the prior mean of coefficient attaching to own variable first order lagged term is assigned a value 1.0 whilst all other coefficients in the equation are assigned prior mean values of 0.0.

$Var[\tilde{b}_{i,j,l}]$ Represents the prior variance of $\tilde{b}_{i,j,l}$. According to (18), all the coefficients attaching to a variable's own first order lagged term are assigned a prior variance of unity i.e. 1.0 whilst all the other coefficients are assigned the same but unknown value of prior variance, w . This is the symmetric case of assignment of priors.

In (17), Prior variances are assigned according to various considerations, represented by hyper-parameters that are indicative of a modeller's confidence that the "true population mean" falls within a certain range within the neighbourhood of the prior mean under consideration. This concept of the true population mean being close to the prior mean is referred to as "tightness" or precision of a prior mean and as such, the smaller the prior variance assigned to a prior mean, the tighter the prior mean. We therefore have four tightness hyper-parameters which are explained as follows.

φ_1 Measures overall tightness of the prior mean. This is assigned an initial value equal to the standard error estimate for the own first order lagged term in the i^{th} variable's $AR(p)$ process. For quarterly data which is likely to feature strong seasonal effects, $AR(p) \forall p = 5$ applies. If seasonal dummies are explicitly modelled to control for seasonality effects in the $AR(p)$ process, then, suffice it using $AR(p) \forall p = 4$. It is recommended that overall tightness should be about 0.1 to 0.2.

$\varphi_2(l)$ Measures and therefore provides for further tightening of the prior mean in terms of the lag length of the variable to which the prior mean under consideration attaches. Consistent with the underlying assumption that the economic variables being modelled can be adequately be represented by random walks with drift processes and considering also the belief that recent information is more useful than old in predicting modelled variables, the modeller is assumed to belief that coefficients attaching to increasing lag lengths in the BVAR would have attached to them increasingly closer to zero values and as such, the longer the lag length, the more confident the modeller will be that the true population mean of the coefficients will be within a small and smaller range of the prior mean of zero. Thus, this hyper-parameter is indexed to lag length and therefore determined from a distributed lag function chosen to conform to either the harmonic or geometric distributed lag functions. The harmonic is preferred to the geometric because the latter is considered to infuse too much tightening too fast. Thus, $\varphi_2(l) = \frac{1}{l} = l^{-1}$ but more generally, $\varphi_2(l) = \frac{1}{l} = l^{-DECAY}$ whereby $DECAY$ is a hyper-parameter whose recommended value is 1.0 or 2.0.

$\varphi_3(i, j)$ Measures and therefore provides for further tightening of the prior mean under consideration according to the other variable, other than own lagged terms, to which the coefficient of interest attaches. For own lagged variables a value of unity is assigned and as such we have $\varphi_3(i, j, l) = 1.0 \forall i = j$. Thus, we will have $\varphi_3(i, j, l), \forall i \neq j$ as free parameters and that will provide us with the general variance-covariance BVAR model case compared to the symmetric model.

In the symmetric case, it is basically one shared free parameter which has been shown to form a good basis for obtaining estimates of the state variables and the state variable estimate's variance covariance matrix. It has been shown that using $w = 0.5$ and $DECAY = 0.2$ yields good results.

In the general case of the variance-covariance prior, one has to assign further tightening relative to the cross terms in the variance-covariance matrix and these would vary across the off-principal diagonal elements instead of using a constant similar value, say, $w = 0.5$. For simplicity, one would use a diffuse or flat prior which is tantamount to saying that the modeller has no good basis for assigning specific priors and as such allows the data to "talk", so to speak, as part of the model estimation process to determine the final estimate of the variance-covariance matrix. The diffuse prior is also used for the constant and, in our case, the other deterministic terms. The prior means of all deterministic terms are set at naught.

$\varphi_4(s_i, s_j)$ Measures and represents further tightening of the prior means which essentially is aimed to correct for any bias brought about to the computed variance-covariance matrix of priors by the differentials in units of measurement of the i^{th} and the j^{th} variables to the endogenous variables' units of measurement. By convention, $\varphi_4(s_i, s_j)$ is indexed to the ratio of the standard error of the i^{th} variable, s_i , to the standard error of the j^{th} variable, s_j . Thus, $\varphi_3(i, j) = \frac{s_i}{s_j}$. In assigning the values of s_i and s_j , the practice is that one sets s_i and s_j equal to the standard error estimates deriving from corresponding variables' $AR(p)$ processes.

To complete assignment of priors, we must choose between time-varying and time-invariant types of state vectors in the BVAR model with implications for the priors assigned to M_t and n_t . Under the time-invariant state values model, $M_t = 0$. Otherwise, $M_t \neq 0$ and M_t is presumed to be known and in which case its initial value must be assigned in order for the Kalman filter iterative process to start. When $M_t = 0$ with the appropriate dimensionality of the null matrix on the right hand side, $n_t = \sigma^2 = 1$; for simplicity. As part of the received wisdom, M_0 is indexed to the prior variance-covariance matrix, Σ_0 .⁴

3.4. Structural Vector Autoregressive (SVAR) Model

We bear in mind that a key objective of this study is to empirically analyze the transmission mechanism of monetary policy in Kenya in terms of, firstly, the dynamic responses of policy objective variables, which are the general level of prices and output to exogenous monetary policy shocks, and, secondly, in terms of the relative contribution of monetary policy shocks to the policy objective variables' forecast error variances. In characterizing monetary policy transmission in Kenya in terms of the impulse responses of selected economic variables to monetary policy shocks, we estimate the moving average representation provided by (7). We certainly had to estimate the structural shocks, u_t , before we would estimate (7) to generate the impulse responses, $\pi(L^p)$, that we plot as impulse response functions.

For very obvious reasons, and as has already been discussed above, we cannot estimate (1) directly to obtain u_t . We can, however, exploit the linear relationship between u_t and e_t which is provided by (3) to recover u_t from e_t . Yet again, we should in the first place, obtain estimates of the UVAR errors, e_t . While finding the state variable estimates according to (15), and which effectively means estimating (6) using the Kalman filter, is as much an end in itself as it is a means for our further empirical analysis, we are more concerned with the later. As an end in itself, however, the state variable estimates are an essential part of the empirical BVAR model for economic forecasting; a matter that we return to in another study.

As a means to our further economic analysis, in this study, we apply the state variable estimates, \hat{B}_t , that are obtained according to (15) to generate estimates of the regression residuals, \hat{e}_t , in (4) according to (19). This is essentially using the estimates obtained in line with (15) in (6) and re-organizing the resultant expression to generate \hat{e}_t as a residual as provided by (19).

$$\hat{e}_t \equiv X_t - \hat{B}\tilde{X}_t \quad (19)$$

How then do we recover estimates of the structural shocks from the BVAR residuals obtained according to (19)? Manipulating (3), mathematically, we obtain a system in which the structural shocks are expressed as a linear function of the BVAR residuals. Then we estimate a just identified variant of the system. This is how.

If we square both sides of (3), we obtain (20) which simplifies to (21).

$$e_t(e_t)^T = A^{-1}u_t(A^{-1}u_t)^T \quad (20)$$

$$e_t(e_t)^T = A^{-1}u_t(u_t)^T(A^{-1})^T \quad (21)$$

If we take expectations of the terms on both sides of (21) as provided by (22) in which E_t is the usual expectations operator, we obtain (23). Under certain simplifying assumptions, $Var[u_t] = I_n$, and (23) reduces to a system of simultaneous equations involving the coefficients of A^{-1} and the variance-covariance matrix of the reduced form regression residuals, $\Sigma_{e,t}$, as provided by (24).

$$E_t[e_t(e_t)^T] = E_t[A^{-1}u_t(u_t)^T(A^{-1})^T] \quad (22)$$

$$Var(e_t) = A^{-1}Var[u_t](A^{-1})^T \quad (23)$$

$$\Sigma_{e,t} = A^{-1}(A^{-1})^T \quad (24)$$

$$\forall \Sigma_{e,t} \equiv Var(e_t)$$

Because of the symmetric nature of the variance-covariance matrix of residuals, $\Sigma_{e,t}$, and considering that (24) represents a system involving n endogenous variables such that we have $(n^2 - n)$ unknown elements of the A^{-1} matrix, the system as it is in (24) is not solvable because we then have more unknowns than we do have independent equations. Because we have $\left(\frac{(n^2 - 1)}{2}\right)$ symmetrical elements

in A^{-1} , we equally have $\left(\frac{(n^2 - 1)}{2}\right)$ fewer independent equations in (24) compared to the n^2 unknown elements of A^{-1} and by extension, n^2 unknowns in (24). In order therefore for us to solve for the structural shocks from the system implied by (3), we need to estimate A^{-1} by initially reducing the number of unknown elements of A^{-1} to be estimated from (24) by assigning, based on our prior knowledge and therefore as guesstimates, values for $\left(\frac{(n^2 - 1)}{2}\right)$ of the unknown elements of A^{-1} ⁵.

The identification problem which one has to confront in the VAR modelling is the lack of one-to-one mapping of a structural model to a reduced form representation of the model. This is because infinitely many structural models, each of which is to a scale factor of δ in the contemporaneous coefficients matrix, A , share a reduced form representation. So, solving the identification problem is essentially selecting, from among the infinitely many potential structures of the economy described by $\delta A \forall \delta \neq 0$, which adequately represents the true structural model of the economy under consideration. In so doing, we shall have effectively consistently linked up the reduced form model provided by (3) with the presumed true structure of the economy in terms of the optimized values of A from (24). Gottschalk (2001) provides an accessible discussion of this point. With the structure of the economy established in that manner, we can proceed to conduct our policy experiments using the estimated structural shocks.

More specifically, once we have solved for the restricted A^{-1} , we call it \tilde{A}^{-1} , we use it together with our estimates of the regression residuals obtained according to (19) to generate the estimated structural shocks, \tilde{u}_t , according to (25). Notice that we obtain (25) upon inversion of (3) so that we explicitly express the structural shocks in terms of the regression residuals, \tilde{e}_t , and \tilde{A} . Then we can fit the moving average representation according to (26) using \tilde{u}_t in line with (7). From (26), we can solve for the impulse responses by taking the partial derivative of the generic impulse response function provided by (26) with respect to the structural shocks \tilde{u}_t for specified periods following occurrence of the shocks, as provided by (27).

$$\tilde{u}_t = \tilde{A}\tilde{e}_t \quad (25)$$

$$X_t \approx \bar{X} + \tilde{\pi}(L^p)\tilde{u}_t \quad (26)$$

$$\frac{\partial X_t}{\partial \tilde{u}_t} (\bar{X} + \tilde{\pi}(L^p)\tilde{u}_t) = \tilde{\pi}(L^p) \quad (27)$$

$$time = t, (t+1), (t+2), \dots, (p-2), (p-1), p$$

In (27), p represents the number of periods following the occurrence of the exogenous shocks, the monetary policy shocks in particular, for which the response of the endogenous variables vector, X_t , are being estimated according to (27) whereby $\tilde{\pi}(L^p)$ is a matrix polynomial in the lag operator, L , to the p^{th} order. This means that $\tilde{\pi}(L^p)$ is a sequence of $n \times n$ impulse response matrices whereby the sequence is ordered by time period so that $\forall p, p \in time$ so that we have $\{\tilde{\pi}(L^p)\}_t^p$. It is to be preferred that p be chosen to provide for sufficient time for the structural shocks to die out so that the impulse responses return to baseline thereby establishing that we are dealing with a stable (and not an explosive) economic system.

But the practical question is: how should we impose the required $\left(\frac{(n^2-1)}{2}\right)$ restrictions so that (24) is estimable thereby solving for A^{-1} which we proceed to use in (26) to generate the structural shocks used in (27) to generate impulse responses?

Available literature proposes two approaches to solving the identification problem. The most commonly applied, owing to its simplicity, is the recursive or Choleski factorization method. The other is the structural factorization. The recursive method which imposes restrictions resulting in a lower triangular restricted matrix, \tilde{A}^{-1} , and therefore imposes a particular ordering of the endogenous variables in the BVAR model is largely discredited for being devoid of theoretical foundations. In the

recent past, however, it has been strongly supported as evidenced in Davoodi, Dixit, and Pinter (2013) and Arnostova and Hurnik (2005).

It would appear as though tables have been turned against the structural identification methods especially those under which contemporaneous restrictions are imposed based on the “timeliness” of availability of current information about certain variables when making the policy decision is not a good basis. It is argued, in for instance Bernanke and Sims (2001), that because data on output arrives with a lag, its corresponding element in the \tilde{A}^{-1} and by extension in the presumed short run monetary policy reaction function should be assigned a value of zero.

The counter argument to this line of thinking by proponents of the recursive identification method is that data on leading economic indicators which is readily available for policy makers to gauge what the current value of real output is and as such the zero-restriction attaching to the element of \tilde{A}^{-1} corresponding to real output in the short run monetary policy reaction function is not well founded. This criticism does not appear to fatally affect the Blanchard and Quah (1989) approach to structural identification since in the Blanchard and Quah (1989) method, restrictions are imposed on long run parameters in a co-integrated VAR system.

For all the trouble it takes one to impose the “so called” theoretically based restrictions within the context of the Bernanke and Sims (2001) kind of identifying restrictions, the gains realized in terms of improved estimates of the structural shocks and by extension impulse responses over those derived from a recursive identification scheme is not worth taking the trouble. Suffice it, therefore, using recursive identification as done in Davoodi, Dixit and Pinter (2013) and Arnostova and Hurnik (2010).

4. Empirical Implementation

4.1. Model Specification

In specifying our VAR model, we state the endogenous variables in sub-section 4.1.1 thereby fixing the value of n which is essentially a measure of the dimension of the VAR system. We also state, in sub-sections 4.1.2 and 4.1.3, the exogenous and the deterministic variables. As we cannot, a priori, state the optimal lags attaching to the endogenous and exogenous variables in the final empirical VAR model, we defer determination of the optimal lags to when we carry out preliminary estimation of the model for these purposes.

4.1.1. Endogenous Variables

Most of the past studies have confined themselves to a limited number of endogenous variables because of data inadequacies.⁶ However, with advancements in estimation techniques, for instance, the use of

Bayesian econometrics, recent studies such as Davoodi, Dixit and Pinter (2013) use a large number of endogenous variables and this has provided a good basis for the comprehensive study of monetary policy transmission mechanism. Using Bayesian estimation techniques also paves way for including a sufficient number of external variables to control for the influence of external economic developments on the study findings.

We therefore follow Davoodi, Dixit and Pinter (2013) in selecting and listing of variables relevant to our analysis. In our benchmark model, we consider six endogenous variables, namely, log of real output (billions, Kenya Shillings), lry_t , log of the headline CPI, lp_t (February 2009=100, rebased to December 2001=100), log of the nominal stock of reserve money (billions, Kenya Shillings), lrm_t , the CBR (annual, percent) as the policy rate, $lcbt_t$,⁷ log of the volume of commercial banks' real credit to the private sector (billions, Kenya Shillings), lrc_t , and the log of the Kenya shilling nominal effective exchange rate (with increments interpreted as appreciation), $lneer_t$. The vector of endogenous variables, X_t , is therefore provided by (28).

$$X_t^T = [lry_t \quad lp_t \quad lrm_t \quad lcbt_t \quad lrc_t \quad lneer_t]$$

(28)

Within this set up of the benchmark model, reserve money is assumed to be the monetary policy variable as it forms a basis for open market operations which is a key monetary policy instrument under the monetary aggregate targeting policy regime. We expect significant liquidity effect following a sudden change in the monetary base.

Under the pure expectations theory of the term structure of interest rates, the policy induced changes in money market interest rates will reflect in longer term interest rates including bank lending rates to the extent that the marginal cost of credit will change accordingly to significantly influence the volume of bank credit to the private sector. Changed term structure of interest rates will most certainly lead to changes in interest rate differentials with implications for net capital inflows and corresponding changes in the domestic currency exchange rates including the log of the nominal effective exchange rate, $lneer_t$.

We further expect delayed and persistent effects of the policy induced changes in the interest rates, volume of bank credit to the private sector and the exchange rate on real output and the general level of prices. One will think of the adverse implications of costly and limited amounts of bank credit used as working capital by firms and by Ricardian households seeking to smooth their life-long consumption with ultimate detrimental effects on real output. Policy induced changes in the exchange rate will also unleash the demand-reducing and demand-switching effects of the real exchange rate with consequences for real output and the general level of prices (considering the exchange rate pass-through effects to domestic prices and inflation). Thus, the setup we have used forms a good basis for tracing the transmission of the effect of a sudden change in the monetary base on interest rates, private

sector credit and the exchange rate (with implications for the operational status of the interest rate, credit and exchange rate channels of monetary policy transmission) to changes in output and the general level of prices.

4.1.2. Exogenous Variables

The vector of exogenous variables is denoted as follows: log of world real output, $lryf$, world CPI, lpf , world oil prices, $loilprice_t$, and the USA 90-Day Treasury Bills interest rate, $ratef$ by Z_t . We have included the world CPI and world oil prices to control for external demand shocks expecting to check incidence of price and exchange rate puzzles, which have afflicted some past studies, from our results. Price puzzling results occur when an exogenous monetary policy tightening induces increased inflation instead of a reduction. An exchange rate puzzle occurs when sudden monetary policy tightening, which should induce exchange rate appreciation, leads to exchange rate depreciation.

We have included foreign real output and the foreign interest rate among the vector of exogenous variables to control for external economic developments such as the global financial and economic crises of 2007/2008.

$$Z_t^T = [lryf_t \quad lpf_t \quad loilprice_t \quad ratef_t] \quad (29)$$

4.1.3. Deterministic Variables

The vector of deterministic terms, D_t , which we provide by (30), has as its elements: the constant term, c_0 , and three seasonal dummies, s_1 , s_2 , and s_3 . We have included seasonal dummy variables as part of the elements of the deterministic terms because unlike past studies which adjust the endogenous and exogenous variables time series data for seasonal effects and therefore end up throwing away potentially useful information regarding the role of seasonal factors in influencing the dynamic responses of policy objective variables to shocks, we explicitly model seasonal effects in a bid to use the information thereby forming a good basis for controlling for the seasonality factors on economic developments in the country.

$$D_t^T = [c_0 \quad s_dummy_3 \quad s_dummy_2 \quad s_dummy_1] \quad (30)$$

4.1.4. Data Description and Sources

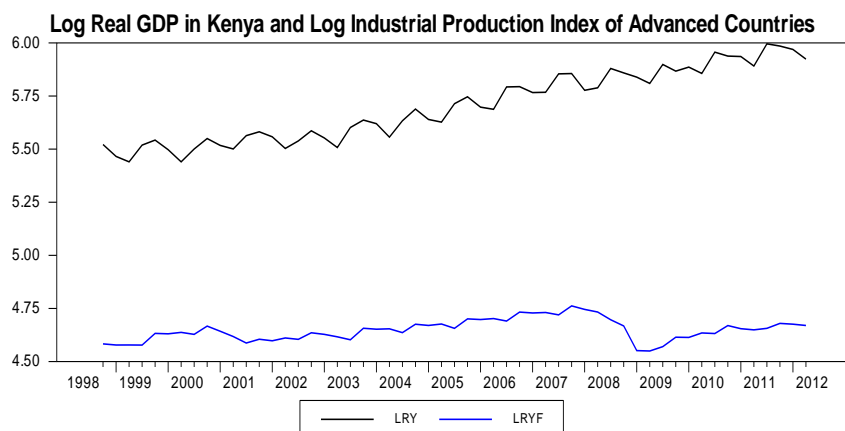
There are three important observations made from the time profile of the data shown in the six panels in Fig. 1 and which have implications on how we model the data. Firstly, except for the data for the

domestic and foreign interest rates, all the data are upward trending. It is common to eliminate the exponential growth in the trending data by log linearization. Hence, the presentation of these data is in logs. Since the interest rate data is not trending, it can be used in the model without log transformation. In this analysis, however, all the endogenous and exogenous variables data, including the interest rates enter the analysis in logs to pave way to interpretation of the impulse responses as elasticities.

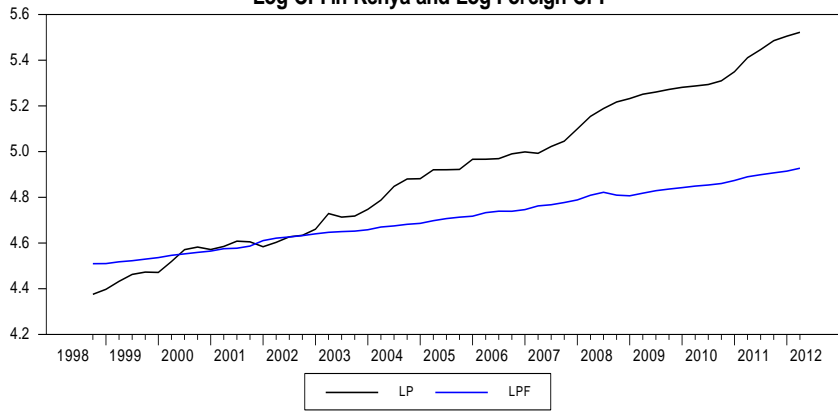
The second observation is that, the financial and real sectors of the rest of the world experienced shocks in 2007/2008. Regarding the global economic crisis, there is, for instance, a sudden fall in the real output for the industrialized countries as shown by the time profile of *lryf* as well as by *lpf* during the period. Compared to corresponding domestic variables, apparently, the global economic crisis would have been felt about 1 to 2 years later. This implies that when controlling for external economic developments, it is necessary to use lagged terms of measures of external economic performance such as real output and the general level of prices. Up to 8 quarters of lagged terms of these variables will be necessary with implications for a more acute challenge of inadequate degrees of freedom. Alternatively, current values of the measures of external economic performance can be used in conjunction with appropriate dummies to capture the structural breaks in the data occasioned by the global economic crisis.

Unlike the global economic crisis, the global financial crisis measured in terms of a sudden reduction in the USA 90-day Treasury bills interest rate seems to have set around mid-2007 and got precipitous in 2008. Recovery from the global financial crisis has been pretty slow and not fully attained by end of 2012. It is notable that Kenya would have been affected by the financial crisis with a lag of about 2 years but recovered swiftly within a year's time.

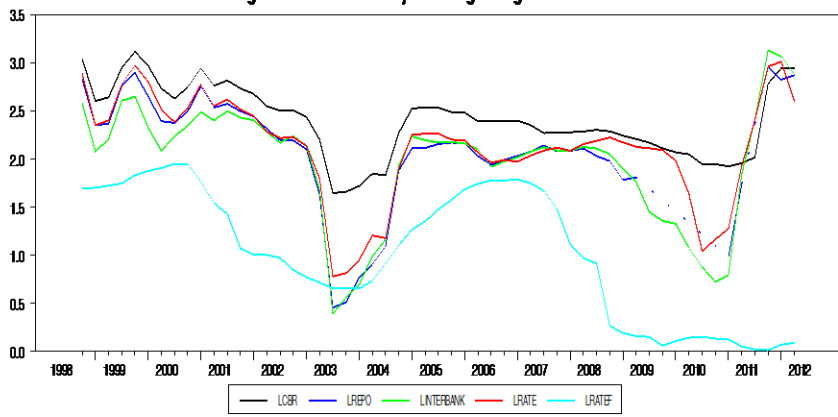
Figure 1. Time Profile of Data



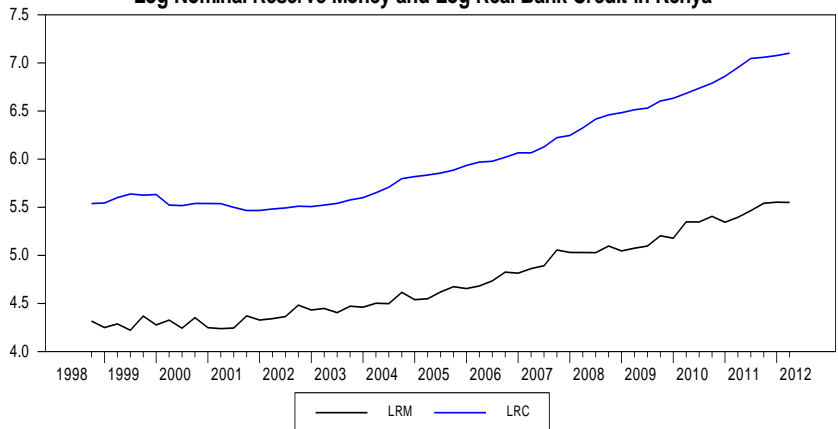
Log CPI in Kenya and Log Foreign CPI

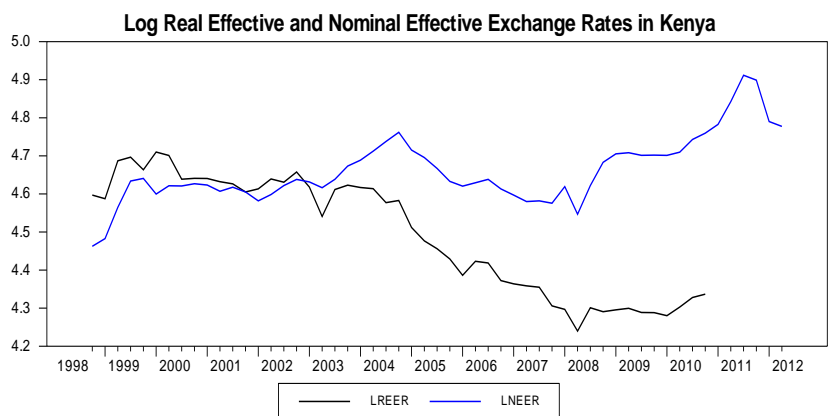
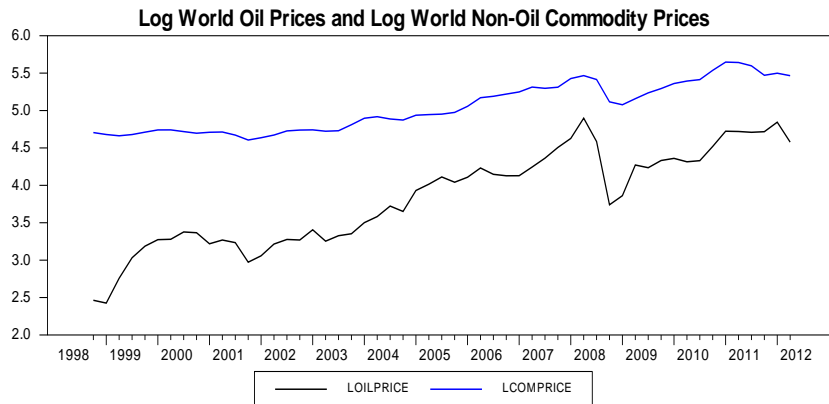


Log Interest Rates in Kenya and Log Foreign Interest Rate



Log Nominal Reserve Money and Log Real Bank Credit in Kenya





4.2. Recursive Identification

Following recent studies such as Davoodi, Dixit and Pinter (2013) and Arnostova and Hurnik (2005), which essentially follow the recursive identification introduced by Sims (1980), our benchmark model is specified as provided by (31). Notice that unlike, Cheng (2006) and Davoodi, Dixit and Pinter (2013), we have not normalized the value of the elements in the principal diagonal of \tilde{A} considering that we have already normalized the elements in the principal diagonal of the variance-covariance matrix of the structural shocks. The implication of this shift in specification is that unlike in Cheng (2006) and in Davoodi, Dixit and Pinter (2013) in which it is therefore assumed that there is one-to-one contemporaneous mapping of own reduced form residuals to own structural shocks is that own reduced form regressions residuals do not necessarily immediately fully reflect in the structural shocks. By relaxing this assumption, we obtain more data coherent empirical results.⁸

$$\begin{bmatrix} \varepsilon_t^{lry} \\ \varepsilon_t^{lp} \\ \varepsilon_t^{lrm} \\ \varepsilon_t^{lcbrr} \\ \varepsilon_t^{lrc} \\ \varepsilon_t^{ln eer} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{bmatrix} e_t^{lry} \\ e_t^{lp} \\ e_t^{lrm} \\ e_t^{lcbrr} \\ e_t^{lrc} \\ e_t^{ln eer} \end{bmatrix} \quad (31)$$

$$\forall \tilde{A} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix}$$

4.3. Estimation Issues

The SVAR estimation problem comprises three systems, namely, (24), (31) and (26). We estimate (24) and (31) using the same recursive identifying restrictions. Estimating (24) essentially aims to obtaining the restricted \tilde{A}^{-1} matrix whose inverse, \tilde{A} , is used in (31) in line with (25). Estimating (31) aims to recover the structural shocks from the BVAR regression residuals which are then used in estimating the moving average representation provided by (26) so as to generate the required impulse responses according to (27).

Because (24) involves nonlinear equations in the parameters that we seek to estimate, we use a nonlinear estimator; maximum likelihood estimator. We also use the variance-covariance estimate for the measurement equation errors, which are estimated according to (19), $\Sigma_{\hat{\eta}_t}$, from the Kalman filter, in estimating (24). In other words, we assume that $\Sigma_{e,t} = \Sigma_{\hat{\eta}_t}$.

Once we have estimated (24), so that \tilde{A} is known, the next step is simply to use \tilde{A} in (31) to factorize the BVAR regression residuals into contemporaneously uncorrelated structural shocks and the contemporaneously correlated components of the BVAR regression residuals. We then proceed to use the recovered structural shocks in (26) and (27) to obtain the impulse response results which we present and discuss in the following section.

5. Empirical Results

5.1. Model Set Up and Preliminary Results

5.1.1. BVAR Optimal Lag

We have principally used three test statistics in determining the optimal lag for our BVAR model. The three test statistics are the multivariate Akaike information criterion (AIC), Schwartz and Bayesian criterion (SBC) and the log likelihood ratio (LR) whose distribution resembles the χ^2 distribution with degrees of freedom equal to the number of imposed restrictions under the test being performed. Since in each case of carrying out the LR test we were comparing models with successively lower lags, with the difference in lags between the two models being one, beginning with an unrestricted model with 5 lags, the restrictions were, in each of the four LR tests, equal to 1.

According to AIC and SBC information criteria, the model reporting the lowest AIC or SBC value is to be preferred to the rest in the comparative analysis. Under the AIC and SBC results presented in Table 1, therefore, the VAR model with 2 lags is the best since it has the lowest computed values of -2633.74 and -2543.07 for the AIC and SBC, respectively.

Conversely, the log likelihood ratio (LR) test statistic results, also presented in Table 1, show that the best BVAR model is the one with 3 lags. This is because the restrictions of lags in the BVAR with 5 lags to one with 4 lags and further from a BVAR with 4 lags to one with 3 lags are acceptable under the test. Restrictions of the lag length from 5 to 4 and then from 4 to 3 were accepted considering that the significance level of the computed values of the LR test statistic are 0.592 and 1.000, respectively. These results mean that 5 and 4 are not optimal lags.

In contrast, the LR test of the restriction of the VAR model with 3 lags to one with 2 lags yield results leading us to infer that the restriction is binding and as such 3 is the optimal lag. The significance level of the LR test statistic is, in this case, $2.87e-012$, which is much lower than the conventional significance level of 5%. Just to be sure, we tested the restriction of the BVAR model with 2 lags to the one with 1 lag and found out that the restriction was binding to which means that a BVAR model with 1 lag is a potential candidate in our empirical analysis.

In view of the mixed results, we consulted with past studies' to note the optimal lag choices used. In their Kenyan case study, using monthly data covering Jan. 2000-Dec.2010, Davoodi, Dixit and Pinter (2013) used the Akaike, Shwartz, Hannan-Quinn and Final Prediction Error information criteria to find that the optimal lag was 3 months which was just about 1 quarter for quarterly data and which could then be supportive of using 1 lag in our analysis. The authors, however, note that 2 to 4 lags are used in similar analyses when quarterly data are used in empirical work for advanced countries. If we assumed that advanced countries' economic systems adjusted relatively faster than developing countries', we

would rule out using 1 lag and prefer adopting 3 to 2 as the optimal lag in our study. We could also proceed with using the optimal lag identified with the Akaike criterion considering that it is the one used in Davoodi, Dixit and Pinter (2013).

Table 1. Selection of Optimal Lag

Lags	AIC	SBC	LR Significance Level
5	544.38	737.05	0.592
4	-162.67	-4.00	1.000
3	-126.01	-1.34	2.87e-012*
2	-2633.74*	-2543.07*	2.36e-008*
1	-751.47	-694.80	

* Selected optimal lag under the test statistic

Our final consideration in choosing the optimal lag is analysis of the incidence of serial correlation in residuals fitted from the VAR with 3 lags compared to one with 2 lags. The reason for using the incidence of serial correlation as a basis for discriminating between a VAR with 3 lags and one with 2 lags is that serial correlation plays a significant role in efficient estimations in regression analysis. Ideally such estimations should be devoid of serial correlation.

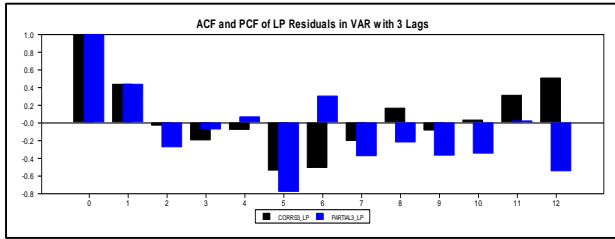
Generally, the auto-correlation and partial autocorrelation coefficient functions of the VAR models with 2 and 3 lags show that the auto-correlation and partial autocorrelation coefficients diminish gradually with time except for a notable spike for the partial autocorrelation function (PACF) of the VAR with 3 lags at the fifth lag. The results show further that the auto-correlation and partial autocorrelation coefficient functions of the BVAR with 2 lags tend to die off faster and this suggests that the VAR system represents a relatively faster adjusting economic system than one that is represented in a VAR with 3 lags.

For illustration and quick reference, we have presented, in Figure 2 Panels A and B, and Figure 2: Panels C and D, the autocorrelation and partial autocorrelation coefficient functions of LRY and LP, which are our principal policy objective variables. Figure 2 panels A and B are for the BVAR model with 2 lags.

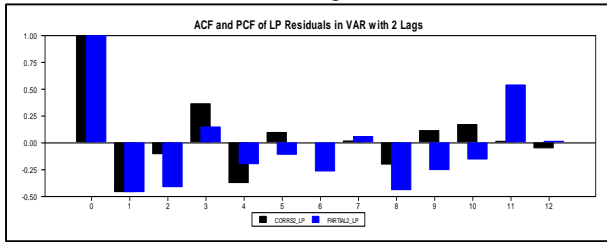
We have also presented Ljung-Box Q-Statistics test statistic test results in Tables 2 and 3 to show that the VAR with 2 lags is better than the BVAR with 3 lags. The results in Tables 2 and 3 show that at 12 periods, the VAR with 2 lags has lower autocorrelation for all the 6 variables than the VAR with 3 lags. The VAR with 2 lags also has lower autocorrelation for 5 of the 6 variables than the VAR with 3 lags. It does better, still, even at 4 periods. These results are therefore supportive of the VAR with 2 lags. We therefore proceed with further empirical analysis using a BVAR model with 2 lags.

Figure 2: Autocorrelation and Partial Autocorrelation Coefficient Functions

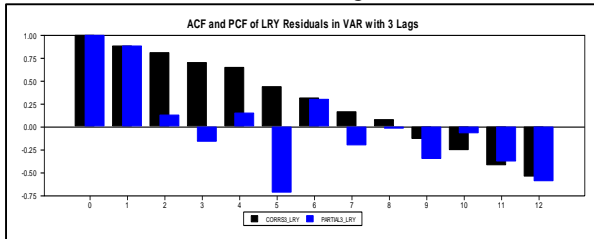
Panel A. LRY in VAR with 2 Lags



Panel B. LP in VAR with 2 Lags



Panel C. LRY in VAR with 3 Lags



Panel D. LP in VAR with 3 Lags

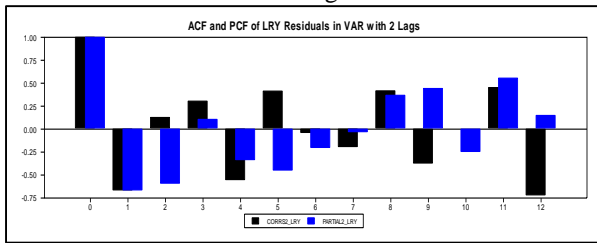


Table 2. Ljung-Box Q-Statistics (VAR with 3 Lags)

Lags	LRY	LP	LRM	LCBR	LRC	LNEER
4	56.37[0.000]	5.50[0.240]	8.28[0.082]	32.06[0.000]	61.78[0.000]	56.37[0.000]
8	66.16[0.000]	24.65[0.002]	9.93[0.270]	33.41[0.000]	75.62[0.000]	66.16[0.000]
12	95.86[0.000]	44.66[0.000]	73.29[0.000]	55.89[0.000]	99.03[0.000]	95.86[0.000]

Table 3. Ljung-Box Q-Statistics (VAR with 2 Lags)

Lags	LRY	LP	LRM	LCBR	LRC	LNEER
4	21.21[0.000]	12.27[0.015]	10.78[0.029]	22.53[0.002]	15.72[0.003]	21.66[0.002]
8	33.84[0.000]	14.11[0.079]	11.70[0.165]	29.79[0.002]	46.02[0.000]	30.35[0.000]
12	80.12[0.000]	16.12[0.186]	22.44[0.033]	48.50[0.000]	85.58[0.000]	43.54[0.000]

5.1.2. Prior Probability Density Function

The prior state mean vector, β_{00} , and the prior variance-covariance matrix, Σ_{00} , that we have used in setting up the BVAR model are provided below. Thus, we have assumed an overall tightness of 0.1. We have also assumed a harmonic distributed lag function with a decay factor of 2 in assigning prior means, further tightness relative to the lag order to which the prior mean is attached.

$$\beta_{00} = [1.0 \ 1.0 \ 1.0 \ 1.0 \ 1.0 \ 1.0] \quad (32)$$

$$\Sigma_{00} = \begin{bmatrix} 1.0 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 1.0 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 1.0 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 1.0 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 1.0 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 1.0 \end{bmatrix} \quad (33)$$

5.1.3. BVAR Model Estimation Procedure

We initially estimate the BVAR model, using Theil mixed estimation procedure over the sub-sample 1997Q4-2007Q4, to obtain a refined set of priors that we proceed to use in the Kalman filter estimation for the sub-sample 2008Q1-2012Q3. The primary estimation results provide us with the one-period-ahead forecast performance indicators, including the Theil U, which show that the BVAR model set up is satisfactory. Most importantly, these results show that we have appropriate initialisation values of the state variables vector and its variance-covariance matrix. We therefore execute the Kalman filter for the period 2008Q1-2012Q2 (saving one period for effecting the last one period ahead forecast through 2012Q3) to obtain the final empirical results that we present in sections 5.2 and 5.3, and discuss in section 5.4.

5.2. Impulse Response Functions

The impulse response function results are presented in Figure 3 which is essentially a 6x6 matrix of a panel of 36 impulse response functions. The impulse response function for the i^{th} variable labelled on the left hand side of the figure to a shock in the j^{th} variable labelled at the top of the figure is located at $impulse(i, j)$ for all values of i and j whereby $i, j = 1, 2, 3, 4, 5, 6$. Accordingly, the extreme top-left corner impulse response function is provided by $impulse(1,1)$ while the extreme bottom-right corner is $impulse(6,6)$. In these cases, $impulse(1,1)$ is the impulse response function of real output, LRY , to an exogenous 1 standard deviation increase in itself. Also, $impulse(6,6)$ represents the impulse response function of the nominal effective exchange rate, $LNEER$, to an exogenous 1 standard deviation increase

in *LNEER*. Analogously, the impulse response function of the headline CPI, *LP*, to an exogenous 1 standard deviation increase in the Central Bank Rate, *LCBR*, which is of particular interest to us in this analysis, is situated at *impulse(2,4)*.

Following Sims and Zha (1999), we compute the confidence bands for the impulse response functions in Figure 3. The confidence bands are the 16% and 84% percentile bands which are equivalent to the 1 standard deviation symmetrical error bands that one obtains from variance estimates. The impulse response function results with the 1 standard deviation symmetrical error bands are provided in Figure 4 for comparison purposes. The distribution of the impulse responses is not quite symmetrical as can be inferred from notable differences in some of the corresponding results in figures 3 and 4. Take the example of the impulse response function of real bank credit to the private sector, *LRC*, to a shock in *LCBR*. It is shown to be clearly significant in Figure 3 but not quite significant in Figure 4. As such, the distribution of the impulse responses is inconsistent with the standard symmetrical normal distribution which cannot therefore form a good basis for carrying out inferential statistical analysis of the empirical results. The results in Figure 3 are preferable to those in Figure 4.

In computing the confidence bands, in line with Sims and Zha (1999), we have applied Monte Carlo Integration which entails “simulation” of the BVAR model that we have estimated using the Kalman filter. This means that the Monte Carlo Integration simulations are initialized using the Kalman filter estimates of the state variables vector of posterior means and its posterior variance-covariance matrix to draw 10000 state variable vectors of posterior means and corresponding variance-covariance matrices per period for 30 periods.⁹ For each pair of state variables vector of posterior means and variance covariance matrix, a corresponding draw of impulse responses is made so that in total we have a sample of 10000 impulse responses for each of the 30 periods. The distribution of each period’s sample of 10000 impulse responses is empirically analyzed by computing the posterior integrated impulse response mean and its 16% and 84% percentiles. The series of posterior integrated impulse response means and corresponding 16% and 84% percentiles for the 30 period can then be plotted as impulse response functions with the 16% and 84% percentile bands across the periods as shown in Figure 3. We have considered 16 quarters out of the maximum 30 quarters in Figure 3 so as to ensure that the figure is legible.

So, how could we describe the results Figure 3 and what do the results really mean?

Firstly, and at a general level, the results are plausible as they are consistent with theoretical predictions. In particular, they are devoid of the exchange rate and price puzzles which afflict a number of past studies including Cheng (2006), and Davoodi, Dixit and Pinter (2013). Secondly, these results are superior to those derived from estimating the VAR model using OLS and those obtained from estimating the BVAR model using Theil’s mixed estimation method. We have presented these comparative results in Appendix 2 Figure A1.1 and Figure A1.2, respectively. These comparative results are not as well defined as those presented in Figure 3. The results in Figure 3 are more efficient

considering that for the same 16% and 84% percentile bands, impulse responses are in some instances statistically significant while those in Figure A1.1 and Figure A1.2 are not.

Overall, the preferred results are a marked improvement over available past findings considering that we have used seasonally unadjusted data while explicitly modelling seasonality effects in the estimable BVAR model to derive empirical results which are devoid of any paradoxes.

Having provided a general description of the results, we now proceed to sub-sections 5.2.1 through 5.2.3 which present detailed interpretation of the results.

Figure 3. BVAR Model Impulse Response Functions with the 16% and 84% Percentile Bands

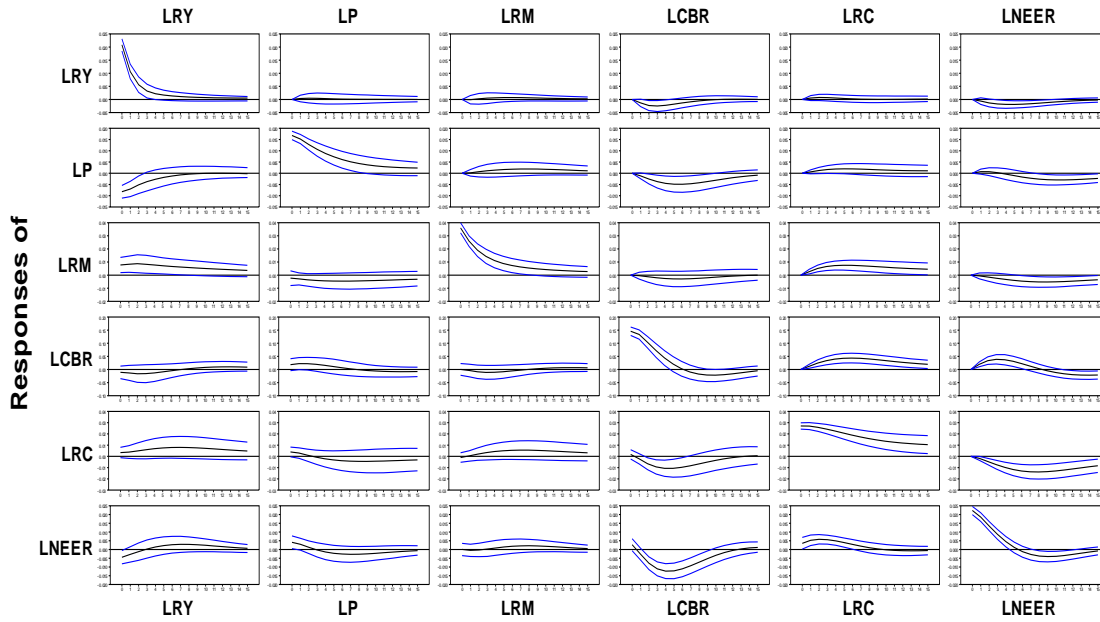
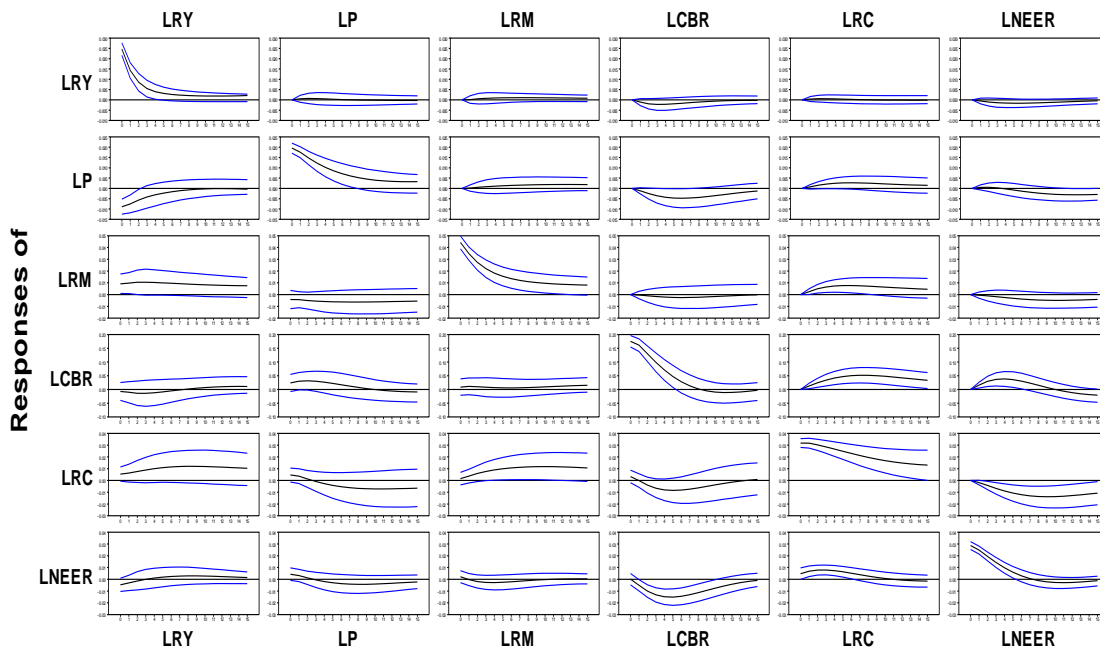


Figure 4. BVAR Model Impulse Response Functions with the 1 Standard Deviation Error Bands



5.2.1. Transmission of Monetary Policy to Output and Prices

The empirical question we attempt to answer in this study is: how do monetary policy objective variables, especially, the domestic general level of prices and real output, respond to a sudden change in the monetary policy instruments. We break the “how” question into the magnitude of effect and timeliness in delivery of the policy induced effect on real output and the prices. For practical purposes and in line with past studies, we identify the lag as the time it takes, following the sudden change in the policy instrument under consideration, for the policy induced effect on the policy objective variables to attain the peak.

For purposes of our analysis, two policy instruments are incorporated in the BVAR model. These are the Central Bank Rate, *LCBR*, and reserve money, *LRM*. We therefore consider exogenous shocks to log of *LCBR* and *LRM* to be representative of monetary policy shocks.

A monetary policy shock measured as a sudden 1 standard deviation increase in *LCBR*, which we interpret to mean sudden monetary tightening, is estimated to be 15 basis points on impact as shown in *impulse(4,4)*. This shock dies off smoothly within 5 quarters during which time it is statistically significant and therefore persistent. In contrast, a monetary policy shock, which is a sudden 1 standard deviation increase in *LRM* and which we interpret to mean sudden monetary policy easing, is estimated at 3.5 basis points and lasts for 8 quarters. The time path of this shock is shown in *impulse(3,3)*.

So how long does it take for output and prices to respond to these shocks? And what are the magnitudes of response of output and prices to the shocks? Apart from the direct channels of effect, namely, the interest rate and the money channels, through what other channels does monetary policy actions taken in terms of sudden increments in the policy rate and/ or reserve money influence output and prices? And, perhaps most importantly, what is the order of magnitude of the trade-off between output and inflation consequent to monetary policy action?

According to the impulse response function provided by *impulse(1,3)*, an exogenous 1 standard deviation innovation in the reserve money, which represents monetary easing, tends to increase real output. The induced increase in real output is however not significant. This outcome is not surprising as it is consistent with the neutrality assumption of money whereby changes in nominal variables including changes in nominal money stock has no permanent effect on real variables such as real output, in this case. The result is, however, surprising to the extent that, under the assumption of inflexible prices during the short run time horizon, we expected to see a significant temporary incremental effect arising from a corresponding increase in real money balances. The response of prices to a shock to reserve money is largely similar to the response of real output which is, also, insignificantly incremental. This result is provided by *impulse(2,3)*. Thus, monetary policy shocks measured in terms of an exogenous increase in reserve money is not, in a significant manner, directly transmitted to real output and prices. This suggests that the money channel for monetary policy transmission mechanism is necessary but not sufficient in bringing about desired changes in output and prices. Not unless, perhaps, it is complemented by further relevant actions such as interest rate

signalling. Otherwise, on its own, the money channel is an ineffective channel of monetary policy transmission mechanism.

In contrast, an exogenous 1 standard deviation increase in the CBR, significantly, albeit temporarily, reduces real output during the 2nd, 3rd and 4th quarters after the shock which is just about the same time such a policy shock exerts its peak impact on output in the case of Canada as shown by Bhuiyan (2008). According to Bhuiyan, real output falls with a lag of over a year (when using monthly data and structural identification within the context of BVAR methodology). The magnitude of effect of the shock on real output is less than proportionate at its peak in the 3rd quarter following occurrence of the shock. It is estimated to be 0.3 basis points. Two important implications arise from these results. Firstly, since the largest reduction in real output occurs in the 3rd quarter, we infer that monetary policy transmission to real output involves a lag of 3 quarters which is equivalent to 9 months. Secondly, the estimated magnitude of effect of the monetary tightening on real output suggests that the loss in real output resultant from monetary tightening works out at the ratio of 15:0.3. This suggests that it will, on average, take monetary policy tightening of the order of 50 basis points of an increase in the policy rate, to reduce output by 1 basis point.

Moreover, a sudden 1 standard deviation increase in the policy rate persistently reduces the headline CPI (and by extension, headline CPI inflation). The effect of the sudden monetary policy tightening is statistically significant for a period of 8 quarters starting with the 2nd quarter following the occurrence of the shock. These results suggest that the effect of monetary policy tightening on the headline CPI, unlike in the case of real output whereby it is transitory, persists. This is an important result in so far as monetary policy management is concerned. Since monetary policy tightening continues to influence the headline CPI for up to 10 quarters, it is prudent to carefully determine the amount of initial policy action and then be cautious not to follow up the initial monetary policy action, say policy tightening, with further tightening in quick succession without taking into consideration the delayed effect of the initial monetary policy action.

Although sudden monetary tightening using the policy rate significantly reduces headline CPI beginning with 2 quarters through 10 quarters whereby the peak reduction occurs in the 6th quarter, the monetary tightening influences prices and output equally quickly (i.e. within 2 quarters). In terms of timeliness in exerting significant impact on real output and headline CPI inflation, the interest rate channel is therefore efficient. Though inefficient to the extent that its limited magnitude of effect on the headline CPI is distributed over 8 quarters, it would as well be argued that the cumulative magnitude of effect over that period is the more appreciable. It is therefore reasonable to infer that monetary policy transmission through the interest rate channel is definitely effective with the effectiveness re-enforced further by the indirect effects on real output and prices which the monetary tightening using the policy rate induces through such intermediate policy variables as the exchange rate and real bank credit to the private sector. We examine exchange rate and the bank credit channels later on in sub-section 5.2.2.

The peak impact in the reduction of the headline CPI, which we estimate to be 0.5 basis points, results in the 6th quarter and this is also an important result. To the extent that the largest decrement in the

headline CPI occurs after 6 quarters following a sudden raise in the policy rate, we infer that the monetary policy transmission lag is 6 quarters or 1½ years. We also infer that a monetary policy tightening effort of 15 basis points results in, at peak impact, only 0.5 basis points of reduction in the headline CPI and which brings to the fore the question regarding the macroeconomic policy stabilization trade-offs between output and prices.

It follows that the gain in price stabilization which is resultant from monetary policy tightening using the policy rate works out at the policy effort to policy objective variable outcome ratio of 15:0.5. It will, therefore on average, take monetary policy tightening, using the policy rate, of the order of 30 basis points to reduce the headline CPI by 1 basis point. In other words, for 30 basis points of monetary policy tightening using the policy rate, we would on average, during the study period of 2008Q1-2012Q3, achieve 1 basis point reduction in the headline CPI.

As if it were a double-edged sword, however, the 30 basis points of monetary policy tightening which leads to 1 basis point of price reduction will also penalize the economy to the extent of 0.6 basis points of reduced real output. This is because monetary policy tightening by 50 basis points of increase in the policy rate will on average reduce real output by 1 basis point and this suggests that the output-price stabilization trade-off resultant from a sudden 1 standard deviation of monetary policy tightening is 10:6. Which means that for every 10 basis points of gain in price stabilization consequent to a sudden 1 standard deviation worth of monetary policy tightening using the policy rate, Kenya would on average, loss 6 basis points in reduced real output (during the model estimation period of 2008Q1-2012Q3). Thus, much as there is a loss in terms of real output consequent to monetary policy tightening, the monetary policy tightening comes with net gain in price stability. It would therefore appear that the output-inflation trade-off resultant from monetary policy is not too severe and this would owe to the efficacy of the expectations channel of monetary policy transmission mechanism as discussed in Maturu, Maana and Kisinguh (2007). One of the study findings in Maturu, Maana and Kisinguh (2007) shows that firms' price-setting model is predominantly forward-looking in expectations formation and as such, when firms' expectations are well anchored on the Central Bank of Kenya's inflation target, then for a relatively minimal policy effort, significant results are to be achieved in terms of desired price stabilization outcomes.

5.2.2. Other Important Impulse Response Function Results

A. Monetary Policy and Exchange Rate Dynamics

The result presented in Figure 3 at *impulse(3,6)* suggests that sudden monetary policy easing to the extent of an exogenous 1 standard deviation innovation in reserve money is inconsequential to the nominal effective exchange rate. However, there is a tendency for the nominal effective exchange rate to depreciate in the long run although such depreciation is statistically insignificant. For purposes of prudent monetary policy management, this result serves to caution against too much monetary easing that can potentially lead to depreciation of the shilling exchange rate in nominal effective terms.

Conversely, the results presented in *impulse(4,6)*, suggest that sudden monetary policy tightening using the policy rate would, during the study period 2008Q1-2012Q3, lead to statistically significant appreciation of the nominal effective exchange rate within 2 quarters. The significant appreciation is persistent as it prevails during the subsequent 8 quarters and therefore through the 9th quarter following the monetary policy tightening. This result means that even when CBK specifically aims to reduce inflation by tightening monetary policy using the policy rate, there would be unintended impact on other macroeconomic variables including the exchange rate and output. Thus, before taking a monetary policy action, due consideration should be given to the unintended impacts on the exchange rate, as well.

It is notable from *impulse(4,6)* that the peak impact of the monetary policy tightening on the exchange rate occurs after 5 quarters following the tightening. The peak impact is estimated at 1.3 basis points. The apparent depreciation of the exchange rate on impact, following the monetary policy tightening, is statistically insignificant and therefore essentially non-existent. Furthermore, the impulse response function result in *impulse(4,6)* suggests that automatic exchange rate adjustment is stable. This is because the impulse response function is devoid of any oscillatory movements that could suggest exchange rate overshooting behaviour that is reminiscent of Dornbusch (1976).

B. Exchange Rate Channel of Monetary Policy Transmission

The exchange rate channel is considered to be particularly important in small open economies and it is therefore useful for us to examine role of the exchange rate in monetary policy transmission in Kenya. Since Kenya practiced a flexible exchange regime during the estimation period, the exchange rate is not a nominal anchor. It is, however, informative to examine its role since there are implications for macroeconomic stabilization. We therefore examine the dynamic responses of real output and the headline CPI to an exogenous 1 standard deviation increase in the nominal effective exchange rate.

An exogenous 1 standard deviation innovation in the nominal effective exchange rate is shown in Figure 3 *impulse(6,6)* and we estimate it to be 2.2 basis points. We notice from *impulse(6,6)* that once the shock materializes, it dies off within about a year.

The dynamic response of real output to the exchange rate shock are provided in Figure 3 by *impulse(6,1)*. A sudden depreciation of the shilling in nominal effective terms imposes a lasting reducing effect on real output which prevails within 4 through 9 quarters of the shock's occurrence. Though statistically significant, the magnitude of effect of the depreciation on output is negligible as it hardly reaches 1 basis point at its peak.

The response of the headline CPI to the exchange rate shock is presented in Figure 3 as *impulse (6,2)*. While the depreciation will in the short run tend to be inflationary, this short run exchange rate pass-through to domestic prices is not statistically significant. However, it induces a statistically significant reduction in the headline CPI after a very long delay; beginning in 9th through the 14th quarter.

Considering that an exchange rate shock has statistically significant effects on output and the headline CPI and that policy action taken using the policy rate has a statistically significant effect on the exchange rate, suggests that the exchange rate channel of monetary policy transmission mechanism in Kenya is operational. However, the channel is a weak one because of the small magnitude of effects on output and the headline CPI resultant from an exchange rate shock.

The response of real output to the exchange rate shock suggests that engineering a shilling exchange rate depreciation hoping to make domestic output competitive and thereby stimulating economic growth is unfounded since the evidence is to the contrary. This result implies that the Marshall-Lerner Condition (MLC), which is that the sum of the absolute values of the elasticity of Kenya's imports and exports exceeds 1, for an exchange rate depreciation (or devaluation) to boost net exports thereby improving the current account balance never held in 2008Q1-2012Q3. The result further implies that shilling exchange rate depreciation permanently exacerbates the current account deficit and it is therefore not advisable to be pursued as a matter of policy.

If the reduction effect of an exchange rate shock is understood within the context of the MLC, we can argue further that following the sudden depreciation, exportable goods are diverted to the domestic economy whilst, inelastic imports are sustained so that the net effect is for improved supply of goods and services that moderates the inflationary situation in the country as shown in Figure 3 *impulse(6,2)*.

C. Bank Lending Shocks and Macroeconomic Stability

According to the results in Figure 3 *impulse (5,1)*, a sudden 1 standard deviation increase in real bank lending to the private sector, which we estimate from *impulse (5,5)* to be 3 basis points, induces an increase in real output on impact and thereafter for a period of 6 quarters. The incremental effect on output is, however, neither statistically significant nor appreciable in magnitude.

The response of the headline CPI to the shock in bank credit to the private sector, which is shown in *impulse (5,2)*, is largely similar to that of real output. In contrast however, consequent to the bank credit shock, the headline CPI increases immediately and permanently. The increase in headline CPI is significant, generally, through the first 5 quarters following the bank credit shock. Now that the link to output and prices through bank credit to the private sector is established to exist, it only requires us to

establish that the link between the policy rate and real bank credit to the private sectors exists so we could infer that the bank credit channel is operational.

D. Monetary Policy and Bank Lending to Private Sector

The impulse response function of real bank credit to the private sector to a sudden increase in the policy rate is provided in Fig. 3 by *impulse(4,5)*. A shock to the policy rate, which takes the form of monetary policy tightening, leads to a statistically significant reduction in real bank credit to the private sector beginning in the 3rd quarter through the 7th following the policy rate shock. The peak impact estimated at 1 basis point occurs in the 5th quarter. Therefore, the bank credit channel is operational in Kenya.

E. Monetary Policy Reaction Function

The results in Figure 3 *impulse(4, j) $\forall j = 1,2,3,4,5,6$* suggest that the three variables which the Monetary Policy Committee would apparently consider when setting the CBR are: the headline CPI (i.e. $j = 2$), the real bank credit to the private sector (i.e. $j = 5$), and the shilling exchange rate (i.e. $j = 6$). This is because the response of the CBR to shocks in the three variables is significant; in the second quarter for prices, and on impact to last for the real bank credit and the exchange rate.

In contrast, real output, real bank credit to the private sector and the exchange rate were important information the Monetary Policy Committee could consider when taking policy action using reserve money. These results are captured in Figure 3 *impulse(3, j) $\forall j = 1,5,6$* . Generally, therefore, the results suggest that the MPC puts into consideration, developments in economic growth, bank credit, exchange rate and inflation when taking monetary policy action.

F. Supply Shocks and Price Stability

It is shown in Figure 3 *impulse(2,1)* that prices respond immediately and in a statistically significant manner to supply shocks. An exogenous 1 standard deviation innovation to real output, which is a positive supply shock that we estimate to be 2 basis points occasions an immediate statistically significant reduction in the headline CPI (and by extension headline inflation) of about 1 basis point. The significant reducing effect prevails during the most part of the year (i.e. from the 1st through the 3rd quarter). It therefore appears from these results, that the best approach to controlling headline consumer price inflation is by boosting domestic real output.

5.3. Variance Decomposition

The variance decomposition results show the relative importance of a given endogenous variable in explaining the out-of-sample forecast error in another endogenous variable of interest under the analysis. We are for instance particularly interested to know the importance of reserve money and the

policy rate in explaining the out-of-sample forecast errors in real output and the headline CPI. The larger the proportion of the out-of-sample forecast errors in real output and the headline CPI explained by reserve money or/and the policy rate, the greater the potential for monetary policy to be effective in being used for macroeconomic stabilization. When the out-of-sample forecast errors explained by the policy rate or reserve money are sufficiently large, it is most likely that the corresponding impulse responses will as well be statistically significant and large in magnitude. This implies that variance decomposition results are useful in validating the impulse response function results.

For purposes of this analysis, we consider reserve money to be indicative of the presence of the money channel, nominal effective exchange rate to be indicative of the exchange rate channel, interest rate to be indicative of the interest rate channel, and bank lending to be indicative of bank credit channel. As to whether or not the exchange rate and the bank lending channels are operational in Kenya, we use the impulse response and the variance decomposition results to show that there is a link running from the policy rate or/and reserve money through the exchange rate and bank credit to real output and the headline CPI. The strength of the exchange rate and the bank credit channels will depend on the magnitude of effects involved, in for instance, the link between the policy rate to the exchange rate (or bank credit) and the link between the exchange rate (or bank credit) and the headline CPI (or real output).

5.3.1. Variance Decomposition of Output and Prices

We have presented the variance decomposition results for real output and the headline CPI in Table 4 and Table 5. For ease of reference, these results are also shown in Figure 6 and Figure 7¹⁰. Generally, the forecast errors for output and headline CPI which are shown in Figure 4 and Figure 5 are not only small in magnitude but also do not grow explosively with increased out-of-sample forecast period. This shows that the estimated BVAR model has the potential to efficiently forecast real output and the headline CPI.

The results presented in Table 4 show that apart from own shocks which account for at least 90% of its 5-year and above out-of-sample forecast errors, the second most important factor in explaining the forecast errors in real output during the short run to medium term period of up to 2¼ years is the policy rate which accounts for 3.7%, while the nominal effective exchange rate accounts for 3.7% of the 9 quarters ahead forecast error in real output.

While the policy rate's importance in explaining fluctuations in real output increases steadily with time through the 17th quarter, its relative importance is overtaken by that of the exchange rate in the 11th quarter so that in the long run, the exchange rate is more important than the policy rate in explaining fluctuations in real output. In the long run, the contributions of the policy rate and the nominal effective exchange rate in explaining fluctuations in real output tend to converge to 3.7% and 4.1%, respectively.

It must, however, be clarified that the policy rate exerts an appreciable influence on some of the other endogenous variables such as the exchange rate which could in turn exert further indirect influence on real output and the headline CPI. We note, for instance, from the variance decomposition results of

LNEER presented in Table 6 that the proportion of forecast errors in the *LNEER* explained by fluctuations in the policy rate rises from 13.5% of the 4 quarters ahead forecast error of the *LNEER* to 33.7% of the 20 quarters ahead forecast error. Yet again, as we have already noted from the results in Table 4, the exchange rate contributes to the explanation of real output fluctuations. These results suggest that, if we take into account both the direct and indirect effects of the policy rate on real output and the headline CPI, the interest rate channel is certainly important in the transmission of monetary policy.

The results in Table 5 show that the headline CPI accounts for 67.0% to 81.7% of its forecast errors over the same out-of-sample forecast periods. Real output shocks are particularly important during the short run to medium term period of 2½ years. The supply shocks, for instance, account for 11.5% and 18.7% of the 10 quarters and the 1 quarter ahead forecast errors, respectively. In comparison, the policy rate accounts for 11.5% of the 10 quarters ahead forecast error and its role increases steadily to 12.1% of the forecast error for the 20 quarters ahead. Thus, the role of the policy rate in accounting for fluctuations in the headline CPI surpasses that of real output shocks during the medium term period of 2 ½ to 5 years. It is also during this period when the exchange rate channel becomes relatively more important compared to the short run when its role in explaining fluctuations in the headline CPI is virtually nil. It is notable that the combined role of the policy rate and the exchange rate in explaining fluctuations in the headline CPI rises from 12.0% of the 9 quarters ahead forecast error to 17.0% of the 20 quarters ahead forecast error.

In comparison to the roles of the interest rate and the exchange rate channels, the roles of the money and credit channels are rather limited. At best, reserve money shocks account for only 2.6% of the 20 quarters ahead forecast error in the headline consumer index when real bank credit to the private sector accounts for 2.5%. The combined role of these two variables in accounting for fluctuations in the headline CPI is basically equal to the role of the exchange rate channel whereby the exchange rate accounts for 4.9% of the 20 quarters ahead forecast error in the headline CPI.

In their order of relative importance, therefore, the channels of monetary policy transmission in Kenya are: the interest rate, the exchange rate, the money and the bank credit channels. It is notable that the bank credit channel is relatively more important over the short to medium term period of 2½ years. Beyond this period, the exchange rate channel overtakes the bank credit channel.

Table 4. Decomposition of Variance for LRY

Step	Std Error	LRY	LP	LRM	LCBR	LRC	LNEER
1	0.0176	100.00	0	0	0	0	0
2	0.0199	99.50	0.03	0.00	0.34	0.06	0.08
3	0.0206	98.03	0.08	0.01	1.29	0.18	0.41
4	0.0209	96.26	0.12	0.06	2.32	0.28	0.97
6	0.0212	93.51	0.16	0.20	3.48	0.37	2.28
8	0.0214	92.11	0.19	0.35	3.68	0.39	3.29
10	0.0215	91.49	0.21	0.44	3.66	0.39	3.81
12	0.0215	91.20	0.23	0.48	3.68	0.40	4.01
14	0.0215	91.06	0.25	0.49	3.72	0.42	4.06
16	0.0215	90.97	0.25	0.50	3.74	0.46	4.07
18	0.0216	90.92	0.26	0.50	3.75	0.50	4.08
20	0.0216	90.87	0.26	0.50	3.74	0.54	4.08

Table 5. Decomposition of Variance for LP

Step	Std Error	LRY	LP	LRM	LCBR	LRC	LNEER
1	0.0160	18.70	81.31	0	0	0	0
2	0.0215	17.88	81.73	0.01	0.24	0.07	0.09
3	0.0246	16.56	81.95	0.06	1.05	0.25	0.13
4	0.0266	15.35	81.38	0.18	2.46	0.52	0.12
6	0.0291	13.42	78.43	0.51	6.24	1.12	0.20
8	0.0306	12.17	74.73	1.12	9.60	1.60	0.78
10	0.0316	11.47	71.66	1.64	11.50	1.90	1.83
12	0.0321	11.13	69.60	2.05	12.19	2.07	2.95
14	0.0325	10.97	68.37	2.33	12.28	2.20	3.85
16	0.0327	10.90	67.68	2.50	12.19	2.31	4.42
18	0.0328	10.86	67.27	2.60	12.11	2.42	4.74
20	0.0328	10.84	67.01	2.64	12.07	2.54	4.91

Figure 4. Forecast Errors in LRY

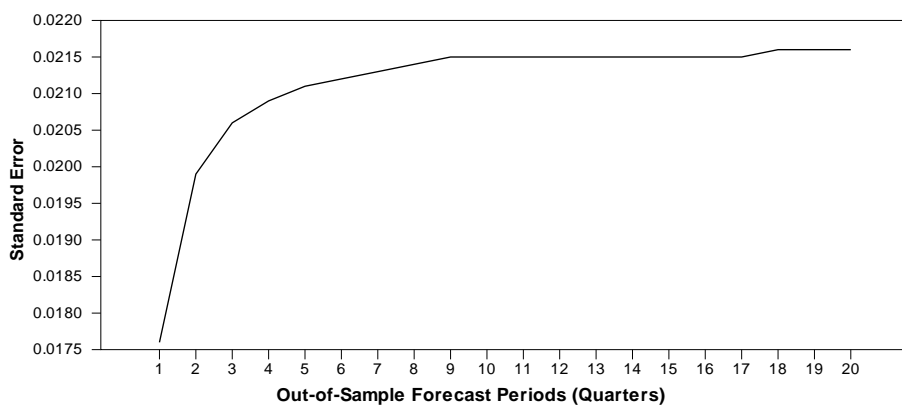


Figure 5. Forecast Errors in LP

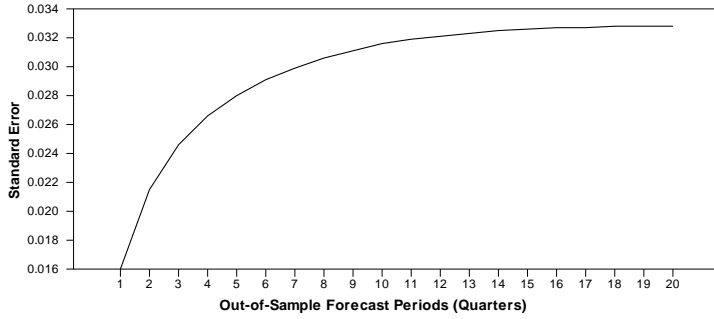


Figure 6. Variance Decomposition for LRY

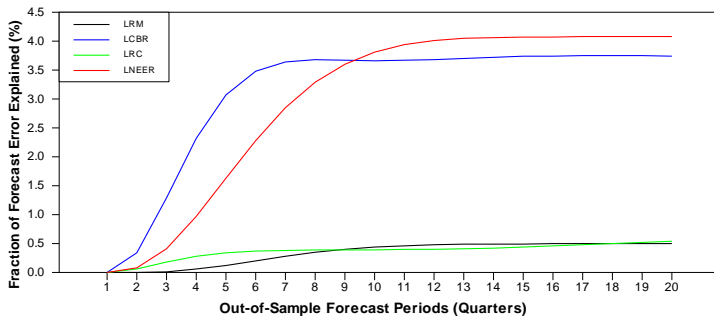
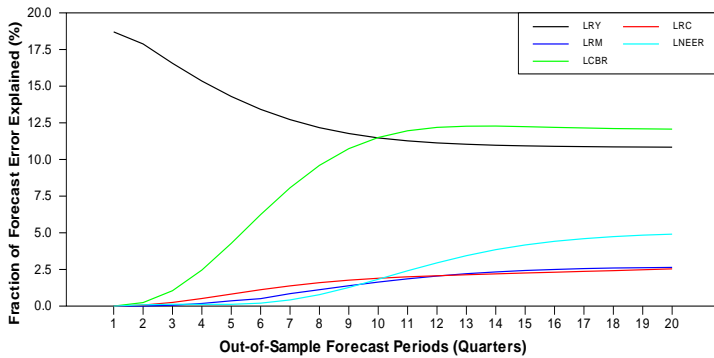


Figure 7. Variance Decomposition for LP



5.3.2. Other Important Variance Decomposition Results

A. Variance Decomposition of the Exchange Rate

We have presented the variance decomposition results of the exchange rate in Table 6. The exchange rate forecast errors at varied out-of-sample periods are shown in column 2 and presented graphically in Figure 8.

The variance decomposition results in columns 3 through 6 are also presented in Figure 9. The results show that the exchange rate is predominantly self-driven as it accounts for over 90% of its 1 period

ahead forecast error. Its role however declines with increasing out-of-sample forecast periods to converge at about 53%.

The second most important factor explaining the nominal effective exchange rate fluctuations is the policy rate which is particularly important over the medium to long term when it accounts for 13.5% to 33.5% of the effective exchange rate’s forecast errors. These estimates are, respectively, for the 4 and 20 quarters ahead forecast errors. Unlike in, for instance, Bhuiyan (2008) in which the exchange rate overshooting phenomenon introduced by Dornbusch (1976) is attained on impact, the exchange rate overshooting phenomenon is fully attained in the 5th quarter following the policy rate shock. Thereafter, the nominal effective exchange rate depreciates to eventually assume its equilibrium once the effect of the policy shock on the exchange rate fizzles out completely within 10 quarters.

The third most important factor is the real bank credit to the private sector which accounts for about 7% of the effective exchange rate’s out-of-sample forecast errors at the 8 to 20 quarters.

Table 6. Decomposition of Variance for LNEER

<i>Step</i>	<i>Std Error</i>	<i>LRY</i>	<i>LP</i>	<i>LRM</i>	<i>LCBR</i>	<i>LRC</i>	<i>LNEER</i>
1	0.0211	3.18	2.80	0	1.24	2.21	90.57
2	0.0276	2.59	2.49	0.03	1.50	4.16	89.23
3	0.0314	2.11	2.04	0.03	6.14	5.94	83.74
4	0.0342	1.79	1.73	0.03	13.48	7.16	75.81
6	0.0382	1.77	1.72	0.16	26.93	7.82	61.60
8	0.0408	2.22	2.12	0.48	33.04	7.39	54.75
10	0.0421	2.65	2.48	0.80	34.03	6.98	53.07
12	0.0430	2.87	2.66	0.99	33.53	6.83	53.12
14	0.0430	2.93	2.72	1.06	33.27	6.81	53.22
16	0.0430	2.92	2.71	1.07	33.39	6.81	53.09
18	0.0430	2.92	2.71	1.07	33.58	6.80	52.94
20	0.0430	2.92	2.70	1.07	33.67	6.79	52.86

Figure 8: Forecast Errors for LNEER

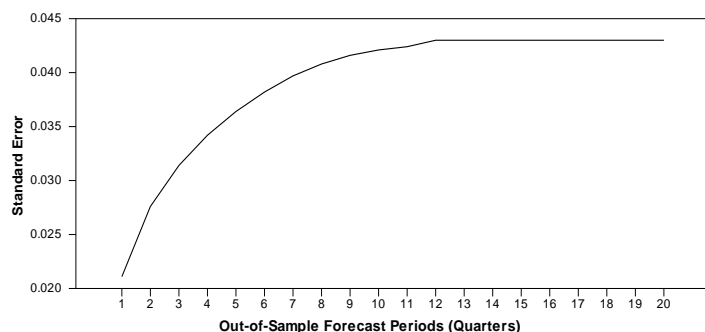
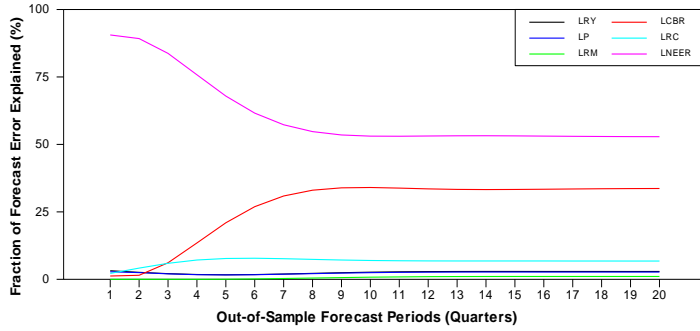


Figure 9. Variance Decomposition for LNEER



B. Variance Decomposition of Bank Credit to Private Sector

The variance decomposition results for real bank credit to the private sector are provided in Table 7 and plotted Figure 10. The forecast errors, though small, tend to increase steadily and smoothly with increased out-of-sample forecast period. This suggests that the estimated BVAR model is potentially useful in generating efficient real bank credit to the private sector forecasts for lengthy out-of-sample periods.

Table 7. Decomposition of Variance of LRC

Step	Std Error	LRY	LP	LRM	LCBR	LRC	LNEER
1	0.0245	1.33	1.91	0.13	0.40	96.24	0.00
2	0.0346	1.53	1.51	0.07	0.50	96.17	0.21
3	0.0424	1.92	1.06	0.23	2.19	93.51	1.09
4	0.0490	2.45	0.80	0.54	4.46	89.11	2.64
6	0.0601	3.64	0.81	1.38	7.71	79.51	6.96
8	0.0684	4.69	1.09	2.18	8.52	72.06	11.47
10	0.0742	5.44	1.38	2.78	8.05	67.26	15.10
12	0.0782	5.90	1.59	3.17	7.37	64.44	17.53
14	0.0809	6.16	1.72	3.38	6.89	62.91	18.94
16	0.0828	6.30	1.80	3.49	6.61	62.15	19.66
18	0.0842	6.37	1.85	3.54	6.44	61.81	19.98
20	0.0852	6.42	1.88	3.57	6.32	61.69	20.13

Figure 10. Forecast Errors for LRC

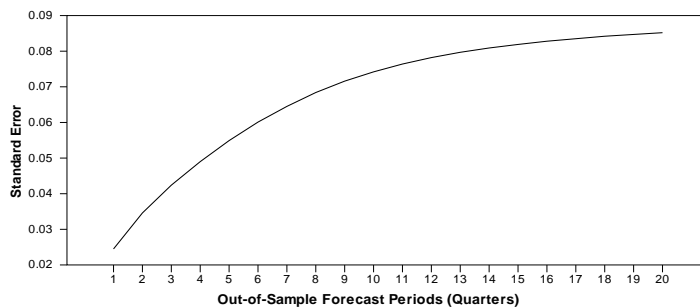


Figure 11. Decomposition of Variance for LRC

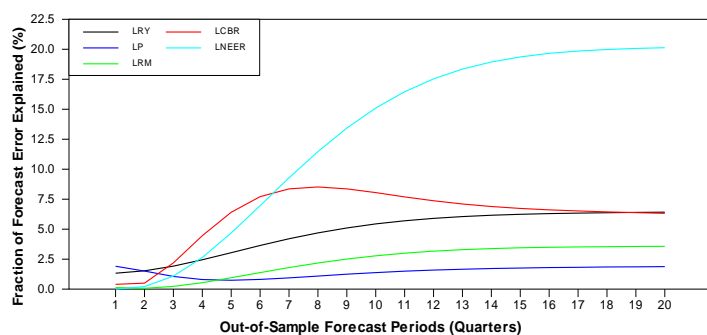


Figure 11 shows that for the 1 year period, the policy rate is most important and reserve money the least. At this out-of-sample forecast of real bank credit, the policy rate accounts for 4.5% of the forecast error when reserve money accounts for 0.5%. These results suggest that the policy rate is relatively more effective at influencing real bank credit to the private sector than reserve money within a year's period of time.

Figure 11 shows further that the distinct roles of all the other endogenous variables in the analysis other than real bank credit itself become clearer for the outer forecast periods. Over a period of time exceeding 2 years, the exchange rate, which incidentally is significantly influenced by the policy rate, becomes relatively more important than the policy rate. For instance, it is shown in Table 6 above that the exchange rate accounts for 11.5% of the forecast error in real bank credit for the 8 quarters out-of-sample forecast and 20% for the 20 quarters. To the extent that the policy rate exerts appreciable impact on the exchange rate, we could as well consider the policy rate to play an important role in influencing the volume of real bank credit to the private sector in the short run, medium term and long term time horizons.

It is not surprising to note that supply shocks play an important role also in observed fluctuations in real bank credit to the private sector. The role of real output tends to 6% over a 5 year period.

5.4. Further General Discussion of the Results

The results that presented and discussed in the preceding section are derived not simply for understanding the past monetary policy exploits of the CBK but most importantly, for application in support of effective monetary policy management in the future. But are these results capable of such application? Yes, they are. This is mainly because the results are robust to changes in the estimation period.

In deriving the empirical results, we have simulated the estimated BVAR model to draw a huge number of samples each of which is very large. The impulse response point estimates are essentially means of each of the 10000 drawn posterior impulse responses. We cannot therefore envisage significant departure of results based on a different estimation period from the impulse response functions presented and discussed above.

Secondly, it is quite clear that the results are to be preferred among other results derived based on other short term nominal interest rates such the 91-Day Treasury bills interest rate, the repo rate and the interbank rate. These alternative results which we derived as part of the robustness tests are presented in Appendix 4 Figure A4.1 - Figure A4.3. It is notable, for instance, that the impulse response function results derived from the 91-Day Treasury bills rate, and which are presented in Figure A4.1 are inconsistent to the extent that they are afflicted with the exchange rate puzzle whereby a significant appreciation of the nominal effective exchange rate, though very temporary, is predicted to result from monetary tightening using the policy rate. The same case applies to the results derived based on the interbank rate and which are presented in Figure A4.3. One possibility is that using the 91-Day Treasury bills rate or the interbank rate does not lead to correct identification of the monetary policy shocks and the policy rate is to be preferred.

It is also notable that the empirical results are robust to the longevity of out-of-sample forecast period. This is because, the variance decomposition results show that the estimated out-of-sample forecast errors are not only very small at any one of the out-of-sample forecast periods ranging from ¼ to 5 years but also that the forecast errors hardly increase much with increasing out-of-sample forecast period for all the endogenous variables under considerations.

We also observed that variation in the prior joint probability density function does not significantly alter the empirical results.

For further empirical work, it will be necessary to relax the assumption about constancy of the state variables vector to time-varying. Time-varying state variables vector forms a good basis for real time forecasting of the endogenous variables including inflation and real output. It should also be useful expanding the BVAR model to include other crucial economic variables such as employment (or unemployment), real investment and the real wage rate so as to pave way to tracking such important economic variables.

6. Summary and Conclusions

This study sought to update available evidence on monetary policy transmission mechanism in Kenya in a bid to support effective monetary policy management by the Bank's Monetary Policy Committee. The study uses quarterly data which poses the challenge of limited degrees of freedom to estimating efficient estimate of the unrestricted VAR model. In order to address the challenge, we applied Bayesian econometric techniques and the Kalman filter to estimate the BVAR model. Unlike past studies which use seasonally adjusted data, this study uses seasonally unadjusted data to avoid discarding useful information in the data. In order to eliminate too much noise that would be occasioned by seasonal factors from the analysis, we control for seasonal effects by incorporating seasonal terms in the BVAR model.

Estimating the BVAR model using the Kalman filter over the period 2008QQ1-2012QQ3 while taking into account all these analytical innovations, we obtain results that are consistent with the stylized facts regarding monetary policy transmission mechanism in a small open economy. Although the magnitude of direct effects of changes in the CBR, which is the monetary policy interest rate, on prices and real output are rather small, the effects are statistically significant and of the expected extent of persistence on output and prices. More specifically, although the impact of sudden monetary policy change is felt

fairly quickly, within a quarter of a year following a change in policy, the peak impact of such a policy change is attained after 1¼ years and by definition, therefore, the monetary policy transmission lag through the interest rate channel is estimated at 1¼ years.

The results suggest further that the total effect of a change in the CBR, which is the effect that takes into account both the direct and the indirect effects (i.e. effects on prices and output by initial corresponding policy induced effects on the intermediate variables including the exchange rate, real bank credit to the private sector and real output) is appreciable. These results suggest that the CBR is an effective instrument of monetary policy and that therefore the interest rate channel of monetary policy transmission mechanism was operational in Kenya during the period 2008Q1-2012Q3.

We also find that most of the fluctuations in the headline CPI are due to the headline CPI's own past innovations. These results imply that there has been substantial inertia in the headline CPI inflation with further implication that once headline inflation sets in, it tends to entrench itself over a long period of time. Vigilance on the current evolution and future prospects of headline CPI inflation is therefore of paramount importance and a pre-emptive monetary policy management strategy is absolutely necessary for effective control over inflation. Otherwise, it must be a daunting task trying to control headline CPI inflation using monetary policy tools which are best suited for controlling demand pull inflation while the headline CPI inflation is predominantly driven by real supply shocks.

The other important result is that, in order of their relative importance, the channels of monetary policy transmission in Kenya are: the interest rate, the exchange rate, the money and the bank credit channels. It is notable that the bank credit channel is relatively more important over the short to medium term period of 2½ years. Beyond this period, the exchange rate channel overtakes the bank credit channel. The response of real output to an exchange rate shock is worth noting. The result implies that the MLC did not hold during the study period, and a depreciation of the shilling permanently exacerbates the current account deficit.

The results show that the gain in price stabilization which is resultant from monetary policy tightening using the policy rate works out at the policy price stabilization effort to policy objective variable outcome ratio of 15:0.5. This means that it would, on average, take monetary policy tightening, using the policy rate, of the order of 30 basis points to reduce the headline CPI by 1 basis point. In other words, for 30 basis points of monetary policy tightening using the policy rate, we would on average, during the study period of 2008Q1-2012Q3, achieve 1 basis point reduction in the headline CPI.

As if it were a double-edged sword, however, the 30 basis points of monetary policy tightening also penalises the economy to the extent of 0.6 basis points of reduced real output. This is because monetary policy tightening by 50 basis points of increase in the policy rate will on average reduce real output by 1 basis point and this suggests that the output-price stabilization trade-off resultant from a sudden 1 standard deviation of monetary policy tightening is 10:6. This means that for every 10 basis points of gain in price stabilization consequent to a sudden 1 standard deviation worth of monetary policy tightening using the policy rate, Kenya would on average, loss 6 basis points in reduced real output

(during the model estimation period of 2008Q1-2012Q3). Thus, much as we loss in terms of real output consequent to monetary policy tightening, the monetary policy tightening comes with net gain in price stability. It would therefore appear that the output-inflation trade-off resultant from monetary policy is not too severe. This may owe to the efficacy of the expectations channel of monetary policy transmission mechanism.

For the further validation of the study findings, an application of structural identification is necessary. It will also be useful expanding the model to incorporate the labour market variables including employment and the real wage rate. Such expansion of the model should also provide for detailed modelling of the production sector to include the role of real investment. It may also be necessary also to estimate the BVAR under the assumption of time-varying state variables vector thereby forming a good basis for real time economic forecasts using the BVAR model.

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Appendix 1: Data Description and Sources

RY = Kenya's real gross domestic product (December 2001=100, KShs, Billion) from Central Bank of Kenya;

P = Kenya's quarterly average of headline consumer price index (December 2001=100, new Series with base in February 2009 spliced for integration with earlier series with October 1997=100), Central Bank of Kenya;

RM = Kenya's stock of monetary base (KShs, Billion), Central Bank of Kenya;

RATE = Kenya's 91-day Treasury bills interest rate (Quarterly weighted average, percent), from Central Bank of Kenya;

INTERBANK = Kenya's interbank interest rate (quarterly weighted average, percent), from Central Bank of Kenya;

RC = Kenya's real stock of bank credit to the private sector (KShs, Billion), from Central Bank of Kenya;

NEER = Kenya's nominal effective exchange rate index (December 2001=100), from Central Bank of Kenya;

YF = Industrial production index of advanced countries as a proxy for output of Kenya's trading partner countries as a measure of the international economic environment (December 2001=100), Central Bank of Kenya/International Financial Statistics (IFS);

PF = Weighted consumer price index of selected countries that are Kenya's key trading partners (December 2001=100), Central Bank of Kenya/ International Financial Statistics (IFS);

OILPRICE = World oil price (Murban Oil, USA Dollars per barrel), Central Bank of Kenya;

COMPRICE = World non-fuel commodity price index (December 2001=100), Central Bank of Kenya;

RATEF = USA 90-Day Treasury bills interest rate (Annual, Percent), Central Bank of Kenya;

CBR = Central Bank Rate which is the policy rate defined as the lowest rate at which the Central Bank of Kenya lends to the commercial banks (in Kenya's banking system); and

REPO RATE = The interest rate at which the Central Bank of Kenya withdraws liquidity from commercial banks under its open market operations (OMOs).

Appendix 2: Comparative CBR Impulse Response Function Results

Figure A2.1: Standard VAR Model Impulse Response Functions (OLS Estimates)

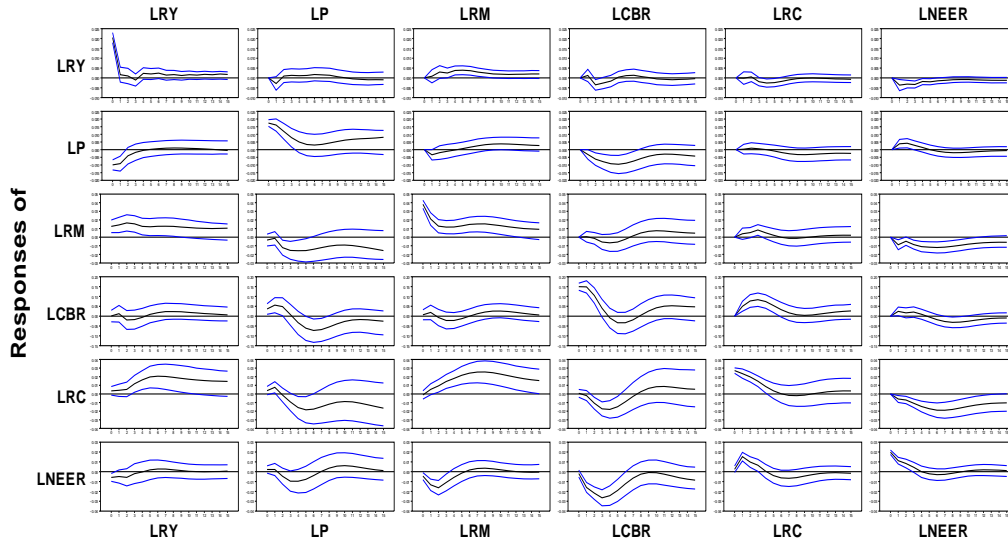
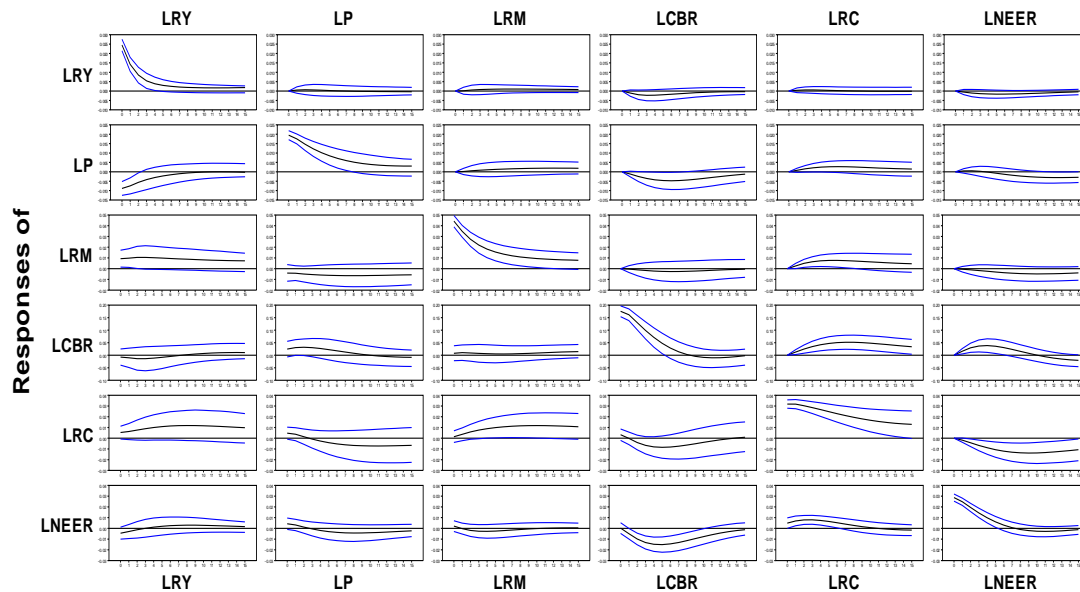


Figure A2.2: BVAR Impulse Response Functions (Theil's Mixed Estimates)



Appendix 3: Variance Decomposition Results

Table A3.1: Decomposition of Variance for Series LRM

Step	Std Error	LRY	LP	LRM	LCBR	LRC	LNEER
1	0.0321	4.091	0.356	95.553	0.000	0.000	0.000
2	0.0340	5.688	0.589	93.344	0.008	0.353	0.018
3	0.0442	7.340	0.948	90.183	0.064	1.365	0.101
4	0.0469	8.637	1.361	86.689	0.191	2.822	0.300
5	0.0489	9.563	1.783	83.169	0.376	4.460	0.650
6	0.0505	10.194	2.183	79.828	0.576	6.069	1.149
7	0.0519	10.616	2.543	76.796	0.749	7.526	1.769
8	0.0531	10.894	2.854	74.138	0.871	8.784	2.460
9	0.0541	11.077	3.114	71.863	0.937	9.840	3.169
10	0.0549	11.194	3.325	69.948	0.960	10.720	3.853
11	0.0557	11.268	3.493	68.353	0.955	11.454	4.478
12	0.0563	11.311	3.623	67.029	0.938	12.072	5.026
13	0.0568	11.333	3.723	65.932	0.921	12.601	5.489
14	0.0572	11.341	3.799	65.020	0.909	13.059	5.871
15	0.0576	11.339	3.856	64.259	0.904	13.463	6.180
16	0.0579	11.331	3.898	63.619	0.904	13.823	6.425
17	0.0582	11.320	3.929	63.078	0.907	14.147	6.620
18	0.0584	11.306	3.953	62.616	0.911	14.440	6.774
19	0.0586	11.293	3.970	62.219	0.915	14.705	6.899
20	0.0588	11.280	3.984	61.875	0.916	14.945	7.000

Table A3.2: Decomposition of Variance for Series LCBR

Step	Std Error	LRY	LP	LRM	LCBR	LRC	LNEER
1	0.1210	0.450	1.423	0.000	98.127	0.000	0.000
2	0.1780	0.597	1.901	0.035	96.084	0.384	1.000
3	0.2045	0.877	2.281	0.174	92.326	1.419	2.923
4	0.2197	1.103	2.528	0.343	87.931	3.076	5.020
5	0.2286	1.217	2.643	0.477	83.723	5.205	6.735
6	0.2341	1.233	2.651	0.550	80.202	7.571	7.794
7	0.2381	1.199	2.595	0.566	77.536	9.904	8.200
8	0.2417	1.171	2.520	0.553	75.629	11.972	8.154
9	0.2451	1.186	2.462	0.541	74.242	13.637	7.932
10	0.2486	1.257	2.436	0.551	73.125	14.869	7.762
11	0.2519	1.376	2.444	0.590	72.106	15.719	7.765
12	0.2550	1.525	2.477	0.654	71.107	16.274	7.963
13	0.2577	1.683	2.523	0.733	70.126	16.624	8.311
14	0.2510	1.832	2.573	0.816	69.196	16.843	8.739
15	0.2619	1.964	2.619	0.895	68.358	16.985	9.179
16	0.2634	2.072	2.657	0.963	67.639	17.085	9.583
17	0.2646	2.156	2.687	1.019	67.051	17.166	9.922
18	0.2654	2.220	2.707	1.062	66.587	17.238	10.186
19	0.2662	2.266	2.722	1.094	66.230	17.308	10.382
20	0.2667	2.299	2.731	1.116	65.957	17.379	10.519

Appendix 4: Additional Impulse Response Function Results

Figure A4.1: BVAR Model with the 91-Day Treasury Bills Rate (LRATE)

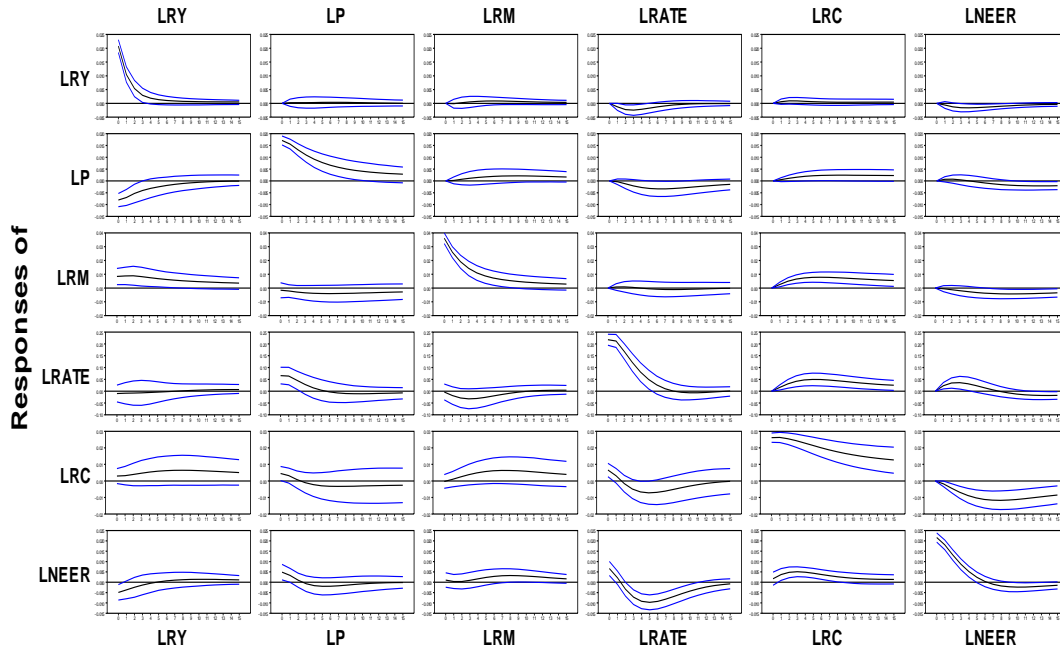


Figure A4.2: BVAR Model with the Repo Rate (LREPO)

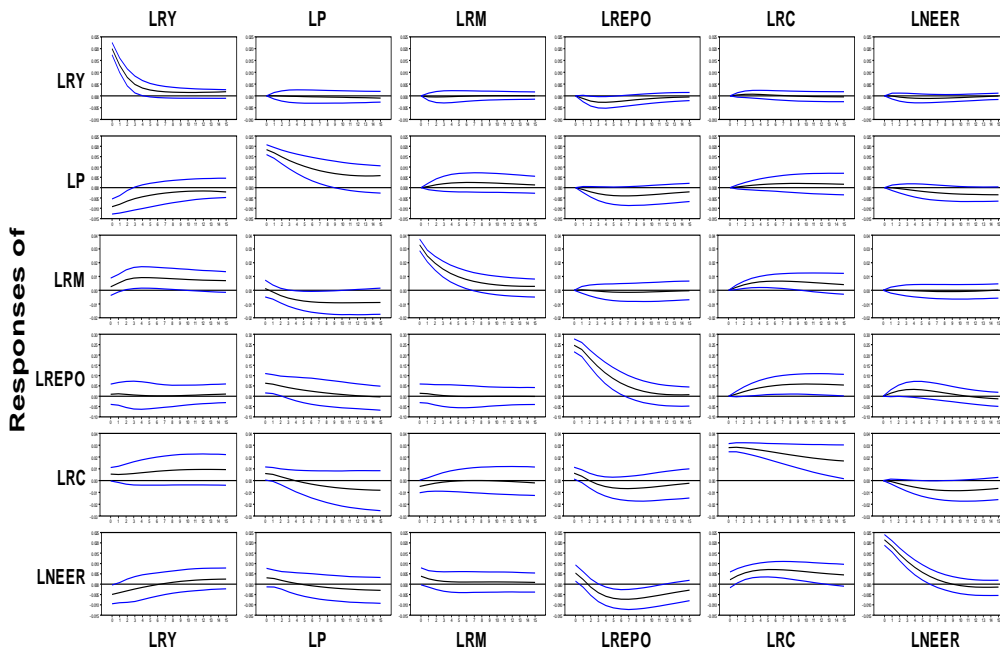
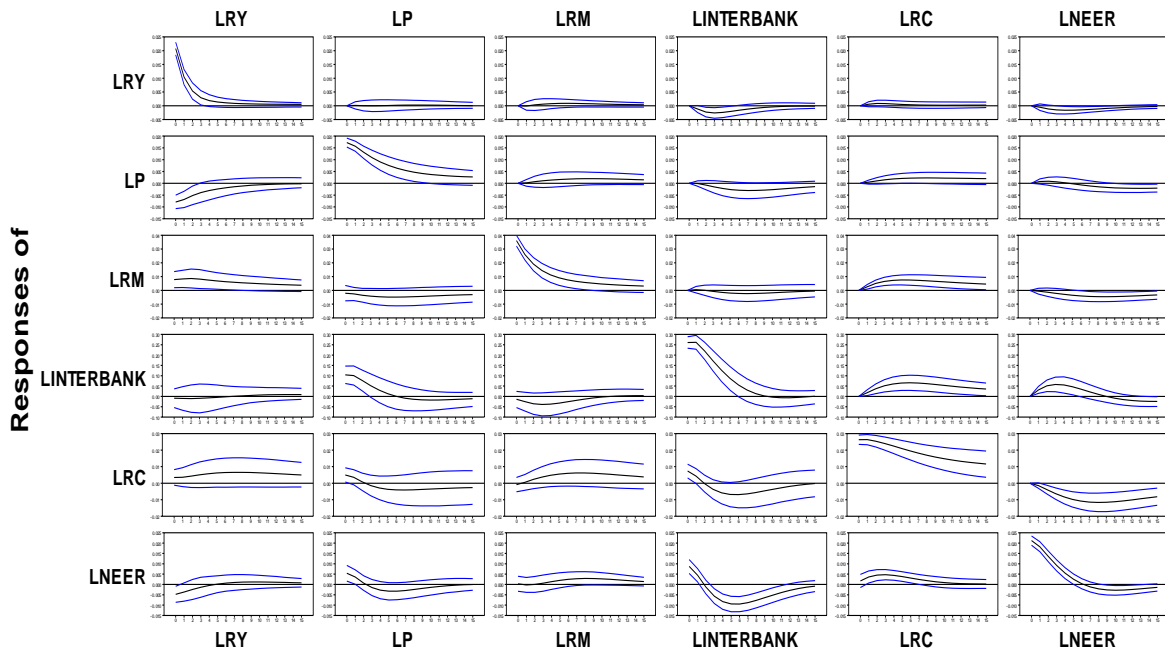


Figure A4.3: BVAR Model with the Interbank Rate (LINTERBANK)



¹ This is a working paper. We are therefore requesting for comments and suggestions that could enable us to improve it. Paper presented at a Central Bank of Kenya (CBK) Technical Retreat in Naivasha, Kenya, held on June 13-14, 2013. The paper has benefited from comments by the participants, and subsequently, by the Governor, Prof. Njuguna Ndung'u. We also take this opportunity to thank our colleagues who provided us with the data that we have used in the empirical analysis. In this regard, we express our sincere thanks to Ms. Roselyn Misati and Mr. Joseph Wambua.

² Assistant Director, (Kenya School of Monetary Studies)

³ The specification provided by (7) is an approximation of the ultimate specification in which $\mathbf{p} = \infty$.

⁴ In our analysis, we have assumed that the state variables vector is constant during the estimation period. The plausibility of this assumption is evaluated using recursive Kalman Filter residuals. Using time-varying state variables vector is a trivial adjustment in the specification of the BVAR model. This includes relaxing the assumption that $\mathbf{M}_t = 0$ to $\mathbf{M}_t \neq 0$.

⁵ Assigning values this way is technically referred to as imposing identifying restrictions.

⁶ For instance, Racette, Raynauld and Sigouin (1994; pg.3) argues, and we quote: "Since the size of the available sample (over which consistent data can be collected for all variables and for which there is no critical regime break), is not large, given the number of lags required to allow for a certain richness of the dynamic interrelations between the variables, we choose a highly selective set of variables to represent the Canadian monetary policy context. The model includes variables that represent instruments, targets, indicators and ultimate goals of the policy and its international environment."

⁷ Whereby, $lcb\bar{r}_t \equiv \log(1 + cb\bar{r}_t)$ to pave way to interpreting the impulse responses to shocks to the policy rate as short run elasticities instead of semi-interest rate elasticities.

⁸ If we followed Cheng (2006) and Davoodi, Dixit and Pinter (2013), we would have then had to specify $\tilde{\mathbf{A}}$ as follows:

$$\tilde{\mathbf{A}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 \end{bmatrix}$$

⁹ Obviously, a period is a quarter of a year in line with the quarterly time series data we are using for the BVAR model estimation.

¹⁰ Additional variance decomposition results are provided in Appendix 3.