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Bayesian vector autoregressive models for modeling inflation rate in Nigeria

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Abstract. This study focused on the Bayesian approach to the estimation of Vector Autoregressive (VAR) model using data on inflation rates in Nigeria. This method allows a combination of prior information and data information .The study provides a description of inflation rates in Nigeria using six different Bayesian VAR priors (diffuse prior, Minnesota prior, natural conjugate prior, independent normal Wishart prior, stochastic search variable selection prior-Wishart and stochastic search variable selection prior-VAR). The performance of various models was evaluated using root mean square error (RMSE). The stochastic search variable selection-Wishart out performs other methods. The impulse response function was estimated. The study concludes that stochastic search variable selection prior-Wishart is the best of all the Bayesian VAR prior to model inflation rate in Nigeria.

Keywords: Bayesian methods, VAR models, inflation rate, forecasting, prior, stochastic search variable selection.

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1. Introduction

Inflation forecasting continues to generate interest from government, financial institutions, researchers, individual, etc. This is because inflation can have a wide consequence on the economy. For instance in 2016, as a result of the global fall in crude oil prices, high dependence on imported goods, weak exchange rate etc. the price of goods and services increased tremendously in Nigeria (Obasi, 2016). The impact of the oil price fall was disastrous on the Nigerian economic system; consumers felt the hit through escalating price of goods and services, massive sack of workers in the labour force among others (Obasi, 2016). There is a connection between low inflation rate and improved standard of living.There is therefore a need for inflation forecasting to ensure that measures are put in place to control the inflation rate.

There are several variables that may affect inflation in any country, such as interest rate, exchange rate, money supply, etc. It becomes pertinent to model inflation using a multivariate time series method. The Vector Autoregressive (VAR) model is commonly used for forecasting systems of interrelated time series and for analysis of the dynamic impact of the random disturbance term on the system of variables (Lutkepohl, 2007). The VAR model in time series econometrics modeling came into prominence in the 1980s when Sims (1980) advocated them to be better than the simultaneous equation models. VAR models have since then gained considerable attention as a major tool in macroeconomic forecasting (Karlsson, 2013). In order to estimate interrelated variables a lot of variables may be considered. For instance, for a three (3) variable dependent VAR of order four a total of 39 parameters can be estimated for the VAR model. This usually leads to a situation of over parameterization which can cause problem of inference (Koop and Korobilis, 2010). The consequence of over parameterization is the lack of precision of inference and unreliable forecast. The estimates can be improved if the analyst has information about the parameters beyond that contained in the

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sample. Bayesian estimation provides a convenient framework for incorporating prior information with as much weight as the analyst feel sit merits (Hamilton, 1994).

Bayesian method provides a complete paradigm shift for both statistical inference and decision making under uncertainty. This is based on a subjective view of probability, which argues that our uncertainty about the inflation rate can be expressed using the rules of probability (Koop, 2003). To solve the problem of over parameterization in VAR, Litterman (1986) proposed the concept of Bayesian VAR. The Bayesian VAR involves a combination of prior (information available to the researcher before seeing the data) and the likelihood (data information) in order to arrive at the posterior. The Bayesian VAR has been found to give a better forecast of inflation rate in many countries (Valeriu, 2015). A number of research has been carried out by various researchers to buttress this fact (Bayesian VAR gives better forecast of inflation rate). Kenny et al (1998), Valeriu (2015), Sevinc and Ergun (2009), Kurmas et al (2012) and Ibanze (2011) to mention but a few. The supremacy of Bayesian VAR models over the classical ones in terms of forecasting accuracy is well documented and generally accepted in the literature on the grounds of overcoming the short sample and overfitting problems (Valeriu, 2015). However, the record is rather limited in the case of Nigeria. This study applies the method of Bayesian VAR in forecasting Nigerian inflation rate and compares the result to the classical VAR.

2. Methodology

A VAR process of order p is given by

$$\mathbf{Y_t}= \mathbf{C_0}+\mathbf{C_1}\mathbf{Y_{t-1}}+\mathbf{C_2}\mathbf{Y_{t-2}}+\cdots+\mathbf{C_p}\mathbf{Y_{t-p}}+\mathbf{e_t} \tag{1}$$

where e_t satisfies the following properties

i. $E(e_t) = 0$.
ii. $E(e_t e_t^I) = \Psi$ full variance-covariance matrix
iii. $E(e_t e_s^I) = 0 \forall s = t$ no serial correlation.

The variable Y_t for $t = 1, 2, ..., T$ is an $n \times 1$ vector containing observations on n time series

- $\mathbf{C_0}$ is a $n \times 1$ vector of intercepts
- $\mathbf{C_i}$ is a $n \times n$ matrix of coefficients for $i = 1, 2, ..., p$
- $\mathbf{e_t}$ is a $n\times 1$ vector of errors, and $\mathbf{e_t}$ is assumed to be independently and identically distributed (iid) normal with mean zero and variance .

Let $\mathbf{C} = (\mathbf{C_0}, \mathbf{C_1}, ..., \mathbf{C_p}); \mathbf{n} \times (\mathbf{np+1})$

$$x_t = \begin{pmatrix} 1 \\ y_{t-1} \\ \vdots \\ y_{t-p} \end{pmatrix}; (np+1)\times n \qquad X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{pmatrix}; T \times (np+1)$$

$$y = \begin{bmatrix} (y_{11} \dots y_{1T})^I \\ \vdots \\ (y_{m1} \dots y_{mT})^I \end{bmatrix}; (Tn \times 1)$$

$\theta = \mathbf{vec}(\mathbf{C})$ that is, an $n(np+1) \times 1$ vector with vec being the vectorization of a matrix, (i.e. a linear transformation that converts a matrix into a column vector). For a $n \times 1$ VAR model with p lags the number of regressors in each equation is $r = (np + 1)$.The total number of coefficients in the VAR is $nr = n(np + 1)$.

The VAR (p) in equation (1) can be rewritten as

$$\mathbf{Y} = (\mathbf{I_n} \otimes \mathbf{X})\theta + \varepsilon \tag{2}$$

where $\varepsilon \sim N(0, \mathbf{\Psi} \otimes \mathbf{I_T})$. This means that all the data are in y and parameters θ and Ψ . Using equation (2), the likelihood function is defined as the joint probability density function of all data conditional on the unknown parameter,$P(y|\theta, \Psi)$. The assumptions about ε i.e.$\varepsilon \sim \mathbf{N(0, \Psi \otimes I_T)}$can be used to work out the precise form of the likelihood function. Using the definition of multivariate normal, the likelihood function for equation (2) is of the form

$$L(\theta, \Psi) = \frac{1}{(2\pi)^{\frac{nT}{2}}} |\Psi \otimes I_T|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}\left(y - (I_n \otimes X)\,\theta\right)^I \left(\Psi^{-1} \otimes I_T\right)\left(y - (I_n \otimes X)\,\theta\right)\right\} \tag{3}$$

Further simplification yield

$$L(\theta, \Psi) \propto N(\theta|\widehat{\theta}, \Psi \otimes \left(X^I X\right)^{-1}) \times iW(\Psi| \left(y - (I_n \otimes X)\,\widehat{\theta}\right)^I \left(y - (I_n \otimes X)\,\widehat{\theta}\right), T - r - n - 1) \tag{4}$$

The likelihood function of VAR (p) from the literature is the product of normal density for θ conditional on θ and Ψ and the inverted Wishart distribution of Ψ conditional on θ. (Koop and Korobilis, 2010). Thus we have

$$\theta|\Psi, y \sim N(\widehat{\theta}, \Psi \otimes (X^I X)^{-1})$$

and

$$\Psi^{-1}|y \sim W(S^{-1}, T - k - m - 1)$$

where $\widehat{C} = \left(X^I X\right)^{-1} X^I Y$ is the OLS estimate of C, $\widehat{\theta} = vec(\widehat{C})$ and $S = (Y - X\widehat{C})^I(Y - X\widehat{C})$

The above expression shows that the parameter θ is conditional on Ψ.

In vector autoregressive models there are two parameter of interest, they are the coefficients of the VAR models, θ and the residual variance-covariance matrix, Ψ. As stated earlier, Bayesian VAR combines prior with the likelihood function, we shall consider the following priors in this study.

i. The Minnesota Prior. The Minnesota prior is a shrinkage method that is used to set most or all the elements of θ towards zero. When the variables in VAR model exhibit random walk, first own lag is set at 1 otherwise the first own lag is set at a value less than 1. The prior for the variance-covariance matrix,Ψ is assumed to be fixed and diagonal. The VAR equation is estimated one at a time using the standard error.

$$\theta \sim N(\theta_0, V_0) \tag{5}$$

$$V_0 = \begin{cases} \frac{c_1}{l^2} & \text{for coefficient of own lag } l = 1, 2, ..., p \\ \frac{c_2\sigma_i^2}{l^2\sigma_j^2} & \text{for coefficients for other lags } j = i \text{ for } l = 1, 2, ..., p \;\; l = 1, 2, ..., p \\ c_3\sigma & \text{for coefficient of constant} \end{cases}$$

where $c_1, c_2 \quad and \quad c_3$ are scalars such that $c_1 > c_2$, l is the number of lags, σ is the standard error (Litterman, 1986).The posterior of the Minnesota prior is a normal distribution

$$\begin{aligned} &\theta|y \sim N(\theta_1, V_1) \\ &where \quad V_1 = \left[V_0 + \left(\Psi^{-1} \otimes (X^I X)\right)\right] \\ &\theta_1 = V_1 \left[V_0^{-1}\theta_0 + \left(\widehat{\Psi}^{-1} \otimes X\right)^I y\right] \end{aligned} \tag{6}$$

ii. Natural Conjugate prior. Here the prior and the likelihood function come from the same family of distribution as equation 3 leading to a posterior with the same distribution. The natural conjugate prior is given by

$$\begin{aligned} &\theta|\Psi \sim N\left(\theta_0, \Psi \otimes V_0\right) \\ &\Psi^{-1} \sim W(S_0^{-1}, \upsilon_0) \end{aligned} \tag{7}$$

where $\theta_0, V_0, \upsilon_0, S_0$ are the hyper parameter chosen by the researcher $\theta|\Psi, y \sim N\left(\theta_1, \Psi \otimes V_1\right)$ (Kadiyala and Karlsson, 1997).

The posterior of the conjugate prior is given by (Kadiyala and Karlsson, 1997)

$$\begin{aligned} &\Psi^{-1}|y \sim W(S_1^{-1}, \upsilon_1) \\ &V_1 = \left[V_0^{-1} + X^I X\right]^{-1} \\ &C_1 = V_1[V_0^{-1}C_0 + X^I XC] \\ &\theta_1 = vec(C_1) \\ &S_1 = S + S_0 + C^I X^I XC + C_0^I V_0^{-1} C_0 - C_1^I (V_0^{-1} + X^I X) C_1 \\ &\text{and} \\ &\upsilon_1 = T + \upsilon_0 \end{aligned} \tag{8}$$

The natural conjugate prior has the advantage of the posterior distribution having an analytical solution. The main disadvantage is that each equation of the VAR model has the same set of explanatory variables and the restrictive nature of the prior covariance which makes the coefficients in any two equations to be proportional to one another.

iii. Independent Normal Wishart Prior. In the natural conjugate prior, the parameter of the VAR coefficient is dependent on the variance- covariance matrix. This assumption can be relaxed to have VAR coefficients and error covariance being independent. To allow VAR coefficients to have different explanatory variables, we have to restrict our VAR coefficient. A different notation will now be used for the restricted VAR coefficient to avoid confusion. ϕ instead of θ will be used and Z for X.

$$\begin{aligned} &P(\phi, \Psi) = P(\phi)P(\Psi) \\ &\text{where} \quad \phi \sim N(\phi_0, V_{0\phi}) \\ &\text{and} \quad \Psi^{-1} \sim W(S^{-1}, \upsilon) \end{aligned} \tag{9}$$

The posterior is given by (Kadiyala and Karlsson, 1997)

$$\begin{aligned} &\phi|y, \Psi^{-1} \sim N(\phi_1, V_{1\phi}) \\ &\text{where} \quad V_{1\phi} = \left(V_{0\phi}^{-1} + \sum_{t=1}^{T} Z_t \Psi^{-1} Z_t\right)^{-1} \\ &\text{and} \quad \phi_1 = V_{1\phi}\left(V_{0\phi}^{-1}\phi_0 + \sum_{t=1}^{T} Z_t^I \Psi^{-1} Y_t\right) \\ &\text{Also} \quad \Psi^{-1}|y, \phi \sim W(S_1^{-1}, \upsilon_1) \\ &\text{where} \quad \upsilon_1 = T + \upsilon_0 \\ &\text{and} \quad S_1 = S_0 + \sum_{t=1}^{T} \left(Y_t - Z_t\phi\right)\left(Y_t - Z_t\phi\right)^1 \end{aligned} \tag{10}$$

The posterior distribution of the independent normal Wishart prior cannot be evaluated using the analytical method, this is because it has no closed form solution.The Gibbs sampling method is therefore used to evaluate the posterior distribution.

iv. Stochastic Search Variable Selection Prior (SSVS SSVS) This method entails specifying a hierarchical prior for VAR coefficients.

$$\begin{aligned} &\theta|\alpha_i \sim (1-\alpha_i)N(0,V_{0i}^2)+\alpha_i N(0,V_{1i}^2) \\ &P(\alpha_i=1)=P_{0i} \\ &P(\alpha_i=0)=1-P_{0i} \end{aligned} \tag{11}$$

The basic idea is to set V_{0i} small and V_{1i} large so that the VAR coefficients will be restricted to be small, i.e., almost zero when $\alpha_i = 0$ and unrestricted when $.\alpha_i = 1$ For $\alpha = (\alpha_1, ..., \alpha_{kn})^I$, the SSVS assumes that each element has a Bernoulli distribution which is independent of each other. When $P_i = 0.5 \forall i$ it means that each coefficient in the prior is equally likely to be included or excluded. George et al (2008) divided the off diagonal elements and diagonal elements of the variance covariance matrix. The prior for off diagonal elements just like the VAR coefficients was the hierarchical prior, $\eta|\lambda_i \sim (1-\lambda_i)N(0,U_{0i}^2)+\lambda_i N(0,U_{1i}^2)$.The gamma distribution prior was used by the researcher for the diagonal elements.

The posterior distribution is given as (George et al., 2008)

$$\begin{aligned} &\theta|y,\alpha,\Psi \sim N(\theta_1,V_1) \\ &\text{where } V_1=\left[(DD)^{-1}+\left(\Psi^{-1}\otimes(X^I X)\right)\right]^{-1} \\ &\theta_1=V_1\left[\Sigma^I\Sigma\otimes\left(X^I X\right)\widehat{\theta}\right] \\ &\widehat{C}=\left(X^I X\right)^{-1}X^I Y \\ &\widehat{\theta}=vec(\widehat{C}) \\ &P_{1i}=\frac{\frac{1}{V_{1i}}\exp\left(\frac{\theta_i^2}{2V_{1i}^2}\right)P_{0i}}{\frac{1}{V_{1i}}\exp\left(\frac{\theta_i^2}{2V_{1i}^2}\right)P_{0i}+\frac{1}{V_{0i}}\exp\left(\frac{\theta_i^2}{2V_{0i}^2}\right)(1-P_{0i})} \end{aligned} \tag{12}$$

v. Stochastic Search Variable Selection Wishart (SSVS Wishart). This approach makes use of restricted VAR unlike (George et al, 2008) that used unrestricted VAR. This applies the independence assumption of equations 8 and 9. The priors is defined as follows

$$\begin{aligned} &\phi \sim N(\phi_0,V_0) \\ &\alpha \sim Bernoulli\,(1,P_i) \\ &\Psi^{-1} \sim Wishart\,(\upsilon,S^{-1}) \end{aligned} \tag{13}$$

The posterior is given by

$$\begin{aligned} &\phi|y,\Psi^{-1} \sim N(\phi_1,V_{1\phi}) \\ &\text{where } V_{1\phi}=\left(V_{0\phi}^{-1}+\sum_{t=1}^{T} Z_t\Psi^{-1}Z_t\right)^{-1} \\ &\text{and}\phi_1=V_{1\phi}\left(V_{0\phi}^{-1}\phi_0+\sum_{t=1}^{T} Z_t^I\Psi^{-1}Y_t\right) \end{aligned} \tag{14}$$

$$\begin{aligned}
&\alpha \sim Bernoulli\,(1, P_{i1})\\
&P_{1i} = \tfrac{l_{0i}}{l_{0i}+l_{1i}} \quad and\\
&l_{0i} = P(y|\phi, \alpha = 1)P_{i1}\\
&l_{1i} = P(y|\phi, \alpha = 0)\,(1 - P_{i1})\\
&l_{0i} = \exp\left(-\tfrac{1}{2}\sum_{t=1}^{T}(Y_t - Z_t\phi)\,\Psi^{-1}\,(Y_t - Z_t\phi)^I\right)P_{0i}\\
&l_{1i} = \exp\left(-\tfrac{1}{2}\sum_{t=1}^{T}(Y_t - Z_t\phi)\,\Psi^{-1}\,(Y_t - Z_t\phi)^I\right)(1 - P_{0i})\\
&\text{also} \quad \Psi^{-1}|y, \phi \sim W(S_1^{-1}, \upsilon_1)\\
&\text{where} \quad \upsilon_1 = T + \upsilon_0\\
&\text{and} \quad S_1^{-1} = \left(S_0 + \sum_{t=1}^{T}(Y_t - Z_t\phi)\,(Y_t - Z_t\phi)^1\right)
\end{aligned} \tag{15}$$

(Korobilis, 2013). The posterior is evaluated using Gibbs sampling.

3. Results and discussion

The data used in this study is monthly data on inflation rate, interest rate and exchange rate in Nigeria from January 2003 to March 2018. The data was obtained from Central Bank of Nigeria official website, https://www.cbn.gov.ng/rates on 25th July, 2018. These three variables (inflation rate, interest rate and exchange rate) are commonly used in literature. Examples of papers where these variables or similar variables were used are Valeriu (2015), Koop and Korobilis (2010), Ibanze(2011), Kurmas et al (2012) to mention but a few. The data are plotted in Figure 1. R software was used

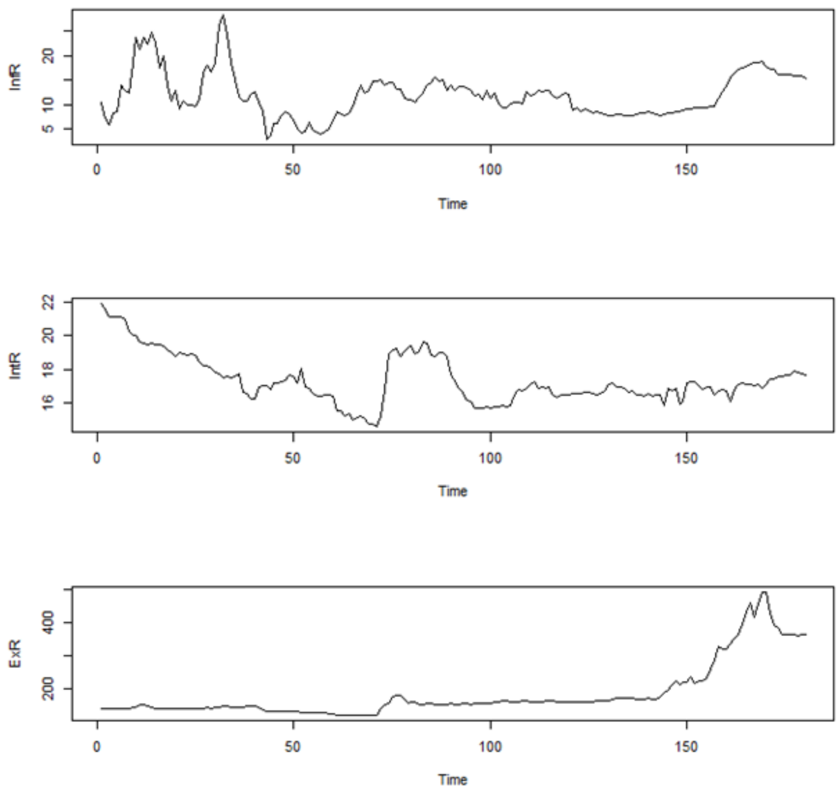

Figure 1. Data used in the study

in analyzing the data. To illustrate Bayesian VAR analysis using this data, we work with an unre-

stricted VAR with an intercept and lagged variables of order four. The paper considers the following six priors:
Diffuse $\theta_0 = 0_{KM\times 1} = 0, V_0 = 100I_{K\times K}, \upsilon_0 = 0, S_0 = 0_{M\times M}$
Natural conjugate: $\theta_0 = 0_{KM\times 1} = 0, V_0 = 10I_K, \upsilon_0 = M + 1, S_0 = I_M$
Minnesota:
Independent Normal-Wishart: $\phi_0 = 0_{KM\times 1}, V_{0\phi} = 10I_{K\times M},\ S^{-1} = I_m, \upsilon_0 = M + 1$
SSVS- Wishart: $c_0 = 0.1, c_1 = 10$ and Wishart prior Ψ^{-1} with $S^{-1} = I_m, \upsilon_0 = M + 1$
SSVS SSVS: The results below are based on 10000 MCMC draws,for which the first 2000 are discarded as burn-in draws.

Table 1. Estimate of posterior mean using six different priors

	Diffuse	Minnesota	Conjugate	Independent	SSVS-Wishart	SSVS-SSVS
constant	-3.2005	-3.1239	-2.8678	-0.1017	-0.2432	-0.3125
Infr-I	1.0294	1.0259	1.0315	0.9861	1.0063	1.0079
intr-I	-0.2713	-0.2741	-0.2845	-0.1974	-0.0027	-0.0035
Exr-I	0.0099	0.0095	0.001	0.0074	0.0005	0.0005
Infr-2	-0.1118	-0.0967	-0.1119	-0.0447	-0.0319	-0.0325
intr-2	0.1128	0.1372	0.1083	0.016	0.025	0.0246
Exr-2	-0.0048	-0.0036	-0.0051	-0.003	0.0007	0.0007
Infr-3	0.0562	0.0258	0.0546	0.0314	-0.027	-0.0138
intr-3	0.2739	0.2475	0.2779	0.1469	0.038	0.0435
Exr-3	0.0036	0.0019	0.0038	0.0026	0.0005	0.0005
Infr-4	-0.1302	-0.1089	-0.1289	-0.1204	-0.0741	-0.0916
intr-4	0.1451	0.144	0.1393	0.1203	0.0251	0.0251
Exr-4	-0.0056	-0.0048	-0.0057	-0.0049	0.0001	0.0001

Table 1 presents posterior means of all the VAR coefficients for six priors: diffuse, Minnesota, Conjugate, Independent, SSVS Wishart and SSVS SSVS priors. Note that the diffuse, Minnesota and Conjugate priors yield similar result, the independent prior is different from the rest while SSVS Wishart and SSVS SSVS are yielding similar results, the independent, SSVS Wishart and SSVS SSVS shrinks the coefficients more towards zero from the estimates of the posterior means in Table 1. The estimates obtain from the various priors in Table 1 will be used in forecasting. The data set was divided into two; the training and test data set. The training data set was from January 2003 to July 2017 and the test data set was from August 2017 to March 2018. It is worthy of note that the training data set was used to build the model as shown in Table 1. From the training data set we obtain forecast for inflation for eight horizon for different priors and compare them with the actual value of inflation that was left in the test data set. The results of the forecast of the six different priors considered are presented in Table 2. From Table 2 it is obvious that the six different priors

Table 2. Forecast of inflation using six different prior

	Actual	Diffuse	Minnesota	Conjugate	Independent	SSVS-Wishart	SSVS-SSVS
h=1	16.01	15.774611	15.761882	12.468701	15.638711	15.767986	15.74958
h=2	15.98	15.865987	15.860193	12.553146	15.773308	15.803236	15.800108
h=3	15.91	15.924993	15.903005	12.611242	15.736437	15.791317	15.790428
h=4	15.9	15.879657	15.861475	12.594839	15.668504	15.732946	15.732324
h=5	15.37	15.977593	15.949251	12.693762	15.727361	15.73459	15.735315
h=6	15.13	15.452604	15.43148	12.163285	15.247102	15.206286	15.20473
h=7	14.33	16.469147	16.632819	16.642535	15.834948	14.848846	14.843872
h=8	13.34	15.35877	14.671126	15.720227	15.825881	13.365433	13.357816

considered performs differently in the forecasting of inflation rate in the h step forecast ahead. The diffuse prior which is the classical VAR gave similar forecast with the Minnesota and Independent priors across the eight horizon considered. The conjugate prior performed badly when you compared the forecast values with the actual and other priors under study. This is in line with the assertion of Kadiyala and Karlsson, (1997) .The forecasting performance of the six priors will now be evaluated using the root mean squared error (RMSE). The RMSE of the various priors are shown in Table 3.

Table 3. Root mean square error of six priors

	Diffuse	Minnesota	Conjugate	Independent	SSVS-Wishart	SSVS-SSVS
h=1	0.235389	0.248118	3.541299	0.371289	0.242014	0.26042
h=2	0.114013	0.119807	3.426854	0.206692	0.176764	0.179892
h=3	0.014993	0.006995	3.298758	0.173563	0.118683	0.119572
h=4	0.020343	0.038525	3.305161	0.231496	0.167054	0.167676
h=5	0.607593	0.579251	2.676238	0.357361	0.36459	0.365315
h=6	0.322604	0.30148	2.966715	0.117102	0.076286	0.07473
h=7	2.139147	2.302819	2.312535	1.504948	0.518846	0.513872
h=8	2.01877	1.331126	2.380227	2.485881	0.025433	0.017816
Mean	0.6598526	0.599346333	3.077315556	0.651780333	0.216253667	0.218032444

From Table 3, using the RMSE of the six priors it is clear that SSVS-Wishart out performs other priors in forecasting inflation rate in Nigeria with the least RMSE, this is followed by SSVS-SSVS, Minnesota prior and so on. The worst prior was the conjugate prior. These results are consistent with the results of Koop (2013). In line with what has been mentioned in the literature (see Ibanze (2011), Kenny et al (1998)), the Bayesian method out performs the classical method. Thus the SSVS Wishart is adopted for inflation forecasting. Figures 2 presents the impulse responses of the three

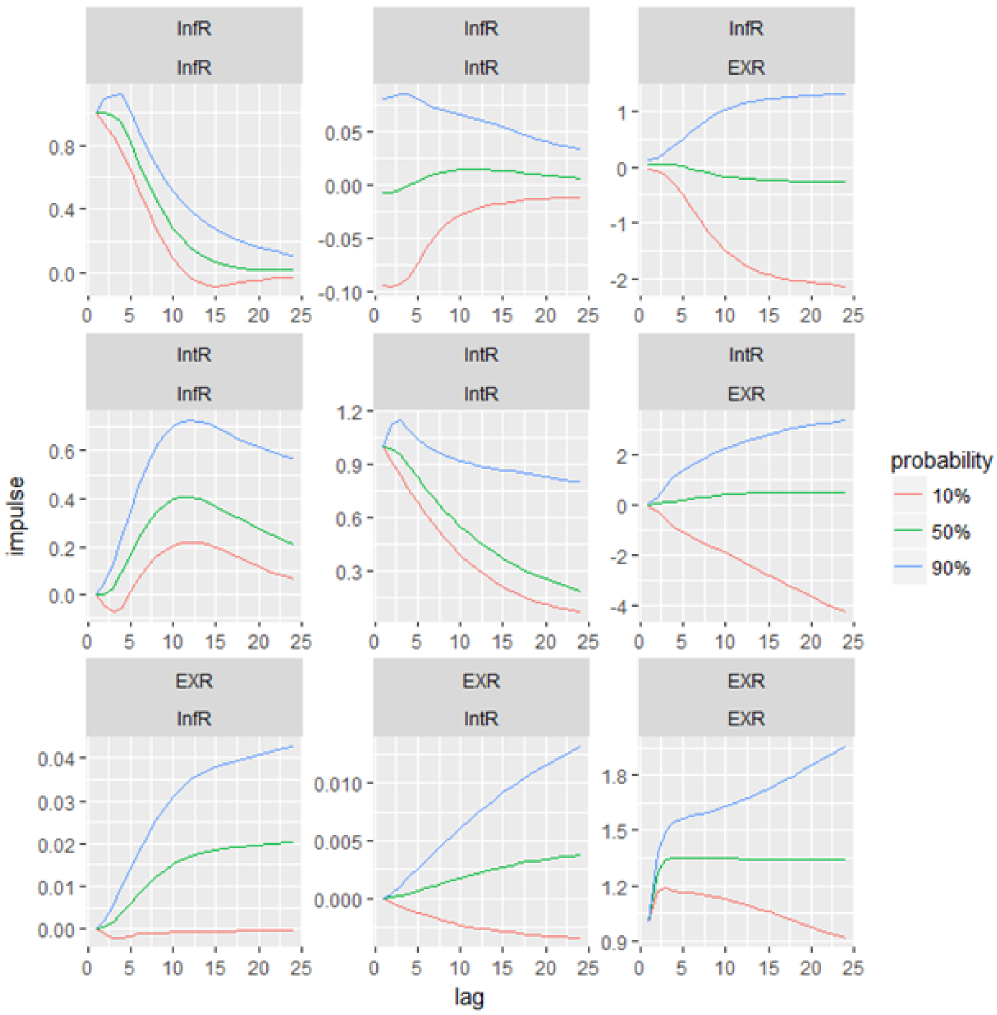

Figure 2. Impulse response function using SSVS Wishart prior

variables to the shocks for SSVS Wishart priors. Impulse response function gives a clue of how a given variable?s shock will impact on other variables since there is dynamic structure in the VAR system. This explains how shocks are propagated. It traces the effect of one time shock to one of the innovations on the present and future values of endogenous variables. The impact of interest rate and exchange rate on inflation is given in Figure 2. These impulse responses all have sensible shapes, similar to those found by other authors Koop and Korobilis (2010), Ibanze(2011), Kurmas et al (2012)). Especially at longer horizons, there is evidence that SSVS leads to slightly more precise inferences (evidenced by a narrower band between the 10th and 90th percentiles due to the shrinkage it provides.

4. Conclusion

Bayesian models have been found to be better than the classical models of inflation. The results obtained in this study have shown that among the class of Bayesian models, the stochastic search variable selection technique gives improved forecast performance. The SSVS Wishart was identified as the best model using RMSE and subsequently used to forecast Nigeria inflation see Table 2 and Table 3. The result of this study will help individuals and relevant institutions that are saddled with the task of inflation control to forecast Nigeria inflation in the short and long run in other to develop appropriate strategies to curtail inflation in Nigeria. The results of this research will be essential to decision makers and regulators to predict inflation in short and long terms in Nigeria. This will enable them come up strategic plans for inflation targeting. It is recommended that other class of stochastic search variable selection prior for Bayesian VAR be considered for further studies.

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