

Forecasting Household Credit in Kenya Using Bayesian Vector Autoregressive (BVAR) Model

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Abstract This research paper use Bayesian VAR framework to forecast the household credit in the dynamic market of foreign remittances inflow to Kenya. The Bayesian VARs model in this study employs the Sims-Zha prior to estimate. Bayesian vector autoregressive (BVAR) uses Bayesian methods to estimate a vector autoregressive (VAR). In that respect, the difference with standard VAR models lies in the fact that the model parameters are treated as random variables, and prior probabilities are assigned to them. This study employed data from the Kenyan Market for the period January 2005-December 2017. The forecast results were compared with the standard ARIMA model and the findings confirm that the BVAR approach outperforms the ARIMA model. Financial institutions can therefore use Bayesian VAR and other Bayesian models in predicting credit uptake given several micro-economic conditions. Banks should also find ways of tapping into these remittances especially those that pass through informal channels to improve their earnings from processing fees and also enhance the financial inclusion agenda through increasing account opening and loan uptake.

Keywords: Bayesian, remittance, household credit

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1. Introduction and Literature Review

1.1. Background of the Study

Bayesian inference has grown over 300 years from its introduction by Thomas and its expansion by Richard Price, Bayes and Price [1]. Bayesian inference uses prior probability distribution of an uncertain parameter say θ . This prior probability distribution expresses uncertainty about θ before taking into account the data to be used, Statisticat [2].

Vector Autoregressive (VAR) Models were proposed by Sims [3] in the paper titled "Macroeconomics and reality". The author argued that VARs should replace large-scale macro econometric models inherited from the 1960s, because the latter imposed incredible restrictions, which were largely inconsistent with the notion that economic agents take the effect of today's choices on tomorrows utility into account. VARs have since been used to model and forecast may macro-economic factors and often used for econometric analysis and in evaluation of proofs of economic theories, some of this studies include; Chen & Liao[4], De Medeiros et al [5] and Pecican [6].

Bayesian vector autoregressive (BVAR) is built on VAR model by employing Bayesian methods to estimate a vector autoregressive (VAR). In that respect, the difference with standard VAR models lies in the fact that the model parameters are treated as random variables, and

prior probabilities are assigned to them. Sims [7] states that the objective aspect of Bayesian inference is the set of rules for transforming an initial distribution into an updated distribution condition on observations. Bayesian priors are often used to restrain the otherwise highly over-parametrized vector autoregressive (VAR) models, Villani [8].

The main advantage of Bayesian vector autoregressive (BVAR) model is that it avoids the problems of collinearity and over-parameterization that often occur with the use of VAR models since BVAR imposes priors on the AR parameters.

Remittances are funds/money sent by an expatriate of a person leaving in a foreign country to his or her home country. Due to the huge sums involved, remittances are now being recognized as an important contributor to the country's growth and development, Central Bank of Kenya [9]. However, the channels of transmission ranges from informal (unrecorded) to formal (through banks and other financial institutions). This means that that the true picture of remittances into Kenya could be much more than what is recorded by Central Bank of Kenya. While most of the remittances are believed to be channeled towards consumptions others believe that some of the remittances find its route into investment and hence boosting the economy, Meyer & Shera [10].

While foreign remittances plays a big role in reduction of poverty and enhance economic development of a country, Khan & Islam[11], credit is equally considered a key player to economic growth especially in developing

nation as it lubricates the economy, Timsina [12]. Equally while many researchers have agreed on the role of credit in boosting various investments options, foreign remittances has received mixed perceptions from increasing inflation, Qurbanalieva [13] to encouraging laziness. The question this paper will also try to examine is, does remittances necessitate the credit uptake borrowing from financial institutions due to increased resources to repay loans or does it hamper borrowing.

1.2. Review of Previous Studies

Mitrović & Jovičić [14] studied Macroeconomic causes and Effects of Remittances in Serbia using econometric time series, for the period December 2000 until February 2006 (63 months). All the relevant time series variables used include; remittances, output level, unemployment rate, average dollar wage, trade deficit, imports and consumer goods imports. The authors employed vector autoregressive model (VAR) with eight lags to investigate both short-run and long-run effects. The results showed that there was very strong adjustment process of consumer goods imports to the remittance inflow. They also found that appreciation of dinar is closely related to the level of remittances in the observed period and finally remittances showed an undoubtedly income increasing effect in Serbia, with their newly estimated figure reaching as much as 10% of GDP.

Meyer & Shera [10] analyzed the impact of worker remittances on economic growth of Albania and five regional countries by using annual panel data from 1999-2013. The authors used multiple regression analysis (MLR). Their results indicated that employing all necessary tests, remittances positively and significantly contribute in the economic growth of six countries. They therefore concluded that contribution of worker remittance is the significant and most important in economic growth. They further argued that the productive use of remittances can help the economy of these countries of subject to maintain and improve the economic growth by investing this money into consumption and investments.

Ramos [15] studied Forecasts of market shares using univariate Box-Jenkins, unrestricted VAR, and BVAR. The usual criteria, e.g. stationarity, autocorrelation, and partial autocorrelation functions, significance of coefficients, and the Akaike Information Criterion, were used to select the best model. The author employed the likelihood ratio test statistic (LR) to determine the optimal lag length of the unrestricted VAR [VAR (U)]. The BVAR approach was entirely based on the likelihood function with the same Gaussian shape. The author found out that BVAR models generally produce more accurate forecasts than the ARIMA and VAR.

Caraiani [16] compared the performance of BVAR with Ordinary Least Squares LS and standard VAR in forecasting the dynamics of output for the Romanian economy. The author found out that BVAR approach outperforms the standard models (OLS and standard VAR).

Sacildi [17] investigated if BVAR Models can Forecast Turkish GDP Better Than UVAR Models. In this study the macroeconomic indicators of monetary aggregate, unemployment rate, exchange rates and interest rates are

taken part in the VAR models in order to compare out-of-sample forecasts of GDP by using Bayesian vector autoregressive and unrestricted vector autoregressive models. The author used quarterly data from 2005(Q4) to 2013(Q3). The BVAR models was estimated using the Minnesota/Litterman prior using different hyperparameters. The author also included the Sims and Zha prior in order to obtain more robust results. Each model's four step ahead forecast performances are evaluated by RMSE and the results showed that BVAR model was better in accuracy for forecasting GDP than UVAR. BVAR models are also have better forecasting performance for monetary aggregate than UVAR model.

The main advantage of incorporating BVAR is because, Bayesian statistics, within a solid decision theoretical framework, incorporates a natural and principled way of combining prior information with data. Wasserman [18]. This means that in our data analysis, we can incorporate past information about a parameter and form a prior distribution for current and future analysis and prediction. This usually follow from Bayes' theorem. In fact, Robert [19] stated that "The important feature of a Bayesian approach is, thus, that Bayes estimators are derived by an eminently logical process: starting from requested properties, summarized in the loss function and the prior distribution, the Bayesian approach derives the best solution satisfying these properties".

1.3. Statement of the Problem

Modelling Financial and economic data can be painstaking due to the dynamic nature financial markets. Quiet often financial and economic data is usually determined by previous events or previous data. As such prior information is usually carried in the current data and or future information data. Villa & Walker [20] for instance argue that Financial returns and markets index values possess extreme value characteristics and such cannot be modelled by normal distribution but models with heavier tails.

Given the fact, financial and economic data carry with it prior information, this paper This implies that, most Bayesian Vector Autoregressive Model (BVAR) is included essentially to capture prior distributions and also and improve out-of-sample performances. BVAR borrows heavily from the traditional vector Autoregressive model (VAR). The only difference is that VAR usually assume linearity and parametric nature of any financial data. The traditional VAR methods has a tendency of over-fitting and over-parameterization.

In consideration to household credit, the market dynamics of micro-economic factors could impact on credit uptake. This implies that credit uptake could be as a result of several prior market dynamics and prior borrower's behavioral factors (credit rating, relationship with the bank and prior income). In fact, Karlsson [21] argued that "he Bayes factor captures the data evidence which can be interpreted in measuring how much our opinion about the models have changed after observing the data. The choice of model should of course take account of the losses associated with making the wrong choice". With all this into perspective it therefore, implies the traditional methods of modelling household credit

could potentially leave out information that would possibly affect the results.

This paper will therefore employ Bayesian Vector Autoregressive (BVAR) model to forecast household credit in the presence of remittances and lending rates. BVAR results will be used to compared with results of Autoregressive Integrated Moving Average (ARIMA) model which does not consider prior information.

1.4. Justification of the Study

Household credit sometimes referred to as consumer credit has gained a lot of interest in recent years. Among them is question of how household credit affects economic growth. While OECD [22] argued that Finance (credit and savings) is a key component that can spur economic growth. Maggio et al [23] believed that consumer credit contributed heavily to the 2008-2009 financial credit. This means that consumer credit expansion can negatively affect economy. Equally, remittances could affect the economy in either way (positively if the cash is invested wisely and negatively is all cash in invested in consumption hence increase money supply and hence inflation). However, the big problem is how remittances affect household credit. Brown & Carmignani [24] believe that inflow of remittances leads to changes in the credit supply and demand. This leads to financial institutions adjusting lending rates and increase profitability depending on the situation at hand. However, no empirical evidence has been carried out in Kenya to determine the true impact of remittances on household credit (That is if the receiving families, increase their loan uptake or not).This research will therefore, examine and add to the existing literature the effect of remittances on household credit while including interest rates as an intervening variable to the study. The study will be helpful to the following groups: (i) researchers and policy makers, (ii) Financial institutions, and (iii) regulators of wise monetary policies.

1.5. Objectives of the Study

The general objective of this study is to forecast household credit using Bayesian VAR model.

2. Methodology

In this study, Bayesian Vector Autoregressive Model (BVAR) will be used. The general model equation will take the form:

$$Y = \alpha_0 + \sum_{i=1}^k \alpha_i (X_i) + \varepsilon. \tag{1}$$

2.1. Bayesian Vector Auto-regressive (BVAR) Model

From equation 1 we can re-write a general VAR (P) model equation as:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + \dots + B_p Y_{t-p} + \varepsilon_t \tag{2}$$

where $Y_t = (Y_{it-1}, Y_{it-2}, \dots, Y_{it-p})$ is a $T \times N$ matrix i.e (Number of observations \times number of endogenous variables).

In Compact form the equation above can be re-written as

$$Y_t = Z_t B + \varepsilon_t$$

where $Y_t = (c_i, Y_{it-1}, Y_{it-2}, \dots, Y_{it-p})$ is a $T \times (1 + N \times P)$ matrix. ε is a white noise with zero and positive definite covariance matrix Σ or $\varepsilon \sim iidN(0, \Sigma)$. Where ε_t is often assumed to be multivariate normal.

Bayes Law:

$$p(B, \Sigma | Y_t) \propto p(Y_t | B, \Sigma) \cdot p(B, \Sigma) \tag{3}$$

where: $p(B, \Sigma | Y_t)$ is the Posterior distribution of parameters, $p(Y_t | B, \Sigma)$ is the likelihood data, and $p(B, \Sigma)$ is the prior distribution of parameters.

Assume that the model parameters are random variable. A prior distribution is specified based on prior information and combined with objective information from observed data to obtain the posterior distribution using Bayes Theorem. The prior distribution specification acts as a barrier, or provides 'shrinkage' preventing the estimated parameters from depicting what are only spurious correlations. One of the non-finance/non-economic studies carried out using with Bayesian VAR was by Brandt & Freeman [25] in Political science.

The likelihood function can be derived from the sampling density, $p(y | \alpha, \Sigma)$. As a function of the parameters, then it can be broken into two parts, that is a distribution for $\alpha | \Sigma$ and Σ^{-1} which has a Wishart distribution. This are shown in equation (4) below;

$$\alpha | \Sigma, r \sim N(\hat{\alpha}, \Sigma \otimes (Z'Z)^{-1}) \tag{4}$$

Where \otimes represents a tensor product of two vectors.

2.1.1. The Natural Conjugate Prior

The natural conjugate prior has the form

$$\alpha | \Sigma, r \sim N(\alpha, \Sigma \otimes V) \tag{5}$$

and

$$\Sigma^{-1} | r \sim W(z, S^{-1}). \tag{6}$$

The Posterior for α is

$$\alpha | \Sigma, r \sim N(\bar{\alpha}, \Sigma \otimes \bar{V}) \tag{7}$$

where $\bar{V} = (V^{-1} + Z'Z)^{-1}$ and

$$\bar{\alpha} = vce(\bar{Z} \text{ with } \bar{Z} = \bar{V} (V^{-1}B + Z'Z\hat{B})).$$

The posterior for Σ is

$$\Sigma^{-1} | r \sim W(\underline{v}, \bar{S}^{-1}) \tag{8}$$

where $\bar{v} = T + \underline{v}$ and

$$\bar{S} = S + \underline{S} + \bar{B}'\bar{Z}'\bar{Z}\bar{B} + \underline{B}'\underline{V}^{-1}\underline{B} - \bar{B}'(\underline{V}^{-1} + \underline{Z}'\underline{Z})\bar{A}.$$

2.1.2. The Independent Normal-Wishart Prior

When two or more coefficients vary, it is tedious to directly model each element of the correlation matrix. Unlike the natural conjugate prior which assumes that each equation has the same explanatory variables and restrictive prior covariance coefficients matrix in any two equations that is proportional to each other. According to Koop & Korobolis [26], the Normal-Wilshart prior is a general prior which does not involve the restrictions inherent in the natural conjugate prior.

We can therefore re-write the VAR model as

$$y_{mt} = z'_{mt} + \varepsilon_{mt} \tag{9}$$

where m are the variables from 1 to M (i.e $m = 1, \dots, M$) and t represents the observations for the m variables ($t = 1, \dots, T$). y_{mt} is the t^{th} observation for the m^{th} variable, z_{mt} is a k_m vector that contains the t^{th} observation of the vector of explanatory variables relevant for the m^{th} variable and β_m is the k_m vector of model coefficients. z_{mt} is said to be unrestricted VAR if $z_{mt} = (1, y'_{t-1}, \dots, y'_{t-p})$ for $m = 1, \dots, M$. However, when employing the Normal-Wilshart, z_{mt} can be allowed to vary across equations hence allowing the the coefficients on the lagged dependent variables to be restricted to zero (i.e allows for the possibility).

Re-writing all the equations into vectors or matrices we get; $y_t = (y_{1t}, \dots, y_{Mt})'$, $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{Mt})'$

$$\beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_M \end{pmatrix}$$

$$Z_t = \begin{pmatrix} Z'_{1t} & 0 & \dots & 0 \\ 0 & Z'_{2t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & Z'_{Mt} \end{pmatrix}.$$

As per our previous assumption ε is assumed to identically and independently distributed with mean Zero and Covariance Σ (i.e $\varepsilon \sim i.i.dN(0, \Sigma)$). β is $k \times 1$ matrix/vector and Z_t is an $M \times k$ Matrix and $k = \sum_{j=1}^M k_j$.

From the above we can re-write our restricted VAR model as

$$y = Z\beta + \varepsilon \tag{10}$$

where

$$y = \begin{pmatrix} y_1 \\ \vdots \\ y_T \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_T \end{pmatrix}, Z = \begin{pmatrix} Z_1 \\ \vdots \\ Z_T \end{pmatrix}$$

and $\varepsilon \sim N(0, I \otimes \Sigma)$. This shows that the restricted VAR looks similar to Ordinary Least Squares (Linear regression model) but with with an error covariance matrix/vector.

The Independent Normal-Wilshart prior for the above model becomes

$$p(\beta, \Sigma^{-1}) = p(\beta) p(\Sigma^{-1}) \tag{11}$$

where

$$\beta \sim N(\underline{\beta}, \underline{V}_\beta) \tag{12}$$

and

$$\Sigma^{-1} \sim W(\underline{S}^{-1}, \underline{v}). \tag{13}$$

We can choose \underline{V}_β to be anything for example by making $\underline{\beta}$ and \underline{V}_β to be exact as the Minnesota prior thereby getting what is called the A noninformative prior by setting $\underline{v} = \underline{S} = \underline{V}_\beta^{-1} = 0$.

From equation (13) above, we get a joint posterior of the form $p(\beta, \Sigma^{-1} | y)$ which however, does not Bayesian Analysis easy. This means that the posterior mean and variance don't have any analytical form. However, Koop and Korobolis [26] stated that conditional posterior distributions $p(\beta | y, \Sigma^{-1})$ and $p(\Sigma^{-1} | y, \beta)$ do have convenient forms as shown below.

$$\beta | y, \Sigma^{-1} \sim N(\bar{\beta}, \bar{V}_\beta) \tag{14}$$

To calculate valid predictions, Z_t should contain lags of the dependent variables, and exogenous variables which are observed at time $t = h$, where h is the desired forecast horizon. This result, along with a Gibbs sampler producing drawn for the Normal $p(\beta | y, \Sigma)$ and the Wilshart $p(\Sigma^{-1} | y, \beta)$. Predictive simulation can be done at each Gibbs sampler draw, although this can be computationally demanding. For forecast horizons greater than one, the direct method can be used.

2.1.3. BVAR Using Sims-Zha Prior (SZBVAR)

We shall employ the estimation of the Bayesian VAR model by Sims & Zha [27]. According to Adenomon et al [28], "The Sims-Zha prior allows for a more general specification and can produce a tractable multivariate normal posterior distribution".

This BVAR model is based on a specification of the dynamic simultaneous equation representation of the model. The prior is constructed for the structural parameters. The prior covariance matrix of the errors, $S(i)$, is initially estimated using a VAR(p) model via OLS, with an intercept and no demeaning of the data.

We can therefore re-write a m-dimensional multivariate reduced VAR model as

$$y_t = c + y_{t-1}B_1 + \dots + y_{t-p}B_p + \varepsilon_t \tag{15}$$

where $t=1, \dots, T$, y_t is an $1 \times m$ matrix of observations, B_i is $m \times m$ matrix of coefficients for i^{th} lag, p is the maximum number of lags and ε are the residuals.

This paper employed the Independent Sims and-Zha prior distribution for the parameters in the model where the estimators are given by;

$$\hat{\beta} = (\Sigma^{-1} + Z'Z)^{-1} (\Sigma^{-1} \bar{\beta} + Z'Y) \tag{16}$$

$$\hat{\Sigma} = T^{-1} (Y'Y - \hat{\beta}'(Z'Z + \Sigma^{-1})\hat{\beta} + \bar{\beta}\Sigma^{-1}\bar{\beta} + \bar{S}). \tag{17}$$

Justification of prior selection: The advantage of Sims & Zha [27] approach is that it allows for a more general specification and can produce a tractable multivariate normal posterior distribution.

$$\text{RMSE} = \sqrt{(T)^{-1} \sum_i^T (y_i^a - y_i^f(n))^2} \tag{18}$$

where: T is the forecast of the computed values and $y_i^*(n)$ is the forecasted value based on n -steps in the future.

RMSE measures the difference between values predicted by a hypothetical model and the observed values. In other words, it measures the quality of the fit between the actual data and the predicted model. For the two measures above, the smaller the value, the better the fit of the model

3. Results and Discussions

3.1. Data

The empirical data analysis is based on a set of monthly data for the period January 2005 to December 2017, Household Credit, foreign remittances into Kenya and average commercial bank lending rates. This data was obtained from Kenya Bankers Association (KBA) publication and the Central Bank of Kenya (CBK) website. The data was analyzed using R Project for Statistical computing. plotted data of Household credit and Foreign remittances is presented in Figure 1 and Figure 2 respectively. The figures depict an exponential increasing trend in both remittances and credit.

Plot Household Credit in Kenya

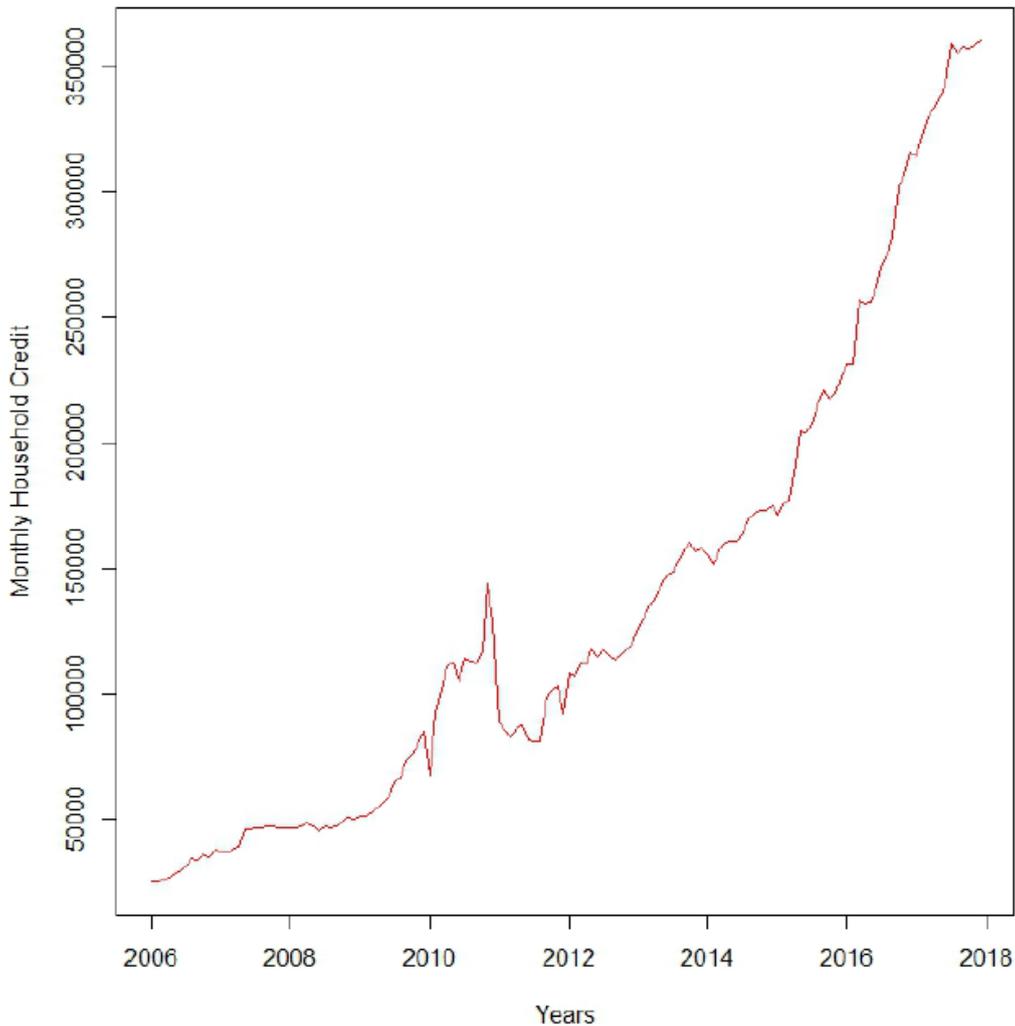


Figure 1. Trend of Household Credit in Kenya

Plot Monthly Foreign Remittance to Kenya

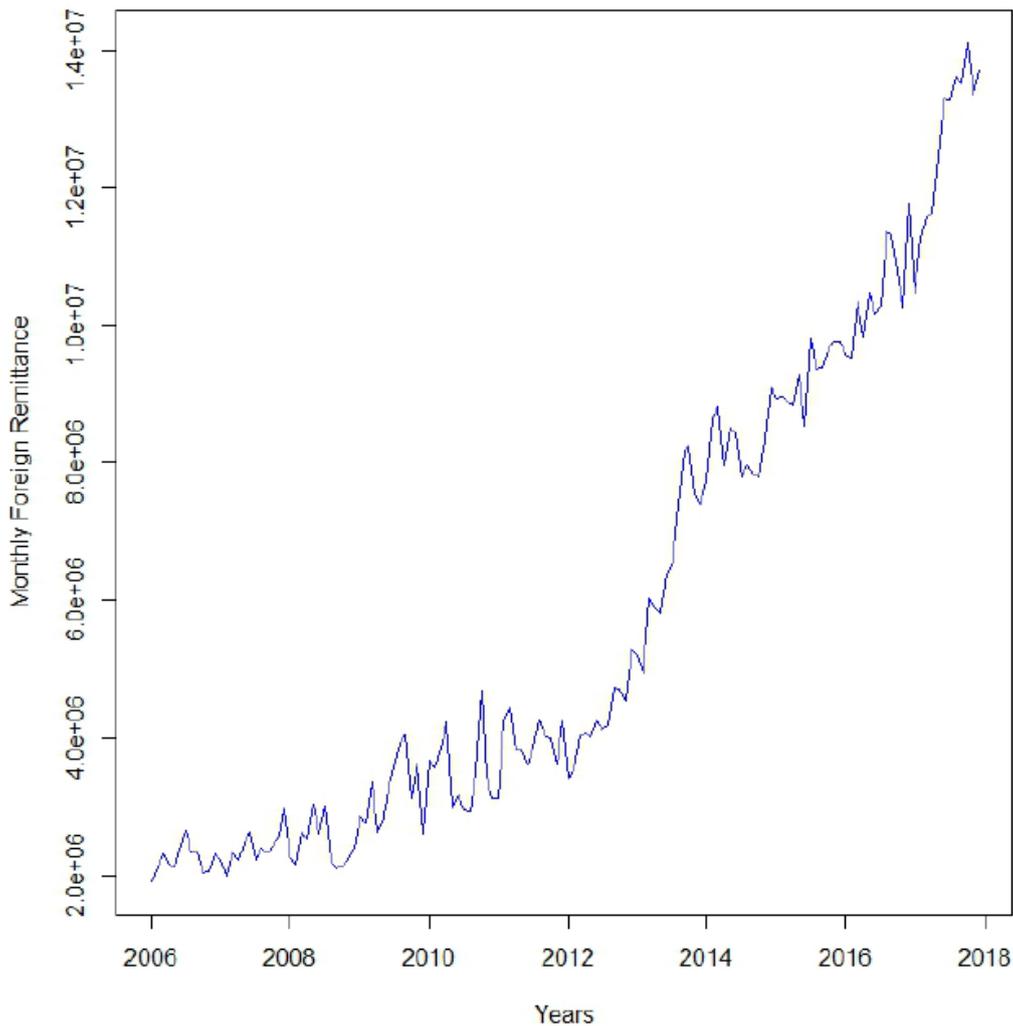


Figure 2. Trend of Remittances to Kenya

3.1.1. Results

This study employs Bayesian VAR using household credit, Remittance and Lending rates. The variables are expressed in logarithmic forms in this analysis and as such the data was not differenced to make it stationary. According to Tiriongo & Abdul [29], Sims (1980) did not recommend differencing the data, since differencing makes the data lose important information on inter-relations between variables and comovements. Several lag length options were tested and the optimal lag length of the BVAR estimation was found to be lag 2. Results of AIC for lags 1 to 10 are presented in the table below.

3.1.2. Interpretation of BVAR Results

Vector autoregressive (VAR) is a stochastic process model used to capture the linear interdependencies among multiple time series. This model framework uses the impulse response functions (IRF) and forecast error variance decomposition (FEVD) interpret the relationships between variables. IRFs are used to track the responses of a system's variables to impulses of the system's shocks. Ronayne [30]. These responses are usually current and Future values for a set of variables to a one standard deviation increase in each of the variables in the system.

On the other hand, forecast error variance decomposition (FEVD) is used to aid in the interpretation of a vector auto regression (VAR) model once it has been fitted. The main work for fevd is to account for variations in variables of interest overtime.

Table 1. BVAR Lag Selection Results

Lags	AIC	BIC	HQ
1	-11.26	-11.00	-11.15
2	-11.39	-10.94	-11.20
3	-11.28	-10.64	-11.02
4	-11.29	-10.46	-10.96
5	-11.29	-10.26	-10.87
6	-11.25	-10.03	-10.75
7	-11.16	-9.74	-10.58
8	-11.07	-9.46	-10.41
9	-11.07	-9.28	-10.34
10	-11.03	-9.04	-10.22

The results of the BVAR are analyzed using impulse response functions as shown in Figure 3 and Figure 4. These impulse response functions (IRFs) are created from one standard deviation shock to innovation. And the estimates are presented as per the equation (19).

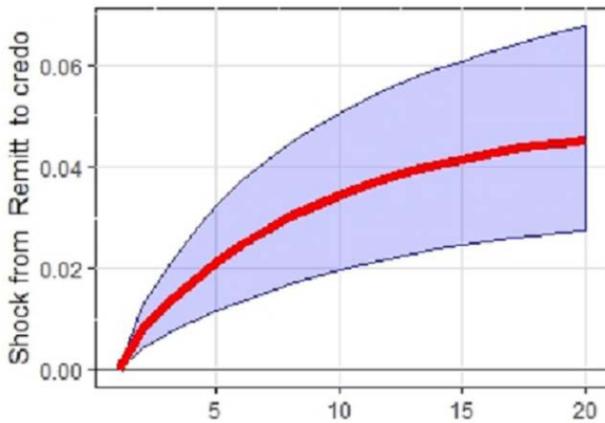


Figure 3. Response of Household Credit to Remittance

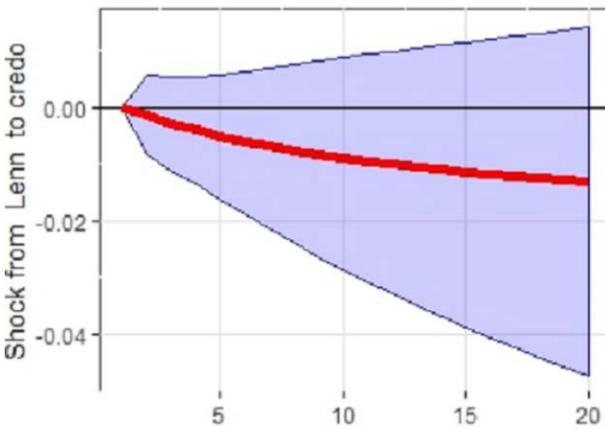


Figure 4. Response of Household Credit to Lending rates

3.1.3. Remittance Innovations

A positive shock in remittance inflows has a significant positive effect in Household credit (Figure 3). This may reflect Increase in loan uptake. This implies that as remittances inflow increases, funds available for repayment of increase and hence borrowers are able to borrow more at will.

3.1.4. Interest rates Innovations

The innovations of lending rates decrease the loan uptake hence the negative output as shown by Figure 4. A unit basis point increase in lending rates decreases the demand for household loans. Increase in Lending rates signify a tightening monetary policy which in effect is means increase in monthly repayment and reduction money supply. Reduction in money supply in the market means hinders loan uptake due to difficulty to meet repayment schedules.

The model equation is then presented as follows

$$\begin{aligned}
 CR = & 0.789*CR(-1) + 0.135*CR(-2) \\
 & + 0.019*LEN(-1) - 0.015*LEN(-2) \\
 & + 0.211*RE(-1) - 0.1525*RE(-2) \\
 & - 0.331 - 0.074*LEN + 0.033*RE.
 \end{aligned}
 \tag{19}$$

3.2. Model Estimation Comparison

This research study employs Akaike Information Criteria (AIC) to select the best model in estimation. AIC

is chosen because it is easier to interpret. AIC is generally used to estimate the information loss and the best model is the one the loses the lowest information. AIC is generally given as

$$AIC = -2\hat{l} + 2.D \tag{20}$$

where \hat{l} is the maximum likelihood for the model, and D is the the free parameter (otherwise known as degrees of freedom).

The author also compared the AIC and BIC with a view to find out if the results would be different. Dziak et al [31] proposed the use of both AIC and BIC in model selection since AIC could perform better in scenarios where a false negative is considered more misleading than a false positive. BIC on the other hand is would preferred better where a false positive is is more misleading than a false negative.

BIC is denoted as

$$BIC = -2 \log \hat{l} + D \log n \tag{21}$$

where \hat{l} is the maximum likelihood for the model, and D is the the free parameter (otherwise known as degrees of freedom). The main advantage of BIC is its consistent as $n \rightarrow \infty$.

From estimation results both AIC and BIC performed the same in model selection as indicated in Table 2, while ARIMA performed better than BVAR in estimation, BVAR outperformed ARIMA in prediction and forecasting as shown in Table 2.

Table 2. Model Performance Results

Model	AIC	BIC	RMSE
BVAR	-11.39	-11.00	0.026254
ARIMA	-378.87	-373.03	0.06321

3.3. Predictive Ability

The last objective of this research is to compare the models in terms of prediction performance in order to make a decision on the forecasting accuracy of the models. The forecasting performance is evaluated root mean square errors (RMSE).

The RMSE is given by:

$$RMSE = \sqrt{\frac{1}{n} \sum (y - \hat{y})^2} \tag{22}$$

Where y is the actual value and \hat{y} is the forecasted one. This is essentially the sample standard deviation of the forecast errors (without any degrees of freedom adjustment).

The results indicate that the ARIMA model outperforms the BVAR estimation using AIC and BIC results. However, BVAR outperforms ARIMA model in predictive accuracy as indicated in Table 2 above. Wooldridge [32] confirms that a model might provide a good fit to a response variable in the sample used to estimate the parameters, but this need not translate to good forecasting performance. This results also confirms that Bayesian Vector Autoregressive models are good in predictive ability due to the nature of using priors in the model. Bayesian Models are also multivariate in nature unlike ARIMA model which is univariate in nature.

4. Conclusion and Recommendations

The exponential increase in foreign remittances has led to speculation in academia and the financial sectors research to examine the extent to which these remittances affect the economy. While many studies have centered on the economy (GDP) little research has been carried out on how remittances affect household credit. This research was therefore geared to determine the extent to which Bayesian VAR performs in forecasting household credit in relation to foreign remittances. It's difficult to forecast credit unilaterally due to the dynamic nature of credit uptake affected by liquidity, inflation, lending rates and above all behavioral factors of borrowers, and hence the reason for this paper to introduce foreign remittances in the model. This paper contributes to the growth of using Bayesian models which has seen greater expansion in finance in recent times to forecast household credit in Kenya. The Bayesian VAR used in this paper was compared with ARIMA model on forecasting accuracy. The results indicate that the BVAR models outperforms the ARIMA model in predicting household credit given foreign remittances.

The results could also be an indicator of how remittances impact of financial inclusion agenda in the country. If increased remittances leads to increased household credit, then it implies that at least from the formal channels, people are expected to not only open new accounts but take credit also and hence contribute to financial inclusion agenda.

Banks, investors and other financial market players can therefore employ Bayesian models in predicting credit uptake given several micro-economic factors including foreign remittances. Given the effects of foreign remittances on household credit, financial institutions should also use this study to enhance tapping foreign remittances from informal channels so as to increase their revenue through processing fees and also improve their short term liquidity. Researchers should expand this study by incorporating other factors not captured in this study and compare the results. A separate study should also be carried out to determine to what extent does remittances contribute to the Financial inclusion in Kenya.

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