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Bayesian Graphical Model Application for Monetary Policy and Macroeconomic Performance in Nigeria

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Abstract

This study applies Bayesian graphical networks (BGN) using Bayesian graphical vector autoregressive (BGVAR) model with efficient Markov chain Monte Carlo (MCMC) Metropolis-Hastings (M-H) sampling algorithm in a dynamic interaction among monetary policies and macroeconomic performances in Nigeria for the period of 1986Q1–2017Q4. The motivation stems from the instability in the movement of exchange rate, inflation rate and interest rate in Nigeria over the past years as a result of the structure of the economy. In this way, the monetary authority periodically applies the various policy instruments to stabilize the economy using reserve and money supply as at when due. This study adapts VAR and SVAR structure to examine the dynamic interaction among variables of interest, using BN, to provide a better understanding of the monetary policy dynamics and fit the changing structure of the Nigeria's economy as regards the dynamics in her economic structure. Our results show that inflation is the strong predictor of interest rate in Nigeria. A monetary policy of broad inflation targeting is recommended for the country.

Keywords: Bayesian graphical networks, SVAR, MCMC, M-H, Granger-causal inference, Nigeria

1. Introduction

A network can be described as a set of items, with nodes or vertices that are related by edges or links for a specific purpose. There are different types of networks. These networks can be social, economic, informational, technological, biological and so on. However, in this paper, we are interested in Bayesian graphical network (BGN) to investigate causal inferences among monetary policies and macroeconomic performances in Nigeria. Causal effects have been used

in economic literature starting from Granger [1], Engle and Granger [2] and Sims [3] using vector autoregression (VAR) to Amisano and Giannini [4] and Blanchard and Quah [5] using structural vector autoregression (SVAR). The progression from VAR to SVAR has been a result of over-parameterization and identification problem associated with VAR that have limited its use for forecasting [6]. SVAR, in a way, has been able to overcome these problems through the application of the recursive and the non-recursive structural model [5]. The advantage of the BGN is that there are directed acyclic graphs (DAG) with nodes or vertices called variables having edges that indicate structural dependence among the variables of interest. Studies that have used graphical models to causal relationships are Pearl [7], Spirites et al. [8], Demiralp and Hoover [9] and Moneta [10], among others. Our intention is to combine BGN with SVAR, in order to examine interrelationship among monetary policies and macroeconomic performances in Nigeria. However, many previous studies have worked on causal inference using BGN-SVAR in developed countries, studies like Swanson and Granger [11], Demiralp and Hoover [9], Moneta and Spirites [12], Corander and Villani [13] and more recently Ahelegbey et al. [6]. The advantage of the BGN-SVAR is that causal influences are tracked down among variables of interest either instantaneously or with time lags using conditional probabilistic inference on the structural model.

Importantly, in this present study, we adopted the BGN-SVAR approach used by Ahelegbey et al. [6] and deal with the identification structure to derive the Bayesian networks using DAG. The Bayesian structural model is then simulated using the multi-move Markov chain Monte Carlo Metropolis-Hastings sampling algorithm. The analyses are done with a view to examine the causal relationship among monetary policy actions and macroeconomic performances in Nigeria. The BGN-SVAR method is more superior to the usual standard Granger causality test, thereby providing an important tool for policy implications, especially for an emerging country like Nigeria where monetary policy stance is a major factor to the macroeconomic performance of the economy. The paper is as follows. Section 2 gives the data source, variable definition and the descriptive statistics, and Section 3 provides an overview of the BGN-SVAR model. While Section 4 highlights the empirical discussion, Section 5 concludes and states the policy recommendation.

2. Data source and variable definition

All the data used for this study were sourced from the Statistical Bulletin [14] published by the Central Bank of Nigeria. The data range from the first quarter of 1986 to the fourth quarter of 2017. The choice of the scope of study is strictly informed by data availability. Monetary policy variable is measured using broad money supply normally referred to as M2, which is defined as the sum of currency in circulation, demand deposit and time deposit in the banking sector. The industrial output (Ind) comprises of crude oil petroleum, natural gas, solid minerals, coal mining, metal ores, quarrying, mining, manufacturing, oil refining and cement production. In addition, interest rate is measured with lending rate (Intr) on banks' credit to the public. Inflation rate (Infl) is measured by the average price index of consumer goods over the period of study. Exchange rate (Exch), on the other hand, is the rate of change of the local

currency, naira, to the United State (US) dollar. The industrial output and money supply are measured in the local currency, naira, while the exchange rate is measured in US dollars.

2.1. Descriptive statistics of variables

The descriptive statistics as presented in **Table 1** shows industrial output, exchange rate, inflation rate, interest rate and money supply variables in their unit form with 124 observations for the period of study. The difference between the average mean value and the maximum value of exchange rate, inflation rate and interest shows the high volatility of these variables. The average values for exchange rate, inflation rate and interest rate are 93.86, 19.25 and 14.1%, respectively, while the maximum values are 304.72, 73.1 and 26.7%. The differences between the average values and the minimum values also support the volatility behaviour of the variables. In addition, the volatility movement in these variables as shown in **Figure 1** equally confirms their fluctuation. The skewness of all the variables implies positive skewness of the data distribution. Finally, the significance of the probability of the Jarque-Bera at 5% indicates that all the variables reject the acceptance of the null hypothesis of normal distribution except for the exchange rate variable.

2.2. Unit root test

In order to ascertain the order of integration of our variables, we used both augmented [15, 16] tests. The results from **Table 2** show that all the variables are nonstationary using ADF test. The PP, on the other hand, shows all the variables to be nonstationary except industrial output. Given the stationarity of industrial output with PP, we further conducted structural break following Perron [17] in that its presence can bias the unit root result. The structural break results show that all the variables are nonstationary and support the ADF test. The structural

	Industrial output	Exchange rate	Inflation rate	Interest rate	Money supply
Mean	32,497.84	93.86	19.25	14.1	4,916,951
Median	30,995.49	117.16	11.25	13.66	1,294,950
Maximum	52,931.79	304.72	73.1	26.7	23,388,300
Minimum	18,998.23	3.76	2.14	6	22,730.8
Std. dev	7778.25	69.49	18.1	4	6,665,696
Skewness	0.53	0.24	1.5	0.39	1.244417
Kurtosis	2.65	2.53	3.88	3.87	3.17
Jarque-Bera	6.53	2.36	50.67	7.17	32.15
Prob.	0.03	0.31	0.00	0.03	0.00
Sum	4030	11,638.86	2386.88	1748.6	6.10E + 08
Sum sq. dev	7.44E + 09	593,982.6	4.03E+04	1977.4	5.47E + 15
Observation	124	124	124	124	124

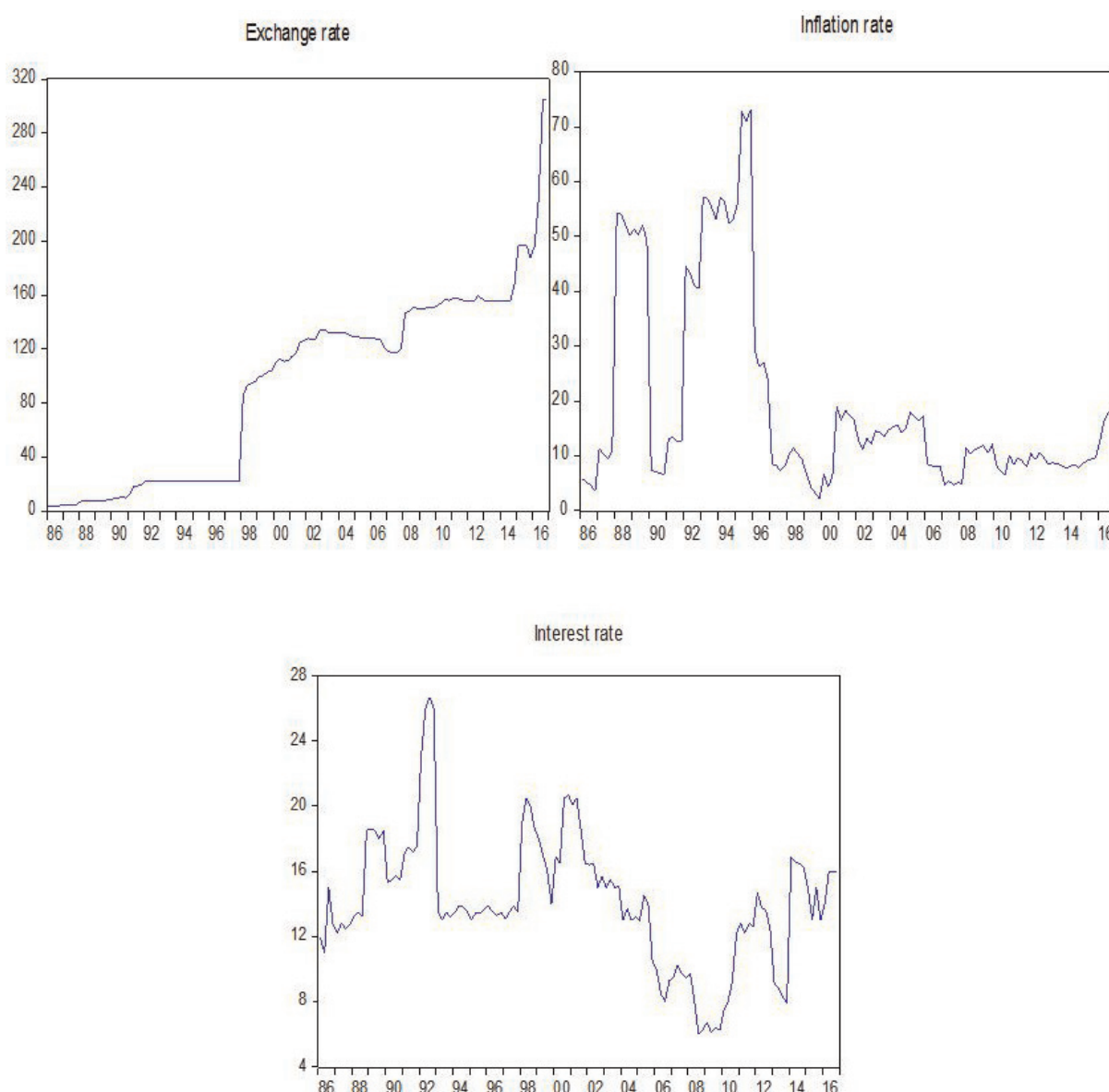**Table 1.** Descriptive statistics for selected variables.

Figure 1. The volatility behaviour of exchange rate, inflation rate and interest rate.

break result is not presented here but available upon request. Given the nonstationarity of all the variables, we proceeded to examine their cointegrating relationship over the period of study.

2.3. Cointegration test

We followed Johansen [18] cointegration technique that compares the trace and the eigenvalue with their critical values for the rejection or acceptance of the null hypothesis of no cointegration. The optimal lag lenght of 1 was chosen following Schwarz Criterion's (SC) result in **Table A4** at the Appendix. The cointegration results presented in **Table 3** show that the trace

	Augmented Dickey-Fuller		**Phillips-Peron**		
Variables	**Levels**	**First diff.**	**Variables**	**Level**	**First diff.**
Ind	−1.7046	−6.2244	Ind	−4.2882	—
Exch	0.8368	−8.4777	Exch	1.2655	−8.3739
Infl	1.4409	−6.4756	Infl	−2.8021	−10.695
Intr	−2.8834	−10.4781	Intr	−2.7495	−11.2467
M2	5.1489	−11.3326	Mss	5.5596	−11.7113

Note: The critical values at 1, 5 and 10%, respectively, are −3.4846, −2.8853 and −2.5749 for both ADF and PP. Ind, Exch, Infl, Intr and M2 indicate industry output, exchange rate, inflation rate, interest rate and money supply, respectively.

Table 2. Unit root tests.

Coint. rank	**Eigenvalue**	**Trace stat.**	**Critical value**	**Prob.**
$r = 0$	0.44	108.64	69.82	0.00
$r \leq 1$	0.13	37.29	47.86	0.33
$r \leq 2$	0.09	19.89	29.8	0.43
$r \leq 3$	0.05	8.28	15.5	0.44
$r \leq 4$	0.01	1.79	3.84	0.18
Coint. rank	Eigenvalue	Eigen stat.	Critical value	Prob.
$r = 0$	0.44	71.35	33.88	0.00
$r \leq 1$	0.13	17.39	27.58	0.54
$r \leq 2$	0.09	11.61	21.13	0.58
$r \leq 3$	0.05	6.48	14.26	0.55
$r \leq 4$	0.01	1.8	3.84	0.18

Note: The null hypothesis, H0, of no cointegration is rejected when the value of the trace and maximal eigen statistics is greater than the critical values at 5% significance level.

Table 3. Johansen cointegration results.

statistics is greater than the critical value at 5% significance level at $r = 0$. This hypothesis testing takes us to the next cointegrating vector, $r \leq 1$, where the trace statistics is less than the critical value. We therefore conclude that there is a long-run relationship among the variables.

3. Bayesian graphical VAR model

The starting point of the BGVAR is from VAR process proposed by Sim [3] as dynamic endogenous variables specified as

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_\rho Y_{t-\rho} + \varepsilon_t \tag{1}$$

Eq. (1) is a vector autoregressive process of order ρ, and it can be respecified in a reduced form as

$$Y_t = B_0 + \sum_{i=1}^{\rho} B_i Y_{t-i} + \varepsilon_t \tag{2}$$

Eq. (2) can further be specified in SVAR process following Amisano and Giannini [4] and Blanchard and Quah [5] with a lower triangular matrix A as

$$AY_t = B_0 + \sum_{i=1}^{\rho} B_i Y_{t-i} + \varepsilon_t \tag{3}$$

Eq. (3) can be written in an inverted form as

$$Y_t = \beta_0 + \sum_{i=1}^{\rho} \beta_i Y_{t-i} + u_t \tag{4}$$

where $\beta_0 = A^{-1} B_0$, $\beta_i = A^{-1} B_i$ and $1 \leq i \leq \rho$ are lags of the parameter matrices and $u_t = A^{-1} \Sigma \varepsilon_t$ where Σ is a diagonal matrix of variance and covariance matrix. Assume in econometric term that $Y_{t-i} = (X_{t-i})'$; then Eq.(4) can be expressed as

$$Y_t = \beta_0 + \sum_{i=1}^{\rho} \beta_i X_{t-i} + u_t \tag{5}$$

Eq. (5) can be written in matrix form as

$$Y = \beta' X + U \tag{6}$$

The solution to the SVAR model can be achieved through the parameter identification by placing restrictions on the lower triangular matrix A or the B diagonal matrix following the relevant economic theories for the underlying variables. The general method of solving the structural dynamics of the SVAR model after placing the necessary restrictions to attain identification is to determine the effects of the shocks on the contemporaneous variables through the impulse response functions. The impulse response function can be represented through the diagonal matrix of the covariance matrix as

$$\Sigma = A^{-1} \Sigma \varepsilon_t (A^{-1}) \tag{7}$$

where $\Sigma \varepsilon_t = \varepsilon_t \varepsilon_t'$ and the covariance matrix are assumed to be an identity matrix. The Cholesky decomposition where all the elements above the diagonal are zero (lower triangular matrix) is the usual way of solving the identification problem in SVAR to identify the structural shocks. The system thus becomes exactly identified by comparing the known elements, $\frac{n^2+n}{2}$,

and the unknown elements, $n^2 - n + n$, of the covariance matrix [5]. Interestingly, the graphical model can be represented in the form of SVAR following Ahelegbey et al. [6] exposition. A graphical model can be described as the representation of the conditional relationships among random variables. Graphical models are generated in nodes and edges. The nodes house the variables, while the edges point to their relationships. A bivariate graphical model can be written as $X \rightarrow Y$, meaning X causes Y, where Y (child) is the dependent variable and X (parent) is the independent variable. In a multivariate setting, the graphical model can be expressed as $X \rightarrow Y \rightarrow Z$ and can be interpreted to mean that the relationship between X and Z is conditional on variable Y. Assume $Y_t = \left(Y_{t-1}^1, Y_{t-2}^2, \cdots, Y_{t-n}^n\right)$ where Y_t^i is a realization of the ith variable at time t. The graphical network of a DAG can be written in the form of Eq. (1) as $Y_{t-s}^J \rightarrow Y_t^i$ where $B_{\rho,ij}^* \neq 0$ and $0 \leq s \leq \rho$. This implies that past value of Y_{t-s}^J at time lag s, with $(s < t)$, causes the future value of Y_t^i. This explains the notion that cause precedes effect in time. Therefore, following past studies such as Corander and Villani [13] and Ahelegbey et al. [6] among others, a network structure of a DAG is described as $G = (V, A)$, where V is a finite set of nodes symbolizing $Y_t = \left(Y_{t-1}^1, Y_{t-2}^2, \cdots, Y_{t-n}^n\right)$ in this case, while A is also a finite set of directed edges denoting $Y_{t-s}^J \rightarrow Y_t^i$ stated earlier. In other words, the graphical model can be specified in VAR representation as $B_s = (G_S, \varphi_s)$, where s is a period lag, B is the structural parameters of the interdependent variable Y_t, G_s is the binary connectivity matrix and φ_s is a matrix of coefficient of lag s. At period s for $0 \leq s \leq \rho$, $G_{s,ij} = 1$ implies a causal effect of $Y_{t-s}^J \rightarrow Y_t^i$, and $G_{s,ij} = 0$ implies no causal relationship between Y_{t-s}^J and Y_t^i with $\varphi_{s,ij}$ indicating the quantity of the causal effects of $Y_{t-s}^J \rightarrow Y_t^i$. The graphical model can further be written in a VAR form from Eq. (2) as.

$$Y_t = \left(G_0, \varphi_0\right) + \sum_{i=1}^{\rho} \left(G_i, \varphi_i\right) Y_{t-i} + \varepsilon_t \tag{8}$$

Following Koop [19], Geweke [20] and Olayungbo [21], the posterior distribution in Bayes' theorem can be written in continuous form as

$$P(\theta|Y) = \frac{P(Y|\theta)P(\theta)}{\int P(Y|\theta)P(\theta)d\theta} \tag{9}$$

where $P(Y|\theta)$ is the likelihood function and $P(\theta)$ is the prior. In proportionality form, Eq. (9) becomes

$$P(\theta|Y) \propto P(Y|\theta)P(\theta) \tag{10}$$

Given the parameters to be estimated in our models, the posterior becomes

$$P\left(\mu, \Sigma_y^{-1}, G|Y\right) \propto P\left(Y|\mu, \Sigma_y^{-1}, G\right) P\left(\Sigma_y^{-1}|G\right) \tag{11}$$

where $\mu = 0$ and the likelihood function is generated with respect to Eq. (8) as

$$P\left(Y|\Sigma_y^{-1}, G\right) = (2\pi)^{\frac{-nT}{2}}\left|\Sigma_y^{-1}\right|^{\frac{T}{2}}\exp\left\{-\frac{1}{2}\left(\Sigma_y^{-1}, \sum_{t=1}^{T} Y_t Y_t'\right)\right\} \tag{12}$$

The prior density, $P(G)$, is chosen from a uniform prior as $P(G) \propto 1$; the inverse of the variance-covariance matrix of the error term follows a Wishart distribution, i.e., $\Sigma_y^{-1} \sim W\left(v, \sum_{t=1}^{T}\left(Y_0 Y_0'\right)^{-1}\right)$; and β is set to 0.5. The prior density is then written as

$$P\left(\Sigma_y^{-1}|G\right) = \frac{1}{K_n(v, (Y_0 Y_0)'}\left|\Sigma_y^{-1}\right|^{\frac{(v-n-1)}{2}}\exp\left\{-\frac{1}{2}\left(\Sigma_y^{-1}, \sum_{t=1}^{T} Y_0 Y_0'\right)\right\} \tag{13}$$

The posterior distribution is written with the likelihood function and prior density in Eqs. (12) and (13) as.

$$\begin{aligned}P\left(\mu, \Sigma_y^{-1}|Y\right) &\propto (2\pi)^{\frac{-nT}{2}}\left|\Sigma_y^{-1}\right|^{\frac{T}{2}}\exp\left\{-\frac{1}{2}\left(\Sigma_y^{-1}, \sum_{t=1}^{T} Y_t Y_t'\right)\right\}\\ &\cdot\frac{1}{K_n(v, (Y_0 Y_0)'}\left|\Sigma_y^{-1}\right|^{\frac{(v-n-1)}{2}}\exp\left\{-\frac{1}{2}\left(\Sigma_y^{-1}, \sum_{t=1}^{T} Y_0 Y_0'\right)\right\}\end{aligned} \tag{14}$$

Eq. (14) which is the posterior distribution with the likelihood function and the prior density in Eqs. (12) and (13) is estimated with Markov chain Monte Carlo sampling methods and Metropolis-Hastings recursively to obtain the posterior means. Samples are drawn from the posterior distribution, $P\left(\Sigma_y^{-1}, G|Y\right)$, given $P\left(Y|\Sigma_y^{-1}, G\right)$ and $P\left(\Sigma_y^{-1}|G\right)$ by using the MCMC and M-H algorithm (see Ahelegbey et al. [6] for more exposition).

3.1. Granger causality test

Following Granger [1], a pairwise Granger causal (P-GC) relationship that conditions a variable on other variables and their time lags is investigated. The reality about the P-GC causality in the graphical network analysis is that it is a directed and forward causal relationship among the dependence variable structures. The P-GC VAR (ρ) model is stated as

$$Y_t^i = \sum_{s=1}^{\rho}\alpha_s Y_{t-s}^i + \sum_{s=0}^{\rho}\beta_s Y_{t-s}^j \tag{15}$$

4. Empirical analysis and discussion

Following Ahelegbey et al. [6], we sampled and derive separately the multivariate auto-regressive (MAR) and the multivariate instantaneous (MIN) system using M-H algorithm specified in Appendix 2. The MAR network is a contemporaneous interaction of the variables from their past realizations to current realizations, while the MIN network is a contemporaneous

interaction of the variables in their current realizations. At the implementation level, we ordered our variables in the Y_t vector as Y_t =(M2, Ind, Infl, Intr, Exch) from Eq. (2). It should be noted that our results are not sensitive to the variable ordering, in which case, any order can be taken.

After choosing an optimal lag length of 1 using Akaike information criterion (AIC) and Schwarz criterion (SC) (see Appendix 1), the BGN-VAR model ran 20,000 Gibbs iteration each for the MAR and MIN, making a total number of iteration to be 40,000, out of which 20,000 was set as burn-ins to achieve convergence. The results of the P-GC VAR for the MIN and MAR are presented in **Figures 2** and **3**. The dark green (light) color implies strong (weak) dependence between the dependent and independent variables. The row variables are the independent or explanatory variables, while the column variables are the dependent or response variables. The result of the MIN in **Figure 2** shows strong evidence of causal relationship with M2→Infl, Ind→Infl, Infl→Intr. The results can be interpreted to mean a stronger evidence of effects of both money supply and industrial output on inflation rate in Nigeria. This implies that the increase of money in circulation increases industrial demand and production; however, the resultant effects lead to inflationary rate due to high cost of production in Nigeria. High cost of production for firms and companies generates increase in prices of goods and services due to the use of generators to produce. The country generates 5000 megawatts (MW) of electricity which is not enough in residential needs let alone industrial needs; hence, most firms result to the use of generating set which results to high cost of production and high prices. We also found stronger effects of inflation rate behaviour on interest rate movement in Nigeria. This implies that instantaneous change in money supply and industrial output are major determinants of inflation rate in Nigeria. We also found strong effects of inflation rate on interest rate. This implies that resultant inflationary effects compel monetary authority and commercial banks to choose high interest rate to stabilize and ensure reasonable returns on investment. Furthermore, **Figure 3** gives the contemporaneous autoregressive structure of the variable of interest. The MAR result shows the causal edges as, firstly, $M2_{t-1}$ →M2, Ind and
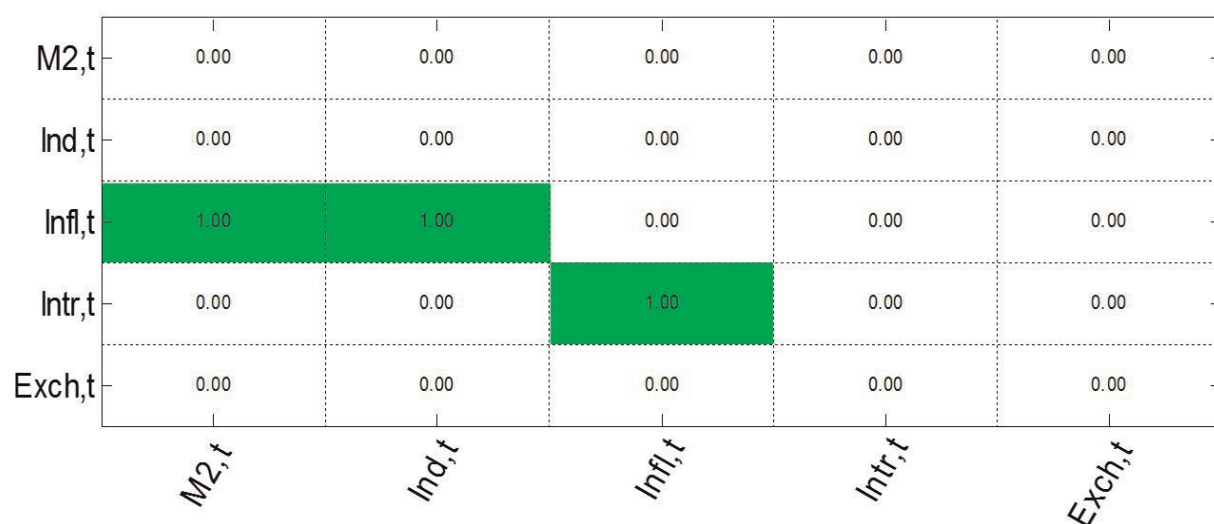

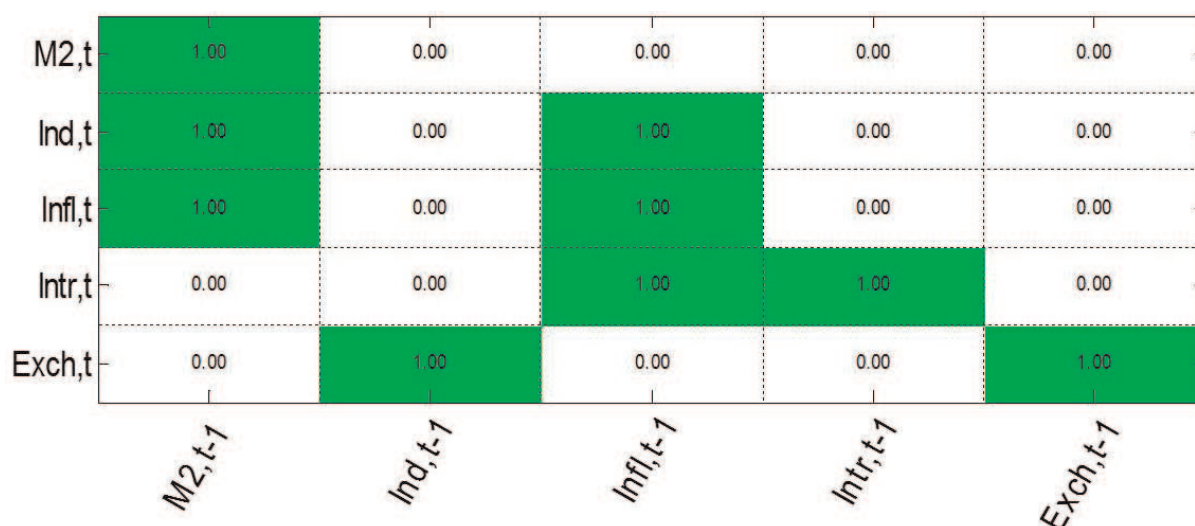**Figure 2.** Multivariate instantaneous structure (MIN).

Figure 3. Multivariate autoregressive structure (MAR).

Infl; secondly, $Ind_{t-1} \rightarrow Exch$; thirdly, $Infl_{t-1} \rightarrow Intr$, Infl and Ind; fourthly, $Intr_{t-1} \rightarrow Intr$; and, lastly, $Exch_{t-1} \rightarrow Exch$. The causal edges can be interpreted to mean that inflation rate, industrial output and money supply respond strongly to immediate past lag of money supply. Furthermore, we found past value of industrial output to Granger-cause exchange rate. In addition, past value of inflation Granger causes interest rate, current inflation and industrial output. This outcome corroborates the MIN result that inflation rate is a strong predictor of interest rate in Nigeria. The fourth and last causal edges can be explained to mean both past interest rate and exchange rate are strong predictors of their current states.

5. Conclusion and policy recommendations

This study examines the dynamic interactions among monetary policies and macroeconomic performances in Nigeria over the period of 1986Q1–2017Q4 with the application of BNG-SVAR. The use of the BNG-SVAR comes from the dynamic response of monetary policy to macroeconomic indicators in Nigeria. The nonstationary process of the data used led to test for their cointegration. The cointegration results show the existence of long-run relationship among the variables of interest. The P-GC results from the BNG-SVAR with the MCMC and M-H sampling techniques show that inflation is a strong predictor of interest rate in Nigeria given both the contemporaneous instantaneous (MIN) and the contemporaneous autoregressive (MAR) results. This is more reason why the Central Bank of Nigeria (CBN) in its period monetary policy committee (MPC) targets the inflation rate by choosing appropriate monetary policy rate (MPR) in response to the inflation rate in the country. This study, therefore, recommends that the inflation targeting in Nigeria should be broad and not limited to changing the MPR only. The fiscal discipline should be ensured from the Ministry of finance and the executive arm of the government. In any case, any fiscal policy should be directed towards the productive sectors of the economy. A major determinant of inflationary pressure

in Nigeria is incessant supply of electricity. There should be massive investment in power generation and transmission in the country to eliminate the additional cost of production that drives prices up through the use of generating sets for production. Finally, the exchange rate policy should be to ensure domestic production to drive prices down rather than reliance on imported goods that promote imported inflation.

A. Appendices

A.1. Appendix 1

See the **Table A4**.

VAR lag order selection criteria					
Endogenous variables: M2, Ind, Infl, Intr, Exch					
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**
0	−4973.01	NA	7.41e + 29	82.96683	83.08297
1	−4220.51	1429.753	4.02e + 24*	70.84180*	71.53868*
2	−4206.64	25.18928	4.85e + 24	71.02738	72.30498
3	−4190.38	28.18071	5.64e + 24	71.17307	73.03140
4	−4168.07	36.81222	5.96e + 24	71.21790	73.65696
5	−4122.25	71.78438*	4.28e + 24	70.87090	73.89069
6	−4100.89	31.68685	4.66e + 24	70.93154	74.53205
7	−4081.64	26.94965	5.32e + 24	71.02738	75.20861
8	−4056.97	32.48824	5.61e + 24	71.03280	75.79476

*Indicates the optimal lag length, where LogL, LR, FPE, AIC and SC indicate log likelihood, likelihood ratio, final prediction error, Akaike information criterion and Schwarz criterion.

Table A4. Optimal lag selection results

A.2. Appendix 2

The MCMC and the M-H algorithms are a proposal distribution to sample a new graph G^* conditioned on a graph G with acceptance probability given as.

$M(G^*|G) = \min \left\{ \frac{P(Y|G^*)}{P(Y|G)} \frac{P(G^*)}{P(G)} \frac{Z(G|G^*)}{Z(G^*|G)}, 1 \right\}$ where $P(Y|G)$ is the likelihood function, $P(G)$ is the prior density and, finally, $Z(G^*|G)$ is the proposal distribution.

A.3. Appendix 3

Inverse Wishart Prior Posterior MCMC

The procedure for Gibbs sampling for the independent-normal Wishart prior is as follows:

1. Draw $G_i^{(k)}$ from the normal $p(G_i|Y,\Sigma)$.

2. Draw $\Sigma_i^{-1(k)}$ from the Wishart $p\left(\Sigma_i^{-1}|Y,G_i\right)$.

3. Repeat steps 1 and 2 N (20,000) times, and discard the first N_{burn} (10,000) iterations as burn-ins.

A.4. Appendix 4

Identification structure of the BGN-VAR results.

$$
B_{-\rho} = \begin{Bmatrix} -0.9 & 0 & 0 & 0 & 0 \\ 0.6 & 0 & 0.5 & 0 & 0 \\ 0.7 & 0 & -0.5 & 0 & 0 \\ 0 & 0 & 0.5 & 0.7 & 0 \\ 0 & 0.6 & 0 & 0 & 0.6 \end{Bmatrix} B_{\_0} = \begin{Bmatrix} 0 & 0 & -0.8 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0 & 0 & -0.5 \\ 0 & 0 & 0 & 0 & 0 \end{Bmatrix}
$$

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