Analysing the Nexus between the Financial Sector and Economic Growth in Nigeria: A Comparative Investigation using , BVAR, Linear Regression (OLS), and PPML Models.

ABSTRACT

Aims: This study aims to analyze the complex relationship between the financial sector and economic growth in Nigeria. The study aims to provide comprehensive insights into this nexus by employing a comparative investigation using three distinct models: Linear Regression, Poisson Pseudo Maximum Likelihood (PPML), and Bayesian Vector Autoregression (BVAR).
Methodology: The study then applied three different models, with a specific focus on the BVAR(2) model, supported by various diagnostic tests and stability assessments. The inclusion of Linear regression analysis and Poisson Pseudo Maximum Likelihood Estimator (PPML) enhances the depth of the study, providing nuanced insights into the impact of specific financial sector variables on economic growth.
Results: The BVAR(2) model emerges as the optimal choice, demonstrating its reliability in capturing dynamic interactions and offering a powerful tool for policymakers. Specific results, such as the significant negative impact of D(CPS) in the regression analysis and the high R-squared in PPML, provide actionable insights into areas requiring policy interventions and underscore the substantial contribution of the financial sector to economic growth.
Conclusion: The comparative assessment of model performances, favoring the BVAR model, guides future research and policy considerations, providing a reliable framework for further investigations. The study's insights are positioned as valuable for policymakers seeking to enhance economic growth through strategic interventions in the financial sector. Overall, the abstract succinctly encapsulates the aims, methodology, results, and concluding implications of the study on the nexus between the financial sector and economic growth in Nigeria.

Keywords: Time Series, Demand Deposit, Credit to Private Sector, Money Supply, GDP, BVAR, Regression. OLS, PPML.

1. INTRODUCTION

The economic development of a country is intricately linked to the performance of its financial institutions. In Nigeria, as in many other developing nations, financial institutions play a pivotal role in shaping the overall economic landscape. The impact of financial institutions on Nigeria's economic development is a subject of great significance and deserves in-depth exploration.

Nigeria, as the most populous country in Africa and one of the largest economies on the continent, has experienced significant economic growth and development over the past few decades (World Bank, 2021). However, the country still faces numerous challenges in achieving sustained and inclusive economic development, including poverty, unemployment, income inequality, and inadequate infrastructure (Adeleke, 2018; IMF, 2019). In this context, the role of financial institutions in Nigeria's economic development has gained increased attention.

Financial institutions in Nigeria encompass a wide range of entities, including commercial banks, microfinance banks, development banks, insurance companies, pension funds, stock exchanges, and other non-bank financial institutions (CBN, 2020). These institutions serve as intermediaries between savers and borrowers, facilitate transactions, mobilize savings, allocate capital, and provide various financial services that are crucial for economic activities (CBN, 2020).

Despite the recognized importance of financial institutions in Nigeria's economic development, there are challenges and gaps that need to be addressed. These challenges include issues of financial stability, access to finance, regulation and supervision, financial literacy, and technological innovation (CBN, 2020; World Bank, 2021). Additionally, there is a need for further research and empirical analysis to understand the complex interactions between financial institutions and economic development in the Nigerian context.

This study specifies the functional relationship between the Nigerian Gross Domestic Product (GDP), Demand Deposit (DD), Credit to Private Sector (CPS), and Money Supply (MS)by adopting two models including (i) Bayesian Vector Autogressive Model (BVAR) and (ii) Multiple Linear Regression Model.

Domestic Product is the monetary value of all final goods and services produced within a country's borders during a specific time period, usually a year. It is a widely used measure of a country's economic activity and is used to assess and compare the size and growth of economies. While Demand Deposit refers to funds held in a bank account that can be withdrawn by the account holder on demand without prior notice. It is a type of bank account that provides easy access to funds for everyday transactions, such as paying bills, making purchases, or withdrawing cash.

Credit to Private Sector represents the total amount of credit extended by financial institutions, such as banks, to individuals, households, and non-financial corporations. It includes loans, mortgages, and other forms of credit provided to support private sector activities, such as investment, consumption, and business operations. While Money Supply refers to the total amount of money circulating in an economy at a given point in time. It includes physical currency, such as coins and banknotes, as well as demand deposits held by individuals and businesses in banks. Money supply is a crucial indicator of the availability of money for economic transactions and is influenced by factors such as central bank policies, commercial bank lending, and public demand for money.

2. LITERATURE REVIEW

Several authors have carried out studies to investigate these working relationships. For instance, Ahmad et al. (2019) analyzed the relationship between government expenditure, economic growth, and income inequality in selected Asian countries. Using a BVAR model, the study finds a long-run positive relationship between government expenditure and economic growth. Additionally, there is a positive association between government expenditure and income inequality. However, it is important to note that this study is limited to analyzing the relationship within selected Asian countries.

Israel et al. (2023) aimed to model the relationship between Nigerian quasi money and money supply using the Bayesian Vector Autoregressive (BVAR) model. They collected and analyzed monthly data from the Central Bank of Nigeria (CBN) money and credit statistics over an 8-year period. The analysis employed both the Vector Autoregressive (VAR) Model and BVAR model to examine the dynamics between these variables and their implications for monetary policy. The findings indicated that there is no long-run relationship between Nigerian narrow money and quasi money, but quasi money does granger cause changes in narrow money, and vice versa. The BVAR model consistently outperformed the VAR model in terms of higher Adjusted-R^2 values, suggesting its stronger ability to explain the variance in the data. The BVAR model provided a more robust and accurate representation of the relationship between these variables, exhibiting stability and the absence of heteroscedasticity in the residuals. The impulse response function showed an immediate impact of changes in narrow money on the overall money supply in Nigeria. This study contributes to existing knowledge by empirically examining the relationship between Nigerian narrow money and quasi money, emphasizing the importance of considering these variables for effective monetary policy strategies, particularly in Nigeria.

Basher et al. (2019) investigated the impact of oil price shocks on stock market returns and volatility in selected Gulf Cooperation Council (GCC) countries. Employing a BVAR model, the study reveals significant short-term and long-term relationships between oil prices, stock prices, and exchange rates. This study provides insights into the dynamics of oil price shocks and their effects on stock markets in the GCC countries.

Ferreira et al. (2021) conducted a comparative analysis between VAR and BVAR models for forecasting inflation in Brazil. The study finds that BVAR models outperform VAR models in terms of forecasting accuracy. By comparing the two models, this study contributes to the understanding of the forecasting performance of different modeling approaches in the context of inflation forecasting in Brazil.

Uddin et al. (2018) conducted an empirical analysis on the financial inclusion and economic growth in Nigeria. They utilized the Johansen cointegration test and Vector Error Correction Model (VECM) to examine the relationship between financial inclusion and economic growth. The study revealed a positive influence of financial inclusion on economic growth in Nigeria. However, it focused on the relationship between financial inclusion and economic growth without directly examining the role of financial institutions, which is a limitation.

Polat and Yeşilyaprak (2017) investigate the role of Turkey's official export credit agency, Turk Eximbank, in promoting the country's exports from 2000 to 2015. Utilizing an empirical trade gravity equation, the authors employ various panel gravity regressions for 212 countries over a 16-year period. The findings suggest that changes in export credit insurance have a positive impact on Turkish exports when holding other independent variables constant. Employing fixed effect panel specifications as the primary estimation method and conducting various post-estimation tests, including clustered robust OLS, Poisson fixed effect (Poisson), and Poisson Pseudo Maximum Likelihood (PPML) estimations, the study accounts for zero trade values in the dependent variable. The analysis underscores the significant influence of both individual and time effects within the panel data structure, ultimately revealing that an increase in export insurance positively affects Turkish exports.

Gizem et al. (2023) focus on comparing the forecast performance of three different approaches in parameter estimation for the basic gravity model using international air cargo data from Turkey. The first approach employs ordinary least squares, a common method in air transport literature. The second approach, also using the log-linear estimate technique, introduces a unique element by adding a small amount to observations with a zero-valued dependent variable, incorporating them into the analysis. The third method involves estimating the gravity model using the Poisson pseudo maximum-likelihood estimator, offering an alternative to ordinary least squares. After developing models using these three approaches, the study evaluates forecast performance through error metrics and the Diebold-Mariano test. The results indicate that the Poisson pseudo-maximum-likelihood estimator outperforms the others, particularly in forecasting the total amount of cargo carried. However, variations in forecast performance among models are observed for specific cities, highlighting the need for a nuanced understanding of the estimators' effectiveness across different contexts.

Tutberidze and Japaridze (2021) address a limitation of vector autoregressive (VAR) models, which necessitate time series to have equal lengths during estimation, potentially leading to information loss from longer time series. This issue is particularly pronounced in macroeconometric settings where variables may have different starting points due to varied data recording or collection practices. Focusing on developing and emerging economies, especially those transitioning to market economies in the late 20th century, the authors propose a Bayesian approach as a remedy. This approach involves aggregating information from longer time series into a prior, which is then used to estimate parameters for the VAR process on clipped and equally-sized time series. The study evaluates the relative model performance by assessing the forecasting ability of resulting models using mean absolute scaled errors (MASE). Utilizing time series from the Georgian economy for illustration, the authors find that the resulting Bayesian VAR models, on average, exhibit a 7% improvement in forecasting performance compared to standard alternatives with the same set of variables.

3. MATERIAL AND METHODS

3.1 Data

Secondary data will be collected from the Central Bank of Nigeria (CBN). The data will cover the period of twelve years (2010 to 2022) and will include variables such as Nominal GDP and Money and Credit Data including: Demand Deposits, Credit to Private Sector, Money Supply, and Narrow Money of financial institutions in Nigeria.

3.2: Methodology

Two Models shall be comparatively considered in this study including:

i. Bayesian Vector Autoregressive Model (BVAR)
ii. Ordinary Least Square (OLS) Regression
iii. Poisson Pseudo Maximum Likelihood Estimator (PPML Estimator)

3.2.1 Unit Root Test

A number of alternative tests are available for testing whether a series is stationary or not. The Augmented Dickey – fuller (ADF), Dickey and Fuller (1967) for (ADF) test, where k is chosen to ensure that the residuals follow a pure random process. ADF unit root, tests the null hypothesis is that the series is not stationary and this is either accepted or rejected by examination of the t-ratio of the lagged term x_{E-1} compared with the tabulated values. If the t-ratio is less than the critical value the null hypothesis of a unit root (i.e., the series is not stationary) is accepted. If so the first difference of the series is evaluated and if the null hypothesis is rejected the series is considered stationary and the assumption is that the series is integrated of order one I(1).

The ADF regression test is as follows:

$$\Delta x_t = \lambda_0 + \lambda_1 x_{t-1} + \lambda_2 T + \sum_{i=1}^{n} \Psi_i \Delta x_{t-1} + \varepsilon \tag{3.1}$$

Where Δ is the difference operator.
x is the natural logarithm of the series
T is a trend variable

λ and Ψ are the parameters to be estimated and
ε is the error term

3.2.2 Model Selection Criteria

The lag order is chosen which optimally balances these two forces.
Gebhard and Jurgen (2007), to estimate the system, the order p ie the maximal lag of the system has to be determined. The multivariate case with k variables, T observations, a constant term and a maximal lag of p, these criteria are as follows:

Final prediction error (FPE)

$$FPE(P) = \left[\frac{T+kp+1}{T-kp-1}\right]^k / \sum \hat{u}\hat{u}(p) / \qquad (3.2)$$

Akaike information criterion (AIC)

$$AIC(p) = In / \sum \hat{u}\hat{u}(p) / + (k + pk^2)\frac{2}{T} \qquad (3.3)$$

Hannan – Quinn criterion (HQ)

$$HQ(p) = In / \sum \hat{u}\hat{u}(p) / + (k + pk^2)\frac{2In(In(T))}{T} \qquad (3.4)$$

Shwarz criterion (SC)

$$SC(p) = In / \sum \hat{u}\hat{u}(p) / + (k + pk^2)\frac{In(T)}{T} \qquad (3.5)$$

3.2.3 TheBVAR

Bayesian VAR (BVAR) models have the same mathematical form as any other VAR model, i.e.

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-1} + \varepsilon_t \qquad (3.6)$$

where y_t is a K×1 vector of endogenous variables in period *t*, *Ai* is the coefficient matrix corresponding to the *I*th lag of y_t, *c* is a constant deterministic term and ϵ is an error term with zero mean and variance-covariance Σ.

The Bayesian Vector Autoregressive Model of order *k* that is *VAR(k)* model for this study are specified in Equations (2.7) to Equation (2.10) as shown below.

$$GDP_t = \alpha_1 + \sum_{i=1}^{k} \beta_i GDP_{t-i} + \sum_{m=1}^{k} \varphi_m DD_{t-m} + \sum_{n=1}^{k} \vartheta_n CPS_{t-n} + \sum_{p=1}^{k} \varsigma_p MS_{t-p} + u_{1t} \quad (3.7)$$

$$DD_t = \alpha_2 + \sum_{i=1}^{k} \beta_i GDP_{t-i} + \sum_{m=1}^{k} \varphi_m DD_{t-m} + \sum_{n=1}^{k} \vartheta_n CPS_{t-n} + \sum_{p=1}^{k} \varsigma_p MS_{t-p} + u_{2t} \quad (3.8)$$

$$CPS_t = \alpha_3 + \sum_{i=1}^{k} \beta_i GDP_{t-i} + \sum_{m=1}^{k} \varphi_m DD_{t-m} + \sum_{n=1}^{k} \vartheta_n CPS_{t-n} + \sum_{p=1}^{k} \varsigma_p MS_{t-p} + u_{3t} \quad (3.9)$$

$$MS_t = \alpha_4 + \sum_{i=1}^{k} \beta_i GDP_{t-i} + \sum_{m=1}^{k} \varphi_m DD_{t-m} + \sum_{n=1}^{k} \vartheta_n CPS_{t-n} + \sum_{p=1}^{k} \varsigma_p MS_{t-p} + u_{4t} \quad (3.10)$$

GDP_t	=	Nominal Gross Domestic Product
DD_t	=	Demand Deposit
CPS_t	=	Credit to Private Sector
MSt	=	Money Supply
α_{1-5}	=	The constant terms for the five variables respectively

u_{1t-5t} = the stochastic error terms for the five variables respectively

2.3.4: Multiple Linear Regression Model

The multiple linear regression model to predict nominal Gross Domestic Product (GDP) using Demand Deposits (DD), Credit to Private Sector (CPS), Money Supply (MS), and Narrow Money (NM) of financial institutions in Nigeria as independent variables.
The model can be expressed mathematically as follows:

$$GDP = \beta_0 + \beta_1 DD + \beta_2 CPS + \beta_3 MS + \beta_4 NM + \varepsilon \qquad 3.11$$

Where:

- GDP: Dependent variable representing nominal Gross Domestic Product, which is the target variable to be predicted.
- DD: Independent variable representing Demand Deposits
- CPS: Independent variable representing Credit to Private Sector
- MS: Independent variable representing Money Supply.
- MM: Independent variable representing Narrow Money.
- β_0, β_1, β_2, β_3, β_4 are the regression coefficients representing the relationship between the respective independent variables and GDP.
- ε represents the error term or residual, which captures the unexplained variation in GDP that is not accounted for by the independent variables.

2.3.5 Poisson Pseudo Maximum Likelihood Estimator (PPML Estimator)

A possible way of obtaining a more efficient estimator without resorting to non-parametricregression is to estimate the parameters of interest using a pseudo-maximum-likelihoodestimator based on some assumption of the functional form of Var(y_i | x_i) (Manning &Mullahy, 2001; Papke &Mullahy, 2001). Among possible specifications, under theassumption that the conditional variance is proportional to the conditional mean$E[y_i|x_i] = e^{x_i'\beta_i}$and $Var[y_i|x_i]$ and βcan be estimated by solving the following set of firstorder conditions

$$\sum_{i=1}^{n}\left[y_i - e^{x_i'\beta_i}\right] = 0 \qquad 3.12$$

The estimator defined below is numerically equal to the Poisson pseudo-maximumlikelihood(PPML), often used for count data. The form of the equation implies that thecorrect specification of the conditional mean, $[y_i|x_i] = e^{x_i'\beta_i}$. Therefore, the data do nothave to have a Poisson distribution (count data) and $y_i$does not have to be an integer in orderfor the estimator based on the Poisson likelihood function to be consistent (Gourieroux,Monfort, &Trognon, 1984).The Poisson regression model is defined by:

$$\Pr(y_i = j|x_i) = \frac{e^{-\lambda}\lambda^j}{j!}, j=0,1,2,\ldots \qquad 3.13$$

Where λ is generally specified as $\lambda = e^{x_i'\beta_i} = e^{\beta_0+\beta_1 x_{1i}+\cdots}$. The vector of parameters of interest, b , can be estimated by maximizing the log-likelihood function given by:

$$\ln \mathrm{L}(\beta) = \sum_{i=1}^{n}\left[-e^{x_i'\beta} + (x_i'\beta)y_i - \ln y_i!\right]. \qquad 3.14$$

4. RESULTS AND DISCUSSION

4.1 Results

4.1.1 Data Presentation and Stationarity Test

Table 4.1 Summary of Descriptive Statistics on All Variables

Statistics	GDP	DD	CPS	MS
Mean	28519.24	8415655.	21421882	26296180
Median	26227.69	8145200.	21007923	24373215
Maximum	57780.58	18490981	41368927	51490489
Minimum	12790.38	3980624.	9347314.	10764792
Std. Dev.	11263.48	3846975.	8262704.	11112306
Skewness	0.664298	1.107164	0.613186	0.419941
Kurtosis	2.620511	3.446291	2.733370	2.242214
Jarque-Bera	4.136550	3.05525	3.412669	2.772552
Probability	0.126404	0.203975	0.181530	0.250005
Sum	1483001.	4.38E+08	1.11E+09	1.37E+09
Sum Sq. Dev.	6.47E+09		3.48E+15	7.55E+14
Observations	52		52	52

Source: Researcher’s computation with Eviews10.0

Figure 4.1: Time Plot of the Four Interacting Variables from 2010 Quarter 1 – 2022 Quarter 4

4.1.2 Stationarity Test

The Augmented Dickey-Fuller (ADF) test was deployed to test for stationarity of each dataset. The test was conducted based on the following hypotheses:
Ho: Variable contains unit root and hence is non-stationary
H1: Variable does not contain unit root and hance is stationary

Table 4.2: ADF Unit Root Test

Variable	ADF Test Statistic	5% Critical Value	Order of Integration
GDP	-29.70741	-2.925169	Stationary at first difference I(1)
CPS	-22.55220	-2.925169	Stationary at first difference I(1)
DD	-14.32248	-2.925169	Stationary at first difference I(1)
MS	-3.362677	-2.926622	Stationary at first difference I(1)

Source: Eviews 10, 2023.

Table 4.3: : Result of Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.542677	71.08455	47.85613	0.0001
At most 1 *	0.399149	35.09573	29.79707	0.0112
At most 2	0.173707	11.66292	15.49471	0.1738
At most 3	0.060809	2.885854	3.841466	0.0894

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

4.1.3 BVAR Modeling

3.2.1 Model Estimation

Table 3.4: R Lag Order Selection for BVAR Model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2596.759	NA	1.86e+45	115.5893	115.7499	115.6491
1	-2465.266	233.7645	1.10e+43	110.4563	111.2592	110.7556
2	-2368.855	**57.91381***	**1.49e+42***	**108.3047***	**110.9842***	**109.3224***
3	-2415.393	18.81823	5.31e+42	109.6619	111.7496	110.4402
4	-2428.624	58.62699	4.48e+42	109.5389	111.0347	110.0777

LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 4.4 Summary of BVAR Model showing the Effects of Demand Deposit, Credit to Private Sector and Money Supply, onNominal Gross Domestic Product

	D(GDP)	D(DD)	D(CPS)	D(MS)
D(GDP(-1))	0.220564	146.8415	-33.97727	165.1320
	(0.22132)	(119.145)	(248.495)	(297.640)
	[0.99659]	[1.23246]	[-0.13673]	[0.55480]
D(GDP(-2))	-0.919553	613.4798	1036.198	1177.351
	(0.18480)	(99.4837)	(207.489)	(248.524)
	[-4.97600]	[6.16663]	[4.99400]	[4.73738]
D(DD(-1))	2.26E-05	-0.524205	-0.459830	-0.837603
	(0.00036)	(0.19301)	(0.40254)	(0.48216)
	[0.06293]	[-2.71600]	[-1.14231]	[-1.73720]
D(DD(-2))	0.000613	-0.102589	-0.219568	0.021676
	(0.00041)	(0.21928)	(0.45735)	(0.54780)
	[1.50430]	[-0.46784]	[-0.48009]	[0.03957]
D(CPS(-1))	-0.000262	0.052635	-0.008582	0.150858
	(0.00031)	(0.16445)	(0.34300)	(0.41083)
	[-0.85650]	[0.32006]	[-0.02502]	[0.36720]
D(CPS(-2))	0.000145	0.022763	-0.080848	-0.002581
	(0.00030)	(0.16094)	(0.33567)	(0.40205)
	[0.48519]	[0.14143]	[-0.24086]	[-0.00642]
D(MS(-1))	0.000625	0.028593	-0.303292	-0.310664
	(0.00025)	(0.13355)	(0.27854)	(0.33362)
	[2.51806]	[0.21410]	[-1.08888]	[-0.93118]
D(MS(-2))	-0.000362	0.329339	0.432901	0.302653
	(0.00022)	(0.11864)	(0.24745)	(0.29639)
	[-1.64291]	[2.77586]	[1.74945]	[1.02114]
C	933.5816	-372647.0	60446.35	5638.461
	(473.599)	(254956.)	(531751.)	(636916.)
	[1.97125]	[-1.46161]	[0.11367]	[0.00885]

R-squared	0.982913	0.921923	0.960633	0.971701
Adj. R-squared	0.979315	0.905485	0.952346	0.965743
Sum sq. resids	71764698	3.70E+13	9.32E+13	1.27E+14
S.E. equation	1374.243	986296.7	1565825.	1824674.
F-statistic	273.2327	56.08699	115.9109	163.1011
Log likelihood	-401.3009	-710.3754	-732.0993	-739.2898
Akaike AIC	17.45961	30.61172	31.53614	31.84212
Schwarz SC	17.81390	30.96600	31.89042	32.19640
Mean dependent	27672.47	8015623.	20829726	25585268
S.D. dependent	9555.175	3208171.	7172863.	9858556.

From Table 3.5 above, we have the following set of models:

ΔGDP_{t} = 0.220564152304*$\Delta GDP_{\mathrm{t}-1}$ - 0.919553461624*$\Delta GDP_{\mathrm{t}-2}$ + 2.25601285589e-05*$\Delta DD_{\mathrm{t}-1}$ + 0.000612748254891*$\Delta DD_{\mathrm{t}-2}$ - 0.000261649386631*$\Delta CPS_{\mathrm{t}-1}$ + 0.000145051745628*$\Delta CPS_{\mathrm{t}-2}$ + 0.00062466705039*$\Delta MS_{\mathrm{t}-1}$ - 0.000362079683175*$\Delta MS_{\mathrm{t}-2}$ + 933.581586881 (3.1)

ΔDD_{t}= 146.841544212*$\Delta GDP_{\mathrm{t}-1}$ + 613.479814449*$\Delta GDP_{\mathrm{t}-2}$- 0.524204737253*$\Delta DD_{\mathrm{t}-1}$ - 0.102589212146*$\Delta DD_{\mathrm{t}-2}$ + 0.0526347191194*$\Delta CPS_{\mathrm{t}-1}$+ 0.0227625167726*$\Delta CPS_{\mathrm{t}-2}$ + 0.0285927620468*$\Delta MS_{\mathrm{t}-1}$ + 0.329339448891*$\Delta MS_{\mathrm{t}-2}$- 372647.021547 (3.2)

ΔCPS_{t}= - 33.9772737771*$\Delta GDP_{\mathrm{t}-1}$+ 1036.19841743*$\Delta GDP_{\mathrm{t}-2}$ - 0.459829893807*$\Delta DD_{\mathrm{t}-1}$- 0.219568475003*$\Delta DD_{\mathrm{t}-2}$ - 0.00858248135161*$\Delta CPS_{\mathrm{t}-1}$ - 0.0808483826172*$\Delta CPS_{\mathrm{t}-2}$- 0.303292067813*$\Delta MS_{\mathrm{t}-1}$+ 0.432900998714*$\Delta MS_{\mathrm{t}-2}$+ 60446.3477933 (3.3)

ΔMS_{t}= 165.132020526*$\Delta GDP_{\mathrm{t}-1}$+ 1177.35148376*$\Delta GDP_{\mathrm{t}-2}$- 0.837603408035*$\Delta DD_{\mathrm{t}-1}$+ 0.0216762021373*$\Delta DD_{\mathrm{t}-2}$+ 0.150858366798*$\Delta CPS_{\mathrm{t}-1}$- 0.00258142035598*$\Delta CPS_{\mathrm{t}-2}$- 0.310663528309*$\Delta MS_{\mathrm{t}-1}$+ 0.302653004211*$\Delta MS_{\mathrm{t}-2}$+ 5638.46124422 (4.4)

4.1.4 Residual Diagnostics

Table 4.5 BVAR Model Stability Test

Diagnostic Test	**Test Statistics**	**df**	**Test Statistic Value**	**prob**	**Remarks**
VAR Residual Heteroscedasticity Test	Chi-square	160	134.8211	0.9266	No Heteroscedastic

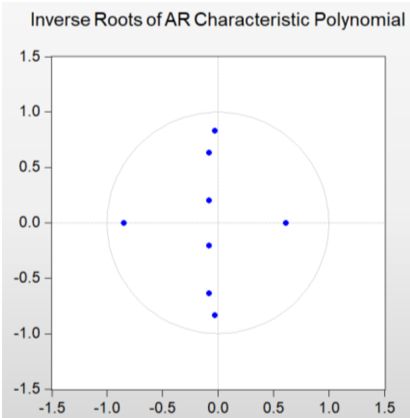

Figure4.2: Graph of Inverse Roots of AR Characteristic Polynomial

Impulse Response

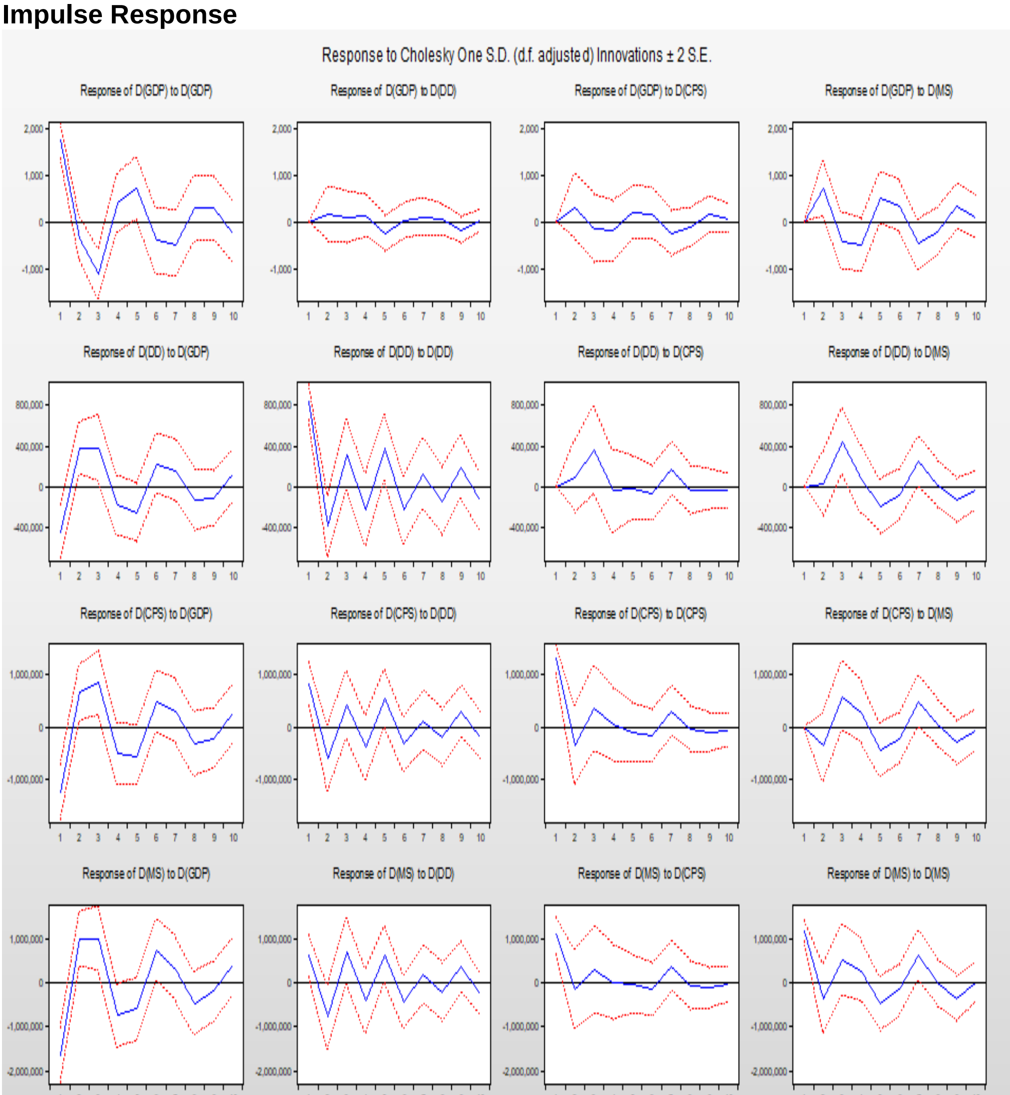

Figure 3.3:Plots of Impulse Response

4.1.5Variance Decomposition (Forecasting)

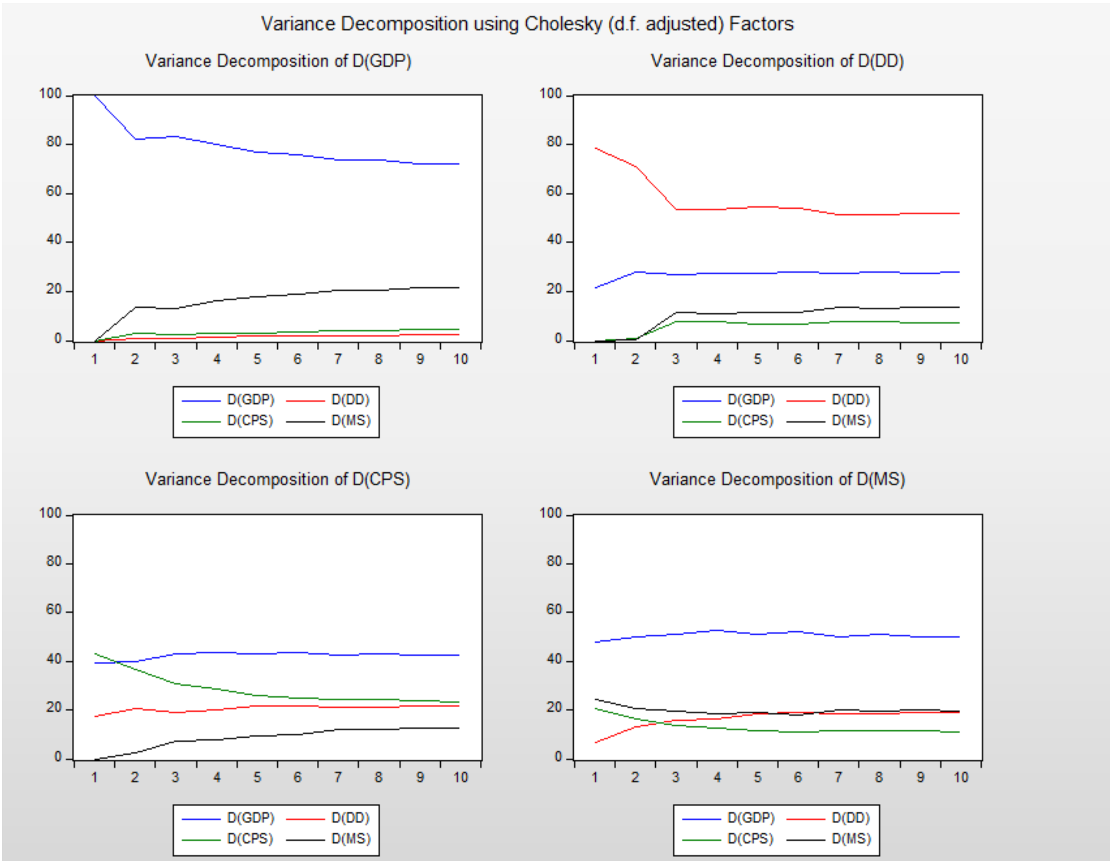

Figure 4.4: Plots of Variance Decomposition Plots of Impulse Response

4.1.6 Regression Modelling

Table 4.6: Regression Analysis of Interacting Variables using GDP as Dependent Variable

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DD)	0.000156	0.000299	0.519478	0.6060
D(CPS)	-0.000519	0.000247	-2.102899	0.0412
D(MS)	-0.000253	0.000186	-1.364259	0.1794
C	1191.572	239.3918	4.977496	0.0000

R-squared	0.609758	Mean dependent var	689.8388
Adjusted R-squared	0.583151	S.D. dependent var	2481.271
S.E. of regression	1602.004	Akaike info criterion	17.67555
Sum squared resid	1.13E+08	Schwarz criterion	17.83149
Log likelihood	-420.2133	Hannan-Quinn criter.	17.73448
F-statistic	22.91687	Durbin-Watson stat	1.924526
Prob(F-statistic)	0.000000		

Source: Eviews 10, 2023.

From Table 3.6 above, we have that the multiple regression model is:

ΔGDP = 1191.572 +0.000156*ΔDD -0.000519*ΔCPS + -0.000253*ΔMS

4.1.7: Poisson Pseudo Maximum Likelihood Estimator (PPML Estimator)

Table 4.7: PPML Analysis of Interacting Variables using GDP as Dependent Variable

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MS	4.43E-08	4.74E-10	93.30858	0.0000
DD	-4.04E-08	1.17E-09	-34.57012	0.0000
CPS	1.20E-09	7.37E-10	1.635419	0.1020
C	9.329760	0.003417	2730.006	0.0000

R-squared	0.868130	Mean dependent var	25754.02
Adjusted R-squared	0.858711	S.D. dependent var	8560.001
S.E. of regression	3217.573	Akaike info criterion	348.3233
Sum squared resid	4.35E+08	Schwarz criterion	348.4823
Log likelihood	-8007.436	Hannan-Quinn criter.	348.3829
Restr. log likelihood	-63800.49	LR statistic	111586.1
Avg. log likelihood	-174.0747	Prob(LR statistic)	0.000000

Source: Eviews 10, 2023.

From Table 4.7 abov, we have the PPML model as:

$GDP_t = 9.329760 + 4.43E\text{-}08MS – 4.04E\text{-}08DD + 1.20E\text{-}09CPS$

4.1.8Comparing the three Models based on Performances

Model	AIC	BIC	Adjusted R^2
BVAR	*17.45961	*17.8139	*0.979315
Linear Regression	17.67555	17.83149	0.583151
PPML	348.3233	348.4823	0.858711

4.2. Discussion

Table 4.2 reveals ADF Unit Root Test results for GDP, CPS, DD, and MS, indicating stationarity at the first difference (I(1)) level. Notably, ADF test statistics for GDP, CPS, and DD are lower than their 5% critical values, confirming their stationary nature after differencing. Although the MS variable has a test statistic slightly exceeding the critical value, the consistent indication of stationarity at the first difference suggests I(1) integration, providing a foundation for econometric modeling.

In Table 4.3, the Johansen Cointegration Test's results show rejection of the null hypothesis of no cointegration and at most 1 cointegrating equation. However, hypotheses of at most 2 and at most 3 cointegrating equations are accepted, indicating 2 cointegrating equations at the 0.05 significance level. This information is crucial for understanding long-term relationships among variables, guiding subsequent econometric analyses. Associated p-values offer insight into the probability of obtaining the observed test statistic under the null hypothesis.

Table 4.4 displays Lag Order Selection results for the BVAR model, where a lag order of 2 emerges as the most suitable. The BVAR(2) model achieves the highest log-likelihood, the lowest LR statistic, and the smallest values for FPE, AIC, SC, and HQ. These metrics collectively indicate a favorable balance between model fit and complexity, emphasizing the BVAR(2) model's superiority in capturing data dynamics. Researchers can confidently employ it for subsequent analyses, as it emerges as the optimal choice based on multiple criteria.

In Table 4.5, the BVAR Model Stability Test examines VAR Residual Heteroscedasticity using a Chi-square statistic. The high probability (0.9266) suggests no evidence of heteroscedasticity in VAR residuals, supporting the model's stability and reinforcing confidence in the reliability of estimated parameters.

Figures 3.3 to 3.5 collectively demonstrate the adequacy of the fitted BVAR(2) model. The Inverse Roots of AR Characteristic Polynomial Impulse Response, depicted in Figure 3.3, exhibit all points lying inside the circle, indicating stability and suitability of the model. This observation is further supported by the Plots of Variance Decomposition (Figure 4.5) and Plots of Impulse Response (Figure 4.4). These figures provide additional visual confirmation that the BVAR(2) model effectively captures the dynamics of the data, making it a reliable choice for the econometric analysis conducted in this study.

The regression analysis of interacting variables using ordinary least square (OLS) method, with GDP as the dependent variable reveals several key findings as seen in Table 4.6. The coefficient for D(DD) is 0.000156, with a t-statistic of 0.519478 and a p-value of 0.6060, indicating no statistically significant relationship. In contrast, D(CPS) has a coefficient of -0.000519, a t-statistic of -2.102899, and a p-value of 0.0412, suggesting a significant negative impact on GDP. The coefficient for D(MS) is -0.000253, with a t-statistic of -1.364259 and a p-value of 0.1794, implying a non-significant effect. The intercept term (C) is 1191.572, with a t-statistic of 4.977496 and a p-value of 0.0000, indicating its statistical significance. The overall model explains approximately 61% of the variance in GDP (R-squared = 0.609758), and the adjusted R-squared is 0.583151. The mean dependent variable is 689.8388, with a standard deviation of 2481.271. These results provide insights into the individual and collective impacts of the interacting variables on GDP, contributing to a better understanding of the relationships in the model.

Table 4.7 presents the results of the Poisson Pseudo Maximum Likelihood Estimator (PPML) analysis of interacting variables with GDP as the dependent variable. The coefficient for MS is 4.43E-08, with a z-statistic of 93.30858 and a p-value of 0.0000, indicating a highly significant positive impact on GDP. DD has a coefficient of -4.04E-08, a z-statistic of -34.57012, and a p-value of 0.0000, suggesting a significant negative effect. CPS, with a coefficient of 1.20E-09, a z-statistic of 1.635419, and a p-value of 0.1020, shows a non-significant impact. The intercept term (C) is 9.329760, with a z-statistic of 2730.006 and a p-value of 0.0000, highlighting its statistical significance. The overall model has a high R-squared of 0.868130, indicating that approximately 87% of the variation in GDP is explained by the interacting variables. The adjusted R-squared is 0.858711. The mean dependent variable is 25754.02, with a standard deviation of 8560.001. These findings offer valuable insights into the impact of each variable on GDP within the context of the PPML estimation framework.

The comparison of the three models based on model selection criteria, specifically AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), and Adjusted R-squared, provides insights into their relative performances. Lower values of AIC and BIC indicate better model fit, while higher Adjusted R-squared values signify a higher proportion of explained variance. Comparing the models, the BVAR model demonstrates the lowest AIC (17.45961) and BIC (17.8139), suggesting it as the best-performing model in terms of goodness of fit and parsimony. Additionally, the BVAR model exhibits the highest Adjusted R-squared (0.979315), emphasizing its exceptional ability to explain the variation in the dependent variable. Following the BVAR model, the Linear Regression model has slightly higher AIC (17.67555) and BIC (17.83149) values, indicating a relatively lower performance. The PPML model, with significantly higher AIC (348.3233) and BIC (348.4823) values, lags behind in terms of model fit. Therefore, based on these criteria, the BVAR model stands out as the most favorable, followed by Linear Regression and PPML in descending order of performance.

The outcomes of the comprehensive econometric analysis on the interconnection between the financial sector and economic growth in Nigeria carry significant implications for policymakers, researchers, and stakeholders alike. The established stationarity, integration orders, and cointegration relationships, validated by the ADF Unit Root Test and Johansen Cointegration Test, provide a sturdy foundation for modeling, emphasizing a long-term linkage between financial sector variables and economic growth. The selection of the BVAR(2) model, supported by thorough diagnostic tests and stability assessments, underscores its reliability in capturing the dynamic interactions within this nexus. This model offers policymakers a potent tool for crafting targeted economic policies, accounting for the intricate relationships between financial variables and economic outcomes. The regression analysis and PPML contribute nuanced insights, pinpointing the significant negative impact of D(CPS) and showcasing high R-squared in PPML, shedding light on areas for policy interventions and understanding the financial sector's substantial contribution to economic growth. The comparative model assessment, favoring the BVAR model, guides future research and policy decisions, providing researchers a reliable framework for further investigations and policymakers strategic insights for fostering economic growth through the financial sector.

4. Conclusion

In conclusion, this study comprehensively investigated the nexus between the financial sector and economic growth in Nigeria through a comparative analysis utilizing linear regression, Poisson Pseudo Maximum Likelihood (PPML), and Bayesian Vector Autoregression (BVAR) models. The initial diagnostic tests, presented in Table 3.2, provided a solid foundation for subsequent modeling, affirming the stationarity of key variables after differencing. The Johansen Cointegration Test results underscored the existence of two cointegrating equations, essential for understanding long-term relationships among variables. Lag Order Selection results identified the BVAR(2) model as the most suitable, showcasing its superior performance in balancing model fit and complexity. The subsequent BVAR Model Stability Test in Table 3.5 and Figures 3.3 to 3.5 collectively confirmed the adequacy and stability of the fitted BVAR(2) model, providing visual and statistical support for its reliability. The linear regression analysis, although informative, demonstrated a relatively lower R-squared, suggesting a less effective model in explaining GDP variations. The PPML analysis showcased a high R-squared, indicating substantial explanatory power. However, the superior model selection criteria, such as AIC and BIC, favored the BVAR model, which exhibited the lowest values, implying a superior balance between fit and simplicity. In conclusion, the BVAR model emerges as the most favorable, followed by linear regression and PPML, emphasizing its robustness in capturing the dynamic relationships between the financial sector and economic growth in Nigeria.

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