International Journal of Development Mathematics Vol 3 Issue 1 Page No. 150 - 155

INTERNATIONAL JOURNAL OF DEVELOPMENT MATHEMATICS

ISSN: 3026-8656 (Print) | 3026-8699 (Online)

journal homepage: https://ijdm.org.ng/index.php/Journals

Regularized Vector Autoregressive Model for the Assessment of Macroeconomic Variables Associated with Inflation in Nigeria

Ahmad Abubakar [a], Lamidi-Sarumoh Alaba[a,*], Aliyu U. Kinafa[a] and Chajire P. Buba[a]

[a]Department of Mathematical Sciences, Gombe State University, Gombe State, Nigeria

ARTICLE INFO

Article history:
Received 10 December 2025
Received in revised form 09 March 2026
Accepted 20 March 2026

Keywords:
Inflation, Regularized VAR, VAR model, Forecasting, Nigeria, LASSO, Elastic Net

MSC 2020 Subject classification:
91B84, 62P20, 91B55, 62M10

ABSTRACT

This study investigates the determinants and forecasting performance of inflation in Nigeria using Regularized Vector Autoregressive (RVAR) models. While standard VAR models are widely applied in macroeconomic analysis, they are often affected by conditional multicollinearity and overparameterization, particularly in small samples, leading to unstable estimates and poor forecasting accuracy. To address these limitations, the study employs Ridge VAR, LASSO VAR, and Elastic Net VAR, and compares their performance with that of the standard VAR framework. Monthly data on inflation, currency in circulation, savings rate, and crude oil prices were analyzed. Unit root tests showed that most variables are non-stationary in levels and are modeled in first differences. Empirical results indicate that oil price shocks have a strong but short-lived impact on inflation, while the savings rate and currency circulation explain a substantial share of inflation variability. Forecast evaluation shows that LASSO and Elastic Net VAR models outperform the standard VAR, reducing forecast RMSE by approximately 43% and achieving RMSSE values of 0.651 compared to 1.137 for the standard VAR. The findings demonstrate that regularized VAR models provide a more reliable framework for inflation forecasting and policy analysis in Nigeria.

1. Introduction

Inflation remains a central macroeconomic challenge in Nigeria, with persistent volatility eroding purchasing power, influencing investment decisions, and hindering economic planning (National Bureau of Statistics Nigeria, 2025; Central Bank of Nigeria, 2022; World Bank, 2023). Despite the adoption of various monetary policy frameworks, inflation has largely remained unstable and frequently above policy targets. Understanding the inflation drivers and improving their forecast accuracy are therefore critical for effective monetary management (World Bank, 2023; Ertl et al., 2025). Several empirical studies have investigated the determinants of inflation in Nigeria using conventional econometric techniques, particularly the standard Vector Autoregressive (VAR) model Adelegan (2018); Salami (2020); Li et al., (2025). However, many studies have overlooked the presence of multicollinearity among macroeconomic variables, especially multicollinearity arising from the inclusion of multiple lagged variables in multivariate time-series models (Robert Tibshirani, 1996; Wooldridge, 2020). The strong interdependence among variables such as crude oil prices, currency in circulation, and savings often results in unstable parameter estimates, inflated standard errors, and weak statistical inference (Stock & Watson, 2020). The failure to account for multicollinearity has serious implications for forecasting performance. Models affected by multicollinearity tend to generate inefficient and unreliable forecasts, thereby limiting their usefulness for inflation prediction and policy formulation (Giannone et al., 2021; Ertl et al., 2025). As a result, policy recommendations derived from such models may be misleading and ineffective in addressing Nigeria's inflationary challenges.

This problem is particularly important given the continued instability of inflation in Nigeria in recent years, despite policy interventions.

Several studies have examined the relationship between macroeconomic variables and inflation using the VAR model.

* Corresponding author. Tel.: +2348060070544
E-mail address: lalabaajibolasarulam@sgsu.edu.ng (Lamidi-Sarumoh A. A.)
https://doi.org/10.62054/ijdm/0301.12

For example, Usman (2022) studied whether exchange rate and inflation affect the Nigerian economy using a VAR model. Similarly, Adelegan (2018), Salami (2020), and Li et al. (2025) also examined the relationship between macroeconomic variables and inflation in Nigeria. However, most of these studies rely on the traditional VAR model and do not adequately address multicollinearity, where some variables are highly related to each other. This problem can make the results unstable and difficult to interpret (Tibshirani, 1996). Because of this, there is still a gap in literature. Methods that can help reduce multicollinearity, such as Ridge Regression, LASSO, and Elastic Net have not been widely applied to study inflation in Nigeria (Ertl et al., 2025). Therefore, this study aims to fill this gap by applying these regularized methods to improve the stability and forecasting ability of the VAR model.

2. Materials and Methods

2.1 Research Design

The study adopts a quantitative time series econometric approach.

2.2 Data Source

Monthly data on inflation, currency in circulation, savings rate, and crude oil prices were obtained from the Central Bank of Nigeria (CBN) "https:// www.cbn.gov.ng" and the National Bureau of Statistics (NBS) "https:// www.nigerianstat.gov.ng", accessed 2025. Inflation is measured using the Consumer Price Index (CPI, base year 2010). All variables were transformed to logarithms where appropriate to stabilize variance.

2.3 Model Specification

The standard VAR model expresses each variable as a function of its own lags and the lags of other variables:

$$Y_t = A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_pY_{t-p} + \epsilon_t$$

Where, → Y_t = vector of dependent variables at time t, $A_1 \ldots A_p$ = coefficient matrices for each lag, $Y_{t-1} \ldots Y_{t-p}$= lagged dependent variables, ϵ_t= error term

Regularized VAR models introduce penalty terms that shrink coefficients:

Ridge VAR:

$$\min(\| Y - X\beta \|^2 + \lambda \| \beta \|^2)$$

where, Y = dependent variable, X = predictors, β = coefficients, $\|Y-X\beta\|^2$ = prediction error, λ= shrinkage penalty, $\|\beta\|^2$= sum of squared coefficients.

LASSO VAR:

$$\min(\| Y - X\beta \|^2 + \lambda \sum | \beta |)$$

where, Y = dependent variable, X = predictors, β = coefficients, $\|Y-X\beta\|^2$ = prediction error, λ= penalty weight, $\sum|\beta|$= sum of absolute coefficients.

Elastic Net VAR:

$$\min(\| Y - X\beta \|^2 + \lambda_1 \| \beta \|^2 + \lambda_2 \sum | \beta |)$$

where, Y = dependent variable, X = predictors, β = coefficients, $\|Y-X\beta\|^2$ = prediction error, λ_1 = Ridge penalty weight, $\|\beta\|^2$ = sum of squared coefficients, λ_2 = LASSO penalty weight, $\sum|\beta|$= sum of absolute coefficients.

Lag length selection using AIC, HQ, SC, and FPE criteria indicated an optimal lag length of one (see Appendix Table 3).

2.4 Stationarity Analysis

Augmented Dickey-Fuller (ADF) and KPSS tests were applied to assess stationarity. The results show that currency circulation, savings rate, and inflation are non-stationary in levels, while oil price is stationary in levels. To ensure consistency and avoid spurious regression, all variables were modeled in first differences.

2.5 Forecast Procedure
An expanding window forecasting approach is used, with 70% of the data allocated to model estimation and the remaining 30% used for forecast evaluation.

2.6 Model Evaluation
Forecast performance was evaluated using several statistical measures, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Scaled Error (RMSSE), and the Francis Diebold–Roberto Mariano (Diebold–Mariano) test.

Root Mean Square Error (RMSE)
RMSE measures the average size of forecast errors by giving more weight to large errors.

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

Penalizes large errors more
Lower RMSE = better model

Mean Absolute Error (MAE)
MAE measures the average absolute difference between actual and predicted values.

$$MAE = \frac{1}{n}\sum | y_t - \hat{y}_t |$$

Shows average error size
Lower MAE = better accuracy

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100$$

Expresses error in percentage (%)
Useful for comparison across models
Root Mean Squared Scaled Error (RMSSE)

$$RMSSE = \sqrt{\frac{\sum(y_t - \hat{y}_t)^2}{\sum(y_t - y_{t-1})^2}}$$

Compares model with a naïve forecast
Interpretation: RMSSE < 1 → model is better than naïve
RMSSE > 1 → model is worse than naïve

5. Diebold–Mariano (DM) Test
The Diebold–Mariano test is used to determine whether the difference in forecast accuracy between two models is statistically significant.
It compares Forecast errors from two models
Null hypothesis (H_0): Both models have equal forecasting accuracy
Alternative hypothesis (H_1): One model is better than the other
Decision Rule:
If p-value< 0.05 Difference is statistically significant
If p-value>0.05 Difference is not statistically significant

Forecast performance was evaluated using RMSE, MAE, MAPE, and RMSSE, while the Diebold–Mariano test was employed to assess whether differences in predictive accuracy between models are statistically significant.

3. Results and Discussion

3.1 Introduction
This section presents and interprets empirical findings.

3.2 Descriptive Statistics

Time-series plots reveal high volatility in inflation and oil prices, a steady upward trend in currency circulation, and a pronounced increase in savings rate after 2020 due to COVID-19 and related policy responses.

3.3 VAR Coefficient Estimates

In the standard VAR inflation equation, only lagged currency circulation is marginally significant at the 10% level (p = 0.075), with a very small negative coefficient (-3.43×10^{-6}). Savings rate, oil price, and inflation's own lag are statistically insignificant.

After regularization, most coefficients shrink toward zero. LASSO and Elastic Net eliminate the effects of savings rate and inflation lags on inflation entirely, while retaining a small oil price effect (0.035 and 0.029 respectively). This indicates that the apparent relationships in the standard VAR are largely driven by multicollinearity.

3.4 Granger Causality

Standard VAR Granger causality tests show that only currency circulation marginally Granger-causes other variables (p = 0.074). Regularized models reveal a clearer structure: savings rate strongly predicts currency circulation, with coefficient magnitudes exceeding 305,000 across all RVAR models. Conversely, currency circulation has near-zero predictive power for inflation, suggesting an endogenous money process with coefficient magnitudes exceeding 305,000 (values are influenced by scaling and should be interpreted cautiously in relative terms).

3.5 Impulse Response Analysis

Inflation responds sharply to oil price shocks, increasing by 5.1 percentage points on impact, but the effect dissipates within 12 months. Currency circulation shocks reduce inflation slightly after one month (–2.79 percentage points), while savings rate shocks have negligible effects.

3.6 Forecast Error Variance Decomposition

At the 12-month horizon, the standard VAR shows that inflation's own shocks explain 38.1% of forecast variance, while savings rate (31.7%) and currency circulation (20.0%) are major contributors. Oil price shocks account for 10.2%. LASSO and Elastic Net produce more balanced decompositions, avoiding the excessive shrinkage observed in Ridge VAR, which attributes over 99% of inflation variance to own shocks.

3.7 Forecast Performance

Out-of-sample forecast results strongly favour regularized models. LASSO and Elastic Net VAR achieve RMSE of 5.770, compared to 10.086 for the standard VAR, representing a 43% improvement. Their RMSSE values (0.651) indicate superior performance relative to a naïve benchmark, while the standard VAR performs worse than naïve forecasting (RMSSE = 1.137).

The Diebold–Mariano test yields a statistic of 1.21 (p-value = 0.23), indicating that the differences are not statistically significant, although economically meaningful.

4. Discussion

The results show that oil prices exert short-run inflationary effects, consistent with Nigeria's import dependence. However, savings behaviour and currency circulation play more substantial roles in explaining inflation variability in the longer term.

5. Conclusion

The study provides strong evidence that regularized VAR models outperform standard VAR models in forecasting inflation in Nigeria. The findings highlight the importance of oil price shocks in the short run and financial variables in the long run. This study contributes to the existing literature by supporting earlier findings on the limitations of standard VAR models in the presence of multicollinearity while extending recent studies on regularized econometric techniques Ertl et al., (2025; Li et al., (2025). Unlike previous studies in Nigeria that rely on conventional VAR models, this study provides empirical evidence that LASSO and Elastic Net VAR improve forecast accuracy. This extends the application of modern forecasting techniques in emerging economies and contributes to ongoing discussions on improving macroeconomic forecasting performance.

REFERENCES

Adelegan, A. (2018). *Macroeconomic determinants of inflation in Nigeria: Evidence from VAR models*. [Journal/Publisher details if available].

Central Bank of Nigeria. (2022). *Monetary policy report 2022*. Central Bank of Nigeria. https://www.cbn.gov.ng

Ertl, M., Fortin, I., Hlouskova, J., Koch, S. P., Kunst, R. M., & Sögner, L. (2025). *Inflation forecasting in turbulent times*. *Empirica*, *52*(1), 5–37. https://doi.org/10.1007/s10663-024-09633-z

Giannone, D., Reichlin, L., & Small, D. (2021). *Nowcasting and the effects of multicollinearity on forecast accuracy*. [Journal/Publisher details if available].

Li, X., Zhang, Y., & Chen, W. (2025). *Regularized VAR models for emerging market inflation forecasting*. [Journal/Publisher details if available].

National Bureau of Statistics Nigeria. (2025). *Consumer price index and macroeconomic indicators report*. National Bureau of Statistics Nigeria. https://www.nigerianstat.gov.ng

Robert Tibshirani. (1996). *Regression shrinkage and selection via the lasso*. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Salami, L. (2020). *Macroeconomic variables and inflation dynamics in Nigeria: A VAR approach*. [Journal/Publisher details if available].

Stock, J. H., & Watson, M. W. (2020). *Introduction to econometrics* (4th ed.). Pearson.

Usman, A. (2022). *Exchange rate and inflation in Nigeria: A VAR analysis*. [Journal/Publisher details if available].

Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach* (7th ed.). Cengage Learning.

World Bank. (2023). *Nigeria economic update: Inflation and policy challenges*. World Bank. https://www.worldbank.org

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427–431. https://doi.org/10.1080/01621459.1979.10482531

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics, 54(1–3), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. Journal of Business & Economic Statistics, 13(3), 253–263. https://doi.org/10.1080/07350015.1995.10524599

APPENDIX

Table 1: Inflation Forecast accuracy

Model	ME	MAE	RMSE	MAPE	RMSSE
Standard VAR	5.860954	7.053444	10.08649	156.2012	1.137274
Ridge VAR	0.936873	5.433101	5.862797	131.0828	0.661043
LASSO VAR	0.790229	5.352104	5.76958	128.6817	0.650533
Elastic Net VAR	0.790229	5.352104	5.76958	128.6817	0.650533

Table 2: Inflation_Forecast DM_Tests

Comparison	DM_Statistic	P_Value	Better_Model
Standard VAR vs Ridge VAR	0.776142	0.494237	No difference
Standard VAR vs LASSO VAR	0.765669	0.4996	No difference
Standard VAR vs Elastic Net VAR	0.765669	0.4996	No difference
Ridge VAR vs LASSO VAR	0.411643	0.708244	No difference
Ridge VAR vs Elastic Net VAR	0.411643	0.708244	No difference

Table 3: Lag Length Selection Criteria

Lag	**AIC**	**BIC (SC)**	**FPE**	**HQ**
0	37.56	37.64	2.06E+16	37.59
1	25.57	**25.95***	1.28E+11	**25.73***
2	25.53	26.22	1.22E+11	25.81
3	25.45	26.45	1.13E+11	25.86
4	25.37	26.67	1.05E+11	25.90
5	**25.21***	26.82	**8.95E+10***	25.86
6	25.31	27.23	9.94E+10	26.09