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Markov Switching VAR-Artificial Neural Network Hybrid Model for Studying Monetary Aggregates in Nigeria

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Abstract. This study examines changes in behaviour and structure of Nigeria's monetary aggregates: Broad Money Supply (M2), Narrow Money Supply (M1), Quasi Money (QM), and Bank Reserves (BR) using a combined analytical approach integrating Markov Switching Vector Autoregressive (MS-VAR) models Markov Switching-Mean (MS-MEAN), Time-Varying Transition Probability Markov Switching (TVTP-MS), and Markov Switching with Exogenous Variables (MSX-VAR) with Artificial Neural Networks (ANN). Monthly data from 1997 to 2025 was sourced from the Central Bank of Nigeria Statistical Bulletin. Results indicate monetary aggregates display distinct regime-dependent behaviours marked by low and high volatility states with lasting periods. MS-Mean models show low-volatility environments correlate with extended stability, while high-volatility conditions reveal substantial variations. TVTP-MS models emphasise evolving transition characteristics, and MSX-VAR captures asymmetric volatility transmission among monetary aggregates. Hybrid MS-ANN models demonstrate minor nonlinear influences, enhancing comprehension of leftover interactions but yielding improvements in predictive performance compared to standard Markov Switching models. Results highlight liquidity cycles are significantly sensitive to different regimes, indicating monetary authorities should implement flexible and regime-conscious methods to manage Nigeria's financial landscape effectively.

Keywords: Monetary Aggregates, Neural Networks, VAR with Markov Switching, Forecasting based on Regimes

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1. Introduction

Monetary aggregates are vital for macroeconomic stability and monetary policy, especially in developing economies like Nigeria, where financial systems are dynamic. Key metrics Broad Money Supply (M2), Narrow Money Supply (M1),

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Quasi Money (QM), and Bank Reserves (BR) are essential tools for central banks to manage liquidity, control inflation, and foster growth (Alemho and Adenomon, 2022). In Nigeria, these aggregates exhibit structural changes and external shocks, making traditional linear models inadequate (Adejumo et al., 2020).

Regime-switching models, particularly Markov Switching Vector Autoregression (MS-VAR), address these challenges by identifying distinct regimes and capturing dynamic interconnections among monetary variables. MS-VAR allows parameters to shift across regimes, providing insights into varying monetary transmission mechanisms (Aneessa et al., 2023). However, MS-VAR still struggles with complex nonlinearities and residual dependencies (Deebom, 2025).

Artificial Neural Networks (ANN) complement this by modeling intricate nonlinear patterns without strict distributional assumptions, using adaptive learning to capture hidden dependencies. The hybrid MSVAR-ANN model integrates regime-switching strengths with ANN's nonlinear mapping to model residual complexities within each regime. This approach enhances forecasting accuracy and captures both abrupt structural changes and nonlinear interactions, improving risk assessment and policy analysis.

The MSVAR-ANN typically identifies regimes via MSVAR, then applies ANN to regime-specific patterns, or embeds ANN within the MSVAR framework. This hybrid aligns with the trend of combining statistical and machine learning techniques for complex data (Okoye et al., 2022). Empirical studies show monetary-macroeconomic relationships are nonlinear and regime-dependent, necessitating regime-responsive frameworks.

Yet conventional models, even MS-VAR, miss deeper nonlinearities (Deebom, 2025). ANN overcomes this, with regime-switching neural networks enhancing volatility and structural shift modeling. The MSVAR-ANN hybrid offers a robust analytical foundation for Nigeria, where monetary aggregates are shaped by policy changes, financial developments, and volatility, providing insights for policymaking.

While other hybrids like HAR-LSTM-GARCH and GARCH-ANN exist (Romdhane and Boubaker, 2026), they often face issues like asymmetric complexity, interpretability loss, sensitivity to QML assumptions, and computational intractability. The MSVAR-ANN explicitly models regime shifts via Markov switching and captures nonlinear dependencies within each regime via ANN, offering superior accuracy and adaptability for financial data with both regime changes and nonlinearities.

Despite these advances, research on hybrid Markov Switching-ANN models for Nigeria's monetary aggregates remains scarce, given the country's complex monetary landscape. This study contributes by combining MS-VAR and ANN to analyze M2, M1, QM, and BR, offering a deeper understanding of dynamic interactions, transmission mechanisms, and regime-specific behaviors.

2. Materials and Methods

This study employs secondary time series data from the Central Bank of Nigeria Statistical Bulletin ranging from 1997 to 2025. The MS-VAR framework is implemented using *Statsmodels* in Python, while ANN components are developed using *TensorFlow* and *Keras*.

2.1 *Markov Switching Vector Autoregressive (MS-VAR) Model*

The MS-VAR model extends conventional VAR by allowing parameters to vary across unobserved regimes governed by a Markov process (Hamilton, 2020):

$$\mathbf{Y}_t = \boldsymbol{\mu}_{S_t} + \sum_{i=1}^{p} \mathbf{A}_{i,S_t} \mathbf{Y}_{t-i} + \boldsymbol{\varepsilon}_{t,S_t} \tag{1}$$

where $\mathbf{Y}_t = [M1_t, M2_t, QM_t, BR_t]'$, $\boldsymbol{\mu}_{S_t}$ represents regime-dependent intercept vectors, $\mathbf{A}_{i,S_t}$ denotes regime-dependent autoregressive coefficient matrices, p is optimal lag length, S_t denotes unobserved regime at time t, and $\boldsymbol{\varepsilon}_{t,S_t} \sim N(0, \Sigma_{S_t})$. Regime transitions follow a first-order Markov process with $P_{ij} = P(S_t = j \mid S_{t-1} = i)$.

2.2 *Markov Switching-Mean (MS-MEAN) Model*

The MS-Mean model allows only the intercept to switch across regimes while slope parameters remain constant:

$$Y_t = \mu_{S_t} + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t \tag{2}$$

where μ_{S_t} is the regime-dependent intercept, A_i are fixed autoregressive coefficient matrices, and $S_t \in \{1, 2, \ldots, K\}$ denotes the unobserved Markov state.

2.3 *Time-Varying Transition Probability MS (TVTP-MS) Model*

This model allows regime transitions to depend on observable macroeconomic indicators:

$$P(S_t = j \mid S_{t-1} = i, Z_t) = \frac{\exp(\gamma'_{ij} Z_t)}{\sum_{k=1}^{K} \exp(\gamma'_{ik} Z_t)} \tag{3}$$

where Z_t is a vector of explanatory variables influencing regime shifts, and γ_{ij} are parameter vectors governing transition dynamics.

2.4 *MSX-VAR Model*

The MSX-VAR model incorporates exogenous variables X_t into the switching structure:

$$Y_t = c_{S_t} + \boldsymbol{\beta}'_{S_t} X_t + \varepsilon_t \tag{4}$$

where $S_t \in \{0, 1\}$ is the regime, c_{S_t} is regime-specific intercept, $\boldsymbol{\beta}_{S_t}$ are regime-dependent slope coefficients, and $\varepsilon_t \sim N(0, \sigma^2_{S_t})$.

2.5 *Artificial Neural Network Model*

A feedforward multilayer perception ANN is adopted:

$$\widehat{Y}_t = f\left(\sum_{j=1}^{H} w_j \, g\left(\sum_{i=1}^{n} v_{ij} X_{it} + b_j\right) + c\right) \tag{5}$$

where X_{it} denotes input variables, v_{ij} represents input-to-hidden layer weights, w_j represents hidden-to-output weights, b_j and c denote bias parameters, $g(\cdot)$ and $f(\cdot)$ denote activation functions, and H represents number of hidden neurons.

2.6 *Hybrid ANN-MS-VAR Model*

The hybrid modelling approach assumes MS-VAR captures linear regime-switching dynamics while ANN captures nonlinear residual patterns:

$$Y_t = \widehat{Y}_{MSVAR,t} + \widehat{e}_{ANN,t} \tag{6}$$

where $\widehat{Y}_{MSVAR,t}$ represents forecasts from the MS-VAR model, and $\widehat{e}_{ANN,t}$ represents nonlinear residual components predicted by ANN. MS-VAR residuals are computed as $e_t = Y_t - \widehat{Y}_{MSVAR,t}$, which serve as target outputs during ANN training.

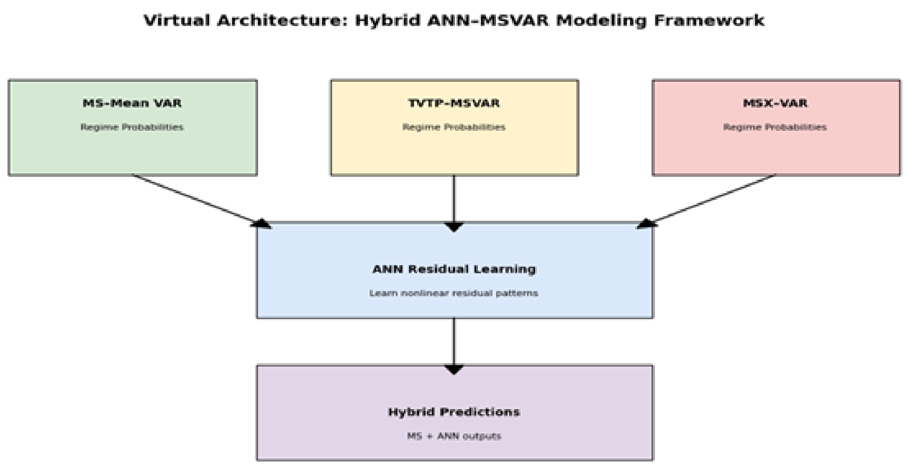

Figure 1: The structure of the hybrid model

2.7 *Estimation Techniques*

All variables are transformed into natural logarithmic form to stabilise variance. Stationarity tests are conducted using ADF procedures. MS-VAR is estimated using Maximum Likelihood Estimation. ANN is trained using MS-VAR residuals as target variables with lagged monetary aggregates as inputs. Forecast accuracy is evaluated using RMSE, MAE, MSE, and MAPE.

3. Results and Discussion

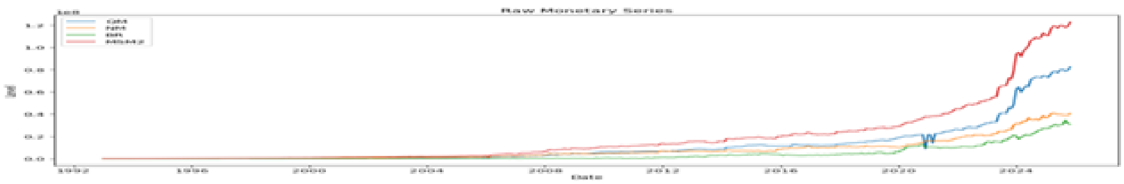

Figure 2: Time Plot for Raw Monetary Series

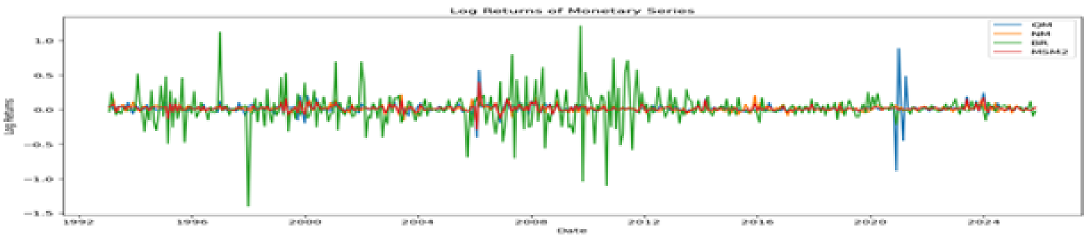

Figure 3: Time Plot for Returns on Monetary Aggregates

Figures 2 and 3 show time-series plots for raw levels and returns of Nigerian monetary aggregates. Raw data exhibit non-stationarity and time-varying variance, necessitating log-return transformation to stabilise variance. Transformed series reveal distinct volatility structures with persistent, high-amplitude fluctuations.

Table 1: Descriptive Statistics: Raw and Log Returns on Monetary Aggregates

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	JB p-value
Panel A: Raw Series						
QM	11,309	4,585,570	17,937	2.4968	5.9280	0.000
NM	7,468	4,569,664	9,528	1.9038	3.2489	0.000
BR	3,934	325,553	6,881	2.3929	5.4437	0.000
MSM2	18,832	9,166,835	27,386	2.2819	4.9261	0.000
Panel B: Log Returns						
LQM	0.0184	0.0136	0.0929	0.0568	46.7116	0.000
LNM	0.0160	0.0146	0.0525	0.4629	3.2773	0.000
LBR	0.0169	0.0078	0.2350	-0.2147	8.5869	0.000
LMSM2	0.0173	0.0121	0.0448	1.0870	18.1388	0.000

Table 1 shows raw monetary aggregates exhibit substantial mean-median divergence confirming asymmetric distributions. High standard deviations indicate significant data dispersion. Positive skewness and leptokurtic kurtosis reveal right-skewed, heavy-tailed distributions. Jarque-Bera test rejects normality for all level series. Log returns show positive mean returns reflecting continuous growth, with volatility dynamics shifting across series.

Table 2: ADF & PP Unit Root Test Results

Variable	**ADF (Level)**		**ADF (1st Diff)**		**PP (1st Diff)**	**Order**
	Stat	**p-value**	**Stat**	**p-value**	**Stat**	
QM	3.424	1.000	-3.2416	0.0177	-24.4691	I(1)
NM	3.577	1.000	-3.0358	0.0317	-22.9685	I(1)
BR	3.956	1.000	-2.9730	0.0375	-21.8554	I(1)
MSM2	1.968	0.999	-2.8162	0.0560	-19.8640	I(1)

Table 2 reveals all variables are non-stationary at levels but become stationary after first differencing, thus integrated of order one, I(1).

3.1 *MS-Mean Model Results*

Regime-Dependent Mean-Variance Parameter Vectors:

$$\boldsymbol{\theta}_0^{(MS-Mean)} = \begin{bmatrix} 0.0126 \\ 0.0005 \end{bmatrix}, \quad \boldsymbol{\theta}_1^{(MS-Mean)} = \begin{bmatrix} 0.0323 \\ 0.0064 \end{bmatrix} \tag{7}$$

Regime Transition Probability Matrix:

$$\mathbf{P}^{(MS-Mean)} = \begin{bmatrix} 0.9577 & 0.0423 \\ 0.1320 & 0.8680 \end{bmatrix} \tag{8}$$

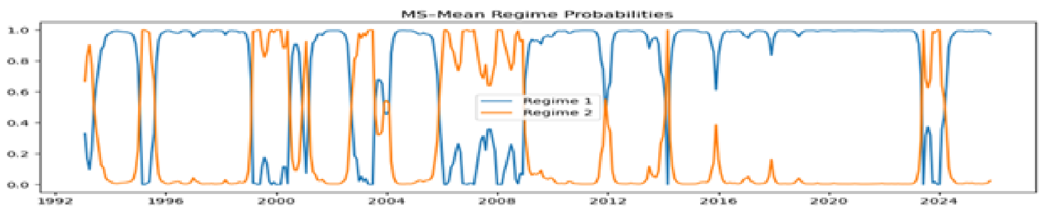

Figure 4: MS-Mean Regime Probabilities of the Log Returns on Monetary Aggregates

Figure 4 shows dual regime dynamics with Regime 0 (low-growth, low-volatility) and Regime 1 (high-growth, high-volatility). The transition probability matrix indicates high persistence in both states.

3.2 *TVTP-MS Model Results*

Regime-Dependent Mean-Variance Parameter Vectors:

$$\boldsymbol{\theta}_0^{(TVTP-MS)} = \begin{bmatrix} 0.0097 \\ 0.0003 \end{bmatrix}, \quad \boldsymbol{\theta}_1^{(TVTP-MS)} = \begin{bmatrix} 0.0264 \\ 0.0038 \end{bmatrix} \tag{9}$$

Time-Varying Transition Index (Logit Form):

$$\gamma = \begin{bmatrix} -1.9769 \\ -0.6013 \end{bmatrix} \tag{10}$$

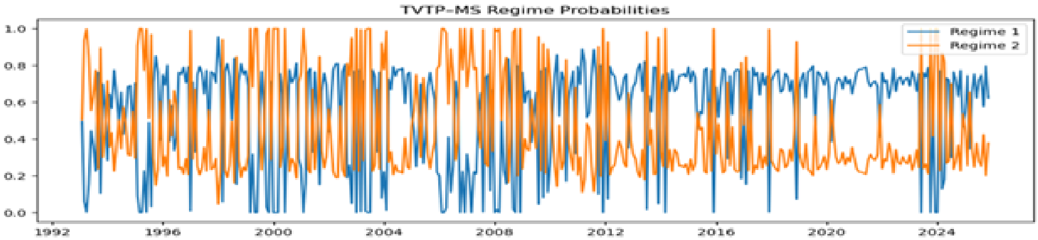

Figure 5: TVTP-MS Regime Probabilities of the Log Returns on Monetary Aggregates

Figure 5 shows Regime 0 captures a stable monetary phase with low conditional mean and compressed variance, while Regime 1 identifies a high-growth state with elevated mean and heightened variance.

3.3 *MSX-VAR Model Results*

Regime 0 (Low-state dynamics):

$$\boldsymbol{\beta}_0 = \begin{bmatrix} 0.0055 \\ -0.0100 \\ 0.1874 \\ -0.0396 \end{bmatrix}, \quad \sigma_0^2 = 7.97 \times 10^{-6} \tag{11}$$

Regime 1 (High-state dynamics):

$$\boldsymbol{\beta}_1 = \begin{bmatrix} 0.0006 \\ 0.4586 \\ 0.5198 \\ 0.0010 \end{bmatrix}, \quad \sigma_1^2 = 2.89 \times 10^{-5} \tag{12}$$

Regime Transition Probability Matrix:

$$\mathbf{P}^{(MSX-VAR)} = \begin{bmatrix} 0.7191 & 0.2809 \\ 0.0052 & 0.9948 \end{bmatrix} \tag{13}$$

Figure 6: MSX-VAR Regime Probabilities of the Log Returns on Monetary Aggregates

Figure 6 shows the MSX-VAR model clarifies evolving interactions between monetary aggregates by permitting variations in the autoregressive framework depending on regimes.

Table 3: Compact Comparative Matrix Summary

Model	Regime 0 Parameters	Regime 1 Parameters	Transition Matrix
MS-Mean	$(0.0126, 0.0005)$	$(0.0323, 0.0064)$	High persistence
TVTP-MS	$(0.0097, 0.0003)$	$(0.0264, 0.0038)$	Time-varying
MSX-VAR	β_0, σ_0^2	β_1, σ_1^2	Asymmetric

3.4 *Hybrid MS-ANN Results*

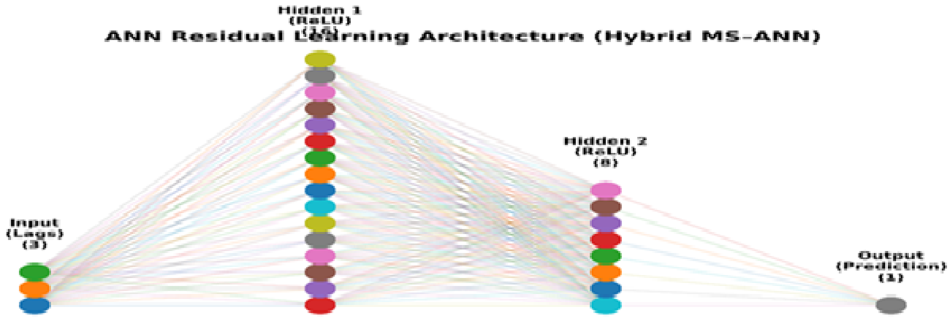

Figure 7: Virtual architecture of the Artificial Neural Network employed for residual learning of Markov Switching Mean GARCH model

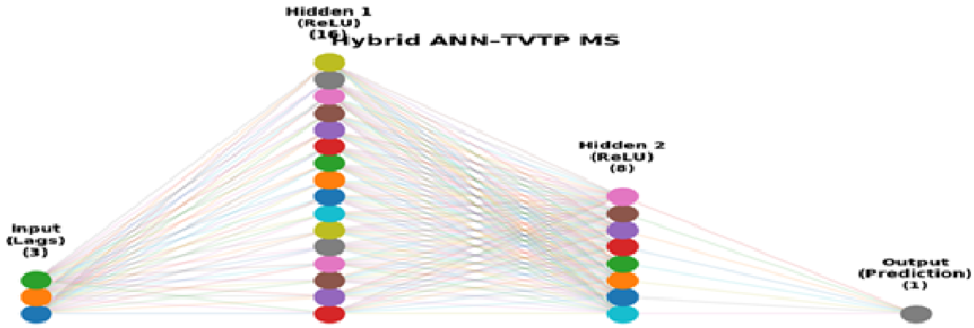

Figure 8: Virtual architecture of the Artificial Neural Network employed for residual learning of Time-Varying Transition Probability Markov Switching Mean GARCH model

Figure 9: Virtual architecture of the Artificial Neural Network employed for residual learning of MSX-VAR Model

The ANN architecture comprises three layers with weight configurations of (3, 16), (16, 8), and (8, 1), with ReLU activation functions in hidden layers.

Table 4: Regime-Dependent Parameters of Monetary Aggregates in Nigeria

Model	Regime	Mean (μ)	Variance (σ^2)	Transition Probability	Remarks
MS-Mean	0 (Low)	0.0126	0.0005	0.9577	Stable monetary phase
MS-Mean	1 (High)	0.0323	0.0064	0.8680	High volatility and growth
TVTP-MS	0 (Low)	0.010	0.0003	Dynamic	Time-varying persistence
TVTP-MS	1 (High)	0.0264	0.0038	Dynamic	High-volatility phases
MSX-VAR	0 (Low)	0.012	7.97×10^{-6}	0.7191	Weak feedback among aggregates
MSX-VAR	1 (High)	0.032	2.89×10^{-5}	0.9948	Strong interaction and volatility

Table 4 details regime-dependent parameters across models. MS-Mean indicates high regime persistence (0.9577 and 0.8680). TVTP-MS confirms time-varying transitions. MSX-VAR reveals low-state persistence of 0.7191 contrasted with high-state probability of 0.9948.

Table 5: Hybrid MS-ANN Architecture and Predictive Performance

Hybrid Model	Input Layer	Hidden Layers	Output Layer	Training Steps	Forecast Performance (MSE)
MS-Mean + ANN	3	$16 \to 8$	1	13/13	Slightly higher MSE vs pure MS, $p = 0.025754$
TVTP-MS + ANN	3	$16 \to 8$	1	13/13	Lower MSE, not statistically significant
MSX-VAR + ANN	3	$16 \to 8$	1	13/13	Lower MSE, not statistically significant

Table 5 shows MS-Mean+ANN exhibits higher MSE ($p = 0.025754$), suggesting less precise forecasts. TVTP-MS+ANN and MSX-VAR+ANN record lower MSE values but not statistically significant.

Table 6: Comparison of Pure Markov Switching (MS) and Hybrid Markov Switching (MS)-ANN

p-Value	Pure Model	Hybrid Model	Pure MSE	Hybrid MSE	t-Statistic
0 0.025754	MS Mean	ANN-MS Mean	0.001919	0.002035	-2.238476
1 0.214405	TVTP MS	ANN-TVTP MS	0.001891	0.001548	1.243570
2 0.112965	MSX VAR	ANN-MSX VAR	0.000028	0.000026	1.588581

Table 6 shows hybrid ANN-MS Mean demonstrates marginally higher MSE significant at 5% ($p = 0.025754$), suggesting nonlinear combination does not enhance forecast precision for this model. TVTP-MS and MSX-VAR hybrid versions yield lower forecast errors but not statistically significant.

3.5 *Discussion of Results*

The study reveals significant nonlinear, regime-dependent behaviour in Nigeria's monetary aggregates. The MS-Mean framework identifies a high-persistence, low-growth regime and a volatile, high-growth phase, corroborating structural market persistence documented by Adejumo et al. (2020) and kurfi et al. (2026). TVTP-MS establishes that macro-financial disturbances induce dynamic shifts where high volatility correlates with monetary growth Bildirici and

Ersin (2018), while low-volatility states align with policy-driven liquidity stability (Deebom, 2025).

MSX-VAR estimations reveal intensified endogenous interactions and significant lagged dependencies during high-volatility states, reflecting asymmetric, long-lasting macroeconomic turbulence observed historically by Wobo and Deebom (2022) and structural dynamics noted by Kurfi et al. (2026). Hybrid ANN-MS frameworks successfully isolate residual nonlinearities, providing marginal improvements in predictive accuracy that remain functionally contingent upon underlying model structure (Oloruntoba et al., 2020).

Collectively, these findings substantiate asymmetric, time-varying interactions within Nigeria's monetary system, reinforcing empirical consensus that linear models are insufficient and validating the necessity for adaptive, regime-sensitive monetary policies (Bildirici and Ersin, 2018; Adejumo et al., 2020; Oloruntoba et al., 2020; Wobo and Deebom, 2022; Kurfi et al., 2026).

4. Conclusion

The study presents compelling evidence that Nigeria's monetary aggregates (M2, M1, QM, BR) demonstrate significant regime-dependent behaviour and nonlinear relationships, where structural changes are essential in influencing liquidity behaviour and monetary policy transmission. MSX-VAR analysis indicates interactions among aggregates become significant during high volatility periods, suggesting disturbances in one aggregate can asymmetrically affect the entire system. ANN incorporation addresses leftover nonlinearities, uncovering intricate relationships that traditional econometric techniques might overlook. This hybrid model is a veritable tool decision-makers should embrace when faced with regime shifts, anticipated changes between stable and unstable scenarios, and nonlinear connections among monetary aggregates to improve policy efficiency, manage risks effectively, and sustain financial stability.

References

Adejumo, O. A., Albert, S. and Asemota, O. J. (2020). Markov Regime-Switching Autoregressive Model of Stock Market Returns in Nigeria. CBN Journal of Applied Statistics, 11(2): 65–83.

Adejumo, O. A., Asemota, O. J., and Olanrewaju, S. O. (2025). Novel neural network state switching models for returns predicting with regime switching: A Monte Carlo simulation approach. American Journal of Applied Statistics and Economics, 4(1): 94–107.

Alemho, J. E. and Adenomon, M. O. (2022). Forecasting Some Selected Macroeconomic Variables With BVAR Models under Natural Conjugate Prior. Benin Journal of Statistics, 5(1): 108—122.

Aneessa, F. J., Ruben, T. and Jason, N. (2023). High frequency volatility forecasting: A new approach using a hybrid ANN?MC?GARCH model. International Journal of Finance Economics, John Wiley & Sons, Ltd., 28(4): 4156-4175.

Bildirici, M. and Ersin, (2018). Markov-switching vector autoregressive neural networks and sensitivity analysis of environment, economic growth and petrol prices. Environmental Science and Pollution Research, doi:10.1007/s11356-018-3062-3.

Deebom, Z. D. (2025). AI-Driven Forecasting of Nigeria Daily Crude Oil Prices Using the Integrated ARLAS Framework: Hybrid Statistical–Machine–Deep Learning Model. AVE Trends in Intelligent Technoprise Letters, 2(3): 143–156.

Emmanuel, T., Kwache, A. J., Okolo, A., and Abdulganiy, G. A. (2025). Nonlinear Time Series Models with Regime Switching for Inflation Rate in Nigeria.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). Deep learning. MIT Press.

Hamilton, J. D. (2020). Regime switching models. In J. D. Hamilton (Ed.), Time series analysis. Princeton University Press.

Kurfi, A. J., Zarma, M. M. and Akanegbu, B. (2026). Regime-switching dynamics of exchange rate movements and stock market performance in Nigeria: A Markovswitching VAR approach.

Okoye, O. R., Tuaneh, G. L., Essi, I. D. and Deebom, Z. D. (2022). Empirical Analysis of Exchange Rate, Interest Rate and Nigerian Agricultural Export Price using VAR with Variance Decomposition Innovation. International Journal of Innovative Mathematics, Statistics Energy Policies 10(4): 20–46.

Oloruntoba, S. O., Augustine, U. and Aminu, A. M. (2020). A Neural Network Scheme for Monetary Policy Rate Validation in Nigeria. American Journal of Artificial Intelligence, 4(2): 62–72.

Romdhane, A. and Boubaker, H. (2026). HAR–LSTM–GARCH Hybrid model.

Wobo, O. G. and Deebom, Z. D. (2022). Detecting Financial Crisis in Nigerian Capital Markets Using Markov Switching Generalized Autoregressive Conditional Heteroscedasticity. IIARD International Journal of Banking And Finance Research, 2695–1886.

Zhang, Q., Aggarwal, C., and Qi, G. (2021). Stock price prediction via discovering multi-frequency trading patterns. Proceedings of the ACM SIGKDD Conference, 2141–2149.