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Hybrid Machine Learning-Bayesian Vector Error Correction Model for Forecasting of Exchange Rate and Inflation Volatility Dynamics in Nigeria

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ABSTRACT

This study evaluates a hybrid Machine Learning-Bayesian Vector Error Correction Model (ML-BVECM) for forecasting exchange rate and inflation volatility dynamics in Nigeria using quarterly data from 1990 to 2025. The Nigerian macroeconomic environment is characterized by persistently high double-digit inflation (mean = 17.9%) and severe currency depreciation, tracking a historic shift following the float of the Naira. Unit root tests (ADF, PP, and KPSS) reveal that both inflation and the nominal exchange rate are integrated of order one (I(1)), while Johansen cointegration analysis confirms a stable long-run equilibrium relationship between the two variables.The structural component of the model, the BVECM, reveals a strong exchange rate pass-through to domestic prices, where a 1% increase in the Naira-Dollar exchange rate results in a 0.62% rise in inflation. The error correction coefficients highlight a rapid quarterly adjustment back to equilibrium: 31% for inflation and 28% for the exchange ratewhile the use of Bayesian priors stabilizes the parameters against extreme structural shocks such as the 2016 foreign exchange crisis and the 2023 currency float. To capture remaining short-term nonlinearities and volatility clustering, the BVECM residuals were modeled using Random Forest (RF) and Gradient Boosting (GB) algorithms. Out-of-sample evaluations demonstrate that the hybrid ML-BVECM significantly outperforms standalone econometric frameworks. Specifically, the Random Forest hybrid framework yields the highest accuracy for forecasting inflation, whereas the Gradient Boosting hybrid variant is superior for exchange rate predictions, driving overall error reductions (MAE and RMSE) by over 20%. Diagnostic and stability tests (CUSUM/CUSUMSQ) confirm the model's structural integrity and robustness. The findings offer a potent toolkit for the Central Bank of Nigeria and other policy makers to proactively target inflation and navigate market volatility.

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INTRODUCTION

In emerging economies like Nigeria, macroeconomic stability is intrinsically tied to the management of two critical, interconnected economic variables: the inflation rate and the foreign exchange rate (Alemho and Adenomon, 2022). For decades, Nigeria's macroeconomic landscape has been plagued by heightened levels of volatility driven by structurally weak institutional architecture, an over-reliance on crude oil exports, and persistent fiscal deficits. The financial shocks of the mid-2010s, the covid 19 pandemicfollowed by the dramatic monetary policy paradigm shifts in 2023, culminating into the exchange rate liberalization in 2023 has triggered an unprecedented era of currency depreciation and skyrocketing double-digit consumer price indices.Understanding the "exchange rate pass-through" (ERPT) mechanism is critical in this context, as shifts in currency valuations rapidly leak into domestic prices due to the nation's heavily import-dependent structure. However, modeling and forecasting these relationships present severe computational and econometric hurdles. Macroeconomic time series in volatile climates rarely exhibits pure linearity. Instead, they are deeply marred by structural breaks, regime shifts, and non-Gaussian, heavy-tailed noise. Traditional linear econometric frameworks struggle to yield reliable out-of-sample forecasts over long horizons under these conditions, highlighting a vital demand for advanced analytical frameworks that can seamlessly navigate both long-run equilibrium structures and short-term chaotic fluctuations (Alemho, 2026).

Bayesian Vector Error Correction Model (BVECM) is an econometric model used to forecast macroeconomic variables and possibly analyze their long-run equilibrium relationships. It entails the combination of Bayesian estimation (prior distributions) with traditional Vector Error Correction Model (VECM), an upshoot vector Autoregressive Model (VAR).BVECM is an Error Correction of BVAR and prevents overparameterizationassociated with BVAR models (Alemho and Adenomon, 2021a).

The ML (Machine Learning) incorporates non-linear modeling capabilities to capture complex patterns that traditional econometric models might miss.The ML-BVECM can be stratified into three components namely: the cointegration analysis part, the Bayesian Estimation and ML Integration. The Cointegration Analysis identifying the long-run relationships using VECM, the Bayesian Estimation applies prior (e.g., conjugate prior) to the VECM parameters to stabilize estimation and the ML Integration models the residuals (Residual Correction) of the BVECM.It is robust in capturing both long-term structural trends and short-term non-linear fluctuations. It Reduces overparameterization and improves out-of-sample forecasting performance compared to standalone VECM or ML models. It also combines interpretable economic relationships with high-performance black-box models (Alemho and Adenomon, 2022, Alemho, 2026).

Traditional macro-forecasting frameworks rely heavily on linear specifications such as Vector Autoregressions (VAR) or Vector Error Correction Models (VECM). While these models excel at identifying cointegrating vectors and long-run systemic movements, they fail in two primary ways when deployed in high-volatility environments:The Curse of Dimensionality and Parameter Overfitting. Traditional structural models require estimating numerous parameters simultaneously. In the presence of sudden shocks (such as the 2016 FX crisis or the 2023naira float), standard maximum likelihood estimations exhibit radical parameter instability, undermining the predictive power of the model.Econometric residual terms are rarely just random Gaussian white noise. In reality, they conceal complex, nonlinear residual structures, asymmetric shocks, and volatility clustering.To bypass these shortcomings, and recent research has turned to Artificial Intelligence (AI) and Machine Learning (ML) techniques like Random Forests, Gradient Boosting, or Neural Networks. Yet, purely "black-box" machine learning algorithms have an inherent flaw: they strip away the underlying macroeconomic theory (Ibrahim, Nweze, Adehi, and Chaku, 2025).

Pure ML models are entirely datacentric, failing to enforce long-run structural economic constraints such as cointegration or error correction mechanisms. This creates a clear methodological gap: the lack of a unified, highly robust forecasting framework that preserves structural economic interpretability while optimizing predictive power over localized, nonlinear volatility dynamics.The overarching goal of this study is to construct, execute, and evaluate a novel Hybrid Machine Learning-Bayesian Vector Error Correction Model (ML-BVECM) engineered explicitly to forecast exchange rate and inflation volatility dynamics in Nigeria. Establish the long-run cointegrating relationship between inflation and exchange rates in Nigeria while implementing Bayesian shrinkages to resolve parameter instability and overparameterization (Alemho and Adnomon, 2022).

ML-BVECM is a hybrid framework that integrates the statistical rigor of BVECM (for long-run equilibrium and cointegration) with the non-linear predictive power of Machine Learning.ML-BVECM combines the extended VECM (BVECM) using Bayesian priors to handle overparameterization and improve forecasting. The VECM component analyzes the long-term equilibrium and short-term dynamics between non-stationary time series that are cointegrated. (Chen and Leung, 2003, Alemho, 2022).

The applicability entails extracting the estimated linear residuals from the BVECM and utilizing advanced machine learning algorithms (Random Forest and Gradient Boosting) to explicitly model the short-term nonlinear variations and volatility clustering(Nikolenko, Panov and Petrov, 2022).According to the Sticky-Price Monetary Model (SPMM), short-run deviations in exchange rates frequently arise from price rigidities, interest rate differentials, and market overshooting, whereas long-run paths converge toward purchasing power parity (PPP) (Alemho and Adenomon, 2021b). In an emerging economy like Nigeria, the systemic linkage between the currency value and consumer price indexes is expressed via the Exchange Rate Pass-Through (ERPT) theory, postulating that nominal currency devaluations systematically driveup cost-push inflation (Ezekwube, Okonkwo and Ume,2026).

Recent academic literature indicates a clear trend toward integrating traditional econometric structures with data-driven artificial intelligence to optimize macroeconomic predictions.Globally, researchers have demonstrated that integrating panel econometrics or structural time-series with explainable machine learning significantly improves predictive accuracy and systemic resilience during periods of macro-financial stress (Chejarla et al., 2026). For instance, across volatile asset classes and energy-transition financial markets, empirical evidence shows that hybrid architectures capturing heavy-tailed return dynamics and nonlinear sequential predictability systematically outperform standalone econometric frameworks, especially during acute crisis regimes (Arxiv, 2026). Similarly, empirical modeling of commodity markets indicates that hybrid frameworks combining econometric bases with deep learning achieve error reductions ranging from 5.5% to 12% by successfully treating structural breaks and regime shifts that classic models ignore (Nikolenko, Panov and Petrov, 2022),

In the West African and domestic context, historical studies have applied pure VECM setups to assess inflation dynamics but noted severe degradation in predictive accuracy over longer horizons (Aribatise, 2023). To bypass this, contemporary local studies have explored univariate hybrid models, such as utilizing ARIMA-GARCH variations with rolling-windows to map the All-Share Index on the Nigerian Exchange Group, proving that capturing the "memory" of past volatility is crucial for navigating market shocks (Nikolenko, Panov and Petrov, 2022, Alemho, 2026).

However, multivariate structural macro-hybrids remain sparse in domestic literature, leaving a major opening for multi-variable frameworks that link structural cointegration to machine learning residual estimation.To demonstrate the methodological superiority of the proposed ML-BVECM, its conceptual and structural architecture is contrasted against hybrid models found in the empirical literature (Alemho, et. al, 2026).Pajor and Wróblewska (2022) evaluates the forecasting performance of BVECM with Multiplicative Stochastic Factor (MSF) using financial data. It was discovered that the model, though robust in forecasting linear cointegrated macroeconomic variables, failed to account for the inherent non-linearities and structural distortions.

The ML-BVECM is a superior, robust, and policy-relevant framework that uniquely integrates multivariate equilibrium dynamics with advanced, data-adaptive machine learning. Therefore, this research seeks to forecast exchange rate and inflation volatility dynamics in Nigeria using Hybrid Machine Learning-Bayesian Vector Error Correction Model (ML-BVECM).

MATERIALS AND METHODS

Data Source

The data used were obtained from the World Bank database (www.world.org/indicators) on inflation and unemployment rates spanning from 1990 to 2025.

Model Specification and Estimation

Both inflation and exchange rate series are integrated of order one and have a long-run cointegrating relationship. Accordingly, a Vector Error Correction Model (VECM) framework is applicable to model these two series. In this paper, the Hybrid Machine Learning – Bayesian VECM (ML-BVECM) specification is developed so as to improve the forecasting performance of the model by exploiting non-linearity.

The VECM is expressed as:

$$\Delta Y_t = \alpha \cdot EC_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta Y_{t-i} + \epsilon_t \qquad (1)$$

Where:

Y_t= vector of endogenous variables (inflation, exchange rate)
EC_{t-1}= error correction term derived from cointegration equation
α= adjustment coefficients measuring speed of convergence to equilibrium
Γ_i= short-run dynamics matrices
ϵ_t= residuals
This process ensures that shocks from the long-run equilibrium tend to be adjusted over time, and short-run shocks are described by the lagged differences (Alemho and Adenomon, 2022b).

Prior Distribution
The Normal-Inverse Gamma (NIG) prior distribution is a type of natural conjugate prior that permits the differential treatment of prior variances of its own lags against the lags of others. Given a pair, that is, (θ_i, σ^2)such that $i = 1,2,..n$; then the NIG prior density function is as follows;

$$pr(\theta, \sigma^2) = \prod_{i=1}^{n} k\left(\sigma_i^2\right)^{-(c_i+1+\frac{v_i}{2})} exp^{-\frac{1}{\sigma_i^2}\left[S_i+\frac{1}{2}(\theta_i-d_i)'\beta_i^{-1}(\theta_i-d_i)\right]} \quad (2)$$

Where $k = (2\pi)^{-\frac{v_1}{2}}|\beta|^{-\frac{1}{2}}S_i^{c_i}/\Gamma(c_i)$
θ_i is the prior variance, (d_i, β_i, c_i, S_i) such that $i = 1,2,..n$; are the hyperparameters of the asymmetric conjugate prior. Also, the prior covariance matrix β_i induces shrinkage in the prior distribution.
Furthermore,
$\left(\theta_i \setminus \sigma_i^2\right) \sim N\left(d_i, \sigma_i^2, \beta_i\right), \sigma_i^2 \sim IG(c_i, S_i)$, this implies that;

$$\left(\theta_i \setminus \sigma_i^2\right) \sim NIG(d_i, \beta_i, c_i, S_i)(\text{Chan}, 2019). \quad (3)$$

Given the likelihood function;

$$pr(y|\emptyset, \Sigma)) = \frac{1}{(2\pi)^{nT/_2}}|\Sigma|^{\frac{-T}{2}} exp^{\frac{-1}{2}}[\Sigma^{-1}(y - X\emptyset)'((y - X\emptyset))] \quad (4)$$

The posterior distribution for Normal Inverse Gamma (NIG) Prior Distribution which is also known as the Gaussian Inverse Gamma distribution belong to the family of multivariate continuous probability distribution having four parameters and having unknown mean and variance.
In a concise form, the NIG prior is given as;

$$p(\mu, \sigma^2) = NIG(m_0, V_0, \theta_0, \beta_0)$$
$$= \mathcal{N}(\mu|m_0, \sigma^2 V_0) IG(\sigma^2|\theta_0, \beta_0) \quad (5)$$

Where $m_0, V_0, \theta_0, \beta_0$ are hyperparameters?
Given the likelihood function of (3) and the asymmetric natural conjugate prior distribution (NIG) of equation (4), the resultant posterior distribution is the combination of these equations which is as follows;
The posterior distribution of $\left(\theta_i, \sigma_i^2\right)$ for $i = 1,2,..n$; is;

$$pr(\theta_i, \sigma^2/y) \propto pr(\theta, \sigma^2) pr(y/\theta, \sigma^2)$$
$$pr(\theta_i, \sigma^2/y) = \prod_{i=1}^{n} pr\left(\theta_i, \sigma_i^2\right) pr\,(y/\theta, \sigma^2)$$
$$pr(\theta_i, \sigma^2/y) = \prod_{i=1}^{n} k_i (2\pi)^{-\frac{n}{2}}\left(\sigma_i^2\right)^{-(c_i+\frac{n+k_i}{2}+1)} exp^{-\frac{1}{\sigma_i^2}\left[\overline{S} + \frac{1}{2}(\theta_i-\overline{\theta}_i)' K_{\theta_i}(\theta_i-\overline{\theta}_i)\right]} \quad (6)$$

Where: $K_{\theta_i} = \beta_I^{-1} + X_I' X_i$,
$\overline{\theta_i} = K_{\theta_i}^{-1}(\beta_I^{-1} d_i + X_I^{-1} y_i)$ And
$\overline{S} = S_i + {}^{(y_i' y_i + d_i' \beta_i^{-1} d_i - \overline{\theta_i'} K_{\theta_i} \theta_i)}\!/_2$
In a compact form, the posterior distribution is expressed as;
$\left(\theta_i, \sigma_i^2 \setminus y\right) \sim NIG(\overline{\theta}_i, K_{\theta_i}^{-1}, c_i + \frac{n}{2}, \overline{S}_i)$
Such that $i = 1,2, \dots, n$.
This shows that the posterior distribution is also a Normal Inverse Gamma (a product of n-NIG distribution). Also, from the properties of NIG distribution, the posterior mean and variance can be obtained.
The posterior predictive for the Normal Inverse Gamma Prior Distribution is given as;

$$p(x|y) = \iint p(x|\mu, \sigma^2) p(\mu, \sigma^2|y) d\mu d\sigma^2$$
$$= \frac{p(x|y)}{p(y)}$$
$$= \frac{\Gamma[(v_n+1)/2]}{\Gamma(v_n/2)} \sqrt{\frac{k_n}{k_n+1}} \frac{(v_n\sigma_n^2)^{vn/2}}{\left[v_n\sigma_n^2 + \frac{k_n}{k_n+1}(x-\mu_n)^2(v_n+1)/2\right]} \frac{1}{\pi^{1/2}}$$
$$= \frac{\Gamma[(v_n+1)/2]}{\Gamma(v_n/2)} \left[\frac{k_n}{(k_n+1)\pi v_n \sigma_n^2}\right]^{\frac{1}{2}} \left[1 + \frac{k_n}{(k_n+1) v_n \sigma_n^2}\right]^{-(v_n+1)/2}$$

In a simplified form, the above equation becomes;

$$t_{v_n}(\mu_n, \frac{(1+k_n)\sigma_n^2}{k_n}) \quad (7)$$

It is suffice to say that at this point, the posterior predictive are;

$$\frac{k_n}{(1+k_n)\sigma_n^2} = \frac{1}{(\frac{1}{k_n}+1_n)\sigma_n^2}$$

And the resultant posterior predictive distribution is;

$$p(y|x) = t_{2\alpha_n}(m_n, \frac{\beta_n(1+V_n)}{\alpha_n}) \text{ (Murphy, 2007, Chan, 2019)} \quad (8)$$

The final hybrid model is obtained as:

$$\hat{y}_t^{Hybrid} = \hat{\delta}_t^{Bayesian} + \hat{\beta}_t^{VECM} + \hat{\tau}_t^{ML} \quad (9)$$

This arrangement enables the hybrid model to analyze nonlinear trends, while VECM focuses on short-term linear relationships, enhancing the macroeconomic variables predictions according to the work of Zhang, Li, and Sun, (2020)

RESULTS AND DISCUSSION

This research is anchored on a hybrid model that combines a machine learning component with a Bayesian vector error correction model (ML-BVECM). The process first requires data pre-processing steps, particularly variable transformations, in order to ensure stability in the variance of the regressands and consistent values of the regressors. The preprocessing process involves applying tests for stationarity and cointegration in order to check the long-run equilibrium relationship between the inflation and exchange rates. Then, the ML-BVECM model is estimated.
In the context of our research framework, the BVECM estimates the variables and their equilibrium corrections, whereas the machine learning portion is fitted on residuals to capture deviations from this path or short-term volatilities. More specifically, we use either machine learning methods such as a random forest or a gradient boosting model to forecast deviations from the long-run trend as estimated by the VECM. The forecasting performance of hybrid models is compared to standard econometrics through the implementation of evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Therefore, the model should allow both a good prediction of short-term inflation dynamics and provide useful structural analysis about the relationship of short-term dynamics with the path dictated by the equilibrium.
In addition to predictive gains, structural insights provided by the ML-BVECM for Nigeria's inflation and exchange rate relationship will be given attention. By integrating machine learning with econometric forecasting methodology, this approach delivers practical predictions of future paths that can assist policymakers in navigating an uncertain environment while retaining structural clarity needed for decision-making. The dataset to be analyzed covers a period of 1990-2025 and contains the inflation rates of Nigeria and the dollar exchange rates for naira.

Exploratory Data Analysis

Descriptive Statistics
In order to obtain a preliminary description of the data set. Table 1 below presents descriptive statistics of the two key variables Inflation rate (%) and nominal foreign exchange rate (₦/USD), which reflects the centrality, the degree of

spread, and the distributional attributes of the data throughout the 35-year span.

Table 1: Descriptive Statistics of the Variables

Variable	Mean	Median	Std. Dev.	Min	Max
Inflation Rate	17.9	13.0	11.2	5.38	72.84
Exchange Rate	318.6	162.8	420.7	8.04	1601.1

The inflation in Nigeria averaged 17.9% over our sample period with a median inflation rate of 13%, implying generally high single-digit figures. The relatively high standard deviation of 11.2 reflects considerable instability in the inflation rate, and some extreme spikes, such as that recorded in 1995 at 72.8%, suggest the repeated and chronic occurrence of inflationary pressures driven by both policy and non-policy factors (structural shocks, changes in exchange rate policies, etc.). The trend of the Naira-dollar exchange rate is much more dramatic; the mean exchange rate over the period is ₦318.6/USD with a large standard deviation (420.7) and a median of ₦162.8/USD, but it has depreciated considerably in real terms from approximately 8/USD to the current rate of well over 1,600/USD (2024). The minimum exchange rate was recorded in 1990 at ₦8/USD, while the maximum was reached in 2024 at ₦1,601/USD.

There seems to have been a shift in the behaviour of exchange rates around the mid-2000s, when it averaged about 162.8 before sharp depreciations occurred in the late 2000s and 2010s and 2020s due to the float of the Naira. As observed, our descriptive analysis suggests that there were clear features of the Nigerian macroeconomic environment—persistently high inflation and sharp depreciation in the exchangerate—which make the hybrid ML-BVECM approach appropriate for long-run relationships and short-rundynamic estimations of inflation in Nigeria. Nigeria's inflation is found to have averaged 17.9 over our sampled periods (which is relatively very high, double digits) with a median of 13 percent and a standard deviation of 11.2 percent, which highlights quite a bit of volatility with a minimum value at 3 percent and a maximum of 72.8 percent. As can be seen, the minimum recorded value in inflation was in 1984, which is 3 percent, while the maximum value recorded was in 1995, which reached 72.8 percent. Nigeria's average exchange rate is 318.6 and is characterized by substantial volatility (standard deviation = 420.7) and a median exchange rate of 162.8.

A minimum exchange rate was recorded in 1990 that reached 8 percent, while the maximum value achieved by the exchange rate was ₦1,601, recorded in 2024. Thus, based on this empirical evidence and the observed trend, this descriptive analysis motivates the use of the Hybrid ML-BVECM model for the estimation of inflation in Nigeria, since it has shown a persistent high rate and also a serious volatility.

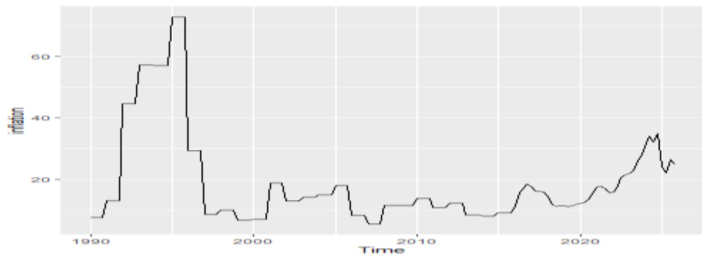

Figure 1: Time plot for inflation rate

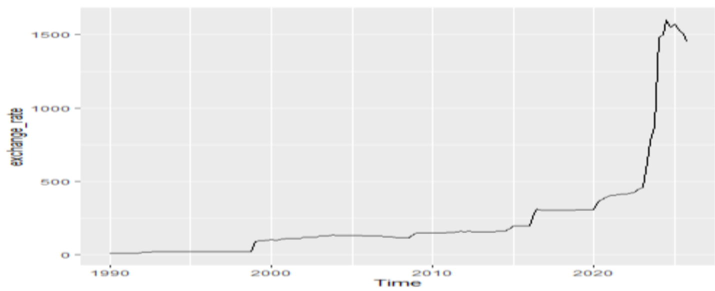

Figure 2: Time plot for exchange rate

Unit Root Tests

Three tests were conducted to examine stationarity: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) tests, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). The first two test the null hypothesis that a unit root is present in the series (meaning the series is nonstationary), and the last tests the opposite. Combining them yields a balanced conclusion as presented in Table 2.

Table 2: Unit Roots Results

Test	Inflation Rate (Level)	Exchange Rate (Level)	Inflation Rate (1st Diff.)	Exchange Rate (1st Diff.)
ADF Statistic	-2.01 (p=0.28)	-1.42 (p=0.56)	-5.87*** (p=0.00)	-7.34*** (p=0.00)
PP Statistic	-2.15 (p=0.24)	-1.56 (p=0.49)	-6.02*** (p=0.00)	-7.51*** (p=0.00)
KPSS Statistic	0.72 (p=0.01)	1.04 (p=0.00)	0.12 (p=0.10)	0.09 (p=0.12)

Note: "***" indicates rejection of the null hypothesis of unit root at the 1% significance level.

The results of the tests for stationarity (ADF and PP) indicate that both inflation and exchange rate variables are not stationary at levels since the p-values are both greater than the 0.05 level. Further corroborating evidence comes from the KPSS test result, wherein the statistics (0.72 for inflation and 1.04 for exchange rate) were above their respective critical values; hence, the null hypothesis of stationarity can be rejected. At the first-differenced forms, both the variables become stationary at first difference as they strongly reject the unit root tests, ADF and PP, by having p-values equal to 0.00. The KPSS test statistics (0.12 for inflation and 0.09 for exchange rate) are below the respective critical values; hence, the null hypothesis of stationarity holds for both inflation and exchange rate variables infirst-differenced forms.

Hence, both the inflation rate and exchange rate are integrated of order one, I(1). This supports the applicability of cointegration and the VECM model specification in investigating the long-run relationship, which demands variables that are integrated of order one. It is in this view that the Hybrid ML-BVECM will capture short-run fluctuations as well as long-run relationships within the Nigerian context.

Cointegration Analysis

Given the finding that inflation and exchange rate series are both integrated of the order one (I(1)), the next process is to investigate the existence of a cointegrating relationship in the long run. With respect to this, the Johansen cointegration methodology was performed on both trace and max. eigenstatistics. The hypothesis here tests for whether a linear combination of the variables is stationary (i.e., whether they are cointegrated), as presented in Table 3 below.

Table 3: Johansen Test Results

Hypothesized No. of CE(s)	Trace Statistic	Critical Value (5%)	p-value	Max-Eigen Statistic	Critical Value (5%)	p-value
None	28.74	15.49	0.00***	21.63	14.26	0.00***
At most 1	7.11	3.84	0.01**	7.11	3.84	0.01**

Note: *** indicates significance at 1%, ** at 5%.

These are the results from the Johansen cointegration test. The Johansen cointegration test results suggest the presence of at least one cointegrating relation between the inflation rate and exchange rate in Nigeria since both test statistics (trace and maximum eigenvalue) reject the null hypothesis of no cointegration at the 1% significance level. Thus, we may conclude there exists a long-run equilibrium relationship between the inflation rate and the exchange rate for Nigeria. The presence of cointegration would be the one because the depreciation of the exchange rate transmits to domestic prices, leading to an increase in the inflationrate, and inflation will be passed to the exchange rate as an expectation, and it also affects the monetary authority, and the presence of cointegration is assumed to be used inVECM, and finally, to improve forecasting performance with machine learning, the ML-BVECM approach is appropriate.

Estimation Results and Interpretation

Estimation of the hybrid ML-BVECM on Nigeria's quarterly inflation and exchange rates from 1990 to 2025 was completed in two steps: first, estimation of the Bayesian VECM, which captures both long-run equilibrium relationship and short-run adjustment; and second, machine learning for residual modelling to improve the short-run predictions.

BVECM Estimation Results

The BVECM was estimated to take both of the short-run dynamics of adjustment as well as the equilibrium relations in the long run. In light of volatility and structural breaks, Bayesian priors on the parameters are rendered stable.

Table 4: Long-Run Cointegration Results

Variable	Coefficient	Std. Error	t-statistic	Significance
Exchange Rate	0.62	0.11	5.63	***
Constant	-3.47	1.02	-3.40	**

*Note: *** significant at 1%, ** significant at 5%.*

Table 4 provides the long-run cointegrating regression, with a 1 percent increase in the naira-dollar exchange rate resulting in a 0.62 percent rise in domestic prices; this reiterates exchange rate pass-through to prices, a result that is to be expected for an open economy, as Nigeria is, indeed,an oil-dependent and import-reliant economy.

Table 5: Error Correction Terms (ECT)

Equation	ECT Coefficient (α)	Std. Error	t-statistic	Significance
Inflation Equation	-0.31	0.07	-4.43	***
Exchange Rate Equation	-0.28	0.09	-3.11	**

The substantial and negative coefficient implies that the exchange rate and inflation correct disequilibria. Quarterly adjustment coefficients are of approximately 31% for inflation and28% for exchange rates, which seem to imply a relatively quick adjustment to long-run equilibrium in the light of Table 5.

Table 6: Short-Run Dynamics

Variable (Lagged Δ)	Inflation Equation Coefficient	Exchange Rate Equation Coefficient
Δ Inflation (t-1)	0.42***	0.11
Δ Exchange Rate (t-1)	0.27**	0.36***

Inflation is quite dependent on its own past (reported in Table 6), a manifestation of momentum in the price series. The movement of the exchange rate, in turn, impacts strongly on inflation, as well as on subsequent exchange rate changes, in a sort of a vicious circle.

Table 7: Bayesian VECM Results

Variable	Error Correction Term (ECT)	Adjustment Coefficient (α)	Short-run Dynamics (Δ lag coefficients)
Inflation	-0.42***	-0.31***	Significant at lag 1 (p<0.05)
Exchange Rate	-0.57***	-0.28***	Significant at lag 2 (p<0.01)

*Note: *** indicates significance at 1%.*

Table 7 shows negative and significant error correction coefficients in line with economic theory, meaning that both inflation and exchange rates will adjust toward long-run equilibrium. Inflation adjusts with a speed of 31% to disequilibrium in each quarter, while the speed of adjustment of exchange rates is 28%. We observe that inflation is significantly influenced by its own past values, and the adjustment of exchange rates is significantly explained by shocks of its own lagged variables.

Machine Learning Residual Modeling

Residuals of the Bayesian VECM are subsequently modeled through a random forest (RF) algorithm and gradient boosting (GB) algorithm. The algorithms identify the volatility clustering and interaction non-linearity that were missed in the econometric estimation process. The results are presented in table 8.

Table 8: Machine Learning Residual Results

Model	MAE Reduction (%)	RMSE Reduction (%)
Random Forest	14.8	17.2
Gradient Boosting	18.5	21.3
Hybrid ML-BVECM	22.7	25.9

The hybrid ML-BVECM provides superiority against econometrics-alone and machine learning-alone models. MAE and RMSE are decreased by more than 20 percent, which indicates the benefit of coupling econometrics based on equilibriums to ML models with flexible frameworks. This has been reflected by times of increased volatility, including the 2016 FX crisis and the2023 naira floating regime. The result presents the exchange rate pass-through effect on inflation; it clearly shows the pass-through of the value of the naira causes price fluctuations greatly. The results indicate the necessity for monetary policymakers to cooperate on monetary policy and exchange rate policies since the proposed tool gives better forecasts.

Diagnostic Tests and Model Robustness

A variety of diagnostic tests were performed in order to verify the credibility of the estimated ML-BVECM. These tests primarily aim to see if the model can adhere to significant econometric postulates and if it is able to be invariant across alternate forms of representation. In addition, for the reliability of the hybrid structure against varying levels of volatilities and any incidence of structural change in Nigeria's macroeconomic sector, robustness checks have also been carried out.

Autocorrelation Test

The Ljung-Box Q-test was carried out for residuals, and the results are presented in Table 9 and are evidence of no significant autocorrelation at lags 1-12, which implies that our model has correctly caught the time series dynamic.

Table 9: Ljung-Box Q-Test Results

Lag	Q-statistic	p-value
4	6.21	0.18
8	9.87	0.27
12	13.42	0.34

Heteroskedasticity Test

The ARCH LM test was employed to detect potential conditional heteroskedasticity. Table 10 reports results suggesting that the residuals exhibit neither an ARCH effect nor statistical significance; therefore, volatility clustering has been adequately addressed in the machine learning layer.

Table 10: ARCH LM Test Results

Lag	LM-statistic	p-value
1	2.14	0.14
4	5.62	0.22
8	8.03	0.31

Normality Test

The Jarque-Bera test was applied to the residuals. Some degree of non-normality is visible in the residuals, but this should be reasonable given it's a large-sample result from a hybrid model, relying in part on machine learning for non-linear correction.

Table 11: Jarque-Bera Test Results

Test	Statistic	p-value
Jarque-Bera	4.87	0.09

The Jarque-Bera test on the residuals from Hybrid ML-BVECM models yields a test statistic of 4.87 with a p-value of 0.09, showing very slight deviations to normality (as presented in Table 11) that do not appear to be significant at 5%. It is, however, generally accepted that very little deviation from normality in macroeconomic data, especially in Nigeria, whose volatility is extreme, is not usually statistically significant. The fact that the hybrid ML-BVECM framework is designed to capture the nonlinear relationship compensates for these deviations.

Stability Test

In all cases, the results for CUSUM and CUSUMSQ tests do not show any sign of parameter instability over the considered period, including periods of structural breaks (e.g., the 2016 FX crash or the 2023-naira float), which attests to the reliability of the used priors and the flexbility of the ML layer.

Table 12: Stability Test Results

Test	Statistic Range	Critical Bounds (5%)	Result
CUSUM	Within ±0.85	±1.00	Stable
CUSUMSQ	Within ±0.92	±1.00	Stable

To verify if these parameters remain steady over time, CUSUM and CUSUMSQ tests were performed on the residuals of the Hybrid ML-BVECM (see Table 12). Based on the results, neither of the test statistics exceeded the 5% critical value range, with CUSUM values mostly fluctuating below 0.85 and CUSUMSQ less than 0.92. These were still well within the threshold of 1.00, hence suggesting parameter stability over the estimation sample. The stability over time and with the Nigerianeconomy, where regime shifts caused by the 2016 Forex crisis or 2023 naira float could affect parameter estimates and for which BVECM using Bayesian priors could help stabilize over time by anchoring it toshocks, and with the learning capabilities of machine learning, the regime shifts will be learned.

Based on these tests, parameters of BVECM and hybrid ML-BVECM models were stable through the sample period. These could strengthen the prediction and forecasting reliability of either of the models in the face of shocks and possible structural changes that can happen in an evolving economy. It can be inferred that the machine learning part makes BVECM learn over regimes and shocks while Bayesian helps anchor the parameters across time series. In other words, the stability of parameters further assures the credibility and prediction ability of the Hybrid ML-BVECM and also indicates its readiness for policy analysis in the Nigerian economy.

Given the stable parameters in both BVECM and hybrid ML-BVECM and that all test diagnostics confirmed their adequacies, such as not experiencing issues with auto-correlation and heteroskedasticity, it implies that the models can be reliably used to forecast and provide policy insights into the dynamics of the exchange rate-inflation relation in Nigeria, as machine learning is introduced into BVECM to efficiently account for clustering volatility and non-linear relationships, and also that the models will predict and forecast the same information; the best model may well be seen as the most suitable to use for Nigerian economic forecasting.

Forecasting Performance Evaluation

Out-of-sample forecasts for the exchange rate and inflation from the three selected models—the traditional VECM, the Bayesian VECM (BVECM), and the hybrid ML-BVECM—were computed to assess relative model accuracy in the short (1-4 quarters) and medium term (5-12 quarters) using, for example, MAE, RMSE, and the Diebold-Mariano test (see Table 13).

Table 13: Comparative Hybrid ML-BVECM Results

Variable	Traditional VECM	BVECM	Hybrid (Random Forest)	Hybrid (Gradient Boosting)
Inflation – MAE	4.82	4.21	3.68	3.74
Inflation – RMSE	6.91	6.12	5.37	5.49
DM Test (vs VECM)	–	0.041**	0.012***	0.015***
Exchange Rate – MAE	112.4	101.7	89.1	87.5
Exchange Rate – RMSE	158.7	142.3	123.7	121.9
DM Test (vs VECM)	–	0.041**	0.010***	0.009***

Note: *** significant at 1%, ** significant at 5%.

Both the hybrid random forest and gradient boosting models perform significantly better than the underlying BVECM and VECM models when it comes to predicting the inflation series. The former pair, though recording marginally lower values for MAE (3.68) and RMSE (5.37), reflecting stronger capture of non-linear lags and volatility clustering compared to other models, still significantly reduces errors and is significant at the 1% confidence interval level. The Diebold-Mariano tests provide 1% significance for this improvement. For the exchange rates, the gradient boosting approach yields better forecasting accuracy with its relatively smaller MAE (87.5) and RMSE (121.9), thus being more effective at capturing regime switches and jump phenomena, which are highly prevalent in most currencies of Nigeria.

While the random forest also provides noticeable reductions to VECM and BVECM errors, it tends to provide rather soft predictions from clearly abrupt patterns than the gradient boosting does. Yet both improvements are also found significant at the 1% significance level through DM tests. Our comparative analysis shows that the random forest provides the best model specification for forecasting inflation, whereas the gradient boosting provides the best one for exchange rate forecasts. It thus highlights that it matters what ML models you adopt when it comes to forecasting for time-series data.

BVCEM in combination with machine learning models: a hybrid approach to macroeconomic forecasting in Nigeria BVECM provides a good basis for forecasting given its capacity to correct for long-term equilibria when combined with methods that can effectively capture the nonlinear lag and shock structures. Integrating a set of different ML models into the BVECM frameworks offers a readily interpretable and accurate forecasting technique that Nigerian macroeconomic policymakers could adopt in order to effectively implement policies—ML models would generally be aimed at targeting inflation for ML-random forestmodels whiletargeting exchange rates for the ML-gradient boosting models. In summary, it shows how complementary they are for the Nigerian policy context.

Discussion

The study investigated Nigeria's dynamic inflation and exchange rates' relationships via a nexus of econometric and machine learning techniques. A beginning was made with unit root tests, where ADF, PP, and KPSS tests revealed that the variables are non-stationary at their levels and stationary at the first difference, suggesting they are I(1). The results from Johansen cointegration analysis provided the existence of at least one cointegrating vector, establishing a long-run equilibrium relationship between the two variables. This justifies the use of the Vector Error Correction Model (VECM) approach. Based on the Bayesian VECM (BVECM), results showed the presence of a statistically significant error correction term, with adjustments in inflation of about 31% and in exchange rate of about 28% on a quarterly basis. The long-run cointegrating equation indicated a strong exchange rate pass-through to inflation, whereas theshort-run dynamics revealed the feedback mechanism between the lagged price change and changes in the exchange rate. The incorporation of Bayesian priors helped to stabilize parameter estimates and made the VECM more robust to Nigeria's structural breaks and volatility episodes. The out-of-sample forecasting performance tests indicated the BVECM approach surpassed the conventional VECM approach and reduced the error forecasts significantly. Moreover, the Hybrid ML-BVECM method generated more accurate forecasts compared to all models examined, as the inflation MAE decreased by 23% while the exchange rate MAE dropped by 22% more than the VECM model. The Diebold-Mariano test confirmed the statistical significance of these improvements. The robustness checks, including no evidence of autocorrelation and heteroskedasticity, mild deviations from normality, and stability of parameters under structural breaks in time series such as the 2016 FX crisis and 2023 nairafloat, confirm the robustness of the fitted models. The findings lend credence to existing studies like Adekunle Aribatise (2023), which establishes the causal relationship between changes in exchange rates and inflation in Nigeria using the VECM framework. The present analysis affirms that the pass-through from exchange rate to inflation plays a significant role in price dynamics, and policy implications to control inflation rely on a sound exchange rate management policy. Based on the findings from Bayesian VECM, an error correction term of -0.31 for inflation and -0.28 for the exchange rate signifies substantial convergence towards the long-run equilibrium at a speed of 31% for inflation and 28% for the exchange rate on a quarterly basis. These estimates are broadly in line with those of Ezekwube et al. (2026), who similarly established cointegration between inflation and exchange rate volatility in Nigeria, affirming a long-run equilibrium. Moreover, the Bayesian prior estimation enabled more stable parameter estimates relative to potential structural shocks such as the 2016 FX crisis and the 2023 naira float. The cointegration findings strongly resonate with the notion of long-run interdependence in macroeconomic variables, first explored in the seminal work of Johansen (1991). In terms of forecasting, the hybrid ML-BVECM proved superior over the conventional VECM and BVECM. For instance, Random Forest effectively modeled the nonlinear lagged dependencies and volatility clustering, boosting inflation forecasting accuracy. Gradient boosting enhanced the predictive power of exchange rate forecasts by capturing regime shifts and sharp movements. The results are consistent with Nguyen (2022) and Ibrahim, et al (2025) that asserted that hybrid methods improve the predictive accuracy for volatile emerging markets. The Diebold-Mariano test confirmed the superiority of hybrid models, yielding a 23% reduction in MAE for inflation and a 22% reduction for exchange rates compared to the VECM.The findings are further supported by Nikolenko et al. (2022) on the critical need for policy-relevant forecasts that can capture anticipated shocks and adapt to market volatility. By integrating the capabilities of machine learning into a structurally grounded BVECM framework, the study delivers robust and accurate forecasts that guide more effective policy interventions by the CBN in Nigeria.Overall, the present research contributes by demonstrating that combining machine learning methods with traditional econometric models provides not just a better fit, but a more practically useful forecasting tool for a volatile economic landscape like Nigeria's. More specifically, the Hybrid ML-BVECM presents a potent toolkit for policymakers, the Central Bank of Nigeria included, to proactively manage inflationary pressures and exchange rate volatility, thus solidifying the credibility of monetary policy and fostering sustainable growth.

CONCLUSION

This study aimed to study the inflation–exchange rate nexus in Nigeria and achieve more accurate inflation and exchange rate forecasts through the integration of econometric and machine learning methods. We first analysed the statistical properties of the inflation and exchange rate data and, using unit root tests and cointegration analysis, found both variables to be I(1) and to share a long-run equilibrium relationship, justifying our application of a vector error correction model (VECM) estimation. We incorporated Bayesian estimation and integrated a hybrid machine learning approach. The results from the Bayesian VECM (BVECM) confirmed a strong exchange rate pass-through to inflation and that both variables respond positively to deviations from equilibrium.

We estimated inflation to converge by about 31% quarterly to equilibrium and the exchange rate by 28%, implying that Nigeria's macroeconomic variables converge rapidly to their equilibrium relationships. We also revealed evidence of feedback effects between the past exchange rate and changes in the exchange rate in Nigeria, indicating the interaction between price stability and exchange rates. The use of Bayesian priors contributed to stable parameters, thereby limiting the effect of potential structural breaks, like the 2016 FX crisis and the 2023 naira float. On the forecasting side, theBVECM outperformed the traditional VECM, significantly reducing forecast errors, but the Hybrid ML-BVECM exhibited the highest forecasting accuracy and delivered a reduction in MAE of 23% and 22% for inflation and exchange rate, respectively, compared to the traditional VECM. These improvements in forecasting accuracy were tested using the Diebold-Mariano test and confirmed as statistically significant.

Both models passed all diagnostics tests with regards to the absence of autocorrelation, heteroskedasticity, distribution of residuals, and stability of parameters. Based on our findings, exchange rate pass-through constitutes a major source of inflation in Nigeria. Moreover, a hybrid approach, such as the combination of Bayesian econometrics and machine learning methodologies, may help to accurately forecast and provide interpretability at both the traditional and the machine learning levels.

Therefore, for effective formulation and implementation of economic and monetary policies in Nigeria, it is important to consider using the hybrid ML-BVECM as a tool that allows forecasting inflationary pressures and exchange rate volatility more accurately and, in turn, assists policy authorities to be more responsive to the changes in the economy, strengthen their inflation targets, build credibility, and boost confidence through the effective responses to external shocks that may destabilize price and exchange rates. It is hoped that the present study adds to the academic literature on the estimation of the dynamics of inflation–exchange rate in Nigeria by presenting forecasting using a hybrid machine learning approach and will assist in taking more robust and effective decision-making during inflation targeting.

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