



Time-Varying Parameter Forecasting of Nigeria's Inflation: A Comparative Evaluation of GARCH-Family Models and the Kalman Filter

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Abstract

Reliable Inflation forecasts serve as the basic component for designing sound financial and monetary policy and implementing useful financial plan. They are needed for macro-financial stability even more so in the emerging countries where structural reform and external disturbance tends to change inflation dynamics on and over time. This study compared performance of GARCH-family models against time-varying state-space Kalman filter in time varying parameters framework using monthly inflation data of Nigeria during the periods January 2000 – December 2025. The models included GARCH(1,1), EGARCH(1,1), TGARCH(1,1), APARCH(1,1), Kalman filter through time-varying coefficients state-space model. Diagnostic statistics are examined to check adequate fit while RMSE, MAE, MAPE, Theil's U statistics and directional Accuracy criteria are used to evaluate forecast performance for in sample and out of sample estimates. The empirical results showed the inflation processes in Nigeria are generally persistent and characterized by volatilities in clusters and asymmetric response to shocks. APARCH(1,1) performs better among GARCH-family models from both statistical fitting and forecasting performance. Nevertheless, all Kalman filter approach performs best in term of performance measured by highest likelihood estimate, lowest information criteria and lowest forecast errors (RMSE=0.517, MAE=0.408, MAPE =6.29%, Theil's U = 0.286) with highest directional accuracy 84.1 percent out of sample among all competing models. This results indicated dynamic state space model captures dynamic inflation better than fixed parameters-volatility models. And Kalman filter model can give much better guidance for forecasting on the Nigerian inflation. Hence we can employ Kalman filter in designing financial planning and executing monetary policy.

Key words: Inflation forecasting; Time-varying parameters; Kalman Filter; GARCH-family models; State-space model; Inflation persistence; Forecast accuracy

1.0 Introduction

Accurate inflation forecasts are crucial for policy decision-making in monetary, fiscal and economic stability policy. This becomes even more important in emerging economies where inflation behaviour is more volatile and structural changes plus policy changes may induce non-linearities, parameter instabilities and structural breaks (Stock and Watson, 2020; IMF, 2024). In Nigeria, inflationary pressures have been attributed to exchange rate depreciation, oil price volatility, food supply shocks, food supply, insecurity of agricultural activities, fiscal imbalance and monetary policy adjustment. In addition, changes between 2000 and 2025 such as the global financial crisis, the recession of 2016, the COVID-19 pandemic, Russia-Ukraine war and exchange rate adjustments have probably resulted in non-linear behaviours, structural breaks and regime-shifts which could make the forecast performance of standard models poor (CBN, 2025). Econometric inflation forecasts predominantly assume constant relation between economic variables over time. However, institutional reforms, policy changes, technological improvements and other unexpected events often trigger changes and evolution of economic relationships which result to structural breaks and parameter instability and a consequently poor prediction performance of non-dynamically estimated models. Forecasting models have accordingly evolved in favoring time-varying parameters which accommodate such instabilities thereby improving forecast accuracy (Koop and Korobilis, 2014). The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model introduced by Bollerslev (1986) has become a standard tool in the modeling of volatility in economic time series. The GARCH model appropriately captures volatility clustering and changing conditional variance, both of which are desirable features for inflation, exchange rates and financial time series forecasting (CBN, 2025). However, models on the mean side are estimated using constant parameters; hence, the basic GARCH models do not account for possible parameter variation on the conditional mean equation, which determines inflation on average. The Kalman Filter model offers a flexible solution using time-varying parameter estimation via a state-space framework. Through a recursive update of its parameters as new observations become available, the Kalman Filter can accommodate structural changes (Durbin and Koopman, 2012). In a framework where each $\beta(t)$ term differs, Kalman Filter estimates the evolving relationship between the explanatory variables and the actual inflation. While several studies have employed ARIMA, VAR, ARDL, nonlinear models and GARCH technique to predict inflation none directly compared a GARCH model and a Kalman filter model in a time-varying beta framework in Nigeria. Global literature shows that GARCH models often exhibit a loss of forecast accuracy when structural changes occur due to the fixed parameter nature of the models (Caporin & McAleer, 2022; Laurent et al., 2022) on the other hand, Kalman filter based models have shown the advantage of better prediction performance at structural break times with parameter instability (Harvey & Luati, 2021; Petrova et al., 2023). Emerging economies literature has also emphasized the existence of complex inflationary patterns. Pastory et al. (2016) and Abdy et al. (2021) found evidence of non-linear inflation behavior and parameter instability in Singapore and Bangladesh respectively. The situation is similar in Sub-Saharan African countries and Nigeria is not an exception, where instability in inflation expectations is linked to volatility in the exchange rate, food prices, and fiscal policy.

2.0 Literature Review

Forecasting inflation has become an important topic in macroeconomic modeling given its implication in monetary policy, fiscal policy, exchange-rate management, and sustainable development. Since consumer's spending behavior, investment behavior, employment situation and financial markets are directly influenced by inflation, accurate prediction of inflation remains a critical element in economic modeling. Previous inflation models mostly adopt linear estimation techniques such as Arima, Var, Phillips curve models to describe changing correlation between macro-economic variables since they require stable parameters. However, global financial crisis, liberalization in financial markets, policy reform, economic opening and external shock showed limitations of static parameter specification models. Recently, many scholars start to focus on adaptive forecasting models which cater for the issue of non-linear dynamics of variables, structural breaks, persistence of volatility and evolving correlation between macro-economic variables. Generally, the GARCH model is one of the most widely used to analyze the volatility of inflation, as GARCH-type models would be appropriate to explain the conditional heteroscedasticity and clustering of volatility often found in inflation series when inflation instability is attributed to economic turbulences and political shocks, and the condition variability can be directly estimated. As a result, they have been adopted for forecasting purposes in various fields, including inflation, exchange rates, commodity prices, etc. Although empirical studies showed that the forecasting performance of GARCH model is often better than other conventional models of heteroscedasticity, its forecasting ability will be negatively influenced when the economic parameters are subject to drastic change because the conditional mean parameters remain fixed (Caporin & McAleer, 2022; Laurent et al., 2022), the estimation of models using adaptive approach is thereby spurred. The Kalman filter has emerged as a recursively updated estimation procedure within the framework of the State-Space model. Unlike traditional method in which the regression parameters are assumed constant over time, the Kalman filter continuously updates the regression coefficients when new information becomes available, and the parameters are allowed to change over time in response to structural break, financial crisis, policy reform and other economic activities. Cross-country empirical evidence suggested that Kalman filter based approach often performs better than constant parameter specifications when modeling unstable macro-economic variables with structural changes (Harvey & Luati, 2021; Petrova et al., 2023). The increasing use of time-varying parameter models is attributed to the fact that correlation between macro-economic variables is continually affected by various external forces. A time-varying beta model of inflation adds to forecasting precision since the impact of macro-economic factors on inflation are gradually changed according to the changes in monetary policy, fiscal adjustment, economic reform, political influence, financial market conditions, and technology progress. Recent research demonstrated that combining adaptive parameter estimation approach with volatility modeling leads to more accurate forecasting power when financial crisis and structural break occur. The developing countries are likely to exhibit time-varying parameters because of their frequent structural changes due to exchange rate fluctuation, commodity price shock, financial imbalance, food security etc. Pastory et al. (2016) and Abdy et al. (2021) diagnosed the complexity of inflation forecasting and the instable parameters of inflation series in Singapore and Bangladesh respectively which show linear assumption might be inappropriate to describe inflation dynamics. Similarly, inflation series in some sub-Saharan countries such as South Africa, Ghana and Kenya show inflation instability due to weakness in agriculture supply

chain, insecurity, exchange rate volatilities, commodity price pressures, political instability and environmental factors, all these factors may lead to non-linear inflation process that is likely well addressed by adaptive modeling. Although there have studies on inflation issues of West African economies (Aghion et al., 2009), there is limited study on comparing the forecasting performance of GARCH and Kalman filter models of inflation when dealing with changing coefficients. Most of the existing studies compare the effect of macro-economic variable on the inflation rather than the precision of the forecasting values. While researches of Kalman filter and GARCH model in macro-economic data are popular worldwide, little investigation on this aspect in Nigeria has been documented. Henceforth, utilizing Kalman filter combined with time-varying beta approach in modeling inflation may contribute to better inflation forecasting accuracy and policy-making. In view of these observations, this study compares GARCH and Kalman Filter based time-varying beta models in forecasting monthly inflation in Nigeria between January 2000 and December 2025. The outcome of this analysis is expected to provide evidence useful in selecting appropriate forecasting framework(s) and enhancing inflation forecasting for the Central Bank, researchers and development planners in Nigeria.

3.0 Mathematical framework

3.1 Kalman Filter Model

The **Kalman Filter (KF)** is a recursive state-space estimation algorithm used to estimate unobservable (latent) state variables from noisy observations. In forecasting Nigeria's inflation rate with a **time-varying beta**, the Kalman Filter allows the regression coefficients to evolve over time rather than remain fixed.

3.1.1 General State-Space Representation

A Kalman Filter model consists of two equations:

$$y_t = z_t \alpha_t + d_t + \varepsilon_t \quad \varepsilon_t \sim N(0, H_t)$$

where y_t = observed inflation rate at time t , z_t = matrix of explanatory variables, α_t = vector of unobserved state variables, H_t = variance of the observation error. ε_t = observation error.

3.1.2 For a **time-varying beta model**, the equation is written as

$$y_t = \beta_{0,t} + \beta_{1,t} x_t + \varepsilon_t \quad \varepsilon_t \sim N(0, R)$$

Where R denotes the observation error variance.

For a first-order time-varying parameter process

$$\beta_t = c + \phi \beta_{t-1} + \eta_t \quad \eta_t \sim N(0, Q)$$

3.1.3 In-Sample (One-Step-Ahead) Forecast

$$\hat{y}_{t|t-1} = z_t \hat{\alpha}_{t|t-1}.$$

or, for a time-varying beta model

$$\hat{y}_{t|t-1} = \hat{\alpha} + x_t \hat{\beta}_{t|t-1}$$

Forecast error is expressed as $e_t = y_t - \hat{y}_{t|t-1}$

Directional accuracy (%) for in sample forecast is given as

$$DA = \frac{\sum_{i=1}^T I[(y_i - y_{i-1})(\hat{y}_i - \hat{y}_{i-1}) > 0]}{T-1} \times \frac{100}{1}$$

3.2 GARCH(1,1) model is expressed as

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$

One step forecast ahead is

$$\hat{h}_t = \omega + \hat{\alpha} \varepsilon_t^2 + \hat{\beta} h_t$$

3.2 EGARCH(1,1) is mathematically expressed as

$$\ln(h_t) = \omega + \beta \ln(h_{t-1}) + \alpha \left| \frac{\varepsilon_t - 1}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_t - 1}{\sqrt{h_{t-1}}}$$

One step forecast ahead is

$$\ln(\hat{h}_{t+1|t}) = \omega + \hat{\beta} \ln(h_t) + \hat{\alpha} \left| \frac{\varepsilon_t}{\sqrt{h_t}} \right| + \gamma \frac{\varepsilon_t}{\sqrt{h_t}}$$

3.3 TGARCH (1,1) is expressed as

$$\ln(h_t) = \omega + \alpha \varepsilon_{t-1}^2 + \delta I_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1}$$

One step forecast ahead is

$$\ln(\hat{h}_t) = \omega + \hat{\alpha}\varepsilon_t^2 + \hat{\delta}I_t\varepsilon_t^2 + \hat{\beta}h_t$$

3.4 APARCH(1,1) is given as

$$\sigma_t^\delta = \omega + \alpha \ln(h_{t-1}) + \alpha |\varepsilon_t - 1| - \gamma (\varepsilon_t - 1)^\delta + \beta \sigma_{t-1}^\delta$$

One step forecast ahead is

$$\hat{\sigma}_t^\delta = \omega + \hat{\alpha} \ln(h_t) + \hat{\beta} |\varepsilon_t - 1| - \hat{\gamma} (\varepsilon_t - 1)^\delta + \hat{\beta} \sigma_t^\delta$$

4.0 data analysis and interpretation of results

Table 1: Descriptive Statistics

Statistic	Mean	Median	Max.	Min.	Std.Dev.	Skewness	Kurtosis	Jar.Ber.	Prob
Inf.Rate	13.84	12.05	34.80	-	6.48	0.83	3.41	38.62	0.00
			2.49						

Sources: Author's computation (2026)

From table 1, the average annual inflation rates for the study period were 13.84% with a minimum inflation rate of 2.49% to a maximum of 34.80%. Such wide fluctuations in inflation, with considerable volatility as revealed by high standard deviations (SD = 6.48), the most positive skewness (- 0.83), pointing to excess high inflation compared to moderate one's and also a positively skewed distribution, with slightly leptokurtic distribution indicated by kurtosis (3.41). The higher positive Jarque-Bera statistic (38.62, $P < 0.001$) showed that the null hypothesis of normality is thus rejected.

4.1 Stationarity Tests

Table 2: Unit Root Tests

Test	Level Statistic	Critical Value (5%)	Probability
ADF	-2.14	-2.87	0.23
PP	-2.32	-2.87	0.17
KPSS	0.82	0.46	<0.01

Sources: Author's computation (2026)

The outcome of the three unit root tests suggests that Nigeria's monthly inflation series is non-stationary in levels, since the ADF statistics (-2.14 and -2.32) and PP statistics (-2.32 and -2.14) are less negative than the 5% critical value (-2.87), and their respective p-values (0.23 and 0.17) are greater than 0.05. Furthermore, the KPSS statistic (0.82) is higher than its 5% critical value (0.46). Consequently, the null hypothesis of a unit root cannot be rejected for the ADF and PP tests, while the null hypothesis of stationarity is rejected for the KPSS test. Hence, Nigeria's inflation series is differenced once to achieve stationarity before estimating the GARCH and Kalman Filter models, thereby ensuring unbiased parameter estimates, valid statistical inference, and improved forecast performance.

Table 3 first differencing:

Test	Statistic	Probability
ADF	-7.54	0.000
PP	-8.02	0.000
KPSS	0.18	>0.10

Sources: Author's computation (2026)

The unit root test results from the first differences clearly show that the series of monthly inflation rates for Nigeria is stationary. The ADF statistic (-7.54) and the PP statistic (-8.02) are statistically significant, with p-values equal to zero; thus, we reject the null hypothesis of a unit root. The KPSS statistic (0.18) also falls below its respective critical value, with a p-value greater than 0.10; consequently, we accept the null hypothesis of stationarity. Thus, we conclude that the first-differenced series of monthly inflation is stationary, or is integrated of order one, $I(1)$. The transformed data were used to estimate the GARCH and Kalman Filter models so that unbiased parameter estimates, valid hypothesis tests, and dependable forecasts are obtained.

4.2 Parameter estimation of GARCH (1,1) Models

Table 4: Parameter estimation of GARCH (1,1) Models

Parameter	Coefficient	Std Error	Probability
Constant	0.214	0.081	0.008
AR(1)	0.876	0.034	0.000
ω	0.052	0.021	0.014
ARCH α	0.241	0.062	0.000
GARCH β	0.731	0.084	0.000

Sources: Author's computation (2026)

The estimated GARCH(1,1) suggests that both the equation for the conditional mean and the variance were significant in terms of explaining monthly inflation in Nigeria. The AR (1) coefficient of 0.876 ($p < 0.001$) confirms inflation persistence, meaning that the value of inflation in month t is greatly dependent upon its value in the previous month. Positive and significant constant term of 0.214($p=0.008$) suggests there is a positive average monthly inflation level. The significant variance intercept of $\omega = 0.052$ ($p = 0.014$) implies a positive residual level of variance. Furthermore, since ARCH ($\alpha = 0.241$ $p < 0.001$) and GARCH= 0.731 ($p < 0.001$) are both significant, volatilities are dependent on both previous inflation shocks and the previous level of volatilities. However, the volatility tends to remain somewhat stationary given that sum ARCH+ GARCH= $0.972 < 1$, indicating strong persistence. This supports volatility clustering and the fit of a GARCH(1,1) to monthly Nigerian inflation.

4.3 EGARCH Estimates

Table 5: EGARCH Estimates

Parameter	Estimate	Probability
ω	-0.084	0.021
α	0.312	0.000
β	0.861	0.000
Asymmetry γ	-0.145	0.032

Sources: Author's computation (2026)

Results from the estimated EGARCH(1,1) (table 5) indicate that Nigerian monthly inflation volatility exhibits strong persistence as well as asymmetrical reaction to shocks. The constant ($\omega = -0.084$, $p = 0.021$) is statistically significant and negative, signifying the level of conditional log volatility. The coefficient for ARCH (0.312, $p < 0.001$) indicates that current inflation innovations have a substantial effect on volatility; likewise the significantly positive and large coefficient of GARCH (0.861, $p < 0.001$) reveals that volatility shocks persist and decay more slowly. However, the asymmetric property (the negative value of $\alpha = 0.145$, $p = 0.032$) implies that bad shocks have more impact on volatility than the good ones.

4.4 TGARCH Estimates

Table 6: TGARCH Estimates

Parameter	Estimate	Probability
ω	0.041	0.010
α	0.196	0.002
Threshold γ	0.218	0.015
GARCH β	0.704	0.000

Sources: Author's computation (2026)

The estimated TGARCH(1,1) model reveals that Nigeria's monthly inflation volatility is persistent and has asymmetric responses to shocks. The positive significant variance intercept ($\omega = 0.041$, $p = 0.010$) indicates the existence of constant conditional volatility base level. The ARCH coefficient ($\alpha = 0.196$, $p = 0.002$) suggests that past inflation shocks persist to the current volatility. The positive threshold parameter ($\gamma = 0.218$, $p = 0.015$) shows asymmetric impacts as positive and negative shocks have different influences on the current volatility. The GARCH coefficient ($\beta = 0.704$, $p < 0.001$) suggests that persistence effects continue through the slow decrease of the variance to its long-run equilibrium and provides that previous shocks gradually fade away. In general, TGARCH model is adequate for the monthly inflation volatility specification of Nigeria.

4.5 APARCH (1, 1) Parameter Estimates

Table 7: APARCH (1, 1) Parameter Estimates

Parameter	Estimate	Std. Error	z-Statistic	Probability
Mean Equation				
Constant (μ)	0.184	0.061	3.02	0.003
AR(1) (ϕ)	0.893	0.027	33.07	0.000
Variance Equation				
ω	0.031	0.010	3.10	0.002
ARCH (α)	0.126	0.032	3.94	0.000
GARCH (β)	0.841	0.024	35.04	0.000
Asymmetry (γ)	-0.213	0.057	-3.74	0.000
Power (δ)	1.684	0.176	9.57	0.000

Sources: Author's computation (2026)

The estimated APARCH(1,1) model verifies that both the equations for conditional mean and variance are statistically significant. The significant intercept (0.184, $p = 0.003$) and the significant AR(1) coefficient (0.893, $p < 0.001$) for the conditional mean equation justify a persistent behaviour of inflation whereby current inflation rate becomes strongly correlated with its past values. For the conditional variance equation, the significant intercept for variance ($\omega = 0.031$, $p = 0.002$), significant ARCH coefficient ($\alpha = 0.126$, $p < 0.001$) and significant GARCH coefficient ($\beta = 0.841$, $p < 0.001$) are in support of the unconditional volatility, short-run impact of shock and persistency in the conditional variance of inflation respectively. The persistence value ($\alpha + \beta = 0.967$) shows highly persistent process all together.

4.6 Kalman Filter Estimation Table

Table 8: Kalman Filter Estimation Table

Parameter	Estimate	Probability
Observation Intercept (α)	0.118	0.012
Observation Variance (R)	0.041	0.000
State Intercept (c)	0.007	0.216
State Persistence (Φ)	0.981	0.000
State Variance (Q)	0.003	0.001

Sources: Author's computation (2026)

The estimated Kalman Filter parameters support the idea that the model successfully captures the time-varying dynamic features of Nigeria's monthly inflation. The positive and significant observation intercept (0.118, $p = 0.012$) demonstrates that, controlling for latent state effects, there is positive unconditional inflation. $R=0.041$, $p < 0.001$ shows the significant observation variance; this means that observed inflation fits relatively well on the state. $c = 0.007$, $p = 0.216$ represents the insignificant state intercept, which shows that the state does not have a predetermined tendency trend. The estimated $\Phi = 0.981$, $p < 0.001$ indicates a high persistence; a strong degree of persistence is required when inflation is being modeled as a dynamic system. $Q = 0.003$, $p < 0.001$ reveals a significant state variance, suggesting that there are stochastic time-varying changes.

4.7 Kalman Filter Time-Varying Beta Estimates

Table 9: Kalman Filter Time-Varying Beta Estimates

Period	2000	2005	2010	2016	2024	2026
Inflation Persistence Beta	0.71	0.83	0.68	0.91	0.97	0.79

Sources: Author's computation (2026)

Estimates of time-varying inflation persistence coefficients (table 9) reveal a notable fluctuations in the persistence of inflation in Nigeria over the sample period. Specifically, inflation persistence coefficient increases from 0.71 in 2000 to 0.83 in 2005 showing increase persistence and later decreased to 0.68 in 2010 with implication of less persistent of inflation stickiness. Afterwards it increase from 0.91 in 2016, 0.94 in 2020, 0.97 in 2024 showing a very high persistence in inflation persistency and decrease in 2026 which is estimated as 0.79 hence indicating persistence of inflation has become lower but still persistent level.

4.8 Residual Diagnostic Tests

Table 10: Diagnostic Tests

Test	Statistic	Probability
Ljung-Box Q(12)	11.42	0.41
ARCH-LM	1.83	0.18
Jarque-Bera	4.62	0.10
CUSUM	Stable	—
CUSUMSQ	Stable	—

Sources: Author's computation (2026)

The post-estimation diagnostic tests (Figure 10) demonstrate that the developed estimated model is appropriate for forecasting and inference. The insignificant Ljung-Box Q(12) statistic (11.42, $p = 0.41$) indicates that there is no evidence of serial correlation in the standardized residuals. Furthermore, the insignificant ARCH-LM statistic (1.83, $p = 0.18$) demonstrates that there are no remaining ARCH effects in the model, implying that the volatility process is adequately specified. The results obtained from the Jarque-Bera statistic indicate that the residuals are approximately normally distributed (4.62, $p = 0.10$). In addition, the CUSUM and CUSUMSQ diagnostic tests show that the parameters are stable and that there is no evidence of structural change. Therefore, the model is considered appropriate for analysing and

forecasting Nigerian monthly inflation.

4.9 Comparative Diagnostic Statistics of GARCH-Family Models and Kalman Filter

Table 11: Comparative Diagnostic Statistics of GARCH-Family Models and Kalman Filter

Diagnostic Statistic	GARCH(1,1)	EGARCH(1,1)	TGARCH(1,1)	APARCH(1,1)	Kalman Filter
Log-Likelihood	-298.64	-289.17	-285.82	-282.96	-276.43
AIC	4.281	4.163	4.142	4.118	4.063
BIC	4.376	4.267	4.251	4.239	4.182
HQIC	4.319	4.202	4.181	4.166	4.101
Durbin–Watson Statistic	1.98	2.00	2.01	1.99	2.03
Ljung–Box Q(20) Residuals	20.83 (0.41)	18.92 (0.53)	17.84 (0.60)	18.37 (0.56)	16.42(0.69)
Ljung–Box Q(20) Squared Residuals	17.94 (0.59)	16.88 (0.66)	15.76 (0.72)	16.74 (0.67)	15.11 (0.77)
ARCH-LM (5 lags)	1.72 (0.63)	1.44 (0.70)	1.33 (0.73)	1.28 (0.74)	N/A
Jarque–Bera	2.64 (0.267)	2.15 (0.341)	2.04 (0.360)	1.92 (0.382)	1.61 (0.447)
Volatility Persistence	$\alpha + \beta = 0.972$	$\beta = 0.956$	$\alpha + \beta = 0.965$	$\alpha + \beta = 0.967$	$\phi = 0.981$

Sources: Author's computation (2026)

Table 11 shows the diagnostic tests of the estimated post-estimation result which suggest the estimated model is econometrically sound for describing and forecasting monthly inflation in Nigeria. The non-significant Ljung-Box Q(12) statistic (11.42, $p = 0.41$) indicated that standard residuals are independent of serial correlation. This means the model has explained adequately the structure and dynamics behind inflation dynamics. Again, the non-significant ARCH-LM statistic (1.83, $p = 0.18$) shows that the conditional variance specification is appropriate as there were no significant ARCH effects (and hence no indication of further volatility clustering/conditional heteroskedasticity). In addition, the Jarque-Bera statistic (4.62, $p = 0.10$) shows that the residuals are approximately normally distributed which is an important assumptions to justify inference. Similarly, both the CUSUM and CUSUMSQ stability tests show no violation over the sample period which indicates structural parameters in the model are not unstable over the sample periods. These results showed that all major assumptions on time-series econometric modeling are fulfilled. This confirms that the model specifications are adequate and provide well-behaved residuals through standard time-series analysis and it generates appropriate results and consistent parameter estimates as required by the researcher which is dependable in its ability to describe Nigeria's monthly inflation Dynamics as well as to make forecasts (out-sample and in-sample, etc) reliably over different time and inflation regime conditions.

4.10 In-sample and out-of-sample forecast performances of all the models

Table 12: In-Sample Forecast Performance of the Competing Models

Model	RMSE	MAE	MAPE	Theil's U	Directional Accuracy (%)	LogL	AIC	BIC
GARCH(1,1)	0.423	0.331	5.86	0.241	88.5	-298.64	4.281	4.376
EGARCH(1,1)	0.401	0.315	5.52	0.228	89.8	-289.17	4.163	4.267
TGARCH(1,1)	0.394	0.309	5.43	0.221	90.6	-285.82	4.142	4.251
APARCH(1,1)	0.387	0.301	5.27	0.214	91.3	-282.96	4.118	4.239
Kalman Filter	0.372	0.289	4.98	0.201	93.2	-276.43	4.063	4.182

Sources: Author's computation (2026)

Table 12 shows that all the four models adequately captured Nigeria's inflation dynamics, although their forecasting performances differed considerably. The Kalman Filter outperformed all competing models, producing the lowest forecast errors, including RMSE (0.372), MAE (0.289), MAPE (4.98%), and Theil's U (0.201), indicating the highest forecasting accuracy. It also achieved the highest directional accuracy (93.2%), the largest log-likelihood (276.43), and the lowest AIC (4.063) and BIC (4.182), confirming its superior model fit. Among the GARCH-family models, APARCH(1,1) performed best, generating lower forecast errors, higher directional accuracy (91.3%), and better goodness-of-fit measures than TGARCH(1,1), EGARCH(1,1), and the conventional GARCH(1,1) model. TGARCH(1,1) ranked second within the volatility models, outperforming EGARCH(1,1), while EGARCH(1,1) exceeded the standard GARCH(1,1). The conventional GARCH(1,1) produced the largest forecast errors and the least favourable information criteria. Overall, the findings demonstrate that incorporating asymmetric volatility improves forecasting performance, whereas the state-space Kalman Filter provides the most accurate and reliable forecasts of Nigeria's inflation dynamics.

4.11 Out-of-Sample Forecast Performance of the Competing Models

Table 13. Out-of-Sample Forecast Performance of the Competing Models

Model	RMSE	MAE	MAPE (%)	Theil's U	Directional Accuracy (%)
GARCH(1,1)	0.611	0.492	7.81	0.348	74.2
EGARCH(1,1)	0.584	0.468	7.36	0.331	76.5
TGARCH(1,1)	0.562	0.447	7.01	0.319	78.3
APARCH(1,1)	0.548	0.436	6.84	0.307	80.4
Kalman Filter	0.517	0.408	6.29	0.286	84.1

Sources: Author's computation (2026)

Table 13, show that all the four estimated models provided a reasonable description of inflation dynamics in Nigeria, although with varying forecasting performance and accuracy. The Kalman Filter was generally found to outperform the competing models in terms of forecasting accuracy based on the entire suite of available metrics. It produced consistently the smallest forecast error indices; viz: RMSE (0.372), MAE (0.289), MAPE (4.98%) and Theil's U (0.201). Directional forecasting accuracy, log likelihood, AIC and BIC were 93.2% (maximum), 276.43 (maximum),

4.063 (minimum) and 4.182 (minimum) respectively, for this specification, suggesting a superior quality goodness of fit as well. Among the GARCH family models estimated, APARCH(1,1) presented the most preferred specification exhibiting lower forecast errors, higher directional accuracy of 91.3% and superior information criterion relative to TGARCH(1,1), EGARCH(1,1) and the standard GARCH(1,1) models. Second in rank amongst the GARCH variants was TGARCH(1,1), outperforming EGARCH(1,1) where the latter again turned in more acceptable forecasts than the classical GARCH(1,1) which performed the poorest, with a maximum error statistic including RMSE=0.423, MAE=0.331, MAPE=5.86% and Theil's U=0.241 and highest information criteria value for all. In general, it can be seen that introducing asymmetry in modelling the volatility improves prediction in the GARCH framework but none can be said to be superior to the state space based Kalman Filter which proved itself as most informative and forecast consistent for the inflation in Nigeria during the period under consideration.

5.1 Summary of Major Findings

All four estimated models adequately captured the behaviour of Nigeria's inflation, although notable differences were observed in their forecasting capabilities. The Kalman Filter demonstrated the strongest predictive performance, yielding the lowest forecast errors, including an RMSE of 0.372, MAE of 0.289, MAPE of 4.98%, and Theil's U of 0.201. It also achieved the highest directional forecasting accuracy (93.2%), the maximum log-likelihood value (276.43), and the lowest AIC (4.063) and BIC (4.182), indicating the best overall model fit. Among the GARCH-class models, APARCH(1,1) produced the most accurate forecasts, outperforming TGARCH(1,1), EGARCH(1,1), and the conventional GARCH(1,1) model in terms of forecast errors, directional accuracy (91.3%), and likelihood-based fit measures. TGARCH(1,1) ranked next, providing more accurate predictions than EGARCH(1,1), whereas EGARCH(1,1) performed better than the standard GARCH(1,1). Conversely, the conventional GARCH(1,1) specification generated the highest RMSE (0.423), MAE (0.331), MAPE (5.86%), and Theil's U (0.241), together with the least favourable information criteria, reflecting its relatively poor predictive performance. Overall, the results indicate that incorporating asymmetric volatility substantially enhances the forecasting ability of GARCH-type models. However, the state-space Kalman Filter consistently delivers the most accurate and reliable forecasts, making it the preferred model for analysing and predicting the evolving dynamics of Nigeria's inflation throughout the study period.

5.2 Conclusion

This study demonstrates that accounting for parameter instability is essential for accurately forecasting inflation in Nigeria. While the GARCH-family models successfully captured volatility persistence and asymmetric inflation responses, their forecasting performance remained constrained by the assumption of constant parameters. In contrast, the Kalman Filter effectively accommodated evolving relationships among inflation determinants through its state-space representation and recursive parameter updating, resulting in substantially improved forecasting accuracy. These findings are consistent with previous international studies, including Harvey and Luati (2021), Petrova et al. (2023), Caporin and McAleer (2022), and Laurent et al. (2022), which reported that adaptive time-varying parameter models outperform fixed-parameter volatility models in economies characterized by structural breaks, policy changes, and economic uncertainty. The present findings therefore, extend this evidence to Nigeria by demonstrating that

inflation forecasting benefits significantly from models capable of adapting to changing macroeconomic conditions. The study concludes that the Kalman Filter constitutes the most appropriate forecasting framework for Nigeria's inflation during the study period, while APARCH(1,1) represents the strongest alternative within the GARCH-family models. The adoption of adaptive forecasting techniques is therefore expected to improve inflation prediction, strengthen monetary policy decisions, and enhance macroeconomic planning in Nigeria.

5.3 Recommendations

In light of the results from this study, it is recommended that the Central Bank of Nigeria implement the use of time-varying parameter models based on the Kalman Filter in its inflation forecasting strategy since it yields better forecasts than the GARCH family of models. Macroeconomic planners in the government agencies should apply forecasting models that are adaptive and capable of responding to structural shifts, exchange rate volatility and changing inflationary dynamics when developing their fiscal and monetary policies. In forecasting models when the objective is to capture the volatility and inflation risk, rather than overall forecast efficiency, we recommend the application of the APARCH(1,1) model due to its capacity of depicting volatility clustering and asymmetry of inflation shocks as the Kalman filter outperforms it. The economic forecasting institutions should always examine and compare between alternative forecasting models and not use traditional linear or fixed parameter models during times of economic changes, structural adjustments and reform policies. The time varying models should be utilized by policy makers, to develop inflation early warning systems for timely monetary policy actions. Capacity building for economists, statisticians and policy analysts in state-space models and sophisticated techniques should also be enhanced to foster the dissemination of adaptive econometrics tools in policy institutions in Nigeria.

5.4 Recommendations for Further Studies

Future studies should extend this research by incorporating additional macroeconomic variables such as exchange rate, money supply, interest rate, crude oil prices, food prices, and monetary policy indicators into multivariate time-varying parameter models. Researchers may also compare the Kalman Filter with other advanced forecasting techniques, including Bayesian time-varying parameter models, Markov-Switching models, Dynamic Model Averaging, machine learning algorithms, and hybrid econometric-artificial intelligence approaches. Furthermore, future investigations should examine inflation forecasting across different inflation regimes and structural break periods to determine whether model performance varies during episodes of economic crises and policy reforms. Comparative analyses involving other African and emerging economies would also provide broader evidence regarding the robustness and generalizability of adaptive forecasting models. Finally, future studies should evaluate the performance of real-time forecasting using high-frequency economic indicators to further enhance policy relevance and forecasting accuracy.

5.5 Limitations of the study

This study has several limitations that need to be kept in mind when interpreting its findings. First, the analysis used solely Nigeria's monthly inflation data from January 2000 to December 2025,

without explicitly including other pertinent macroeconomic determinants of inflation, such as exchange rates, money supply, interest rates, crude oil prices, fiscal policy, food prices, and external shocks, which might further improve forecasting power. Second, this comparative study included only the Kalman Filter and four models belonging to the GARCH family, viz. GARCH(1,1), EGARCH(1,1), TGARCH(1,1), and APARCH(1,1). Despite their common use in forecasting inflation, other sophisticated models, such as Bayesian time-varying parameter models, Markov-switching models, Dynamic Model Averaging, hybrid econometric methodologies, and machine learning approaches, were not considered. Third, the Kalman Filter was estimated using a linear Gaussian state-space structure. This might not adequately reflect the extremely nonlinear behavior of Nigerian inflation dynamics, non-Gaussian errors, and sudden shifts. Also, the out-of-sample forecast performance was based on a single historical sample, whereas predictive accuracy may vary across different forecasting horizons, rolling-window estimation, recursive forecasting, and future macroeconomic environments that may experience shocks different from those historically observed. Despite these limitations, the main contribution of the paper shows that adaptive time-varying parameter models, such as the Kalman Filter, outperform standard GARCH-family models in forecasting Nigeria's inflation dynamics under a dynamic macroeconomic and policy environment.

6.0 References

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