



Can Monetary and Money-Market Indicators Improve Inflation Forecasts in Nigeria? Evidence from Econometric and Machine-Learning Models, 2006-2026

Ofiero hor Ufuoma Earnest

University of Port Harcourt, Nigeria

ORCID: <https://orcid.org/0009-0002-7468-8082>

Abstract: This paper asks whether the monetary policy rate, the Treasury bill rate and the interbank call rate help to forecast Nigerian headline inflation one month ahead. Using monthly Central Bank of Nigeria data from 2006 to April 2026, I compare a random walk, an AR(3), an autoregressive distributed-lag (ARDL) model with money-market indicators, a ridge regression and two random forests, one fitted to the level of inflation and one to its monthly change. All models are re-estimated each month and evaluated on forecasts for January 2022 to April 2026, a period that includes the steepest inflation surge in two decades and the rebasing of the consumer price index in January 2025. The ARDL model is the most accurate, with a root mean squared error of 0.844 percentage points against 0.972 for the random walk and 0.894 for the AR(3), and its gains are statistically significant (Diebold–Mariano $p = 0.043$ against the random walk; Clark–West $p < 0.001$ against the AR(3)). It is also the best model in each sub-period, and its advantage over the AR(3) survives rolling estimation windows and a three-month horizon, although its advantage over the random walk does not. A random forest fitted to inflation levels is the worst model by a wide margin (RMSE 3.78) because it cannot predict values above those in its training data, which never exceeded 18.7 per cent before 2022. Fitting the same forest to monthly changes removes this problem and brings its accuracy close to that of the AR(3). The money-market variables are jointly significant in-sample over the full period ($F = 2.87$, $p = 0.016$) but not before 2022, suggesting that their predictive content emerged during the recent high-inflation episode. The rebasing month itself produces a forecast error of about seven points in every model and is best treated as a measurement break rather than a forecasting failure.

Keywords: inflation forecasting; monetary policy; money-market rates; random forest; forecast evaluation; Nigeria

JEL classification: E31; E37; E52; C53

1. INTRODUCTION

Nigerian inflation rose from 15.6 per cent in December 2021 to 34.8 per cent in December 2024. Over the same period the Central Bank of Nigeria (CBN) raised the monetary policy rate (MPR) from 11.5 to 27.5 per cent, the naira lost most of its value against the US dollar after the exchange-rate unification of June 2023, and the petrol subsidy was removed. Every institution that prices assets or sets wages in naira needed a view on where inflation was going next. The CBN needed one too, since its policy decisions depend on forecasts of inflation as much as on its current level.

Inflation forecasts often draw on financial-market information. Treasury bill yields reflect investors' expectations about future short rates and inflation, interbank rates show the immediate cost of liquidity, and the policy rate summarises the central bank's own stance. If these rates contain information about future price pressure, they should improve forecasts relative to models that use inflation's own history alone. Whether they actually do is an empirical question, and the international evidence is mixed. Stock and Watson (1999) found that real-activity indicators improve US inflation forecasts, but Atkeson and Ohanian (2001) showed that a simple random walk forecast of annual inflation was hard to beat after the mid-1980s. Stock and Watson (2007) later attributed this to a change in the time-series properties of US inflation, which became less predictable as its persistence fell.

Machine-learning methods have added a new dimension to the debate. Medeiros et al. (2021) report substantial gains from random forests in forecasting US consumer price inflation, and Goulet Coulombe et al. (2022) find that nonlinearity is the main reason machine-learning methods help in macroeconomic forecasting. In Nigeria, recent studies have applied neural networks, support vector machines and random forests to inflation data, often in combination with ARIMA models (Mazona & Obadina, 2026). These studies typically find that hybrid or machine-



learning models outperform linear ones. Less attention has been paid to a basic limitation of tree-based methods: they cannot forecast values outside the range of their training data. When inflation moves to unprecedented levels, as it did in Nigeria after 2022, this limitation can dominate everything else.

This paper makes three contributions. First, it compares six forecasting models on a common, strictly lagged information set, re-estimating each one every month and testing differences in accuracy formally (Diebold & Mariano, 1995; Harvey et al., 1997; Clark & West, 2007). Second, it shows that the poor performance of random forests in this setting is caused by extrapolation and that it can be fixed by modelling the change in inflation rather than its level. Third, it deals explicitly with the CPI rebasing of January 2025, which creates a break in the inflation series that any study extending past 2024 must address. The main finding is that a transparent ARDL model with money-market indicators beats both the random walk and an autoregression, consistently across the high-inflation and post-rebasing periods.

Section 2 reviews the literature. Section 3 describes the data. Section 4 sets out the models and evaluation design. Section 5 presents the results, Section 6 discusses them and Section 7 concludes.

2. LITERATURE REVIEW

2.1 Why inflation is hard to forecast

Inflation forecasting has a humbling record. Atkeson and Ohanian (2001) showed that, for the United States between 1984 and 1999, Phillips-curve models did no better than a naive forecast that next year's inflation would equal this year's. Stock and Watson (2007) explained the result with an unobserved-components model in which the permanent component of inflation became less volatile after the mid-1980s, which made inflation both less persistent and harder to forecast with other variables. In a broad review, Faust and Wright (2013) conclude that judgemental forecasts and simple models that anchor on a slowly moving trend are difficult to beat, and that the gains from adding predictors are usually modest and unstable. Rossi (2013) documents how forecasting relationships in macroeconomics shift over time, so that a predictor that helps in one period may hurt in another.

These findings come mostly from advanced economies with credible inflation targets. In economies where inflation is higher, more volatile and more exposed to exchange-rate and food-price shocks, there is more variation to explain, and the balance between persistence and predictability may be different. That is one reason Nigerian evidence is worth having in its own right.

2.2 Financial variables as predictors

Interest rates can predict inflation for several reasons. Under the Fisher relation, nominal yields embed expected inflation, so a rise in bill yields may signal that markets expect higher inflation. The policy rate summarises the central bank's assessment of inflationary pressure and its intended response. Money-market rates also capture liquidity conditions that may affect spending and exchange-rate pressure. The difficulty is that these relationships run in both directions. A central bank that raises its policy rate when it expects inflation to rise will produce a positive correlation between the policy rate and future inflation even if the rate increase itself lowers inflation. Forecasting models can exploit this correlation, but their coefficients cannot be interpreted as policy effects.

2.3 Evidence for Nigeria

Several studies have built short-term inflation forecasting models for Nigeria. Doguwa and Alade (2013) estimate seasonal ARIMA (SARIMA) and SARIMAX models for headline, food and core inflation and find that SARIMAX models with exogenous variables are preferred for headline inflation. Udoh and Isaiah (2018) use quarterly data for 1995–2016 and find that lagged interest rates and money supply are significant predictors of inflation. Ajobo et al. (2026) fit SARIMA models to monthly headline, food and core inflation from 2003 to 2023. Mazona and Obadina (2026) combine ARIMA models with artificial neural networks, support vector regression and random forests for 2010–2024 and report that the hybrids beat standalone models in rolling out-of-sample tests.

Most of this work either ends before the inflation surge of 2022–2024 or does not compare models against simple benchmarks with formal tests. None addresses the CPI rebasing. The present paper fills these gaps by evaluating forecasts through the surge and the rebasing, with explicit benchmarks and formal tests.

2.4 Machine learning and the extrapolation problem

A random forest predicts by averaging outcomes in the terminal nodes of many regression trees (Breiman, 2001). Each prediction is a weighted average of training outcomes, so a forest can never predict a value above the largest or below



the smallest outcome it has seen. This property is harmless when the target is stationary and its future range is covered by the past. It is a serious problem for a persistent series that drifts to new levels. Medeiros et al. (2021) avoid it partly because US inflation in their sample rarely left its historical range. Ridge regression shrinks coefficients towards zero to reduce variance when predictors are correlated (Hoerl & Kennard, 1970), but heavy shrinkage of the coefficient on lagged inflation can bias forecasts of a near-unit-root series towards its sample mean. Both issues are relevant for Nigeria and are examined directly here.

2.5 Hypotheses

H1: Money-market indicators do not improve one-month-ahead inflation forecasts relative to an autoregressive benchmark.

H2: Machine-learning models do not improve on linear models when inflation moves outside its historical range.

3. DATA

3.1 Sources and variables

Headline, food and core inflation are year-on-year changes in the consumer price index, compiled by the National Bureau of Statistics (NBS) and published in the CBN inflation series (Central Bank of Nigeria, 2026a). Core inflation excludes farm produce and energy. The money-market variables are the MPR, the Treasury bill rate and the interbank call rate from the CBN money-market indicators series (Central Bank of Nigeria, 2026b). Before December 2006 the minimum rediscount rate is used in place of the MPR. The bill-rate series contains two months recorded as zero (December 2017 and December 2018) and the interbank series four such months; these are treated as missing and interpolated, since they reflect missing quotations rather than zero rates.

Inflation data are available from 2003, which allows twelve-month lags to be formed from the start of the money-market data in 2006. The estimation sample has 242 target months from March 2006 to April 2026.

3.2 The CPI rebasing

In February 2025 the NBS released consumer price data on a new base, with 2024 replacing 2009 as the reference year and with updated weights (National Bureau of Statistics, 2025). The NBS reported headline inflation of 24.48 per cent for January 2025; the CBN series used here records 27.61 per cent, against 34.80 per cent in December 2024. Either way, the fall of seven to ten points in a single month reflects the change in methodology at least as much as any change in price pressure. A forecaster in December 2024 could not have predicted it from economic data. I therefore treat January 2025 as a measurement break. It is excluded from the estimation sample (equivalent to an impulse dummy), and it is excluded from the main forecast evaluation, although results including it are also reported.

3.3 Descriptive statistics

Over January 2006 to April 2026 headline inflation averaged 14.32 per cent with a standard deviation of 6.67 points, ranging from 3.0 to 34.8 per cent. Food inflation was higher on average (15.63 per cent) and more volatile, peaking at 40.87 per cent in June 2024. Core inflation averaged 12.64 per cent. Figure 1 plots the three series. The surge after 2022 stands out, as does the rebasing break and the sharp decline in measured inflation during 2025. Food inflation fell faster than the headline rate in late 2025, reaching single digits in January 2026.

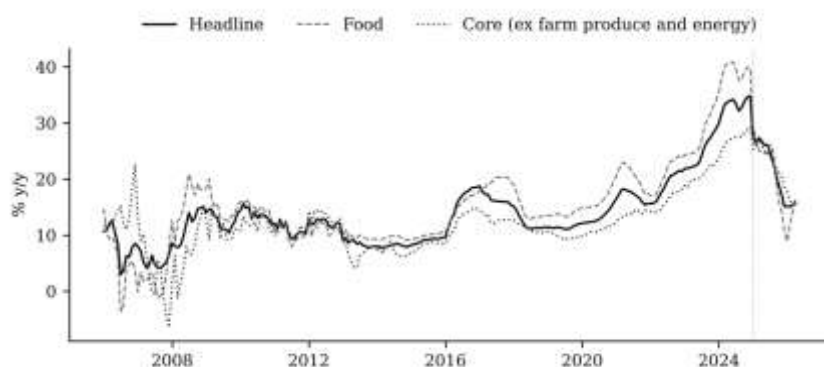


Figure 1. Headline, food and core inflation, January 2006 – April 2026 (year-on-year). The dotted line marks the CPI rebasing in January 2025. Source: Central Bank of Nigeria; National Bureau of Statistics.



For 2006–2024, before the break, the augmented Dickey–Fuller test does not reject a unit root in headline inflation (statistic -0.11 , $p = 0.948$) but rejects it in first differences ($p = 0.017$). The KPSS test rejects stationarity in levels (1.291). The Zivot–Andrews test, allowing one break, also fails to reject a unit root (-3.04 , with the break placed in February 2022). Inflation is highly persistent, which is why a random walk is a demanding benchmark.

4. METHODOLOGY

4.1 Information set

The target is headline inflation π_t . Every predictor is dated $t-1$ or earlier, so each forecast uses only information that would have been published before the target month. The predictors are inflation at lags 1, 2, 3 and 12; the policy rate m_{t-1} , the bill rate b_{t-1} and the interbank rate c_{t-1} ; and the one-month changes Δm_{t-1} and Δb_{t-1} . The data are final revised values rather than the vintages available in real time. Interest-rate data are rarely revised, and revisions to monthly inflation in Nigeria are small outside the rebasing.

4.2 Models

1. **Random walk:** $\pi_t = \pi_{t-1}$.
2. **AR(3):** $\pi_t = \alpha + \sum_{k=1}^3 \phi_k \pi_{t-k} + \varepsilon_t$.
3. **ARDL macro:** the AR(3) augmented with the twelfth lag of inflation and the five money-market variables,

$$\pi_t = \alpha + \sum_{k=1}^3 \phi_k \pi_{t-k} + \phi_{12} \pi_{t-12} + \beta_1 m_{t-1} + \beta_2 b_{t-1} + \beta_3 c_{t-1} + \beta_4 \Delta m_{t-1} + \beta_5 \Delta b_{t-1} + \varepsilon_t$$
4. **Ridge:** the ARDL predictors, standardised, with a fixed penalty of 10.
5. **Random forest (levels):** 500 trees on the ARDL predictors, minimum leaf size eight, 75 per cent of predictors considered at each split.
6. **Random forest (changes):** the same forest fitted to $\Delta \pi_t$; the forecast is π_{t-1} plus the predicted change.

The ridge penalty and forest settings were fixed before the evaluation and not tuned on the test period. The random seed is fixed for reproducibility. The sixth model is the only one not found in the earlier literature on Nigerian inflation. It uses exactly the same information as the fifth but changes the target so that the forest predicts a quantity whose range is stable over time.

4.3 Evaluation

The initial training window contains the 190 target months from March 2006 to December 2021. Every model is re-estimated each month on all data before the target month and then used to forecast it. This gives 52 forecasts from January 2022 to April 2026. The main evaluation excludes January 2025 for the reasons given in Section 3.2, leaving 51 forecasts. Results are also reported for all 52 months and separately for January 2022 – December 2024 (36 forecasts) and February 2025 – April 2026 (15 forecasts).

Accuracy is measured by the root mean squared error (RMSE), the mean absolute error (MAE) and the mean error (actual minus forecast). Equal predictive accuracy is tested with the Diebold–Mariano statistic using the Harvey et al. (1997) small-sample correction. Because the ARDL and ridge models nest the AR(3), they are also compared with it by the one-sided Clark–West test.

5. RESULTS

5.1 Forecast accuracy

Table 1 presents the main results. The ARDL model with money-market indicators is the most accurate, with an RMSE of 0.844 and an MAE of 0.666 percentage points. The random walk has an RMSE of 0.972 and the AR(3) 0.894. The ARDL model therefore reduces RMSE by 13 per cent relative to the random walk and by 6 per cent relative to the AR(3). Both improvements are statistically significant. The Diebold–Mariano test rejects equal accuracy against the random walk at the 5 per cent level ($p = 0.043$) and against the AR(3) at the 1 per cent level ($p = 0.009$). The Clark–West statistic for the ARDL against the nested AR(3) is 3.49 ($p < 0.001$). H_1 is rejected: money-market indicators improve inflation forecasts.



Table 1 Out-of-sample forecast accuracy, January 2022 – April 2026 excluding January 2025 (51 forecasts)

Model	RMSE	MAE	Bias	DM vs RW	<i>p</i>	DM vs AR(3)	<i>p</i>	CW vs AR(3)	<i>p</i>
Random walk	0.972	0.763	0.142	—	—	—	—	—	—
AR(3)	0.894	0.723	0.194	1.345	0.185	—	—	—	—
ARDL macro	0.844	0.666	0.163	2.077	0.043	2.727	0.009	3.487	0.000
Ridge	1.333	1.016	0.209	-2.387	0.021	-2.384	0.021	-0.874	0.809
RF (levels)	3.780	3.144	1.966	-5.747	0.000	-5.716	0.000	—	—
RF (changes)	0.902	0.761	0.138	1.127	0.265	-0.131	0.896	—	—

Note. Errors in percentage points of year-on-year inflation; bias = mean of actual minus forecast. DM = Diebold–Mariano statistic with the Harvey et al. (1997) correction; positive values favour the model in the row. CW = Clark–West statistic for nested models, one-sided *p*-value. RF = random forest.

The ridge regression does worse than the unpenalised ARDL model despite using the same predictors, and it is significantly worse than both benchmarks. The penalty shrinks the coefficient on lagged inflation, which dominates the forecast, and pulls predictions towards the pre-2022 sample mean of about 11.6 per cent. In a period when inflation was more than twice that level, the shrinkage introduces bias rather than reducing variance. This does not mean that penalised regression is unsuitable, but it does mean that a penalty chosen for a stable period can be badly wrong when the series shifts.

5.2 The failure of the random forest in levels

The random forest fitted to inflation levels is by far the worst model, with an RMSE of 3.78 and a mean error of 1.97 points. Figure 2 shows why. The highest inflation rate in the initial training sample was 18.72 per cent. From mid-2022 actual inflation rose well above that level, and the forest's forecasts flattened out below it. As new observations were added to the training window the ceiling rose, but always with a lag, and the forest under-predicted inflation by three to four points through most of 2023 and 2024. In the 2022–2024 sub-period its mean error was 3.58 points and its RMSE 4.17.

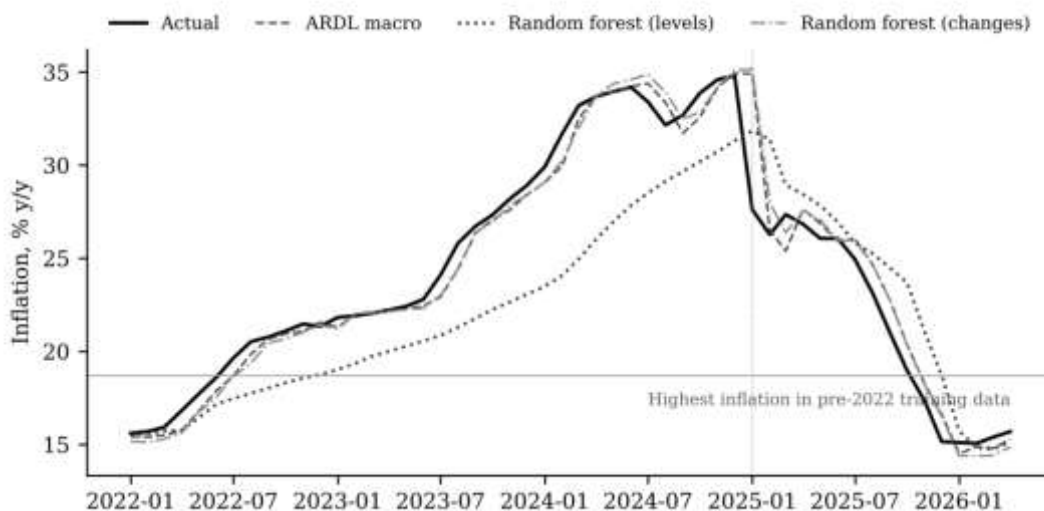


Figure 2. Actual inflation and one-month-ahead forecasts from the ARDL model and the two random forests, January 2022 – April 2026. The horizontal line marks the highest inflation rate in the pre-2022 training sample. Source: author's calculations.

The random forest fitted to monthly changes uses exactly the same information but does not suffer from this problem, because monthly changes in inflation stayed within their historical range even as the level rose. Its RMSE of 0.902 is almost a quarter of that of the levels forest and is close to the AR(3). It is better than the random walk on RMSE, although not significantly so ($p = 0.265$). H_2 is therefore not rejected: the machine-learning models do not beat the linear ARDL model. But the comparison shows that most of the apparent weakness of random forests in this setting comes from how the problem is posed, not from the method itself.



5.3 Sub-periods and the rebasing month

Table 2 reports RMSEs for the two sub-periods and for the full set of 52 forecasts. The ranking is remarkably stable. The ARDL model is the most accurate linear model in both 2022–2024 and 2025–2026, and the Clark–West test favours it over the AR(3) in each sub-period ($p = 0.008$ and 0.004). During 2022–2024 the random walk is the weakest of the linear benchmarks because inflation was rising almost every month, so a no-change forecast was persistently too low; its mean error in that period was 0.53 points. After the rebasing, when inflation was falling, the random walk's errors changed sign but remained large.

Table 2 Root mean squared errors by evaluation period

Model	2022–2024 (36)	Feb 2025 – Apr 2026 (15)	All 52 months incl. Jan 2025
Random walk	0.808	1.282	1.386
AR(3)	0.762	1.152	1.359
ARDL macro	0.718	1.088	1.313
Ridge	1.089	1.789	1.633
RF (levels)	4.170	2.613	3.789
RF (changes)	0.793	1.122	1.377

Note. Number of forecasts in parentheses. CW tests of ARDL macro against AR(3): $p = 0.008$ (2022–2024), 0.004 (2025–2026), 0.001 (all 52 months).

Including January 2025 raises the RMSE of every model except the levels forest by between 0.3 and 0.5 points, because every model predicted inflation of about 35 per cent for that month and the recorded figure was 27.61 per cent. The miss is almost identical across models and does not change the ranking. It is better understood as a change in the measuring instrument than as a forecast failure.

5.4 In-sample estimates

Table 3 reports the ARDL forecasting equation estimated on 2006–2021 and on the full sample. Lagged inflation dominates both, with the first lag above one and the sum of the autoregressive coefficients close to one (1.01 over the full sample), confirming the near-unit-root behaviour found in Section 3.3. Before 2022 none of the money-market variables is significant, individually or jointly ($F = 0.63$, $p = 0.679$). Over the full sample the policy rate, bill rate and interbank rate are all individually significant at the 5 per cent level and jointly significant ($F = 2.87$, $p = 0.016$).

Table 3 ARDL forecasting equation for headline inflation

Regressor	2006–2021 coef.	HAC s.e.	Full sample coef.	HAC s.e.
Intercept	0.737*	0.399	0.272	0.181
Inflation ($t-1$)	1.080***	0.090	1.179***	0.070
Inflation ($t-2$)	-0.033	0.180	-0.153	0.144
Inflation ($t-3$)	-0.081	0.124	-0.018	0.108
Inflation ($t-12$)	-0.036	0.026	-0.041*	0.022
Policy rate ($t-1$)	0.032	0.034	0.050**	0.023
T-bill rate ($t-1$)	-0.020	0.018	-0.028**	0.014
Interbank rate ($t-1$)	-0.007	0.005	-0.014**	0.006
Δ Policy rate ($t-1$)	0.036	0.143	0.068	0.107
Δ T-bill rate ($t-1$)	0.034	0.055	0.048	0.030
January 2025 dummy	–	–	-7.016***	0.239
Observations	190		242	
R^2	0.934		0.983	
Joint test, money-market variables	$F = 0.63$ ($p = 0.679$)		$F = 2.87$ ($p = 0.016$)	

Note. Dependent variable: headline inflation at t . Newey–West HAC standard errors with six lags. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The signs are informative but should be read with care. The positive coefficient on the policy rate does not mean that raising the MPR raises inflation. It reflects the fact that the CBN raised the policy rate when it saw inflationary pressure building, so a high policy rate signals that inflation is likely to keep rising in the short run. The negative coefficients on the bill and interbank rates indicate that, given the policy rate, tighter money-market conditions were followed by slightly lower inflation. That pattern is consistent with the view that liquidity conditions in the money market, rather



than the announced policy rate, carry the more direct signal about the monetary stance in Nigeria, a theme that recurs in the literature on weak policy-rate transmission (Mishra et al., 2012). The predictive content of these variables appears only when the 2022–2026 period is included, which matches the out-of-sample results and suggests that their usefulness is tied to episodes of large policy and liquidity movements.

5.5 Rolling windows and a three-month horizon

Two further checks examine how far the main result depends on the evaluation design. Table 4 reports them. With a rolling 120-month estimation window instead of an expanding one, the ARDL model remains more accurate than both benchmarks on RMSE (0.936 against 0.972 for the random walk and 1.003 for the AR(3)), and its advantage over the AR(3) is close to significant on the Clark–West test ($p = 0.051$), but the difference from the random walk is no longer significant ($p = 0.812$). At a three-month horizon, using direct forecasts with all predictors dated three months before the target, the ARDL model is again clearly better than the AR(3) (Clark–West $p < 0.001$ with an expanding window) but only level with the random walk (RMSE 2.584 against 2.589). With a rolling window at three months, none of the models beats the random walk.

Table 4 Robustness of forecast accuracy to the estimation window and horizon (RMSE, percentage points)

Horizon and window	Random walk	AR(3)	ARDL macro	DM, ARDL vs RW (p)	CW, ARDL vs AR(3) (p)
1 month, expanding	0.972	0.894	0.844	0.043	0.000
1 month, rolling 120	0.972	1.003	0.936	0.812	0.051
3 months, expanding	2.589	2.733	2.584	0.936	0.000
3 months, rolling 120	2.589	2.879	2.786	0.548	0.219

Note. One-month results exclude January 2025 (51 forecasts); three-month results exclude the target months January to March 2025, whose year-on-year rates straddle the rebasing (49 forecasts). Direct three-month forecasts use predictors dated $t - 3$. DM = Diebold–Mariano p -value with the Harvey et al. (1997) correction; CW = one-sided Clark–West p -value.

The robust finding, then, is that money-market indicators consistently improve on an autoregression that uses inflation's own history. Whether they also beat the simplest possible forecast, that next month's inflation will equal this month's, depends on the design: they do so significantly only at the one-month horizon with an expanding window. This pattern is familiar from the international literature, in which the random walk is a notoriously hard benchmark for inflation (Atkeson & Ohanian, 2001; Faust & Wright, 2013).

6. DISCUSSION

The results lead to a fairly clear conclusion. A simple linear model that adds three money-market rates and their changes to lagged inflation gives better one-month-ahead forecasts than either a random walk or an autoregression, and it does so consistently through the inflation surge of 2022–2024 and the disinflation that followed the rebasing. The improvement is modest in absolute terms, about 0.13 percentage points of RMSE relative to the random walk. The gain over the autoregression is robust to the estimation window and the forecast horizon; the gain over the random walk is significant only in the main design.

The comparison with machine-learning methods is just as important. A random forest applied naively to the level of inflation produced the worst forecasts in the study by a wide margin. The reason is structural rather than a matter of tuning. Tree ensembles interpolate within the range of their training data and cannot extrapolate beyond it. When Nigerian inflation broke through its historical ceiling in 2022, the forest's forecasts stayed below that ceiling. Reformulating the problem in terms of monthly changes, which did not leave their historical range, made the forest competitive with the autoregressive benchmark. This lesson is general. Before applying a tree-based model to a persistent macroeconomic series, the researcher should ask whether the target is likely to move outside the range of the training sample and, if so, transform it.

The weakness of the ridge regression has a related cause. With a single fixed penalty, the model shrank the coefficient on lagged inflation and pulled forecasts towards the historical mean. Penalised regression is most useful when there are many weak predictors; here there is one dominant predictor and a few weak ones, and shrinking the dominant one is costly.



The in-sample results show that the predictive content of money-market rates is not constant. Before 2022 these variables added nothing; over the full sample they are jointly significant. This is consistent with Rossi's (2013) evidence that forecasting relationships shift over time and with Faust and Wright's (2013) observation that the gains from additional predictors tend to be episodic. In Nigeria, the episode that made money-market rates informative was the combination of aggressive policy tightening and large liquidity operations after 2022. Whether that information will remain useful as inflation falls is an open question.

6.1 Implications

For analysts at the CBN, commercial banks and asset managers, the results suggest that a transparent ARDL model with money-market rates is a reasonable short-term forecasting tool and a sensible benchmark against which more complex models should be judged. For researchers applying machine learning to Nigerian macroeconomic data, the paper shows that model choice matters less than problem formulation: a forest fitted to the right target performs reasonably, while the same forest fitted to the wrong one fails badly. For anyone working with Nigerian inflation data after 2024, the rebasing must be handled explicitly; a single unadjusted month can add up to half a point to a model's RMSE.

6.2 Limitations

The evaluation period of 51 months is short, and although the main results hold in both sub-periods, the post-rebasing sample of 15 months is small. The models use final rather than real-time data. Only one-month-ahead forecasts are considered; the value of money-market information may differ at the policy-relevant horizons of six to twelve months. The ridge penalty and forest hyperparameters were fixed rather than tuned, which avoids overfitting the evaluation period but may understate what carefully tuned models could achieve. Finally, the rebased and old CPI series are not strictly comparable, and the lags of inflation used in 2025 mix observations from the two bases. Future work could use the NBS back-cast series, once available, to construct a consistent history.

7. CONCLUSION

Money-market indicators do help to forecast Nigerian inflation. Adding the policy rate, Treasury bill rate and interbank rate to an autoregressive model reduced the one-month-ahead RMSE by 13 per cent relative to a random walk over January 2022 to April 2026, and the gains are statistically significant and consistent across sub-periods. The improvement over an autoregression survives rolling windows and a three-month horizon, while the improvement over the random walk is more fragile. The predictive content of these variables appears only in the recent high-inflation period. A random forest fitted to inflation levels failed because it could not extrapolate beyond its training range, but the same forest fitted to monthly changes performed close to an autoregressive benchmark. The CPI rebasing of January 2025 produced a seven-point forecast miss in every model and should be treated as a break in measurement. The broader lesson is that careful problem formulation and honest benchmarking matter more for inflation forecasting than the choice between econometric and machine-learning methods.

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