



Does Monetary Policy Improve Bank Lending-Rate Forecasts in Nigeria? Evidence from Econometric and Machine-Learning Models, 2006-2026

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Abstract: Nigerian borrowers do not pay the monetary policy rate; they pay a bank lending rate that is set by commercial banks with one eye on the Central Bank of Nigeria (CBN) and another on their own funding costs. This paper asks whether the policy rate and related money-market indicators help to forecast the prime lending rate one month ahead, over and above what the lending rate's own history already tells us. Using monthly CBN data from January 2006 to March 2026 (242 forecast pairs), I compare a random walk, a first-order autoregression, an autoregressive distributed-lag (ARDL) regression with the policy rate, Treasury bill rate, interbank rate and inflation, a ridge regression and a random forest. Each model is re-estimated every month and evaluated on 51 out-of-sample forecasts from January 2022 to March 2026. The prime lending rate is extremely persistent, and the linear models are statistically indistinguishable from one another (root mean squared errors of 0.454 to 0.460 percentage points), while the random forest is significantly less accurate (RMSE 0.618; Diebold–Mariano $p = 0.004$). At a three-month horizon, however, the macro-financial model reduces forecast error by about 13 per cent and is significantly more accurate than the autoregression (Clark–West $p < 0.001$). The macro-financial variables are individually insignificant in the forecasting equation but jointly significant ($F = 3.32$, $p = 0.011$), and policy-rate changes pass through to the prime rate only partially, with a cumulative three-month coefficient of 0.27. A bounds test finds no stable long-run relationship between the prime rate, the policy rate, Treasury bills and inflation. I also show that a single mis-recorded observation in the source file (September 2025) roughly triples forecast errors and reverses the model ranking if left uncorrected. The results point to slow, partial repricing of bank loans in Nigeria and caution against treating flexible machine-learning models as a shortcut to better forecasts in short, regime-prone samples.

Keywords: monetary policy transmission; prime lending rate; interest-rate pass-through; forecasting; random forest; Nigeria

JEL classification: E43; E52; G21; C53

1. INTRODUCTION

The CBN can move the monetary policy rate (MPR) by several hundred basis points at a single Monetary Policy Committee meeting. Between April 2022 and November 2024 it did exactly that, raising the MPR from 11.5 per cent to 27.5 per cent. Over the same period the average prime lending rate reported by deposit money banks rose from 11.83 per cent to 18.39 per cent, an increase of about 6.6 percentage points against a 16-point rise in the policy rate. Whatever else this tells us, it shows that the rate at which Nigerian firms borrow does not follow the policy rate one for one, and that the link between the two is worth studying with some care.

There are two ways to frame that link. The first is structural: how much of a policy change eventually reaches loan rates, and how quickly? A large literature on interest-rate pass-through, beginning with Cottarelli and Kourelis (1994), addresses this question, and several Nigerian studies have estimated pass-through coefficients with cointegration and nonlinear ARDL methods (Tule, 2014; Jibrilla & Balami, 2022; Oyadeyi, 2023). The second framing is predictive and is the one taken here. A bank treasurer, a corporate borrower negotiating a facility, or an analyst at the central bank wants to know what the lending rate will be next month. If the policy rate carries useful information about future lending rates, it should improve forecasts relative to a model that uses only the lending rate's own past. If it does not, then whatever effect monetary policy has on loan pricing is either too slow, too small or too noisy to show up at a one-month horizon.



The predictive question has practical value of its own and it also provides a demanding test of the transmission story. Stock and Watson (2002) and many later papers show that variables which look important in-sample often add little out of sample. Machine-learning methods have sharpened this debate. Medeiros et al. (2021) find that random forests improve inflation forecasts for the United States, but there is little evidence on whether such gains carry over to a short, structurally unstable sample like Nigeria's, where the policy framework, the exchange-rate regime and even the consumer price index have changed within the last few years.

This paper makes three contributions. First, it builds a monthly dataset directly from the CBN money-market and inflation releases for January 2006 to March 2026 and documents several problems in the published series that affect any analysis using them, including zero values recorded for months with no Treasury bill or interbank quotation and an implausible prime lending rate for September 2025. Second, it runs a forecast comparison of five models with an expanding estimation window, monthly re-estimation, and formal tests of equal predictive accuracy (Diebold & Mariano, 1995; Harvey et al., 1997; Clark & West, 2007). Third, it supplements the forecast comparison with in-sample evidence on short-run pass-through and on the existence of a long-run relationship, using the bounds-testing approach of Pesaran et al. (2001). Taken together, these pieces explain why the policy rate matters for lending rates in a statistical sense while adding very little to one-month-ahead forecasts.

The main findings can be summarised briefly. The prime lending rate behaves almost like a random walk at a monthly frequency. Adding the policy rate, Treasury bill rate, interbank rate and inflation lowers the root mean squared forecast error by about one per cent, a gain that is not statistically significant. The random forest does markedly worse than every linear model. In-sample, the four macro-financial variables are jointly significant even though none is individually significant, and changes in the policy rate are followed by changes in the prime rate that cumulate to about 0.27 within three months. There is no evidence of cointegration among the levels. The rest of the paper is organised as follows. Section 2 reviews the literature. Section 3 describes the data. Section 4 sets out the models and the evaluation design. Section 5 presents the results, Section 6 discusses them and Section 7 concludes.

2. LITERATURE REVIEW

2.1 How policy rates reach loan rates

The idea that monetary policy works partly through bank lending rates goes back to the credit-channel literature. Bernanke and Blinder (1992) show that the federal funds rate is a good indicator of the stance of US monetary policy and that bank loans respond to it with a lag. Bernanke and Gertler (1995) explain why frictions in credit markets can amplify or dampen the effect of a policy change, depending on the balance sheets of borrowers and lenders. In both accounts, banks are not passive conduits. They decide how much of a change in their funding costs to pass on and how fast.

The pass-through literature measures that decision directly. Cottarelli and Kourelis (1994) estimate the response of lending rates to money-market rates across 31 countries and find that pass-through is slower where banking is less competitive and money markets are less developed. De Bondt (2005) reports similar heterogeneity across euro-area retail products, with immediate pass-through well below one and long-run pass-through closer to complete. Two explanations for slow adjustment recur in this work. Hannan and Berger (1991) attribute rigidity in deposit rates to market concentration, while Stiglitz and Weiss (1981) show that adverse selection can make banks reluctant to raise loan rates fully when their costs rise, because higher rates change the mix of borrowers who apply. Both mechanisms imply that lending rates should move less than policy rates in the short run and that the adjustment may differ between increases and decreases.

In a meta-analysis of this literature, Gregor et al. (2021) find that short-run pass-through to loan rates is typically incomplete and that estimates vary substantially across countries, loan types and estimation methods.

2.2 Evidence from Nigeria and other low-income economies

The case for expecting weak transmission in economies like Nigeria is set out by Mishra et al. (2012), who argue that shallow interbank and bond markets, concentrated banking systems and a large informal sector all reduce the influence of the policy rate on market rates. In a survey of the empirical evidence, Mishra and Montiel (2013) find that most studies of low-income countries report weak and unreliable effects of monetary policy on lending rates, although they caution that many of these studies are not well identified.

Nigerian evidence is broadly consistent with that view. Tule (2014) estimates a vector autoregression with the interbank rate as a proxy for the policy stance and finds that long-run pass-through is stronger to the prime and



maximum lending rates than to Treasury bill and deposit rates, with different responses to increases and decreases. Jibrilla and Balami (2022) use an asymmetric cointegration framework and report incomplete pass-through to both lending and deposit rates, stronger before financial liberalisation than after, with banks slower to raise loan rates than to cut them. Oyadeyi (2023) uses annual data from 1981 to 2021 and finds that pass-through from the policy rate to money-market, lending and deposit rates is incomplete and is weakened, rather than strengthened, by financial development. In a nonlinear ARDL extension, Oyadeyi (2024) shows that positive and negative changes in monetary policy affect the transmission channels differently. Nadani et al. (2026), using annual data from 1970 to 2024, also find incomplete long-run pass-through and faster responses of lending rates to policy increases than to cuts. Apanisile (2024) examines the effect of the 2008–2009 crisis and the subsequent banking reforms on the transmission mechanism and concludes that the credit channel became the most influential channel after the reforms.

These studies agree that pass-through in Nigeria is partial. They are less informative about timing at a monthly frequency, since most rely on annual or quarterly data, and none asks whether the policy rate improves real-time forecasts of lending rates. That is the gap this paper addresses.

2.3 Forecasting with many predictors and with machine learning

The forecasting literature offers a useful discipline. Stock and Watson (2002) show that information from a large panel of predictors can improve macroeconomic forecasts, but the improvement has to be demonstrated against simple benchmarks rather than assumed. In exchange-rate forecasting, Meese and Rogoff (1983) famously found that structural models could not beat a random walk out of sample. For persistent series such as administered interest rates, a random walk or a low-order autoregression is a natural and hard-to-beat benchmark.

Penalised and nonlinear methods are now standard additions to such comparisons. Ridge regression shrinks coefficients towards zero to reduce variance when predictors are correlated (Hoerl & Kennard, 1970), as the policy rate, Treasury bill rate and interbank rate clearly are. Random forests average many regression trees grown on bootstrap samples and can capture nonlinearities and interactions without a parametric model (Breiman, 2001). Medeiros et al. (2021) find meaningful gains from random forests in forecasting US inflation. Tree-based models have a known weakness, however: they cannot predict values outside the range of the training data, which matters when a series trends or moves into a new regime.

Comparing forecasts also requires formal tests. Diebold and Mariano (1995) propose a test of equal predictive accuracy based on the loss differential between two forecasts, and Harvey et al. (1997) provide a small-sample correction. When one model nests another, as an autoregression is nested in an ARDL model, the Diebold–Mariano statistic is undersized and the adjusted test of Clark and West (2007) is more appropriate. Hyndman and Athanasopoulos (2021) describe the rolling-origin evaluation used here, in which every forecast is produced using only data available before the target month.

2.4 Hypotheses

The literature leads to two testable hypotheses. The first concerns prediction:

H1: Adding the policy rate, Treasury bill rate, interbank rate and inflation to an autoregressive model of the prime lending rate does not reduce one-month-ahead forecast errors.

The second concerns the in-sample relationship:

H2: Changes in the policy rate are not followed by changes in the prime lending rate, and the levels of the two rates do not share a long-run relationship.

Rejecting H1 would show that monetary and money-market indicators carry predictive information about lending rates. Rejecting H2 would show that policy changes are transmitted to loan pricing even if that transmission is too small or too slow to improve monthly forecasts.

3. DATA

3.1 Sources and definitions

All data come from the CBN. Interest rates are taken from the CBN money-market indicators series (Central Bank of Nigeria, 2026b), which reports monthly averages of the interbank call rate, the Treasury bill rate, deposit rates at several maturities, the prime lending rate and the maximum lending rate. Headline inflation is the year-on-year change in the all-items consumer price index, from the CBN inflation series (Central Bank of Nigeria, 2026a), which reproduces the National Bureau of Statistics (NBS) figures. The common sample runs from January 2006 to March 2026, giving 243 monthly observations. Because the target is next month's prime rate, the forecasting sample contains 242 pairs, with target months running from February 2006 to March 2026.



The policy rate requires one adjustment. The CBN replaced the minimum rediscount rate (MRR) with the MPR as its main policy instrument in December 2006. I use the MRR for January to November 2006 and the MPR from December 2006 onwards. The two rates played the same role in signalling the policy stance, but they were embedded in different operating frameworks, so the first eleven months should be treated with some caution.

3.2 Data screening

Working directly with the published series revealed three problems that are worth reporting because they would affect any study using the same data. First, the Treasury bill rate is recorded as 0.00 per cent in December 2017 and December 2018. Treasury bill yields at the time were above 10 per cent, and these entries almost certainly reflect months in which no rate was reported rather than zero yields. Second, the interbank call rate is recorded as 0.00 in October 2020, December 2021, September 2022 and October 2022. Interbank rates did fall to very low levels in late 2020 when the CBN restricted access to its standing deposit facility, but exact zeros are best read as missing quotations. Third, the prime lending rate for September 2025 is 11.90 per cent, while the values for August and October 2025 are 18.88 and 18.89 per cent. A seven-point fall and recovery in a single month is not plausible for an administered rate that moves, on average, by 0.28 percentage points a month, and I treat it as a recording error. In all seven cases the value is set to missing and filled by linear interpolation between adjacent months. Section 5.5 reports how the main results change if the series are used as published.

3.3 Descriptive statistics

Table 1 summarises the five series. The prime lending rate averaged 16.1 per cent and ranged from 11.13 to 19.66 per cent. It is far less volatile than the money-market rates: its standard deviation of 2.04 percentage points compares with 4.72 for the Treasury bill rate and 8.64 for the interbank rate. The interbank rate is the most erratic series in the sample, with a maximum of 64.58 per cent during the liquidity squeezes of 2016-2017 and a kurtosis of nearly eight. Inflation averaged 14.3 per cent but rose to 34.8 per cent in December 2024 before the NBS rebased the consumer price index in January 2025. The Jarque–Bera test rejects normality for every series.

Table 1 Descriptive statistics, January 2006 – March 2026 (per cent)

Variable	Mean	SD	Min	Median	Max	Skewness	Kurtosis	JB <i>p</i>
Prime lending rate	16.10	2.04	11.13	16.57	19.66	-0.86	3.27	0.000
Monetary policy rate	13.50	5.37	6.00	12.00	27.50	1.37	4.55	0.000
Treasury bill rate	8.81	4.72	0.03	9.11	19.07	0.07	2.10	0.015
Interbank call rate	13.08	8.64	0.77	11.15	64.58	1.60	7.89	0.000
Headline inflation	14.32	6.68	3.00	12.60	34.80	1.25	4.39	0.000

Note. *N* = 243 for each series. JB = Jarque–Bera test of normality. The policy rate is the minimum rediscount rate until November 2006 and the monetary policy rate thereafter.

Figure 1 plots the prime rate against the policy rate and the Treasury bill rate. Three episodes stand out. Between 2006 and 2015 the policy rate and the prime rate moved in a fairly narrow band and the Treasury bill rate tracked the policy rate closely. From late 2019 to 2021, following the CBN's restriction of open market operation (OMO) bills to banks and foreign investors, Treasury bill yields collapsed to near zero while both the policy rate and the prime rate stayed broadly unchanged. From 2022, the policy rate was raised steeply and the prime rate followed, but by much less.

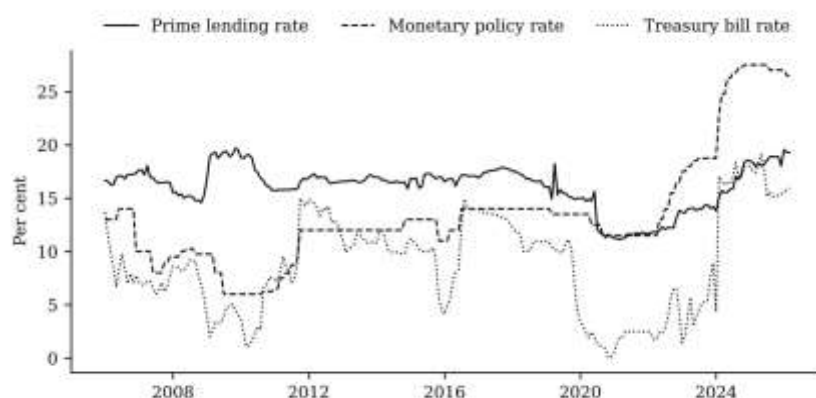


Figure 1. Prime lending rate, monetary policy rate and Treasury bill rate, January 2006 – March 2026. Source: Central Bank of Nigeria; author's calculations.



3.4 Unit-root properties

Table 2 reports augmented Dickey–Fuller (ADF) tests (Dickey & Fuller, 1979), KPSS tests (Kwiatkowski et al., 1992) and Zivot–Andrews tests that allow a single break in the intercept (Zivot & Andrews, 1992). The ADF test does not reject a unit root in the level of any series at the 5 per cent level, and the KPSS test rejects level stationarity for the prime rate, the policy rate, the interbank rate and inflation. The Treasury bill rate is the one ambiguous case, with neither test rejecting. All five series are stationary in first differences. Allowing for a break does not change these conclusions; the Zivot–Andrews statistics are well short of their critical values, and the estimated break dates cluster in 2021–2023, when inflation accelerated and the CBN began its tightening cycle. I therefore treat the variables as integrated of order one, which matters for interpreting the levels regressions in Section 5 and motivates the bounds test.

Table 2 Unit-root and stationarity tests

Series	ADF level	ADF p	KPSS level	ADF Δ	KPSS Δ	ZA stat.	ZA break
Prime lending rate	−1.521	0.523	0.507	−10.810	0.166	−2.293	2023-02
Monetary policy rate	−0.364	0.916	1.361	−4.809	0.381	−4.057	2022-04
Treasury bill rate	−2.093	0.247	0.163	−15.574	0.133	−3.071	2023-02
Interbank call rate	−2.717	0.071	0.701	−11.039	0.210	−4.105	2017-10
Headline inflation	−2.014	0.281	1.292	−8.731	0.078	−3.736	2021-11

Note. ADF regressions include a constant, with lag length chosen by AIC. KPSS 5 per cent critical value = 0.463 (null: stationarity). Δ denotes the first difference; all ADF statistics on first differences have $p < 0.001$. Zivot–Andrews (ZA) 5 per cent critical value = −4.80 (break in intercept).

4. METHODOLOGY

4.1 Forecast target and information set

Let y_t denote the prime lending rate in month t . The forecast target is y_{t+1} , and every predictor is dated t . The information set therefore contains the current prime rate, the policy rate m_t , the Treasury bill rate b_t , the interbank call rate c_t and headline inflation π_t . Because the NBS rebased the consumer price index in January 2025, which lowered measured inflation by about seven percentage points in a single month, the ARDL, ridge and random forest models also include a dummy variable D_t equal to one from January 2025. The series used here are the latest published values, not the data that were available in real time, so the exercise is a pseudo-out-of-sample comparison rather than a real-time one. Revisions to interest-rate series are rare, but inflation figures are occasionally revised.

4.2 Competing models

Five forecasting models are compared.

1. **Random walk.** The forecast is the current value: $\hat{y}_{t+1} = y_t$.
2. **AR(1).** $y_{t+1} = \alpha + \phi y_t + \varepsilon_{t+1}$, estimated by ordinary least squares (OLS).
3. **ARDL macro.** The AR(1) is augmented with the macro-financial variables:

$$y_{t+1} = \alpha + \phi y_t + \beta_1 m_t + \beta_2 b_t + \beta_3 c_t + \beta_4 \pi_t + \delta D_t + \varepsilon_{t+1}.$$
4. **Ridge regression.** The same predictors as the ARDL model, standardised, with the penalty chosen from a grid of 30 values between 0.01 and 1,000 by five-fold time-series cross-validation inside each training window. The cross-validation folds respect time order, so the penalty is never chosen using observations later than the training data.
5. **Random forest.** 500 regression trees using the same predictors, with a maximum depth of four and a minimum of five observations per leaf. These settings are fixed in advance and not tuned on the evaluation period. The random seed is fixed for reproducibility.

4.3 Evaluation design

The initial estimation window contains the 191 target months from February 2006 to December 2021. Each model is then used to forecast January 2022. The window is extended by one month, all five models are re-estimated, and the next month is forecast. This continues until March 2026, giving 51 out-of-sample forecasts per model. The evaluation period was chosen because it contains the most demanding test for any forecasting model in the sample: the 2022–2024 tightening cycle, the exchange-rate unification of June 2023, the 400-basis-point MPR increase of February 2024, the CPI rebasing and the first rate cuts of 2025–2026.

Forecast accuracy is summarised by the root mean squared error (RMSE), the mean absolute error (MAE) and the mean forecast error (bias), defined as actual minus forecast. Equal predictive accuracy is tested with the Diebold–



Mariano statistic using squared-error loss and the Harvey et al. (1997) correction. Because the ARDL and ridge models nest the AR(1), they are also compared with it using the one-sided Clark–West test.

4.4 In-sample analysis

Three in-sample exercises complement the forecast comparison. First, the ARDL forecasting equation is estimated on the full sample and on the pre-2022 sample with Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors using six lags (Newey & West, 1987), and a Wald test is used to examine whether the four macro-financial variables are jointly significant. Second, short-run pass-through is estimated from a regression in first differences:

$$\Delta y_t = \alpha + \sum_{k=0}^3 \gamma_k \Delta m_{t-k} + \rho \Delta y_{t-1} + u_t,$$

where the sum $\sum_k \gamma_k$ measures the cumulative change in the prime rate in the three months following a one-point change in the policy rate. Third, the existence of a long-run relationship among the levels of the prime rate, the policy rate, the Treasury bill rate and inflation is tested with the ARDL bounds procedure of Pesaran et al. (2001), with lag lengths selected by the Akaike information criterion from up to six lags.

5. RESULTS

5.1 Out-of-sample forecast accuracy

Table 3 presents the main results. The four linear models are almost indistinguishable. The random walk has an RMSE of 0.460 percentage points, the AR(1) 0.457, and the ARDL and ridge models 0.454. In other words, adding the policy rate, Treasury bill rate, interbank rate and inflation reduces the RMSE of the autoregressive benchmark by less than one per cent. On MAE the ordering reverses slightly, with the random walk best at 0.298 and the ARDL model worst among the linear models at 0.309. None of these differences is close to statistical significance. The Diebold–Mariano p -values for the linear models against the AR(1) are all above 0.75, and the Clark–West tests, which are designed to give the larger nested model its best chance, give p -values of 0.131 for the ARDL model and 0.178 for ridge regression. H1 cannot be rejected.

Table 3 Out-of-sample forecast accuracy, January 2022 – March 2026 (51 forecasts)

Model	RMSE	MAE	Bias	DM vs AR(1)	p	CW vs AR(1)	p
Random walk	0.460	0.298	0.149	−0.319	0.751	—	—
AR(1)	0.457	0.301	0.138	—	—	—	—
ARDL macro	0.454	0.309	0.099	0.206	0.838	1.123	0.131
Ridge	0.454	0.306	0.116	0.232	0.817	0.921	0.178
Random forest	0.618	0.474	0.351	−2.997	0.004	—	—

Note. Errors in percentage points; bias = mean of actual minus forecast. DM = Diebold–Mariano statistic with the Harvey et al. (1997) correction, squared-error loss; a positive value means the model is more accurate than the AR(1). CW = Clark–West (2007) statistic for nested models, one-sided p -value.

The random forest is the clear exception. Its RMSE of 0.618 is 35 per cent higher than that of the AR(1), and the Diebold–Mariano test rejects equal accuracy at the 1 per cent level ($p = 0.004$). The test against the random walk gives the same result. The forest also has by far the largest bias: on average it under-predicts the prime rate by 0.35 percentage points. The reason is visible in Figure 2. During 2024 and 2025 the prime rate rose to levels above almost all of the training data, and a tree ensemble, which forecasts by averaging past outcomes in similar regions of the predictor space, cannot predict values it has not seen. The linear models extrapolate naturally and track the rise.

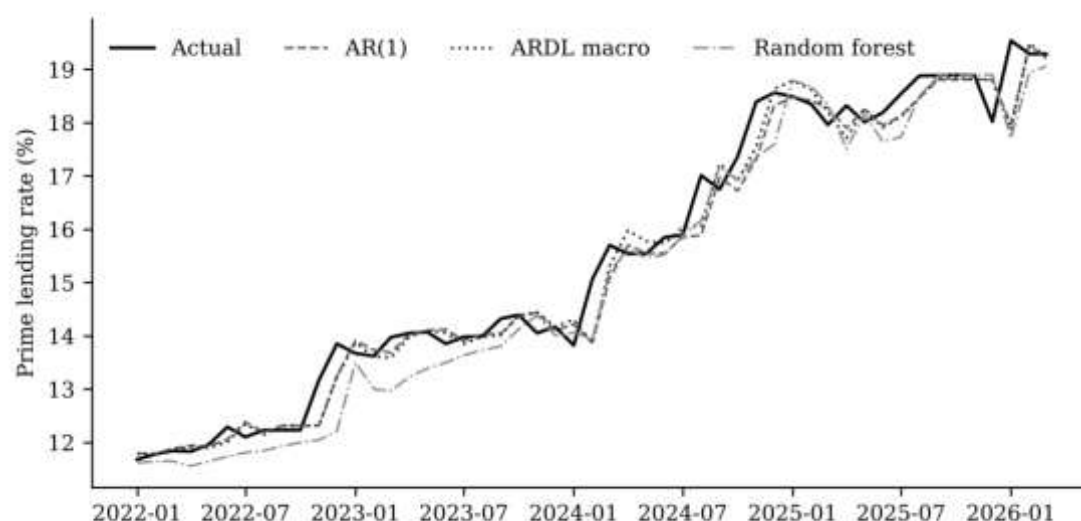


Figure 2. Actual prime lending rate and one-month-ahead forecasts, January 2022 – March 2026. Source: author's calculations.

All models share a positive bias, meaning that they under-predicted the prime rate during a period in which it was mostly rising. The largest errors occurred in months when the prime rate jumped. In February 2024, the month in which the MPR was raised by 400 basis points to 22.75 per cent, the prime rate rose from 13.82 to 15.06 per cent, and the AR(1) forecast missed by 1.19 points. In January 2026 the prime rate rose by about 1.5 points, again producing a miss of about the same size. No model anticipated these jumps, which suggests that the timing of large repricing events is not well predicted by the information in the previous month's rates.

5.2 What the forecasting equation says in-sample

Table 4 reports the ARDL forecasting equation estimated on the pre-2022 window and on the full sample. The lagged prime rate dominates, with a coefficient of 0.950 before 2022 and 0.955 over the full sample, and the equation explains 91 to 93 per cent of the variation in next month's prime rate. None of the four macro-financial variables is individually significant in either sample, and the CPI-rebasing dummy is close to zero.

Table 4 Forecasting equation for next month's prime lending rate

Regressor	Pre-2022 coef.	HAC s.e.	Full-sample coef.	HAC s.e.
Intercept	0.779	0.585	0.513	0.387
Prime lending rate (t)	0.950***	0.032	0.955***	0.026
Monetary policy rate (t)	-0.019	0.022	-0.004	0.014
Treasury bill rate (t)	0.019	0.019	0.016	0.015
Interbank call rate (t)	0.003	0.003	0.002	0.003
Headline inflation (t)	0.003	0.008	0.008	0.007
CPI rebasing dummy	—	—	0.003	0.164
Observations	191		242	
R^2	0.912		0.934	
Wald test, four macro variables = 0			$F = 3.32$ ($p = 0.011$)	

Note. Dependent variable: prime lending rate at $t+1$. Newey–West HAC standard errors with six lags. *** $p < 0.01$.

The joint test tells a different story from the individual coefficients. The Wald statistic for the null that all four macro-financial coefficients are zero is 3.32, with a p -value of 0.011. The four variables are highly correlated with one another, which inflates the individual standard errors, but taken together they carry information about next month's prime rate beyond its current value. That information is real but small: it improves the in-sample fit by a fraction of a percentage point of R^2 , and Section 5.1 shows that it does not translate into a measurable gain out of sample. Because the levels of these series contain unit roots, the levels coefficients in Table 4 should not be read as long-run elasticities. They are useful as a description of the forecasting equation but not as estimates of pass-through.



5.3 Short-run pass-through

The regression in first differences gives a clearer picture of how the prime rate responds to policy changes. The contemporaneous coefficient on the change in the policy rate is 0.114 (HAC *s.e.* 0.060, $p = 0.058$), and the coefficients on the first three lags are 0.030, 0.073 and 0.052. None of the lagged coefficients is significant on its own, but their sum, the cumulative three-month pass-through, is 0.27, and a Wald test rejects the null that it is zero ($p = 0.005$). A one-percentage-point increase in the MPR is therefore associated with an increase of roughly a quarter of a point in the prime lending rate over the following three months. The coefficient on the lagged change in the prime rate is negative (-0.231) but insignificant, which suggests some mild reversal of monthly moves.

This estimate sits at the lower end of the range found in other Nigerian studies and well below the complete long-run pass-through implied by a frictionless model. It is consistent with the descriptive evidence in the introduction, where the prime rate rose by about 0.41 points for each point of policy tightening between 2022 and 2024. H2 is rejected in its short-run form: policy changes are transmitted to the prime rate, but only partially.

5.4 Is there a long-run relationship?

The bounds test selects an ARDL(2, 1) specification for the prime rate with the policy rate, Treasury bill rate and inflation as long-run forcing variables. The F -statistic is 2.20, below the 5 per cent lower bound of 2.88 for the case with an unrestricted intercept and no trend, so the null of no level relationship cannot be rejected even if all regressors are treated as stationary. The error-correction coefficient is small and insignificant (-0.029 , $p = 0.187$), which would imply a half-life of adjustment of almost two years if it were taken at face value. The data therefore do not support a stable long-run relationship between the prime rate and the policy rate over 2006–2026. The most likely reason is that the relationship itself shifted: the prime rate exceeded the policy rate by between 4 and 12 points in every year before 2016, the gap closed to almost nothing in 2020–2021, and from 2022 the policy rate sat above the prime rate, by an average of more than 9 points in 2024.

5.5 Sensitivity to data screening

Section 3.2 describes seven observations that were treated as missing and interpolated. Of these, the one that matters most for the forecasting exercise is the prime rate for September 2025. If the series is used as published, it enters the evaluation period twice: once as a target that every model misses by about seven points, and once as a predictor that produces a second miss of the same size in October 2025. Table 5 shows the effect. The RMSE of every linear model roughly triples, from about 0.46 to between 1.43 and 1.51 percentage points, and the ranking changes. With the uncorrected series, the random forest has the lowest RMSE, because its forecasts are less sensitive to a single extreme input, while the ARDL and ridge models appear worse than the AR(1).

Table 5 Forecast accuracy with the prime lending rate as published (including September 2025 = 11.90%)

Model	RMSE	MAE	DM vs AR(1)	p
Random walk	1.458	0.572	-1.261	0.213
AR(1)	1.432	0.569	—	—
ARDL macro	1.510	0.591	-1.010	0.317
Ridge	1.499	0.586	-1.006	0.320
Random forest	1.415	0.749	0.167	0.868

Note. Same design as Table 3. Only the treatment of the seven screened observations differs.

This sensitivity is the strongest practical lesson of the exercise. One mis-recorded number among 243 is enough to change which model appears best on the most widely reported accuracy measure. Any forecasting study using the published CBN money-market series should screen it for zero entries and isolated outliers before estimation.

5.6 Forecast horizon, rolling windows and the rebasing dummy

Three further checks address choices that a reader might question. The first concerns the CPI-rebasing dummy. Because it is a step dummy estimated from only a few post-2025 observations, it adds noise to the 2025–2026 forecasts. Without it, the ARDL model's one-month RMSE falls from 0.454 to 0.446, and the Clark–West test against the AR(1) becomes significant at the 5 per cent level ($p = 0.041$), although the Diebold–Mariano test still does not reject equal accuracy ($p = 0.488$). The second check uses a rolling 120-month estimation window instead of an expanding one. The random walk remains the most accurate model (RMSE 0.460), the ARDL model is slightly worse than the AR(1) on RMSE, and the Clark–West test again gives a p -value just below 5 per cent (0.037).

The third check is the most informative. Table 6 repeats the comparison for a three-month horizon, using direct forecasts in which every predictor is dated three months before the target. At this horizon the macro-financial information matters much more. With an expanding window, the ARDL model's RMSE is 0.663 against 0.764 for the AR(1) and 0.774 for the random walk, a reduction of about 13 per cent; the Clark–West statistic is 3.30 ($p < 0.001$) and



the Diebold–Mariano test favours the ARDL model at the 10 per cent level ($p = 0.093$). With a rolling window the advantage over the AR(1) remains significant on the Clark–West test ($p = 0.003$), but neither model beats the random walk.

Table 6 Forecast accuracy at one- and three-month horizons, January 2022 – March 2026 (51 forecasts)

Horizon and window	Random walk RMSE	AR(1) RMSE	ARDL macro RMSE	CW, ARDL vs AR(1)	p
1 month, expanding	0.460	0.457	0.446	1.741	0.041
1 month, rolling 120	0.460	0.467	0.480	1.784	0.037
3 months, expanding	0.774	0.764	0.663	3.304	0.000
3 months, rolling 120	0.774	0.807	0.822	2.733	0.003

Note. Models estimated without the CPI-rebasing dummy. Three-month forecasts are direct: the target is the prime rate in month $t + 3$ and every predictor is dated t . CW = Clark–West statistic, one-sided p -value.

These results refine the main conclusion rather than overturn it. At a one-month horizon the macro-financial variables add, at best, a small and fragile improvement. Over a quarter, when policy changes have had time to pass through, they carry clearer information about where the prime rate is heading. This is exactly what the slow, partial pass-through found in Section 5.3 would lead one to expect.

6. DISCUSSION

The results fit together more neatly than the individual numbers might suggest, and the horizon results in Section 5.6 tie them together. In-sample, the policy rate matters: policy changes are followed by partial changes in the prime rate, and the macro-financial variables are jointly significant in the forecasting equation. Out of sample, these effects are too small relative to the noise in monthly lending-rate changes to improve forecasts. A cumulative three-month pass-through of about 0.27 means that a typical 50-basis-point policy move would change the prime rate by roughly 13 basis points over a quarter, and only a fraction of that within the first month. The median monthly change in the prime rate is 14 basis points. Information of this size is easily swamped by the idiosyncratic month-to-month movement in the series.

Why is pass-through so incomplete? The data cannot settle this, but the pattern is consistent with the explanations in the literature. Nigerian banks fund themselves largely through low-cost current and savings deposits whose rates rarely move with the MPR, so a policy increase raises their marginal funding cost by less than the headline change. The cash reserve requirement, which the CBN has also used heavily, affects bank margins through a different channel that the MPR does not capture. Concentration in the banking market and the credit-rationing logic of Stiglitz and Weiss (1981) both predict that banks adjust quantities and non-price terms rather than the posted prime rate. Finally, the prime rate is by construction the rate charged to the most creditworthy customers, and it may be the stickiest point in the loan-rate distribution.

The breakdown of any stable long-run relationship deserves emphasis. For most of the sample, the prime rate exceeded the policy rate by several points. By 2024 the MPR exceeded the prime rate by a wide margin, a configuration that is unusual by international standards and that reflects both the scale of the CBN's tightening and the weak link between the policy rate and bank funding costs. A model estimated on 2006–2021 data would not have anticipated this inversion. This is one reason the error-correction framework favoured by much of the pass-through literature fits the Nigerian data poorly over this period.

The poor performance of the random forest is also informative. Its failure comes from a well-known limitation rather than from overfitting in the usual sense. Because a regression tree predicts the average outcome in each terminal node, a forest cannot forecast a value higher than the largest value seen in training. When the prime rate rose to new highs in 2024 and 2025, the forest was structurally unable to follow. This limitation is easy to overlook when machine-learning methods are applied to macroeconomic series that trend or shift between regimes. It does not mean that tree-based methods are useless for Nigerian data, but it does mean that they should be applied to transformations, such as changes or spreads, that stay within a stable range.

For practitioners, the main implication is that the current prime rate is the best simple guide to next month's rate, and that policy announcements should be expected to move it slowly and partially. A borrower anticipating a policy



increase should expect a fraction of the change to reach the prime rate within a quarter, with larger and faster adjustments at the riskier end of the loan market. For the CBN, the weak pass-through suggests that the MPR on its own is a blunt instrument for influencing bank lending costs and that its effect on loan pricing depends heavily on complementary measures such as liquidity management and reserve requirements.

6.1 Limitations

Several limitations should be noted. The prime lending rate is a reported average of the rates banks charge their best customers, not a transaction-weighted average of new loan rates, and it may understate how much loan pricing actually responds to policy. The forecasts use final revised data, which slightly overstates the information available in real time. The splice between the MRR and the MPR in late 2006 combines two operating frameworks. The 51-month evaluation period is long enough to include several distinct episodes, but it is still short for tests of equal predictive accuracy, and the test results should be read with that in mind. Finally, the analysis does not identify exogenous monetary policy shocks. The policy rate responds to inflation and exchange-rate conditions that also affect bank funding costs, so the pass-through estimates are conditional associations rather than causal effects. A natural extension would use bank-level loan data and high-frequency identification of policy surprises around Monetary Policy Committee announcements.

7. CONCLUSION

This paper has asked whether the monetary policy rate and related money-market indicators improve forecasts of Nigeria's prime lending rate. One month ahead, over January 2022 to March 2026, they add little. The prime rate is so persistent that a random walk is almost impossible to beat, and an ARDL model with the policy rate, Treasury bill rate, interbank rate and inflation improves on an autoregression by about one to two per cent, a gain that is significant only on the nested Clark–West test and only in some specifications. Three months ahead the picture changes: the same information reduces forecast error by about 13 per cent and is clearly significant against the autoregression. A random forest does significantly worse than every linear model because it cannot extrapolate beyond the range of its training data.

The absence of forecasting gains does not mean that monetary policy has no effect on lending rates. In-sample, the macro-financial variables are jointly significant, and changes in the policy rate are followed by changes in the prime rate that cumulate to about a quarter of the policy change within three months. What the evidence shows is that this transmission is partial, slow and unstable over time, with no long-run relationship that survives the regime changes of 2016–2025. The paper also shows that a single mis-recorded observation in the published data can reverse the conclusions of a forecast comparison, which is a useful reminder that data screening deserves as much attention as model choice.

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