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Financial Market Stress and Monetary Policy Transmission in Nigeria: Evidence from Regime-Switching Models and Machine Learning.

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Abstract: This paper asks whether the link between the monetary policy rate and the interbank call rate in Nigeria changes when the money market is under stress, and whether models that allow for such changes forecast better. Using monthly Central Bank of Nigeria data for August 2006 to March 2026 (236 observations), I estimate a two-state Markov-switching model of interbank-rate changes, a Markov-switching regression with regime-dependent policy effects, and a threshold regression in which stress is defined by recent interbank volatility. The Markov model separates a calm regime, with a variance of 4.2 squared percentage points and an expected duration of 21 months, from a turbulent regime with a variance of 204 and an expected duration of nine months; the turbulent regime covers 30 per cent of the sample and was dominant in 2015–2018. In the calm regime, a one-point policy change is followed by a 1.09-point change in the interbank rate ($p = 0.001$); in the turbulent regime the response is imprecisely estimated and not significant. The threshold regression initially suggests that policy changes have the opposite effect under stress (interaction −3.80, $p = 0.008$), but this result disappears when the gap between the interbank rate and the policy rate is controlled for and when the stress threshold is moved. The main force driving interbank changes is a strong pull back towards the policy corridor. Out of sample, over January 2022 to March 2026, a linear model has the lowest root mean squared error, and the threshold model, a corridor model and a random forest all do worse. Stress clearly changes the behaviour of the interbank market, but it does not make policy transmission easier to predict.

Keywords: financial stress; interbank market; monetary policy transmission; Markov switching; threshold regression; Nigeria

JEL classification: E43; E52; G12; C22; C53

1. INTRODUCTION

The interbank call rate is the first market price that the Central Bank of Nigeria's (CBN) policy decisions are supposed to influence. Under the corridor system introduced with the monetary policy rate (MPR) in December 2006, the CBN offers a standing lending facility above the MPR and a standing deposit facility below it, and in normal conditions the interbank rate should trade within that corridor. In practice the Nigerian interbank market has gone through long periods of calm interrupted by episodes in which the rate jumps by twenty or thirty percentage points in a month and then falls back. In April 2017 the monthly average call rate reached 64.6 per cent, more than four times the MPR. At other times, notably late 2020, it fell close to zero.

Such episodes matter for monetary policy. If the interbank rate responds reliably to policy changes when markets are calm but erratically when they are stressed, the CBN's ability to transmit policy depends on market conditions. A policy increase made during a liquidity squeeze may have a different effect from the same increase made in normal times. For banks and treasury desks, the question is also practical: should funding plans assume that the interbank rate will follow the MPR, or should they allow for the possibility that market conditions will dominate?

Two econometric tools are designed for this kind of question. Markov-switching models (Hamilton, 1989, 1990) allow the parameters of a time series to change according to an unobserved state that follows a Markov chain. They identify regimes from the data without the researcher having to define them in advance. Threshold models (Hansen, 2000) instead define regimes by whether an observable variable, such as recent volatility, exceeds a cut-off. The two approaches are complementary: Markov models describe the regimes; threshold models can be used for forecasting, because the regime is known in real time.

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This paper applies both to the Nigerian interbank market and makes three contributions. First, it documents the regime structure of interbank-rate changes over 2006–2026, including the duration and timing of turbulent periods. Second, it estimates how the response of the interbank rate to policy changes differs between regimes, using a Markov-switching regression with regime-dependent coefficients and a threshold regression with an observable stress indicator. It shows that an apparently strong interaction between policy changes and stress in the threshold model is fragile and largely reflects the pull of the interbank rate back towards the policy rate. Third, it compares out-of-sample forecasts from linear, threshold, corridor and random forest models over 2022–2026. The results suggest that stress changes the behaviour of the market, but that a simple linear model remains the best forecasting tool.

Section 2 reviews the literature. Section 3 describes the data, Section 4 the methods and Section 5 the results. Section 6 discusses the findings and Section 7 concludes.

2. LITERATURE REVIEW

2.1 Interbank markets and the policy corridor

In most modern operating frameworks, the central bank steers the overnight interbank rate by setting a corridor of standing facilities around its policy rate and adjusting the supply of reserves through open market operations. Poole (1968) showed how banks' demand for reserves under uncertainty about end-of-day balances determines the overnight rate, and why the rate becomes volatile when reserves are scarce. Bindseil (2014) describes how corridor systems work in practice and why the overnight rate can deviate from the policy rate when liquidity conditions are unbalanced or when access to facilities is restricted.

Financial frictions can make these deviations large. Brunnermeier and Pedersen (2009) show how funding liquidity and market liquidity reinforce one another, so that a shock to one can produce a spiral that pushes prices far from fundamentals. Bernanke and Gertler (1995) argue more broadly that credit-market frictions alter the transmission of monetary policy. In low-income countries, where interbank markets are thin and segmented, these frictions are likely to be more severe (Mishra et al., 2012).

2.2 Measuring financial stress

Several studies construct composite indicators of financial stress. Illing and Liu (2006) build a daily index for Canada from banking, foreign-exchange, debt and equity market indicators. Hakkio and Keeton (2009) develop the Kansas City Financial Stress Index and describe the features that characterise stress: uncertainty about fundamental values, uncertainty about the behaviour of other investors, asymmetric information, flight to quality and flight to liquidity. For Nigeria, Ilesanmi and Tewari (2019) construct a financial stress index using equal-variance and principal-component weights and show that it identifies the main episodes of stress in the Nigerian system. These indices are useful summaries, but they require data on many markets. A simpler approach, used in this paper, is to measure stress in the money market by the volatility of the interbank rate itself.

2.3 Regime-switching models

Hamilton (1989) introduced the Markov-switching model to describe business cycles as switches between expansion and recession regimes, and Hamilton (1990) extended the estimation method to general time series. Kim and Nelson (1999) develop the state-space version and its applications. Markov-switching models have been widely used to describe volatility regimes in interest rates and asset returns. In Nigeria, Chuku (2010) uses a Markov-switching state-space model to study the interaction of monetary and fiscal policy and finds periods in which the two offset each other. Threshold models, studied formally by Hansen (2000), define regimes by an observable variable. They are easier to interpret and to use for forecasting, but inference about the threshold is non-standard when it is estimated from the same data.

2.4 Transmission through the Nigerian corridor

Two recent CBN studies examine transmission through the standing facilities. Eleam et al. (2021a) find that changes in the standing facility rates pass through to retail bank rates slowly, with no clear evidence of asymmetry. Eleam et al. (2021b), using a vector error-correction model with breaks, conclude that retail and money-market rates adjust slowly to changes in the corridor and that the corridor is a weak transmission tool. Neither study allows the transmission mechanism to vary with market conditions.

2.5 Hypotheses

H1: The response of the interbank rate to policy-rate changes is the same in calm and stressed market conditions.

H2: Models that allow for regime-dependent responses do not forecast interbank-rate changes better than a linear model.

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3. DATA

3.1 Sources and construction

The interbank call rate, the MPR and inflation are monthly series from the CBN money-market indicators and inflation releases (Central Bank of Nigeria, 2026a, 2026b), covering January 2006 to March 2026. The policy rate is the minimum rediscount rate (MRR) until November 2006 and the MPR from December 2006. The change in the policy rate in December 2006, when the 14 per cent MRR was replaced by the 10 per cent MPR, is set to zero because it reflects a change of instrument rather than of stance. The interbank series records values of exactly zero for October 2020, December 2021, September 2022 and October 2022; these are treated as missing quotations and interpolated.

The dependent variable is the monthly change in the interbank rate, $\Delta\, i_t$. The regressors are the lagged change $\Delta\, i_{t-1}$, the lagged change in the policy rate $\Delta\, p_{t-1}$, lagged inflation π_{t-1} and, in some specifications, the lagged gap between the interbank rate and the policy rate, $i_{t-1} - p_{t-1}$, which measures how far the interbank rate is from the centre of the corridor. The stress indicator H_t equals one when the standard deviation of the six interbank changes before month t exceeds the 75th percentile of that statistic in the pre-2022 sample, which is 10.42 percentage points. The indicator therefore uses only information available before the month it describes. Building the lags and the volatility measure leaves 236 observations from August 2006 to March 2026, of which 185 fall before January 2022.

3.2 Descriptive statistics

The monthly change in the interbank rate has a mean close to zero (0.08 points) but a standard deviation of 7.99 points and a range from −43.3 to +51.5. Its kurtosis of 15.0 indicates that a few very large changes coexist with many small ones. The six-month volatility measure averages 5.86 points, with a median of 3.01 and a maximum of 32.1. The stress indicator is on in 19.5 per cent of months, all of them before 2022.

4. METHODOLOGY

4.1 Markov-switching models

The first Markov model allows the mean and variance of interbank changes to depend on an unobserved state $S_t \in \{0, 1\}$:

$$\Delta\, i_t = \mu_S t\sim\sim + \varepsilon_t,\ \varepsilon_t \text{ sim } N(0, \sigma^2_S t\sim\sim),$$

where S_t follows a first-order Markov chain with transition probabilities $p_{jk} = P(S_t = k \mid S_{t-1} = j)$. The second model adds the lagged policy change and the lagged interbank change, with regime-dependent coefficients:

$$\Delta\, i_t = \mu_S t\sim\sim + \beta_S t\sim\sim\, \Delta\, p_{t-1} + \varphi_S t\sim\sim\, \Delta\, i_{t-1} + \varepsilon_t,\ \varepsilon_t \text{ sim } N(0, \sigma^2_S t\sim\sim).$$

Both models are estimated by maximum likelihood over the full sample, using 50 random starting values to avoid local maxima. The smoothed regime probabilities use the whole sample and are used for description only, not for forecasting.

4.2 Threshold regression

The threshold model is

$$\Delta\, i_t = \alpha + \varphi\, \Delta\, i_{t-1} + \beta\, \Delta\, p_{t-1} + \gamma\, \pi_{t-1} + \lambda\, H_t + \delta\, (H_t \times \Delta\, p_{t-1}) + u_t.$$

The response to a policy change is β in calm months and $\beta + \delta$ in stressed months, so H1 implies $\delta = 0$. Because the threshold is fixed from the pre-2022 sample rather than estimated by searching over all possible cut-offs, standard inference applies, but the results may depend on the choice of cut-off. I therefore re-estimate the model with cut-offs at the 66th and 90th percentiles. A further specification adds the lagged interbank–policy gap, which captures the tendency of the interbank rate to return towards the corridor. All threshold and linear regressions are estimated by ordinary least squares with Newey and West (1987) standard errors using six lags.

4.3 Forecast evaluation

Five forecasts of $\Delta\, i_t$ are compared: no change, the linear model (the threshold model without H_t terms), the threshold model with the cut-off re-estimated at each forecast origin, the linear model with the interbank–policy gap, and a random forest (Breiman, 2001) with 500 trees, maximum depth five and minimum leaf size six, using the linear-model predictors plus volatility and the gap. All models are re-estimated every month with an expanding window, so each

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forecast uses all the information available at the time. The evaluation covers the 51 months from January 2022 to March 2026. Accuracy is measured by the root mean squared error (RMSE) and mean absolute error (MAE), and models are compared with the Diebold and Mariano (1995) test using the Harvey et al. (1997) correction.

5. RESULTS

5.1 Volatility regimes

Table 1 reports the two Markov-switching models. In the first, the two regimes differ sharply in variance but not in mean. The calm regime has a variance of 4.24 squared percentage points (a standard deviation of about 2.1 points) and the turbulent regime a variance of 204 (a standard deviation of about 14.3 points). Neither regime mean is significantly different from zero. Both regimes are persistent. The probability of staying in the calm regime is 0.95, giving an expected duration of 21 months, and the probability of leaving the turbulent regime is 0.11, giving an expected duration of 8.8 months.

Table 1 Markov-switching models of monthly interbank-rate changes

Parameter	Model 1: calm	Model 1: turbulent	Model 2: calm	Model 2: turbulent
Intercept	−0.081 (0.168)	0.460 (1.713)	−0.130 (0.170)	0.517 (1.484)
ΔPolicy rate (t−1)			1.086*** (0.326)	1.776 (3.270)
ΔInterbank (t−1)			−0.125* (0.073)	−0.515*** (0.106)
Variance σ²	4.236*** (0.535)	203.98*** (36.59)	4.196*** (0.534)	151.02*** (26.66)
P(stay in calm regime)	0.952***		0.958***	
P(turbulent → calm)	0.113**		0.099**	
Expected duration (months)	21.0	8.8		
Log-likelihood	−678.15		−663.74	

Note. N = 236 (August 2006 – March 2026). Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 1 plots the interbank changes and shades the months in which the smoothed probability of the turbulent regime exceeds 0.5. These months make up 30.1 per cent of the sample. The turbulent regime dominated in 2015–2018, when the CBN tightened liquidity heavily through open market operations and cash reserve requirements in the aftermath of the oil-price collapse, and in 2006 and 2009, around the introduction of the corridor and the banking crisis. In the recent period, the model places August 2023 to March 2024 in the turbulent regime, the months following the exchange-rate unification and leading up to the steep MPR increases of February and March 2024.

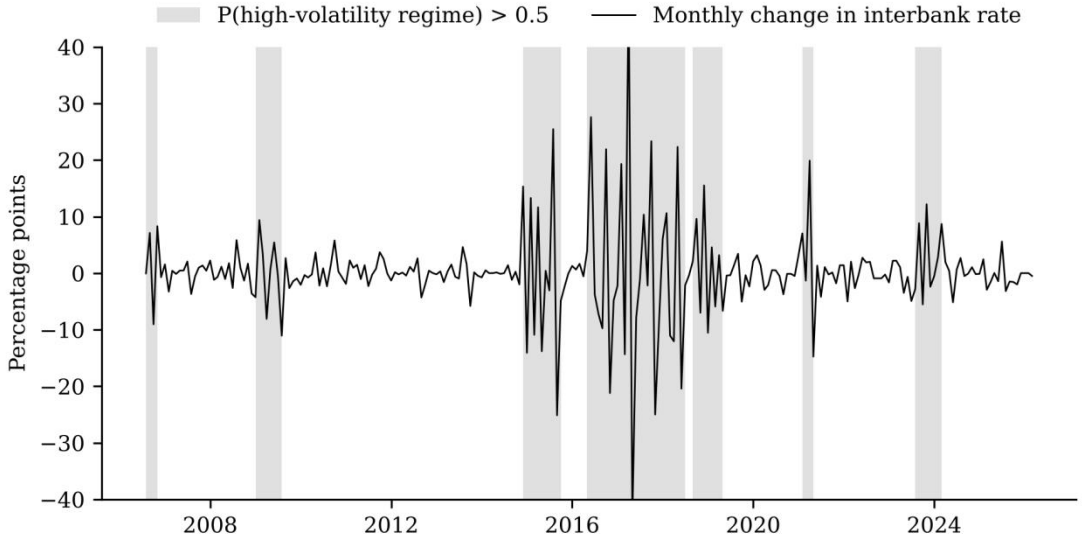


Figure 1. Monthly changes in the interbank call rate and months in which the smoothed probability of the high-volatility regime exceeds 0.5 (shaded). Source: author's calculations based on Central Bank of Nigeria data.

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5.2 Does the policy response differ across regimes?

The second Markov model allows the response to policy changes to differ between regimes. In the calm regime a one-point change in the policy rate is followed by a 1.09-point change in the interbank rate the next month, which is highly significant (p = 0.001) and close to one-for-one. In the turbulent regime the point estimate is larger (1.78) but its standard error is 3.27, so it is not significantly different from zero, nor from the calm-regime estimate. The clearest difference between the regimes lies in the dynamics of the interbank rate itself. In the turbulent regime the coefficient on the lagged interbank change is −0.52 ($p < 0.001$), so about half of any large move is reversed the next month; in the calm regime the reversal is weak (−0.13, p = 0.085). Stress makes the interbank rate noisier and more prone to reversal, and it makes the policy signal harder to detect, but it does not reverse its direction.

5.3 Threshold models

Table 2 reports the linear and threshold regressions. In the linear model, a one-point policy change is followed by a 1.40-point change in the interbank rate (p = 0.028), and the lagged interbank change has a coefficient of −0.48, again indicating strong reversal. The threshold model appears to tell a more dramatic story. In calm months the policy coefficient rises to 1.81 ($p < 0.001$), while the interaction with the stress indicator is −3.80 (p = 0.008). Taken at face value, this implies that policy changes in stressed months were followed by interbank moves in the opposite direction, with a combined slope of −1.99. The combined slope is not significantly different from zero (p = 0.142), however, and two further checks show that the interaction is not robust.

Table 2 Linear and threshold regressions for monthly interbank-rate changes

Regressor	Linear	Threshold	Threshold + corridor gap
Intercept	−0.259 (0.462)	0.091 (0.454)	−0.958 (0.730)
ΔInterbank (t−1)	−0.480*** (0.078)	−0.484*** (0.074)	−0.220*** (0.083)
ΔPolicy rate (t−1)	1.404** (0.641)	1.812*** (0.517)	1.123** (0.531)
Inflation (t−1)	0.019 (0.031)	0.014 (0.032)	0.045 (0.045)
High-stress indicator		−1.583* (0.926)	0.882 (1.630)
ΔPolicy × high stress		−3.802*** (1.426)	0.502 (1.362)
Interbank − policy rate (t−1)			−0.518*** (0.110)
R^2	0.235	0.248	0.366

Note. N = 236. Dependent variable: monthly change in the interbank call rate (percentage points). Newey–West HAC standard errors with six lags in parentheses. The stress indicator equals one when the standard deviation of the previous six interbank changes exceeds 10.42 points (75th percentile, pre-2022). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The first check moves the threshold. With a cut-off at the 66th percentile (6.41 points), which classifies 28.8 per cent of months as stressed, the interaction falls to −0.09 (p = 0.954). With a cut-off at the 90th percentile (16.16 points), the indicator is never on in a month that follows a policy change, so the interaction cannot be estimated at all. The negative interaction at the 75th percentile rests on a handful of policy changes that happened to fall in high-volatility months.

The second check adds the lagged gap between the interbank rate and the policy rate. Its coefficient is −0.52 ($p <$ 0.001): when the interbank rate is above the policy rate, it tends to fall the next month by about half of the gap, and when it is below, it tends to rise. Including the gap raises the R^2 from 0.248 to 0.366 and makes the stress interaction small, positive and insignificant (0.50, p = 0.712). The policy coefficient remains positive and significant (1.12, p = 0.035). What the threshold model was capturing was not a change in the effect of policy under stress but the fact that, in volatile months, the interbank rate was often far from the corridor and was about to move back. H1 cannot be rejected once this corridor pull is taken into account.

The same conclusion holds when stress is measured over different windows. With a three-month volatility window, the stress interaction is −2.99 ($p < 0.001$) without the corridor gap and −0.56 (p = 0.602) with it; with a twelve-month window it is −3.61 (p = 0.020) without the gap and −0.36 (p = 0.787) with it. In every case the coefficient on the corridor gap is about −0.45 to −0.52 and highly significant. The apparent reversal of policy effects under stress is an artefact of omitting the pull towards the corridor, whatever window is used to define stress.

5.4 Out-of-sample forecasts

Table 3 reports the forecasting results. The linear model has the lowest RMSE (3.18), and the no-change forecast the lowest MAE (2.29). The threshold model is worse than the linear model on both measures, and the difference is

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marginally significant ($p = 0.098$). The model with the corridor gap, which fits the data best in-sample, forecasts badly out of sample (RMSE 4.16; $p = 0.066$ against the linear model). The random forest is the worst of all, with an RMSE of 4.22 and an MAE of 3.61, and it is significantly worse than both the linear model ($p = 0.001$) and the no-change forecast ($p = 0.007$). H2 cannot be rejected; if anything, the regime-dependent and nonlinear models do worse.

Table 3 Out-of-sample forecasts of monthly interbank-rate changes, January 2022 – March 2026 (51 forecasts)

Model	RMSE	MAE	DM vs no change	*p*	DM vs linear	*p*
No change	3.344	2.285	–	–	–	–
Linear	3.179	2.396	0.518	0.607	–	–
Threshold	3.420	2.645	−0.183	0.856	−1.684	0.098
Linear + corridor gap	4.163	3.261	−1.239	0.221	−1.877	0.066
Random forest	4.225	3.609	−2.794	0.007	−3.715	0.001

Note. Percentage points. All models are re-estimated monthly with an expanding window. DM = Diebold–Mariano statistic with the Harvey et al. (1997) correction; positive values favour the model in the row.

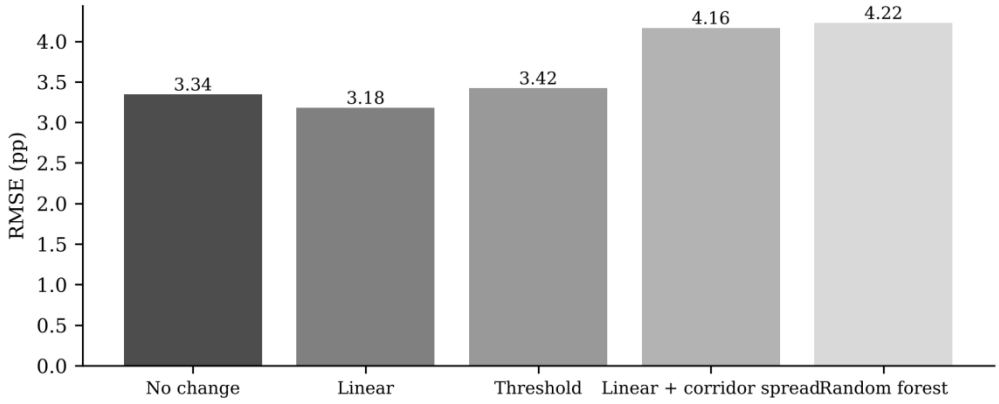


Figure 2. Out-of-sample root mean squared error by model, January 2022 – March 2026. Source: author's calculations.

The poor out-of-sample performance of the corridor model is worth noting. Over 2022–2026 the relationship between the interbank rate and the policy rate shifted, as the CBN adjusted the width and symmetry of the corridor several times and as the policy rate rose by 16 points in less than three years. A model that pulls the interbank rate towards a historical average gap was therefore pulling it towards the wrong level. The threshold model has a different problem: with the stress cut-off estimated from history, the indicator was rarely triggered in the evaluation period, even though the Markov model identifies August 2023 to March 2024 as turbulent, so the extra parameters added noise without adding information.

6. DISCUSSION

The results draw a clear distinction between describing instability and exploiting it. The Nigerian interbank market plainly has two regimes. In calm periods, which last on average almost two years, monthly changes in the call rate are small and track the policy rate closely, with a response close to one for one. In turbulent periods, which last nine months on average and have covered almost a third of the last twenty years, changes are seven times as volatile, large moves are quickly half-reversed, and the policy signal is lost in the noise.

What the data do not support is the stronger claim that policy works in the opposite direction under stress. That impression comes from one particular threshold choice and disappears when the corridor pull is controlled for. This is a useful caution for applied work on threshold effects. Interaction terms estimated on a small number of events in a volatile series can be large and significant without being robust, and they should be checked against alternative thresholds and against omitted variables that are correlated with both the regime and the outcome.

The importance of the corridor pull fits the institutional design. The CBN's standing facilities put a ceiling and a floor on the rates at which banks can borrow from and lend to the central bank, so a rate far outside the corridor creates

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arbitrage pressure that brings it back. When access to the facilities has been restricted, as with the cap on remunerable standing deposits introduced in 2019, the floor weakens and the interbank rate can fall well below the corridor, as it did in late 2020. Periods of very high rates, such as 2016–2017, coincided with aggressive liquidity mop-ups through open market operations and cash reserve debits. In both cases, the deviation from the corridor was large and was followed by a reversal. That pattern, rather than a change in the effect of the policy rate, is what dominates the turbulent regime.

For forecasting, the lesson is that complexity does not pay in this market. The linear model with the lagged policy change and lagged interbank change was the most accurate model on RMSE, while every attempt to model regimes, corridor dynamics or nonlinearities did worse out of sample. This is in line with the broader evidence that structural instability penalises richer models more than simple ones, and with the slow and imperfect transmission through the corridor found by Eleam et al. (2021a, 2021b).

6.1 Implications

For the CBN, the results suggest that the effectiveness of the policy rate in steering the interbank rate depends on keeping the market in the calm regime, which in turn depends on liquidity management and on keeping the standing facilities open and predictable. Policy changes made in turbulent conditions are unlikely to be transmitted cleanly. For bank treasurers, the Markov model offers a way to recognise turbulent regimes, but forecasts of the interbank rate during such periods should come with wide error bands. For researchers, the paper shows how an apparently strong nonlinear effect can be an artefact of threshold choice and omitted dynamics.

6.2 Limitations

The analysis uses monthly averages, which smooth out the daily spikes that characterise stress in interbank markets. The stress indicator is based only on interbank volatility and does not use the broader information that a composite index such as that of Ilesanmi and Tewari (2019) would provide. The Markov models are estimated on the full sample and are descriptive. Policy-rate changes are not exogenous; the CBN may have changed the rate in response to conditions in the money market. The analysis also does not separate the effects of the MPR from those of the cash reserve requirement and the corridor width, which the CBN often changed at the same time. A natural extension would use daily interbank and open-buy-back rates together with a record of corridor and reserve-requirement changes.

7. CONCLUSION

Nigeria's interbank market switches between a calm regime, in which the call rate follows the policy rate closely, and a turbulent regime, in which it is seven times as volatile and large moves are quickly reversed. The turbulent regime has covered about 30 per cent of the period since 2006 and was dominant in 2015–2018. An apparent reversal of the policy effect under stress turns out to be fragile: it disappears when the threshold is changed or when the pull of the rate back towards the corridor is taken into account. Out of sample, a simple linear model forecasts better than threshold, corridor or random forest models. Stress changes how the interbank market behaves, but it does not make policy transmission any easier to predict.

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