



Do Foreign-Exchange Reserves Predict Naira Depreciation? Evidence from Nigeria

Ofiero hor Ufuoma Earnest

University of Port Harcourt, Nigeria

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

Abstract: Nigeria's external reserves are watched closely as a signal of the central bank's capacity to defend the naira. This paper tests whether monthly changes in reserves help to forecast the next month's change in the official naira-US dollar exchange rate. Using Central Bank of Nigeria Statistical Bulletin data for January 2000 to December 2025, I estimate predictive regressions in which next-month depreciation depends on reserve growth, the current rate of depreciation, recent exchange-rate volatility and three-month momentum, with an extension that adds the change in the Bonny Light oil price. Over the full sample of 308 months, reserve growth has a negative and significant coefficient (-0.117 , HAC $p = 0.008$): faster reserve accumulation is followed by less depreciation. The relationship survives the exclusion of the large administrative devaluations of 2016, 2023 and 2024 and is weaker but still present before 2016. Oil-price changes add no significant information once reserves are included. Out of sample, however, the picture changes. Over the 83 months from February 2019 to December 2025, no model beats a random walk; the full model's root mean squared error is 8.53 against 7.45 for the random walk, and five devaluation months account for nearly 90 per cent of the random walk's squared forecast error. Adding reserve growth to an autoregression reduces the error slightly, but not significantly, and the same is true at a three-month horizon, where reserves have their largest in-sample effect. Reserves matter for the exchange rate, but in Nigeria the timing of large moves has been set by policy decisions that reserve data do not anticipate.

Keywords: external reserves; exchange rate; naira; forecasting; random walk; Nigeria

JEL classification: F31; F37; E58; C53

1. INTRODUCTION

Few statistics receive as much attention in Nigeria as the level of the Central Bank of Nigeria's (CBN) gross external reserves. Reserves rose from under US\$6 billion in January 2000 to a peak of US\$62 billion in September 2008, fell below US\$24 billion in 2016 and ended 2025 at about US\$46 billion. Over the same period the official exchange rate went from 99 to 1,451 naira per US dollar, which means that the naira lost about 93 per cent of its value against the dollar. The biggest moves came in a handful of months: the move to a flexible interbank market in June 2016, the unification of the official windows in June 2023 and the adjustments of February to May 2024.

It is widely believed that falling reserves foreshadow depreciation. The logic is straightforward. A central bank that defends a currency must sell foreign exchange, and when reserves run low, its ability to keep defending declines and the market anticipates a devaluation. Models of currency crises formalise this idea, and empirical studies of crisis prediction find that reserve losses are among the most reliable warning signs (Kaminsky et al., 1998; Frankel & Saravelos, 2012). The question for Nigeria is whether the same information is useful at the monthly frequency at which reserves are published and watched.

There is a strong reason to be sceptical. Meese and Rogoff (1983) showed that structural exchange-rate models fail to beat a random walk out of sample, and four decades of research have only partly overturned that finding (Engel & West, 2005; Rossi, 2013). A variable may be associated with exchange-rate movements in-sample and still be useless for forecasting, because the relationship is unstable or because most of the variation in the exchange rate comes from events the variable does not anticipate. In Nigeria the official rate has been managed for most of the period, so its largest movements reflect policy decisions rather than market pressure.

This paper examines both sides of the question. It makes three contributions. First, it estimates the predictive relationship between reserve growth and next-month depreciation over 2000–2025, covering the 2023–2025 reforms by combining the CBN's 2024 Statistical Bulletin with its fourth-quarter 2025 bulletin. Second, it checks whether the relationship survives the exclusion of large administrative devaluations, a pre-2016 subsample and the inclusion of oil



prices. Third, it evaluates out-of-sample forecasts against a random walk and an autoregression, with formal tests of predictive accuracy. The main finding is that reserves carry information about subsequent depreciation in-sample, but not enough to improve forecasts in a period dominated by discrete policy changes.

The rest of the paper is organised as follows. 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 Reserves and exchange-rate stability

Reserves serve several purposes. Aizenman and Lee (2007) distinguish a precautionary motive, in which countries hold reserves as self-insurance against sudden stops in capital inflows, from a mercantilist motive, in which reserve accumulation is a by-product of keeping the currency undervalued; they find that the precautionary motive is the more important. Obstfeld et al. (2010) show that reserve holdings are better explained by the size of the domestic financial system, and hence the potential demand for foreign currency in a crisis, than by trade flows. For exchange-rate behaviour, the key point is that reserves give the central bank the capacity to intervene. Fratzscher et al. (2019), using intervention data for 33 countries, find that intervention is often effective in smoothing the exchange rate and in keeping it within a band, especially when it is large and accompanied by communication.

2.2 Reserves as early-warning indicators

The early-warning literature asks whether reserves help to predict currency crises. Kaminsky et al. (1998) review a large set of potential indicators and find that falling reserves, real exchange-rate overvaluation and slowing exports are among the most informative. Frankel and Saravelos (2012), examining which countries were hit hardest in the 2008–2009 crisis, find that pre-crisis reserve levels and real exchange-rate overvaluation were the two most useful predictors. These studies look at crises as discrete events across countries, usually at an annual frequency. Whether monthly reserve changes help to predict monthly exchange-rate changes within one country is a different and harder question.

2.3 The difficulty of forecasting exchange rates

Meese and Rogoff (1983) found that monetary and portfolio-balance models could not beat a random walk at horizons of one to twelve months, even when the models were given the actual future values of their fundamentals. Engel and West (2005) offered an explanation: when fundamentals are close to random walks and the discount factor is near one, the exchange rate itself will behave almost like a random walk even if it is determined by fundamentals. In a comprehensive review, Rossi (2013) concludes that some predictors, in particular Taylor-rule fundamentals and net foreign assets, occasionally help out of sample, but that predictability is unstable and depends heavily on the sample, the horizon and the benchmark. Cheung et al. (2019), revisiting a wide range of models with newer data and more currencies, reach a similar verdict: no model consistently beats the random walk, and models that do well at one horizon or in one period often fail at another.

2.4 Evidence for Nigeria

Two CBN studies examine the relationship between reserves and the exchange rate directly. Ajibola et al. (2015), using quarterly data for 1990–2012, find threshold cointegration between the two: the long-run relationship holds only when deviations from equilibrium exceed an estimated threshold, and it is reserves rather than the exchange rate that adjust, consistent with the CBN using reserves to stabilise the naira. Nwachukwu et al. (2016), using daily data for 2014–2015, find a similar threshold relationship between external reserves and the bureau-de-change rate, with adjustment running from reserves to the exchange rate. Neither study evaluates out-of-sample forecasts, and both end before the reforms of 2016 and 2023–2024.

2.5 Hypotheses

H1: Monthly reserve growth has no association with next-month depreciation of the naira, conditional on recent exchange-rate movements.

H2: Adding reserve growth to a time-series model does not reduce out-of-sample forecast errors relative to a random walk.

3. DATA

3.1 Sources

The official exchange rate is the monthly average naira–US dollar rate from Table D.4.1 of the CBN Statistical Bulletin 2024, External Sector (Central Bank of Nigeria, 2025). External reserves are from Table D.3.1 of the same bulletin, in millions of US dollars. To extend the sample through 2025, I use Tables D.13 (exchange rates of the naira) and D.12

(gross external reserves) of the CBN's fourth-quarter 2025 Statistical Bulletin (Central Bank of Nigeria, 2026). For 2025 the official rate is the monthly average of the Nigerian Foreign Exchange Market (NFEM), the official window into which the previous segments were unified; for 2024, where the two bulletins overlap, the D.4.1 series coincides with the NFEM average and the two reserve series are identical, so the two sources join without a break. The Bonny Light spot price is from Table C.7 of the fourth-quarter 2025 bulletin.

The official rate is not a market-clearing price for most of the sample. The CBN operated a series of auction and interbank windows, the Retail Dutch Auction System was closed in February 2015, the interbank rate became the reference rate thereafter, and the Investors' and Exporters' window became the reference rate in May 2021 before the unification of June 2023. Parallel-market rates often diverged substantially from the official rate. The results therefore concern the official rate that applies to government transactions and much of formal trade, not the rate faced by every market participant.

3.2 Variables

Let S_t be the official rate (naira per dollar) and R_t gross reserves. Monthly depreciation is $d_t = 100 \ln(S_t/S_{t-1})$, so a positive value means the naira weakened. Reserve growth is $g_t = 100 \ln(R_t/R_{t-1})$, and the oil-price change o_t is defined in the same way. Recent volatility v_t is the standard deviation of d over the last three months, and momentum $mom_t = 100 \ln(S_t/S_{t-3})$ is the depreciation over the last three months. The target is next month's depreciation, d_{t+1} , and every predictor is observed in month t . The estimation panel contains 308 predictor months from April 2000 to November 2025, with targets from May 2000 to December 2025.

3.3 Descriptive statistics

Table 1 summarises the variables. Monthly depreciation averaged 0.86 per cent, but its median was almost zero and its distribution is extraordinarily skewed and fat-tailed, with a kurtosis above 50. In most months the official rate barely moved; in a few it moved by double digits. The largest depreciation was 46.7 per cent (log-change basis) in February 2024 and the largest appreciation 20.0 per cent in April 2024. Reserve growth averaged 0.67 per cent a month and was much less extreme. The oil price was the most volatile variable, with monthly changes ranging from -82 to +67 per cent.

Table 1 Descriptive statistics, February 2000 – December 2025

Variable	N	Mean	SD	Min	Median	Max	Skewness	Kurtosis
Monthly depreciation (%)	311	0.86	4.33	-20.03	0.00	46.65	5.61	53.53
Reserve growth (%)	311	0.67	4.31	-18.00	-0.07	14.46	0.27	4.39
Oil price change (%)	311	0.29	11.39	-81.59	0.92	66.98	-1.22	16.60

Note. Monthly log changes $\times 100$. Jarque–Bera tests reject normality for all three series ($p < 0.001$).

Figure 1 plots the exchange rate and reserves. Reserves rose steadily until 2008, fell sharply with the oil price in 2008–2009 and again in 2014–2016, recovered to more than US\$45 billion in 2018–2019 and then declined until 2024. The exchange rate moved in long flat stretches broken by sudden steps. Most of the large steps coincided with, or followed, periods of falling reserves, which is the pattern that motivates the question.

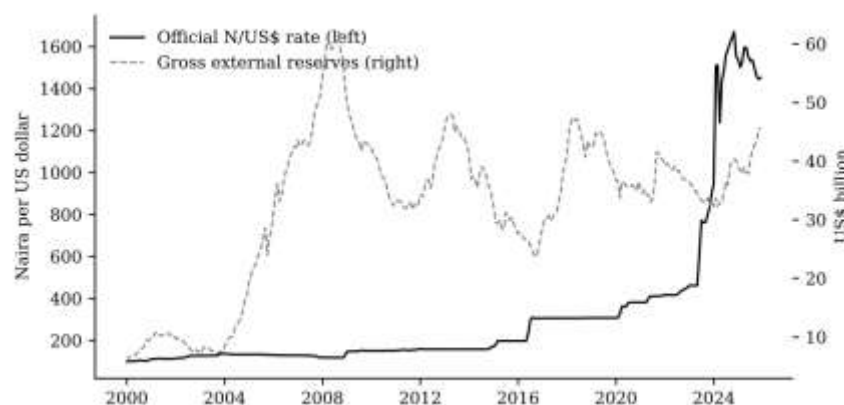


Figure 1. Official naira–US dollar exchange rate and gross external reserves, January 2000 – December 2025. Source: Central Bank of Nigeria Statistical Bulletin 2024 and Q4 2025 bulletin.



The log exchange rate is clearly non-stationary (ADF statistic 0.37, $p = 0.980$; KPSS 2.19), and so are log reserves according to the ADF and KPSS tests (ADF $p = 0.165$; KPSS 1.26), although a Zivot–Andrews test with a break in December 2003 rejects a unit root in reserves ($p = 0.023$). All variables used in the regressions are monthly growth rates, which are stationary.

4. METHODOLOGY

4.1 Predictive regression

The baseline model is

$$d_{t+1} = \alpha + \beta_1 d_t + \beta_2 g_t + \beta_3 v_t + \beta_4 mom_t + \varepsilon_{t+1},$$

estimated by ordinary least squares with Newey and West (1987) standard errors using three lags. H1 implies $\beta_2 = 0$. A negative β_2 would mean that months of reserve accumulation are followed by less depreciation and months of reserve loss by more. The other regressors control for the persistence and recent volatility of the exchange rate, so that the reserve coefficient is not simply picking up the fact that reserves tend to fall when the naira is already under pressure. A second specification adds the oil-price change o_t , since oil exports are Nigeria's main source of foreign exchange and might drive both reserves and the exchange rate.

The coefficients describe predictive associations. Reserves and the exchange rate are jointly determined by oil revenues, capital flows and CBN intervention, and a negative β_2 does not tell us that adding to reserves would cause the naira to appreciate. It tells us whether the reserve figure for this month contains information about the exchange-rate change next month.

4.2 Robustness

Three robustness checks are reported. The first re-estimates the model for 2000–2015, before the move to a more flexible regime in June 2016. The second excludes the seven months with the largest administrative adjustments of the official rate: June and July 2016, June and July 2023, and February, April and May 2024. The third adds the oil-price change.

4.3 Forecast evaluation

Five forecasts of next-month depreciation are compared: a random walk for the exchange rate level (zero forecast depreciation), an AR(1) for depreciation, an AR(1) augmented with reserve growth, the full model of Section 4.1 and the full model with oil. Each is re-estimated each month on all earlier data, and forecasts are produced for the 83 months from February 2019 to December 2025. Accuracy is measured by the root mean squared error (RMSE) and the mean absolute error (MAE). Each model is compared with the random walk by the Diebold and Mariano (1995) test with the Harvey et al. (1997) correction, and the AR(1) with reserves is compared with the nested AR(1) using the Clark and West (2007) test. The comparison is repeated excluding the devaluation months in the evaluation period.

5. RESULTS

5.1 Do reserves predict depreciation?

Table 2 reports the predictive regressions. In the full sample, reserve growth has a coefficient of -0.117 with a HAC standard error of 0.044 ($p = 0.008$). A month in which reserves grow by one percentage point more than usual is followed, on average, by about 0.12 percentage points less depreciation. A typical swing in reserve growth of one standard deviation (4.3 points) is therefore associated with about half a percentage point of depreciation the following month. The current rate of depreciation also enters positively (0.253 , $p = 0.086$), indicating some persistence, while volatility and momentum are insignificant. The model explains 7.8 per cent of the variation in next-month depreciation. H1 is rejected.

Table 2 Predictive regressions for next-month naira depreciation

Regressor	Full sample	With oil	2000–2015	Excluding devaluation months
Intercept	0.655** (0.308)	0.659** (0.304)	0.230** (0.105)	0.371*** (0.132)
Depreciation (<i>t</i>)	0.253* (0.147)	0.240 (0.147)	0.342** (0.138)	0.112* (0.068)
Reserve growth (<i>t</i>)	−0.117*** (0.044)	−0.115*** (0.043)	−0.062* (0.034)	−0.089** (0.035)
3-month volatility (<i>t</i>)	0.198 (0.193)	0.197 (0.192)	0.155 (0.196)	0.113* (0.058)
3-month depreciation (<i>t</i>)	−0.089 (0.084)	−0.083 (0.084)	−0.057 (0.102)	−0.043* (0.022)
Oil price change (<i>t</i>)		−0.027 (0.017)		
Observations	308	308	189	301
<i>R</i> ²	0.078	0.083	0.164	0.111

Note. Dependent variable: depreciation of the official naira–US dollar rate in month *t* + 1 (log change × 100).

Newey–West HAC standard errors with three lags in parentheses. The last column drops predictor months whose target is June or July 2016, June or July 2023, or February, April or May 2024. *** *p* < 0.01, ** *p* < 0.05, * *p* < 0.10.

The reserve effect is robust. Adding the oil-price change leaves it almost unchanged (−0.115, *p* = 0.008), and oil itself is not significant (*p* = 0.118). Reserves therefore carry information beyond what oil prices already contain, probably because they reflect the CBN’s actual foreign-exchange position after intervention, debt service and other outflows. Excluding the seven devaluation months reduces the coefficient to −0.089 but leaves it significant (*p* = 0.010), and the model’s *R*² actually rises to 0.111 because the extreme months add noise that no linear model can explain. Before 2016 the coefficient is about half as large (−0.062) and significant only at the 10 per cent level, but the *R*² is higher (0.164), mainly because depreciation was more persistent in the managed-rate period.

A simple comparison confirms the regression result. In months when reserve growth was in its bottom quartile, the naira depreciated by an average of 1.57 per cent the following month, compared with 0.63 per cent in other months. The medians, however, are almost zero in both groups (0.02 and 0.00 per cent). The difference in means comes from a small number of large devaluations that followed periods of reserve loss, not from a steady tendency for the naira to drift lower when reserves fall.

5.2 Out-of-sample forecasts

Table 3 reports the forecasting results. Over February 2019 to December 2025, the random walk has the lowest RMSE (7.45) and the lowest MAE (2.90). The AR(1) and the AR(1) with reserves are slightly worse, and the full model is clearly worse, with an RMSE of 8.53. None of the differences from the random walk is statistically significant. Adding reserves to the AR(1) lowers its RMSE from 7.64 to 7.58, but the Clark–West test does not reject equal accuracy (*p* = 0.147). Adding oil makes almost no difference. *H*₂ cannot be rejected.

Table 3 Out-of-sample forecasts of monthly depreciation, February 2019 – December 2025

Model	RMSE	MAE	DM vs RW	<i>p</i>	RMSE excl. devaluations	MAE excl. devaluations
Random walk	7.446	2.898	—	—	2.490	1.382
AR(1)	7.636	3.101	−0.274	0.785	3.929	1.729
AR(1) + reserves	7.579	3.137	−0.203	0.840	3.797	1.758
Full model	8.530	3.445	−1.004	0.319	3.887	1.897
Full model + oil	8.519	3.452	−1.022	0.310	3.861	1.896

Note. 83 one-month-ahead forecasts; the last two columns exclude the five devaluation months in the evaluation period (78 forecasts). Errors in percentage points of monthly log depreciation. DM = Diebold–Mariano statistic with the Harvey et al. (1997) correction; negative values favour the random walk. Clark–West test of AR(1) + reserves against AR(1): statistic 1.05, one-sided *p* = 0.147 (all months); 1.28, *p* = 0.101 (excluding devaluations).

Figure 2 shows why. The evaluation period contains several enormous monthly moves, and the forecast errors are dominated by them. The five devaluation months in the evaluation period account for 89 per cent of the random walk’s squared forecast errors. No model anticipated them, and the models that use recent depreciation and volatility then over-predicted further depreciation in the months that followed, which is why the full model does worst.

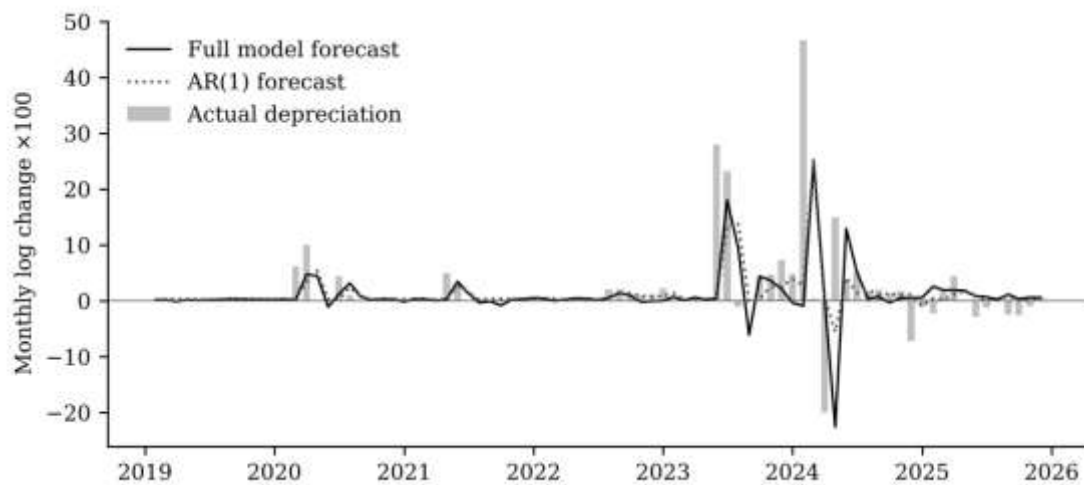


Figure 2. Actual monthly depreciation and one-month-ahead forecasts from the full model and the AR(1), February 2019 – December 2025. Source: author's calculations.

Excluding the devaluation months does not rescue the models. Without them the random walk's RMSE falls to 2.49, while the AR(1) and the reserve-augmented models remain above 3.7. The models embed an average depreciation drift and a positive persistence coefficient estimated from a history full of steps, and in the quiet months between steps they predict depreciation that does not happen.

5.3 Longer horizons and rolling windows

Reserves might matter more for the direction of the exchange rate over a quarter than over a month. Regressing cumulative depreciation over the next three months on the same predictors gives a reserve-growth coefficient of -0.328 (HAC $p < 0.001$), almost three times the one-month coefficient. Out of sample the three-month results are more favourable to reserves as well. Over March 2019 to December 2025 (82 forecasts), the AR(1) with reserve growth has the lowest RMSE of all models (13.51 percentage points with an expanding window and 13.27 with a rolling 120-month window, against 14.02 for the random walk). The improvement is about 4 to 5 per cent, but it is not statistically significant (Diebold–Mariano $p = 0.395$ and 0.233). At the one-month horizon, a rolling window leaves the conclusions of Table 3 unchanged: the random walk remains the most accurate forecast.

6. DISCUSSION

The results present a familiar contrast between in-sample association and out-of-sample usefulness, but with a specifically Nigerian explanation. In-sample, reserves clearly matter. Months of reserve loss have been followed by more depreciation, and the relationship survives several robustness checks, including the exclusion of the largest devaluations. This is consistent with the threshold relationships found by Ajibola et al. (2015) and Nwachukwu et al. (2016), in which reserves adjust to defend the exchange rate until the pressure becomes too great.

Out of sample, the information does not translate into better forecasts, because the timing of the large moves is a policy decision. When the CBN allowed the naira to float in June 2016, unified the windows in June 2023 or adjusted the NFEM rate in early 2024, the decision followed a long period of reserve pressure, but the exact month was set by policy considerations that the reserve series cannot reveal. A model that knows reserves are falling knows that a devaluation is more likely, but it does not know when. In a monthly forecasting exercise, that is the information that matters most. This is the same pattern that Rossi (2013) describes for advanced economies: fundamentals may be related to exchange rates, but the relationship is too unstable and too dominated by rare events to improve monthly point forecasts.

The weakness of oil prices as a predictor is also informative. Oil revenue is the main source of Nigeria's foreign-exchange earnings, but its effect on the official rate is filtered through the CBN's reserve management. Once the reserve figure is known, oil prices add nothing. This suggests that analysts interested in exchange-rate pressure should watch reserves rather than oil prices, while remembering that neither tells them when the official rate will move.



6.1 Implications

For businesses and investors with dollar exposure, the results suggest that falling reserves are a reasonable warning sign of rising devaluation risk but not a timing signal. A firm with dollar liabilities should treat periods of reserve decline as periods in which to hedge, rather than as a forecast of the next month's rate. For the CBN, the in-sample evidence supports the view that reserve adequacy matters for exchange-rate stability, while the forecasting evidence shows how much of the variation in the official rate in recent years has come from discrete policy decisions rather than gradual market adjustment. Since the 2023 unification, the official rate has become more market-determined, and it would be useful to revisit these results after several years of the new regime.

6.2 Limitations

The official rate is a managed price for most of the sample, and the parallel-market rate, which may respond differently to reserves, is not studied here. Gross reserves include assets that may not be fully usable for intervention, and the CBN's net reserve position after forward contracts and swaps may be more relevant. The analysis uses reserve growth rather than reserve adequacy relative to imports or short-term debt. The predictive regressions do not identify causal effects. Finally, the evaluation period is dominated by a few very large adjustments, so the out-of-sample results are sensitive to how those months are treated, as Table 3 shows.

7. CONCLUSION

Over 2000–2025, faster growth in Nigeria's external reserves was followed by less depreciation of the official naira rate. The relationship is statistically significant, it survives the exclusion of large devaluations and the inclusion of oil prices, and it is consistent with earlier Nigerian evidence on the link between reserves and the exchange rate. Yet reserves do not improve one-month-ahead forecasts. Over 2019–2025 no model beat a random walk, because most of the forecast error came from a handful of policy-driven devaluations whose timing reserves could not anticipate. Reserves tell us when the naira is vulnerable; they do not tell us when it will move.

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