

Does Exchange-Rate Volatility Constrain Manufacturing Growth? Evidence from Nigeria, 1981–2024

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Research Article

Keywords: exchange-rate volatility, manufacturing output, GARCH, ARDL bounds test, wild bootstrap, Nigeria

Posted Date: September 23rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10807616/v1>

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Additional Declarations: No competing interests reported.

Abstract

Nigeria's official exchange rate remained unchanged for long intervals and then adjusted sharply, which makes annual observations a weak basis for measuring currency uncertainty. This paper examines 1981–2024 using monthly official exchange rates and annual manufacturing data from the Central Bank of Nigeria. Monthly log returns are fitted with a generalized autoregressive conditional heteroskedasticity model, GARCH(1,1), and the conditional standard deviations are averaged within each year. Unit-root tests are followed by an autoregressive distributed lag bounds test. Because the bounds statistic does not support a level relationship, the paper does not estimate long-run coefficients or an error-correction model; manufacturing growth is instead modelled in stationary form with HC3 heteroskedasticity-consistent and wild-bootstrap inference. The variance equation yields an ARCH coefficient of 0.697 and a GARCH coefficient of 0.260, giving persistence of 0.958 and a shock half-life of roughly 16 months. In the annual equation, the volatility coefficient is negative (-2.568) but imprecisely estimated (HC3 $p = 0.773$; wild-bootstrap $p = 0.760$). Trade openness and external reserves are also imprecise, and Toda–Yamamoto tests do not identify predictive direction. Alternative volatility measures, annual depreciation and World Development Indicators manufacturing output leave the inference unchanged. The aggregate data establish persistent currency shocks but do not identify a stable average manufacturing response.

JEL classification: C22; F31; L60; O14; O55

1. Introduction

Exchange-rate movements reach Nigerian manufacturers mainly through the prices and availability of imported machinery, spare parts, chemicals and intermediate goods. Depreciation raises the naira cost of these inputs. Uncertainty adds a different problem: a firm may know that an input will become more expensive yet remain unable to set a credible budget when the timing and size of the currency adjustment are unclear. Export receipts can offset part of that exposure, but the balance depends on the firm's imported-input share, invoicing currency and access to foreign exchange (Campa and Goldberg 1999; Nucci and Pozzolo 2001).

That distinction matters in Nigeria because the official exchange rate has often moved by regime change rather than by small, continuous adjustments. The Structural Adjustment Programme introduced a market-based auction in 1986. Subsequent arrangements combined official intervention with varying degrees of market allocation. In 2023, the Central Bank of Nigeria (CBN) moved transactions to a willing-buyer, willing-seller framework and collapsed earlier market segments into the Investors' and Exporters' window, later renamed the Nigerian Foreign Exchange Market (CBN 2025a). In the study data, the annual average official rate rose from ₦645.19 per US dollar in 2023 to ₦1,478.97 in 2024. The change was large enough to affect both working-capital requirements and the valuation of foreign-currency obligations.

Manufacturing output did not move in a simple inverse relation to the currency. Real manufacturing output fell through much of the 1980s and 1990s, expanded rapidly after 2010, and grew modestly in

2023 and 2024 despite the exchange-rate adjustment. Such aggregate movements reflect demand, energy supply, credit conditions, industrial composition and statistical revisions as well as exchange-rate exposure. A regression that assigns all co-movement to currency conditions risks overstating what the data can support.

Nigerian studies report both adverse and favourable exchange-rate effects. Opaluwa et al. (2010) associated currency fluctuations with weaker manufacturing performance. Akinlo and Lawal (2015) found no short-run depreciation effect on industrial production but reported a positive long-run coefficient. Orji et al. (2018) also obtained a positive response in part of their analysis. Studies that estimate a volatility measure are no less divided: Ojeyinka (2019) reported positive short- and long-run coefficients, whereas Onwuka (2021) found negative effects. More recent work continues to describe an adverse connection, although the samples, output measures and volatility proxies differ (Oladipo et al. 2023; Muritala 2024).

Three empirical choices help explain the disagreement. First, an exchange-rate level or annual percentage change is sometimes labelled “volatility,” even though it measures depreciation rather than conditional uncertainty. Second, a GARCH model fitted to forty or fewer annual observations cannot recover a credible variance process. Conditional heteroskedasticity is a high-frequency feature; estimating it from monthly observations and aggregating the fitted variance to the annual output frequency is the more defensible sequence. Third, some papers report error-correction coefficients without first establishing a non-degenerate level relationship. When the bounds test fails, a long-run coefficient and an error-correction term have no valid interpretation (Pesaran et al. 2001; Sam et al. 2019).

The empirical analysis uses a dataset assembled from identified CBN tables and covering 1981–2024. Monthly official naira–US dollar rates generate 527 log returns for the variance equation. Annual real manufacturing output, merchandise trade, current-price GDP and external reserves come from the CBN’s 2024 Statistical Bulletin. The analysis asks two questions. How persistent are shocks to the monthly official exchange rate? After the integration properties and the possibility of a level relationship are considered, does the annual evidence associate currency volatility with manufacturing output growth?

The contribution lies as much in the sequence of inference as in the additional year of data. Volatility is estimated before it enters the output equation; depreciation is kept conceptually separate and introduced as a sensitivity check because it is highly correlated with the volatility measure. Small-sample critical values for the bounds statistic are simulated for the actual specification. When that test rejects a level relationship, the analysis moves to stationary transformations rather than reporting an ECM. HC3 standard errors and wild-bootstrap p-values address the limited annual sample and non-normal residuals. This sequence supports a cautious conclusion: exchange-rate shocks are persistent, but the aggregate annual data do not locate a statistically discernible manufacturing response.

The next section develops the relevant transmission channels and reviews the empirical evidence. Section 3 explains the data construction and estimation sequence. Section 4 presents the empirical

results. Section 5 draws the conclusion, discusses policy interpretation and sets out the limits of the aggregate design.

2. Literature Review

2.1 Exchange-rate exposure in manufacturing

A manufacturer's exchange-rate exposure is the net effect of foreign-currency revenues and costs. Campa and Goldberg (1999) show that investment responses depend on export orientation and imported-input use. Nucci and Pozzolo (2001) reach a related result with firm-level data: depreciation can raise the domestic value of export revenue while increasing the cost of imported capital and intermediate goods. The sign of the output response cannot be read from the direction of the exchange-rate change alone.

Price setting adds another layer. Under dominant-currency invoicing, many traded goods are priced in a major currency, particularly the US dollar. A depreciation may then pass quickly into local-currency import prices while the foreign-currency price faced by buyers abroad changes little (Gopinath et al. 2020). For an import-dependent producer selling mainly in the domestic market, the cost channel can arrive before any competitiveness gain. The effect should be strongest where foreign inputs have few local substitutes or where working-capital finance is expensive.

This sectoral exposure framework is more informative for the present question than a mechanical appeal to purchasing power parity. Relative-price adjustment can affect manufacturing demand, but the production response turns on invoicing, input structure and financing. Similarly, the Mundell–Fleming model describes how exchange rates transmit macroeconomic policy in an open economy, yet it does not determine whether a particular manufacturing industry is a net exporter or a net user of foreign currency. The empirical specification therefore treats the sign of the aggregate response as an open question.

2.2 Uncertainty, irreversibility and financing

Volatility differs from a predictable depreciation because it changes the distribution of future costs and revenues. Investment is partly irreversible: machinery cannot always be resold without loss, and imported equipment commits the firm to future foreign-currency expenditure on parts and servicing. When the option value of waiting rises, firms may postpone investment until the exchange-rate outlook becomes clearer. Servén (2003) found that real-exchange-rate uncertainty reduced private investment in developing economies, particularly where trade exposure was high and financial systems were less developed.

Financial conditions can either absorb or magnify this uncertainty. Aghion et al. (2009) report that the effect of real-exchange-rate volatility on productivity growth depends on financial development. Firms with access to hedging, longer-term credit or natural foreign-currency revenue can carry short-run losses

more easily. Nigerian manufacturers often operate with short loan tenors and limited formal hedging instruments. Even so, the aggregate coefficient need not be negative if export-oriented producers, local-input firms and import-dependent firms are combined in one sectoral total.

2.3 Openness and reserves

Trade openness captures exposure, not an unambiguous policy benefit. A higher trade ratio can widen export markets and improve access to capital goods. It can also increase the share of costs priced in foreign currency and expose domestic producers to import competition. The net coefficient depends on trade composition. A merchandise trade ratio cannot distinguish machinery imports from consumer goods or separate exporters from firms serving the domestic market.

External reserves are included as an indicator of foreign-exchange liquidity rather than as a direct production input. A larger reserve stock may give the monetary authority more room to supply the market and smooth disorderly conditions. Manufacturers benefit only if that capacity translates into predictable access at a relevant rate. Gross reserves can therefore rise without removing rationing, payment delays or a parallel-market premium. The expected association is positive, but its magnitude is an empirical matter.

2.4 Evidence beyond Nigeria

Cross-country results do not support a universal coefficient. Bleaney and Greenaway (2001) found that real-exchange-rate volatility weakened investment and growth in sub-Saharan Africa. Bahmani-Oskooee and Gelan (2018) reported heterogeneous trade responses across twelve African economies, consistent with differences in exchange-rate regimes and production structures. Mlambo (2020) likewise found that manufacturing responses varied across Southern African Customs Union economies.

The level of aggregation matters. Disaggregated export studies often identify opposing industry effects that disappear in a national total. Vo et al. (2019), for example, show variation across manufacturing export categories in an emerging economy. Jyoti and Bhatt (2024) also report mixed short- and long-run effects across Indian manufacturing exports. Those results caution against interpreting a weak aggregate coefficient as evidence that no firm bears exchange-rate risk.

2.5 Nigerian evidence and the empirical gap

Early Nigerian work generally stressed the imported-input channel. Opaluwa et al. (2010), using data for 1986–2005, reported an adverse effect on manufacturing output. Later studies produced different signs. Akinlo and Lawal (2015) found a positive long-run depreciation effect on industrial production, while Orji et al. (2018) documented circumstances in which exchange-rate movements supported manufacturing output. Orji and Ezeanyaeji (2023) returned to a negative interpretation.

Volatility-based studies are similarly divided. Ojeyinka (2019) used an ARDL model for 1981–2016 and obtained a positive volatility coefficient in both horizons. Onwuka (2021), covering 1981–2020, combined ARCH–GARCH and ARDL methods and reported a negative response. Oladipo et al. (2023)

estimated GARCH volatility and described an adverse manufacturing effect. Muritala (2024), using descriptive evidence for 2014–2024, also linked currency instability to production costs and a lower manufacturing share.

These papers are not directly comparable. Manufacturing value added, industrial production, manufacturing share and capacity utilisation measure different outcomes. Official, parallel and effective exchange rates represent different prices. Some samples include long administered-rate intervals, while others focus on market-based episodes. The use of annual observations in a variance model is a further source of instability. A null result based on monthly volatility and a transparent decision against an ECM is therefore informative: it shows whether the adverse coefficient survives a measurement design that separates conditional uncertainty from an annual exchange-rate change.

3. Methodology

3.1 Research design and data

The analysis combines monthly and annual time series. The monthly sample contains the CBN’s average official naira–US dollar exchange rate from January 1981 to December 2024. It provides 528 rate observations and 527 log returns. The annual sample covers the same 44 calendar years. All main variables are drawn from the CBN’s 2024 Statistical Bulletin, released in 2025 (CBN 2025b). The source workbook and table number for each series are recorded in Table 1.

Real manufacturing output is measured at 2010 constant basic prices. Merchandise trade openness is total merchandise trade divided by GDP at current market prices, multiplied by 100. The trade series includes the CBN estimate of informal cross-border trade from 2008; the 2024 observation is marked provisional in the bulletin. External reserves are the arithmetic mean of the twelve monthly reserve observations in each year. The annual exchange-rate level is the mean of the monthly official rates. World Development Indicators manufacturing value added at constant 2015 US dollars is used only to check whether the output source drives the result (World Bank 2026).

Table 1
Variables, construction and sources

Variable	Construction	Frequency used	Source
Real manufacturing output (M _{it})	Manufacturing GDP at 2010 constant basic prices, ₦ billion; logarithm used in the level equation	Annual, 1981–2024	CBN Table C.1.2
Official exchange rate (E _{it})	Monthly average naira per US dollar	Monthly, 1981M1–2024M12	CBN Table D.4.1
GARCH volatility (V _{it})	Annual mean of monthly conditional standard deviations; logarithm used in annual models	Monthly estimate, annual aggregation	Authors' calculation from Table D.4.1
Merchandise trade openness (OPEN _{it})	Total merchandise trade/(GDP at current market prices × 1,000) × 100	Annual, 1981–2024	CBN Tables D.1.1 and C.1.1
External reserves (RES _{it})	Annual mean of monthly gross external reserves, US\$ million; logarithm used	Monthly source, annual aggregation	CBN Table D.3.1
Annual depreciation (DEP _{it})	100 Δln of the annual average official rate	Annual, 1982–2024	Authors' calculation
<i>Note: CBN GDP observations marked provisional and the provisional 2024 trade observation are retained as published. Online Resource 1 provides the assembled series, transformations and econometric output.</i>			

3.2 Measuring monthly exchange-rate volatility

Monthly exchange-rate returns are calculated as

$$r_m = 100 [\ln(E_m) - \ln(E_{m-1})].$$

The mean and conditional variance equations are

$$r_m = \mu + \epsilon_m, \quad \epsilon_m | \mathcal{F}_{m-1} \sim (0, h_m).$$

$$h_m = \omega + \alpha \epsilon_{m-1}^2 + \beta h_{m-1}.$$

The parameters satisfy $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$. A covariance-stationary GARCH(1,1) process also requires $\alpha + \beta < 1$ (Engle 1982; Bollerslev 1986). The sum $\alpha + \beta$ measures persistence; the shock half-life is $\ln(0.5)/\ln(\alpha + \beta)$ months. Because the return distribution contains long intervals of small official-rate changes and a few large adjustments, the model is estimated by Gaussian quasi-maximum likelihood with sandwich standard errors. Serial correlation in standardised residuals and squared standardised residuals is checked with Ljung–Box statistics. Realised annual volatility, calculated from the within-year standard deviation of monthly returns, is used as an alternative measure.

For each year, monthly conditional standard deviations are averaged and logged:

$$\ln V_t = \ln \left(\frac{1}{n_t} \sum_{m \in t} \sqrt{\widehat{h}_m} \right).$$

There are eleven returns in 1981 because no December 1980 observation is introduced from a different source; every later year contains twelve.

3.3 Integration and the ARDL decision rule

The level relation of interest is

$$\ln M_t = \beta_0 + \beta_1 \ln V_t + \beta_2 OPEN_t + \beta_3 \ln RES_t + u_t.$$

Augmented Dickey–Fuller (ADF) tests are paired with Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests because the two procedures reverse the null hypothesis (Dickey and Fuller 1979; Kwiatkowski et al. 1992). Lag length in the ADF regression is selected by the Bayesian information criterion, with three annual lags as the maximum; finite-sample ADF decisions use MacKinnon’s response-surface critical values (MacKinnon 2010). The ARDL bounds procedure permits a mixture of $I(0)$ and $I(1)$ regressors but not an $I(2)$ series (Pesaran et al. 2001).

With one lag selected by BIC, the unrestricted conditional error-correction regression is

$$\Delta \ln M_t = c + \lambda_M \ln M_{t-1} + \lambda_V \ln V_{t-1} + \lambda_O OPEN_{t-1} + \lambda_R \ln RES_{t-1} + z_t,$$

where

$$z_t = \delta_V \Delta \ln V_t + \delta_O \Delta OPEN_t + \delta_R \Delta \ln RES_t + e_t.$$

The bounds statistic tests $H_0 : \lambda_M = \lambda_V = \lambda_O = \lambda_R = 0$. With only 44 annual observations, asymptotic tables can give misleading precision. The reported lower and upper critical values are therefore obtained from 20,000 Monte Carlo replications using the actual sample length and equation dimensions. The lower-bound simulation treats the regressors as stationary; the upper-bound simulation treats them as independent random walks. The dependent variable is generated as a random walk under the null in both cases.

The decision rule is consequential. A statistic above the upper bound supports a level relationship. A statistic below the lower bound does not. Only the first outcome would justify long-run coefficients and an ECM. This paper obtains the second outcome, so no error-correction term is interpreted.

3.4 Stationary manufacturing-growth model

Because the bounds test does not support a level relationship, the annual equation is estimated in stationary form:

$$g_t = a + \rho g_{t-1} + \theta \ln V_t + \phi \Delta OPEN_t + \gamma \Delta \ln RES_t + \nu_t,$$

where $g_t = 100\Delta \ln M_t$. The coefficient θ is the contemporaneous association between log conditional volatility and percentage growth in real manufacturing output. A 10 per cent change in volatility corresponds approximately to 0.095θ percentage points of manufacturing growth. One lag of output growth is retained by BIC; additional lags worsen the criterion and reduce already limited degrees of freedom.

Inference is reported with HC3 standard errors. A Rademacher wild bootstrap with 4,999 replications and the null imposed provides a second p-value for each coefficient (Davidson and Flachaire 2008). This step is used because the residual normality test is sensitive to a small number of annual contractions. Diagnostic checks cover first-order serial correlation, remaining ARCH effects, the Breusch–Pagan statistic, Ramsey’s RESET and an OLS-residual CUSUM test.

3.5 Predictive tests and sensitivity analysis

A bivariate Toda–Yamamoto procedure examines predictive ordering between $\ln M_t$ and $\ln V_t$ without requiring a prior cointegration classification (Toda and Yamamoto 1995). BIC selects one VAR lag; one additional lag is included for the maximum integration order, and the Wald restriction is applied only to the first lag.

Three checks assess sensitivity. First, log realised volatility replaces log GARCH volatility. Second, annual official-rate depreciation enters the growth equation. That specification is not the baseline because depreciation and log conditional volatility have a sample correlation of 0.940, which makes their separate coefficients unstable. Third, CBN real manufacturing output is replaced by World Development Indicators manufacturing value added at constant 2015 US dollars. The assembled data, transparent transformations and reported estimates are provided in Online Resource 1.

4. Results and Discussion

4.1 Data patterns

Table 2 reports the descriptive statistics for the variables used in the analysis. Real manufacturing output averages ₦4,392.62 billion at 2010 prices. Its minimum occurs in 1995, while the highest value is the provisional 2024 estimate. Conditional volatility averages 9.41 and reaches 24.17 in 1999. Merchandise trade openness ranges from 7.52 per cent in 1986 to 55.02 per cent in 1995.

Table 2
Descriptive statistics, 1981–2024

Variable	Obs.	Mean	Std. dev.	Minimum	Median	Maximum
Real manufacturing output (₹ bn 2010 prices)	44	4,392.621	1,418.991	2,898.474	3,636.058	6,848.461
GARCH conditional volatility	44	9.408	3.485	7.893	7.985	24.171
Annual official-rate depreciation (%)	43	18.124	29.521	−5.948	7.755	144.345
Merchandise trade openness (%)	44	29.643	11.518	7.523	30.534	55.021
Average external reserves (US\$ mn)	44	19,868.844	17,514.549	456.642	9,434.746	58,472.883

Source: Authors' calculations from CBN (2025b).

Figure 1 places the real output and volatility series on separate panels. Output contracted sharply in the early part of the sample, recovered unevenly, and then rose after 2010. The volatility spikes in 1986 and 1999 coincide with large changes in the official exchange-rate regime. The 2023–2024 increase is substantial but smaller than the fitted spikes around 1986 and 1999. These paths do not display a stable one-for-one relation. For example, manufacturing output rose modestly in 2024 even as official-rate volatility increased.

4.2 Integration tests

The stationarity results appear in Table 3. Log manufacturing output and log reserves are non-stationary in levels and stationary after first differencing. Log volatility is stationary in levels under both tests. For trade openness, the ADF test does not reject a unit root, while the KPSS statistic does not reject level stationarity. It is treated conservatively as $I(1)$; either classification is admissible in the bounds framework. Annual depreciation behaves as a stationary rate. No series shows evidence of $I(2)$ behaviour.

Table 3
ADF and KPSS stationarity tests

Variable	ADF level	ADF lag	KPSS level	ADF first difference	KPSS first difference	Classification used
Log manufacturing output	-0.843	0	0.631	-5.182	0.354	I(1)
Log GARCH volatility	-5.819	0	0.240	-9.693	0.123	I(0)
Trade openness	-2.001	3	0.309	-4.498	0.108	I(1), conservative
Log external reserves	-2.605	3	1.045	-6.012	0.077	I(1)
Annual depreciation	-2.926	3	0.174	-4.514	0.108	I(0)
<i>Note: Rejection at 5 per cent requires an ADF statistic below approximately - 2.93. The 5 per cent KPSS critical value is 0.463; values above it reject level stationarity. A constant is included in both tests.</i>						

4.3 Monthly variance process

Table 4 gives the GARCH estimates. New shocks receive a large weight: $\hat{\alpha} = 0.697$ with a QML p-value below 0.001. The lagged variance coefficient is 0.260 and lies close to the 5 per cent boundary ($p = 0.053$). Their sum is 0.958. It remains below one, but the implied half-life of a variance shock is about 16 months. Exchange-rate adjustments in the official market therefore continue to influence fitted uncertainty well beyond the month in which they occur.

Table 4
Monthly GARCH(1,1) estimates and residual checks

Parameter/test	Estimate/statistic	QML std. error	p-value
Mean return (μ)	0.204	0.977	0.835
Variance constant (ω)	46.062	41.396	0.266
ARCH term (α)	0.697	0.095	< 0.001
GARCH term (β)	0.260	0.134	0.053
Persistence ($\alpha + \beta$)	0.958	—	—
Ljung–Box Q(12), standardised residuals	2.588	—	0.998
Ljung–Box Q(12), squared standardised residuals	0.118	—	> 0.999

The Ljung–Box tests find no remaining linear or squared-residual dependence. The standardised residuals are nevertheless strongly non-normal because a few official-rate adjustments are very large.

Gaussian QML rather than normal-theory maximum-likelihood inference is used for that reason. The realised-volatility check in Section 4.8 reduces reliance on the fitted conditional distribution.

4.4 Bounds test

The computed bounds statistic is 2.649 (Table 5). It falls below the simulated 10 per cent lower bound of 2.907 and well below the 5 per cent lower bound of 3.544. The null of no level relationship is not rejected. The study therefore reports neither long-run coefficients nor an error-correction term because, in the absence of a level relationship, those parameters have no valid interpretation.

Table 5
ARDL bounds test with finite-sample simulated critical values

Item	10%	5%	1%
I(0) lower critical value	2.907	3.544	5.015
I(1) upper critical value	4.070	4.847	6.663
Computed F-statistic	2.649	2.649	2.649
<i>Note: 20,000 Monte Carlo replications; 43 regression observations; four restrictions; unrestricted intercept and no deterministic trend.</i>			

4.5 Manufacturing-growth equation

Table 6 reports the stationary growth model. The volatility coefficient is – 2.568. Its sign accords with the imported-input and investment-delay channels, but the estimate is too imprecise to distinguish from zero. A 10 per cent increase in conditional volatility corresponds to a point estimate of about 0.24 percentage point lower annual manufacturing growth; the HC3 standard error allows effects of either sign. The wild-bootstrap p-value is 0.760.

Neither control variable is precisely estimated. A one-percentage-point increase in merchandise trade openness relative to the previous year carries a coefficient of 0.057. A 10 per cent reserve increase corresponds to roughly 0.55 percentage point higher growth at the point estimate, but the bootstrap p-value is 0.290. Lagged manufacturing growth is positive, suggesting some persistence, yet its p-value remains above conventional thresholds. The adjusted R^2 is 0.049. Annual manufacturing growth is evidently driven by factors not represented in this compact currency-liquidity equation.

Table 6
Stationary manufacturing-growth model, 1983–2024

Variable	Coefficient	HC3 std. error	HC3 t-statistic	Wild-bootstrap p-value
Constant	5.755	19.260	0.299	0.742
Manufacturing growth, $t - 1$	0.289	0.198	1.460	0.119
Log GARCH volatility	-2.568	8.846	-0.290	0.760
Change in trade openness	0.057	0.245	0.234	0.762
Change in log external reserves	5.755	5.418	1.062	0.290

Note: Dependent variable is $100\Delta\ln$ real manufacturing output. $n = 42$; $R^2 = 0.141$; adjusted $R^2 = 0.049$. Wild-bootstrap p-values use 4,999 Rademacher replications with the null imposed.

The absence of a detectable average effect should not be restated as proof that volatility is harmless. The 95 per cent HC3 interval around the volatility coefficient is wide, and the aggregate sector combines firms with very different exposures. The inference is narrower: these annual data do not establish a stable long-run manufacturing effect.

4.6 Diagnostics

Serial correlation, remaining ARCH effects, heteroskedasticity and functional-form error are not detected at 5 per cent (Table 7). The OLS-residual CUSUM statistic also remains within its reference limit. Normality is rejected at $p = 0.039$, largely because manufacturing growth contains several large contractions. HC3 and wild-bootstrap inference are retained rather than treating the residuals as Gaussian.

Table 7
Diagnostics for the manufacturing-growth equation

Test	Statistic	p-value	Assessment
Breusch–Godfrey LM(1)	1.417	0.234	No first-order serial correlation detected
ARCH LM(1)	0.569	0.451	No remaining conditional heteroskedasticity detected
Breusch–Pagan	2.384	0.666	No general heteroskedasticity detected
Jarque–Bera	6.503	0.039	Normality rejected
Ramsey RESET	0.569	0.571	No functional-form rejection
OLS-residual CUSUM	0.789	0.563	Parameter stability not rejected

4.7 Predictive ordering

The Toda–Yamamoto results provide no predictive direction between volatility and manufacturing output (Table 8). The null that log volatility does not predict log manufacturing output has a p-value of 0.626. The reverse restriction has a p-value of 0.577. More broadly, temporal precedence would not by itself identify a structural effect because monetary policy, oil receipts and domestic demand can move both series.

Table 8
Toda–Yamamoto predictive tests

Null restriction	Wald χ^2	df	p-value	Decision
Log volatility does not predict log manufacturing output	0.237	1	0.626	Do not reject
Log manufacturing output does not predict log volatility	0.311	1	0.577	Do not reject
<i>Note: BIC selects one VAR lag; one additional lag is included for the maximum integration order.</i>				

4.8 Sensitivity checks

The three checks in Table 9 leave the substantive inference unchanged. Realised volatility produces a smaller negative coefficient and a p-value of 0.666. When annual depreciation is added, the volatility coefficient becomes more negative but much less precise. The instability is expected because depreciation and conditional volatility have a correlation of 0.940 in this sample; sharp official-rate adjustments raise both measures. Replacing CBN output with the World Bank’s constant-dollar manufacturing series yields a coefficient close to the baseline and a p-value of 0.758.

Table 9
Sensitivity of the volatility coefficient

Specification	Volatility coefficient	HC3 std. error	p-value	Adjusted R ²
Realised volatility	-0.859	1.977	0.666	0.051
Add annual depreciation	-15.090	34.120	0.661	0.036
World Bank manufacturing output	-2.769	8.928	0.758	0.030

The sensitivity checks clarify rather than strengthen the point estimate. The data repeatedly return a negative sign, but they also return uncertainty too large for a directional conclusion. Interpreting the negative signs without accounting for the standard errors would overstate the evidence.

4.9 Comparison with existing evidence

The persistence estimate is consistent with the experience of manufacturers who face extended adjustment after a currency shock. It does not, however, imply that aggregate manufacturing output must fall. The GARCH model describes the exchange-rate process; the annual equation asks whether that process maps into a stable sector-wide growth response. The first relationship is clear, while the second is not.

This result differs from the adverse coefficients in Opaluwa et al. (2010), Onwuka (2021) and Oladipo et al. (2023). Part of the difference is measurement. The present volatility series is estimated from monthly returns rather than annual levels. Part is econometric: the failure of the bounds test prevents a long-run coefficient from being reported. The result is closer to work that finds weak or mixed sectoral responses once time horizon and industry composition are considered (Bahmani-Oskooee and Gelan 2018; Jyoti and Bhatt 2024).

The positive but imprecise reserve coefficient also deserves restraint. Gross reserves can improve the authorities' capacity to supply foreign exchange, yet the aggregate stock does not measure the price, timing or administrative conditions under which a manufacturer obtains currency. A firm can face rationing even while reserves rise. The trade coefficient is similarly muted because the numerator combines exports and imports; capital-goods imports and consumer-goods imports need not have the same production effect.

5. Conclusion and Policy Implications

5.1 Conclusion

Two results define the empirical conclusion. First, monthly official exchange-rate returns exhibit persistent conditional variance: the GARCH parameters sum to 0.958, and the estimated half-life of a

shock is roughly 16 months. That finding is sufficiently stable to describe currency uncertainty during the sample.

The annual output evidence is different. The finite-sample ARDL bounds statistic lies below the lower critical value, so a long-run relation is not established. Once the equation is estimated in stationary growth form, exchange-rate volatility carries a negative point estimate but a wild-bootstrap p-value of 0.760. Trade openness and reserves are also estimated imprecisely. Predictive tests and three sensitivity checks do not alter the conclusion.

The appropriate statement is not that exchange-rate volatility has no cost. Rather, aggregate annual data for 1981–2024 do not identify a stable average manufacturing-output effect under the stated measurement and decision rules. The sector combines exporters, firms that source locally and firms dependent on imported inputs. Their responses can offset one another in the national total.

5.2 Policy implications

Exchange-rate policy should still reduce avoidable uncertainty. Clear market rules, timely settlement and transparent intervention make input budgeting easier, regardless of whether an aggregate coefficient is precisely estimated. The case for those practices rests on market functioning and firm-level risk management; it does not depend on a long-run coefficient that the bounds test does not support.

Reserve accumulation should not be treated as an industrial-policy target in isolation. What matters to manufacturers is usable foreign-exchange liquidity: the spread between relevant market rates, the time required to execute payments and the predictability of access. Publishing those measures would permit a more direct test than gross reserves alone.

Local input development is most defensible where domestic suppliers can meet cost and quality requirements. A general import-substitution recommendation would ignore the productivity role of machinery and specialised intermediates. Supplier development, standards certification and infrastructure improvements can reduce exposure without forcing firms to replace inputs for which no efficient domestic alternative exists.

5.3 Limitations and further research

Four limits should accompany any use of the results. The official rate does not measure the parallel-market premium faced by firms during periods of rationing. Annual manufacturing output conceals adjustments within the year and differences across subsectors. The CBN trade series begins to include estimated informal cross-border trade in 2008, and several recent GDP and trade observations are provisional. Finally, administered-rate intervals followed by large discrete adjustments produce a heavy-tailed return distribution; the realised-volatility check helps, but no single GARCH specification can remove that institutional feature.

Future work should combine quarterly or monthly production indicators with official and parallel exchange-rate measures. Firm-level panels could interact volatility with imported-input shares, export

receipts, foreign-currency debt and access to hedging. Those data would test the mechanism more directly and would distinguish a genuinely small effect from offsetting responses hidden by aggregation.

Declarations

Funding

No funding was received for conducting this study.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Author contributions

Bosede Esther Akanbi: conceptualization. Daniel Adedokun: methodology and formal analysis. Adesina Thomas Oyegbade: writing - original draft. Akin George Ogunleye: supervision.

Ethics approval and consent to participate

Not applicable. The study uses publicly available aggregate macroeconomic data and does not involve human participants or animals.

Data availability

The public source data are available from the Central Bank of Nigeria 2024 Statistical Bulletin and the World Development Indicators.

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Figures

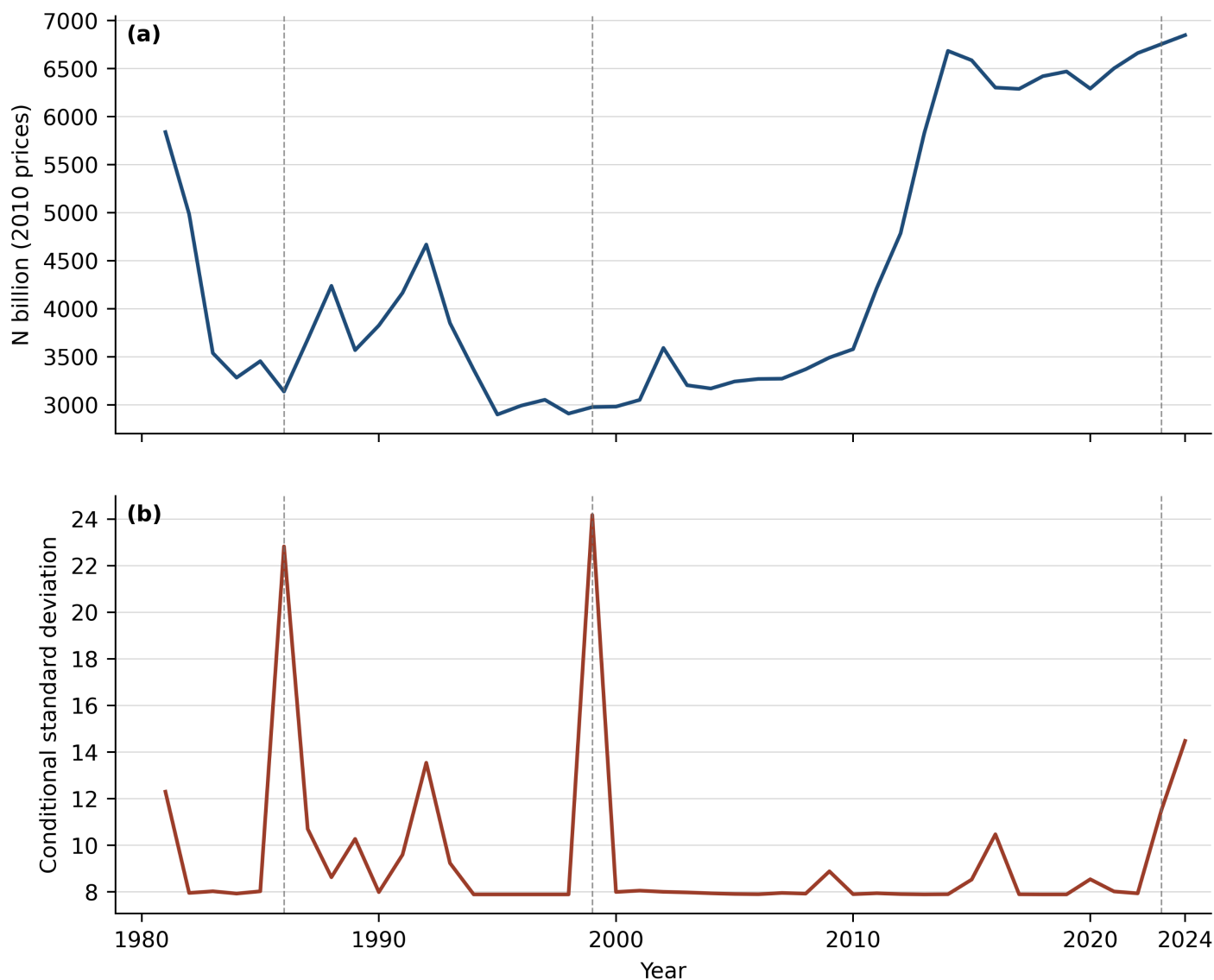


Figure 1

Real manufacturing output and annual exchange-rate volatility, 1981–2024. Panel (a) reports real manufacturing output at 2010 constant prices; panel (b) reports the annual mean of monthly GARCH conditional standard deviations. Dashed lines mark 1986, 1999 and 2023, years with sharp official-rate adjustments. Source: authors' calculations from CBN (2025b); graphic prepared in Matplotlib