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DISTRIBUTIONAL PROPERTIES OF NAIRA EXCHANGE RATE VOLATILITY: AN INVERSE GAMMA PERSPECTIVE

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ABSTRACT

This study investigates the distributional properties of monthly exchange rate volatility of the Nigerian Naira, with particular emphasis on inverse gamma behavior. Monthly exchange rate data for the Naira against the US Dollar (USD), Euro (EUR), and Pounds Sterling (GBP) from January 2020 to December 2024 are analyzed. Exchange rate volatility is proxied using squared logarithmic returns. Descriptive statistics indicate that the volatility series are strictly positive, highly right-skewed, and extremely leptokurtic, with skewness values exceeding 5 and kurtosis values above 30 for all currencies, confirming pronounced heavy-tailed behavior. The inverse gamma distribution is estimated using maximum likelihood techniques, and goodness-of-fit is assessed using the Kolmogorov–Smirnov test and graphical diagnostics. The Kolmogorov–Smirnov test rejects the null hypothesis of an exact inverse gamma distribution for all currency pairs; however, quantile–quantile plots show strong alignment between empirical and theoretical quantiles in the upper tail. Comparative volatility analysis reveals that the Naira–Pounds Sterling exchange rate exhibits the highest volatility, followed by the Naira–Euro and the Naira–US Dollar exchange rates. Although alternative distributions such as the gamma and lognormal achieve higher log-likelihood values, the inverse gamma distribution remains useful for capturing extreme exchange rate volatility, which is of primary interest in financial risk analysis.

Keywords: Exchange rate volatility, Inverse gamma distribution, Heavy-tailed volatility, Naira exchange rate, Tail risk, Emerging markets

INTRODUCTION

Exchange rate volatility is a central issue in international finance because of its implications for macroeconomic stability, trade performance, investment decisions, and financial risk management. In emerging economies, exchange rate movements are often more volatile than in advanced economies due to structural constraints, policy uncertainty, and exposure to external shocks (Aghion et al., 2009). In Nigeria, fluctuations in the value of the Naira against major international currencies such as the US Dollar, Euro, and Pounds Sterling have been persistent, reflecting changing exchange rate regimes, foreign exchange market interventions, and vulnerability to global economic disturbances. As a result, understanding the statistical behavior of exchange rate volatility remains an important empirical concern.

The empirical literature on exchange rate volatility has traditionally focused on modeling volatility dynamics using conditional heteroskedasticity frameworks such as the Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982) and its generalization by Bollerslev (1986). These models are effective in capturing volatility clustering, a key stylized fact of financial time series. However, they often impose restrictive assumptions about the underlying distribution of volatility innovations, frequently relying on normal or thin-tailed distributions. Extensive empirical evidence shows that financial return and volatility series exhibit strong departures from normality, characterized by positive skewness, excess kurtosis, and heavy tails (Mandelbrot, 1963; Cont, 2001). Such characteristics imply that extreme movements occur more frequently than predicted by Gaussian models.

Recent studies have therefore emphasized the importance of examining not only the dynamics of volatility but also its distributional properties. Distribution-based approaches provide insight into the probabilistic structure of volatility realizations and are particularly relevant for understanding extreme events and tail risk. In this context, the inverse gamma distribution has received considerable attention in stochastic volatility theory and Bayesian econometrics due to its support on the positive real line and its flexibility in modeling heavy-tailed variance processes (Kim, Shephard, and Chib, 1998; Chib, Omori, and Asai, 2006). The inverse gamma distribution naturally accommodates skewness and leptokurtosis and has been widely used as a prior or marginal distribution for volatility in financial models.

Despite its theoretical appeal, empirical applications of the inverse gamma distribution to observed exchange rate volatility remain relatively limited, particularly in emerging market settings and at lower data frequencies such as monthly observations. Most studies involving exchange rate volatility in Nigeria continue to rely on conditional variance models, with little attention given to whether the realized volatility itself follows a specific heavy-tailed distribution. This represents an important gap in the literature, especially given that emerging market exchange rates are often subject to abrupt and extreme movements that may not be adequately captured by traditional modeling assumptions.

Motivated by this gap, this study investigates whether monthly Naira exchange rate volatility follows an inverse gamma distribution. Using monthly exchange rate data for the Naira against the US Dollar, Euro, and Pounds Sterling over the period January 2020 to December 2024, volatility is proxied by squared logarithmic returns, a widely accepted measure in financial econometrics (Taylor, 1986; Andersen and Bollerslev, 1998). The study first examines the statistical properties of the volatility series, focusing on skewness, kurtosis, and volatility clustering. It then estimates the parameters of the inverse gamma distribution using maximum likelihood methods and evaluates model adequacy through goodness-of-fit tests and graphical diagnostics. Finally, volatility behavior is compared across currencies in order to identify differences in volatility magnitude and exposure to extreme fluctuations.

By adopting a distribution-based perspective, this study contributes to the exchange rate volatility literature in several important ways. First, it provides empirical evidence on the heavy-tailed nature of monthly Naira exchange rate volatility. Second, it evaluates the suitability of the inverse gamma distribution as a statistical model for exchange rate volatility in an emerging market context. Third, it offers a comparative assessment of volatility behavior across major international currencies, identifying the most volatile exchange rate relative to the Nigerian Naira. The findings are relevant for policymakers concerned with exchange rate stability, as well as for investors and financial institutions involved in exchange rate risk management, where accurate modeling of extreme volatility is crucial (Embrechts, Klüppelberg, and Mikosch, 1997).

MATERIALS AND METHODS

Research Design

This study adopts a quantitative, empirical research design using monthly Naira exchange rate data against USD, EUR, and GBP from January 2020 to December 2024. The study focuses on statistical distributional analysis of exchange rate volatility, specifically testing whether volatility follows an inverse gamma distribution. The design is observational, relying on historical data for analysis without any manipulation or intervention.

Area of the Study

The study focuses on the Nigerian foreign exchange market, analyzing the Naira against three major currencies: USD, EUR, and GBP. The chosen period captures recent exchange rate behavior and provides a sufficient number of monthly observations (60 months per currency) for robust statistical analysis.

Method of Data Collection

Monthly average Naira exchange rates against USD, EUR and GBP were obtained from the Central Bank of Nigeria (CBN) official website covering a period of January 2020 to December 2024.

Method of Data Analysis

The analysis proceeds through four main stages with all analysis carried out using python statistical software.

i. Transformation of exchange rates into returns
ii. Construction of volatility series
iii. specification and estimation of the inverse gamma model
iv. Goodness-of-fit testing and comparative evaluation

Exchange Rate Returns

Let $E_t^{(i)}$ denote the monthly average exchange rate of the Naira relative to currency i, where: $i \in$ {USD,EUR,GBP}

The monthly log return is defined as:

$$r_t^{(i)} = \ln\left(\frac{E_t^{(i)}}{E_{t-1}^{(i)}}\right), \quad t = 2,3,\dots,T \tag{1}$$

Log returns are used because they are scale-free, time additive, and standard in financial volatility analysis

Construction of Exchange Rate Volatility

Monthly exchange rate volatility is proxied using squared log returns, defined as:

$$V_t^{(i)} = \left(r_t^{(i)}\right)^2 \tag{2}$$

This proxy satisfies two important properties:

i. $V_t^{(i)} > 0$ for all t,
ii. It captures the magnitude of exchange rate fluctuations, regardless of direction

Thus, the volatility series is suitable for modeling with positive-support distributions, such as the inverse gamma distribution.

Model Specification

Inverse Gamma Distribution

The study assumes that the monthly volatility series follows an inverse gamma distribution, given by:

$$V_t^{(i)} \sim IG(\alpha_i, \beta_i) \tag{3}$$

The probability density function (pdf) is:

$$f(v) = \frac{\beta_i^{\alpha_i}}{\Gamma(\alpha_i)} v^{-(\alpha_i+1)} \exp\left(-\frac{\beta_i}{v}\right), \quad v > 0 \tag{4}$$

where:

i. $\alpha_i > 0$ is the shape parameter (controls tail heaviness)?
ii. $\beta_i > 0$ is the scale parameter,
iii. $\Gamma(.)$ is the gamma function.

Moments of the Inverse Gamma Distribution

The mean and variance of the inverse gamma distribution are:

$$\mathbb{E}\left[V_t^{(i)}\right] = \frac{\beta_i}{\alpha_i - 1}, \quad \alpha_i > 1 \tag{5}$$

$$Var\left(V_t^{(i)}\right) = \frac{\beta_i^2}{(\alpha_i-1)^2(\alpha_i-2)}, \quad \alpha_i > 2 \tag{6}$$

These expressions help interpret estimated parameters in terms of average volatility and dispersion.

Parameter Estimation Using Maximum Likelihood

$Let V_1^{(i)}, V_2^{(i)}, V_3^{(i)}$ be the volatility observations for currency i.

Likelihood Function

$$\mathcal{L}(\alpha_i, \beta_i) = \prod_{t=1}^{n} \frac{\beta_i^{\alpha_i}}{\Gamma(\alpha_i)} \left(V_t^{(i)}\right)^{-(\alpha_i+1)} \exp\left(-\frac{\beta_i}{V_t^{(i)}}\right) \tag{7}$$

Log-Likelihood Function

$$\ell(\alpha_i, \beta_i) = n\alpha_i \ln\beta_i - n\ln\Gamma(\alpha_i) - (\alpha_i + 1)\sum_{t=1}^{n} \ln V_t^{(i)} - \beta_i \sum_{t=1}^{n} \frac{1}{V_t^{(i)}} \tag{8}$$

Score Equations

The MLEs of α_i and β_i are obtained by solving:

$$\frac{\partial \ell}{\partial \alpha_i} = n\ln\beta_i - n\psi(\alpha_i) - \sum_{t=1}^{n} \ln V_t^{(i)} = 0 \tag{9}$$

$$\frac{\partial \ell}{\partial \beta_i} = \frac{n\alpha_i}{\beta_i} - \sum_{t=1}^{n} \frac{1}{V_t^{(i)}} = 0 \tag{10}$$

where $\psi(.)$ denotes the digamma function.

These equations are solved numerically.

Goodness -of-Fit Testing

To determine whether volatility follows an inverse gamma distribution, the following tests are employed:

i. Kolmogorov–Smirnov (K-S) Test
   a. Null hypothesis: volatility follows inverse gamma distribution
   b. Alternative hypothesis: volatility does not follow inverse gamma distribution
ii. Anderson-Darling (A-D) Test
   a. Emphasize tail behavior
iii. Quantile-Quantile (Q-Q) Plots
   a. Visual comparison of empirical and theoretical quantiles

Comparison with Alternative Distributions

For robustness, the inverse gamma model is compared with:

Gamma Distribution

$$f(v) = \frac{1}{\Gamma(k)\theta^k} v^{k-1} \exp\left(-\frac{v}{\theta}\right), \quad v > 0 \tag{11}$$

Lognormal Distribution

$$f(v) = \frac{1}{v\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln v-\mu)^2}{2\sigma^2}\right) \quad (12)$$

Model comparison is based on likelihood values and goodness-of-fit statistics.

Cross-Currency Comparative Analysis

Estimated parameters are compared across USD, EUR, and GBP to assess:

i. Differences in tail heaviness,
ii. Differences in volatility intensity,
iii. Relative exposure to extreme exchange rate movements.

RESULTS AND DISCUSSION

Log Returns and Volatility Construction

Monthly exchange rate series for Naira/USD, Naira/EUR, and Naira/GBP were transformed into logarithmic returns, and volatility was proxied using squared log returns. Table 1 presents the first five observations of the volatility series. For instance, in March 2020, the USD volatility rose sharply to, while EUR and GBP recorded volatility levels of 0.00594 and 0.00021, respectively. An even more pronounced increase was observed in April 2020, where GBP volatility peaked at 0.01079, reflecting extreme exchange rate instability during that period.

These large squared returns correspond to heightened uncertainty in the foreign exchange market, particularly during periods associated with macroeconomic disruptions. The volatility series are non-negative, satisfying the domain requirements for inverse gamma modeling, which is defined strictly over the positive real line.

Table 1: Squared Returns Proxy Monthly Exchange Rate Volatility (First 5)

Date	USD	EUR	GBP
2/2020	2.179058 X 10-10	0.000312	0.000068
3/2020	4.235216 x 10-03	0.005938	0.000214
4/2020	9.475561 x 10-03	0.006599	0.010792
5/2020	0.000000	0.000011	0.000079
6/2020	0.000000	0.001050	0.000336

Descriptive Statistics of Exchange Rate Volatility

Table 2 summarizes the descriptive statistics of the volatility series. The mean volatility values are 0.00776 for USD, 0.00829 for EUR, and 0.00865 for GBP, indicating that, on average, the Naira/GBP exchange rate exhibits the highest volatility. This is further supported by the standard deviations, where GBP volatility records the largest dispersion (0.03139), followed closely by USD (0.03114) and EUR (0.03042).

Table 2: Descriptive Statistics of Exchange Rate Volatility

	Count	Mean	Std	Skewness	Kurtosis
USD	59	0.007759	0.031138	5.933700	38.831919
EUR	59	0.008289	0.030419	5.609696	35.030383
GBP	59	0.008652	0.031392	5.479263	33.446778

All three volatility series display strong positive skewness, with skewness values of 5.93 (USD), 5.61 (EUR), and 5.48 (GBP). These values indicate a pronounced right-tailed distribution, implying that extreme volatility episodes occur more frequently than moderate ones. Additionally, the kurtosis values are exceptionally high, 38.83 for USD, 35.03 for EUR, and 33.45 for GBP, confirming extreme leptokurtosis.

Such high skewness and kurtosis are well-documented stylized facts of financial volatility and strongly reject the assumption of normality (Cont, 2001). The magnitude of these values provides early statistical evidence in favor of heavy-tailed distributions, such as the inverse gamma distribution, for modeling exchange rate volatility.

Time Series Behavior of Exchange Rate Volatility

Figure 1 illustrates the time-varying behavior of volatility across the three currencies. The volatility series exhibit clear clustering, where periods of high volatility are followed by further high volatility, while periods of calm persist over time. This behavior is consistent with the volatility clustering phenomenon originally documented by Mandelbrot (1963) and formally modeled by Engle (1982).

Notably, volatility spikes appear simultaneously across USD, EUR, and GBP during certain periods, suggesting the presence of common macroeconomic or global shocks affecting Nigeria's foreign exchange market.

Figure 1: Monthly Exchange Rate Volatility

Distributional Shape: Histogram and Boxplot Evidence

The histogram in Figure 2 reveals that the majority of volatility observations are concentrated near zero, with a long right tail extending toward higher values. This asymmetric shape is characteristic of inverse gamma distributions, which allow for infrequent but extreme realizations.

The boxplot in Figure 3 further emphasizes this behavior by revealing multiple upper-tail outliers across all currencies. GBP displays the most pronounced upper outliers, reinforcing its relatively higher exposure to extreme volatility events. Similar distributional features have been reported in empirical volatility studies by Andersen et al. (2003).

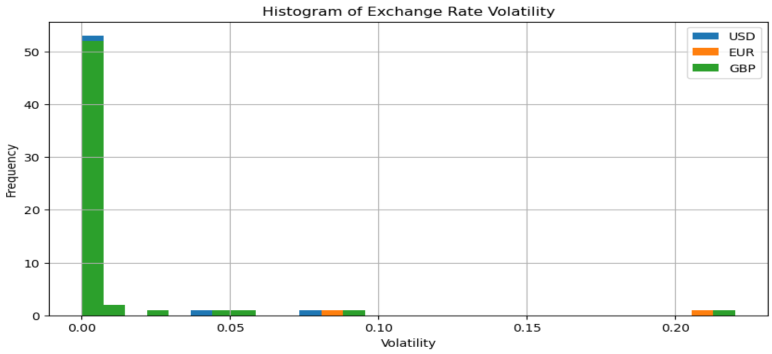

Figure 2: Histogram of Exchange Rate Volatility

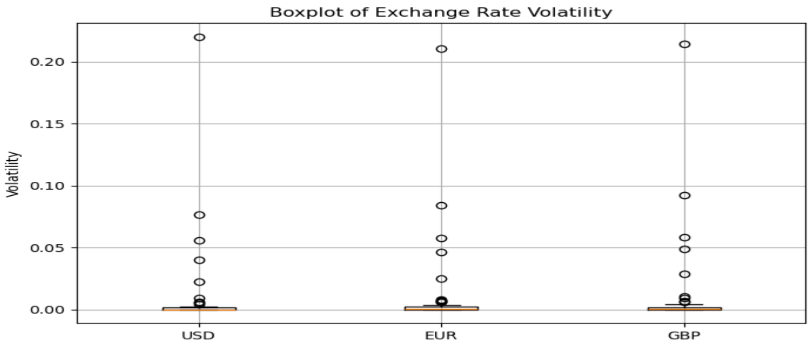

Figure 3: Boxplot of Exchange Rate Volatility

Inverse Gamma Parameter Estimates

Table 3 presents the maximum likelihood estimates of the inverse gamma parameters. The shape parameter α is notably small for USD (0.066), compared to EUR (0.189) and GBP (0.195). A smaller shape parameter implies heavier tails, suggesting that USD volatility is more prone to extreme realizations, even if they occur less frequently.

The scale parameter $\boldsymbol{\beta}$, which governs the magnitude of volatility, varies substantially across currencies. USD records an extremely small $\boldsymbol{\beta}$ value (2.90×10^{-26}), whereas EUR and GBP exhibit much larger scale parameters of 1.07×10^{-6} and 1.39×10^{-6}, respectively. These estimates indicate that while USD volatility is highly heavy-tailed, GBP volatility tends to occur at larger magnitudes.

Table 3: Inverse Gamma Parameter Estimates

	Alpha (α)	Beta ($\boldsymbol{\beta}$)
USD	0.066151	2.897953×10^{-26}
EUR	0.188828	1.068814×10^{-06}
GBP	0.195416	1.394487×10^{-06}

Goodness-of-Fit

K–S Test and Q–Q Analysis

Table 4 reports the Kolmogorov–Smirnov (K–S) test results. For USD, the K–S statistic is 0.769 with a p-value of 3.888586×10^{-37}, indicating a statistically significant deviation from the theoretical distribution. EUR and GBP exhibit lower K–S statistics (0.228 and 0.256) with p-values of 3.504182×10^{-03} and 6.856250×10^{-04}, respectively.

Although the K–S test rejects the null hypothesis at conventional significance levels, the inverse gamma Q–Q plots in Figure 4 show strong alignment between empirical and theoretical quantiles, particularly in the upper tail. This suggests that while the inverse gamma distribution may not perfectly capture the entire distribution, it performs well in modeling extreme volatility, which is of primary interest in financial risk analysis (Embrechts et al., 1997).

Table 4: K-S Test Results

	K-S Statistics	p-value
USD	0.769249	3.888586×10^{-37}
EUR	0.228172	3.504182×10^{-03}
GBP	0.255756	6.856250×10^{-04}

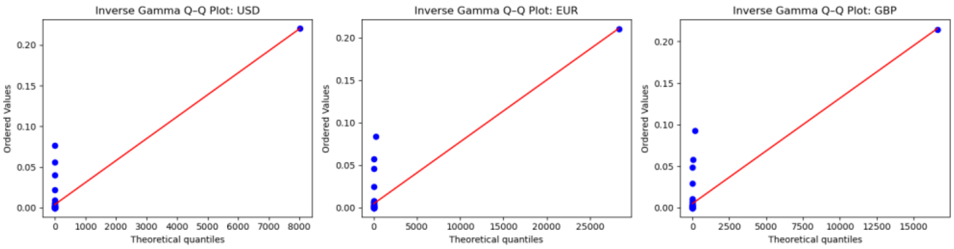

Figure 4: Inverse Gamma Q-Q Plot of the Currencies Exchange Rate

Comparative Volatility Analysis Across Currencies

Table 5 compares volatility across currencies using mean volatility, standard deviation, and inverse gamma scale parameters. GBP emerges as the most volatile currency, with the highest mean volatility (0.00865), the largest standard deviation (0.03139), and the largest inverse gamma scale parameter (1.394487×10^{-06}). EUR ranks second, while USD consistently records the lowest values across these measures. Figures 5 and 6 visually reinforce these findings by showing more frequent and larger volatility spikes for GBP, particularly in extreme periods exceeding the 95th percentile.

Table 5: Volatility Comparison across Currencies

	Mean Volatility	Std of Volatility	Inverse Gamma beta
USD	0.007759	0.031138	2.897953×10^{-26}
EUR	0.008289	0.030419	1.068814×10^{-06}
GBP	0.008652	0.031392	1.394487×10^{-06}

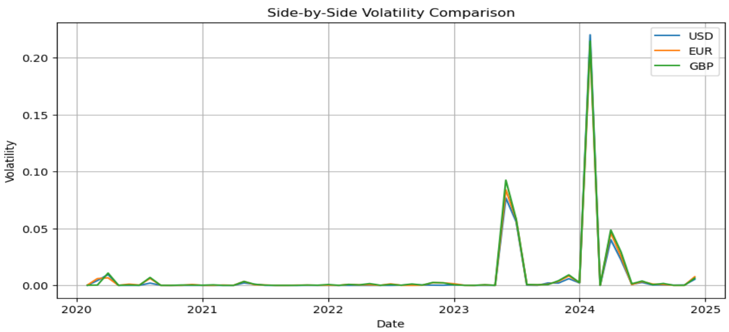

Figure 5: Side-by-Side Volatility Comparison

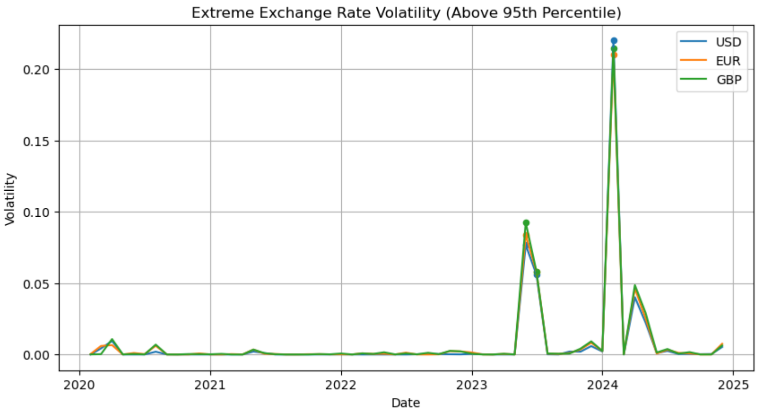

Figure 6: Extreme Exchange Rate Volatility

Comparison with Alternative Distributions

Table 6 compares the inverse gamma distribution with the gamma and lognormal distributions using log-likelihood values. For USD, the gamma (521.25) and lognormal (520.99) distributions outperform the inverse gamma (376.07). Similar patterns are observed for EUR and GBP, where the lognormal distribution achieves the highest likelihood values. Despite this, the inverse gamma distribution remains theoretically appealing due to its ability to capture heavy-tailed behavior and its widespread use in stochastic volatility modeling (Kim, Shephard, and Chib, 1998). Its performance in capturing tail behavior justifies its application in this study.

Table 6: Log-Likelihood Comparison of Distributions

	Inverse Gamma	Gamma	Lognormal
USD	376.072497	521.250610	520.988271
EUR	313.767700	320.636745	331.749809
GBP	310.903229	316.489720	328.402144

CONCLUSION

This study examined the distributional characteristics of monthly exchange rate volatility of the Nigerian Naira using data for the Naira against the US Dollar, Euro, and Pounds Sterling from January 2020 to December 2024. Volatility was measured using squared logarithmic returns, allowing direct analysis of the magnitude of exchange rate fluctuations.

The empirical results show that exchange rate volatility across all three currencies is characterized by extreme right skewness and very high kurtosis. Specifically, skewness values range between 5.48 and 5.93, while kurtosis values exceed 33 for all series, indicating strong departures from normality and the presence of heavy-tailed behavior. These findings are consistent with well-documented stylized facts of financial volatility and justify the consideration of heavy-tailed distributions.

Maximum likelihood estimates of the inverse gamma parameters reveal meaningful differences across currencies. The shape parameter is smallest for the Naira/US Dollar exchange rate, implying heavier tails, while the scale parameter is largest for the Naira/Pounds Sterling exchange rate, indicating larger volatility magnitudes. Consistent with descriptive statistics and scale parameter estimates, comparative analysis identifies the Naira/Pounds Sterling exchange rate as the most volatile, followed by the Naira/Euro and the Naira/US Dollar exchange rates.

Goodness-of-fit results based on the Kolmogorov–Smirnov test reject the hypothesis of an exact inverse gamma distribution for the full volatility series. However, graphical evidence from quantile–quantile plots demonstrates strong agreement between empirical and theoretical distributions in the upper tail. This indicates that, although the inverse gamma distribution does not perfectly describe the entire volatility distribution, it performs well in modeling extreme volatility realizations. Further comparison with alternative distributions shows that the gamma and lognormal distributions provide better overall likelihood fit, but this does not diminish the relevance of the inverse gamma distribution for tail-focused volatility analysis.

Overall, the findings indicate that monthly Naira exchange rate volatility exhibits heavy-tailed behavior consistent with inverse gamma characteristics, particularly in the upper tail. Rather than asserting optimality, the study demonstrates that the inverse gamma distribution provides a theoretically motivated and empirically useful framework for capturing extreme exchange rate volatility in Nigeria. This distribution-based approach complements conventional volatility modeling methods and offers valuable insights for exchange rate risk assessment in an emerging market context.

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