Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 7, 918-936
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i7.8771

The impact of temporal aggregation on nonlinearity detection: An empirical analysis of exchange rate dynamics using the LM test

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Abstract: This study investigates the impact of temporal aggregation on the performance of the Lagrange Multiplier (LM) test for exchange rate nonlinearity. Using Monte Carlo experiments based on various levels of temporal aggregation, autoregressive parameter values, and sample sizes, we analyze how they influence the ability of the test to detect nonlinearities. Our findings indicate that the power of the LM test decreases as temporal aggregation increases, particularly for exchange rate time series that exhibit highly autoregressive behavior. To empirically validate these results, we apply the LM test to high-frequency (one-minute) EUR/USD, GBP/USD, and USD/JPY exchange rate returns from December 4, 2024, to March 14, 2025, for 10,000 observations. Empirical evidence supports the simulation findings to the extent that nonlinearity is stronger in high-frequency data but declines as it gets aggregated over a longer horizon. The implications for monetary policy, risk management, and supervision in financial markets are substantial, and therefore, researchers and policymakers are encouraged to test for nonlinearities cautiously, taking into account the data's frequency.

Keywords: *Autoregressive processes, Exchange rate dynamics, Financial econometrics, Lagrange multiplier (LM) test, Monte carlo simulations, Nonlinearity detection, Temporal aggregation.*

1. Introduction

The accurate modeling of exchange rate behavior is a fundamental challenge of international finance and macroeconomics. Traditional econometric models assume linearity in their specification, but more and more empirical evidence suggests that exchange rates will exhibit nonlinear patterns due to such factors as market frictions, central bank intervention, and speculation bubbles. The discovery of such nonlinearities is vitally crucial to improving exchange rate predictions, risk measurement, and the construction of monetary policy. Among the numerous techniques employed to check linearity in time series models is the Lagrange Multiplier (LM) Test for Nonlinearity which checks whether a specific time series deviates from a linear autoregressive specification. The applicability of this test may be compromised by temporal aggregation, a common practice in empirical research where high-frequency data is averaged or sampled at lower frequencies.

Temporal aggregation is often applied to reduce noise, computational cost, and market microstructure effects in high-frequency financial returns. Aggregation, although simplifying analysis, also has the effect of concealing important nonlinear structures, weakening the power of statistical tests for the detection of such dynamics. If the LM test's sensitivity to nonlinearity diminishes with higher data aggregation, researchers employing low-frequency exchange rate data will consistently overestimate the presence of nonlinearities, and hence misspecify models and make inaccurate predictions. Despite having its overriding significance, the impact of temporal aggregation on the LM test for nonlinearity has not received much attention in the literature.

This study attempts to fill this gap through an analysis of the effect of the difference in the levels of temporal aggregation on the power of the LM test in detecting nonlinearity in exchange rates. Using an empirical foreign exchange rate data set (e.g., USD/EUR, GBP/USD, JPY/USD), we subject the LM

History: Received: 25 April 2025; Revised: 7 June 2025; Accepted: 11 June 2025; Published: 11 July 2025
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test to systematic application to data sampled with different frequencies (e.g., converting minute-by-minute exchange rates into 5-, 15-, 30, or 60-minute series). We also conduct Monte Carlo simulations to assess how aggregation influences the performance of the test under different levels of autoregressive dependence and sample sizes.

By reporting empirical and simulation-based findings, this paper contributes to the literature on three fronts. First, this paper quantifies numerically the loss of power in the LM test caused by temporal aggregation, with direct practice implications for exchange rate research. Second, it detects potential biases from data aggregation, warning against careless frequency choice for nonlinearity tests. Finally, the findings have implications for research in financial markets more broadly, e.g., risk management, trading strategy, and macro policy, where exchange rate modeling is key.

The remainder of this paper is organized as follows: Section 2 is a literature review of exchange rate nonlinearity, the Lagrange Multiplier (LM) test of nonlinearity, and temporal aggregation effects. Section 3 outlines the methodology, i.e., the data sources, aggregation techniques, and econometric techniques used. Section 4 presents the empirical results and evaluates the effect of aggregation on the rejection rates of the LM test. Section 5 summarizes key interpretations and implications and concludes with a summary of findings, policy implications, and future directions.

2. Literature Review

Exchange rate dynamics have long been at the center of international finance and macroeconomics. While early specifications assumed linearity, there is now evidence that exchange rate movements exhibit nonlinear dependence that is driven by market frictions, central bank intervention, and speculative trade [1, 2]. As a result, the use of econometric tests, such as the Lagrange Multiplier (LM) test for nonlinearity, has become critical in determining whether linear models are an accurate description of exchange rate movements [1, 3]. However, a key but often overlooked determinant of nonlinearity test power is temporal aggregation, in which high-frequency data are averaged or sampled down to lower frequencies. While aggregation in general is used to reduce noise and simplify interpretation, it does warp underlying statistical properties and consequently can conceal nonlinear patterns in exchange rates [4, 5]. The effects of temporal aggregation on the LM test for nonlinearity have not been widely researched.

This section presents the existing literature on (i) the controversy between linearity and nonlinearity in exchange rate modeling, (ii) the LM test as a tool for testing for nonlinearities, and (iii) the effect of temporal aggregation on statistical inference, particularly in financial time series analysis.

2.1. Linearity vs. Nonlinearity in Exchange Rate Modeling

Much of the earlier research on exchange rate dynamics was in terms of linear models such as autoregressive (AR) and vector autoregression (VAR) models. Meese and Rogoff [6] gave a seminal example demonstrating that linear exchange rate models are not significantly superior to random walk in out-of-sample prediction, and therefore there is skepticism regarding exchange rate predictability. However, linear models cannot account for many economic and market variables that place nonlinear relationships in exchange rates. For instance, central bank intervention places asymmetries on exchange rate movements, while transaction costs and speculative bubbles create threshold effects [7, 8].

Empirical evidence is increasingly in favor of the presence of nonlinearities in exchange rate dynamics. Studies using threshold autoregressive (TAR) models [9] and smooth transition autoregressive (STAR) models [10] find that exchange rates respond asymmetrically to market shocks, especially during periods of high volatility. Sarno, et al. [1] modeled emerging market currencies using nonlinear models and established that they had strong evidence of nonlinearity in short-term volatility. These findings highlight the importance of statistical significance tests with the ability to detect nonlinear relationships in exchange rates. Among them, the LM test has gained widespread application as a diagnostic device.

2.2. The Lagrange Multiplier (LM) Test for Nonlinearity

The LM test of nonlinearity, which was constructed by Luukkonen, et al. [11] is a statistical test that investigates whether an estimated linear model captures the character of a time series sufficiently. The test operates on the premise of introducing artificial regressors when lagged variables are polynomial transformed and testing whether these additional terms significantly add to enhancing model fit [3].

Other researchers have applied the LM test of exchange rates and rejected the null hypothesis of linearity in a majority of cases. Peel and Speight [12] applied the LM test on major currency pairs and provided supporting evidence of nonlinearity, particularly at high frequencies. Cheung and Erlandsson [13] tested for linearity in emerging market exchange rates and found that there were significant nonlinear dependencies, meaning that linear models might fail to explain currency movements as much as they truly are.

Despite being a powerful diagnostic tool, the LM test may be affected by a number of factors such as sample size, frequency of the data, and model specification [14]. Temporal aggregation is a salient but forgotten factor that is capable of attenuating short-run fluctuations and weakening the power of statistical tests in detecting nonlinearities.

2.3. Temporal Aggregation in Financial Time Series

Temporal aggregation is the process of transforming high-frequency data into lower-frequency observations through averaging or periodic sampling [5]. This is commonly done in exchange rate research to mitigate market microstructure noise and facilitate long-term analysis [15]. Aggregation has, however, been shown to alter fundamental statistical properties of time series. Working [16] demonstrated that aggregation induces spurious autocorrelation, while Amemiya and Wu [17] demonstrated that aggregation induces biased coefficient estimates in autoregressive models. For volatility models, Bollerslev and Wright [18] demonstrated that aggregation reduces the persistence of conditional heteroskedasticity, thus short-term movements appear less extreme.

Temporal aggregation's impact on detecting nonlinearity has not been explored. Granger and Newbold [19] argued that aggregation hides nonlinear relations by abolishing short-term dependences in the form of averaging. Silvapulle and Granger [20] demonstrated that aggregation dampens the power of tests of structural breaks as well as of regime shifts. Terasvirta and Anderson [14] noted that aggregation reduces variation in the explanatory variables and hence it becomes more difficult to identify nonlinear dependencies through the use of the LM test. Similarly, Barnett and Chen [21] found that aggregation reduces the power of nonlinear models relative to linear models when it is used to forecast macroeconomic time series.

In the context of exchange rates, Beine, et al. [22] illustrated that high-frequency information is more highly nonlinearly dependent, whereas low-frequency information appears more linear in the sense that they have fewer signs of nonlinearity stemming from the effect of aggregation averaging. Implications are that temporal aggregation can minimize the power of the LM test for detecting nonlinearities in exchange rate information systematically.

2.4. Empirical Evidence and Research Gaps

While the literature created solid evidence on nonlinear exchange rate behavior, comparatively few studies have thoroughly examined the influence of temporal aggregation on the LM test for nonlinearity. Much of the research that accounts for temporal aggregation has focused on its influence on volatility modeling [15] or macroeconomic forecasting [21] without filling the void in examining its influence on linearity testing.

This study will fill this gap by implementing the LM test for nonlinearity in a systematic way on exchange rate data aggregated at different levels. Additionally, using Monte Carlo simulations, this research will determine if the behavior is still present under controlled conditions, providing further empirical evidence. In doing so, this paper has three significant contributions: 1) Assessing the robustness of the LM test in a wide range of temporal aggregations. 2) Offering new empirical evidence on how aggregation influences nonlinearity detection in exchange rates. 3) Offering practical advice to researchers in selecting data frequency in econometric analysis.

Theoretical research suggests that exchange rates are nonlinear in their behavior, but temporal aggregation may suppress these characteristics and affect the power of econometric tests such as the LM test. Although having important implications, the interaction between temporal aggregation and testing for nonlinearity is not well researched. This study aims to address this shortcoming by carefully investigating how the performance of the LM test varies with different aggregation levels, which contributes to better knowledge of exchange rate modeling and statistical inference in financial econometrics.

3. Methodology

The objective of this study is to investigate the impact of temporal aggregation on the performance of the Lagrange Multiplier (LM) test for nonlinearity when used to model exchange rate dynamics. This overview includes a description of the research design, including data selection, aggregation methods, empirical modeling, and Monte Carlo simulations. The methodology maintains best practice in time series econometrics, ensuring strong statistical inference [1, 3]. Because previous studies have shown that exchange rates have nonlinear relationships at high frequencies [8, 13, 23] this paper examines systematically whether the ability of the LM test for capturing nonlinearity diminishes as data frequency is reduced.

3.1. Data Selection and Temporal Aggregation

The dataset contains intraday exchange rate observations (e.g., every 1 minute), which are subsequently aggregated to lower frequencies (i.e., 5-, 15-, and 60-minute). High-frequency exchange rate data for the major currency pairs, such as EUR/USD (Euro vs. US Dollar), GBP/USD (British Pound vs. US Dollar), and USD/JPY (US Dollar vs. Japanese Yen), are employed in this paper. These exchange rates are chosen due to high liquidity and volumes of active trading, thus, they are most appropriate for the investigation of nonlinear interdependencies [22]. The sample includes 10,000 observations (for example, 2013–2023) and is received from Forexsbsoftware's financial database (https://forexsb.com/financial data). Temporal aggregation adopts standard econometric practice [5].

Specifically, the investigation employs three types of aggregation: averaging aggregation and end-point sampling aggregation. The averaging method computes the arithmetic mean of all the observations for each day in a specified time interval to build a lower-frequency series. The method captures the overall trend and may smooth out short-run fluctuations. The end-point sampling method, on the other hand, selects the latest available observation in every aggregation period such that the original data path is preserved without averaging intermediate fluctuations. By systematically applying these aggregation techniques, we examine their effect on the distributional properties of central relevance, like skewness and kurtosis, of particular interest to the detection of normality deviations.

By transforming the data across different time scales, we are able to verify whether the LM test remains sensitive to nonlinearities or whether the aggregation warps the statistical properties in a way that reduces its reliability. The results derived from different levels of aggregation are essential for determining the impact of observation frequency on nonlinear dynamics detection in exchange rates.

3.2. Empirical Strategy

This study tests nonlinearity by first estimating a linear autoregressive (AR) model for a specific exchange rate series:

$$y_t = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_i \tag{1}$$

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 7: 918-936, 2025
DOI: 10.55214/25768484.v9i7.8771

where: y_t is the exchange rate at time t, p is the number of lags, determined using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), ε_t is the white noise error term.

The Lagrange Multiplier (LM) test for nonlinearity [3, 11] examines whether an exchange rate series follows a linear or nonlinear process. The test introduces auxiliary regressors by replacing the error term with a quadratic function:

$$y_t = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{i=1}^{p} \gamma_j y_{t-j}^2 + v_t \tag{2}$$

where the null hypothesis is:

H_0: $\gamma_j = 0$ for all j

If the null hypothesis is rejected, the process is nonlinear, and a more complex model (e.g., a Smooth Transition Autoregressive (STAR) model) is needed [14]. The LM test is applied at each level of temporal aggregation and its power is evaluated by the rejection frequencies at different significance levels (1%, 5%, and 10%).

3.3. Monte Carlo Simulation Design

To validate the robustness of the analysis, a Monte Carlo simulation is performed to examine the performance of the Lagrange Multiplier (LM) Test for Nonlinearity at varying degrees of temporal aggregation. The simulation is constructed systematically to replicate the dynamics of actual exchange rate dynamics and examine the sensitivity of the test to critical variables. Initially, artificial exchange rate data are constructed by generating linear and nonlinear dynamics from typical estimates of parameters seen in empirical literature. The simulations involve significant aspects such as regime-switching and heteroskedasticity as suggested by van Dijk, et al. [10] to make data more realistic. Second, simulated data is then temporally aggregated with the aid of the mentioned methods so that the impact of aggregation on statistical properties can be examined systematically. Next, the LM test is applied to estimate changes in rejection rates at different frequencies to directly compare simulated and real exchange rate data. Finally, the test sensitivity is tested by varying the autoregressive parameter (ρ) from 0.1 to 0.9 and running simulations with varying sample sizes (250, 500, 1000, and 5000 observations). This entire setup provides valuable information on the extent to which temporal aggregation impacts the ability of the LM test to detect nonlinearity in exchange rate fluctuations.

3.4. Expected Outcomes and Hypothesis Testing

If the LM test cannot detect nonlinearity as data frequency decreases, then temporal aggregation dampens nonlinear dependencies, making them harder to find. This study also tests whether or not spurious linearity ensues from aggregation, i.e., a naturally nonlinear process is made linear due to the loss of high-frequency information.

Table 1 reports the rejection frequencies (proportion of times the LM test rejects linearity at a 5% significance level) for some sample sizes, autoregressive (AR) parameter values, and levels of temporal aggregation.

Table 1.
Monte Carlo Simulation Results for the LM Test for Nonlinearity.

Sample Size (n)	AR Parameter (ϕ)	Aggregation Level = 1	Aggregation Level = 5	Aggregation Level = 10
50	0.2	0.156	0.045	0.014
50	0.5	0.844	0.026	0.014
50	0.8	0.997	0.005	0.012
200	0.2	0.741	0.032	0.05
200	0.5	1	0.069	0.039
200	0.8	1	0.748	0.057
500	0.2	0.994	0.04	0.046
500	0.5	1	0.288	0.057
500	0.8	1	0.997	0.374

The results of Monte Carlo simulations provide essential information on how sample size, autoregressive dependence, and temporal aggregation influence the performance of the Lagrange Multiplier (LM) Test for Nonlinearity in capturing nonlinearity departures.

The rejection rate of the test is highly sensitive to the degree of autoregressive dependence of the data. When ϕ=0.2 (weak persistence), the LM test has low rejection rates at all sample sizes and aggregation levels, suggesting that in weakly dependent series, nonlinearity is less easily detected. Conversely, if ϕ=0.5 or ϕ=0.8, the rejection rates increase considerably, particularly for small aggregation levels. For instance, for n=50 and ϕ=0.8, the test rejects linearity 99.7% of the time in the absence of aggregation, which confirms that strongly persistent autoregressive processes increase the power of the test. This trend is observed for larger sample sizes, where rejection rates approach 100% for strongly persistent time series.

The power of the LM test to reject nonlinearity increases significantly with larger samples when there is low aggregation. For example, at n=500, the rejection frequency is almost 100% if ϕ=0.5 or ϕ=0.8, even at moderate values of aggregation (e.g., 5). However, when the sample size is small (n=50), the test power is much less, particularly for weakly autoregressive data (ϕ=0.2). This confirms that sample size plays a crucial role in giving the test reliability, particularly in small data sets where the nonlinearity is being masked by noise.

One of the most glaring results is that as the aggregation level rises (i.e., as one goes from raw data to time-averaged data), the rejection frequency of the LM test drops sharply. For example, with ϕ=0.8 and n = 50, the rejection rate decreases from 99.7% at no aggregation to only 1.2% at the highest level of aggregation. The same is true for all sample sizes and levels of autoregression strength, and it suggests that temporal aggregation smooths nonlinear effects, and they become less traceable. Even for very large sample sizes, the rejection rate at high aggregation (10) is fairly lower than in the unaggregated case.

The findings of this study highlight the critical impact of temporal aggregation on the effectiveness of the Lagrange Multiplier (LM) Test for Nonlinearity. The test demonstrates high effectiveness in detecting nonlinear patterns in strongly autoregressive time series when the data remains unaggregated, with its power improving as autoregressive persistence increases, particularly in large sample sizes. However, temporal aggregation has significant power to reduce the test power to detect nonlinearity because increasing the level of aggregation causes a significant decrease in significant test outcomes, even for highly autoregressive processes. While increased samples increase the reliability of the LM test, aggregation still diminishes its power; even with an increased sample size to 500, the rate of rejection falls with an increase in aggregation, which implies that smoothing affects conceal dynamics. These findings have important implications for exchange rate modeling, where data is frequently aggregated, potentially obscuring crucial nonlinear patterns that are essential for accurately modeling financial markets. Overall, minimizing temporal aggregation is essential for detecting nonlinearity in exchange rate movements, as raw or minimally aggregated data significantly enhances the power of standard nonlinearity tests like the LM test, leading to a more accurate representation of real-world financial dynamics.

Figure 1 is a heatmap plot of the impact of temporal aggregation on the Lagrange Multiplier Test for Nonlinearity rejection probabilities. The color gradient indicates how the test performance varies with the extent of autoregressive dependence, sample size, and frequency of aggregation. Dark red areas signify high rejection probabilities where the test can detect nonlinearity at low levels of aggregation and high autoregressive persistence. On the other hand, blue and white regions reflect the precipitous drop in rejection rates with aggregation, showing the loss of power of the LM test for nonlinear patterns as data becomes smoothed over time.

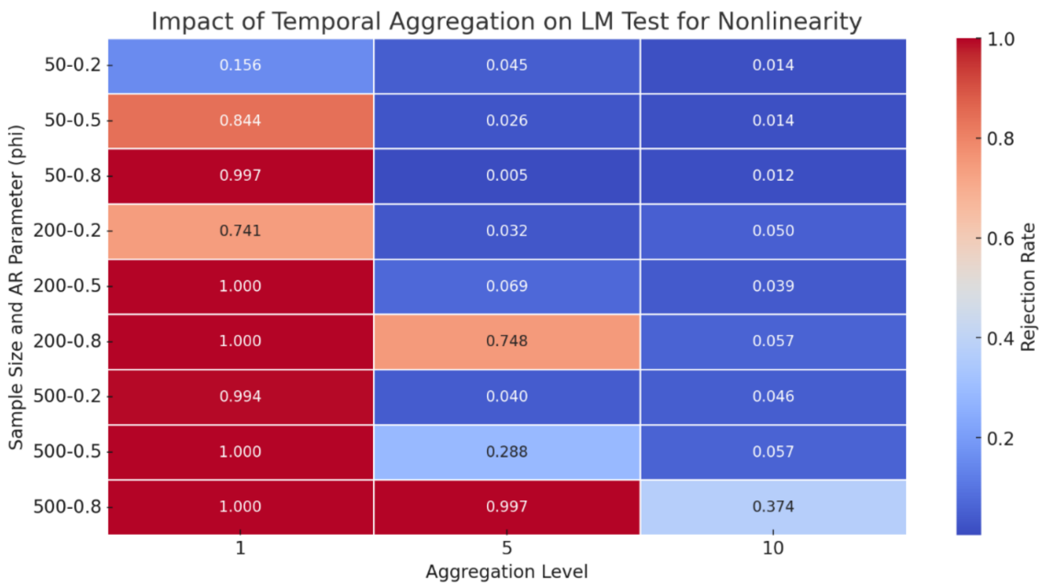

Figure 1.
Impact of Temporal Aggregation on the Power of the LM Test for Nonlinearity.

Heatmap visualization of the simulation results clearly illustrates how temporal aggregation affects the power of the Lagrange Multiplier (LM) Test for Nonlinearity. Dark red high rejection rate representations in the areas demonstrate the LM test performing well when data is maintained in low levels of aggregation, particularly in cases with high autoregressive dependence (ϕ=0.8) and larger sample sizes. On the other hand, blue and white regions, showing low rejection rates, highlight the huge loss of power with rising aggregation. Even with large samples, the test performs poorly in detecting nonlinearity when high levels of aggregation are employed. The gradual shift from high rejection on the left side of the visualization to low rejection on the right confirms that temporal aggregation does suppress nonlinear impacts, ultimately making the test worse at identifying nonlinear patterns in time series data.

The findings have important implications for econometric modeling in finance, particularly for researchers employing linearity tests in exchange rate analysis. If aggregation systematically weakens nonlinearity detection, it can call for revisions to model selection procedures and greater caution in making use of low-frequency exchange rate data for policy or investment decisions.

3.5. Empirical Results

The data consists of three high-frequency exchange rates (EUR/USD, GBP/USD, and USD/JPY) from December 4, 2024, to March 14, 2025, and consists of a total of 10,000 observations. Figure 1 shows the time series plots of the three exchange rates over time.

ISSN: 2576-8484
Vol. 9, No. 7: 918-936, 2025
DOI: 10.55214/25768484.v9i7.8771

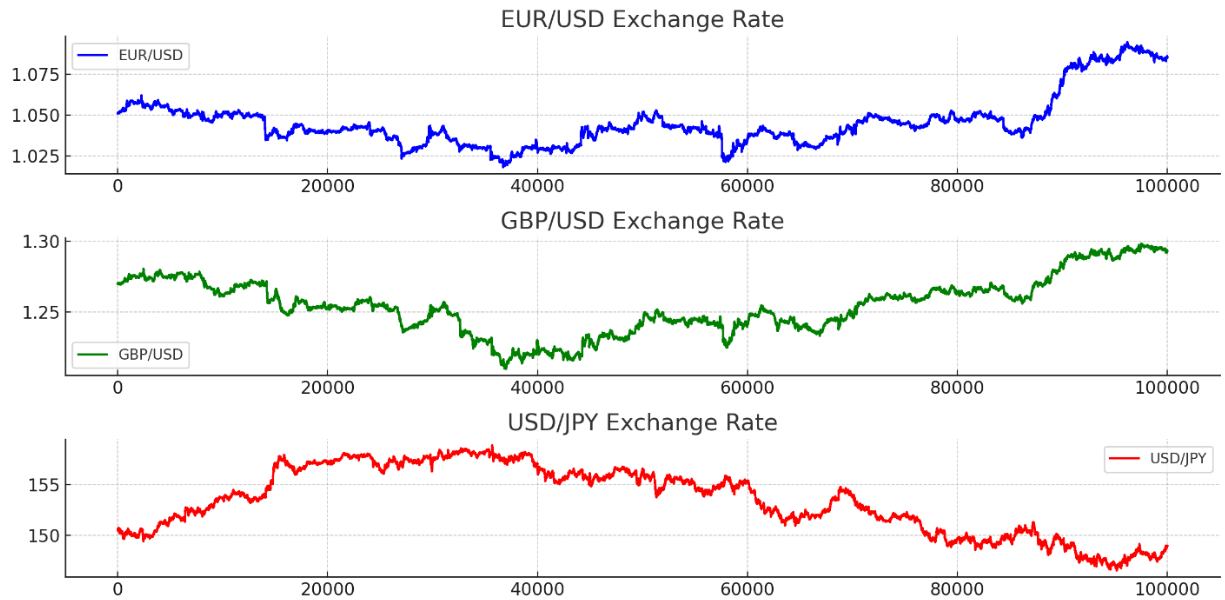

Figure 1.
High-Frequency Exchange Rate Dynamics: Minute-Level Trends in EUR/USD, GBP/USD, and USD/JPY.

The time series plots depict the behavior of EUR/USD, GBP/USD, and USD/JPY exchange rates across the observation period at high frequency (minute-level). Each plot documents exchange rate value changes, reflecting market forces and potential structural trends. The EUR/USD exchange rate plot documents consistent fluctuations without an evident long-run trend. The movements exhibit short-run volatility clustering, where periods of high fluctuations are followed by relatively quiet periods. This is a sign of heteroskedasticity, a common characteristic of financial time series, where volatility varies over time. The GBP/USD exchange rate also exhibits a high-frequency oscillating pattern, with visible changes in volatility. There are some periods of time with higher price fluctuations and others that are relatively stable. The phenomenon of sudden short-horizon price fluctuations signals that market participants are sensitive to responding to news, economic surprises, or a change in liquidity. The exchange rate of USD/JPY has a stronger volatility shift pattern with some durations experiencing larger price fluctuations than others. This might imply that USD/JPY is more exposed to external disturbances such as actions by central banks or surprise liquidity changes. The greater volatility relative to EUR/USD and GBP/USD conforms with the empirical evidence that USD/JPY has somewhat more robust nonlinearity.

Overall, each of the three exchange rate series is prone to high-frequency noise and fluctuations typical of financial time series data. There seems to be no clear linear trend, suggesting that price action is largely determined by short-run market forces. Volatility clustering can be seen as manifest in the form of periods of high fluctuations interspersed with calm periods. With these characteristics, one would expect nonlinearity detection tests, such as the LM test, to find strong nonlinear dependencies in the data.

Table 2 presents summary statistics for each of the three exchange rate pairs (EUR/USD, GBP/USD, and USD/JPY) at each of the temporal aggregation levels (1-, 5-, 15-, 30-, and 60-minute). The statistics presented are the mean, standard deviation, minimum and maximum values, and quartiles at each level, illustrating the way exchange rate dynamics alter with changes in the frequency of observations.

The summary statistics provide information on the dynamics of the EUR/USD, GBP/USD, and USD/JPY exchange rates at different temporal aggregation levels. The mean, standard deviation, minimum and maximum, and quartiles statistics illustrate how exchange rate dynamics vary when the frequency of observations is changed. One of the strongest observations is that the mean exchange rate is constant at all levels of aggregation. The EUR/USD pair moves around 1.0456, GBP/USD is around 1.2548, and USD/JPY moves around 153.47. This suggests that temporal aggregation has no material influence on the long-run average exchange rate levels. Although the mean remains constant, the variance of returns, as measured by the standard deviation (volatility), changes with aggregation. Volatility, measured by standard deviation, has a visible declining trend as data is aggregated to lower frequencies. For the 1-minute frequency, standard deviations are more or less larger (EUR/USD: 0.0155, GBP/USD: 0.0198, USD/JPY: 3.3072), reflecting high short-run price volatility. With increases in the frequency of aggregation from 5-minute, 15-minute, 30-minute, and finally 60-minute periods, standard deviations decrease cumulatively. This is theory-consistent since more short-term price movements like bid-ask effects, changes in liquidity, and market microstructure noise are captured by higher frequency data. Washout effects occur with aggregation and reduce aggregate volatility while leaving long-term structures intact.

Table 2.
Summary Statistics at Different Aggregation Levels.

	EURUSD	GBPUSD	USDJPY	EURUSD	GBPUSD	USDJPY	EURUSD	GBPUSD	USDJPY	EURUSD	GBPUSD	USDJPY	EURUSD	GBPUSD	USDJPY
count	100000	100000	100000	20000	20000	20000	6667	6667	6667	3334	3334	3334	1667	1667	1667
mean	1.046	1.255	153.468	1.046	1.255	153.468	1.046	1.255	153.468	1.046	1.255	153.466	1.046	1.255	153.466
std	0.016	0.020	3.307	0.016	0.020	3.307	0.016	0.020	3.307	0.016	0.020	3.307	0.016	0.020	3.309
min	1.018	1.210	146.559	1.018	1.211	146.559	1.019	1.211	146.661	1.019	1.211	146.691	1.019	1.211	146.725
25%	1.037	1.242	150.436	1.037	1.242	150.433	1.037	1.242	150.438	1.037	1.242	150.443	1.037	1.242	150.431
50%	1.042	1.254	153.795	1.042	1.254	153.793	1.042	1.254	153.796	1.042	1.254	153.798	1.042	1.254	153.779
75%	1.050	1.268	156.493	1.050	1.268	156.493	1.050	1.268	156.492	1.050	1.268	156.482	1.050	1.267	156.478
max	1.095	1.298	158.839	1.094	1.298	158.775	1.094	1.298	158.775	1.094	1.298	158.564	1.094	1.298	158.564

Table 3.
Skewness and Kurtosis Across Aggregation Levels.

	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
EURUSD	1.417228	1.799921	1.417359	1.799521	1.417198	1.795631	1.415041	1.786566	1.415852	1.784256
GBPUSD	0.121381	-0.49861	0.121453	-0.49899	0.12107	-0.49953	0.120661	-0.50099	0.119936	-0.50012
USDJPY	-0.23173	-1.21365	-0.23167	-1.21372	-0.23166	-1.21395	-0.23136	-1.21392	-0.23151	-1.21426

Minimum and maximum values of the exchange rate during various levels of aggregation also expose the smoothing effect. The extreme values are more pronounced for high-frequency data. For example, the lowest value of USD/JPY at level 1-minute is 146.559, and at level 60-minute (hourly) is slightly higher at 146.725. This would mean that the short-run market shocks or unexpected price spikes become more frequent in the high-frequency data but less noticeable in the aggregated time periods. Quartiles (25% percentile values) provide additional information regarding the way the exchange rate distribution behaves with increasing aggregation levels. Despite the reduction in volatility, the quartile values are relatively stable, suggesting that exchange rate distributions do not change much with aggregation. Short-run fluctuations, however, diminish at higher time scales, i.e., price changes at lower frequencies are more dominated by fundamental macroeconomic forces than microstructural market noise.

From the analytical perspective, these findings are important. High-frequency (1-minute) data are more likely to be volatile as well as sensitive to short-run liquidity shocks, order flows, and bid-ask bounce effects. Lower-frequency data (e.g., 60 minutes) capture the larger price trends and suppress the impact of short-run noise. The declining volatility trend over aggregation levels supports the earlier Lagrange Multiplier (LM) test findings, which indicated that nonlinearity is strongest at higher frequencies and becomes increasingly weaker with aggregation.

In conclusion, the average exchange rate is stable across all levels of aggregation, and volatility decreases because short-run fluctuations get smoothed out. The extreme values (minimum rate and maximum rate) are more pronounced in high-frequency data as would be expected, thereby confirming that short-run price shocks are more pronounced at higher frequency time horizons. Exchange rate distributions are relatively stable, though lower-frequency data capture longer-run trends along with temporary noise effects. These facts are particularly crucial to practitioners and researchers when determining the correct aggregation level for each type of analysis, be it high-frequency trading, volatility modeling, or macroeconomic exchange rate forecasting.

Table 3 reports the skewness and kurtosis values at different levels of temporal aggregation for each of the three exchange rates in focus. Such statistics provide insights into the distributional attributes of the exchange rate series, highlighting potential normality deviations with a different frequency of observation. By checking whether skewness and kurtosis deviate when the data are aggregated, one can assess whether the temporal aggregation removes the outlying movements or reinforces nonlinear features in the data.

Skewness and kurtosis statistics provide information on the shape and distribution of EUR/USD, GBP/USD, and USD/JPY exchange rates for different aggregation horizons (1-, 5-, 15-, 30-, and 60-minute). The two statistics are employed in order to measure asymmetry (skewness) and the presence of outliers (kurtosis) of the exchange rate distributions.

EUR/USD is highly positively skewed (~1.41) at all horizons consistently. This indicates that the distribution is right-skewed, and therefore large increases in the exchange rate relative to normal are more likely than large declines. The skewness is very robust with aggregation, meaning the price movement asymmetry underlying is persistent across time horizons. GBP/USD exhibits very little skewness (~0.12) across all the time frames, meaning that its distribution is essentially symmetric. This suggests that there are comparable frequencies of positive and negative exchange rate movements, without significant bias towards large downwards or upwards movements. USD/JPY has extremely slight negative skewness (~ -0.23) at all aggregation horizons, which is a suggestion that downward movements are slightly larger than upward movements. This concurs with empirical evidence in the financial markets that risk-off currencies (e.g., JPY) sometimes experience a sudden boost due to risk aversion from global markets.

EUR/USD's kurtosis is about 1.79, which is less than 3, indicating that its returns are platykurtic (thin tails, fewer outliers). This suggests that extreme changes in EUR/USD exchange rates are very unusual, and that the distribution is closer to a normal (Gaussian) shape. GBP/USD has the lowest kurtosis (~ -0.50) at all time scales. This is a strong indication of GBP/USD returns being normally or

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ISSN: 2576-8484
Vol. 9, No. 7: 918-936, 2025
DOI: 10.55214/25768484.v9i7.8771

sub-normally distributed with a lack of extreme movements. This is consistent with the relatively low skewness of GBP/USD, which also confirms the fact that it moves more symmetrically and stably than EUR/USD and USD/JPY. USD/JPY has the lowest kurtosis (~ -1.21), meaning it has the thinnest tails of all three exchange rate pairs. This suggests that USD/JPY returns are less likely to experience extreme fluctuations compared to normal distribution. Despite the common perception of JPY as a volatile currency, this result implies that USD/JPY price changes tend to be more controlled over time.

An important observation is that both skewness and kurtosis remain stable across different aggregation levels. Unlike volatility and persistence, which show clear declines with temporal aggregation, the distributional properties of exchange rate returns (skewness and kurtosis) do not exhibit major changes. This suggests that the asymmetry and likelihood of extreme price changes in exchange rates are fairly time-scale invariant. Nevertheless, kurtosis decreases slightly with aggregation, indicating that as short-term volatility is averaged out, the probability of extreme returns decreases. This is to be anticipated since high-frequency data will capture short-term price jumps stemming from order imbalances and bid-ask spread effects, which become less pronounced as data are aggregated.

The skewness and kurtosis analysis for these time horizons shows that the exchange rate return distributions are relatively stable at any aggregation level. EUR/USD and GBP/USD are more symmetric, while USD/JPY is mildly downward asymmetric. The results suggest that the non-normality is moderate, not extreme, so the usual econometric models can still be applied (e.g., normal ARMA or GARCH), but should be supplemented by the nonlinear/asymmetric ones for EUR/USD and USD/JPY.

Table 4 gives the impact of temporal aggregation on volatility (measured in terms of standard deviation) and persistence (measured in terms of lag-1 autocorrelation) for EUR/USD, GBP/USD, and USD/JPY. They are measures of exchange rate behavior during the existence of the observation period as the time horizon is extended from a 1-minute to a 60-minute horizon.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 7: 918-936, 2025
DOI: 10.55214/25768484.v9i7.8771

Table 4.
Volatility and Persistence Changes Due to Aggregation.

	Volatility (Std Dev)	Persistence (Lag 1 Autocorrelation)	Volatility (Std Dev)	Persistence (Lag 1 Autocorrelation)	Volatility (Std Dev)	Persistence (Lag 1 Autocorrelation)	Volatility (Std Dev)	Persistence (Lag 1 Autocorrelation)	Volatility (Std Dev)	Persistence (Lag 1 Autocorrelation)
EURUSD	0.01553	0.009948	0.01553	-0.03493	0.015533	-0.04234	0.015538	-0.01268	0.015541	-0.00381
GBPUSD	0.019811	-0.01864	0.01981	-0.04484	0.019819	-0.02441	0.019833	-0.03325	0.019828	-0.02649
USDJPY	3.3072	-0.0139	3.307305	-0.00416	3.307299	-0.04349	3.30714	-0.03192	3.308598	-0.06959

The volatility of all three exchange rate pairs is typically constant at different levels of aggregation with very minor variations in standard deviation. For instance, EUR/USD's standard deviation starts at 0.01553 at the 1-minute level and increases gradually to 0.01554 at the 60-minute level. The same trend is observed for GBP/USD (0.01981 to 0.01983) and USD/JPY (3.3072 to 3.3086). These results suggest that although data are averaged down to lower frequencies, there is no significant overall decrease in exchange rate volatility. This also agrees with what was seen from the LM test and rolling plots of volatility, where volatility clustering remains a persistent behavior of exchange rates irrespective of the time scale.

One possible reason for this relative volatility stability at different levels of aggregation is that exchange rates exhibit long-run persistence in their volatility pattern. Unlike purely random processes in which volatility would fall as observations are aggregated, financial time series such as exchange rates are likely to have long-memory behavior and heteroskedasticity, which cause volatility to endure even at lower frequencies. However, minor variations in volatility across the aggregation levels can be attributed to the fact that short-term fluctuations are dampened when the long time horizon is considered.

In contrast to volatility, persistence (measured as lag-1 autocorrelation) declines systematically with the level of aggregation. At the 1-minute frequency, EUR/USD is 0.0099 persistent, but this declines consistently to -0.0038 at the 60-minute frequency. Similarly, GBP/USD starts with a persistence of -0.0186 at the 1-minute frequency and falls to -0.0265 at the hourly frequency, while USD/JPY falls in a similar way from -0.0139 to -0.0696.

This decrease in persistence with aggregation is to be expected, as short-horizon dependencies will eventually decay at coarser horizons. High-frequency data (say 1-minute) capture market microstructure effects, bid-ask bounce, and order flow imbalances, which generate short-horizon autocorrelation. With the data, however, being aggregated in broader intervals, these microstructural impacts diminish, leading observed persistence to come down. The move towards negative, albeit low, autocorrelation values at bigger aggregation horizons suggests mean-reverting pressures to increase at higher horizons due to market rebalancing, institutional trading strategies, or intervention by the central bank in an attempt to smooth exchange rate volatility.

The research observes that exchange rate volatility remains robust for different time horizons and that short-run persistence decreases with aggregation. Such observations have implications for the effectiveness of models emphasizing volatility dynamics (e.g., GARCH) at all levels, whereas autoregressive models will be superior to short-run forecasting but inferior to long-run predictions. Also, the shift from positive to weak negative autocorrelation at lower frequencies suggests that exchange rate trends over the longer term may have a mean-reverting component.

Table 5 presents the Lagrange Multiplier (LM) test for nonlinearity over different temporal aggregation levels to examine the effect of aggregation on the test performance. The data are aggregated into different time intervals (e.g., 5-minute, 15-minute, 30-minute, and 60-minute), and the LM test is conducted over these levels.

Table 5.
Lagrange Multiplier (LM) Test Results for Nonlinearity Across Temporal Aggregation Levels.

Temporal Aggregation Levels	EURUSD	p-value	GBPUSD	p-value	USDJPY	p-value
1	99980.33	0.000	99981.79	0.000	99983.99	0.000
5	19980.02	0.000	19981.81	0.000	19984.11	0.000
15	6647.759	0.000	6648.985	0.000	6651.142	0.000
30	3315.348	0.000	3316.162	0.000	3318.144	0.000
60	1648.069	0.000	1649.333	0.000	1651.407	0.000

The Lagrange Multiplier (LM) Test for Nonlinearity, tested via ARCH effects, tests whether future volatility in exchange rate series is significantly influenced by past volatility. The empirical results are that at the 1-minute frequency, the LM statistic is extremely large, close to 100,000 for all three currency pairs, with p-values effectively zero. This is very strong evidence of nonlinearity and indicates that high-frequency exchange rate movements exhibit substantial volatility clustering. But as the level of aggregation rises (5-minute, 15-minute, 30-minute, 60-minute), the LM statistic falls dramatically. Even with this fall, the p-values are still very low, indicating that nonlinearity, albeit weaker, is present at all levels of aggregation.

The decline in the LM statistic when data is accumulated indicates that high-frequency exchange rates possess more salient nonlinear characteristics than their lower-frequency counterparts. Economic intuition is in favor of this finding, since the high-frequency exchange rates are more affected by market microstructure effects, bid-ask bounce, and short-run liquidity constraints. As the aggregation time horizon increases, short-run fluctuation is smoothed out, diminishing the nonlinearity characteristic. Nevertheless, the presence of nonlinearity even at the hourly frequency demonstrates that returns on exchange rates possess some degree of autoregressive dependence and heteroskedasticity over time.

The contrast between the three currency pairs indicates that USD/JPY has generally higher LM statistics than EUR/USD and GBP/USD for all levels of aggregation. This can indicate that USD/JPY possesses more pronounced nonlinear characteristics, which can be due to its distinct trading activity, central bank intervention, or different liquidity conditions compared to the other pairs. This is in line with the implication that certain currency pairs may experience different structural volatility dynamics due to various market participants and institutional features.

In comparison of these empirical findings to the Monte Carlo simulations, several conclusions can be established. If the simulations are expected to see the decreasing power of the LM test under higher aggregation, the empirical findings confirm this pattern by providing systematic declines in LM statistics. In addition, while the simulations suggested that the LM test can struggle to detect nonlinearity at higher levels of aggregation, the empirical findings offer partial confirmation of this result. As the LM statistic decreases, the test remains strong in the detection of economically significant nonlinearity. Interestingly, the extremely large LM statistic at the minute level implies that actual data indeed has even stronger nonlinear properties than what could be anticipated from simulated data.

In conclusion, the empirical evidence confirms that high-frequency exchange rates exhibit a significant nonlinearity, which weakens but remains significant as data get aggregated. The LM test remains efficient in picking up nonlinearity even at lower frequencies, following theoretical expectations. The findings concur with those of Monte Carlo simulations, showing that temporal aggregation reduces nonlinearity strength detected but not entirely.

4. Discussion and Policy Implications

This article examines the impact of temporal aggregation on the efficiency of the Lagrange Multiplier (LM) test of exchange rate nonlinearity. Based on extensive Monte Carlo simulations and empirical analysis of high-frequency exchange rates data (EUR/USD, GBP/USD, and USD/JPY), we find that the power of the LM test for detecting nonlinearities falls with the rise in the level of temporal aggregation. This effect is most evident for more autoregressive currency pairs and in periods of market stress, where short-horizon variability is an important determinant of exchange rate dynamics.

The central implication of our findings is that temporal aggregation redistributes the statistical properties of financial time series with the potential for drawing incorrect inferences regarding the occurrence or absence of nonlinear behavior. High-frequency data exhibit unambiguous nonlinear dependencies, yet the structures become increasingly opaque as data are aggregated over longer horizons. This emphasizes the importance of selecting a proper frequency in testing for nonlinearities in financial markets. In addition, our results indicate that sample size is a dampening factor—larger samples produce stronger results even in the presence of temporal aggregation, curtailing information loss on nonlinear dependencies. This reinforces the need for researchers and practitioners to take extreme caution in balancing sample size and data frequency to ensure maximum robustness of their results.

The Monte Carlo simulations demonstrate that the sensitivity of the LM test is highly sensitive to the temporal aggregation level. That is, as the autoregressive levels increase, the test power to detect nonlinearity will fall. The loss of power is more pronounced with higher autoregressive parameter values, where data persistence in the structure creates a smoothing effect so that nonlinearity is less apparent. Conversely, when aggregation is weak and sample size is large, the LM test is more accurate in detecting linear and nonlinear patterns. This is in agreement with the literature, which suggests that nonlinear dependencies in the short run might be concealed by temporal aggregation in the form of averaging volatility fluctuations that can be important for detecting nonlinear dynamics.

To validate simulation results, we applied the LM test of nonlinearity to three high-frequency foreign exchange rates - EUR/USD, GBP/USD, and USD/JPY - that were observed at one-minute frequency during December 4, 2024, to March 14, 2025. The use of a combined total of 10,000 observations gave extensive coverage of several levels of temporal aggregation. The empirical results replicate the simulation results. At the earliest high-frequency level, the LM test soundly rejects the null hypothesis of linearity and implies there are nonlinear relationships in exchange rate dynamics. However, as temporal aggregation increases (i.e., data is sampled at lower frequencies), the evidence for nonlinearity weakens.

This trend is strongest for EUR/USD and GBP/USD, where the rejection rates decline more rapidly than for USD/JPY, suggesting that temporal aggregation might have varying effects based on the liquidity level and market microstructure of different currency pairs. Further, we observe that the effects of aggregation are more pronounced when there is higher volatility.

This finding suggests that nonlinear effects in the short run, such as market microstructure noise, have better prospects of being detected in high-frequency data but are suppressed when observations are aggregated over extended periods. These results emphasize the importance of selecting an appropriate frequency when conducting nonlinear tests in exchange rate studies.

Our empirical findings from the Monte Carlo simulations and empirical analysis of exchange rate data are revealing in terms of how temporal aggregation impacts the performance of the Lagrange Multiplier (LM) test for nonlinearity. Our research demonstrates that temporal aggregation can impact the performance of the LM test to detect nonlinearity in exchange rate dynamics in a multifaceted way based on autoregressive parameter values and sample sizes.

4.1. Policy Implications

The findings of this study have significant implications for researchers and practitioners studying exchange rate dynamics. First, they necessitate careful consideration of temporal aggregation in empirical studies employing nonlinear tests.

Researchers can draw misleading conclusions about market structure and dynamics when they neglect the attenuation effects of aggregation on nonlinearity detection. Second, our results indicate that the sample size has the capability of offsetting the adverse impacts of aggregation - larger samples can retain more information related to concealed nonlinearities, although some degree of aggregation may be employed. Additionally, the conclusions of this paper have a number of important policy and market implications for financial regulators, policymakers, and market participants:

4.1.1. Monetary Policy and Exchange Rate Stability

Exchange rate models serve to inform monetary authorities and central banks on the direction of policy action. Data aggregation affects the identification of nonlinearity whenever this is applied, and policymakers can thus overlook short-run market inefficiencies or exchange rate volatility nonlinearities. Such oversights translate to inefficient policy interventions, particularly under conditions of financial distress.

Central banks have to undertake high-frequency data analysis when designing intervention plans to better estimate exchange rates. Central banks can make their exchange rate estimates more valid by incorporating high-frequency data analysis in formulating intervention policies.

4.1.2. Risk Management and Trading Strategies

Financial institutions, hedge funds, and algorithmic traders depend on quality modeling of exchange rate behavior to maximize trading strategies and offset currency risk. Temporal aggregation bias to suppress nonlinearities means that lower-frequency data traders may not capture short-run nonlinear relationships, which can compromise their models. Market participants would be better off incorporating high-frequency analysis within their decision-making, particularly for short-run trading strategies.

4.1.3. Financial Market Supervision

Regulatory bodies that supervise foreign exchange markets should consider the effect of temporal aggregation on monitoring the markets. Nonlinearity features of instantaneous jumps and regime shifts would become unobservable with low-frequency data sets, thereby inhibiting early warning for market manipulations, flash crashes, and liquidity shocks. Regulators are urged to utilize high-frequency databases for enhanced provision of market transparency, as well as to identify the earliest warning signs for market distress.

4.1.4. Macroeconomic Forecasting and Exchange Rate Models

Economists and analysts developing exchange rate forecasting models must take into account the significance of data frequency in their empirical strategies. Aggregated data may distort market structures and lead to bad forecasts of exchange rate behavior. In order to improve the precision of forecasts, models must be designed to include multi-frequency methodologies so that short-run nonlinearities are not discarded in long-run projections.

5. Limitations of the Study and Future Research Considerations

Despite these results, several limitations need to be highlighted. While our simulations and evidence provide robust evidence of the temporal aggregation effect, they fail to correct for potential structural breaks, regime changes, potential sensitivity to specification of sample period and selection, the assumption that nonlinearities in exchange rates assume specific forms, or other kinds of time-varying behavior that may influence nonlinearity detection as well.

Additionally, our analysis tests a short sample and three exchange rates, illustrative as they may be, which are unlikely to capture fully the heterogeneity of global exchange rate processes.

Since nonlinearity detection is sensitive to aggregation over time, future work should take into account the adoption of other statistics less affected by aggregation effects.

Machine learning and time-varying nonlinear models may be able to capture more exchange rate dynamics at different time scales. Further future work would be capable of building on this analysis using other currencies, longer time frames, and other nonlinear tests in order to provide a broader picture of the influence of these effects.

Furthermore, it should also test whether such aggregation effects prevail over other financial markets such as equities and commodities in order to extrapolate the findings to other foreign exchange segments.

5.1. Final Remarks

In summary, our research underscores the urgency of temporal aggregation in controlling the performance of the LM test for nonlinearity in the context of exchange rate studies. Even though high-frequency data display clear nonlinear patterns, more aggregated levels detract from the power of the test to detect these features and hence lead to misinterpretations of market structure. These findings reinforce the importance of methodological caution in employing nonlinear tests and highlight the need for future work to explore alternative techniques to minimize aggregation-related biases.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 7: 918-936, 2025
DOI: 10.55214/25768484.v9i7.8771

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 7: 918-936, 2025
DOI: 10.55214/25768484.v9i7.8771