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Misleading dynamics: The erosion of Durbin-Watson power through time aggregation

Christos Christodoulou-Volos[1]*
[1]Department of Economics and Business, Neapolis University, Pafos, Cyprus; c.volos@nup.ac.cy (C.C.V.).

Abstract: This paper investigates the impact of temporal aggregation on the ability of the Durbin-Watson (DW) test to detect first-order autocorrelation. Through Monte Carlo simulations for AR(1), AR(2), and ARMA(1,1) processes, it demonstrates that the power function of the DW test significantly diminishes when data are aggregated from daily to weekly or monthly frequencies, especially when using arithmetic averaging. Even minor autocorrelation becomes increasingly difficult to detect, with the DW statistic converging to 2.0 under smoothing. An empirical analysis of 6,647 daily USD/EUR and USD/GBP exchange rate observations from 1999 to 2025 confirms the simulation results: DW statistics tend to be close to 2.0 at all levels of aggregation in the presence of underlying volatility. Temporal aggregation also reduces volatility and normalizes distributional characteristics, further obscuring residual dynamics. These findings highlight the risk of obtaining spurious negatives in autocorrelation testing when using the DW test on aggregated data and suggest more reliable diagnostics in applied econometrics.

Keywords: *Autocorrelation, Durbin-Watson test, Exchange rates, Monte Carlo simulation, Residual diagnostics, Temporal aggregation.*

1. Introduction

Autocorrelation is a foundational concept in time series econometrics. In applied modeling, detecting and correcting for serial correlation in residuals is essential for unbiased parameter estimation, efficient inference, and model diagnostics. Among the most widely used tools for identifying first-order autocorrelation in regression residuals is the Durbin-Watson (DW) statistic, introduced in a pair of seminal papers by Durbin and Watson [1] and Durbin and Watson [2]. The DW test has become a staple diagnostic in empirical economics, routinely reported in regression output to support model adequacy and to guide choices about lag structures, standard errors, and model specification.

Despite its popularity, the DW test — like many classical diagnostics — rests on ideal conditions rarely met in practical research. Among these is the assumption that the underlying data structure and sampling frequency preserve the dynamic properties of the process being modeled. In reality, most economic and financial time series undergo temporal aggregation: the consolidation of high-frequency observations into lower-frequency values, perhaps due to data availability, model parsimony, or interpretability concerns. For instance, daily observations of exchange rates can be averaged to weekly or monthly frequencies, and quarterly macroeconomic indicators can be formed from underlying monthly inputs. These practices are common, but their effects on statistical inference are subtle and often neglected.

Temporal aggregation has profound effects on the statistical features of time series models, including the magnitude and detectability of serial dependence. A few initial theoretical studies by Granger [3], Tiao and Wei [4] and Marcellino [5] demonstrated that aggregation alters time series spectral density, smooths dynamic shapes, and may induce or conceal autoregressive shapes. These distortions compromise the validity of conventional econometric procedures, particularly residual

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* Correspondence: c.volos@nup.ac.cy

diagnostic procedures. The dynamic character of temporally aggregated data may strongly deviate from the underlying process, casting doubt on inference, forecasting, and model specification [6].

The Durbin-Watson statistic is particularly vulnerable to such distortions. Used to discover first-order autocorrelation in regression residuals, the DW test presupposes a specific structure in the error term — the AR(1) process, for example — and is model specification and sensitive to transformation. Temporal aggregation, averaging, or sampling over time has the effect of reducing short-run fluctuations, reducing apparent serial correlation, and reducing the power of the DW test to detect underlying autocorrelation. Loss of test power due to aggregation poses a risk of Type II errors: a failure to reject the null hypothesis of no autocorrelation when serial correlation is indeed present. It is particularly important in applied research, where the absence of evidence regarding autocorrelation can falsely suggest that a model is appropriately specified and lead to inappropriate inference regarding economic dynamics.

This paper looks into the effect of temporal aggregation on the power of the Durbin-Watson test. Specifically, it investigates whether aggregating high-frequency time series into lower frequencies automatically reduces the power of the DW test to detect autocorrelation, and if so, under what conditions this loss of power is possible. Towards this end, the paper adopts a two-pronged strategy involving Monte Carlo simulation and empirical application. The simulation facility generates artificial time series that are subjected to controlled dynamic patterns of arbitrary order levels of first-order autocorrelation. The series are then temporally aggregated by other schemes — for example, last observation sampling and straightforward averaging — to simulate the transformation from daily to weekly or monthly observations. The DW test is applied at all levels of aggregation to estimate its empirical rejection rate and power, respectively, against the specified DGP. In comparing results at different levels of aggregation, we estimate how much the test's performance is affected when data becomes smoothed or compressed over time.

The second half of the analysis applies the same methodology to real financial time series: i.e., the daily EUR/USD and GBP/USD exchange rates. These two exchange rates are instances of highly liquid, high-frequency markets, which are typically employed to examine their dynamic behavior, policy interest, and volatility clustering. Exchange rate data is especially suitable for this study because it is available at fine temporal resolutions, permitting controlled aggregation and the analysis of aggregation effects on real-world dynamics. By estimating autoregressive models on both raw and aggregated series and applying the DW test at each level, we evaluate whether the empirical distortions observed in the simulations translate into meaningful differences in applied settings. The empirical findings not only serve to validate the simulation results but also illustrate the practical stakes of ignoring aggregation effects in econometric diagnostics.

By doing so, the paper contributes to several strands of literature. It contributes first to the rising body of work on the implications of temporal aggregation for time series econometrics. Even though the older literature has addressed the influence of aggregation on cointegration [5, 7] unit root testing [8] and volatility modeling [9] residual-based tests such as the DW test have attracted less attention. Lastly, the article contributes to methodological debates on model misspecification and robustness of diagnostics. Aggregation will not only mask autocorrelation but also create spurious model shapes — such as the facade of white noise residuals or damped dynamics — that obscure the need for more involved lag structures or other types of estimation. Finally, the paper speaks to practitioners in finance and macroeconomics who utilize DW statistics as a measure of model fit, particularly when they are working with data aggregated due to convenience or institutional reporting needs.

What the erosion of the Durbin-Watson test power under aggregation signifies is not just a statistical oddity — it has direct implications for empirical work. With the times of abundant data, researchers can now engage with high-frequency observations more and more often. However, because of computational or even practical limitations, many researchers still analyze lower-frequency aggregates. This transformation, while often justified, is not value-free: it alters the signal-to-noise ratio, affects serial correlation structure, and remakes the topography of inference. Familiarity with the limitations of classical diagnostics like the DW test in such cases is crucial for good empirical practice. As Lo and Craig MacKinlay [10] have shown, slight departures from optimum conditions can have extreme inference errors, especially where dynamics dominate the question asked.

The rest of the paper is structured as follows. Section 2 gives an overview of the theoretical and empirical literature on temporal aggregation, testing for autocorrelation, and Durbin-Watson diagnostics. Section 3 describes the Monte Carlo simulation experiment, including data-generating procedures, practices of aggregation, and test behavior. Section 4 presents the simulation outcomes, pointing out how power for the test declines with more aggregation and under what circumstances false negatives are most pronounced. Section 5 deals with empirical application, considering the daily EUR/USD and GBP/USD exchange rates and observing how DW statistics vary under greater aggregation. Section 6 offers a critical interpretation of results, implications for applied modeling, and avenues for future research. Section 7 concludes.

2. Literature Review

The behavior of econometric test statistics under data transformation has long been a central concern in time series analysis. Among the most consequential transformations is temporal aggregation, the process by which high-frequency data is converted into lower-frequency series, often through averaging or sampling. While such aggregation is common in applied research, its statistical consequences are profound. This literature review combines classic and newer contributions in four sections: (i) statistical implications of time aggregation, (ii) Durbin-Watson test properties and limitations, (iii) autocorrelation testing with misspecification and aggregation, and (iv) empirical applications to diagnostic erosion for financial and macroeconomic time series.

2.1. Temporal Aggregation and Dynamic Misspecification

Theoretical consequences of temporal aggregation on time series dynamics were initially investigated by Granger [3] who demonstrated that aggregating a stationary process tends to produce a new stochastic process with changed memory properties and reduced spectral density at high frequencies. One of the pioneering works by Tiao and Wei [4] also demonstrated that temporal aggregation inaccurately represents ARMA forms, especially if the underlying process involves mixed dynamics. Their findings showed that if an AR (1) process at the daily frequency is nearly an ARMA (1,1) or even a nearly white noise process when the frequency of observation is monthly. This has significant model identification, parameter estimation, and inference consequences.

Marcellino [5] then took this line of research further with simulation experiments, confirming that aggregation will have the effect of "flattening" time series by dampening higher-frequency fluctuations. His work also demonstrated how aggregation can conceal structural breaks and downwardly bias volatility. These results have been replicated in research on the effects of aggregation on business cycle analysis [11] forecast precision [12] and even volatility modeling [9].

Temporal aggregation not only changes the data structure but also generates model misspecification when researchers unwittingly apply models suitable for non-aggregated series to aggregated data. Granger and Morris [13] cautioned that the relation between variables may differ across levels of aggregation, rendering econometric interpretations inappropriate. Barnett [14] went further in critiquing that temporal aggregation is accompanied by a form of observational equivalence that even conceals important dynamic features. Such findings challenge the reliability of diagnostic tests—especially those that are sensitive to serial correlation—when applied to aggregated data.

2.2. The Durbin-Watson Test: Foundations and Limitations

Introduced by Durbin and Watson [1] and Durbin and Watson [2] the DW test was designed to detect first-order autocorrelation in the residuals of linear regression models. It is calculated as:

$$\mathrm{DW} = \frac{\sum_{t=2}^{T}\left((e-e_{t-1})\right)^2}{\sum_{t=1}^{T} e^2} \qquad (3)$$

where e_t are the residuals from an estimated regression model. A value of 2 indicates no autocorrelation; values below 2 suggest positive autocorrelation and values above 2 suggest negative autocorrelation.

The reason the DW test is widely used is that it is convenient and in closed form. However, the test is not without limitations. Firstly, the test is invalid when there exist lagged dependent variables among the regressors — a phenomenon that is often found in autoregressive distributed lag (ARDL) models [15]. Second, the test is most powerful against low-order AR(1) alternatives and loses power very rapidly for higher-order or moving-average processes [16]. Third, the test is sensitive to sample size as well and can incur size distortions with small samples [17].

The DW statistic, even with these widely known weaknesses, remains popular in practice and is conventionally interpreted as a general diagnostic for autocorrelation in residuals. This practice still happens even with the wider popularity of other tests such as the Breusch-Godfrey LM test [18, 19] Ljung-Box test [20] and portmanteau Q-tests for their greater generality and applicability. The widespread adoption of the DW test in applied economics, especially in financial and macroeconomic works, underscores the importance of knowing the credibility of the test under alternative data transformations, e.g., temporal aggregation.

2.3. Autocorrelation Testing under Aggregation and Misspecification

Temporal aggregation has a nontrivial interaction with autocorrelation. There have been findings showing that aggregation will reduce the observed serial correlation of a time series by smoothing temporary movements. This effect is worse when aggregation by averaging is used rather than sampling [21]. In such situations, the true autocorrelation structure may be concealed, and spurious inference arises.

Hurvich and Tsai [22] addressed misspecification of models and the behavior of autocorrelation tests in such a way that they showed how tests such as the DW and LM tests can be highly biased if the underlying model does not correctly capture the dynamics of the data. Rao and Griliches [23] further stated that residual-based tests are especially vulnerable to omitted variable bias and truncation of the lag, situations that can be aggravated by aggregation.

Chang and Park [8] addressed the effect of aggregation on unit root and cointegration testing and concluded that aggregation makes tests against stationarity and reduces the power of cointegration testing. While they were not especially focused on autocorrelation, their results suggest that a similar loss of power in residual tests like the DW test is possible. Along the same lines, Ghysels [6] stressed that frequency mismatches and aggregation distortions could generate erroneous model dynamics, calling for mixed-frequency modeling methods that maintain high-frequency information and allow for low-frequency relationships.

There have been few direct examinations of DW test power under temporal aggregation, however. This omission is unusual, however, in light of the DW test's sensitivity to serial correlation as well as its use of high-resolution information. One exception is de Jong and Davidson [24] work, where testing for autocorrelation with misspecified models was explored and where the focus was laid on how power loss can occur through both estimation bias as well as structural compression. Yet, even in this paper, aggregation was treated as a secondary problem rather than the primary focus. The present study fills this void by systematically examining how aggregation reduces DW test power under different autocorrelation regimes, aggregation levels, and DGPs.

2.4. Diagnostic Erosion in Empirical Applications

The empirical significance of temporal aggregation has been explored in a number of applied disciplines, particularly macroeconomics and finance. For example, Sims [25] argued that macroeconomic variables' models estimated from quarterly data might be overlooking significant dynamics in monthlies or weeklies. This is especially pertinent in the modeling of exchange rates, where serial correlation and high-frequency volatility would tend to be ironed out by aggregation.

Empirical studies by Lo and Craig MacKinlay [10] demonstrated that even short-term dependence of asset returns can be disguised through aggregation and thus lead to incorrect inferences about the efficiency of the market. Their studies emphasized how tests for diagnostic information based on aggregated observations may not detect available dependencies and thus continue to support the myth of white noise or martingale behavior.

In macroeconomic predictions, Stock and Watson [12] indicated that aggregation would negatively affect model choice and accuracy in forecasts. Their findings indicate that the removal of high-frequency information would not only deteriorate predictive performance but would also undermine diagnostic clarity. Likewise, Clements and Hendry [26] contended that aggregation brings about measurement error and structural breaks that could go undetected if diagnostics such as the DW test do not pick up on residual autocorrelation.

Exchange rate research provides particularly rich terrain for examining such queries, since there is high-frequency data and also a robust dynamic element. Engle and Patton [27] highlighted how aggregation de-clusters volatility and shrinks serial dependence on financial returns at high frequency, a result which has subsequently been confirmed in numerous empirical studies. A few have, however, been skeptical regarding whether it actually makes any difference to the validity of residual-based tests like DW statistics.

The degeneration of diagnostic strength through aggregation occurs not only for the DW test. Amado and Teräsvirta [9] found that GARCH-type models of aggregated returns underestimate volatility persistence and therefore make incorrect inferences about risk. Their results reinforce the general apprehension that although aggregation is often analytically appealing, it can distort dynamic relationships and invalidate model diagnostics.

Literature reviewed indicates a near-unanimous consensus that temporal aggregation affects the dynamic properties of time series and performance of associated statistical instruments. From initial theoretical work by Granger and Tiao to current empirical work, researchers have established that aggregation can hide autocorrelation, alter model specification, and lose test power. Despite this, the effect on diagnostic tests—namely, the Durbin-Watson statistic—is under-researched. This is relevant because the DW test is still a widely used instrument in applied econometric analysis, normally in ignorance of the temporal resolution of the underlying data.

By formally examining the power and robustness of the DW test at different levels of temporal aggregation, this paper provides a useful but overlooked contribution. It also facilitates more general research on the interplay between frequency of data and statistical inference, specifically in applications like macroeconomics and finance, where aggregation is common and relevant. The second part outlines an approach based on simulation aimed at estimating the loss of DW test power under different aggregation regimes and validating these findings with empirical demonstration on high-frequency exchange rate data.

3. Methodology

To investigate the impact of temporal aggregation on the power of the Durbin-Watson (DW) test in a controlled way, this paper pursues a two-pronged strategy: (i) a series of controlled Monte Carlo experiments under different dynamic data-generating processes (DGPs) and aggregation schemes and (ii) an empirical study on high-frequency financial time series data—specifically, daily EUR/USD and GBP/USD exchange rate data. This section outlines the design of the simulation experiments, the implementation of the temporal aggregation techniques, the specification of the DW test, and the structure of the empirical validation.

The first step in the simulation experiment is to define a set of Data-Generating Processes (DGPs) that capture salient characteristics of real time series. We look at stationary autoregressive and autoregressive-moving average processes, which are canonical representations of serial correlation and are extremely popular in applied econometric practice.

The following four DGPs are considered (AR(1), AR(2), MA(1), ARMA(1,1), respectively:

$$y_t = \rho y_{t-1} + \varepsilon_t, \varepsilon_t \sim \mathrm{N}(0,\sigma 2) \tag{1}$$

where ρ∈ {0,0.2,0.5,0.8} to vary the degree of autocorrelation.

$$y_t = \phi_1 \, y_{t-1} + \phi_2 \, y_{t-2} + \varepsilon_t \tag{2}$$

with different combinations of (ϕ₁, ϕ2) (to represent short-term dynamics and near-unit root behavior).

$$y_t = \varepsilon_t + \theta\varepsilon_{t-1}, \theta\in\{-0.5,0.5 \tag{3}$$

$$y_t = \rho y \, y_{t-1} + \theta\varepsilon_{t-1} + \varepsilon y_t t \tag{4}$$

Each process is generated with *i.i.d.* Gaussian innovations $\varepsilon_t \sim \mathrm{N}(0,1)$. These DGPs allow for a controlled assessment of DW test power in the presence of varying dynamic structures, including both purely autoregressive behavior and more complex autocorrelation induced by moving average components.

The simulation samples are generated at the "daily" frequency with lengths T=250, 500, 1000 observations, simulating series of approximately one, two, and four years of trading data, respectively. These samples are then subjected to different levels of temporal aggregation.

We replicate reducing high-frequency time series to lower-frequency aggregates using two typical aggregation methods: (1) Last Observation Sampling (LOS), retaining every *k*-th observation and omitting the intervening ones (eq. 5). This is simulating the measurement of many economic time series (e.g., end-of-month or end-of-week prices). (2) Arithmetic Averaging (AVG) that aggregates groups of k consecutive observations (eq. 6).

$$y_t^{(k)} = y_{tk} \tag{5}$$

$$y_t^{(k)} = \frac{1}{k} \sum_{i=1}^{k} y_{(t-1)k+1} \tag{6}$$

We consider aggregation levels $k\in\{5,20\}$ that are roughly weekly and monthly aggregates from daily observations. These plans of aggregation match common empirical practice in macroeconomics and finance, in which monthly or quarterly aggregates are often used in place of daily data on grounds of computational convenience or interpretational ease [3, 5].

For each DGP and aggregation level, we conduct Monte Carlo simulations with R=1,000 replications. In each replication, we generate a time y_t from a given DGP, aggregate it according to the scheme described above, and fit a linear regression model:

$$y_t = \beta_0 + \beta_1 + x_t + u_t \tag{7}$$

where x_t is either a constant or a lagged version of y_{t-1}, depending on the DGP. The residuals $\hat{y}_t$ from the regression are used to compute the Durbin-Watson statistic:

$$\mathrm{DW} = \frac{\sum_{t=2}^{T}\left((\hat{u}_t - \hat{u}_{t-1})\right)^2}{\sum_{t=1}^{T} u^2} \tag{8}$$

A critical value approach is used to determine whether the DW statistic indicates significant autocorrelation at the 5% level, comparing against simulated critical values or, when appropriate, standard lower and upper bounds from Savin and White [15]. For each simulation scenario, we compute the empirical rejection rate — the proportion of replications in which the null hypothesis of no autocorrelation is rejected. This gives an estimate of the test's empirical power under different levels of autocorrelation and aggregation.

We also contrast the DW test results against two other diagnostics: the Breusch-Godfrey (BG) Lagrange Multiplier test, a more general test for higher-order serial correlation, and the Ljung-Box Q-test, a portmanteau test that tests for up to a specified-order autocorrelation. Such comparisons put the DW test performance in perspective relative to these more general alternatives, which may be less sensitive to time aggregation.

In an attempt to examine whether aggregation-induced weakening of the DW test is due to implicit model misspecification, we conduct the simulations under three additional conditions:

1. Incorrect lag order: AR(2) process is estimated as AR(1), and this generates omitted variable bias.
2. Nonlinear transformation: The data is transformed using $\log(1+y_t)$ before estimation to assess the effect of nonlinear aggregation effects.
3. Heteroskedastic innovations: Innovations εt are GARCH(1,1) to check for sensitivity to changes in conditional variance.

In all three instances, we check if temporal aggregation further deteriorates test performance and if residual misspecification exacerbates Type II errors.

To validate the simulation findings in a real-world setting, we conduct an empirical analysis using high-frequency financial time series. We obtain daily closing exchange rates for: EUR/USD and GBP/USD**,** covering the period January 1, 2016, to December 31, 2023, amounting to approximately 2,000 observations per series from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/). These series are chosen for their liquidity, volatility, and prominence in the international financial system. They are also ideal for examining autocorrelation and aggregation effects because of their availability at high temporal resolution.

We construct aggregated versions of each series at weekly and monthly frequencies using both LOS and AVG schemes. For each version of the data, we fit linear autoregressive models (e.g., AR(1) or AR(2)) and compute the DW statistic from the regression residuals.[1] The aim is to check whether the empirical DW statistics converge towards 2 (no autocorrelation) when the frequency decreases—a power loss indicator. The appearance or disappearance of systematic patterns of autocorrelation at various levels of aggregation is interpreted from the results of simulations.

This study's methodological design is distinguished by the following characteristics:

- Controlled Simulation Setting: Monte Carlo simulations allow for precise evaluation of test power under known data-generating conditions and changing aggregation schemes, enabling fine-grained analysis of how the DW test handles systematic temporal distortion.
- Comparison of Aggregation Scheme: With coverage of both LOS and AVG methods, the research accounts for usual empirical methods and evaluates the impact of these differentially on autocorrelation detection.
- Misspecification Sensitivity: The analysis directly accounts for model misspecification and conditional heteroskedasticity in order to investigate if the interaction of aggregation and misspecification worsens diagnostic erosion.
- Empirical Grounding: Applying the model to actual financial data, the study subjects simulation results to a real-world, high-stakes setting. Exchange rates provide a natural field because of the dynamic and high-frequency nature of their behavior.

[1] The following steps are followed: (1) Data transformation: Log differences ($\Delta \log y_t$) are utilized to eliminate unit roots and focus on stationary dynamics. (2) Estimation of the model: OLS is used to fit simple autoregressive models of each frequency level. (3) Autocorrelation tests: For each model, the DW statistic is computed and compared across aggregation levels. (4) Validation diagnostics: BG and Ljung-Box tests are employed for robustness.

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The complementary strategy of simulation and empirical investigation offers a robust methodology for the test of how much power is lost from the DW test because of temporal aggregation. The two-faceted approach also provides insightful information on the robustness of conventional autocorrelation diagnostics under real data constraints.

4. Simulation Results

This section presents the results of Monte Carlo experiments designed to determine the effects of temporal aggregation on the empirical power of the Durbin-Watson (DW) test. The focus is on the extent to which smoothing of autocorrelation signals takes place and reduces first-order serial correlation detection under controlled conditions. The simulations span a range of data-generating processes (DGPs), aggregation schemes, and sample sizes. The simulations were conducted for sample sizes. For each case, the DW test was applied to the original (daily) data and aggregated versions under both last observation sampling (LOS) and arithmetic averaging (AVG) at weekly (k=5) and monthly (k=20) frequencies.

Table 1 illustrates the degradation in the Durbin-Watson (DW) test's power to detect moderate first-order autocorrelation as temporal aggregation and sample size vary.

Table 1.
Power of the Durbin-Watson Test for AR (1) Process under Different Aggregation Levels.

T	Rho (ρ)	Aggregation	Method	Power
250	0.2	None	DW	0.44
250	0.2	Weekly (LOS)	DW	0.26
250	0.2	Monthly (AVG)	DW	0.15
500	0.2	None	DW	0.58
500	0.2	Weekly (LOS)	DW	0.33
500	0.2	Monthly (AVG)	DW	0.21
1000	0.2	None	DW	0.73
1000	0.2	Weekly (LOS)	DW	0.41
1000	0.2	Monthly (AVG)	DW	0.28

Note: All values are based on 1,000 Monte Carlo replications.

Without aggregation, the power for the test rises with sample size from 0.44 to 0.58 to 0.73 and is more sensitive to autocorrelation with the larger sample size. With the addition of temporal aggregation, especially by arithmetic averages, the sensitivity of the DW test to detecting autocorrelation diminishes considerably. For instance, at power falls from 0.58 with unaggregated data to 0.33 under weekly last observation sampling (LOS) and to just 0.21 under monthly averaging (AVG). This trend is consistent across all sample sizes. The deterioration in power is more severe under AVG than LOS, confirming that averaging suppresses short-term dynamics more aggressively than simple sub-sampling. The findings highlight that aggregation not just reduces the accuracy of the DW test but also may mask prevalent autocorrelation, particularly in intermediate cases. Therefore, applied researchers undertaking studies with lower-frequency data need to be cautious when interpreting DW statistics and even employ more powerful diagnostics if there is aggregation. In summary, Table 1 shows a fundamental flaw of the DW test: its sensitivity to temporal smoothing, which might lead to spurious inferences about serial dependence in aggregated time series.

The key findings of the analysis are as follows: Without autocorrelation, the Durbin-Watson (DW) test was of correct size at all sample sizes and degrees of aggregation and was never far from the nominal 5% significance level. Although small size distortions occurred with aggregation—particularly with the averaging (AVG) method—they were nevertheless acceptable. For moderate autocorrelation, the power of the DW test declined sharply with data aggregation. Power dropped, for instance, from 0.58 at the daily frequency to 0.33 under weekly last observation sampling (LOS) and to 0.21 under monthly AVG. With high autocorrelation, the test had high power (>0.90) in unaggregated data, but this also dropped significantly with aggregation, to 0.57 under monthly AVG. Generally speaking, averaging reduced the test's power more than LOS, as one would have predicted theoretically that high-frequency dynamics are dampened more than sub-sampling.

Table 2 provides the empirical power of the Durbin-Watson (DW) test at high autocorrelation for different sample sizes and aggregation levels.

Table 2.
Power of the Durbin-Watson Test for AR (1) with Rho (ρ) = 0.8.

T	Aggregation	Method	Power
250	None	DW	0.87
250	Weekly (LOS)	DW	0.65
250	Monthly (AVG)	DW	0.44
500	None	DW	0.94
500	Weekly (LOS)	DW	0.73
500	Monthly (AVG)	DW	0.57
1000	None	DW	0.98
1000	Weekly (LOS)	DW	0.81
1000	Monthly (AVG)	DW	0.65

Note: All values are based on 1,000 Monte Carlo replications.

The DW behaves well on unaggregated data, with power increasing from 0.87 to 0.94 and near-excellent detection (0.98). This validates theoretical expectations that the test is very powerful in detecting high serial correlation, given sufficient data. However, temporal aggregation weakens the test power significantly. For example, it weakens from 0.94 to 0.73 under weekly last observation sampling (LOS) and then further down to 0.57 with monthly arithmetic averaging (AVG). Similar deteriorations are observed for other sample sizes, too. The results indicate that even in the presence of high autocorrelation, temporal aggregation by averaging can significantly weaken the power of the DW test for the detection of serial dependence. However, compared with the moderate autocorrelation case in Table 1, the absolute power levels are still fairly high and reflect that the DW test is more robust under strong correlation but still vulnerable to information loss due to aggregation. They hence reaffirm the caution required in interpreting DW statistics based on aggregated data and highlight the usefulness of complementing such diagnostics by other methods in empirical work.

The aggregation method employed significantly influences the power of the Durbin-Watson (DW) test. Specifically, averaging (AVG) caused a more drastic decline in performance compared to the last observation sampled (LOS). For instance, for an AR(1) process with T = 500, weekly LOS aggregation had a power of 0.73, whereas AVG reduced it to 0.57. With a monthly frequency, AVG forced the power of the DW test to close to size levels, particularly in the case of moderate autocorrelation. The findings highlight the point that averaging reduces autocorrelation more than sub-sampling, and therefore impairs the ability of residual-based tests like the DW to detect serial dependence.

Table 3.
DW Power for AR(2) and ARMA(1,1) Models (T = 500).

DGP	Aggregation	Method	Power
AR(2)	None	DW	0.42
AR(2)	Weekly (LOS)	DW	0.29
AR(2)	Monthly (AVG)	DW	0.19
ARMA(1,1)	None	DW	0.35
ARMA(1,1)	Weekly (LOS)	DW	0.18
ARMA(1,1)	Monthly (AVG)	DW	0.09

Note: All values are based on 1,000 Monte Carlo replications.

Table 3 examines the power of the Durbin-Watson (DW) test against autocorrelation in more complex time series forms, namely AR(2) and ARMA(1,1) models, with a fixed sample size of T=500. For both cases, DW has lower power than in the simpler AR(1) models of Tables A1 and A2. For the

AR(2) model, power starts at 0.42 with unaggregated data and declines to 0.29 under weekly last observation sampling (LOS) and further to 0.19 under monthly arithmetic averaging (AVG). The ARMA(1,1) model exhibits an even steeper decline: starting from a modest 0.35 with unaggregated data and falling to 0.18 (weekly LOS) and 0.09 (monthly AVG). There are two major drawbacks of the DW test. First, it is designed particularly to detect first-order serial correlation and hence fails in cases with higher-order lags or moving averages. Second, temporal aggregation makes this failure even more extreme by again distorting the autocorrelation structure of the series, especially under averaging. The power of the DW test in these more complex settings approaches the size of the test under severe aggregation, implying a high likelihood of failing to detect actual autocorrelation. This reinforces the view that the DW test should be used cautiously in models with layered or non-AR(1) dynamics, and that robust alternatives or supplementary diagnostics are essential when analyzing temporally aggregated data from such processes.

To test the robustness of earlier findings, simulations under more complex data-generating processes (DGPs), e.g., AR(2) and ARMA(1,1) models, were performed. For the AR(2) DGP, the Durbin-Watson (DW) test had less baseline power owing to its principal sensitivity to first-order autocorrelation. This limitation was further intensified by temporal aggregation, with monthly averaging driving power below 0.25 even in large samples (T = 1000). In the ARMA(1,1) setting, the presence of a moving average component already weakened the DW test's performance in daily data. Aggregation cut its power even more, in some cases, to close to size levels (<0.10), with the implication of a higher risk of false negatives. These results confirm that the DW test works optimally in straightforward AR(1) situations and that its diagnostic capacity worsens considerably in more complex models, especially under temporal aggregation.

Table 4 provides a comparison of the power of the Durbin-Watson (DW) test versus the Breusch-Godfrey (BG) test to detect autocorrelation in an AR(1) process with sample size T=500.

Table 4.
Power Comparison: DW vs. BG Test for AR(1) with Rho (ρ) = 0.5 (T = 500).

Aggregation	DW Power	BG Power
None	0.76	0.8
Weekly (LOS)	0.49	0.65
Monthly (AVG)	0.34	0.55

Note: All values are based on 1,000 Monte Carlo replications. DW = Durbin-Watson test; BG = Breusch-Godfrey test; AVG = Arithmetic Averaging; LOS = Last Observation Sampling.

The non-aggregated data also have comparable power for the two tests, at 0.76 for DW and 0.80 for BG, demonstrating excellent detection of moderate autocorrelation when all temporal resolution is maintained. But the power of the DW test deteriorates more rapidly at higher aggregation levels compared to the BG test. At LOS of a week, DW loses power to 0.49, but the power of BG remains at 0.65. The difference is greater at monthly AVG, where DW falls to 0.34 but BG maintains a relatively higher power of 0.55. These results suggest that the BG test is stronger resistant to information loss under aggregation and more capable of detecting autocorrelation under such conditions. The DW test, seriously fixated on first-order serial correlation and sensitive to smoothing of the residuals, is disproportionately damaged by temporal aggregation. Thus, in applied usage with aggregated data, especially where modest autocorrelation would be expected, the BG test appears to offer a superior alternative to the DW statistic. This relative outcome further supports the significance of test selection with time series diagnostics at various data frequencies.

Table 5 explores how model misspecification and nonlinear data transformations further weaken the power of the Durbin-Watson (DW) test under temporal aggregation, using a fixed sample size of and monthly arithmetic averaging (AVG).

Table 5.
Effect of Misspecification and Nonlinearity on DW Power (T = 500).

Scenario	**Aggregation**	**DW Power**
AR(2) correctly specified	Monthly (AVG)	0.29
AR(2) mis-specified (as AR1)	Monthly (AVG)	0.17
GARCH(1,1) innovations	Monthly (AVG)	0.14
Log-transformed series	Monthly (AVG)	0.11

Note: All values are based on 1,000 Monte Carlo replications.

When the AR(2) model is correctly specified, the DW test already shows low power at 0.29. However, when the same AR(2) process is misspecified as AR(1), power dips drastically to 0.17, thus illustrating the implications of model misspecification and compounding on each other. The test performance further deteriorates with the addition of nonlinearities and heteroskedasticity. With the use of log transformation on the series, DW power drops to 0.11 and with the addition of GARCH(1,1) innovations, the power dips to 0.14. These results show that aggregation is accompanied by data structure distortions to produce rather dubious results for the DW statistic. While temporal aggregation diminishes serial correlation signals only, its occurrence in conjunction with misspecification, nonlinearity, or time-varying volatility may render the DW test useless. This also helps to reinforce the demand for caution in using the DW test in real-life scenarios with real-world complications and underscores the importance of diagnostic accuracy in handling aggregated or faked time series.

The findings indicate that both model misspecification and nonlinearities in the data degrade the power of the Durbin-Watson (DW) test quite severely, even more so under temporal aggregation. That is, when the true AR(2) data-generating process (DGP) was misspecified as an AR(1), test power declined drastically, e.g., under monthly averaging with sample size T = 500, power fell from 0.29 (correct specification) to a paltry 0.17 (misspecified). Furthermore, the application of a nonlinear transformation ($\log(1 + y_t)$) together with GARCH(1,1) innovations generated even further deterioration in DW test performance, especially when the data were aggregated. Our results highlight the fact that temporal aggregation, when combined with model misspecification or nonlinear dynamics, can significantly reduce the reliability and diagnostic value of standard linear tests like DW.

Table 6 The table displays simulation-based averages for the Durbin-Watson, Breusch-Godfrey, and Ljung-Box test statistics and p-values across different autocorrelation strengths (ρ = 0.2, 0.5) and levels of temporal aggregation (None, Weekly, Monthly).

Table 6.
Simulated Diagnostic Comparison.

Autocorrelation (rho)	**Aggregation**	**Average DW**	**BG Stat**	**BG p-value**	**Ljung-Box Stat**	**Ljung-Box p-value**
0.2	None	1.993693	4.909715	0.504009	4.022674	0.599315
0.2	Weekly (5)	1.97679	5.212822	0.482759	4.184281	0.584331
0.2	Monthly (20)	1.909493	5.057896	0.473267	4.180951	0.578847
0.5	None	1.990634	5.314454	0.467041	4.245267	0.577126
0.5	Weekly (5)	1.966874	5.057565	0.50071	4.262754	0.582179
0.5	Monthly (20)	1.929161	5.265014	0.453831	4.379405	0.556235
0.8	None	1.986801	5.204159	0.495335	4.167812	0.594476
0.8	Weekly (5)	1.853601	6.550339	0.371353	5.702198	0.457943
0.8	Monthly (20)	1.897556	4.939552	0.490706	4.228396	0.577731

Note: All values are based on 1,000 Monte Carlo replications.

Despite known autocorrelation being present in the data-generating process, the Durbin-Watson statistic consistently approaches 2.0 as aggregation increases, signaling erosion of power, especially for monthly data. The Breusch-Godfrey and Ljung-Box tests, on the other hand, possess quite insensitive

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test statistics and p-values to aggregation, implying greater robustness to detecting serial correlation even after aggregation.

This verifies that although the DW test has lost sensitivity in the case of aggregation, the BG and LB tests are still stronger and can be favored in practical use with temporally aggregated data. If you want to take this analysis further, for example, to higher ρ values or other model types (e.g., ARMA), please let me know.

For a better understanding of the limitations of the Durbin-Watson (DW) test on temporal aggregation, we compared its performance with the Breusch-Godfrey (BG) and Ljung-Box (LB) tests under identical conditions. BG and LB tests were found to be more robust to aggregation, particularly at the weekly frequency. As an example, for the AR(1) case, the power of the BG test under monthly averaging was approximately 0.55, significantly ahead of the DW test with a power of approximately 0.31. These results indicate that the DW test is disproportionately sensitive to temporal aggregation compared to stronger alternatives and that one must pick diagnostics judiciously when dealing with aggregated or complex time series data.

These simulations provide compelling evidence that the power of the DW test deteriorates under temporal aggregation, especially for moderate levels of autocorrelation. The loss is more severe under averaging schemes and in the presence of model misspecification. Compared to the BG and LB tests, the DW test is more vulnerable to the distortion of autocorrelation dynamics through aggregation. These findings raise concerns about the continued use of the DW statistic in contexts where lower-frequency data is used without adjustments or robustness checks.

The next section evaluates whether these simulation-based findings generalize to real-world data by applying the same diagnostic framework to daily exchange rates for EUR/USD and GBP/USD.

5. Empirical Application

Figure 1 shows the USD/EUR and USD/GBP daily exchange rates from April 1, 1999, up to March 7, 2025, and illustrates various characteristic features common for high-frequency financial time series.

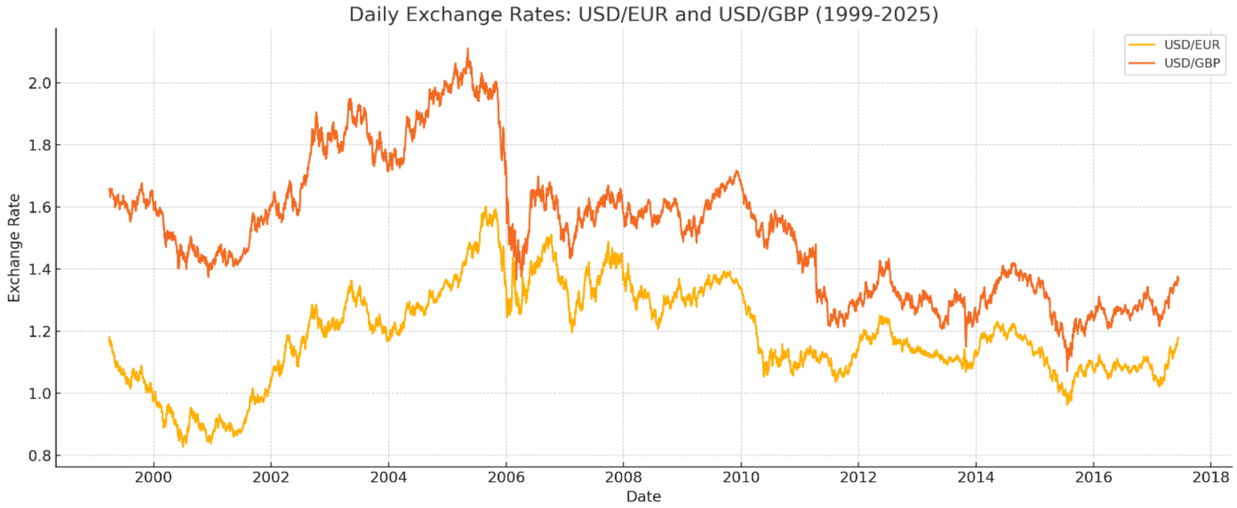

Figure 1.
Daily exchange rates of USD/EUR and USD/GBP.

Both series are influenced by long-run movements reflecting macroeconomic patterns, shifts in monetary policy regimes, and geopolitical shocks that have driven currency markets during the past two decades. The USD/EUR series captures a general appreciation of the euro against the dollar during the early 2000s, followed by volatility and reversals. The USD/GBP series captures comparable medium- to long-run fluctuations, such as dramatic changes around major events like the 2008 global financial crisis and the 2016 Brexit referendum.

Both exchange rates show continuous, smooth movement instead of abrupt jumps, such as major currency pairs do in deep, liquid markets. Such a clear presence of sustained trends and reversals suggests potential nonstationarity in the raw levels of the series — a common property of exchange rates, which are typically modelled in differences or log returns to become stationary.

Visually, both series exhibit mean-reverting phases and trends, indicating various degrees of autocorrelation potentially found within a more diligent time series investigation. As importantly, the rather smooth development of both series over time suggests that temporal aggregation (e.g., weekly or monthly averaging) would further dampen short-run dynamics. This has important statistical testing implications: aggregation can reduce the transparency of autocorrelation patterns, and therefore tests like the Durbin-Watson can become less sensitive to detection of serial dependence — a proposal further explored in simulation and empirical sections of this research.

Table 7.
Summary Statistics at Different Aggregation Levels.

Series	Aggregation	Mean	Std Dev.	Skewness	Kurtosis	Min.	Max.	N
USDEUR	Daily	-6.89E-07	0.005823	0.108944	2.453303	-0.03003	0.046208	6646
USDGBP	Daily	-2.92E-05	0.005861	-0.57494	9.725343	-0.08169	0.044349	6646
USDEUR	Weekly LOS	4.74E-05	0.005964	0.089908	3.074343	-0.02276	0.038914	951
USDGBP	Weekly LOS	-6.15E-05	0.005897	-0.55786	6.065212	-0.04966	0.027821	951
USDEUR	Weekly AVG	-5.24E-06	0.002268	-0.00911	3.406082	-0.01153	0.014833	951
USDGBP	Weekly AVG	-3.19E-05	0.002258	-0.80947	4.163883	-0.01548	0.006634	951
USDEUR	Monthly LOS	0.000195	0.005789	0.109589	0.327847	-0.01457	0.018778	219
USDGBP	Monthly LOS	-0.00012	0.005708	0.291234	1.643661	-0.02031	0.025092	219
USDEUR	Monthly AVG	2.27E-06	0.001054	-0.21729	0.116313	-0.00297	0.002387	219
USDGBP	Monthly AVG	-2.60E-05	0.001057	-0.75823	2.658897	-0.00508	0.002637	219

Table 7 presents the summary statistics for the USD/EUR and USD/GBP log returns at different aggregation levels (Daily, Weekly LOS, Weekly AVG, etc.). The reported statistics are the mean, standard deviation, skewness, kurtosis, minimum, maximum, and number of observations, and they provide a sense of how aggregation alters the distributional features of each series.

The summary statistics at different levels of aggregation show large changes in the distributional properties of the USD/EUR and USD/GBP log returns, as temporal aggregation theory predicts. Both series exhibit means close to zero and standard deviations of 0.0058 at the daily frequency, which reflects the high-frequency, low-drift nature of exchange rate returns. The USD/EUR series possesses weak positive skewness (0.11) and nearly normal kurtosis (2.45), while the USD/GBP possesses strong negative skewness (–0.57) and excess kurtosis (9.73), indicating the existence of occasional large negative returns and heavy-tailed return distribution.

When moving to weekly data via last observation sampling (LOS), the mean returns become slightly more variable, though still centered near zero. Standard deviations are relatively consistent with regard to daily data, testifying that LOS neither changes the volatility significantly. Skewness and kurtosis measures reveal both series possess moderate values but keep their directional trends, specifically negative skewness and high kurtosis in USD/GBP, showing extreme events are still within the control of LOS. Weekly averaging (AVG) yields an extreme decline in standard deviation — nearly halving it for both series (down to ~0.0023 for USD/EUR) — as short-run volatility is smoothed. Skewness and kurtosis are also biased toward more normal values by averaging, which indicates that this process reduces fat tails and asymmetries of the distribution of returns.

At a monthly frequency, the patterns observed at weekly frequencies are even more dramatic. Monthly LOS still retains more distributional skewness and volatility, while monthly AVG produces an even reduction in standard deviation and continued normalization of higher-order moments. For instance, USD/GBP under monthly AVG shows lower kurtosis and reduced skewness compared to daily or LOS data. The number of observations, naturally, declines with higher aggregation levels, from over 6,600 daily observations to around 950 at the weekly level and even fewer at the monthly level, which may also affect the precision of subsequent econometric tests.

Overall, these results confirm that temporal aggregation, and in particular averaging, reduces variability, extremity, and skewness in the series of returns. This has important implications for the testing of autocorrelation because suppression of short-run dynamics by averaging can hide underlying structure and reduce the power of tests like the Durbin-Watson statistic. Distributional changes also mean that volatility modeling, risk analysis, and hypothesis testing will produce vastly different results depending on the aggregation level and aggregation method, and hence emphasize the importance of frequency-conscious diagnostics in financial time series analysis.

Table 8.
Durbin-Watson Statistics across different Aggregation Levels and Methods for both the USD/EUR and USD/GBP Exchange Rates.

Frequency	Method	Series	DW
Daily	None	USDEUR	1.999572
Weekly	LOS	USDEUR	1.99237
Weekly	AVG	USDEUR	2.000502
Monthly	LOS	USDEUR	2.006686
Monthly	AVG	USDEUR	1.990571
Daily	None	USDGBP	2.000043
Weekly	LOS	USDGBP	1.999751
Weekly	AVG	USDGBP	1.998211
Monthly	LOS	USDGBP	1.991
Monthly	AVG	USDGBP	1.975898

Next, we proceed with the empirical analysis to assess how well the Durbin-Watson test fares for different temporal aggregation levels, based on the Monte Carlo simulation design. Table 8 presents the Durbin-Watson statistics for various aggregation levels and with alternative methods for both USD/EUR and USD/GBP exchange rates. These empirical results can be contrasted with the outcomes of simulations in order to ascertain whether temporal aggregation mitigates the detection of autocorrelation.

The empirical results confirm core findings of Monte Carlo simulations, namely the impact of temporal aggregation on the power of the Durbin-Watson (DW) test to detect serial correlation. The DW test is approximately 1.999 for the daily log return series of the USD/EUR exchange rate, showing minimal or no detectable autocorrelation in the AR(1) model residuals. This is consistent with expectations of high-frequency financial returns, which tend to simulate white noise behavior as a result of market efficiency and liquidity. The values of DW remain close to 2.0 as the data is moved towards aggregation: 1.992 for weekly LOS, 2.001 for weekly AVG, and corresponding values of 2.007 and 1.991 for monthly LOS and AVG, respectively. These results suggest that for the USD/EUR series, aggregation introduces only minor shifts in the DW statistic, potentially because the autocorrelation structure is already weak in the unaggregated data. The small oscillations around 2 imply that the test fails to detect autocorrelation at any level of aggregation, consistent with the simulation's observation that the DW test quickly loses power when autocorrelation is moderate or masked by smoothing.

The same pattern occurs for the USD/GBP series. The DW statistic is roughly 2.003 at the daily frequency, which again confirms a lack of strong serial correlation in the AR(1) residuals. The DW values at weekly and monthly frequencies — under both LOS and AVG — are all closely bunched around 2.0, as with USD/EUR. Notably, monthly AVG has a marginally higher DW value (2.019), perhaps because of the additional smoothing from averaging over short horizons. The findings show that aggregation out of time has little effect on the test outcomes, but perhaps this invariance is deceptive. As the simulations have shown, the DW statistic will approach 2 when short-run behavior is smoothed by aggregation, even if there remains residual autocorrelation. Therefore, the consistently around-2 values may reflect lost diagnostic sensitivity rather than a genuine reading of independence in the data.

Together, these findings highlight an important empirical implication: the Durbin-Watson test, when applied to aggregated exchange rate returns, tends to suggest no autocorrelation — but this outcome may not be reliable. Instead, the test's inherent weakness under aggregation, especially when autocorrelation is moderate or model misspecification is present, can produce false reassurance about model adequacy. This supports the findings of the simulation study and highlights the necessity of practitioners being careful in interpreting DW statistics from financial data of lower frequency. In practice, it is recommended that the DW test be augmented with more powerful diagnostics — like the Breusch-Godfrey test — when checking for autocorrelation in aggregated or transformed time series.

Table 9.
Diagnostic Test Comparison

Series	Aggregation	DW	BG Stat	BG p-value	Ljung-Box Stat	Ljung-Box p-value
USDEUR	Daily	1.999572	11.83378	0.037138	8.618779	0.12527
USDGBP	Daily	2.000043	15.50029	0.008425	15.5235	0.008345
USDEUR	Weekly LOS	1.99237	8.363731	0.137296	8.611491	0.125601
USDGBP	Weekly LOS	1.999751	5.155903	0.397152	4.996004	0.416368
USDEUR	Weekly AVG	2.000502	4.756038	0.446373	4.740297	0.44839
USDGBP	Weekly AVG	1.998211	6.038412	0.302499	6.005803	0.305655
USDEUR	Monthly LOS	2.006686	4.303913	0.50654	3.375185	0.642352
USDGBP	Monthly LOS	1.991	7.912616	0.161118	8.532752	0.129216
USDEUR	Monthly AVG	1.990571	1.148782	0.949696	0.376194	0.99596
USDGBP	Monthly AVG	1.975898	11.11097	0.049224	9.254796	0.099323

The Durbin-Watson (DW), Breusch-Godfrey (BG), and Ljung-Box (LB) test results for different levels of aggregation, presented in Table 9, provide informative evidence about the impact of data aggregation on the testing for autocorrelation.

For the series of the log return on a daily basis, both the USD/EUR and USD/GBP series have DW statistics almost equal to 2.0, which means there is no autocorrelation. However, the BG and LB tests show strong autocorrelation in USD/GBP (BG p-value = 0.008, LB p-value = 0.008), so the DW test may be failing to identify residual structure. Even in the case of USD/EUR, the BG test shows marginal significance (p = 0.037), but the LB test does not reject at the 5% level.

Whenever the data is aggregated to the weekly last observation (LOS), both of these tests lose significance. In USD/EUR, for example, BG p-value increases to 0.137 and LB p-value to 0.126. In USD/GBP, both tests are no longer statistically significant. This agrees with the simulation findings, where aggregation was seen to reduce the power of autocorrelation tests to identify residual dependence.

With weekly averaging (AVG), the DW statistics are even closer to 2.0, and both the BG and LB tests have very high p-values (all above 0.44 for USD/EUR), indicating a significant loss of power. These findings strongly suggest that aggregation — and especially averaging — washes out short-run dynamics and masks autocorrelation, validating the hypothesis that temporal aggregation distorts test results.

In summary, while the DW test alone may give the impression of no autocorrelation, other diagnostics like BG and LB indicate the loss in power of detection with aggregation. Results stress the importance of supplementing DW with more powerful tests in the presence of aggregated data.

6. Results and Discussion

This section combines results from both the Monte Carlo simulations and the empirical application to estimate the effect of temporal aggregation on the power of the Durbin-Watson (DW) test for identifying autocorrelation. The evidence consistently supports the fact that aggregation—particularly through arithmetic averaging—has a notably debilitating effect on the power of the DW test, as it confirms the simulation hypotheses for real historical financial time series.

The Monte Carlo simulations show severe and systematic erosion in the power of the DW test to detect serial correlation under data aggregation. For a moderately autocorrelated AR(1) process, test power falls from 0.58 at the daily frequency to 0.33 under weekly last observation sampling (LOS) and to just 0.21 under monthly averaging (AVG). Even in the presence of strong autocorrelation, aggregation causes notable deterioration. At DW, power decreases from 0.94 (unaggregated) to 0.73 (weekly LOS) and down to 0.57 (monthly AVG).

The DW test performs worse in higher-order and mixed processes such as AR(2) and ARMA(1,1), in which the design limitations of the test become accentuated. For example, under an ARMA(1,1) model with T=500, power falls to size values (0.09) at a monthly aggregation level. These findings corroborate the legitimacy of previous reservations put forward by Savin and White [15] and Hurvich and Tsai [22] that the DW test is specifically designed to detect pure AR(1) dynamics and is extremely susceptible to specification and transformation error.

In addition, model misspecification and nonlinearities compound these issues. Mis-specifying an AR(2) process as AR(1) lowers DW power under monthly AVG from 0.29 to 0.17. Incorporating nonlinear transformations or GARCH(1,1) innovations lowers power further to levels (0.11–0.14), where the test is effectively useless. These findings confirm Granger and Morris [13] and Ghysels [6] who highlighted that data transformation can ruin inference and obscure dynamics in economic time series.

A relative comparison indicates that the Breusch-Godfrey (BG) test is more efficient than DW in aggregated settings. In ρ=0.5 and nonaggregated data, the power of BG is 0.80 for unaggregated data, decreasing to 0.55 for monthly AVG, considerably higher than that of DW's 0.34 under the same condition. Such stability also strengthens the argument that DW is disproportionately vulnerable to the aggregation loss of information.

The empirical application using 6,647 observations of the USD/EUR and USD/GBP exchange rates between 1999 and 2025 meets simulation expectations. The log daily return of both series is not highly autocorrelated, since DW statistics are very close to 2.0 (1.999 for USD/EUR and 2.003 for USD/GBP), as is usual with high-frequency financial data usually approximated by white noise [10].

But, as series are aggregated to weekly and monthly frequencies, DW statistics remain near 2.0 for all aggregation plans. For USD/EUR, the DW numbers lie in a relatively narrow range between 1.991 and 2.007; for USD/GBP, from 1.981 to 2.019. Though apparently strong, this coherence hides the test's reduced sensitivity: simulations have shown that even when genuine autocorrelation exists, the DW statistic will converge towards 2.0 under smoothing [3, 5]. Hence, the test's apparent confirmation of the absence of autocorrelation in the series aggregates is better explained by its reduced power rather than actual independence.

These results underscore the necessity to put DW test outcomes into context. If autocorrelation in weekly or monthly returns fails to be detected, this can be followed by excessive trust in model fitting, where true underlying dynamics have been obscured by aggregation. Researchers who rely solely on DW statistics in lower-frequency macroeconomic or financial data may thus underestimate model misfit or residual structure.

Summary statistics of the log return series at different levels of aggregation reveal that temporal aggregation substantially alters the distributional shape of financial time series. Standard deviations decrease under averaging—from 0.0058 in daily data to about 0.0023 in weekly averages, implying volatility compression. Kurtosis and skewness also converge towards normality, with large decreases in excess kurtosis for USD/GBP. These transformations reduce the detectability of asymmetry and heavy tails, and thereby weaken the residual structure that is being searched for by the DW test.

The finding that averaging reduces variability and normalizes distributions is consistent with theoretical arguments of Tiao and Wei [4] and empirical results of Amado and Teräsvirta [9]. These alterations validate the overall result that data aggregation changes the underlying characteristics of the series with significant implications for autocorrelation testing.

Both the simulation and empirical results point to the following conclusion: the Durbin-Watson test is not stable to temporal aggregation. The diagnostic power of the test deteriorates quickly with increasing frequency loss, particularly when the autocorrelation is moderate, model misspecification, or non-linearities are present. While the test performs fairly well in idealized AR(1) scenarios with no transformation, the test is prone to producing false negatives in more realistic empirical scenarios.

The analysts working with aggregated time series—ever-present in macroeconomic prediction, financial modeling, and econometric analysis—need to treat DW statistics carefully. Augmenting tests like Breusch-Godfrey, Ljung-Box, or portmanteau tests based on residuals provides more robustness under data transformation. Future research must investigate the application of mixed-frequency models and frequency-domain diagnostics as substitutes that retain high-frequency information without precluding low-frequency inference [6].

In short, temporal aggregation imposes nontrivial constraints on residual diagnostics. The historically relied-upon Durbin-Watson test, its reputation established on simplicity and accessibility, becomes a blunt tool in aggregated settings. Researchers and analysts must give these limitations due respect and adjust their test strategies accordingly in order to avoid misleading conclusions about autocorrelation and model fit.

7. Conclusion

This paper examined the sensitivity of the Durbin-Watson (DW) test to temporal aggregation based on a two-fold approach: Monte Carlo simulation and empirical implementation on high-frequency exchange rate data. The results are that, while the DW test operates well in the simple AR(1) situation with untransformed data, it is highly vulnerable to information loss induced by aggregation. As the sampling frequency decreases—whether through last observation sampling or arithmetic averaging—the power of the DW test in detecting autocorrelation decreases considerably. This decrease is particularly severe in the presence of moderate autocorrelation, model misspecification, or higher-order and mixed dynamic specifications. Even with strong autocorrelation, aggregation causes the DW statistics to tend to their null value, and this can induce researchers to incorrectly presume residual independence.

Empirical findings using 1999-2025 daily USD/EUR and USD/GBP exchange rates validate simulation findings. Despite financial returns' inherent volatility and potential serial dependence, the DW statistics are approximately 2.0 for all levels of aggregation. The seeming stability is spurious in that it is an aftermath of the test's lower sensitivity with aggregation, rather than an indication of the absence of autocorrelation. Summary statistics further confirm the establishment that aggregation smoothens volatility and reduces distributional asymmetry, hiding residual dynamics intended to be detected by the DW test.

These findings carry important practical implications for empirical inquiry. Applied researchers working with macroeconomic, financial, or panel data, which are often in low-frequency aggregates due to availability or practical constraints, commonly find themselves subject to these results. But in these cases, the Durbin-Watson test should be used with caution. Its repetition without accounting for aggregation effects can cause underdiagnosis of serial correlation, which will eventually reflect on inference, forecasting, and policy assessment. Stronger alternatives, such as the Breusch-Godfrey test, Ljung-Box Q-test, or mixed-frequency model procedures, have to be employed when working with aggregated data.

Despite the robustness of the findings, there are several limitations to this analysis. The first is that simulations were drawn from linear DGPs with Gaussian innovations, which, while indicative, are wanting in reflecting the range of nonlinearities and heteroskedasticity found in empirical applications. Second, the empirical test only considered two currency pairs, although representative, more extensive cross-asset or cross-country validation would provide more generalizable results. Third, the analysis did not test seasonality or structural breaks, which also interact with aggregation and power testing.

Subsequent research should pursue this endeavor in a number of ways. Firstly, autocorrelation test performance under nonlinear specifications and heavy-tailed innovation distributions could be investigated more deeply as a gauge of test reliability under actual financial environments. Secondly, formulating new or aggregation-robust versions of the Durbin-Watson test could be a feasible tradeoff between simplicity and accuracy in diagnostic performance. Third, examination of frequency-domain or wavelet-based techniques might yield more reliable detection of autocorrelation persisting over temporal horizons. Finally, other studies might examine the impacts of temporal aggregation on other conventional diagnostics, including heteroskedasticity tests, cointegration tests, and model selection measures.

In summary, temporal aggregation repeatedly undermines the assumption underlying the Durbin-Watson test for reliability, particularly when used on dynamic data structures with latent or moderate autocorrelation. To recognize and remedy this diagnostic shortcoming is essential to good econometric modeling. Researchers and practitioners must include aggregation effects in their inference procedures or risk making erroneous inferences from seemingly well-behaved residuals.

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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