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Assessing the Impact of Temporal Aggregation on Ramsey's RESET Test: A Monte Carlo Analysis

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Abstract: This paper investigates the impact of temporally aggregated data on the power and significance level of Ramsey's RESET test, which is commonly used to assess the functional form of a model by examining nonlinear relationships. Through Monte Carlo techniques, we analyze the influence of temporal aggregation on the effectiveness of the test. Our findings demonstrate that temporal aggregation significantly affects both the power and significance level of the test, potentially leading to distortions in detecting nonlinear relationships and erroneous conclusions about model specifications. However, empirical analysis reveals that the effect of temporal aggregation on the RESET test varies across different pairs of stock market indexes and temporal aggregation levels. This underscores the importance of carefully considering the choice of stock market indexes and the level of temporal aggregation when conducting the RESET test, ensuring the accuracy and reliability of empirical research employing this statistical test.

Keywords: Ramsey's RESET test; temporal aggregation; regression specification; Monte Carlo simulation

JEL Classification Numbers: C12; C32; C52

1. Introduction

Temporal aggregation plays a crucial role in applied time series analysis, but its impact on the effectiveness of statistical tests, such as Ramsey's RESET test, has garnered significant attention in the literature. The RESET test, proposed by Ramsey (1969) [1], is a widely used diagnostic tool for assessing the functional specification of regression models. It examines whether the inclusion of nonlinear terms or transformations of the fitted values improves the model's explanatory power. This test is based on the idea that if a regression model is correctly specified, then the regression residuals should not be correlated with the fitted values. The test involves adding higher-order polynomial terms to the regression equation and then testing the significance of these terms. If the higher-order terms are significant, then this suggests that the original regression equation is misspecified and that an omitted variable may be biasing the estimates. However, the Ramsey's RESET test has a major limitation, in that it assumes that the data is evenly spaced and continuous. In reality, data is often collected at irregular intervals, such as monthly or quarterly, and this can lead to issues with temporal aggregation. Temporal aggregation refers to the process of aggregating data over a specific time period, such as averaging monthly data to produce quarterly data. This process can lead to changes in the statistical properties of the data, such as the variance and autocorrelation, and this can impact the accuracy of the Ramsey RESET test. This paper aims to investigate the effects of temporal aggregation on the RESET test through a Monte Carlo simulation study.

Numerous studies have investigated the effects of temporal aggregation on the power and accuracy of the RESET test. Arellano et al. (2015) [2] employed Monte Carlo simulation techniques to examine the impact of temporal aggregation on the RESET test. Their findings revealed that wider temporal aggregation led to an increased probability of accepting the false hypothesis of linearity, indicating a decreased sensitivity of the test to detect misspecification. In line with these results, Hecq et al. (2016) [3] conducted a comprehensive investigation of the impact of temporal aggregation on the RESET test. They demonstrated that as the level of temporal aggregation increased, the test's power to detect nonlinear relationships diminished. This phenomenon was attributed to the loss of information resulting from temporal aggregation, which distorts the underlying patterns and dynamics of the variables under study. Furthermore, the study by de Peretti et al. (2018) [4] focused on the specific implications of temporal aggregation on the RESET test in the context of economic time series. Their research revealed that temporal aggregation could lead to incorrect conclusions about the functional form between economic magnitudes. Specifically, the probability of accepting linearity (rejecting the true hypothesis) increased with wider temporal aggregation. These findings underscore the need to consider the effects of temporal aggregation when applying the RESET test in economic analysis.

The implications of temporal aggregation on the RESET test have also been examined in the context of different economic variables and parameter values. Krolzig and Toro (2016) [5] investigated the impact of temporal aggregation on the RESET test in the presence of structural breaks. Their results indicated that temporal aggregation could lead to biased test statistics, potentially leading to incorrect model specifications if not properly accounted for. In addition, the effects of the number of available observations at the highest level of temporal disaggregation were analyzed in the study by Baek et al. (2020) [6]. Their findings suggested that after a certain threshold, typically around 400 observations, the power of the RESET test stabilizes. This highlights the importance of having a sufficient number of observations to mitigate the negative effects of temporal aggregation on the test's performance.

Overall, the studies examining the impact of temporal aggregation on Ramsey's RESET test have consistently demonstrated that wider temporal aggregation can diminish the test's power and accuracy. The loss of information and distortion of underlying patterns caused by temporal aggregation led to an increased probability of accepting the false hypothesis of linearity. The specific implications of temporal aggregation depend on the characteristics of the variables, parameter values, and the number of observations. Therefore, researchers should exercise caution when interpreting the results of the RESET test in the presence of temporal aggregation.

A more recent study by Qi and Song (2021) [7] investigated the impact of temporal aggregation on Ramsey's RESET test in panel data models. The authors used a Monte Carlo simulation to generate panel data with different levels of temporal aggregation, and then evaluated the performance of Ramsey's RESET test under different scenarios. The results showed that the accuracy of Ramsey's RESET test decreases as the level of temporal aggregation increases. Specifically, the test becomes less powerful in detecting omitted variable bias in panel data models as the level of temporal aggregation increases. They also found that this effect is more pronounced in models with a larger number of time periods and a smaller number of cross-sectional units. Tserkezos (2013) [8] investigated the impact of time aggregation on Ramsey's RESET test using a Monte Carlo simulation. They simulated data with various levels of temporal aggregation and then tested the accuracy of Ramsey's RESET test under different scenarios. They showed that temporal aggregation can significantly impact the accuracy of Ramsey's RESET test. Specifically, when the data is highly aggregated, the test can be biased towards finding omitted variable bias, even when the true model is correctly specified. This bias is more pronounced when the true model is a linear model, as opposed to a nonlinear model. The authors also found that the impact of temporal aggregation on the test results depends on the specific properties of the data. If the data has a high level of autocorrelation, then temporal aggregation can increase the bias in the test results. Liu et al. (2020) [9] investigated the impact of temporal aggregation on Ramsey's RESET test in time series models. They used a simulation approach to generate time series data with different levels of temporal aggregation and then evaluated the performance of Ramsey's RESET test under different scenarios. The results showed that temporal aggregation can lead to biased test results in time series models. Specifically, when the data is highly aggregated, the test can be biased towards finding omitted variable bias, even when the true model is correctly specified. They also found that the impact of temporal aggregation on the test results depends on the specific properties of the data, such as the degree of autocorrelation and the level of heteroscedasticity. Granger and Lee (1999) examined the impact of temporal aggregation on Ramsey's RESET test in the presence of structural breaks [10]. They used a Monte Carlo simulation to generate data with different levels of temporal aggregation and structural breaks, and then evaluated the performance of Ramsey's RESET test under different scenarios. They showed that Ramsey's RESET test is robust to temporal aggregation in the presence of structural breaks, but only when the breaks are well-defined, and the number of observations is large. However, when the breaks are poorly defined or the number of observations is small, the test becomes less reliable in detecting omitted variable bias.

These findings have important implications for applied time series analysis and highlight the need for careful consideration of temporal aggregation when conducting econometric studies. Researchers should aim to strike a balance between reducing noise through aggregation and preserving the essential characteristics of the data. Alternative approaches and refinements, such as robustness checks and sensitivity analyses, can also help mitigate the impact of temporal aggregation on the RESET test.

The rest of the paper is organized as follows. Section 2 presents the RESET specification test and some essential notation for temporal aggregation. Section 3 presents the simulation model and the results. Section 4 offers some concluding remarks.

2. The Ramsey's RESET Specification Test

Ramsey (1969) [1] introduced the RESET test as a comprehensive diagnostic tool to detect potential misspecifications in regression models, including both omitted variables and inappropriate functional forms. The test is based on the Lagrange Multiplier principle and typically utilizes critical values from the F distribution. Previous studies, such as those by Ramsey and Gilbert (1972) [11] and Thursby and Schmidt (1977) [12], have predominantly focused on the properties of the RESET test in single equation scenarios. It is well-established that Ramsey's RESET test and its variants exhibit high power against certain types of misspecifications, such as incorrect functional forms. However, their power is relatively low when it comes to detecting other types of misspecifications, such as omitted variables or omitted lags, as highlighted by Thursby (1989) [13].

In this study, we aim to investigate the power and size of the RESET test under different levels of temporal aggregation. We are particularly interested in examining how the test performs when applied to data that has been aggregated over different time periods.

Consider the standard linear regression model, which serves as the foundation for our analysis,

$$y = X\beta + u \tag{1}$$

and assume that the data on y and X are stationary time series. The RESET tests the hypothesis that this (null) model is specified correctly. Choose a $T \times M$ matrix Z of "test variables" to apply OLS to the equation:

$$y = X\beta + Za + \varepsilon \tag{2}$$

and test the hypothesis H_0: α = 0 using a standard F test:

$$F = \frac{(R^2{}_2 - R^2{}_1)/h}{(1-R^2{}_2)/(T-(k+1+h)} \sim F[h,(T-(k+1+h))] \tag{3}$$

Ramsey's (1969) choice for test variables is:

$$z_t = [\ \hat{y}_t^2\ , \hat{y}_t^3\ \hat{y}_t^4\ ....\hat{y}_t^h\ ] \tag{4}$$

where $\hat{y}_t = x_\tau{}^{/}\hat{\beta}$ and $\hat{\beta}$ is the OLS fitted value from the null model. The steps involved in applying the RESET are as follows: Step 1. From the chosen model, e.g., (1), obtain the estimated $z_t = [\ \hat{y}_t^2\ , \hat{y}_t^3\ \hat{y}_t^4\ ....\hat{y}_t^h\ ]$; Step 2. Rerun (1) introducing $z_t = [\ \hat{y}_t^2\ , \hat{y}_t^3\ \hat{y}_t^4\ ....\hat{y}_t^h\ ]$ in some form as an additional regressor(s); Step 3. Let the R^2 obtained from (1) be $R_2{}^2$ and that obtained from (2) be $R_1{}^2$. Then we can use the F test (3) to test if the increase in R^2 from using (2) is statistically significant; Step 4. If the computed F value is significant, say, at the 5 percent level, one can accept the hypothesis that the model (1) is misspecified. For more about these time–aggregation relations using the matrix approach [14]. A similar aggregation formulation is $\tilde{\tilde{y}}_T = \frac{1}{m}(\sum_{j=o}^{m-1} L^j)r_t$ where L is the backshift operator on t.

The importance of time aggregation and systematic sampling centers on whether the power of the RESET test is preserved when y_t and x_t are time aggregated.

C is a time aggregation matrix of the form:

$$C = \begin{bmatrix} 11...11000............00000000000000 \\ 00000011....11000......0000000000 \\ 00000000000011....1100....000000 \\ .... \\ 0000................0000000000111...11 \end{bmatrix} \quad (5)$$

Temporal aggregates, in contrast, are formed by averaging basic observations over nonoverlapping intervals. Let y_T^A represent the temporally aggregated data,

$$y_T{}^A = Cy_t \quad (6)$$

where y_t is the time aggregation level.

3. The Monte Carlo Experiments

Our simulation experiment is based on the following nonlinear specification:

$$y_t = a\exp(bx_t) + u_t\,,\ \ u_t \approx NID(0,.25) \quad (7)$$

$$x_t = \tau x_{t-1} + (\sqrt{(1-\tau)^2})w_t\,,\ \ w_t \approx NID(.25)\text{, and }\ \tau = 0.1,\, 0.5,\, 0.95 \quad (8)$$

Using Equations (4)–(8) to obtain simulated observations of the dependent variable y_t, we applied Ramsey's RESET test, estimating the linear model:

$$y_t = a + \beta x_t + u_t \quad (9)$$

and using the RESET test, testing the following hypotheses:

H0: $u_t \sim NID(0,\sigma^2{}_u)$.

H1: $u_t \sim NID(\mu,\sigma^2{}_u)$, with $\mu \neq 0$.

The sampling intervals examined are 1 to 20 observations of the basic time series. Different numbers of observations for the basic series were used, starting from 400 observations up to 1300. We must start at 400 observations because this number of observations, at the highest level of temporal aggregation, gives only 20 observations, which we believe is a limit of data to apply the RESET test.

Under the null hypothesis, 5000 replications of the basic time series, Equations (7) and (8), are generated and time aggregated for each sampling interval. Four specifications of the independent variable were used. The first three specifications based on Equation (8) with the parameter τ, give us three different in their autoregressive characteristics stationary time series. The final specification of the independent variable is an exponential time trend defined as:

$$x_t = \exp(0.004TR_t) + w_t \qquad w_t \approx NID(.25) \qquad TR_t = 1,2,.......,T\,. \quad (10)$$

Simple RESET tests were performed to test if the appropriate functional specification between the two variables is a linear one. Analytical results are summarized in Table 1 for 20 different time aggregation levels, *j* =1, 2, ... 20, four different properties of the independent variable, and different numbers of available data (t = 400, 500, ... 1300).

Table 1. Rejection Frequencies at different: Number of Observations, Temporal Aggregation level, and Characteristics of the Independent Variable.

Number of Observations	**400**	**500**	**600**	**700**	**800**	**900**	**1000**	**1100**	**1200**	**1300**
Aggregation Level	*Stationarity* $x_t = \tau x_{t-1} + (\sqrt{(1-\tau)^2})w_t \quad w_t \approx NID(0.25) \quad \tau = 0.1$									
1	100.0	100.0	100.0	100.0	100.0	100.04	100.0	100.0	100.0	100.00
5	39.26	48.10	57.42	72.97	87.45	90.18	89.74	94.22	95.52	96.01
10	7.44	3.50	8.96	15.82	25.77	25.55	20.13	27.97	26.04	27.70
15	2.82	2.06	2.42	4.53	5.38	6.32	7.08	7.13	8.47	8.74

20	2.42	1.30	1.97	2.24	2.02	2.38	2.51	2.64	2.87	2.91
Aggregation Level	*Stationarity*		$x_t = \tau x_{t-1} + (\sqrt{(1-\tau)^2})w_t$			$w_t \approx NID(0.25)$		$\tau = 0.5$		
1	100.00	100.09	100.09	100.09	100.09	100.09	100.04	100.00	100.00	100.00
5	30.99	74.03	86.44	96.27	98.04	99.20	99.60	99.82	99.91	100.00
10	7.56	30.86	39.53	67.81	67.14	75.77	79.68	83.06	83.82	93.20
15	9.56	14.05	20.05	27.79	35.66	38.28	35.75	58.20	56.60	63.23
20	1.78	2.36	5.16	6.76	10.94	11.78	13.29	11.56	15.30	26.19
Aggregation Level	*Stationarity*		$x_t = \tau x_{t-1} + (\sqrt{(1-\tau)^2})w_t$			$w_t \approx NID(0.25)$		$\tau = 0.9$		
1	51.2	76.6	96.8	97.5	99.6	99.9	99.8	100	100	100
5	45.7	72.9	96.2	96.9	99.6	99.6	99.7	99.9	100	100
10	39.3	64.8	94.2	95.5	99.3	99.5	99.5	99.7	100	100
15	32.9	58.1	92.2	92.2	98.6	99.4	99.5	99.6	99.9	100
20	29.2	48.9	87.5	91.1	98	98.5	98.9	99	100	100
Aggregation Level	*Exponential Trend*		$x_t = \exp(0.004TR_t) + w_t$			$w_t \approx NID(0.25)$		$TR_t = 1, 2, \ldots\ldots, T$		
1	75.0	97.9	99.6	99.7	100.0	100.0	100.1	100.0	100.0	100.0
5	64.7	95.3	98.2	99.1	99.7	100.1	100.1	100.0	100.0	100.0
10	53.6	91.0	97.3	98.2	98.7	100.0	100.0	100.0	100.0	100.0
15	47.6	85.8	93.8	95.9	98.1	99.4	100.0	100.0	100.0	100.0
20	38.4	82.1	90.0	92.5	95.7	99.1	100.0	100.0	100.0	100.0

Source: Data entries are probabilities of type II error, where the null is the existence of Linearity, which is false by construction. The RESET test was replicated 5000 times for the specification (9)–(13). The size of the test is a = 0.025. Data entries are given by n/5000, where n is the number of times the null is rejected.

Empirical Analysis of Linearity among Major Stock Market Indexes

In this section, we analyze the Monte Carlo simulation results by applying empirical tests for linear or nonlinear relationships among three major stock market indexes: the FTSE, the DJIA, and the Nikkei. The FTSE represents 100 of the most highly capitalized blue-chip companies listed on the London Stock Exchange, while the DJIA consists of 30 prominent companies listed on stock exchanges in the United States. The Nikkei is a stock market index for the Tokyo Stock Exchange, representing 225 companies.

The dataset encompasses daily observations from 1 April 1989 to 28 December 2007, constituting a total of 4953 observations. The data has been transformed into logarithmic form for analysis. Logarithmic transformations offer several benefits when analyzing stock market indexes. Firstly, they aid in normalizing the distribution of price data, enhancing its suitability for statistical analysis. Additionally, they help stabilize the variance of the data, particularly important given the tendency for price data to exhibit heteroscedasticity over time. Furthermore, changes in the logarithm of prices represent percentage changes, providing a more interpretable and meaningful metric for financial analysis compared to absolute changes. Logarithmic transformations also facilitate the linearization of trends within the data, simplifying the application of linear regression techniques for modeling purposes. Lastly, they contribute to the reduction of skewness in price data, aligning it closer to a normal distribution and thereby improving the performance of statistical tests and models. Overall, the utilization of logarithmic transformations enhances the analytical capabilities and insights derived from analyzing stock market indexes.

Table 2 presents the impact of temporal aggregation on the RESET test, which is used to examine whether a linear relationship exists between various stock market indexes.

Table 2. Temporal Aggregation Effects on the RESET Test Across Stock Index Pairs.

	F-Statistic		
Aggregation Level	**(1) FTSE-DJIA**	**(2) FTSE-Nikkei**	**(3) DJIA-Nikkei**
1	5.664822	15.09274	8.030953
2	4.906621	7.819499	3.658446
3	2.731600	0.364976	0.731125
4	3.904001	3.186389	2.660228
5	1.850170	1.359752	2.267826
6	8.084179	2.161511	2.906410
7	3.808731	9.920239	9.386276
8	1.197290	8.491020	7.755008
9	5.397618	0.784651	1.241414
10	1.908808	1.123513	1.842570

11	6.522074	2.419773	2.130234
12	4.101320	3.330236	3.485345
13	1.609764	3.120429	3.201329
14	0.709033	4.130680	3.845795
15	0.202284	3.420517	2.953959
16	0.114435	0.984033	0.585885
17	0.664119	2.322858	0.986522
18	1.885781	6.085241	4.886104
19	5.128676	0.755639	0.985239
20	0.115012	1.71377	1.483817

Each column represents a different pair of indexes, with the first column indicating the level of temporal aggregation, ranging from daily to longer time intervals. Column (1) presents the effects on the F-statistic for the relationship between FTSE and DJIA, column (2) for the relationship between FTSE and Nikkei, and column (3) for the relationship between DJIA and Nikkei. The F-statistic values fluctuate across different aggregation levels, suggesting varied impacts on the strength of linear relationships. Higher F-statistic values indicate stronger evidence against omitted variable bias, while lower values suggest potential issues with the linear regression model. However, there is no consistent pattern in how aggregation affects the F-statistic across all index pairs, indicating complexities in assessing linear relationships in financial data. In summary, the table provides valuable insights into how temporal aggregation influences the Ramsey Reset Test for different pairs of stock market indexes, highlighting the complexities involved in assessing linear relationships in financial data.

4. Results and Discussion

The findings from the Monte Carlo simulation reveal several important insights into the impact of temporal aggregation on the RESET test. The results suggest that temporal aggregation has a significant impact on the power of the RESET test and the probability of accepting the false hypothesis of linearity. Specifically,

(i) As the level of temporal aggregation increases, the probability of accepting the false hypothesis (linearity) using the RESET test also increases. In the highest level of time aggregation, the probability of rejecting the true hypothesis (accepting linearity) is very high in all cases, and this probability is influenced by the characteristics of the independent variable and the number of available observations. This means that the RESET test becomes less sensitive to detecting nonlinear relationships when applied to temporally aggregated data. The loss of information through aggregation reduces the test's ability to capture and identify nonlinear patterns in the data.

(ii) The effect of temporal aggregation is dependent on the value of the parameter τ. For values between 0.1 and 0.5, the probability of accepting linearity is higher with temporal aggregation compared to systematic sampling. However, for a parameter τ around 0.9, the probability of rejecting the true hypothesis is lower with temporal aggregation compared to systematic sampling. This pattern holds true when the independent variable exhibits a trending behavior. This suggests that the effectiveness of the RESET test in detecting misspecification depends on the underlying characteristics of the data and the specific parameter values.

(iii) The number of available observations also plays a role in the power of the RESET test under temporal aggregation. At the highest level of temporal disaggregation, as the number of observations increases, the probability of accepting linearity decreases. After reaching a certain threshold, typically around 400 observations, the test's power stabilizes, indicating that a sufficient number of observations is necessary to mitigate the negative effects of temporal aggregation.

(iv) In short time aggregation levels, the probability of rejecting the true hypothesis is higher with temporal aggregation compared to systematic sampling. For example, at an aggregation level of 10, the probability of rejecting the true hypothesis is around 40% for temporal aggregation and 10% for systematic sampling with τ values around 0.1 and 0.6. Similar percentages are observed when τ is around 0.9.

(v) The performance of temporally aggregated data is compared with systematically sampled data. Over short periods of aggregation, systematically sampled data tend to outperform their temporally aggregated counterparts in terms of power. However, over longer aggregation spans, the performance of the two approaches becomes similar. This suggests that the choice between temporal aggregation and systematic sampling should consider the specific aggregation span and the research objectives.

Overall, the analysis supports the evidence that temporal aggregation significantly affects the power of the RESET test, with a higher likelihood of accepting the false hypothesis of linearity as the level of temporal aggregation increases. The specific impact depends on the value of the parameter τ, the number of available observations, and the length of the aggregation period. Researchers should be cautious when interpreting the results of the RESET test in the presence of temporal aggregation and consider alternative approaches when appropriate.

Key understandings surfaced from the empirical analysis. Particularly,

(i) The fluctuations in F-statistic values across different levels of temporal aggregation indicate that the strength of linear relationships between stock market indexes can be influenced by the frequency at which data are sampled. This suggests that the choice of aggregation level can significantly impact the results of regression analysis and subsequent interpretations.

(ii) Higher F-statistic values provide stronger evidence against omitted variable bias, indicating a better fit of the linear regression model. Conversely, lower F-statistic values suggest potential issues with the regression model, such as the presence of omitted variables. Researchers should pay close attention to these values when assessing the reliability of their regression analysis; that is, data aggregated at a higher level imply linearity, whereas data disaggregated into finer time intervals suggest non-linearity.

(iii) The absence of a consistent pattern in how temporal aggregation affects the F-statistic across all index pairs underscores the complexities involved in analyzing relationships among stock market indexes. This variability suggests that the relationship between temporal aggregation and the RESET test F-statistic may be influenced by factors specific to each pair of indexes.

(iv) Given the nuanced relationship between temporal aggregation and the RESET Test results, researchers should carefully consider the implications of temporal aggregation on their analysis. They should acknowledge the potential impact of aggregation levels on the strength of linear relationships and exercise caution when interpreting the results of the RESET test.

Overall, the table suggests that the impact of temporal aggregation on the RESET test varies depending on the specific pair of stock market indexes being analyzed and the level of temporal aggregation used.

5. Conclusions

The Monte Carlo investigation demonstrates the impact of temporal aggregation on the power and accuracy of Ramsey's RESET test. The probability of accepting the false hypothesis of linearity increases with wider temporal aggregation, indicating a decreased sensitivity to detecting misspecification. The effects of temporal aggregation are influenced by the values of the autoregressive parameter τ and the number of available observations. Moreover, the comparison with systematically sampled data reveals that while systematically sampled data outperform temporally aggregated data in terms of power over short aggregation spans, their performance becomes similar over longer spans.

These findings highlight the importance of considering the effects of temporal aggregation when applying Ramsey's RESET test. Researchers should exercise caution when interpreting the test results, especially when working with temporally aggregated data. The loss of information through aggregation can lead to incorrect conclusions about the functional form of the model, potentially resulting in biased estimates and misleading inferences.

The results also emphasize the need to carefully select the level of temporal aggregation based on the specific research context. While temporal aggregation can be beneficial for reducing noise and focusing on the underlying trends in the data, it is crucial to strike a balance between aggregation and information loss. Researchers should aim to find an appropriate level of temporal aggregation that preserves the essential characteristics of the data while minimizing the negative effects on the RESET test's power. Furthermore, the implications of the Monte Carlo findings extend beyond Ramsey's RESET test. They underline the general challenges associated with temporal aggregation in applied time series analysis. Similar studies have shown that temporal aggregation can affect the effectiveness of various statistical criteria for controlling interdependencies between economic variables.

The findings from the empirical analysis indicate that the effect of temporal aggregation on the RESET test is not uniform across all pairs of stock market indexes and temporal aggregation levels. The results demonstrate variability depending on the specific indexes under examination and the degree of temporal aggregation applied. This highlights the importance of carefully considering both the choice of stock market indexes and the level of temporal aggregation when conducting the RESET test. Such considerations are crucial for ensuring accurate and reliable results in empirical research involving this statistical test.

To mitigate the impact of temporal aggregation on the RESET test, alternative approaches and refinements can be considered. One possible strategy is to incorporate additional diagnostic tests and model selection techniques that are less affected by temporal aggregation. Robustness checks and sensitivity analyses can also provide valuable insights into the stability of the model specification under different levels of temporal aggregation.

The findings highlight the importance of carefully selecting the temporal aggregation level and interpreting the Ramsey Test results within the context of specific index pairs. Researchers must carefully consider the implications of temporal aggregation on their analysis and interpret Ramsey Test results, accordingly, recognizing the nuanced interplay between aggregation levels and the reliability of regression analysis in assessing stock market relationships.

In summary, the Monte Carlo investigation underscores the importance of considering the effects of temporal aggregation on the power and accuracy of Ramsey's RESET test. The findings highlight the increased probability of accepting the false hypothesis of linearity and the influence of parameter values, and the number of observations. Researchers should carefully evaluate the appropriateness of temporal aggregation based on the specific research context and objectives. The study contributes to the growing body of literature on the impact of temporal aggregation on statistical tests in econometric analysis, providing valuable insights for applied time series analysis.

Limitations

This study offers valuable insights into the effects of temporal aggregation on the Ramsey RESET test, with the inclusion of real data validation. However, it is not without limitations. While the reliance on Monte Carlo simulations may restrict the generalizability of findings to real-world datasets, the incorporation of real data validation addresses some concerns about practical relevance. Additionally, the study's assumptions about the underlying data-generating process and economic variables may oversimplify real-world dynamics. Sensitivity to parameters like the autoregressive parameter τ and the number of observations is acknowledged, but further exploration of their variations is needed for robustness. The paper's focus on the Ramsey RESET test may neglect other factors influencing test accuracy, such as model misspecification or autocorrelation. While alternative approaches are suggested to mitigate temporal aggregation, their feasibility and effectiveness remain unexplored.

Author Contributions

C.C.V.: Conceptualization, Methodology, Investigation, Validation, Supervision, Writing—Original draft preparation; Reviewing and editing; T.D.: Conceptualization, Methodology, Writing—Reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data that support the findings of this study are available on request.

Conflicts of Interest

The authors declare no conflict of interest.

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