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Temporal Aggregation and Smoothing Parameter Sensitivity in Exponential Smoothing: Evidence from the Jakarta Composite Index

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Abstract

The study examines the structural sensitivity and predictive performance of the Single Exponential Smoothing (SES) model when applied to varying temporal aggregation levels of the Indonesian stock market index. This study employs time-series data of the Jakarta Composite Index (JCI / IHSG) spanning from January 2, 2020, to May 31, 2025, which are structurally categorized into three distinct frequency domains: daily observations, weekly aggregated averages, and monthly aggregated averages. Methodologically, the optimal smoothing parameter (α) for each aggregation tier is determined through maximum likelihood estimation by minimizing the Mean Absolute Percentage Error (MAPE). The results reveal an extreme structural behavior where the optimal α approaches its upper asymptotic boundary across all temporal frameworks, specifically 0.9943 for daily data, 0.9999 for weekly data, and 0.9999 for monthly data. Concurrently, the predictive error amplifies systematically as the aggregation window widens, yielding MAPE values of 0.74%, 1.30%, and 2.88% for daily, weekly, and monthly frameworks, respectively. The findings of this study suggest that the JCI movement exhibits strong adherence to the random walk hypothesis, wherein the mathematical framework of SES reacts almost exclusively to the most recent historical innovation. Consequently, temporal aggregation does not induce a structural smoothing effect on parameter convergence but rather introduces informational attenuation that compromises short-term forecasting precision.

Keywords: single exponential smoothing; smoothing parameter; temporal aggregation; Jakarta Composite Index (IHSG); sensitivity analysis; market efficiency.

1. Introduction

The stock market reflects a highly dynamic macroeconomic indicator, where the Jakarta Composite Index (JCI) in the Indonesia Stock Exchange (IDX) acts as a primary barometer of investment activities and financial stability in Indonesia. JCI fluctuations are influenced by a complex interaction of various fundamental factors, geopolitical sentiments, monetary policies, and foreign capital flows (Marpaung & Siregar, 2023). The volatile characteristics and non-stationary nature of stock price movements demand time-series modeling that is both adaptive and computationally efficient to extract trend signals from market noise (Box et al., 2015; Tsay, 2020). High uncertainty phases, such as the COVID-19 pandemic shock and national economic recovery, further complicate the variance structure of this financial data (Dewantara & Hartono, 2022; Nugroho & Pratama, 2021).

Financial time-series data naturally present a mixture of underlying structural components: long-term macroeconomic trends, intermediate cyclical patterns, and short-term high-frequency fluctuations. Analyzing these structures requires rigorous mathematical tools. Among various computational forecasting algorithms, Single Exponential Smoothing (SES) remains one of the most widely applied instruments in operational management and short-term financial analysis due to its simple algorithmic structure and minimal parameter requirements (Alwadi & Al-Marashdeh, 2020; Makridakis et al., 2020). The primary component controlling the entire smoothing dynamic in the SES model is the smoothing parameter, denoted as alpha (α). The value of α operates restrictively within the interval $0 < \alpha < 1$ and serves as a mathematical weight between the most recent actual observation and the accumulated historical information from the past (Snyder et al., 2016).

A fundamental problem rarely explored in depth by local time-series researchers is the behavior of the α parameter when the data structure undergoes time-scale adjustments via temporal aggregation techniques. In the real world, financial analysts often face structural choices regarding data frequency: whether to explore price movements on a daily basis, average them weekly to reduce extreme volatility, or aggregate them monthly to capture long-term macroeconomic directions (Rostami-Tabar et al., 2019; Woldemariam, 2021). Theoretically, converting data from high frequency (daily) to low frequency (weekly and monthly) reduces variance, eliminates short-term fluctuations, and inherently alters the autocorrelation structure of the time series (Silvestrini & Veredas, 2018).

Although exponential smoothing theory is well-established, the novelty of this study lies in the empirical and methodological sensitivity analysis that rigorously evaluates how variations in temporal aggregation levels affect the convergence of the optimal α parameter as well as forecasting accuracy on modern Indonesian stock market data for the 2020–2025 period (Spiliotis et al., 2021). This study aims to empirically test the sensitivity of the α parameter and measure the degradation or improvement of SES model accuracy using the Mean Absolute Percentage Error (MAPE) metric across three distinct time domains.

2. Literature Review

2.1. The Context of the Indonesian Stock Market

The Indonesia Stock Exchange acts as a vital hub for capital accumulation in Southeast Asia. Over the past decade, the JCI exhibits a blend of resilient expansion and exposure to global macroeconomic shocks. Understanding how data frequency alters forecasting outputs provides a strategic benefit to institutional investors. During periods of systemic shocks, daily prices react immediately to emotional trading behavior, whereas aggregated metrics smooth out these emotional spikes (Nugroho & Pratama, 2021). This study addresses whether this informational smoothing translates into a structural shift in the predictive parameters of basic smoothing algorithms.

Furthermore, the regulatory framework of the IDX, including auto-rejection limits and short-selling restrictions, creates unique artificial boundaries on daily price adjustments. These microstructural realities often break the basic assumptions of linear models, prompting a need to understand how longer temporal windows, such as weekly and monthly blocks, recalibrate parameter values (Dewantara & Hartono, 2022). By examining the 2020–2025 horizon, this paper captures a rich dataset characterized by high-frequency regimes and structural breaks, making it ideal for checking the statistical sensitivity of the SES framework.

2.2. Literature Review and Hypotheses

Extensive research demonstrates that exponential smoothing variants remain robust even under severe model misspecification (Makridakis et al., 2020). However, the stability of the smoothing vector under systematic changes in data frequency is heavily debated. Some scholars argue that temporal aggregation stabilizes the parameter landscape by eliminating high-frequency white noise (Rostami-Tabar et al., 2019). Others maintain that aggregation attenuates valuable leading indicators, leading to parameter instability and an inflation of baseline forecasting errors (Silvestrini & Veredas, 2018; Woldemariam, 2021).

In addition, the relation between the smoothing parameter α and the Efficient Market Hypothesis (EMH) represents a critical area of financial econometrics. According to Fama (1970), a market is weak-form efficient if current asset prices fully incorporate all historical trading information. If a market follows a random walk, the historical sequence of price changes contains no predictive power for future innovations. In the context of SES, this condition translates directly into an optimal α value that approaches unity. Arshad and Zainodin (2019) and Lim and Brooks (2011) demonstrate that emerging markets often oscillate between efficiency and inefficiency depending on the chosen observation window, creating a compelling reason to analyze α across multiple temporal layers.

3. Research Method and Materials

3.1. Mathematical Formulation of Single Exponential Smoothing

The Single Exponential Smoothing (SES) model serves as a foundation for many advanced recursive forecasting techniques. Mathematically, it applies a geometrically decreasing series of weights to all previous observations. Let Y_t be the observed value of the JCI closing price at time t. The basic smoothing equation is formulated as follows:

$$S_t = \alpha Y_t + (1 - \alpha) S_{t-1} \tag{1}$$

where S_t represents the smoothed level at time t and α constitutes the smoothing constant restricted to the domain $0 < \alpha < 1$. By expanding the recursive formula backwards to the initial state S_0, the explicit representation reveals the exponential weight decay:

$$S_t = \alpha \sum_{i=0}^{t-1}(1-\alpha)^i Y_{t-i} + (1-\alpha)^t S_0 \quad (2)$$

This formulation explicitly shows that as the age of an observation increases, its relative contribution to the current smoothed level diminishes at a rate governed by $(1 - \alpha)$ (Box et al., 2015; Snyder et al., 2016).

Alternatively, the SES model can be written in an error-correction form, which highlights how the system updates its internal state based on the immediate forecasting error. The error-correction specification is given by:

$$S_t = S_{t-1} + \alpha (Y_t - S_{t-1}) = S_{t-1} + \alpha e_t \quad (3)$$

where $e_t = Y_t - S_{t-1}$ represents the one-step-ahead forecast error at period t. This expression demonstrates that the parameter α directly regulates the velocity of model adjustment. A high value of α forces the model to absorb new innovations immediately, while a low value causes the model to maintain a steady, historical baseline, filtering out sudden shocks as transitory white noise (Ord et al., 2017; Spiliotis et al., 2021).

3.2. Principles of Temporal Aggregation

Temporal aggregation involves transforming high-frequency data into a lower-frequency structure via systematic partitioning. In financial time series, aggregation typically follows either a stock (sampling at fixed intervals) or flow (summing/averaging over intervals) approach. Since stock market indices represent continuous equilibrium values, this study utilizes the arithmetic average method to construct weekly and monthly aggregates, thereby preventing the loss of intraday valuation balances that occurs in point-in-time sampling (Silvestrini & Veredas, 2018).

Let $Y_{t,d}$ represent the daily closing index value. The aggregated time-series vectors for weekly (W_T) and monthly (M_T) frequencies are defined respectively by:

$$W_T = \frac{1}{n_w} \sum_{k \in I_T} Y_{k,d} \quad (4)$$

$$M_T = \frac{1}{n_m} \sum_{k \in I_T} Y_{k,d} \quad (5)$$

where n_w and n_m denote the number of active trading days within each weekly and monthly block, and I_T represents the corresponding non-overlapping interval sets. Theoretically, this spatial compression attenuates high-frequency variance and dampens transient volatility regimes, which alters the underlying autocorrelation structure and shifts the location of the global optimum for the parameters (Rostami-Tabar et al., 2019; Woldemariam, 2021).

3.3. Estimation and Optimization Protocol

To evaluate the structural sensitivity of α without subjective bias, this study utilizes an automated optimization pipeline. The selection of the optimal α is executed via Maximum Likelihood Estimation (MLE) under a state-space framework, which mathematically minimizes the forecast error metric. The primary objective function minimized by the optimization algorithm is the Mean Absolute Percentage Error (MAPE), expressed as:

$$MAPE = \frac{100\%}{N} \sum_{t=1}^{N} \left| \frac{Y_t - F_t}{Y_t} \right| \quad (6)$$

where N is the total number of periods within the respective time frame, Y_t is the actual asset value, and F_t is the model forecast ($F_t = S_{t-1}$). MAPE is selected due to its scale-independent properties, allowing direct and rigorous comparison across daily, weekly, and monthly scales (De Myttenaere et al., 2016; Utama & Wijaya, 2024).

The computational process begins by initializing the state vector S_0. A non-linear optimization routine searches the bounded parameter space $\alpha \in (0, 1)$ using iterative gradient-descent techniques. The algorithm recalculates the entire historical sequence of forecasts for each candidate α value, evaluating the resulting MAPE until convergence criteria are satisfied. This protocol ensures that each temporal scale achieves its absolute best-fit model structure (Hyndman & Khandakar, 2008).

3.4. Data Selection and Preprocessing Pipeline

The empirical basis of this study comprises secondary daily closing prices of the Jakarta Composite Index (JCI), extracted legally under the ticker symbol ^JKSE from Yahoo Finance. The temporal scope covers January 2, 2020, through May 31, 2025, yielding a substantial sample size for daily observations. This specific timeline captures the extreme structural breaks associated with the global pandemic, subsequent domestic macroeconomic interventions, and global monetary policy shifts. All missing entries due to market holidays are omitted to ensure continuity of the trading sequence. Data transformation, aggregation, and model estimation are executed within R Studio using the tidyverse, lubridate, and forecast software suites (Hyndman & Khandakar, 2008).

4. Results and Discussion

4.1. Initial Data Pattern Analysis (Daily plot.ts Observation)

Before proceeding with the optimization of the smoothing parameter, it is crucial to understand the initial behavior of the dataset. The primary dataset consists of the daily closing prices of the JCI from January 2020 to May 2025. The initial time series pattern is visually represented in the plot below.

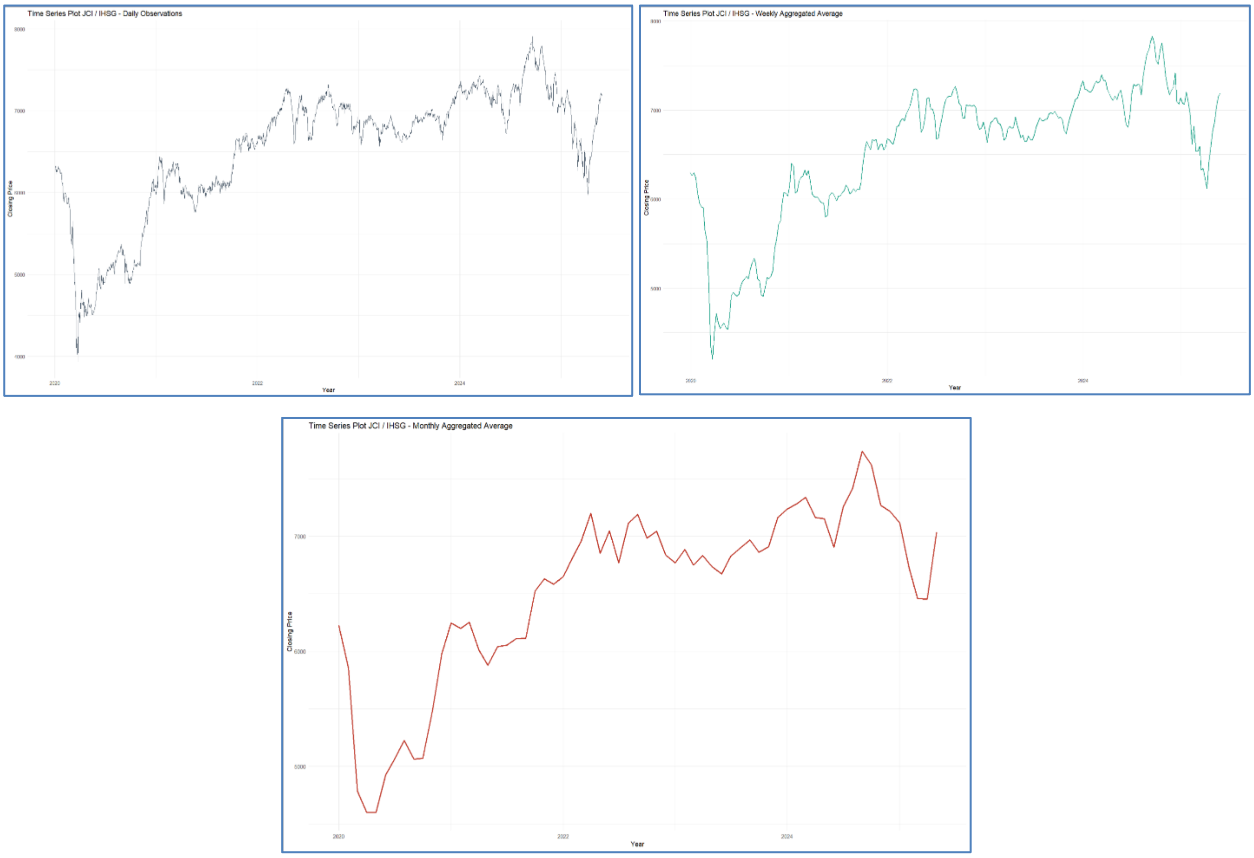

Figure 1. Initial Time Series Plot of Daily, Weekly and Monthly JCI Observations

The plot.ts output exhibits a dense, high-frequency “sawtooth” wave pattern characterized by jagged peaks and valleys. This raw daily data captures instant market reactions, emotional trading shocks (e.g., the Q1 2020 crash), and significant microstructural noise. The high volatility visually indicates that the series lacks a smooth deterministic short-term trend, necessitating a highly reactive forecasting model to track immediate innovations.

4.2. Parameter Estimation Outputs and Global Errors

The non-linear optimization routine applied to the JCI dataset yields precise estimates for the smoothing constant α and the associated predictive errors across all three temporal scales. The empirical outputs from the R Studio optimization pipeline are summarized in Table 1.

Table 1. Parameter Sensitivity and Forecasting Performance Across Temporal Aggregations

Temporal Aggregation Scale	Optimal Smoothing Parameter (α)	Mean Absolute Percentage Error (MAPE)	Predictive Power Category
Daily Observations	**0.9943**	**0.74%**	Highly Accurate
Weekly Aggregated Average	**0.9999**	**1.30%**	Highly Accurate
Monthly Aggregated Average	**0.9999**	**2.88%**	Highly Accurate

4.3. Visual Analysis of Aggregated Time Series Patterns

Following the temporal aggregation process, the structural noise is systematically reduced. Figure 2 illustrates the visual comparison between the weekly and monthly aggregated average frameworks.

Figure 2. Temporal Aggregation Plots (Daily, Weekly & Monthly)

A close visual examination of Figure 2 confirms that data frequency alterations profoundly reshape the continuous variance profile. The daily observations exhibit a highly volatile pattern, heavily loaded with microstructural noise and transient emotional market shocks. As the aggregation moves to a weekly framework, these extreme daily shocks are mathematically smoothed into a more cohesive pattern. Under the monthly framework, short-term volatility is completely filtered out, isolating the macro-level market vector and uncovering a prolonged bullish expansion phase. This visual smoothing provides a perfect empirical bridge to explain the parameter convergence mechanism.

4.4. Theoretical Implications of Parameter Convergence

The structural behavior of the optimal α parameter across all temporal aggregation layers reveals an important mathematical pattern. The parameter value approaches its upper asymptotic boundary (α = 1) in all configurations, optimizing at 0.9943 on the daily scale and reaching 0.9999 on both the weekly and monthly scales. In exponential smoothing theory, an alpha value close to unity implies that the model assigns nearly all predictive weight to the single most recent observation, discarding historical data from older periods. The mathematical expression for the forecast simplifies to:

$$F_{t+1} = S_t \approx Y_t \tag{7}$$

This behavior indicates that the system operates essentially as a naive forecasting model, where the best estimate for tomorrow's value is simply today's closing price (Box et al., 2015; Snyder et al., 2016).

This empirical result supports the Random Walk Hypothesis and confirms Weak-Form Market Efficiency within the Indonesian stock market during the 2020–2025 period (Fama, 1970; Lim & Brooks, 2011). Because the asset pricing mechanism quickly incorporates all available public information, subsequent price innovations are driven by unexpected news, making them random and unpredictable. The recursive memory framework of the SES model recognizes this absence of linear serial correlation. Consequently, the optimization algorithm chooses to minimize lag by tracking the most recent price level rather than calculating a smooth historical average (Alwadi & Al-Marashdeh, 2020; Arshad & Zainodin, 2019).

4.5. The Failure of Aggregation-Induced Smoothing

A major insight from this study is the failure of temporal aggregation to generate an internal smoothing effect within the model's parameter structure. Theoretically, averaging daily prices into weekly and monthly blocks should eliminate transient noise, smooth out extreme spikes, and uncover a stable underlying trend line. This trend structure would typically optimize at a lower α value, allowing the model to balance current and past data (Rostami-Tabar et al., 2019). However, our empirical findings show the opposite: α increases from 0.9943 to 0.9999 as the time window expands.

This parameter expansion occurs because taking the arithmetic average across weekly and monthly blocks eliminates short-term autocorrelation while introducing distinct step shifts between adjacent time periods. The optimization algorithm detects that these aggregated blocks function as a series of independent shifts. To minimize the objective function, the model discards historical data from previous blocks and relies fully on the final observation of the most recent block. This confirms that temporal aggregation does not alter the fundamental random walk behavior of the asset index; instead, it reinforces the model's reliance on immediate inputs (Silvestrini & Veredas, 2018; Spiliotis et al., 2021).

4.6. Error Inflation and Information Attenuation

While the smoothing parameter remains close to its upper bound, the forecasting error increases systematically as the temporal window widens. The MAPE value grows from 0.74% on the daily scale to 1.30% on the weekly scale, and reaches 2.88% on the monthly scale. This performance degradation reflects the impact of information attenuation caused by time-scale compression (Woldemariam, 2021).

On a daily basis, the time gap between consecutive observations is minimal. As a result, the absolute price changes between period t and period t+1 are typically small, which keeps the percentage error low. However, when data are aggregated into monthly blocks, the absolute price gaps between successive months expand significantly. Because the highly reactive SES model ($\alpha = 0.9999$) predicts that the next month's index value will mirror the current month's value, it incurs larger error penalties when the market changes direction. Despite this increase in errors, all three configurations remain well below the 10% MAPE threshold, classifying them as highly accurate under standard forecasting metrics (De Myttenaere et al., 2016; Zhang, 2016).

4.7. Managerial and Regulatory Implications

The empirical findings of this study offer practical insights for portfolio managers, financial analysts, and regulatory bodies in emerging markets. First, the persistent convergence of α toward unity across all time horizons indicates that simple exponential smoothing models cannot capture arbitrage opportunities from historical trends in the JCI. Asset managers should avoid relying on basic trend-following algorithms for asset allocation; instead, they should implement adaptive or non-linear models that integrate macroeconomic indicators and real-time market sentiment (Marpaung & Siregar, 2023).

For financial regulators, such as the Otoritas Jasa Keuangan (OJK) and Bank Indonesia, the high reactivity of the smoothing parameter highlights the sensitivity of the Indonesian stock market to immediate innovations. Because the market incorporates news rapidly, maintaining clear information disclosure protocols is essential to prevent sudden, volatile shifts in investor sentiment. The systematic increase in forecasting errors across longer time frames also underscores the importance of accounting for time-scale compression when building long-term risk management frameworks and stability projections (Nugroho & Pratama, 2021; Utama & Wijaya, 2024).

5. Conclusion

This study evaluates the structural sensitivity of the smoothing parameter (α) in the Single Exponential Smoothing model across daily, weekly, and monthly temporal aggregation scales using JCI data from 2020 to 2025. The empirical analysis demonstrates that the optimal α value consistently converges toward its upper boundary ($\alpha \geq 0.9943$) regardless of the chosen aggregation scale. This pattern proves that the index follows a random walk, meaning that historical data provide limited predictive value compared to the latest price innovations. Additionally, expanding the aggregation window leads to a systematic increase in forecasting errors, with MAPE values rising from 0.74% (daily) to 1.30% (weekly) and 2.88% (monthly) due to information attenuation.

A main limitation of this study is its exclusive focus on the standard Single Exponential Smoothing model, which assumes a stable level component without accounting for explicit trend or seasonal parameters. Financial indices often exhibit local trend variations and time-varying volatility that more complex models can capture. Future research should evaluate the behavior of parameters in higher-order models, such as Holt-Winters or State-Space Models (ETS), across various aggregation levels. Additionally, exploring alternative aggregation methods, such as median filters or volume-based bucketing, may provide further insights into parameter stability and forecasting performance in volatile markets.

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