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Detection of Structural Break in Indonesia Composite Index Volatility Using HAR Model and CUSUM Test

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Abstract: This paper investigates whether Indonesia Composite Index (IHSG) volatility persistence exhibits statistically significant structural breaks over 2019–2024 and how short-, medium-, and long-term components shift across regimes. Using daily closing prices from the Indonesia Stock Exchange (IDX), realized volatility is modeled via HAR specification with daily, weekly, and monthly components. Structural stability is tested using CUSUM, CUSUMSQ, and Bai–Perron procedures, identifying breaks in April 2020 (COVID-19) and February 2024 (election). Pre-COVID, the weekly component dominates, indicating medium-term persistence; post-COVID, the monthly component leads, reflecting long-horizon uncertainty. Pre-election adjusted R^2 drops sharply (0.044), signaling transitory political volatility. Findings demonstrate regime-dependent volatility in emerging markets, showing that ignoring structural breaks biases risk assessment and market monitoring strategies for regulators and investors.

Keywords: Indonesia Composite Index; Volatility; HAR model; Structural break; CUSUM; Emerging markets

1. Introduction

The Indonesia Composite Index (IHSG) is the primary indicator that reflects the aggregate performance of Indonesia's capital market. As a composite index covering all listed stocks on the Indonesia Stock Exchange (IDX), IHSG serves as a barometer of national economic dynamics and investor sentiment toward macroeconomic conditions (Chen et al., 1986; Cont, 2001; Kristoufek, 2015; Schwert, 1989). Its movements are influenced not only by domestic economic variables such as inflation, interest rates, and fiscal policy but also by external factors including global market turbulence, international monetary policy shifts, and geopolitical crises (Diebold & Yilmaz, 2012; Poon & Granger, 2003). Consequently, IHSG is widely regarded as a leading indicator for assessing the direction and stability of Indonesia's economy.

During the 2019–2024 period, IHSG demonstrated considerable resilience to multiple economic disturbances, including the COVID-19 pandemic and political uncertainties surrounding national elections. Although the index experienced a sharp decline in early 2020, it recovered rapidly, reflecting the adaptability of the real sector and the effectiveness of policy interventions implemented by the government and Bank Indonesia (Baur & Lucey, 2010; McAleer, 2014). Domestic consumption stability, fiscal stimulus, and foreign capital inflows further enhanced the IHSG's role as a gauge of market confidence. These phenomena suggest that Indonesia's capital market exhibits a relatively strong structural foundation in absorbing external pressures.

In investment decision-making and economic policy formulation, IHSG holds strategic importance as a central reference point. Investors rely on the index to evaluate risk–return trade-offs, while market analysts use it as the basis for forecasting models and trend identification (Baker et al., 2020; Rossi, 2013). Policymakers likewise monitor IHSG movements to evaluate the effectiveness of fiscal and monetary policies. Hence, the IHSG functions not only as a measurement of market performance but also as an analytical instrument supporting evidence-based decision-making.

IHSG's sustained growth in recent years reflects increasing investor confidence in Indonesia's economic prospects. Rising domestic investor participation and improved market liquidity have contributed to the index's stability. Additionally, the entry of foreign capital, often viewed as affirmation of Indonesia's economic potential, acts as a catalyst for deepening the capital market (Goodell, 2020; Zhang et al., 2020). However, IHSG movements do not always purely reflect economic fundamentals; market sentiment, speculative behavior, and emotional responses to economic news may introduce substantial distortions (Al-Awadhi et al., 2020; Ding et al., 1993; Schwert, 1989).

Although IHSG has been widely examined in academic literature, existing studies predominantly focus on return behavior, short-term volatility forecasting, or the effects of macroeconomic variables, while largely assuming parameter stability over time (Gujarati & Porter, 2009; Hamilton, 1994). Relatively limited attention has been given to examining whether major external shocks induce statistically significant structural breaks in the long-term volatility structure of IHSG, particularly in an emerging market context (Al-Awadhi et al., 2020; Baur & Lucey, 2010; Goodell, 2020). Political events such as elections, shifts in fiscal or monetary policy, and global shocks, including pandemics or energy crises, may generate asymmetric and nonlinear responses in financial markets, which are difficult to capture using conventional linear volatility models (Bloom, 2009; Engle, 2002).

A major challenge in analyzing IHSG volatility lies in accurately capturing volatility dynamics across multiple time horizons under conditions of limited real-time information. Volatility is a critical input for risk management, portfolio allocation, and policy evaluation; therefore, measurement errors or model misspecification may lead to suboptimal decisions (Baker et al., 2020; Bauwens et al., 2006).

The HAR model introduced by Corsi (2009) offers a relevant framework in this context. By modeling daily, weekly, and monthly volatility jointly, the HAR model effectively captures long-memory characteristics and volatility clustering typical in financial markets (Corsi, 2009; Kristoufek, 2015). However, applications of the HAR model in emerging markets such as Indonesia remain relatively scarce, and existing studies often overlook the possibility of structural breaks and parameter instability, which may bias inference and reduce forecasting reliability (Bai & Perron, 2003; Engle, 1982; Zhang et al., 2020).

While prior studies have examined IHSG volatility using conventional ARCH/GARCH or short-horizon models, most implicitly assume parameter stability over time. This assumption may be inappropriate in an emerging market characterized by recurrent systemic shocks and political events. Rather than focusing solely on volatility magnitude, this study narrows its scope to volatility persistence across multiple time horizons and its regime-dependent behavior.

Accordingly, the central research question of this study is formulated as follows:

Does IHSG volatility persistence exhibit statistically significant structural breaks during the 2019–2024 period, and how do the relative contributions of short-, medium-, and long-term volatility components change across regimes associated with major economic and political shocks?

To address this question, this study integrates the HAR model with formal structural break tests, namely the cumulative sum test, the cumulative sum of squares test, and the Bai–Perron multiple breakpoint procedure, allowing breakpoints to be identified in a data-driven manner prior to economic interpretation. With particular emphasis on the COVID-19 pandemic and the 2024 general election, this study provides empirical evidence on how major shocks alter volatility regimes and their implications for investment strategies and economic policy in Indonesia.

2. Methodology

2.1 Data

This study employs secondary data consisting of daily closing prices of the Indonesia Composite Stock Index obtained from the official database of the IDX for the period January 2019 to August 2024. The selected period covers both tranquil and turbulent market conditions, including the COVID-19 pandemic and the 2024 General Election, which are widely documented as sources of structural change in emerging financial markets (Al-Awadhi et al., 2020; Goodell, 2020).

Daily logarithmic returns are computed as:

$$r_t = ln\,(P_t) - ln\,(P_{t-1}) \tag{1}$$

where, P_t denotes the IHSG closing price at time *t*.

Logarithmic returns are preferred due to their statistical stability and widespread use in empirical financial studies (Bollerslev, 1986; Campbell et al., 1997; Corsi, 2009; Gujarati & Porter, 2009). Volatility is proxied by squared returns aggregated over daily, weekly, and monthly horizons, following standard practice in realized volatility modeling (Kristoufek, 2015; Rossi, 2013). All data used in this study are publicly available from the IDX, and no restrictions apply to their use.

2.2 Volatility Model

This study adopts the HAR model proposed by Corsi (2009) to capture volatility persistence across multiple time horizons. The HAR model is a well-established framework and is therefore introduced briefly without derivation. It incorporates daily, weekly, and monthly volatility components to approximate long-memory behavior in financial markets (Kristoufek, 2015; Schwert, 1989).

Conceptually, the HAR model assumes that market volatility reflects the aggregation of heterogeneous investor expectations operating at different time horizons. Daily volatility captures short-term reactions to news, weekly volatility reflects medium-term adjustment by institutional investors, while monthly volatility represents long-horizon risk perception. This structure allows the HAR model to approximate long-memory behavior without imposing fractional integration, making it particularly suitable for emerging markets with limited market depth.

The HAR (3) specification is expressed as:

$$RV_t = \beta_0 + \beta_1 RV_{t-1} + \beta_2 RV_{t-1}^{(w)} + \beta_3 RV_{t-1}^{(m)} + \varepsilon_t \tag{2}$$

where, RV_t denotes realized volatility at time t, and the superscripts (w) and (m) represent weekly and monthly aggregated volatility components, respectively.

Model estimation is conducted using ordinary least squares with heteroskedasticity-robust standard errors. This approach yields consistent parameter estimates and facilitates interpretation of volatility persistence across horizons (Andersen et al., 2003; Bollerslev, 1986; Bollerslev et al., 1992).

2.3 Structural Break Analysis

To examine the stability of volatility dynamics, this study applies three established structural break tests: the CUSUM test, the CUSUMSQ test, and the Bai–Perron multiple breakpoint test (Bai & Perron, 2003). These methods are widely used in financial econometrics and are introduced concisely, as detailed methodological discussions are available in the cited literature.

Importantly, breakpoints are identified in a data-driven manner prior to economic interpretation, reducing subjectivity in regime classification. All analyses are conducted using standard statistical software for time-series modeling, and the codes used for estimation and testing can be made available upon reasonable request.

3. Results

3.1 Evaluation of the HAR Model

The HAR (3) model employed in this study follows Eq. (1). Using IHSG data from January 2019 to August 2024, the estimation results obtained from R software are summarized in Table 1.

Table 1. Estimation results of the HAR (3) model for Indonesia Composite Index (IHSG) volatility (2019–2024)

Parameter	Estimate	Std. Error	*t*-Value	*p*-Value	Interpretation
(Intercept)	4.866	2.081	2.338	0.0195	A positive and significant intercept indicates the presence of baseline volatility even in the absence of lagged effects.
β_1 (RV_lag1)	-0.0854	0.0322	-2.652	0.0081	Significant negative daily effect, suggesting mean reversion high volatility today tends to decline the following day, consistent with known volatility dynamics (Andersen et al., 2003; Baker et al., 2020).
β_2 (RV_week)	0.6490	0.0645	10.057	<0.001	Weekly volatility component is the dominant and most significant factor, indicating medium-term persistence (Corsi, 2009; Kristoufek, 2015).
β_3 (RV_month)	0.2177	0.0667	3.265	0.0011	Monthly component is significant, showing long-memory characteristics, although weaker than the weekly component (Rossi, 2013; Schwert, 1989).
Adjusted R^2	0.204				HAR (3) explains 20.4% of volatility variation, typical for high-volatility emerging markets (Bollerslev, 1986; Engle, 1982)

The estimation results indicate that IHSG volatility is significantly explained by its lagged components across multiple time horizons. The adjusted R^2 value of 0.204 suggests that approximately 20.4% of the variation in realized volatility is captured by the HAR (3) model. Although this explanatory power may appear moderate, it is consistent with empirical findings for emerging stock markets, where volatility is strongly affected by external shocks and structural instability (Goodell, 2020; Zhang et al., 2020).

The weekly volatility component (β_2 = 0.6490, p < 0.001) emerges as the most dominant factor, indicating pronounced medium-term volatility persistence. This finding implies that market participants in Indonesia tend to react to information over a one-week horizon rather than instantaneously, a behavior commonly observed in financial volatility dynamics (Corsi, 2009; Kristoufek, 2015; Schwert, 1989).

The daily component exhibits a significant negative coefficient (β_1 = -0.0854), suggesting short-term mean reversion in volatility, whereby extreme fluctuations are partially corrected in subsequent trading days (Campbell et al., 1997). Meanwhile, the monthly component remains positive and statistically significant, reflecting the presence of long-memory characteristics, although its influence is weaker than that of the weekly component (Kristoufek, 2015; Rossi, 2013).

3.2 Diagnostic Test of Model Assumptions

To ensure the reliability of the HAR (3) estimation results, several diagnostic tests are conducted, as reported in Table 2.

Table 2. Diagnostic tests for model assumptions

Test	Statistic	*p*-Value	Conclusion	Interpretation
Durbin–Watson (Autocorrelation)	1.9983	0.4681	No autocorrelation	The DW statistic is close to 2, indicating that residuals are independent.
Breusch–Pagan (Heteroskedasticity)	222.07	<0.001	Heteroskedasticity	Residual variance is not constant, consistent with volatility clustering in financial markets.

The Durbin–Watson statistic is close to the benchmark value of 2, indicating the absence of residual autocorrelation. This confirms that the HAR (3) specification adequately captures the dynamic structure of IHSG volatility.

In contrast, the Breusch–Pagan test strongly rejects the null hypothesis of homoskedasticity, indicating the presence of heteroskedasticity. This result is consistent with the well-documented phenomenon of volatility clustering in financial markets (Bollerslev, 1986; Bollerslev et al., 1992; Ding et al., 1993; Engle, 1982). Accordingly, heteroskedasticity-robust standard errors are employed to ensure valid statistical inference.

3.3 Structural Stability Analysis

3.3.1 CUSUM and CUSUMQ test

The stability of the HAR (3) parameters is first evaluated using the CUSUM and CUSUMSQ tests, with results summarized in Table 3.

Table 3. Structural stability tests

Test	Statistic (S_0)	*p*-Value	Conclusion	Interpretation
CUSUM Test	1.0531	0.2174	Not significant	HAR (3) parameters remain stable throughout most of the sample period.
CUSUMSQ Test	1.294	0.0702	Borderline significant	Indicates emerging variance instability around early 2020, likely due to the COVID-19 shock.

The CUSUM test does not indicate significant parameter instability in the mean equation, suggesting that the overall structure of the HAR (3) model remains stable for most of the sample period. However, the CUSUMSQ test yields borderline significance, pointing to emerging variance instability around early 2020.

This pattern suggests that while the average dynamics of volatility persistence remain relatively stable, the intensity of volatility undergoes substantial changes during crisis periods, particularly at the onset of the COVID-19 pandemic (Al-Awadhi et al., 2020; Baur & Lucey, 2010).

3.3.2 Bai–Perron multiple breakpoint test

To identify the exact timing of structural changes, the Bai–Perron multiple breakpoint test is applied to the HAR (3) model. The procedure selects breakpoints by minimizing the residual sum of squares with a Bayesian Information Criterion penalty (Bai & Perron, 2003).

The test identifies three candidate breakpoints, which are mapped to calendar dates and summarized in Table 4. Among these, two breakpoints, early April 2020 and mid-February 2024, are statistically robust and economically meaningful.

The April 2020 breakpoint coincides with the onset of the COVID-19 crisis, reflecting a systemic shock that triggered extreme volatility, liquidity stress, and capital outflows in Indonesia's equity market (Baker et al., 2020). The February 2024 breakpoint corresponds to heightened political uncertainty ahead of the general election, indicating increased investor sensitivity to domestic political risk (Goodell, 2020).

Table 4. Structural break dates and economic interpretation

Break Date	Economic Event	Statistical Interpretation	Impact on Indonesia Composite Index (IHSG) Volatility
22 May 2019	2019 Indonesian Presidential Election	Break occurs immediately after the election, statistically indicating a parameter shift	Short-term volatility spike, stabilizing by mid-2019.
1 April 2020	Start of COVID-19 Crisis	CUSUMSQ and Bai–Perron indicate a significant structural shift in both variance and parameters	Extreme volatility surge due to global market shock.
14 February 2024	Ahead of 2024 Election	A moderate break toward the end of the sample, statistically confirming parameter instability	Increased investor sensitivity to political risk.

3.3.3 Regime based HAR model re-estimation

Re-estimating the HAR (3) model across structurally identified regimes serves as a robustness check to verify whether volatility persistence parameters remain stable or shift meaningfully following detected breakpoints. By estimating separate HAR specifications for each regime, this approach allows for a direct comparison of short-, medium-, and long-term volatility dynamics before and after major economic and political shocks.

Following breakpoint detection, the HAR (3) model is re-estimated across distinct volatility regimes, as reported in Table 5.

Table 5. HAR (3) re-estimation by structural regime

Period	β_1 (Daily)	β_2 (Weekly)	β_3 (Monthly)	Adj. R^2	Interpretation
Pre-COVID (Jan 2019–Mar 2020)	-0.126	0.766	0.107	0.204	Stable market; strong medium-term memory via weekly component.
Post-COVID (Apr 2020–Jan 2024)	0.034	0.106	0.685	0.181	Short-term effects weaken; long-term volatility becomes dominant, consistent with prolonged macroeconomic uncertainty.
Pre-Election 2024 (Feb–Aug 2024)	-0.085	0.287	0.340	0.044	Rising political uncertainty; volatility increases but remains less extreme than during COVID-19.

During the pre-COVID-19 period, volatility dynamics are dominated by the weekly component, indicating a relatively stable market environment characterized by medium-term persistence. This suggests that market participants primarily adjust to information over a weekly horizon under normal conditions.

In contrast, the post-COVID-19 regime exhibits a substantial increase in the influence of the monthly volatility component, indicating a shift toward long-term volatility persistence. This pattern suggests that the pandemic shock fundamentally altered investor risk perception, leading to prolonged uncertainty and sustained volatility effects (Al-Awadhi et al., 2020; Goodell, 2020).

In the period leading up to the 2024 general election, volatility increases again, although its magnitude and persistence remain lower than during the pandemic period. The relatively reduced explanatory power of the HAR model during this regime suggests that election-related volatility is more transitory in nature, reinforcing the view that political uncertainty generates weaker and less persistent volatility effects compared to global systemic crises.

3.4 Visualization of IHSG Volatility Dynamics

Figure 1 illustrates the evolution of IHSG volatility measured by squared daily returns over the period 2019–2024. Pronounced volatility clustering is observed during early 2020, coinciding with the onset of the COVID-19 pandemic, followed by a gradual normalization phase. A secondary increase in volatility intensity emerges ahead of the 2024 General Election, reflecting heightened political uncertainty. Such volatility clustering and shock-induced persistence are well-documented stylized facts in financial markets, particularly in emerging economies (Al-Awadhi et al., 2020; Bollerslev, 1986; Engle, 1982). These visual patterns motivate the application of formal structural break tests to identify regime shifts in volatility dynamics.

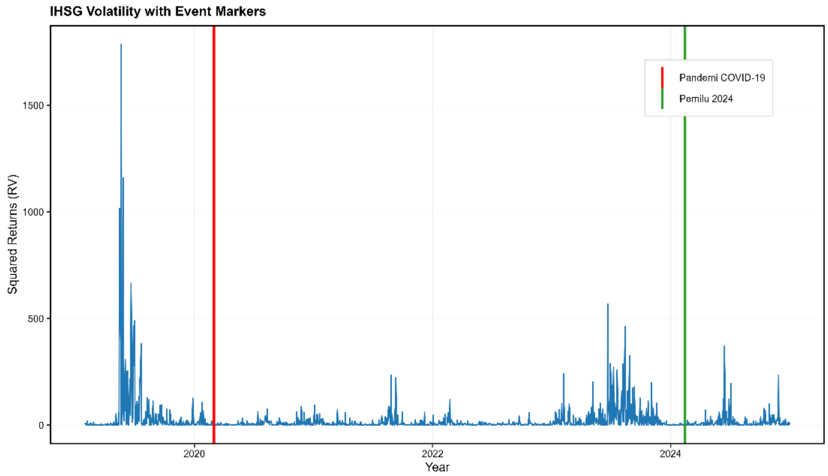

Figure 1. Indonesia Composite Index (IHSG) RV_t evolution 2019-2024 showing COVID spike and election volatility

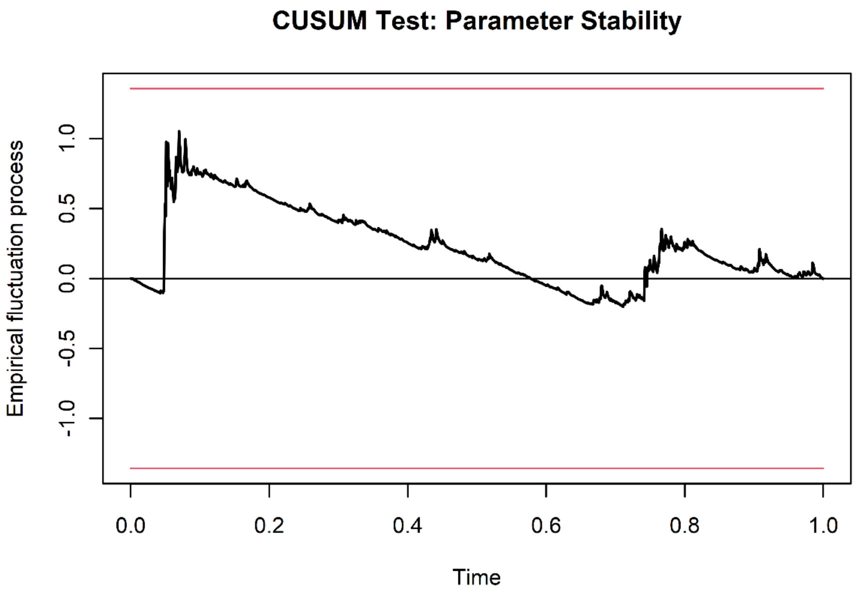

Figure 2. CUSUM test for HAR (3) parameter stability

Figure 2 presents the CUSUM test results for assessing parameter stability of the HAR (3) volatility model. The empirical fluctuation process remains within the 5% confidence bounds, indicating overall stability of mean parameters across most of the sample period. However, noticeable deviations are observed around early 2020 and early 2024, suggesting increased pressure on parameter stability during periods of major economic and political shocks. The CUSUM test is widely used for detecting structural instability in financial time-series models and has been applied extensively in volatility studies (Al-Awadhi et al., 2020; Bai & Perron, 2003; Rossi, 2013).

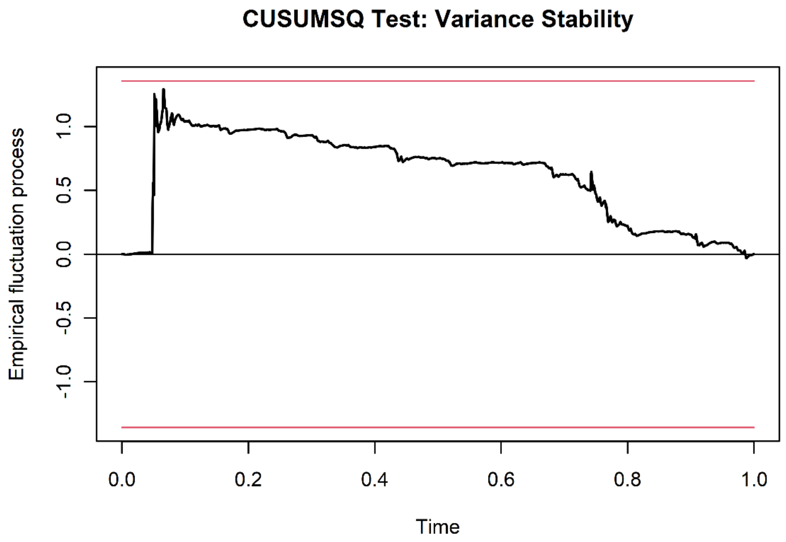

Figure 3. CUSUMSQ test for variance stability

Figure 3 presents the results of the CUSUMSQ test for assessing variance stability in the HAR (3) model residuals. The empirical fluctuation process approaches and partially deviates toward the confidence bounds around March 2020 and February 2024, indicating periods of increased variance instability. While the test does not uniformly reject the null hypothesis of variance stability over the entire sample, these deviations suggest heightened volatility pressure during major economic and political events. Such patterns are consistent with prior empirical evidence showing that large-scale shocks tend to amplify variance dynamics in financial markets, particularly in emerging economies (Al-Awadhi et al., 2020; Goodell, 2020; Rossi, 2013).

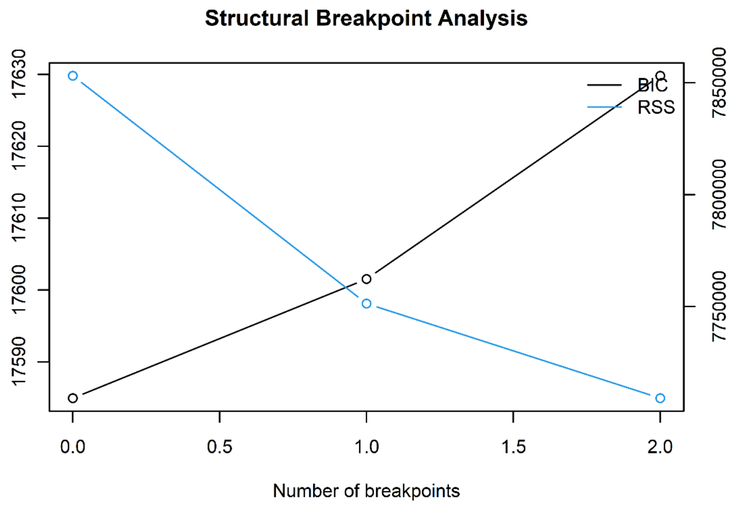

Figure 4. Bai–Perron structural breakpoints

Figure 4 illustrates the structural breakpoints identified using the Bai–Perron multiple breakpoint procedure applied to the HAR (3) volatility specification. Two statistically significant breakpoints are detected in early April 2020 and mid-February 2024. These breakpoints broadly coincide with periods of heightened market uncertainty and are consistent with indications of variance instability observed in the CUSUMSQ test. While the Bai–Perron method identifies breaks in a purely data-driven manner, their timing aligns with major economic and political events, supporting existing evidence that emerging equity markets are sensitive to large-scale crises and political uncertainty (Goodell, 2020; Zhang et al., 2020).

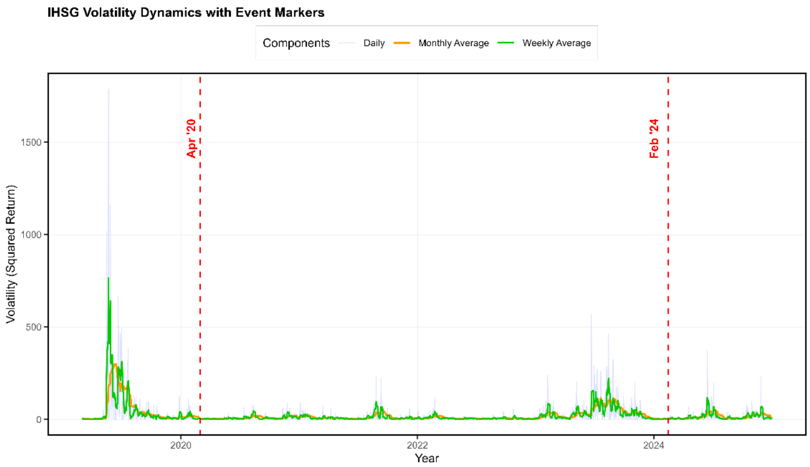

Figure 5. Dynamics of Indonesia Composite Index (IHSG) volatility and structural breaks (2019–2024)

To facilitate interpretation of the volatility decomposition presented in Figure 5, Table 6 summarizes the economic meaning of each volatility component across different time horizons. This mapping provides conceptual intuition for how short-, medium-, and long-term volatility dynamics are captured within the HAR framework and motivates the subsequent structural break analysis.

Table 6. Interpretation of Indonesia Composite Index (IHSG) Volatility Dynamics and Structural Breaks (2019–2024)

Line Colors	Interpretation
Blue (Daily)	Captures short-term volatility fluctuations that are highly responsive to economic news, policy announcements, and global shocks. This behavior reflects high-frequency sensitivities and rapid information processing typical of financial markets (Bollerslev, 1986; Engle, 1982).
Green (Weekly)	Represents smoother volatility movements and reflects medium-term persistence driven by portfolio rebalancing and institutional investor adjustments. This component aligns with the core structure of the HAR model, which captures volatility aggregation across intermediate horizons (Corsi, 2009; Kristoufek, 2015).
Orange (Monthly)	Illustrates long-term volatility dynamics, reflecting investors' long-horizon risk perception and gradual structural adjustments in response to sustained macroeconomic and systemic uncertainty (Rossi, 2013; Zhang et al., 2020).

4. Discussion

The primary objective of this study is to examine whether IHSG volatility exhibits statistically significant structural breaks in response to major economic and political shocks during the 2019–2024 period. The empirical findings provide strong evidence that IHSG volatility dynamics are regime-dependent and highly sensitive to external disturbances, thereby directly addressing the central research question of this study.

The identification of a structural breakpoint in early April 2020 coincides with the onset of the COVID-19 pandemic and reflects a systemic shock that fundamentally altered volatility behavior in Indonesia's equity market. During this regime, the dominance of the monthly volatility component indicates a pronounced shift toward long-horizon risk perception. This suggests that investors reassessed uncertainty over extended time horizons rather than reacting solely to short-term information. Such behavior is consistent with prior evidence from emerging markets, where global crises generate persistent volatility even after observable price recovery, reflecting prolonged macroeconomic and institutional uncertainty (Al-Awadhi et al., 2020; Cont, 2001; Ding et al., 1993; Goodell, 2020).

In contrast, the volatility regime surrounding the 2024 General Election exhibits markedly different dynamics. Although structural instability is detected, both the magnitude and persistence of volatility are substantially weaker than during the pandemic period. Regime-based re-estimation of the HAR model reveals a notable decline in explanatory power, indicating that historical realized volatility contributes less to explaining contemporaneous volatility during this episode.

The reduced explanatory performance of the HAR model following the 2024 election suggests that volatility during this period may be driven by factors beyond historical volatility patterns, such as rapid information resolution, short-lived speculative trading, or policy signaling effects. Unlike the pandemic shock, election-related uncertainty appears to dissipate relatively quickly, resulting in weaker volatility persistence and diminished long-memory characteristics. This finding highlights the asymmetric nature of political versus systemic shocks in emerging financial markets.

This asymmetry underscores a critical distinction between global systemic crises and domestic political events. Systemic shocks tend to induce enduring uncertainty that reshapes long-term volatility structures, whereas political shocks particularly in markets with established electoral institutions—are more likely to generate temporary volatility spikes that normalize once uncertainty is resolved. This interpretation is consistent with the observed reversion toward shorter-term volatility components and the reduction in long-term persistence following the election period.

From a regulatory perspective, these findings emphasize the importance of distinguishing between sources of volatility when designing market stabilization policies. Regulatory authorities such as the Financial Services Authority and the IDX may benefit from incorporating regime-specific volatility monitoring frameworks that differentiate between systemic and political shocks. Early identification of shifts toward long-term volatility dominance may justify stronger intervention measures, while short-lived political volatility may warrant more calibrated policy responses.

For investors, recognizing transitions in volatility regimes provides valuable guidance for portfolio allocation and risk management strategies. The shift from medium-term dominance in stable periods to long-term persistence during systemic crises implies that investment horizons and hedging intensity should be adjusted dynamically in response to structural changes. Conversely, the weaker persistence observed during the post-election period suggests that excessively conservative positioning in response to political events may result in forgone returns once uncertainty dissipates.

Overall, this study contributes to the volatility literature by demonstrating that integrating multi-horizon volatility models with formal structural break analysis offers a more nuanced understanding of market dynamics in emerging economies. The results underscore that shocks do not exert symmetric effects on volatility persistence, reinforcing the need for adaptive modeling frameworks capable of capturing regime-dependent behavior in financial markets (Campbell et al., 1997; Gujarati & Porter, 2009).

5. Conclusions

This study examines the volatility dynamics of the IHSG during the 2019–2024 period by integrating a multi-horizon volatility framework with formal structural break analysis. The empirical evidence confirms the presence of two statistically significant structural breakpoints, occurring in April 2020 and February 2024, corresponding to the COVID-19 pandemic and the 2024 General Election, respectively. These events led to observable shifts in both the intensity and persistence structure of market volatility.

The HAR (3) model effectively captures short-, medium-, and long-term volatility components of IHSG. Prior to the pandemic, weekly volatility emerged as the dominant driver, indicating medium-term information assimilation by market participants.

Following the onset of COVID-19, volatility dynamics shifted toward the long-term (monthly) component, reflecting prolonged uncertainty and a structural change in investor risk perception. This transition highlights the sensitivity of emerging markets to systemic shocks and underscores the importance of accounting for regime-dependent volatility behavior.

After the 2024 election, the explanatory power of the HAR model declines, suggesting a partial normalization of market conditions or the emergence of new volatility drivers not captured by the linear HAR framework. This finding implies that political shocks, while impactful, tend to generate less persistent volatility effects compared to global systemic crises.

From a practical perspective, the identification of structural breakpoints and dominant volatility horizons provides valuable insights for investors, market analysts, and policymakers. Investors may use regime-specific volatility information to improve portfolio allocation and risk management strategies, while regulatory institutions such as Financial Services Authority and IDX can employ these findings to enhance early-warning systems and implement adaptive market stabilization policies during periods of heightened uncertainty.

This study is subject to several limitations. First, the analysis relies solely on return-based volatility measures and does not explicitly incorporate macroeconomic or global financial variables. Second, the linear HAR framework may not fully capture nonlinear dynamics during extreme market conditions.

Future research is encouraged to extend this framework by incorporating macroeconomic indicators such as inflation, interest rates, and exchange rate volatility or by applying nonlinear and high-frequency volatility models to better capture evolving market structures in emerging economies.

Author Contributions

Conceptualization, M.M.; methodology, M.M.; software, M.M.; validation, M.M. and G.D.; formal analysis, M.M.; investigation, M.M.; resources, M.M.; data curation, M.M. and A.A.S.; writing original draft preparation, M.M.; writing review and editing, M.M., G.D., and A.A.S.; visualization, M.M.; supervision, G.D.; project administration, G.D. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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