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High-frequency dynamics of the Vietnam stock market

Tran Manh Ha*, Tran Ngoc Mai

Banking Academy of Vietnam

No. 12 Chua Boc Street, Dong Da District, Hanoi, Vietnam

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Abstract: This study examines the high-frequency dynamics of the VNINDEX by utilizing 1-minute data over a sample of 160,677 observations from February 2022 to February 2025 to assess market efficiency, the volume-price relationship and the intraday volatility pattern. Our findings suggest delayed information diffusion and liquidity constraints, reflecting inefficiencies typical of Vietnam stock markets with retail-heavy participation. This paper offers opportunities for momentum trading and highlights the need to enhance market depth to mitigate speculative spikes, contributing to the understanding of high-frequency behavior in the Vietnam stock market.

Keywords: High-frequency data, market efficiency, high frequency trading.

1. Introduction

The VNINDEX, tracking the Ho Chi Minh Stock Exchange (HOSE), serves as a vital indicator of Vietnam's economic ascent, reflecting a market that has evolved from a nascent frontier to a dynamic emerging hub since its inception in 2000. By February 2025, with over 400 listed firms and a market capitalization nearing $200 billion, the VNINDEX captures a blend of domestic retail enthusiasm and rising foreign investment, fueled by Vietnam's robust GDP growth and strategic position in ASEAN. Yet, despite its growing prominence, the literature on the characteristics of VNINDEX mainly focuses on the inefficiencies of the market utilizing low-frequency data (Truong et al., 2010; Vo, 2016; Pham et al., 2015).

The relevance of high-frequency data (HFD) to emerging markets, such as the VNINDEX, is particularly pronounced given their distinct market structures. Emerging markets often have lower liquidity, higher volatility, and a higher proportion of retail investors compared to institutional traders, which can lead to different intraday dynamics. Given Vietnam's economic growth and increasing global financial integration, understanding its high-frequency dynamics is crucial.

The motivation for this research stems from both academic and practical imperatives. HFD illuminates market behavior with precision—capturing volatility surges from news releases (Andersen & Bollerslev, 1997), efficiency deviations from rapid trades (Fama, 1970; Lo & MacKinlay, 1988), and volume-driven price shifts (Karpoff, 1987)—that daily data masks. While developed markets and other emerging markets have extensive studies (Hasbrouck, 1995; Bekaert & Harvey, 1997), the Vietnam

* Corresponding author
E-mail address: hatm@hvnh.edu.vn
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stock market, characterized by retail-driven trading and thinner liquidity (Truong et al., 2010; Pham et al., 2015), is underexplored. This research aims to fill this gap, providing academic insights into market dynamics and practical guidance for traders and regulators in Vietnam.

Using a unique dataset of VNINDEX prices at 1-minute intervals from February 2022 to February 2025, the paper shows that the intraday volatility pattern of VNINDEX follows a modified U-shape with a pronounced peak at 13:00–14:00hrs, reflecting distinct periods of information assimilation and liquidity fluctuations. The intraday returns exhibit strong momentum and volume changes display clustering, however, the cross-effects between volume-price are weak, with only marginal volume-to-returns predictability. All the findings reject weak-form efficiency of VNINDEX.

This paper's significance is twofold. First, it pioneers high-frequency analysis of the Vietnam stock market, enriches emerging market literature. Second, it delivers insight characteristics of VNINDEX in trading times, risk signals and efficiency benchmarks for market participants.

2. Literature review

Introduction to high-frequency data in finance

HFD refers to data recorded at very short intervals, typically ranging from seconds to minutes, and in some cases, milliseconds (Engle, 2000). This level of granularity allows for a detailed analysis of market dynamics that are not discernible with lower frequency data, such as daily, weekly, or monthly observations (Hasbrouck, 2007). The importance of HFD lies in its ability to capture the immediate responses of market participants to new information, the dynamics of order flow, and the effects of trading strategies that operate on short time frames (Aldridge, 2013).

Compared to lower frequency data, HFD offers a significantly more detailed view of market movements. Daily data aggregates all intraday fluctuations into a single observation, potentially masking important patterns such as intraday volatility spikes, price jumps due to specific events, or the impact of trading halts (Wood et al., 1985). HFD, by contrast, allows for the observation of these dynamics, enabling researchers to identify patterns like the U-shaped volatility curve, where volatility is higher at the market open and close, attributed to the release of overnight information and position squaring, respectively (Admati & Pfleiderer, 1988).

Several key concepts are central to the analysis of HFD in finance. One of the most prominent is realized volatility (RV), calculated as the sum of squared returns over short intervals, typically minutes or seconds (Andersen & Bollerslev, 1998). This measure is considered superior to traditional volatility estimates because it leverages the high density of observations, providing a more accurate reflection of market risk (Barndorff-Nielsen & Shephard, 2002). Another critical concept is market microstructure noise, which refers to the noise in observed prices that is not related to fundamental value changes but rather to the mechanics of the trading process, including factors such as the bid-ask bounce, order imbalances, and the actions of high-frequency traders (O'Hara, 1995).

Market efficiency at high frequency

The EMH posits that asset prices reflect all available information, implying unpredictable returns (Fama, 1970). HFD tests this at a granular level, capturing short-term market responses unobservable in daily data (Engle & Russell, 2018). Hendershott et al. (2015) analyzed NYSE stocks using tick-level data, finding weak-form efficiency in stable conditions, though short-term anomalies emerged during high-volatility periods, suggesting conditional predictability. Variance ratio (VR) tests, widely applied in high-frequency contexts, have validated random walk behavior in developed markets with ratios near 1, yet deviations persist under stress (Chordia et al., 2018).

Emerging markets, however, challenge this framework. Bekaert and Harvey (2017) argued that inefficiencies stem from illiquidity, regulatory limits, and information asymmetries, amplifying deviations in developing indices. Griffin et al. (2021) examined 60 global markets, reporting higher autocorrelation in emerging markets, indicating exploitable patterns tied to market frictions. In Asia, Kim et al. (2016) found Korea's KOSPI exhibited non-random behavior during volatile periods post-2010, driven by retail trading and thin liquidity.

Volume-price relationship

The relationship between trading volume and price movements constitutes a fundamental inquiry within market microstructure research, elucidating how information and liquidity dynamics shape asset pricing. In developed markets, Admati and Pfleiderer (1988) proposed a theoretical framework wherein informed traders concentrate their activities during periods of elevated trading volume, thereby exerting a significant influence on price adjustments—a hypothesis empirically substantiated by Karpoff (1987), who identified positive correlations between volume and return volatility in U.S. equity markets. Easley et al. (1996) utilized tick-level data and demonstrated that trading volume precedes price jumps, underscoring its role as a conduit for information flow into prices. Hasbrouck (1991) exemplified Vector autoregression (VAR) models and quantified these lead-lag dynamics, thus highlighting the predictive capacity of trading activity in high-frequency settings.

Emerging markets present a counterpoint. Chan and Fong (2000) observed reverse causality in Hong Kong—price changes spurred volume—attributed to momentum trading[1] by retail investors. This finding suggests that in Hong Kong's market, significant price increases (or decreases) trigger heightened trading activity as retail traders chase these trends, amplifying volume rather than volume driving price as in informed-trading models. Momentum trading here acts as a behavioral mechanism, where retail investors react to price signals, perceiving them as indicative of continued movement, thus reversing the typical causality direction observed in liquid, institution-driven markets (Chordia & Swaminathan, 2000).

The volume-price relationship is central to market microstructure. Admati and Pfleiderer (1988) theorized informed traders trade during high-volume periods, leading to positive volume-price volatility correlations, confirmed by Karpoff (1987). At high frequency, Hamao and Hasbrouck (1995) found volume tend to lead price movements in the Japanese market, suggesting a forward flow of information. Conversely, Kwapien et al. (2015) found price leads volume on the Warsaw Stock Exchange, indicating reactive trading, highlighting market-specific dynamics.

Volatility patterns in high-frequency data

Volatility exhibits distinct intraday patterns when observed at high frequency. Intraday volatility patterns provide critical insights into the temporal distribution of price variability, reflecting underlying market dynamics such as information flow, liquidity provision, and trader behavior (Andersen & Bollerslev, 1997). In emerging markets, these patterns often deviate from the well-documented U-shaped profiles of developed exchanges, influenced by structural frictions and participant composition (Bekaert & Harvey, 1997).

Andersen and Bollerslev (1998) pioneered the use of RV—computed as the sum of squared intraday returns—to capture these dynamics in U.S. equity markets. Their work revealed a U-shaped pattern: Volatility peaks at market open due to overnight information accumulation and at close from position squaring, a finding replicated across developed indices like the S&P 500 and the Nikkei 225 (Wood et al., 1985; Hamao & Hasbrouck, 1995). This periodicity reflects microstructural effects such as order flow imbalances and trader reactions to scheduled news.

Subsequent studies refined these insights. Heston et al. (2011) employed GARCH models on 5-minute data, confirming volatility clustering—where large price changes beget further instability—a universal trait of financial time series. In Asia, Hamao and Hasbrouck (1995) observed similar U-shapes in Japan's Nikkei, though midday dips reflected cultural trading pauses. However, emerging markets deviate from this norm. Aloui and Hkiri (2014) found flatter or L-shaped patterns in Gulf Cooperation Council indices, attributing this to lower liquidity and sporadic trading—a plausible hypothesis for Vietnam, given its thinner market depth.

3. Methodology

This study employs a multifaceted analytical framework to investigate the high-frequency dynamics of the VNINDEX using 1-minute intraday data. The methodology is structured around three primary objectives (1) assessing market efficiency at a 1-minute frequency, (2) examining the dynamic relationship between trading volume and price movements and (3) investigating volatility patterns. Each approach leverages established econometric techniques, adapted to the unique characteristics of VNINDEX, and is implemented using MATLAB.

Data collection

The dataset consists of 160,677 observations of VNINDEX intraday data at 1-minute intervals, including index prices and trading volume, spanning from Feb 2022 to Feb 2025[2] to

[1] Momentum trading refers to a strategy in financial markets where investors capitalize on the persistence of price trends by buying assets that have recently increased in value and selling those that have declined, anticipating that these trends will continue over a short horizon (Jegadeesh & Titman, 1993).

[2] The dataset is provided by FiinGroup.

avoid any effect of COVID-19 period on the stock market. The VNINDEX operates from 9:00 AM to 3:00 PM local time, yielding approximately 235 observations per trading day. Due to missing values, a common high-frequency data challenges potentially because of low trading activity and the limitation of the trading record system. Log returns are calculated as:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where P_t is the price at minute t.

Market efficiency analysis

Market efficiency is assessed through two complementary tests of the weak-form EMH, which posits that past prices cannot predict future returns. First, we compute the autocorrelation function (ACF) of 1-minute returns for lags 1 to 10, testing for serial dependence. Significant autocorrelation suggests inefficiency, as returns may be predictable. Second, we conduct the VR test (Lo & MacKinlay, 1988) to compare the variance of 1-minute returns to that of aggregated returns over 5-minute and 10-minute intervals. The VR is defined as:

$$VR(k) = \frac{Var(r_t(k))/k}{Var(r_t)}$$

where $r_t(k)$ is the return over k minutes.

Volume-price relationship analysis

This paper examines the volume-price linkage in the VNINDEX by employing the VAR model to capture short-term dynamics and Impulse Response Functions (IRFs) to assess bidirectional causality and dynamic interactions.

To examine the dynamic interplay between trading volume and price movements, we employ the VAR model, contingent on volume data availability. VAR models, introduced by Sims (1980), are well-suited for capturing the dynamic interdependencies between multiple time series, such as returns and volume changes, without imposing *a priori* structural assumptions, making them ideal for microstructure research (Hasbrouck, 1991). The choice of two lags specifically balances the need to model short-term dynamics, ensure statistical robustness, and maintain computational feasibility given tour dataset's granularity and size. Indeed, the two-lag specification aligns with the rapid adjustment processes characteristic of high-frequency data, where market responses to information and trading activity occur within minutes rather than hours or days (Engle & Russell, 2018). In the VNINDEX context, with trading hours spanning 09:00-11:30 and 13:00-15:00, a 1-minute interval implies significant activity concentration within short windows. A two-lag structure (covering 2 minutes) captures immediate lead-lag effects—such as volume anticipating price jumps or price momentum influencing subsequent volume—consistent with prior high-frequency studies (Easley et al., 1996). This short horizon reflects the fast-paced nature of intraday trading, where longer lags might dilute relevant dynamics with noise or irrelevant historical effects.

The VAR(2) model, with two lags, is specified as:

$$\begin{bmatrix} r_t \\ v_t \end{bmatrix} = \begin{bmatrix} c_r \\ c_v \end{bmatrix} + \sum_{i=1}^{2} \begin{bmatrix} \phi_{r,i} & \phi_{rv,i} \\ \phi_{vr,i} & \phi_{v,i} \end{bmatrix} \begin{bmatrix} r_{t-i} \\ v_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{r,t} \\ \varepsilon_{v,t} \end{bmatrix}$$

where r_t is the return, v_t is the log volume change, c terms are constants, ϕ terms are coefficients, and ϵ terms are errors. The model estimates bidirectional influences of whether volume leads returns (information-driven trading) or vice versa (momentum effects). IRFs are plotted to illustrate how a shock in one variable affects the other over 10 minutes, providing dynamic insights.

Volatility analysis

To examine the hourly volatility pattern of the VNINDEX, we compute RV as the sum of squared returns over five trading-hour intervals: 09:00-10:00, 10:00-11:00, 11:00-11:30, 13:00-14:00, and 14:00-15:00. By aggregating RV across days and averaging by hour, we uncover distinct intraday trends, contributing to the understanding of volatility dynamics in Vietnam's emerging equity market.

To characterize intraday volatility patterns, we compute hourly RV as the sum of squared returns over one hour interval, as:

$$RV_h = \sqrt{\sum_{i=1}^{M} r_{t_i}^2}$$

where h denotes each trading hour (e.g., 9:00-10:00 AM), aggregating squared 1-minute returns over 60-minute blocks (or fewer for the final hour). This yields a time-of-day profile, plotted to test for patterns such as the U-shape (high at open and close) or L-shape (declining after open), common in equity markets.

4. Empirical results

Market efficiency analysis

The autocorrelation test was conducted to assess serial dependence and test weak-form market efficiency. Autocorrelation coefficients were estimated for lags 0 to 20, with significance determined against a 95% confidence threshold. The test result in Table 1 presents significant serial dependence in VNINDEX 1-minute returns, with positive autocorrelation at lags 1-4 (e.g., 0.1245 at lag 1, $p < 0.05$) indicating momentum, followed by negative autocorrelation at lags 6–10 (e.g., -0.032497 at lag 9, $p < 0.05$) suggesting mean reversion. Beyond lag 10, coefficients approach zero, with most insignificant (e.g., 0.0092975 at lag 20). These findings reject weak-form efficiency, underscoring short-term predictability in this emerging market.

The VR test compares the variance of returns over different time intervals to test if price movements are random, or uncorrelated. The test results show significant positive autocorrelation in VNINDEX 1-minute returns, with VR values of 1.3815 (5 minutes), 1.421 (10 minutes), and 1.3821 (15 minutes), rejecting weak-form efficiency. This indicates short-term momentum, peaking at 10 minutes. These results suggest that VNINDEX prices do not follow a random walk, consistent with emerging market inefficiencies driven by persistent trading patterns. Indeed, the VNINDEX's 7% daily price change limit, imposed by HOSE, constrains price movements within a fixed range, disrupting the random walk assumption of independent and identically distributed returns (Fama, 1970). This cap/floor mechanism truncates extreme price changes, induces autocorrelation by deferring adjustments across days, and elevates variance ratios beyond unity (Lo & MacKinlay, 1988). Consequently, the limit impedes immediate information incorporation, fostering inefficiencies inconsistent with a random walk (Bekaert & Harvey, 2017). The observed momentum aligns with prior autocorrelation findings, highlighting predictable price behavior over short horizons.

In brief, these tests show that the VNINDEX exhibits significant short-term momentum and medium-term mean reversion, thereby rejecting the weak-form efficiency of the market This is due to Vietnam's stock market possibly having thinner liquidity or slower information diffusion compared to developed markets, leading to predictable patterns. The result reflects delayed information processing and liquidity constraints economically, while practically, it offers momentum opportunities (1-5 minutes) and reversal trades (6-10 minutes), highlighting exploitable inefficiencies in this emerging market. Specifically, traders can take advantage of trend-following trades in the first 5 minutes, while keeping contrarian strategies post-momentum in the interval of 6-10 minutes and avoiding long holes as predictability fades beyond 10 minutes. For a risk manager, the high VR and autocorrelation signal short-term volatility risks, valuable for risk management and regulatory oversight in Vietnam's high-frequency trading environment.

The VAR(2) results highlight a sharp contrast in VNINDEX dynamics: Returns display significant momentum, while volume changes exhibit clustering, yet their cross-effects are weak. The strong autoregressive coefficients for returns (AR{1}(1,1) = 0.1965, AR{2}(1,1) = 0.14779) corroborate earlier autocorrelation findings (e.g., lag 1 = 0.1245, $p < 0.05$) and variance ratio results (e.g., VR = 1.421 at 10 minutes), collectively rejecting weak-form efficiency. This momentum suggests a delayed incorporation of information, consistent with models of under reaction in markets with limited arbitrage (Hong & Stein, 1999). The insignificant volume-to-returns effects ($p > 0.79$) contrast with theoretical expectations that trading volume proxies for information flow (Kyle, 1985). This discrepancy may reflect microstructural frictions in the VNINDEX, such as thin liquidity or asymmetric information among traders, preventing volume from exerting a robust influence on prices. Conversely, the marginal returns-to-volume effect at lag 2 ($p = 0.053049$) aligns with feedback models where price trends spur trading activity (Chordia & Swaminathan, 2000), though its weakness underscores a muted response.

Table 1: The autocorrelation test results

Lag	Autocorrelation	Significant
0	1	1
1	0.1245	1
2	0.10336	1
3	0.05491	1
4	0.023029	1
5	-0.0024633	0
6	-0.026321	1
7	-0.02612	1
8	-0.032041	1
9	-0.032497	1
10	-0.021809	1
11	-0.019081	0
12	-0.014601	0
13	-0.010706	0
14	-0.0048021	0
15	-0.001406	0
16	0.0042554	0
17	0.005412	0
18	0.0090712	0
19	0.0094788	0
20	0.0092975	0

Source: Authors' estimation on MATLAB.

Volume – price analysis

Volume's persistence (AR{1}(2,2), AR{2}(2,2)) mirrors findings in high-frequency studies of clustered trading (Engle & Russell, 1998), likely driven by speculative or momentum-driven retail activity in Vietnam's market. The small negative residual correlation (-0.0642) suggests a minor contemporaneous link, possibly from simultaneous reactions to news, but it does not dominate the lagged dynamics.

Dynamic interactions via IRFs

The IRFs elucidate the temporal evolution of shocks, reinforcing the VAR findings. A return shock's persistent effect on returns (0.1965 at 1 minute, 0.1864 at 2 minutes) mirrors the momentum identified earlier, decaying gradually over 10 minutes. The small, shifting spill to volume (-0.1484 → 0.0952) suggests a minor, delayed reaction, possibly from traders adjusting positions after price moves, though its magnitude limits practical significance.

A volume shock's negligible impact on returns (0.0000 → -0.0291) aligns with the insignificant VAR coefficients, confirming volume's limited role in driving price changes. Conversely, the volume's response to its own shock (1.0000 → 0.0189 → 0.0383) reflects a cumulative persistence, growing to 0.057% over 3 minutes, consistent with clustered trading dynamics.

Practical implications

The findings highlight opportunities and risks for market participants. The significant return momentum and variance ratio peak suggest that high-frequency traders can profit from trend-following strategies, entering positions after a 1-minute price move and holding for 5-10 minutes to capture a potential 0.1-0.2% return, with exits timed before the momentum wanes around 15 minutes. Conversely, the minimal IRF cross-effects indicate that volume is an unreliable predictor of price, limiting its use as a leading signal; however, its persistence offers value for liquidity timing, enabling traders to anticipate clustered activity and adjust execution strategies accordingly. Portfolio managers face heightened short-term volatility risks from this momentum, necessitating tight stop-losses or hedging within 2-3 minutes, while the lack of strong returns-to-volume feedback suggests price-driven volume spikes are unlikely, reducing the need for volume-based risk buffers. Regulators may find the subdued volume-price linkage and persistent dynamics indicative of illiquidity or speculative trading, prompting policies to enhance market depth or curb high-frequency volatility in Vietnam's emerging market.

Table 2: The AR-stationary 2-dimensional VAR(2) model summary

Sample size: 160677
Number of estimated parameters: 10

Parameter	Estimated value	Standard error	T-stats	P-value
Constant(1)	-2.91E-06	1.19E-06	-2.4505	0.014268
Constant(2)	0.014212	0.00027259	52.136	0
AR{1}(1,1)	0.1965	0.0024724	79.478	0
AR{1}(2,1)	-0.1484	0.56814	-0.2612	0.79394
AR{1}(1,2)	1.13E-05	1.09E-05	1.0426	0.29713
AR{1}(2,2)	0.018947	0.0024995	7.5806	3.44E-14
AR{2}(1,1)	0.14779	0.0024723	59.778	0
AR{2}(2,1)	0.12439	0.56812	0.21894	0.8267
AR{2}(1,2)	2.10E-05	1.09E-05	1.9345	0.053049
AR{2}(2,2)	0.015936	0.0024993	6.3762	1.82E-10

Source: Authors' estimation on MATLAB.

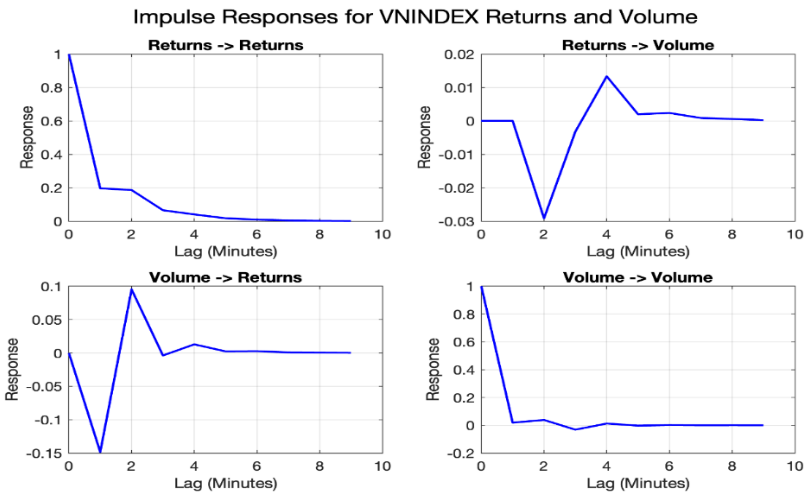

Figure 1: The impulse responses for returns and volume of VNINDEX
Source: Authors' estimation on MATLAB.

Volatility analysis

From Figure 2, the intraday volatility pattern of the VNINDEX exhibits a non-standard U-shape, characterized by elevated volatility at the opening and post-midday periods, a pronounced trough during late morning, and a notable spike in the early afternoon. The opening hour (09:00–10:00) records an RV of 3.4672e-05, indicative of significant price variability as the market assimilates overnight information and traders establish positions (Wood et al., 1985; Andersen & Bollerslev, 1997). This declines sharply to a daily minimum of 7.4828e-06 in the 10:00-11:00 interval, a 78% reduction, suggesting a period of relative stability or reduced trading intensity (a stabilization phase), potentially due to diminished information arrivals or reduced trader engagement, consistent with lower liquidity during mid-session lulls (Admati & Pfleiderer, 1988). Volatility rebounds to 3.4220e-05 in the 11:00–11:30 half-hour, approaching opening levels, potentially reflecting pre-break adjustments.

The striking peak at 13:00-14:00 (RV = 6.4275e-05) suggests a significant post-break volatility surge, possibly driven by the incorporation of midday news, economic announcements, or a rush of retail trading activity following the resumption of trading. This contrasts with the typical closing peak in developed markets, highlighting Vietnam-specific dynamics such as concentrated order flow or liquidity shocks post-halt (Bekaert & Harvey, 1997). The decline to 2.0110e-05 at 14:00-15:00 reflects a partial stabilization as trading winds down, though it remains above the midday low, indicating lingering uncertainty or profit-taking.

For market participants, the volatility pattern offers actionable insights into trading and risk management strategies. The high RV at 09:00-10:00 and 13:00-14:00 presents opportunities for momentum-based trades, leveraging the larger price swings during these volatile windows, consistent with earlier findings of return predictability. Traders might enter positions at 09:00 or 13:00, holding for 30-60 minutes to capture volatility and exiting before volatility subsides. The midday trough at 10:00-11:00 offers a low-risk period for position unwinding or arbitrage, minimizing exposure to price fluctuations.

The pre-break spike at 11:00-11:30 and closing moderation at 14:00-15:00 suggest potential for reversal strategies, exploiting mean-reverting tendencies observed in autocorrelation. Portfolio managers should heighten risk controls during the 13:00-14:00 peak, where volatility triples the midday low, employing hedging or reduced leverage to manage the risk, while the closing decline allows for safer position adjustments. Regulators may interpret the afternoon surge as a sign of speculative excess or liquidity gaps, warranting policies to enhance market depth or stabilize trading post-break.

Compared to developed markets, where intraday volatility typically follows a U-shape with pronounced opening and closing peaks (Heston et al., 2010), the VNINDEX pattern exhibits a distinctive midday peak at 13:00–14:00, likely driven by its bifurcated trading schedule and retail dominance. This deviation echoes findings in other emerging markets, where volatility clusters around structural breaks or information shocks rather than smoothing intraday (Bekaert & Harvey, 1997).

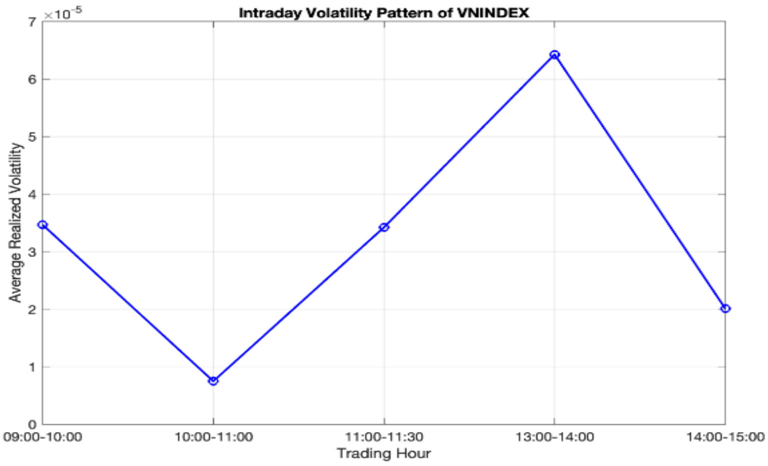

Figure 2: Intraday volatility pattern of VNINDEX
Source: Authors' estimation on MATLAB.

5. Conclusion and implications

This study investigates the high-frequency dynamics of the VNINDEX by utilizing 1-minute data to examine intraday volatility patterns, market efficiency, and the volume-price relationship. The intraday volatility pattern reveals a modified U-shape with a pronounced peak at 13:00–14:00, elevated volatility at opening and pre-break, a midday trough and a decline toward close, reflecting distinct periods of information assimilation and liquidity fluctuations. Market efficiency tests further underscore inefficiencies and indicate significant positive serial dependence at short lags and negative dependence at medium lags, while rejecting the random walk hypothesis. Complementing these findings, the volume-price analysis highlights a sharp contrast in dynamics: Returns exhibit strong momentum and volume changes display clustering.

The findings of the paper have several implications for market participants. Traders can exploit momentum opportunities during volatile hours for 5-10 minute trend-following, leverage the midday trough for low-risk strategies, and use volume persistence for liquidity timing, though its weak predictive power limits its role as a price signal. Portfolio managers face heightened volatility risks at peak hours, necessitating dynamic risk controls, while regulators may consider enhancing market depth to mitigate speculative spikes, particularly post-break.

While this study advances the understanding of VNINDEX high-frequency dynamics, several limitations related to data and alternative analytical approaches merit attention. First, the reliance on a single dataset of 160,677 one-minute observations from the HOSE restricts the scope to a specific exchange and time frame, potentially omitting broader market dynamics from the Hanoi Stock Exchange (HNX) or significant events such as Tet holidays or regulatory shifts that could influence intraday patterns. Second, the data quality is subject to potential microstructure noise inherent in high-frequency observations—such as bid-ask bounce or order imbalances—which may distort price and volume measurements without noise-filtering techniques, as proposed by Barndorff-Nielsen et al. (2008). This noise could exaggerate volatility estimates or mask subtle price-volume interactions.

The findings of this study on the VNINDEX's high-frequency dynamics open several avenues for future research to deepen the understanding of Vietnam's emerging equity market and its broader implications. First, expanding the dataset to include the HNX and a longer time frame could enhance generalizability and capture market-specific events. Incorporating high-frequency data across multiple years would allow for event studies to isolate exogenous shocks, such as macroeconomic announcements or policy changes, and their intraday impacts. Besides, future research could explore the drivers of the midday volatility peak or investigate the impact of regulatory interventions on these dynamics.

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