High-Frequency Periodicity in Trading Volume in the Chinese A-Share Market: Evidence from a Spectral Decomposition Approach

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Abstract. The proliferation of algorithmic trading has reshaped market microstructure, manifesting as periodic fluctuations in high-frequency trading volume series. Based on tick-by-tick data for all A-share stocks in China from 2017 to 2025, this paper constructs a spectral decomposition model tailored to 100ms high-frequency series to systematically identify and measure the periodicity intensity of trading volume. The study reveals five strongest periodic frequencies—3s, 1.5s, 1s, 0.5s, and 0.25s—in the A-share market in recent years, and this high-frequency periodicity exists significantly in the majority of stocks. Further analysis demonstrates a strong positive correlation between periodicity intensity and algorithmic trading activity, and stocks with stronger periodicity exhibit higher price efficiency.

Keywords: Periodicity, Trading volume, Algorithmic trading.

1 Introduction

Algorithmic trading executes strategies automatically through computer programs at the millisecond level and has become an important component of modern financial markets. Its widespread adoption has introduced new patterns in market microstructure, prompting a growing body of research to examine market behavior at high-frequency time scales.

In high-frequency trading environments, trading volume and price series may exhibit specific periodic structures due to execution algorithms such as TWAP and VWAP[1]. Empirical evidence shows that trading volume and transaction counts often display peaks at fixed time intervals (e.g., every 5 or 10 minutes), a pattern commonly attributed to the tendency of algorithmic trading systems to concentrate order execution around round timestamps[2] . The pioneering study of Muravyev and Picard[3] documents significant second-level trading periodicity in U.S. markets, which is attributed to algorithms executing instructions in repeated cycles with fixed time steps. Giudici and Grossmann[4] further find that persistent periodic spikes remain in trading volume even after controlling for opening and closing effects, suggesting that such regularities are likely driven by algorithmic execution strategies. Wu et al.[5] analyzing 3-second

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trading volume series in both the U.S. and Chinese stock markets, document widespread minute-level volume periodicity and show that these patterns are strongly associated with algorithmic trading activity.

To systematically separate and quantify such micro-level periodicities, an increasing number of studies adopt spectral analysis and shift the focus from the time domain to the frequency domain. Although spectral methods have a long history in macroeconomics, their application in high-frequency finance remains a relatively new frontier. Dew-Becker and Giglio[6] demonstrate the effectiveness of spectral decomposition in asset pricing and business cycle analysis. Closer to the market microstructure literature, Hasbrouck [7] employs frequency-domain representations to evaluate the informational efficiency of high-frequency quotes, while Andersen et al.[8] use spectral decomposition to analyze periodic patterns in intraday volatility curves.

However, existing studies on trading volume periodicity mainly focus on minute-level or second-level data, with relatively little attention paid to millisecond-level high-frequency periodic structures. Using tick-by-tick transaction data, this paper follows the trading-volume spectral decomposition framework proposed by Wu et al.[5] to systematically identify and analyze millisecond-level high-frequency periodicity in the Chinese A-share market. This analysis not only helps reveal the influence of algorithmic trading on market microstructure but also provides new empirical evidence for understanding high-frequency trading behavior in the Chinese market.

Specifically, this study uses tick-level order submission and transaction data from the Chinese A-share market to investigate the high-frequency periodic structure in stock trading volume series. The sample covers tick-level transaction data for all listed stocks from 2017 to 2025, and the raw data are aggregated at 100-millisecond intervals to construct high-frequency trading volume time series. Compared with the minute-level or second-level data commonly used in previous studies, this higher-frequency dataset allows for a more refined characterization of market trading behavior and provides a foundation for identifying sub-second trading rhythms.

Based on these data, this paper develops a spectral decomposition framework tailored for high-frequency trading volume series. Using this approach, significant high-frequency periodic structures are identified at both the individual-stock and market-wide levels. The most prominent cycles are concentrated at time scales of approximately 3 seconds, 1.5 seconds, 1 second, 0.5 seconds, and 0.25 seconds. Further empirical analysis shows that the intensity of these high-frequency cycles is significantly correlated with proxy measures of algorithmic trading activity, including order submission frequency, the degree of order splitting, and price efficiency indicators. This finding is consistent with the mechanism by which algorithmic trading executes large orders through scheduled order splitting[9].

The remainder of this paper is organized as follows. Section 2 constructs a spectral decomposition model based on tick-level data and describes the data processing and periodicity identification methods. Section 3 presents the empirical analysis from two perspectives: the identification of high-frequency periodicity and its association with algorithmic trading activity. The final section summarizes the main findings.

2 Research Design

This chapter develops a rigorous analytical framework for high-frequency trading volume. First, the data sources, cleaning procedures, and aggregation methods are introduced. Second, descriptive statistical observations are used to reveal both the macro- and micro-level intraday patterns of trading volume in the Chinese A-share market. Finally, the core tool for identifying high-frequency periodicity—the Trading Volume Spectral Decomposition Model—is presented in detail.

2.1 Data Sample and Processing

The sample used in this study covers all stocks in the Chinese A-share market from January 2017 to December 2025. Unlike traditional studies that rely on minute-level or 3-second data, the fundamental dataset in this study consists of tick-level order submission and transaction records. The empirical dataset used in this study consists of the cleaned and validated tick-by-tick transaction data for the entire Chinese A-share market provided by RiceQuant. Stocks that were suspended from trading or subject to abnormal trading status (e.g., ST) are excluded from the sample. The raw data are recorded at a 10 ms tick frequency. In this study, the ten consecutive ticks within each 100 ms interval during the continuous trading session are aggregated to construct a 100-millisecond time series.

To preserve high-frequency characteristics while filtering out microstructure noise and maintaining computational feasibility for large-scale data processing, the raw data are aggregated at 100 ms intervals. In addition, according to the Nyquist sampling law, capturing a signal with a period of 0.2 seconds requires a sampling frequency of at least 0.1 seconds. A sampling interval of 100 ms therefore provides an appropriate balance between retaining high-frequency information and mitigating microstructure noise. Compared with longer time windows (e.g., 1 second), the 100 ms frequency also enables the identification of sub-second algorithmic trading pulses.

The feature variables extracted in this study (hereafter collectively referred to as trading volume features) include:

- Count-based indicators: Number of order submissions, trades, and cancellations under buy, sell, and total categories.
- Value-based indicators: Corresponding transaction values and order submission values.

In most subsequent analyses, Trade Numbers are used as the primary variable of interest because they directly reflect actual trading activity and are relatively robust to extreme observations caused by unusually large trades during volatile market conditions. Section 2.3.3 further compares the substantial heterogeneity in periodic patterns across different trading volume features.

2.2 Intraday Patterns of Trading Volume

Intraday trading activity in the Chinese A-share market is influenced by the midday trading break, resulting in a typical "double-U" intraday pattern. To illustrate this feature, we first aggregate all trade counts across the entire market in 2024 and construct a 100 ms aggregated time series.

Figure 1 show that, superimposed on the macro-level double-U shape, there exist numerous minute-level periodic patterns. Significant trading volume pulses occur at time points corresponding to 30 minutes, 15 minutes, 5 minutes, and even 1 minute, which is consistent with findings documented in previous studies.

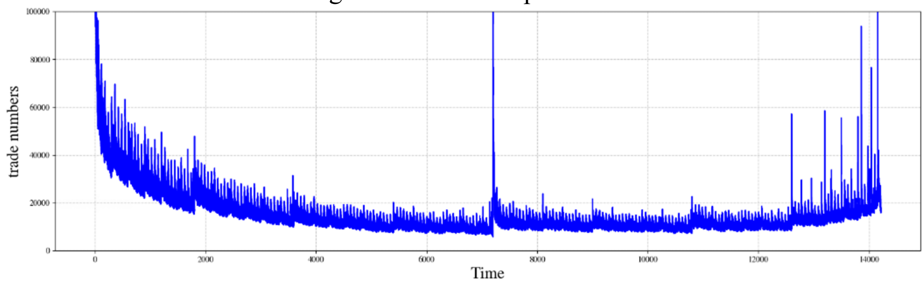

Fig. 1. Average Intraday Trading Numbers for Chinese Stock Market in 2024.

However, the focus of this study lies at a much finer time scale. By examining a 30-second interval between 10:06:30 and 10:07:00 in 2024, it can be observed in Figure 2 that trading pulses still occur regularly even within such a narrow time window. Preliminary inspection reveals pronounced fluctuations at 3-second and 1-second intervals, along with additional higher-frequency periodic components. In the next section, we construct a trading volume spectral decomposition model to estimate these high-frequency periodic features and their corresponding strengths.

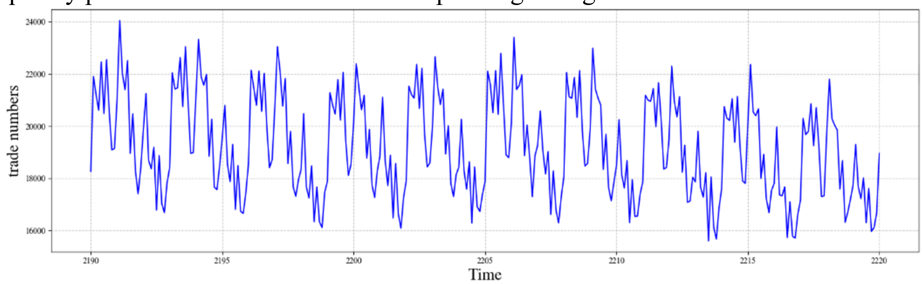

Fig. 2. Average Intraday Trading Numbers for Chinese Stock Market between 10:06:30 and 10:07:00 in 2024.

2.3 Trading Volume Spectral Decomposition Model

To extract clean periodic signals from noisy high-frequency sequences, this study constructs a spectral decomposition model optimized for 100 ms high-frequency time series.

Basic Assumptions.

Let $V_t(t = 1,2, \dots T)$ denote the trading volume series, the series can be decomposed as:

$$V_t \coloneqq m_t + X_t = m_t + \sum_{j=1}^{n} a_j \cos(\lambda_j t) + \varepsilon_t, \quad 0 < \lambda_1 < \cdots < \lambda_j < \cdots < \lambda_n < \pi \ (1)$$

where

- m_t: the trend component, representing the slow-moving "double-U" intraday pattern
- X_t: the detrended stationary component

The stationary component X_t can be further decomposed into n periodic components, where each term $\cos(\lambda_j t)$ corresponds to a specific frequency:

- a_j: the periodic intensity coefficient associated with frequency λ_j
- ε_t: the random noise component

The primary objective of the model is to estimate the periodic intensity coefficients a_j, where a larger absolute value indicates stronger periodicity for the j-th component.

Specifically, the model adopts $\lambda_j = \frac{j\pi}{n}, \quad j = 1, \dots, n$, so that the period corresponding to the j-th component is $\frac{2n}{j} * 0.1s$. Based on the empirical observations in Section 2.2, this study sets $n = 600$ allowing the identification of periodic frequencies such as 5 seconds, 3 seconds, and down to 0.25 seconds.

Given a dataset of intraday trading volume time series $\{\{(V_{t,s,d})_{t=1}^{T}\}_{d=1}^{D}\}_{s=1}^{S}$, where S denotes the number of stocks and D denotes the number of trading days, the trading volume series for stock s on day d can be expressed as:

$$V_{t,s,d} \coloneqq m_{t,s,d} + X_{t,s,d} = m_{t,s,d} + \sum_{j=1}^{n} a_{j,s,d} \cos(\lambda_j t) + \varepsilon_{t,s,d}. \quad (2)$$

We then compute the average intraday trading volume series across all D trading days: $\overline{V_{t,s,\cdot}} = \frac{1}{D}\sum_{d=1}^{D} V_{t,s,d}$, which can be written as:

$$\overline{V_{t,s,\cdot}} = \overline{m_{t,s,\cdot}} + \overline{X_{t,s,\cdot}} = \overline{m_{t,s,\cdot}} + \sum_{j=1}^{n} \overline{a_{j,s,\cdot}} \cos(\lambda_j t) + \overline{\varepsilon_{t,s,\cdot}} \quad (3)$$

Where $\overline{m_{t,s,\cdot}}, \overline{X_{t,s,\cdot}}, \overline{a_{j,s,\cdot}}, \overline{\varepsilon_{t,s,\cdot}}$ represent the averages of the corresponding components across the D trading days:

$$\overline{m_{t,s,\cdot}} = \frac{1}{D}\sum_{d=1}^{D} m_{t,s,d}\,,\ \overline{X_{t,s,\cdot}} = \frac{1}{D}\sum_{d=1}^{D} X_{t,s,d}\,,\ \overline{a_{j,s,\cdot}} = \frac{1}{D}\sum_{d=1}^{D} a_{j,s,d}\,, \overline{\varepsilon_{t,s,\cdot}} = \frac{1}{D}\sum_{d=1}^{D} \varepsilon_{t,s,d} \quad (4)$$

For each stock, the following steps are used to estimate the average periodic intensity coefficients $\overline{a_{j,s,\cdot}}$ across all D trading days.

Model Estimation Procedure.

Step 1: Removing the Trend Component.

To eliminate the effect of the intraday double-U distribution, a moving average filter is applied to remove the trend component $\overline{m_{t,s,\cdot}}$. The window length is set to $q = 30$, ensuring that low-frequency fluctuations with periods longer than 6 seconds are filtered out while retaining higher-frequency signals.

$$\widehat{\overline{m_{t,s,\cdot}}} = \frac{1}{2q+1}\sum_{j=-q}^{q} \overline{V_{t+j,s,\cdot}}, \quad q+1 \le t \le T-q \tag{5}$$

Step 2: Estimating the Autocovariance Sequence.

The detrended series $\overline{V_{t,s,\cdot}} - \widehat{\overline{m_{t,s,\cdot}}}$ is treated as the observed $\overline{X_{t,s,\cdot}}$. Its autocovariance function $\gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(h), -n \le h \le n$ is estimated as:

$$\gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(h) = \frac{1}{T-2q-h}\sum_{t=q+1}^{T-q-h}\left(\overline{X_{t,s,\cdot}} - \frac{1}{T-2q}\sum_{t=q+1}^{T-q}\overline{X_{t,s,\cdot}}\right)\left(\overline{X_{t+h,s,\cdot}} - \frac{1}{T-2q}\sum_{t=q+1}^{T-q}\overline{X_{t,s,\cdot}}\right) \tag{6}$$

Step 3: Estimating Periodic Intensity Coefficients.

When T is sufficiently large, the sequence

$$\gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(-n), \gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(-n+1), \dots, \gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(0), \dots, \gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(n-1), \gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(n) \tag{7}$$

can be approximated as the discrete Fourier transform of the sequence

$$\overline{a_{n,s,\cdot}^2}, \overline{a_{n-1,s,\cdot}^2}, \dots, \sigma_s^2, \dots, \overline{a_{n-1,s,\cdot}^2}, \overline{a_{n,s,\cdot}^2} \tag{8}$$

Therefore, applying the inverse discrete Fourier transform to the autocovariance function $\gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(h)$ yields the estimated intensity coefficients:

$$\widehat{\overline{a_{j,s,\cdot}^2}} = \frac{2}{n}\sum_{h=1}^{n}\gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(h)\left(e^{-i\frac{\pi}{n}hj} + e^{i\frac{\pi}{n}hj}\right) + \gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(0) = \frac{2}{n}\left(2\sum_{h=1}^{n}\gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(h)\cos\left(\frac{j\pi}{n}h\right)\right) + \gamma_T^{\widehat{\overline{X_{s,\cdot}}}}(0) \tag{9}$$

Periodic Intensity Coefficient.

The spectral decomposition model above produces the intensity coefficient for each periodic component. To further evaluate the relative importance of different periodic components, the frequency variance ratio of the j-th component is defined as

$$\mathrm{fVR}_j := \frac{a_j^2}{2\sigma^2 + \sum_{i=1}^{n} a_i^2} \tag{10}$$

This indicator measures the proportion of variance explained by each frequency relative to the total variance of the detrended trading volume time series.

When measuring periodic intensity within a continuous time interval, the above formula can be applied directly. However, when estimating the periodic intensity over a full trading day in the A-share market, the analysis is conducted separately for the morning and afternoon sessions. Therefore, the results from the two sessions are combined as follows:

$$\mathrm{fVR}_j := \frac{a_{j,\text{morning}}^2 + a_{j,\text{afternoon}}^2}{2\sigma_{\text{morning}}^2 + \sum_{i=1}^{n} a_{i,\text{morning}}^2 + 2\sigma_{\text{afternoon}}^2 + \sum_{i=1}^{n} a_{i,\text{afternoon}}^2} \tag{11}$$

3 Empirical Analysis of High-Frequency Periodicity

3.1 High-Frequency Periodicity at the Individual-Stock and Market-Wide Levels

We begin with the trading count series of Midea Group in 2024 as the primary case study.First, the trend component is removed following Step 1 of the spectral decomposition procedure. Because the A-share market has a midday trading break, the morning continuous trading session and the afternoon continuous trading session are analyzed separately. Figure 3 display the smoothed series for the morning session, respectively. It can be observed that the strong U-shaped background pattern in the raw series is effectively filtered out, leaving a relatively stationary residual sequence.

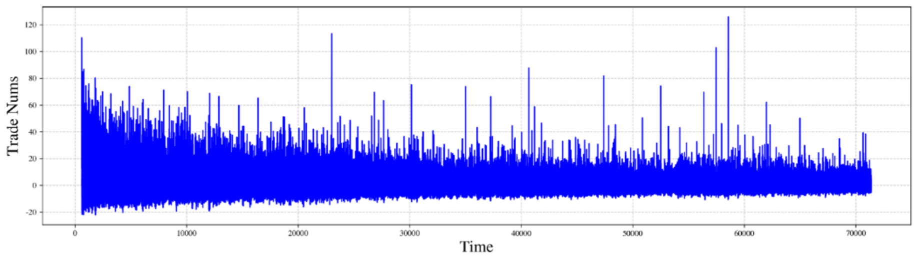

Fig. 3. Morning-session trade-number series of Midea Group after the first-step smoothing.

Next, Step 2 computes the lag-$\boldsymbol{j}$ autocovariance of the detrended trade-number series, producing the autocovariance sequence. The autocovariance series for the morning session are shown in Figure 4, revealing highly regular and pronounced periodic fluctuations.

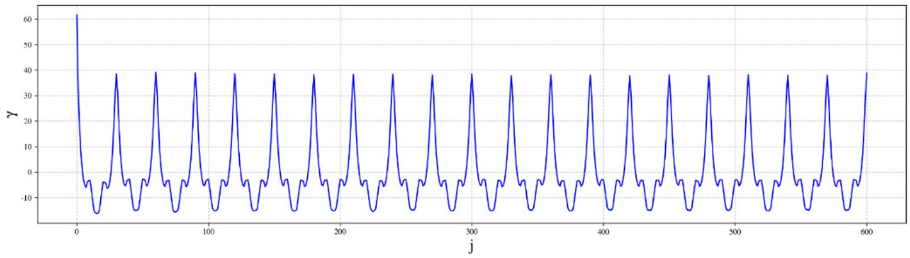

Fig. 4. Morning-session autocovariance series of Midea Group after the second step.

Finally, Step 3 applies the inverse discrete Fourier transform (iDFT) to the auto-covariance sequence, extracting the squared intensity coefficient corresponding to each j. The resulting squared intensity coefficient sequences for the morning session are shown in Figure 5.

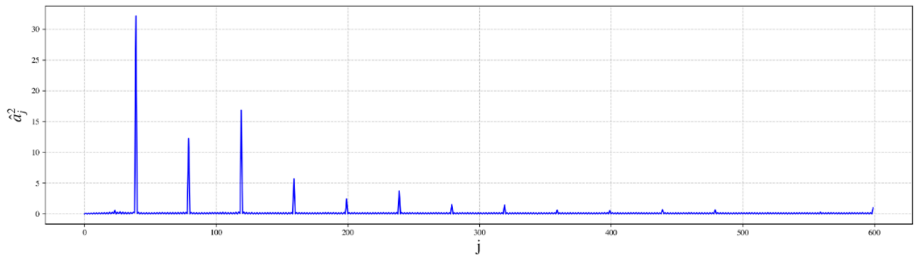

Fig. 5. Morning-session squared intensity coefficient sequences of Midea Group.

From the curve describing the squared intensity coefficient as a function of jjj, several peaks can be observed. The three largest peaks occur at $j = 40, 80, 120$, which correspond to the time intervals of 3 seconds, 1.5 seconds, and 1 second, respectively.

The above results illustrate the three steps of the spectral decomposition procedure in detail. The decomposition results are remarkably clear: the trading activity of Midea Group exhibits very similar periodic structures in both the morning and afternoon sessions, with the three strongest peaks occurring at 3 s, 1.5 s, and 1 s.

After obtaining the spectral decomposition results, we next compute the frequency variance ratio (fVR) sequence for each stock, including Midea Group, based on the periodic intensity formula (11).

In addition, we construct a market-wide aggregate trade-number series by summing the raw trade counts across all stocks:

$$V_{Total,t} = \sum_{s=1}^{S} V_{s,t} \tag{12}$$

We then apply the same spectral decomposition procedure to the sequence $\{V_{Total,t}\}_{t=1}^{T}$ and compute the market-wide fVR sequence.

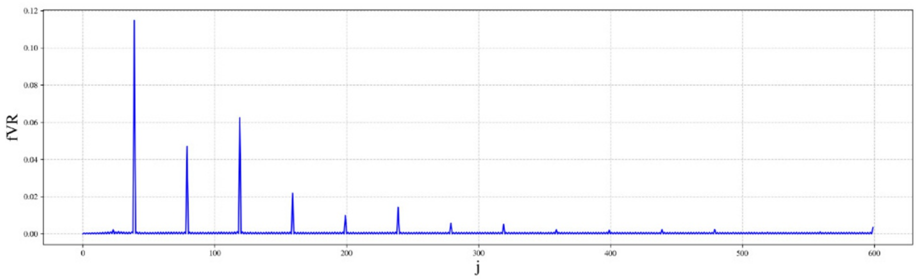

Fig. 6. fVR curve for Midea Group.

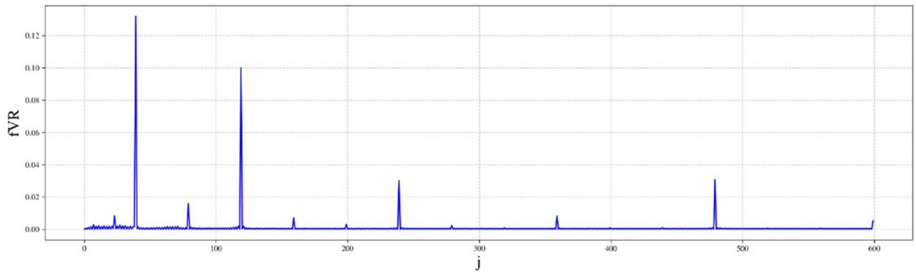

Fig. 7. fVR curve for market-wide aggregate series.

Figure 6 and Figure 7 show the fVR curves for Midea Group and the market-wide aggregate series, respectively. At the market level, the five strongest peaks occur at $j = 40, 80, 120, 240, 480$, corresponding to periodicities of 3 s, 1.5 s, 1 s, 0.5 s, and 0.25 s.

Interestingly, the fVR value at $j = 24$, corresponding to a 5-second period, is very weak, whereas the nearby 3-second frequency exhibits the strongest signal. One possible explanation is that 3 seconds corresponds to the update frequency of exchange snapshot data, suggesting that high-frequency trading cycles may be coupled with the exchange snapshot update frequency.

Finally, we aggregate the fVR results for all stocks and present box plots of fVR values at the five strongest frequencies. According to the framework proposed by Wu et al.[5], the model incorporates n = 600 periodic components. In the absence of periodic structures, the benchmark value of the frequency Variance Ratio (fVR) should be 1/600. Therefore, when the fVR corresponding to a given frequency is significantly larger than 1/600, the presence of a statistically significant periodic component at that frequency can be inferred. The results in Figure 8 show that for most stocks, the fVR values at the selected frequencies are significantly larger than the baseline level of $1/600$. In particular, the median fVR at the 3-second frequency is approximately 8%.

Taken together, these results suggest that the periodicity observed in Midea Group is not an isolated phenomenon, but rather a widely prevalent feature across the A-share market.

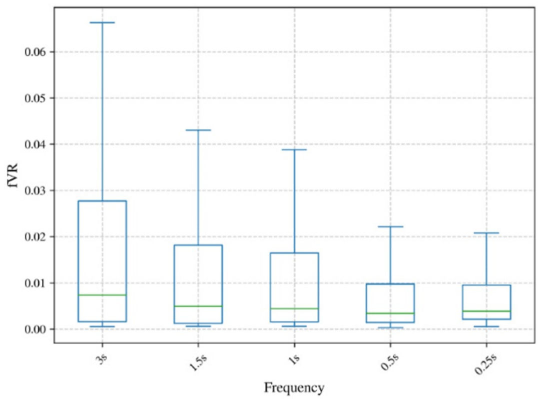

Fig. 8. Boxplot of fVR for all stocks at the five strongest frequencies.

Robustness Test.

To verify the robustness of our theoretical framework and empirical findings, we conduct an additional spectral analysis using the raw 10 ms trade-count series for the entire market in 2024. In this specification, the parameter is set to n = 6000. As shown in Figure 9, the five frequencies with the strongest fVR values correspond to j = 40, 120, 240, 960, and 480, which map to periodicities of 3s, 1s, 0.25s, 0.125s, and 0.5s, respectively.

Because the sampling frequency is increased to 10 milliseconds, periodic structures with frequencies as short as 20 milliseconds and above become detectable. Compared with the baseline 100-millisecond series, the higher-frequency data allow us to identify an additional periodic component at 0.125 seconds, while the 1.5-second cycle appears as the sixth strongest component. Overall, the key empirical findings remain stable after altering the sampling frequency, indicating that the results are robust to changes in temporal resolution.

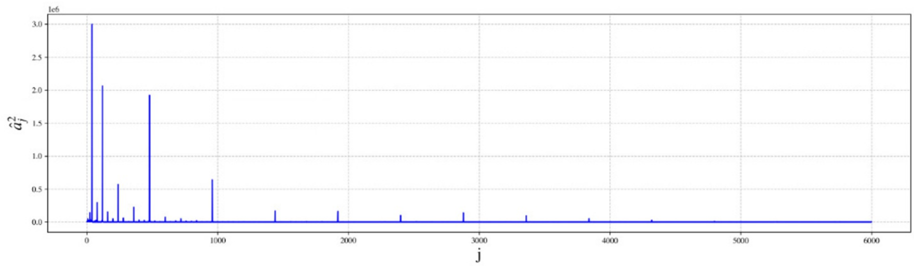

Fig. 9. fVR curve for market-wide raw series.

3.2 High-Frequency Periodicity and Algorithmic Trading

After identifying widespread periodic trading pulses in the market, this section investigates the intrinsic relationship between high-frequency periodicity and algorithmic trading behavior through rigorous empirical regression analysis.

Indicator Construction and Variable Definition.

To quantify this relationship, we construct a dependent variable representing high-frequency periodic strength for each stock, along with several proxy variables that capture algorithmic trading activity.

Dependent Variable: High-Frequency Periodicity Strength (ASP)

Based on the spectral decomposition results, we select the five most representative frequencies observed in the market and define ASP (Aggregated Signal Power) as the sum of fVR values at these core periodicities:

$$ASP_s = \sum_{j \in \{3s, 1.5s, 1s, 0.5s, 0.25s\}} fVR_{s,j} \tag{13}$$

Explanatory Variables: Algorithmic Trading Proxies

We adopt proxy variables widely used in the literature to measure the intensity of algorithmic trading.

MESS: Hendershott, Jones, and Menkveld[9] propose that a higher number of daily order messages—including order submissions and cancellations—can serve as a proxy for higher algorithmic trading activity.

$$MESS_s = \frac{Total\_Orders_s + Total\_Cancels_s}{T} \quad (14)$$

NVDMESS: A key characteristic of algorithmic trading is the order-splitting pattern. By taking the negative value of the average order size, this measure increases when orders are split into smaller pieces.

$$NVDMESS_s = -\frac{\sum Amt_s}{Total\_Orders_s} \quad (15)$$

VARRAT: Algorithmic trading typically enhances price efficiency by rapidly eliminating arbitrage opportunities[10]. The variance ratio between 2-minute and 1-minute returns measures deviations from a random walk. Larger deviations from the theoretical value of 2 indicate lower price efficiency.

$$VARRAT_s = \left| \frac{Var(r_{2min,s})}{Var(r_{1min,s})} - 2 \right| \quad (16)$$

Control Variables:

Log_Size: $\ln(Market\_Cap)$, controlling for the influence of firm size on order message activity.

RV (Realized Volatility): Controls for the potential impact of volatility on price efficiency.

Regression Model and Empirical Results.

We employ an OLS regression model to examine the relationship between ASP and the proxy variables. To improve coefficient comparability, all variables are standardized using Z-score normalization prior to estimation.

$$ASP_s = \beta_0 + \beta_1 MESS_s + \beta_2 NVDMESS_s + \beta_3 VARRAT_s + \sum \gamma_k Control_{k,s} + \epsilon_s \quad (17)$$

Table 1. Regression Results of the ASP.

Variable	Coef.	t-statistic	P-value	Direction
MESS	0.0621	5.177	0.000***	Positive
NVDMESS	0.0419	3.442	0.001***	Positive
VARRAT	-0.7673	-72.319	0.000***	Negative
Log_Size	0.1384	9.557	0.000***	Positive
RV	-0.0616	-5.984	0.000***	Negative

It can be seen from Table 1 that the coefficients of MESS and NVDMESS are significantly positive, and the coefficient of VARRAT is significantly negative. The directions and significance levels of these three proxy variables are all consistent with the prior hypotheses. These results suggest that the strength of high-frequency periodicity is strongly correlated with the intensity of algorithmic trading activity.

Notably, the coefficient on VARRAT is as large as -0.7673, indicating a strong negative relationship. This result implies that stocks with stronger periodic signals tend to exhibit higher price efficiency. In other words, timer-driven algorithmic quoting not only provides liquidity but also accelerates the incorporation of information into prices, making price dynamics closer to a random walk process.

Temporal Evolution of High-Frequency Periodicity: Indirect Evidence of Algorithmic Trading.

To further examine the relationship between high-frequency periodicity and algorithmic trading, we compute the annual fVR and ASP measures across different frequencies. The results in Figure 10 reveal a three-stage evolution of high-frequency periodic structures in the Chinese A-share market.

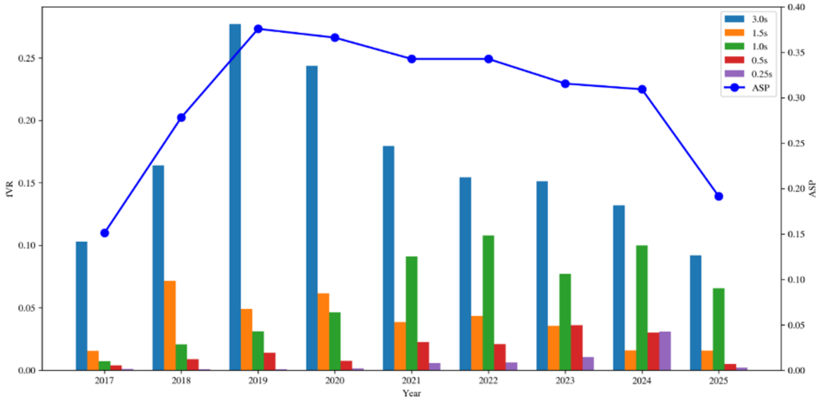

Fig. 10. Annual Distribution of Market-Wide fVR and ASP, 2017–2025.

Stage 1: Rapid expansion of high-frequency periodicity (2017–2019). During this period, high-frequency periodic signals increased dramatically. The 3-second cycle contributed the largest share of the increase and accounted for most of the growth in the overall ASP indicator. This pattern coincides with the rapid rise of quantitative trading in the Chinese market and the large-scale adoption of algorithmic execution systems. At this stage, the frequency structure was relatively concentrated, with the 3-second cycle dominating the observed periodic signals.

Stage 2: Regularization and dispersion of periodicity (2020–2024). Between 2020 and 2024, the overall ASP signal intensity remained persistently high, although its internal frequency composition changed substantially. The fVR of the 3-second cycle declined steadily, while the 1-second, 0.5-second, and 0.25-second frequencies gradually strengthened. In particular, the 0.25-second component experienced a pronounced increase in 2024. This evolution reflects the normalization of quantitative trading activity and suggests that competition among algorithmic traders has shifted toward increasingly high-frequency execution horizons.

Stage 3: Sharp decline in periodicity and the "stealth" of algorithmic trading (2025). A particularly striking pattern emerges in 2025, when the market-wide ASP indicator exhibits a sudden and dramatic decline. Importantly, this decline does not necessarily imply a retreat of algorithmic trading. Instead, it likely reflects a strategic "stealth" adaptation in algorithmic execution logic. As market participants become increasingly aware of deterministic execution schedules, leading quantitative funds and high-frequency service providers may introduce randomized timing perturbations (jittering) into previously fixed execution intervals. Such randomization smooths the originally discrete pulses in the frequency domain, effectively masking periodic signals at the statistical level.

Taken together, the three stages described above illustrate the evolving nature of high-frequency periodic structures in the Chinese A-share market and provide important indirect evidence linking these periodic patterns to the development of algorithmic trading activity.

4 Conclusion

This paper investigates the high-frequency structural characteristics of trading activity in the Chinese A-share market, with a particular focus on the hidden micro-periodic patterns in trading volume time series and their potential connection with algorithmic trading behavior. Using tick-level order submission and transaction data, the study develops a spectral decomposition framework tailored for ultra-high-frequency data and conducts a systematic identification and empirical analysis of periodic structures in transaction count series in the A-share market.

From a methodological perspective, this paper proposes a trading-volume spectral decomposition model optimized for 100-millisecond high-frequency sequences. This approach effectively identifies hidden periodicities in transaction series and enables cross-sectional comparisons of periodic strength across stocks using a unified dimensionless metric.

Empirical results reveal that trading activity in the A-share market exhibits significant and stable periodic structures at sub-second time scales. Taking Midea Group as an example, the spectral decomposition results show clear periodic patterns in its transaction count series at cycles of 3s, 1.5s, and 1s. Extending the analysis to the market level further shows that the five most prominent cycles across the entire market correspond to 3s, 1.5s, 1s, 0.5s, and 0.25s. Among them, the 3s cycle exhibits the strongest high-frequency periodic intensity and is significantly above the theoretical benchmark for the majority of stocks. These findings suggest that high-frequency trading periodicity is not an idiosyncratic phenomenon of individual stocks but rather a common structural feature arising from the market's trading mechanism. Robustness analyses confirm the consistency of the empirical results.

Furthermore, this study explores the potential mechanism underlying high-frequency periodicity from the perspective of algorithmic trading behavior. Cross-sectional OLS regressions show that stocks with more active algorithmic trading exhibit stronger high-frequency periodic signals in their transaction series. In addition, stocks with stronger periodicity tend to display higher price efficiency. Moreover, an examination of the temporal evolution of high-frequency periodicity provides indirect evidence of a close connection between these periodic structures and algorithmic trading activity.

Overall, the findings of this paper reveal the existence of stable and pronounced periodic structures in transaction activity at sub-second time scales in the Chinese A-share market. Empirical evidence further indicates that these periodic patterns are closely associated with algorithmic trading behavior. These results provide useful insights for market participants and regulators in understanding the microstructural effects of algorithmic trading in modern electronic markets.

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