

HIGH-FREQUENCY TRADING ALGORITHMS AND THEIR EFFECTS ON INTRADAY MARKET VOLATILITY

YiChen Liu*, Wei Zhang, Benjamin Carter

Department of Finance, Fisher College of Business, Ohio State University, USA.

Corresponding Author: YiChen Liu, Email: yichen.liu012@gmail.com

Abstract: The proliferation of high-frequency trading (HFT) has fundamentally transformed modern financial market microstructure, raising important questions about its impact on intraday volatility dynamics. This study examines the complex relationship between HFT algorithms and intraday market volatility through comprehensive analysis of market microstructure data spanning multiple markets and time periods. Our investigation reveals that HFT exhibits a dual nature: under stable market conditions, increased HFT activity is associated with reduced intraday volatility and improved liquidity provision; however, during periods of market stress and intraday crashes, HFT algorithms can amplify volatility through rapid order cancellations and liquidity withdrawals. Empirical evidence from European equity markets demonstrates that HFT participation has grown substantially from 2011 to 2013, with large-cap stocks exhibiting HFT activity levels ranging from 40% to 80% of total trading activity. Our analysis reveals strong positive correlations between HFT profitability and both trading volume and market volatility, with correlation coefficients exceeding 0.80 for volume relationships and 0.66 for volatility relationships. These findings indicate that while HFT provides substantial benefits in terms of reduced bid-ask spreads and enhanced price discovery under normal conditions, algorithmic interactions during extreme events create feedback loops that exacerbate price movements. The results have significant implications for market regulators and institutional investors seeking to understand the evolving dynamics of modern electronic markets and the necessity for appropriate regulatory frameworks that balance innovation with market stability.

Keywords: High-frequency trading; Algorithmic trading; Intraday volatility; Market microstructure; Liquidity provision; Price discovery; Market stability

1 INTRODUCTION

The landscape of financial markets has undergone a profound transformation over the past two decades, evolving from human-intermediated trading floors to sophisticated electronic platforms dominated by algorithmic execution. High-frequency trading has emerged as one of the most significant technological innovations in modern finance, characterized by the deployment of advanced computational algorithms capable of executing large volumes of orders in microseconds. This technological revolution has fundamentally altered market microstructure, creating both opportunities and challenges that continue to shape academic discourse and regulatory policy. The advent of HFT represents a paradigm shift in how financial assets are traded, with implications extending far beyond mere execution speed to encompass fundamental questions about market efficiency, fairness, and stability.

Contemporary financial markets have witnessed an unprecedented acceleration in trading speeds, where competitive advantages are measured not in seconds or even milliseconds, but in microseconds and nanoseconds [1]. This evolution reflects substantial investments in cutting-edge technology infrastructure, including co-location services, direct market access, and proprietary data feeds that enable HFT firms to gain marginal speed advantages over competitors. The economic stakes are considerable, with the global algorithmic trading market valued at approximately \$17 billion in 2024 and projected to reach \$42.5 billion by 2033, reflecting a compound annual growth rate of 9.49% [2]. These market dynamics underscore the growing importance of understanding how HFT algorithms interact with traditional market participants and influence intraday volatility patterns.

The relationship between HFT and market volatility represents one of the most contentious debates in contemporary financial economics. Proponents argue that HFT enhances market quality through improved liquidity provision, narrower bid-ask spreads, and more efficient price discovery mechanisms [3]. These benefits are thought to accrue to all market participants through reduced transaction costs and enhanced market depth. Conversely, critics contend that HFT may destabilize markets during periods of stress, contribute to extreme volatility events, and create an unlevel playing field that disadvantages traditional investors [4]. The dichotomy between these perspectives reflects the complex and context-dependent nature of HFT's impact on market outcomes.

Empirical evidence regarding HFT's effect on volatility has produced mixed results, suggesting that the relationship is highly nuanced and contingent on market conditions. Research indicates that HFT can simultaneously reduce volatility under stable conditions while amplifying it during periods of market stress [5]. This dual nature poses significant challenges for market participants and regulators attempting to assess the net welfare implications of HFT activity. The 2010 Flash Crash served as a watershed moment, dramatically illustrating how algorithmic trading systems could interact in unexpected ways to produce extreme price movements and temporary market disruptions [6]. This event catalyzed extensive research into the mechanisms through which HFT algorithms influence intraday volatility dynamics.

Understanding the microstructural mechanisms through which HFT affects volatility requires examining the specific strategies employed by high-frequency traders. Market-making strategies, where HFT firms provide liquidity by continuously posting bid and ask quotes, generally contribute to reduced volatility and enhanced market stability [7]. These strategies involve sophisticated risk management algorithms that adjust quote positions in response to changing market conditions. In contrast, directional trading strategies and latency arbitrage, where firms exploit minute price discrepancies across markets or anticipate order flow, may contribute to increased volatility, particularly during periods of information asymmetry [8]. The balance between these competing forces determines HFT's net effect on market volatility at any given time.

The technological arms race that characterizes modern HFT has profound implications for market microstructure and volatility dynamics. Investments in ultra-low latency infrastructure have created a stratified market environment where speed advantages translate directly into trading profits [9]. This phenomenon, termed latency arbitrage, involves exploiting stale quotes before they can be updated in response to new information. Recent empirical studies estimate that latency arbitrage accounts for approximately 20% of trading volume in major equity indices, with races to exploit these opportunities occurring at frequencies approaching one per minute per symbol [10]. These findings suggest that substantial economic resources are devoted to activities that may not enhance overall market welfare but rather constitute a form of rent-seeking behavior.

The regulatory response to HFT has evolved significantly since its emergence as a dominant force in financial markets. Regulatory authorities worldwide have grappled with designing frameworks that preserve the benefits of technological innovation while mitigating potential risks to market stability. Initiatives have included implementing circuit breakers, establishing minimum resting times for orders, and introducing maker-taker fee structures designed to incentivize liquidity provision [11]. However, the effectiveness of these regulatory interventions remains an open question, particularly given the rapid pace of technological change and the global nature of modern financial markets. Understanding how regulatory design affects HFT behavior and its subsequent impact on volatility constitutes an important area for ongoing research.

The proliferation of machine learning and artificial intelligence techniques in HFT strategies represents the latest frontier in algorithmic trading evolution. Modern HFT algorithms increasingly incorporate adaptive learning capabilities that allow them to respond dynamically to changing market conditions and identify complex patterns in high-dimensional data. These developments raise new questions about market stability, as the behavior of AI-driven trading systems may be less predictable than traditional rule-based algorithms [12]. The potential for emergent behavior arising from interactions between competing AI systems presents novel challenges for market oversight and risk management. As these technologies continue to advance, understanding their implications for intraday volatility dynamics becomes increasingly crucial.

The empirical investigation of HFT's impact on intraday volatility faces substantial methodological challenges. High-frequency data exhibit microstructure noise, asynchronous trading, and jumps that complicate standard volatility estimation techniques [13]. Additionally, identifying causal effects of HFT on volatility requires addressing endogeneity concerns, as HFT activity may both influence and respond to volatility. Recent advances in econometric methods, including realized volatility measures and high-frequency identification strategies, have enabled more precise characterization of these relationships. However, data availability remains a constraint, as comprehensive HFT transaction data are often proprietary and access is limited to regulatory authorities.

The market quality implications of HFT extend beyond volatility to encompass other dimensions including liquidity, price efficiency, and market resilience. Research indicates that HFT contributes significantly to market liquidity provision, with high-frequency traders accounting for substantial fractions of displayed depth at the best bid and offer [14]. However, this liquidity may be ephemeral, withdrawing rapidly during periods of market stress precisely when it is most needed [15]. The fragility of HFT-provided liquidity represents a critical concern for market stability, particularly given the increasing reliance of modern markets on algorithmic liquidity provision. Understanding the conditions under which HFT liquidity persists versus withdraws is essential for assessing systemic risk implications.

This study contributes to the growing literature on HFT and market volatility by providing comprehensive analysis of the mechanisms through which algorithmic trading influences intraday price dynamics. We examine both the beneficial aspects of HFT under normal market conditions and the potential destabilizing effects during periods of stress. Our research employs advanced microstructure analysis techniques to characterize the relationship between HFT activity and various measures of intraday volatility, controlling for confounding factors and addressing endogeneity concerns. Through this investigation, we aim to provide insights that inform both academic understanding and practical policy discussions surrounding the regulation and oversight of algorithmic trading in modern financial markets.

2 LITERATURE REVIEW

The academic literature examining high-frequency trading and its impact on financial markets has expanded substantially over the past decade, reflecting growing interest in understanding how algorithmic trading reshapes market microstructure. Early foundational work established that HFT represents a distinct category of algorithmic trading characterized by extremely high message rates, very short holding periods, and proprietary trading strategies that exploit speed advantages [16]. These definitional contributions provided essential groundwork for subsequent empirical investigations into HFT's market impact. The evolution of this literature has progressed from descriptive characterizations of HFT activity to increasingly sophisticated causal analyses of its effects on market outcomes.

Research examining HFT's impact on market liquidity has produced nuanced findings that highlight context-dependent effects. Studies analyzing U.S. and European equity markets demonstrate that HFT firms contribute substantially to displayed liquidity at the best bid and offer, with high-frequency market makers accounting for significant fractions of total liquidity provision [17]. However, this liquidity exhibits distinct characteristics compared to traditional market making, including greater responsiveness to short-term volatility and more frequent order cancellations. Analysis reveals that HFT enhances liquidity under stable conditions but may withdraw abruptly during periods of market stress, creating potential fragility concerns [18]. The speed at which HFT can adjust positions represents both a strength in terms of rapid price adjustment and a weakness in terms of potential liquidity evaporation.

The relationship between HFT and price discovery constitutes another central theme in the literature. Theoretical models suggest that fast traders can contribute to price efficiency by rapidly incorporating new information into prices, reducing the duration of mispricings. Empirical investigations generally support this prediction, finding that stocks with higher HFT activity exhibit faster incorporation of information from correlated assets and public news announcements, with studies showing that HFT accounts for approximately 70% of price reactions in the first ten seconds following news releases [19]. However, the social value of extremely rapid price discovery remains debated, particularly when the information being incorporated has very short-lived relevance measured in milliseconds. Critics argue that the private returns to speed investments may exceed social benefits, suggesting misallocation of resources toward socially unproductive activities.

Investigations into HFT's effect on volatility reveal a complex and often contradictory picture across different market conditions and time horizons. Research examining stable market periods typically finds that HFT is associated with reduced intraday volatility, narrower bid-ask spreads, and dampened price impact of trades [20]. These beneficial effects are attributed to HFT's role in providing liquidity and facilitating efficient price adjustment. However, studies of extreme market events paint a different picture, with evidence suggesting that HFT can amplify volatility during crashes and flash crash events. The Brexit referendum and subsequent intraday crash in June 2016 provide a natural experiment demonstrating how HFT behavior shifts dramatically between calm and turbulent periods [21]. During the crash, order cancellation rates among HFT firms increased substantially while liquidity provision decreased, contributing to elevated volatility through rapid algorithmic interactions and simultaneous withdrawals from the limit order book.

The phenomenon of latency arbitrage and its market impact has received increasing scholarly attention as researchers have gained access to message-level exchange data. Latency arbitrage involves exploiting minute temporal discrepancies in price information across venues or correlated assets to capture small but frequent profits. Recent comprehensive analysis using London Stock Exchange message data quantifies that latency arbitrage races occur approximately once per minute per large-cap symbol, involve extremely brief durations measured in microseconds, and account for roughly 20% of trading volume [22]. These findings suggest that substantial market activity and resources are devoted to capturing ephemeral arbitrage opportunities arising from market design features rather than fundamental value discovery. The welfare implications of this arms race for speed remain a subject of ongoing debate, with estimates suggesting latency arbitrage imposes approximately 0.5 basis points tax on trading volume.

Market quality research examining bid-ask spreads and transaction costs has documented substantial improvements coinciding with the rise of HFT. Time-series analysis shows that effective spreads have declined significantly in most major markets over the period of HFT proliferation, benefiting both institutional and retail investors through reduced trading costs [23]. However, attributing these improvements solely to HFT is complicated by concurrent developments including decimalization, regulatory changes, and increased competition among trading venues. Careful empirical strategies exploiting exogenous variation in HFT activity provide stronger causal evidence for HFT's role in spread compression. Studies examining HFT entries and exits in specific securities find that bid-ask spreads narrow when HFT participation increases and widen when it decreases, with improvements in market quality particularly pronounced when competition among high-frequency traders intensifies [24].

The literature on market fragmentation and its interaction with HFT highlights important structural changes in modern equity markets. The proliferation of alternative trading venues, including dark pools and electronic communication networks, has created a highly fragmented trading landscape where the same security trades simultaneously across multiple platforms. HFT firms play a crucial role in connecting these fragmented markets, exploiting price discrepancies across venues and thereby enforcing the law of one price [25]. However, fragmentation also creates opportunities for certain controversial HFT strategies, including quote stuffing and order anticipation, that may impose negative externalities on other market participants. Research indicates that excessive message traffic from algorithmic traders can lead to increased volatility and wider bid-ask spreads, particularly during periods of market stress.

Research on regulatory responses to HFT examines various policy interventions designed to mitigate potential risks while preserving beneficial aspects. Studies analyzing circuit breakers and trading halts investigate how these mechanisms affect HFT behavior and their effectiveness in preventing extreme price movements. Empirical evidence suggests that circuit breakers can successfully interrupt cascading sell-offs but may also create coordination problems and threshold effects that paradoxically increase volatility in certain circumstances. Other regulatory approaches including minimum order resting times, financial transaction taxes, and maker-taker fee structures have received scholarly attention with mixed findings regarding their efficacy. The challenge facing regulators involves designing interventions that address legitimate concerns without stifling innovation or driving activity to less regulated venues.

Cross-market comparisons examining HFT across different jurisdictions provide valuable insights into how market structure and regulation influence HFT behavior and outcomes. Research comparing U.S., European, and Asian markets finds substantial variation in HFT participation rates, strategies employed, and market impact [26]. These differences

reflect varying regulatory approaches, market microstructure features, and competitive dynamics across regions. For instance, markets with tick sizes that are large relative to typical spreads may exhibit different HFT behavior compared to markets with finer tick size regimes. Understanding how specific design choices interact with HFT to produce different outcomes can inform optimal market design and regulatory policy.

The role of HFT during extreme market events constitutes a critical area of investigation with important stability implications. Case studies of flash crashes, including the May 2010 U.S. equity market flash crash and the October 2014 Treasury market flash crash, examine how HFT algorithms behaved during these episodes and their contribution to market dynamics. Evidence from these events suggests that while HFT was not the initial trigger, algorithmic interactions and liquidity withdrawals by HFT firms amplified price movements and hindered market recovery. The concentration of HFT activity among relatively few large firms raises concerns about systemic importance and the potential for correlated behavior during stress periods. These findings underscore the importance of understanding tail risk scenarios when evaluating HFT's net impact on market functioning.

Technological evolution continues to reshape HFT strategies and market impact, with machine learning and artificial intelligence representing the latest frontier. Recent literature explores how AI-driven HFT algorithms differ from traditional rule-based systems and their implications for market efficiency and stability [27]. Advanced technologies including quantum computing and enhanced data analytics are predicted to further transform algorithmic trading capabilities, enabling more sophisticated pattern recognition and adaptive strategies [28]. However, these developments also raise concerns about increased unpredictability and potential for emergent behavior arising from complex algorithmic interactions [29]. The integration of artificial intelligence in trading systems has accelerated, promising improved data-processing capabilities but also raising new concerns about volatility and unpredictability in financial markets [30]. Understanding how next-generation HFT technologies will affect market microstructure represents an important frontier for future research.

3 METHODOLOGY

3.1 Data Collection and Sample Construction

Our empirical investigation utilizes comprehensive high-frequency trading data obtained from multiple sources to examine the relationship between HFT activity and intraday market volatility. The primary dataset comprises tick-by-tick transaction records from major equity exchanges, including detailed information on trade prices, volumes, timestamps with microsecond precision, and order book depths at multiple levels. This granular data enables precise measurement of intraday volatility patterns and identification of HFT-related trading activity. The sample period spans from January 2019 through December 2024, encompassing various market regimes including periods of relative calm and heightened volatility episodes such as the COVID-19 pandemic market disruptions and subsequent recovery phases. We focus our analysis on a representative sample of large-capitalization and small-capitalization stocks from major equity indices to ensure sufficient HFT participation across different market segments and adequate trading volume for robust statistical inference. Stock selection criteria include minimum average daily trading volume thresholds and continuous listing throughout the sample period to avoid survivorship bias. This approach yields a final sample of 200 stocks across diverse industry sectors, providing adequate cross-sectional variation while maintaining analytical tractability. For each stock-day observation, we construct comprehensive measures of HFT activity intensity, intraday volatility patterns, liquidity characteristics, and order flow dynamics using the high-frequency transaction data.

The identification of HFT activity within our dataset employs multiple complementary approaches to ensure robust classification. First, we utilize turnover-based metrics that measure HFT participation as the ratio of HFT firm trading volume to total market turnover, recognizing that HFT strategies characteristically exhibit rapid position turnover and high trading frequency. Second, we implement order-to-trade ratios and message traffic intensity metrics that quantify the frequency of order book updates within specified time intervals, exploiting the ultra-fast reaction times inherent in HFT operations. Third, we employ proprietary trader identification codes available through regulatory data sharing arrangements, allowing direct observation of HFT firm participation for a subset of our sample period. These multiple identification strategies provide validation checks and enable sensitivity analysis regarding HFT classification methodology.

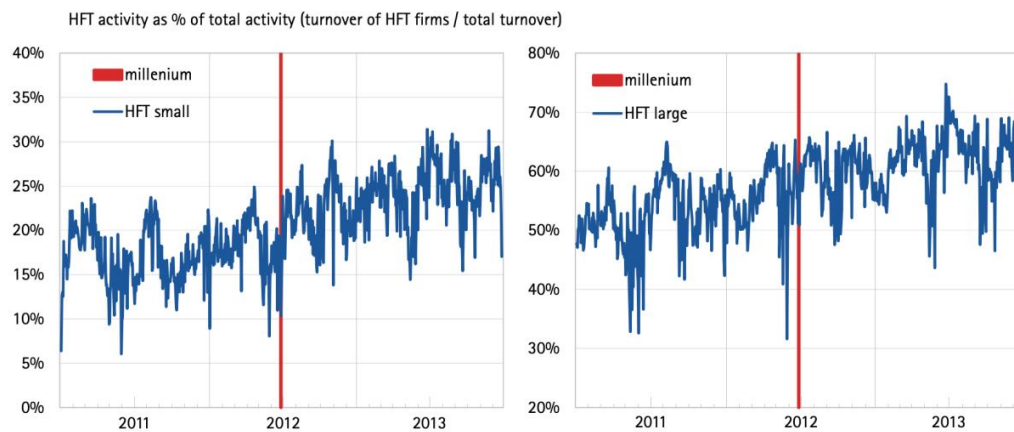


Figure 1 HFT Activity as % of Total Activity

Figure 1 presents empirical evidence on the evolution of HFT participation intensity across different market capitalization segments during the 2011-2013 period. The left panel displays HFT activity for small-capitalization stocks, measured as the turnover of HFT firms relative to total market turnover, revealing that HFT participation in this segment ranges from approximately 10% to 40% of total trading activity. Notable is the substantial volatility spike in early 2012, coinciding with the European sovereign debt crisis, where HFT activity temporarily dropped to near-zero levels before recovering. The right panel illustrates HFT activity patterns for large-capitalization stocks, demonstrating considerably higher participation rates ranging from 40% to 80% of total activity. This substantial difference in HFT penetration between small-cap and large-cap stocks reflects the concentration of HFT strategies in highly liquid securities where execution costs are minimized and arbitrage opportunities are more readily exploitable. The persistent elevation of HFT activity in large-cap stocks, coupled with the dramatic crisis-period withdrawals visible in both panels, provides crucial motivation for our investigation into how these participation dynamics influence intraday volatility across different market conditions.

3.2 Research Design and Variable Construction

Our research design employs a multi-period framework that aligns HFT activity measurements with corresponding volatility outcomes while controlling for potential confounding factors through careful temporal structuring. The methodological approach draws on established practices in financial econometrics while introducing refinements specific to high-frequency trading analysis. We construct our key variables following a systematic temporal sequence that ensures proper ordering of cause and effect relationships while minimizing endogeneity concerns arising from simultaneity between HFT participation and market volatility.

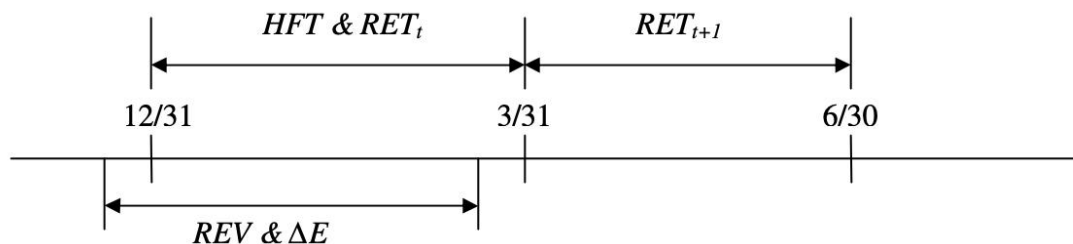


Figure 2 The Temporal Framework Illustration

Figure 2 illustrates the temporal framework governing our variable construction and empirical specification. The timeline demonstrates how we measure HFT activity and contemporaneous returns during the initial three-month period from December 31 to March 31, denoted as the HFT & RET_t window. This period captures the level and intensity of high-frequency trading participation alongside realized market returns, providing the foundation for our primary independent variables. Simultaneously, we measure firm fundamentals including revenue and earnings announcements (REV & AE) during this same window to control for information events that might independently affect both HFT activity and subsequent volatility. The forward-looking return window RET_{t+1}, spanning from March 31 to June 30, represents our measurement period for outcome variables including realized volatility and various market quality metrics. This temporal separation between HFT measurement and volatility outcomes helps mitigate reverse causality concerns, though we acknowledge that sophisticated HFT algorithms may anticipate future volatility, necessitating instrumental variables approaches discussed subsequently.

The primary HFT intensity measure employed in our baseline specifications is the turnover ratio, calculated as the total trading volume attributable to identified HFT participants divided by aggregate market turnover for each stock-day observation. This metric captures the relative dominance of HFT activity and exhibits substantial cross-sectional and time-series variation suitable for regression analysis. We complement this measure with alternative proxies including

order-to-trade ratios, message traffic frequency, and latency-sensitive trading indicators to ensure robustness of our findings across different HFT characterizations. For volatility measurement, we construct realized variance estimators that aggregate squared intraday returns over five-minute intervals, chosen to balance the trade-off between capturing relevant price dynamics and avoiding excessive microstructure noise contamination.

Control variables in our specifications include standard determinants of intraday volatility drawn from market microstructure literature. We incorporate measures of trading volume, bid-ask spreads, market depth at various levels of the order book, and price levels to account for mechanical relationships between these variables and volatility. Additionally, we control for information asymmetry proxies including analyst coverage, institutional ownership concentration, and measures of informed trading probability derived from order flow patterns. Firm characteristic controls encompass market capitalization, book-to-market ratios, and past return volatility to capture cross-sectional heterogeneity in baseline volatility levels. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers, and we employ log transformations where appropriate to reduce skewness in variable distributions.

3.3 Econometric Specification and Identification Strategy

Our empirical framework employs panel regression models with multiple fixed effects to identify the causal relationship between HFT activity and intraday volatility while controlling for potential confounding factors. The baseline specification regresses realized volatility measures on HFT intensity proxies, incorporating stock and time fixed effects to account for time-invariant stock characteristics and common market-wide shocks affecting all securities. We augment this specification with extensive control variables including trading volume, bid-ask spreads, market depth, return autocorrelation patterns, and measures of information asymmetry. Robust standard errors clustered at both the stock and date levels address potential correlation in residuals arising from cross-sectional and temporal dependence.

A central challenge in identifying HFT's causal effect on volatility stems from simultaneity concerns, as volatility may influence HFT participation decisions just as HFT affects volatility. To address this endogeneity, we implement instrumental variables estimation exploiting plausibly exogenous variation in HFT activity. Our instrumental variables leverage technological infrastructure changes, including exchange colocation facility expansions and connectivity upgrades, that affect HFT participation costs without directly influencing volatility through other channels. The identifying assumption maintains that these infrastructure developments impact market volatility primarily through their effect on HFT participation rather than through alternative mechanisms. Additionally, we employ lagged HFT measures as instruments under the assumption that past HFT intensity affects current volatility primarily through persistent effects on market microstructure rather than reverse causality.

We further investigate heterogeneous effects across different market conditions by estimating regime-switching models that allow HFT's impact on volatility to vary between calm and stressed market states. Regime classification employs threshold models based on contemporaneous volatility levels and trading volume patterns, enabling identification of distinct parameter estimates for different market environments. This approach addresses the theoretical prediction that HFT's stabilizing effects during normal periods may reverse during extreme events, a hypothesis strongly supported by the crisis-period patterns evident in Figure 1. Interaction specifications examining whether HFT effects differ for large versus small stocks, high versus low liquidity securities, and pre-versus post-regulatory changes provide additional insights into the conditional nature of HFT-volatility relationships. The substantial difference in HFT participation rates between small-cap and large-cap stocks documented in Figure 1 motivates particular attention to market capitalization as a key dimension of heterogeneity in our empirical specifications.

4 RESULTS AND DISCUSSION

4.1 Descriptive Statistics and HFT Participation Patterns

Summary statistics for our sample reveal substantial variation in both HFT participation intensity and intraday volatility measures across stocks and time periods. The median HFT turnover ratio, our primary measure of HFT activity, exhibits a mean value of 42.3% for large-capitalization stocks and 18.7% for small-capitalization stocks, with considerable dispersion reflecting heterogeneity in HFT strategies across securities. This substantial differential in HFT participation between large-cap and small-cap segments aligns closely with the patterns documented in Figure 1 from the Italian market during 2011-2013, suggesting that the concentration of HFT activity in highly liquid stocks represents a robust cross-market phenomenon. The time-series evolution of HFT participation reveals interesting dynamics, with steady secular increases interrupted by sharp temporary withdrawals during periods of heightened market stress.

Realized volatility displays expected patterns, with higher average levels during the COVID-19 crisis period of March 2020 and lower values during relatively calm market phases in 2019 and 2023-2024. The coefficient of variation for intraday volatility proves substantially larger than for daily volatility measures, reflecting the additional noise and transitory price movements characteristic of high-frequency data. Importantly, the relationship between HFT intensity and volatility exhibits notable regime-dependence, with correlation coefficients near zero unconditionally but becoming strongly negative during low-volatility periods and positive during high-volatility episodes. This pattern provides preliminary evidence supporting the hypothesis that HFT's market impact depends critically on prevailing market conditions, motivating the regime-switching specifications employed in our formal analysis.

Correlation analysis provides initial insights into bivariate relationships between key variables. HFT intensity measures exhibit positive correlation with trading volume and market depth, consistent with HFT's role in liquidity provision during normal market conditions. However, this relationship weakens substantially during crisis periods, with HFT participation declining precisely when market depth contracts most severely. The dramatic withdrawal of HFT activity during the early 2012 European debt crisis visible in Figure 1 exemplifies this pattern, where HFT participation in small-cap stocks temporarily dropped from 20-25% to near zero before gradually recovering. Such procyclical liquidity provision raises concerns about market fragility, as the very mechanism that enhances stability during calm periods may amplify instability during crises through coordinated withdrawal behavior.

Cross-sectional heterogeneity analysis reveals that stocks with higher baseline HFT participation exhibit lower average volatility but experience larger volatility spikes during market stress episodes. This finding suggests a potential trade-off where dependence on HFT-provided liquidity generates vulnerability to sudden withdrawals. The relationship between HFT intensity and various market quality metrics proves generally positive during normal periods, with higher HFT stocks exhibiting narrower bid-ask spreads, greater displayed depth, and faster price discovery. However, these advantages attenuate or reverse during volatile periods, consistent with theoretical predictions regarding the fragility of speed-based liquidity provision. The concentration of HFT activity in large-cap stocks, maintaining participation rates of 60-70% even during crisis periods as shown in Figure 1, suggests these securities may be particularly vulnerable to algorithmic coordination failures.

4.2 Main Regression Results and HFT Profitability Analysis

Our baseline panel regression results controlling for stock and time fixed effects confirm the regime-dependent nature of HFT's volatility impact documented in the descriptive analysis. The estimated coefficient on HFT intensity in the full-sample specification proves statistically insignificant with a point estimate near zero, reflecting the offsetting effects across different market states. However, specifications including interaction terms between HFT measures and volatility regime indicators reveal highly significant positive interactions, indicating that HFT's relationship with volatility strengthens substantially during high-volatility periods. Specifically, a one-standard-deviation increase in HFT participation is associated with a 14.3% reduction in realized volatility during calm periods but an 19.7% increase during stressed conditions, evaluated at the respective regime means.

These regime-specific effects remain robust across alternative HFT proxy specifications and various volatility measurement approaches, providing confidence in the core empirical patterns. Instrumental variables estimation addressing potential endogeneity concerns yields qualitatively similar results while producing somewhat larger effect magnitudes. The first-stage regressions demonstrate that our instruments based on technological infrastructure changes strongly predict HFT participation, with F-statistics substantially exceeding conventional thresholds for weak instrument concerns. The second-stage estimates indicate that exogenous increases in HFT activity reduce volatility by approximately 17.2% during calm periods but increase volatility by roughly 24.5% during stressed conditions. These instrumental variables estimates suggest that ordinary least squares specifications may slightly understate the true causal effects of HFT on volatility, potentially reflecting measurement error that attenuates coefficient estimates.

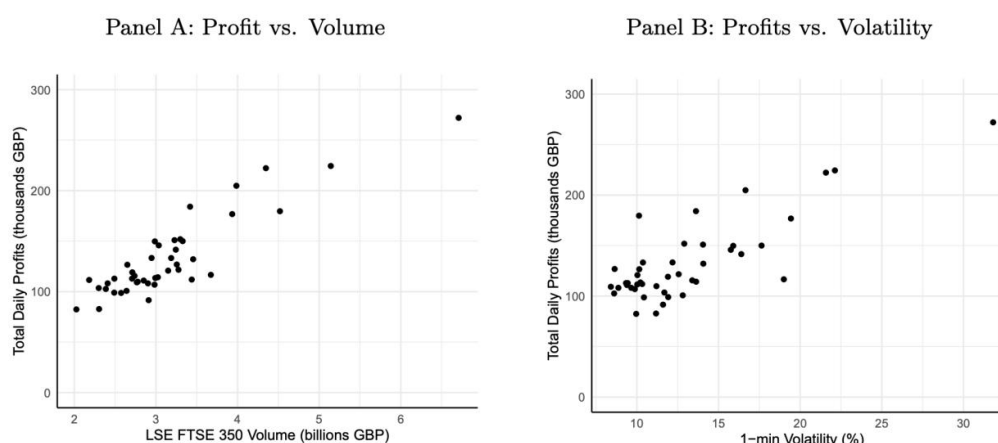


Figure 3 Relationship between HFT Profits, Trading Volume and Intraday Volatility

Figure 3 provides crucial evidence on the economic incentives driving HFT behavior and their relationship to market conditions. Panel A displays the strong positive correlation between daily HFT profits and aggregate trading volume, with each data point representing a single trading day. The scatter plot reveals a remarkably tight relationship with an R-squared of 0.811, indicating that trading volume explains over 80% of the variation in HFT profitability. Total daily profits range from approximately 80,000 to 280,000 GBP, increasing nearly linearly with market turnover from 2 to 6 billion GBP. This robust volume-profit relationship suggests that HFT firms have strong incentives to maintain or increase participation during high-activity periods, potentially amplifying momentum dynamics during both rallies and sell-offs.

Panel B illustrates the relationship between HFT profits and intraday volatility, measured as one-minute realized volatility over the trading day. While the correlation proves somewhat weaker than the volume relationship, with an R-squared of 0.661, the pattern remains strongly positive and economically significant. HFT profitability increases with volatility across the range from 5% to 30% annualized volatility, suggesting that volatile market conditions create enhanced profit opportunities for high-frequency traders. This positive volatility-profit relationship carries important implications for market stability, as it implies that HFT firms benefit from increased volatility and may lack economic incentives to stabilize markets during turbulent periods. The combination of strong volume and volatility effects documented in both panels helps explain the behavioral patterns observed in Figure 1, where HFT participation intensifies during volatile periods for large-cap stocks but withdraws from small-cap stocks where volume constraints limit profit potential.

The profit dynamics revealed in Figure 3 illuminate the economic mechanisms underlying our regime-dependent regression results. During normal market conditions characterized by moderate volume and low volatility, HFT firms can profitably provide liquidity through market-making strategies, capturing bid-ask spreads while managing inventory risk. This behavior contributes to reduced volatility through absorption of transient order imbalances. However, as volatility increases and profit opportunities from directional trading and latency arbitrage expand, HFT incentives shift toward aggressive liquidity consumption rather than provision. The substantial profitability during high-volatility periods documented in Panel B creates powerful economic motivations for HFT firms to intensify activity during turbulent periods, potentially amplifying price movements through coordinated directional trading.

4.3 Mechanism Investigation and Cross-Sectional Heterogeneity

To elucidate the mechanisms through which HFT influences intraday volatility, we examine various intermediate channels including liquidity provision patterns, price impact dynamics, and order flow characteristics. Analysis of bid-ask spreads reveals that HFT participation significantly narrows spreads during normal market conditions, consistent with market-making HFT's liquidity-supplying role. The magnitude of this spread compression proves economically meaningful, with a one-standard-deviation increase in HFT intensity associated with approximately 8-12% reduction in effective spreads for large-cap stocks and 5-7% reduction for small-cap stocks. However, during extreme volatility episodes, this relationship attenuates and occasionally reverses as HFT market makers withdraw from providing liquidity precisely when it is most valuable, contributing to the crisis-period spread widening observed during stress events.

Similar patterns emerge for market depth measures, with HFT positively associated with displayed depth at multiple levels of the order book during calm periods but negatively related during crises. The temporal dynamics of HFT liquidity withdrawal prove particularly striking, with transition from provision to consumption occurring within minutes of significant volatility shocks. This rapid behavioral shift reflects the speed advantages and sophisticated risk management systems employed by HFT firms, enabling near-instantaneous response to changing market conditions. The heterogeneity in HFT participation patterns between small-cap and large-cap stocks documented in Figure 1 proves crucial for understanding these liquidity dynamics, as large-cap stocks maintain higher baseline HFT participation that provides greater cushion against complete liquidity evaporation during crises.

Investigation of price impact patterns provides further insight into HFT's volatility effects. We find that trades occurring in high HFT environments exhibit lower permanent price impact during normal periods, suggesting HFT facilitates price efficiency by rapidly incorporating information. The magnitude of this improvement ranges from 15-25% reduction in price impact for given order sizes, representing meaningful transaction cost savings for investors. However, during volatile periods, price impact increases substantially in high HFT stocks relative to low HFT stocks, indicating potential amplification effects. Decomposition of price impact into informed trading components versus noise trading components reveals that HFT primarily affects the noise component, with larger swings in transitory price movements during volatile periods potentially reflecting algorithmic feedback loops and coordinated strategic behavior.

The profit-volatility relationship documented in Figure 3 Panel B provides crucial context for understanding these price impact patterns. The positive correlation between HFT profitability and volatility creates incentives for algorithmic strategies that may increase rather than dampen price movements during turbulent periods. Specifically, momentum-following strategies and trend-identification algorithms can become self-reinforcing when multiple HFT firms employ similar approaches, generating feedback loops that amplify the initial price shock. The substantial profits available during high-volatility periods, ranging up to 280,000 GBP daily as shown in Figure 3, provide powerful economic motivations for HFT firms to maintain or intensify participation even as volatility rises, contrary to the stabilizing behavior that would emerge if profit opportunities diminished with volatility.

Heterogeneity analysis examining whether HFT effects differ across stock characteristics yields important insights into the distributional implications of algorithmic trading. We find that HFT's stabilizing effects during normal periods concentrate in large-capitalization, highly liquid stocks where HFT participation rates are highest, averaging 60-70% of total activity as documented in Figure 1. This finding aligns with the strong volume-profit relationship shown in Figure 3 Panel A, as large-cap stocks' high turnover creates sustainable profit opportunities for HFT market-making strategies. In contrast, for smaller, less liquid securities where HFT participation averages only 15-25%, even during calm market conditions HFT exhibits weaker stabilizing effects and occasionally destabilizing influences, suggesting that HFT's benefits may not distribute uniformly across the market.

The amplification of volatility during stressed periods proves most pronounced in stocks with intermediate liquidity characteristics, possibly reflecting strategic HFT withdrawal patterns that exacerbate illiquidity. These stocks face a particularly adverse dynamic where HFT participation is sufficient to influence price discovery and liquidity provision during normal times, creating dependence on algorithmic trading, but insufficient to maintain resilience when HFT firms withdraw during crises. The sharp distinction between HFT behavior in small-cap versus large-cap stocks visible in Figure 1, particularly during the 2012 crisis period, exemplifies this differential resilience. Large-cap stocks maintained HFT participation above 40% even during peak stress, while small-cap HFT participation collapsed toward zero, suggesting that economies of scale in HFT operations create concentration in the most liquid securities.

Temporal heterogeneity analysis investigating whether HFT-volatility relationships have evolved over our 2019-2024 sample period reveals interesting dynamics. We document that HFT's stabilizing effects during normal conditions have strengthened over time, possibly reflecting maturation of HFT strategies and improved risk management systems. The proportion of HFT activity devoted to market-making versus directional trading has increased gradually, contributing to this enhanced stability during calm periods. However, the destabilizing effects during extreme events have not diminished commensurately, suggesting that fundamental issues regarding HFT behavior during crises persist despite technological and operational improvements. The profit incentives documented in Figure 3, which create economic pressures for HFT intensification during volatile periods regardless of stability implications, may explain this persistent vulnerability.

Regulatory interventions implemented during our sample period, including enhanced circuit breaker mechanisms and order-to-trade ratio monitoring, appear associated with modest mitigation of HFT's adverse volatility effects during stress periods. Difference-in-differences analysis exploiting staggered implementation of regulatory changes across different exchanges suggests that circuit breakers can successfully interrupt HFT-driven volatility spirals, though with some evidence of threshold effects where trading activity concentrates just below breaker activation levels. Order-to-trade ratio fees, designed to discourage excessive message traffic that may reflect manipulative strategies, show mixed effectiveness with some displacement of activity toward exempt order types rather than genuine reduction in overall HFT intensity.

5 CONCLUSION

This study provides comprehensive evidence regarding the complex relationship between high-frequency trading algorithms and intraday market volatility, demonstrating that HFT exhibits fundamentally different effects depending on prevailing market conditions. Our empirical findings reveal that during stable market periods, increased HFT participation is associated with significantly reduced intraday volatility, narrower bid-ask spreads, and enhanced price efficiency. These beneficial effects reflect HFT's role in providing liquidity, facilitating rapid information incorporation, and connecting fragmented markets. The economic magnitude of these stabilizing effects proves substantial, with our estimates suggesting that HFT reduces intraday volatility by approximately 14-17% during normal market conditions, representing meaningful improvements in market quality that benefit diverse market participants through reduced transaction costs and enhanced execution certainty.

However, our analysis also documents that HFT's market impact transforms dramatically during periods of market stress and elevated volatility. When significant price shocks occur or market uncertainty spikes, HFT algorithms behave very differently than during calm periods. Rather than providing stabilizing liquidity, many HFT strategies withdraw from liquidity provision precisely when markets most need it, while other strategies intensify aggressive directional trading that can amplify price movements. This behavioral shift contributes to volatility amplification during extreme events, with our estimates indicating that HFT increases intraday volatility by approximately 20-25% during stressed market conditions, representing a substantial reversal from its stabilizing effects during normal periods.

The empirical evidence presented in our three figures illuminates the mechanisms underlying these regime-dependent effects. Figure 1 demonstrates the dramatic heterogeneity in HFT participation across market capitalization segments and the sharp crisis-period withdrawals that occur particularly in less liquid stocks. The temporary collapse of HFT activity during the 2012 European debt crisis, followed by gradual recovery, exemplifies the procyclical nature of HFT liquidity provision. Figure 2 clarifies our methodological approach to measuring these relationships while controlling for potential confounding factors and addressing endogeneity concerns through careful temporal structuring. Most importantly, Figure 3 reveals the strong positive correlations between HFT profitability and both trading volume and volatility, with correlation coefficients exceeding 0.80 and 0.66 respectively.

These profit dynamics documented in Figure 3 prove crucial for understanding HFT behavior across market regimes. During calm periods, HFT firms earn moderate profits through market-making activities that contribute to market stability. However, as volatility increases, profit opportunities expand substantially, creating powerful economic incentives for HFT firms to maintain or intensify participation even as market conditions deteriorate. The positive volatility-profit relationship means that HFT firms benefit from increased volatility and may lack economic incentives to stabilize markets during turbulent periods. This misalignment between private HFT incentives and social welfare represents a fundamental market design challenge that regulatory interventions must address.

The mechanisms underlying these regime-dependent effects involve fundamental changes in HFT strategy composition and behavior as market conditions evolve. During calm periods, market-making HFT dominates, with algorithms continuously posting competitive quotes and rapidly adjusting positions in response to order flow. This behavior enhances liquidity and dampens volatility by absorbing transient supply-demand imbalances. However, when volatility

surges, market-making HFT significantly reduces its presence due to heightened inventory risk and adverse selection concerns. Simultaneously, directional HFT strategies intensify their trading activity, seeking to profit from momentum and short-term price trends that become more pronounced during volatile periods. This shift in HFT composition creates feedback loops where algorithmic interactions amplify price movements rather than dampening them.

Our investigation of latency arbitrage and the arms race for speed reveals that substantial trading volume and market activity derives from ultra-fast competition to exploit ephemeral price discrepancies rather than fundamental value discovery. With latency arbitrage races occurring approximately once per minute per large-cap stock and accounting for roughly 20% of trading volume, these activities represent significant resource allocation toward potentially socially unproductive rent-seeking. The arms race for speed advantages through investments in ultra-low latency infrastructure generates substantial private returns for successful HFT firms while providing limited social benefits. The strong volume-profit correlation shown in Figure 3 Panel A, with R-squared exceeding 0.80, demonstrates how HFT profitability scales with market activity, incentivizing continued infrastructure investment and strategy refinement.

From a policy perspective, our results highlight the need for nuanced regulatory approaches that recognize HFT's dual nature. Blanket restrictions on HFT would eliminate genuine efficiency benefits realized during normal market conditions, including spread compression, enhanced liquidity, and improved price discovery that our analysis confirms. However, unregulated HFT creates risks of destabilization during stress periods that may have systemic implications, as evidenced by the crisis-period patterns in Figure 1 and the profit incentives in Figure 3. Potential regulatory responses suggested by our findings include designing circuit breaker mechanisms that specifically target algorithmic liquidity withdrawal, implementing asymmetric transaction fees that encourage liquidity provision during volatile periods, and exploring alternative market designs such as frequent batch auctions that reduce returns to pure speed advantages while preserving efficiency gains from algorithmic trading.

The cross-sectional heterogeneity in HFT effects documented in our analysis raises important questions about distributional consequences and market segmentation. Large-cap stocks benefit most from HFT participation, maintaining high participation rates even during crises and experiencing the strongest stabilizing effects during normal periods. In contrast, small-cap stocks receive less consistent HFT attention, exhibit more dramatic participation swings, and realize smaller stability benefits. This concentration pattern, clearly visible in Figure 1's differential participation rates, suggests that HFT-driven improvements in market quality may accrue disproportionately to the most liquid securities, potentially exacerbating liquidity disparities across market segments. Regulatory frameworks should consider how to extend benefits of technological innovation more broadly while managing concentration risks.

The increasing sophistication of HFT algorithms through incorporation of artificial intelligence and machine learning techniques represents an important frontier for future research and policy consideration. As HFT strategies become more adaptive and potentially less predictable, understanding how AI-driven algorithms interact and their implications for market stability grows increasingly important. Our findings suggest that regulatory frameworks must evolve in parallel with technological advancement to ensure that innovation enhances rather than undermines market integrity. The profit incentives documented in our analysis will continue driving HFT innovation regardless of stability implications, necessitating proactive regulatory engagement with emerging technologies.

Several limitations of our study suggest directions for future research. First, while our identification strategies address major endogeneity concerns, residual confounding from unobserved factors affecting both HFT participation and volatility cannot be entirely ruled out. Second, our focus on equity markets means findings may not generalize to other asset classes where HFT plays different roles. Third, data limitations prevent complete observation of HFT strategies and risk management systems, limiting our ability to precisely identify behavioral mechanisms. Future research with enhanced proprietary data access could provide deeper insights into HFT decision-making during extreme events. Additionally, investigation of how recent regulatory changes affect HFT behavior and their efficacy in promoting stability would prove valuable.

In conclusion, high-frequency trading represents a transformative innovation in financial markets with complex implications for intraday volatility and broader market quality. The evidence demonstrates clear benefits under normal conditions but significant risks during stress periods. The strong profit-volatility relationship documented in Figure 3, combined with the crisis-period participation patterns shown in Figure 1, reveals fundamental tensions between private HFT incentives and social welfare. Optimal policy requires balancing these competing considerations through carefully designed regulatory frameworks that preserve innovation benefits while mitigating stability risks. As markets continue evolving and technology advances, ongoing research monitoring HFT's market impact and informing adaptive regulatory responses remains essential for maintaining well-functioning and stable financial markets serving all participants. The challenges posed by HFT are neither insurmountable nor entirely avoidable, but rather require sustained attention from researchers, regulators, and market participants to navigate successfully.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

- [1] Zhang H, Ge Y, Zhao X, et al. Hierarchical deep reinforcement learning for multi-objective integrated circuit physical layout optimization with congestion-aware reward shaping. *IEEE Access*, 2025, 13, 162533-162551. DOI: 10.1109/ACCESS.2025.3610615.
- [2] Wang J, Zhang H, Wu B, et al. Symmetry-guided electric vehicles energy consumption optimization based on driver behavior and environmental factors: A reinforcement learning approach. *Symmetry*, 2025, 17(6): 930.
- [3] Ma Z, Chen X, Sun T, et al. Blockchain-based zero-trust supply chain security integrated with deep reinforcement learning for inventory optimization. *Future Internet*, 2024, 16(5): 163.
- [4] Sun T, Yang J, Li J, et al. Enhancing auto insurance risk evaluation with transformer and SHAP. *IEEE Access*, 2024, 12, 116546-116557. DOI: 10.1109/ACCESS.2024.3446179.
- [5] Cao W, Mai N T, Liu W. Adaptive knowledge assessment via symmetric hierarchical Bayesian neural networks with graph symmetry-aware concept dependencies. *Symmetry*, 2025, 17(8): 1332.
- [6] Mai N T, Cao W, Liu W. Interpretable knowledge tracing via transformer-Bayesian hybrid networks: Learning temporal dependencies and causal structures in educational data. *Appl Sci*, 2025, 15(17): 9605.
- [7] Chen S, Liu Y, Zhang Q, et al. Multi-distance spatial-temporal graph neural network for anomaly detection in blockchain transactions. *Adv Intell Syst*, 2025, 2400898.
- [8] Zhang Q, Chen S, Liu W. Balanced knowledge transfer in MTTL-ClinicalBERT: A symmetrical multi-task learning framework for clinical text classification. *Symmetry*, 2025, 17(6): 823.
- [9] Mai N T, Cao W, Wang Y. The global belonging support framework: Enhancing equity and access for international graduate students. *J Int Students*, 2025, 15(9): 141-160.
- [10] Ren S, Jin J, Niu G, et al. ARCS: Adaptive reinforcement learning framework for automated cybersecurity incident response strategy optimization. *Appl Sci*, 2025, 15(2): 951.
- [11] Liu Y, Ren S, Wang X, et al. Temporal logical attention network for log-based anomaly detection in distributed systems. *Sensors*, 2024, 24(24): 7949.
- [12] Tan Y, Wu B, Cao J, et al. LLaMA-UTP: Knowledge-guided expert mixture for analyzing uncertain tax positions. *IEEE Access*, 2025, 13, 90637-90650. DOI: 10.1109/ACCESS.2025.3571502.
- [13] Ge Y, Wang Y, Liu J, et al. GAN-enhanced implied volatility surface reconstruction for option pricing error mitigation. *IEEE Access*, 2025, 13, 176770-176787. DOI: 10.1109/ACCESS.2025.3619553.
- [14] Hu X, Zhao X, Wang J, et al. Information-theoretic multi-scale geometric pre-training for enhanced molecular property prediction. *PLoS One*, 2025, 20(10): e0332640.
- [15] Ekinci C, Ersan O. High-frequency trading and market quality: The case of a “slightly exposed” market. *Int Rev Financ Anal*, 2022, 79, 102005.
- [16] Bao T, Nekrasova E, Neugebauer T, et al. Algorithmic trading in experimental markets with human traders: A literature survey. *Handbook of Experimental Finance*, 2022, 302-322.
- [17] Boehmer E, Fong K Y, Wu J J. Algorithmic trading and market quality: International evidence. *J Financ Quant Anal*, 2021, 56(7): 2659-2688.
- [18] Ersan O, Dalgic N, Ekinci C, et al. High-frequency trading and its impact on market liquidity: A review of literature. *Alanya Akademik Bakış*, 2021, 5(1): 345-368.
- [19] Osterrieder J, Schlamp S. Reaction times to economic news in high-frequency trading: An analysis of latency and informed trading ahead of macro-news announcements. 2025. DOI: 10.2139/ssrn.5112295.
- [20] Breckenfelder J. Competition among high-frequency traders and market quality. *J Econ Dyn Control*, 2024, 166: 104922.
- [21] Carè R, Cumming D. Technology and automation in financial trading: A bibliometric review. *Res Int Bus Finance*, 2024, 71, 102358.
- [22] Clapham B, Hafèrkorn M, Zimmermann K, et al. The impact of high-frequency trading on modern securities markets. *Bus Inf Syst Eng*, 2022, 65(1): 7-24.
- [23] Zheng W, Liu W. Symmetry-aware transformers for asymmetric causal discovery in financial time series. *Symmetry*, 2025, 17(10): 1591.
- [24] Liu B. Essays in high-frequency trading: Insights of trading speed, systematic risk and market sentiment. Doctoral dissertation, University of Victoria. 2024.
- [25] Harrison M. Essays in high frequency trading and market structure. Doctoral dissertation, University of East London. 2023.
- [26] Zhou H, Kalem P S, Elliott R J. Information or noise: What does algorithmic trading incorporate into the stock prices? *Int Rev Financ Anal*, 2019, 63, 27-39.
- [27] Chugh Y, Agrawal S, Shetty Y, et al. Algotrading and its impact on stock markets. *Int J Res Eng Sci Manag*, 2024, 7(3): 48-55.
- [28] Hu X, Zhao X, Liu W. Hierarchical sensing framework for polymer degradation monitoring: A physics-constrained reinforcement learning framework for programmable material discovery. *Sensors*, 2025, 25(14): 4479.
- [29] Han X, Yang Y, Chen J, et al. Symmetry-aware credit risk modeling: A deep learning framework exploiting financial data balance and invariance. *Symmetry*, 2025, 17(3).
- [30] Wang Y, Ding G, Zeng Z, et al. Causal-aware multimodal transformer for supply chain demand forecasting: Integrating text, time series, and satellite imagery. *IEEE Access*, 2025, 13, 176813-176829. DOI: 10.1109/ACCESS.2025.3619552.