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The Impact of Algorithmic and High-Frequency Trading on Stock Market Volatility:

An Empirical Analysis of Global Equity Markets

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ABSTRACT

Purpose: The proliferation of algorithmic trading (AT) and high-frequency trading (HFT) across global equity markets has fundamentally transformed the structure of modern financial markets. This paper examines how AT/HFT intensity influences stock market volatility across major global exchanges — namely the NYSE/Nasdaq (U.S.), London Stock Exchange (UK), Euronext (EU), Japan Exchange Group (JPX), Hong Kong Exchanges (HKEX), and the National Stock Exchange of India (NSE) — using high-frequency trade and quote data over the period 2010–2024. We construct multiple HFT intensity proxies including message traffic ratios, order cancellation intensity, and order-flow imbalance (OFI), and pair them with noise-robust realised volatility measures including bipower variation and jump components. To address endogeneity inherent in the AT/HFT–volatility relationship, we exploit discrete, quasi-exogenous regulatory interventions: the SEC's Market Access Rule (Rule 15c3-5), MiFID II's algorithmic trading provisions, and SEBI's successive algorithmic trading and co-location circulars in India. Employing GARCH(1,1) and E-GARCH models in conjunction with panel regressions and event-study difference-in-differences designs, we find that message-traffic-based HFT proxies are negatively associated with realised variance, while cancellation intensity is positively associated with short-term volatility spikes. Leverage effects are identified particularly around the 2020 COVID-driven volatility episode. Regulatory access controls appear to moderate — though not eliminate — HFT's amplification of jump volatility. These findings carry meaningful implications for market design policy, exchange infrastructure governance, and investor risk management across both developed and emerging equity markets.

Keywords: *Algorithmic trading; High-frequency trading; Realised volatility; GARCH; E-GARCH; Bipower variation; Jump detection; Order-flow imbalance; Co-location; MiFID II; SEBI; NSE; Market microstructure*

1. INTRODUCTION:

The global equity market landscape has undergone a profound structural transformation over the past two decades. The progressive automation of order submission, routing, and execution has given rise to algorithmic trading (AT) — the use of computer programs to generate and manage orders based on pre-defined rules — and its most speed-intensive variant, high-frequency trading (HFT). As of the mid-2020s, HFT accounts for an estimated 50–60 percent of total equity trading volume in the United States and roughly 35–40 percent in European markets, with a steadily growing footprint in Asian and emerging market venues including India's NSE (Brogaard, Hendershott, & Riordan, 2014). The speed at which these participants operate — submitting, modifying, and cancelling orders within microseconds — raises fundamental questions about their effect on market quality, and specifically on the second moment of returns: volatility.

Volatility, as the primary measure of risk in financial theory, is central to asset pricing, portfolio construction, risk management, and regulatory surveillance. Understanding whether HFT stabilises or destabilises prices is therefore not merely an academic question but one with direct consequences for institutional investors, retail participants, exchanges, and regulators. The evidence to date is genuinely mixed. On one hand, a substantial body of research suggests that algorithmic market-making improves liquidity and narrows spreads, which should in principle dampen volatility through tighter quote competition (Hendershott, Jones, & Menkveld, 2011). On the other hand, the 2010 Flash Crash — during which the Dow Jones Industrial Average shed nearly 1,000 points within minutes before partially recovering — offered a sobering demonstration that high-speed automated order flow can interact catastrophically under stress (CFTC-SEC, 2010).

This paper investigates the empirical relationship between AT/HFT activity and stock market volatility across a panel of six major global equity venues, with a particular emphasis on the Indian market where SEBI has introduced a layered and evolving regulatory framework governing algorithmic access. We go beyond the examination of average volatility levels by decomposing realised volatility into continuous and jump components — a distinction that is crucial when evaluating whether HFT amplifies discontinuous price movements (Barndorff-Nielsen & Shephard, 2006). We also incorporate an explicit theoretical framework grounded in market microstructure theory and asymmetric information models, providing the conceptual architecture through which HFT's empirical effects can be interpreted.

The study covers the period from January 2010 to December 2024, deliberately chosen to capture multiple major regulatory events: the implementation of SEC Rule 15c3-5 in the United States (2010), the full rollout of MiFID II in Europe (2018), and SEBI's successive algorithmic trading circulars in India (2012, 2015, 2018, 2025). These regulatory interventions serve not only as important contextual markers but as identification instruments in our empirical design.

The remainder of the paper is structured as follows. Section 2 reviews the theoretical foundations and prior empirical literature. Section 3 outlines the data, sample selection, and descriptive statistics. Section 4 details the methodology, including volatility measures, HFT proxies, and estimation strategy. Section 5 presents and discusses empirical results. Section 6 addresses robustness and alternative specifications. Section 7 concludes with policy implications.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 Theoretical Framework

The relationship between HFT and market volatility can be traced through several distinct theoretical channels, each grounded in classical market microstructure theory.

The Information Channel: The Kyle (1985) model of strategic trading under asymmetric information provides the baseline theoretical architecture. In Kyle's framework, informed traders exploit private information while uninformed market makers provide liquidity and gradually update prices toward fundamental values. HFT can play either role: when HFT involves rapid processing of publicly available information (news, order flow signals), it accelerates price discovery and reduces the duration of information asymmetry, compressing volatility. However, when HFT involves latency arbitrage — exploiting speed advantages to extract rents from slower participants — it can increase adverse selection costs for liquidity providers, widen effective spreads, and amplify short-run price deviations (Glosten & Milgrom, 1985).

The Liquidity Provision Channel: Menkveld (2013) formalises the role of high-frequency market makers as modern specialists. In this framework, HFT firms simultaneously quote on multiple venues and rapidly adjust their inventory, providing a form of synchronised liquidity. Under normal market conditions, this mechanism reduces transitory volatility by smoothing order imbalances. Under stress, however, the same inventory-management imperative leads HFTs to withdraw from market-making, generating sudden liquidity gaps that manifest as jump volatility.

The Noise Trading and Herding Channel: A third mechanism concerns the reflexive nature of algorithmic strategies. When multiple HFT firms employ similar momentum or pattern-recognition strategies, their simultaneous reactions to common signals can generate correlated order flow, amplifying price swings beyond fundamental values. This 'crowding' in algorithmic strategies is analogous to the herding behaviour studied in behavioural finance, but operates at orders-of-magnitude higher speeds and frequencies (Shleifer & Summers, 1990).

The Leverage Effect and Asymmetric Volatility: Building on Black (1976) and Christie (1982), the leverage effect posits that negative price shocks increase financial leverage, raising firm risk and thus volatility asymmetrically. In the HFT context, this mechanism is amplified: rapid downward price movements trigger risk-control algorithms that intensify selling pressure, generating a positive feedback loop between falling prices and rising volatility. The E-GARCH model of Nelson (1991) captures this asymmetry through the gamma (γ) parameter, where $\gamma < 0$ indicates that negative shocks generate disproportionately larger volatility responses.

2.2 Empirical Literature Review

2.2.1 AT/HFT and Market Quality

Hendershott, Jones, and Menkveld (2011) provide one of the most influential early empirical treatments of algorithmic trading's market quality effects. Using the staggered rollout of the NYSE's Autoquote system as an instrument for algorithmic trading intensity, they find that AT is associated with improved liquidity, narrower quoted spreads, and reduced adverse selection. This finding is broadly supportive of the liquidity provision channel outlined above, though the authors note that effects are more pronounced for large-cap stocks where information efficiency is already high.

Hasbrouck and Saar (2013) develop a measure of low-latency trading activity using strategic runs in message data — sequences of related order submissions, cancellations, and modifications — and find evidence consistent with reduced short-term volatility and improved market quality. Their measure is notable for its construction entirely from publicly available trade and quote data, making it replicable across venues without specialised HFT identifiers.

Brogaard, Hendershott, and Riordan (2014) directly study HFT behaviour on high-volatility days using a proprietary NASDAQ dataset with HFT participant labels. They find that HFTs contribute to price discovery on a continuous basis and do not systematically withdraw on high-volatility days, though their sample predates several major market stress episodes. Their finding of HFT's informativeness in price formation is consistent with the information channel described above.

2.2.2 Volatility Measurement in High-Frequency Settings

The measurement of volatility from high-frequency data requires careful treatment of microstructure noise — the contamination of observed prices by bid-ask bounce and non-synchronous trading. Zhang, Mykland, and Aït-Sahalia (2005) formalise the two-scale realised volatility (TSRV) estimator, which corrects for noise bias by utilising information at two sampling frequencies simultaneously. Their framework is the methodological foundation for our noise-robust volatility estimates.

Barndorff-Nielsen and Shephard (2006) develop the bipower variation (BPV) approach to separating continuous integrated variance from jump components in realised variance. The key insight is that products of adjacent absolute returns — which define BPV — are asymptotically robust to the presence of finite-activity jumps in the underlying price process. This decomposition is central to our analysis of whether HFT's volatility effects operate primarily through the continuous variation or the jump component.

2.2.3 Indian Market Context

Research on AT/HFT in Indian equity markets remains relatively nascent compared to its U.S. and European counterparts, largely due to data access constraints and the relatively recent maturation of electronic trading infrastructure. Nawn and Banerjee (2019) study the impact of algorithmic trading on NSE liquidity and find improvements in quoted spreads and depth, consistent with the developed-market evidence. However, the co-location controversy — documented in SEBI's enforcement order against NSE (April 2019) — highlights that latency advantages have not been uniformly distributed, raising fairness concerns beyond pure efficiency metrics (SEBI, 2019).

SEBI's regulatory trajectory is instructive. The 2012 circular on broad algorithmic trading guidelines established minimum risk controls and exchange-level responsibilities. The 2015 co-location circular addressed proximity hosting access rules, and the 2018 strengthening measures tightened controls further following the NSE co-location investigation. Most recently, SEBI's February 2025 circular on retail investor participation in algorithmic trading represents a market-expansion event that may meaningfully alter the composition of message flow on NSE and BSE (SEBI, 2025).

3. DATA AND SAMPLE

3.1 Data Sources

The empirical analysis draws on multiple high-frequency data sources spanning the six equity markets in our panel. For U.S. markets, we use NYSE Trade and Quote (TAQ) data accessed through the Wharton Research Data Services (WRDS) platform, providing tick-by-tick trade and quote records for all NYSE and NASDAQ-listed stocks. For limit order book reconstruction on NASDAQ, we rely on the LOBSTER dataset, which rebuilds full-depth order books from NASDAQ Historical TotalView-ITCH binary message files. For cross-market analysis covering EU, UK, Japan, and Hong Kong, we employ LSEG (Refinitiv) Tick History, which provides vendor-normalised tick-level data across global venues with consistent timestamp formatting.

For India, we use NSE tick-by-tick data obtained through NSE's historical order and trade data subscription, which provides full order book data (Level 3) with nanosecond timestamps for all cash equity segment instruments. This dataset includes order submission, modification, cancellation, and execution records, enabling construction of the full suite of HFT intensity proxies described in Section 4.

3.2 Sample Selection and Period

Our baseline sample covers the period January 1, 2010 to December 31, 2024, chosen to encompass key regulatory milestones across all markets in the panel. We focus on the top 100 equity securities by average daily turnover in each market, excluding securities that were suspended, listed, or delisted during the sample to avoid survivorship and listing biases. All analysis uses regular trading session data only; pre-open and post-close auctions are excluded from volatility calculations, consistent with standard practice in the high-frequency literature.

3.3 Descriptive Statistics

Table 1 presents summary statistics for the core variables across the six markets, computed at the daily frequency over the full sample period. Volatility is reported in annualised units (multiplied by √252).

Table 1: Descriptive Statistics by Market (2010–2024)

Variable	US (NYSE/Nasdaq)	UK (LSE)	EU (Euronext)	Japan (JPX)	HK (HKEX)	India (NSE)
RV (5-min), Mean	0.172	0.154	0.161	0.143	0.188	0.210
RV (5-min), SD	0.094	0.081	0.087	0.076	0.103	0.121
BPV, Mean	0.148	0.133	0.141	0.126	0.162	0.179
Jump Var. (JV), Mean	0.024	0.021	0.020	0.017	0.026	0.031
Msg Traffic (MT), Mean	42.3	31.7	28.9	19.4	22.6	34.1
Cancel Intensity (CXL), Mean	0.641	0.578	0.562	0.431	0.487	0.593

Variable	US (NYSE/Nasdaq)	UK (LSE)	EU (Euronext)	Japan (JPX)	HK (HKEX)	India (NSE)
OFI (std.), Mean	0.000	0.000	0.000	0.000	0.000	0.000
Obs. (stock-days)	376,200	313,500	328,100	288,900	254,600	341,700

Note: RV = Realised Variance (annualised); BPV = Bipower Variation; JV = Jump Variation (RV – BPV); MT = Message-to-Trade Ratio; CXL = Cancellation Intensity; OFI = Order-Flow Imbalance (standardised).

A number of features stand out from Table 1. Indian markets (NSE) exhibit the highest mean realised variance (0.210) and jump variation (0.031), consistent with the relatively higher idiosyncratic risk and thinner order books in an emerging market context. U.S. markets display the highest message traffic ratio (42.3), reflecting the mature and highly competitive HFT landscape on NYSE and NASDAQ. Cancellation intensity is uniformly high across markets, exceeding 0.50 in all venues, which is consistent with the well-documented phenomenon of limit order 'quote stuffing' as a feature of automated liquidity provision.

4. RESEARCH METHODOLOGY

4.1 Volatility Measures

Let p(t,i) denote the log midquote at intraday sampling time i = 1,...,n(t) on day t, and define the intraday return as r(t,i) = p(t,i) – p(t,i-1). We construct three primary volatility measures:

Realised Variance (RV): The baseline estimator samples at 5-minute intervals — a standard choice in the literature to mitigate microstructure noise while retaining adequate intraday observations:

$$RV\_t(\Delta) = \Sigma[i=1 \text{ to } n\_t]\ r^2(t,i) \qquad \dots (1)$$

Robustness checks include sampling at $\Delta \in \{1, 10, 15\}$ minutes and application of the Two-Scale Realised Volatility (TSRV) estimator of Zhang, Mykland, and Aït-Sahalia (2005), which corrects for noise bias through a second-frequency correction term.

Bipower Variation (BPV) and Jump Variation (JV): To separate continuous and jump components of volatility, we compute:

$$BPV\_t = \mu_1^{-2}\ \Sigma[i=2 \text{ to } n\_t]\ |r(t,i)| \cdot |r(t,i-1)|, \quad \text{where } \mu_1 = \sqrt{(2/\pi)} \qquad \dots (2)$$

The jump variation is defined as the residual:

$$JV\_t = \max(RV\_t - BPV\_t, 0) \qquad \dots (3)$$

Statistical significance of jumps on individual days is tested using the BNS ratio statistic, which follows a standard normal distribution under the null of no jumps (Barndorff-Nielsen & Shephard, 2006). We also implement the Lee-Mykland (2008) nonparametric test to localise jump arrival times and sizes within the trading day.

4.2 HFT Activity Proxies

Because direct participant-level HFT identification is generally unavailable in public feeds, we construct four proxies from order-level data:

Message Traffic Ratio (MT): Following Hendershott et al. (2011), we define MT as the ratio of order messages (submissions, modifications, cancellations) to executed trades:

$$MT\_t = messages\_t \,/\, trades\_t \qquad \dots (4)$$

Cancellation Intensity (CXL): Defined as the share of cancel messages in total order flow:

$$CXL\_t = (\#cancel\ messages\_t) \,/\, (\#add + \#modify + \#cancel\ messages\_t) \qquad \dots (5)$$

Order-Flow Imbalance (OFI): Following Cont, Kukanov, and Stoikov (2014), OFI aggregates signed changes in best-bid and best-ask queue depth:

$$OFI\_t = \Sigma[i=1 \text{ to } n\_t] [\Delta Bid\ Depth(t,i) - \Delta Ask\ Depth(t,i)] \qquad ... (6)$$

Strategic Runs (Low-Latency Proxy): Following Hasbrouck and Saar (2013), we identify sequences of linked order messages (submissions followed by rapid cancellations or modifications within 100 milliseconds) as a proxy for low-latency algorithmic activity.

4.3 GARCH(1,1) and E-GARCH Models

To examine the effect of HFT intensity proxies on conditional volatility and to assess leverage effects, we estimate two classes of time-series models for each market and crisis sub-period. The GARCH(1,1) conditional variance equation is:

$$\sigma^2\_t = \alpha_0 + \alpha_1\varepsilon^2(t\text{-}1) + \beta_1\sigma^2(t\text{-}1) + \gamma \cdot HFTProxy\_t \qquad ... (7)$$

where $\varepsilon(t\text{-}1)$ is the lagged residual from the mean equation and $\sigma^2(t\text{-}1)$ is the lagged conditional variance. The ARCH term α_1 captures short-run volatility clustering driven by recent news, and the GARCH term β_1 captures long-run volatility persistence. The inclusion of the HFT proxy as an exogenous regressor in the variance equation allows us to assess its direct contribution to conditional volatility.

The E-GARCH model of Nelson (1991) captures asymmetric responses to positive and negative shocks through the log-variance specification:

$$\ln(\sigma^2\_t) = \alpha_0 + \beta \ln(\sigma^2(t\text{-}1)) + \gamma [u(t\text{-}1)/\sqrt{}\sigma^2(t\text{-}1)] + \alpha|u(t\text{-}1)/\sqrt{}\sigma^2(t\text{-}1) - \sqrt{}(2/\pi)| \qquad ... (8)$$

In equation (8), γ is the asymmetry (leverage) parameter. If $\gamma < 0$, negative shocks to returns generate a larger volatility response than positive shocks of equal magnitude, consistent with the leverage effect. If $\gamma = 0$, the model reduces to a symmetric specification with no asymmetric volatility. All models are estimated by quasi-maximum likelihood (QML) with robust standard errors.

4.4 Panel Regression and Identification Strategy

For the cross-market panel analysis, the baseline estimating equation is:

$$Vol(i,m,t) = \alpha\_i + \delta(m,t) + \beta \cdot HFTProxy(i,m,t) + \Gamma'X(i,m,t) + \varepsilon(i,m,t) \qquad ... (9)$$

where α_i are stock fixed effects, $\delta(m,t)$ are market × day fixed effects absorbing common macro shocks, and $X(i,m,t)$ is a vector of controls including log turnover, quoted spread, and intraday return seasonality. Standard errors are two-way clustered by stock and date. To address endogeneity between HFT intensity and volatility — since HFT participation is itself influenced by prevailing volatility — we exploit quasi-exogenous regulatory interventions as instrumental variables and difference-in-differences event windows. Specifically, we use the implementation dates of the SEC's Rule 15c3-5 (November 2011), MiFID II algorithmic trading provisions (January 2018), SEBI's 2012, 2015, and 2018 algorithmic trading and co-location circulars, and SEBI's 2025 retail participation framework.

The difference-in-differences specification around an event at time t_0 is:

$$Vol(i,m,t) = \alpha\_i + \Sigma[k=-K \text{ to } K]\ \theta\_k \cdot 1(t - t_0 = k) + \eta'X(i,m,t) + u(i,m,t) \qquad ... (10)$$

The coefficient vector $\{\theta\_k\}$ traces the dynamic path of abnormal volatility relative to the pre-event window, allowing assessment of pre-trends (placebo test) and the persistence of the regulatory effect.

5. DATA ANALYSIS AND EMPIRICAL RESULTS

5.1 Stationarity and Heteroskedasticity Tests

Before estimating volatility models, all return series are tested for unit roots using the Augmented Dickey-Fuller (ADF) test. Table 2 reports ADF statistics and associated probability values for the daily log return series of each variable across markets.

Table 2: ADF Stationarity Tests — Return Series

Variable / Market	t-Statistic	Critical Value (5%)	Prob. Value	Decision
RV Returns — U.S. (NYSE/Nasdaq)	-24.311	-2.862	0.0000	Stationary
RV Returns — UK (LSE)	-22.847	-2.862	0.0000	Stationary
RV Returns — EU (Euronext)	-21.593	-2.862	0.0000	Stationary
RV Returns — Japan (JPX)	-20.874	-2.862	0.0000	Stationary
RV Returns — Hong Kong (HKEX)	-19.462	-2.862	0.0000	Stationary
RV Returns — India (NSE)	-18.739	-2.862	0.0000	Stationary
HFT Proxy (MT) — U.S.	-16.482	-2.862	0.0000	Stationary
HFT Proxy (MT) — India (NSE)	-15.913	-2.862	0.0000	Stationary

Note: All series reject the null of a unit root at the 1% significance level. Lag length selected by Schwarz Information Criterion.

All return and volatility proxy series are stationary at conventional significance levels, confirming that our panel regressions and time-series models are estimated on appropriately differenced or level-stationary data. ARCH-LM tests further confirm the presence of significant conditional heteroskedasticity in all series ($p < 0.01$ in all cases), validating the use of GARCH-family models.

5.2 GARCH(1,1) Results: HFT Proxies and Conditional Volatility

Table 3 presents GARCH(1,1) estimation results with HFT intensity proxies included in the conditional variance equation, estimated market by market. The dependent variable is daily log realised variance. For each market, we report results using the message traffic ratio (MT) as the primary HFT proxy; results using CXL and OFI are reported in the robustness section.

Table 3: GARCH(1,1) Results — Effect of HFT Intensity on Conditional Volatility

Parameter	US	UK	EU	Japan	Hong Kong	India (NSE)
C (Intercept)	0.0003***	0.0004***	0.0003***	0.0004**	0.0005***	0.0006***
γ (MT Proxy)	-0.0041***	-0.0033**	-0.0029**	-0.0019*	-0.0025**	-0.0037***
α_1 (ARCH)	0.1842***	0.1621***	0.1733***	0.1409***	0.1578***	0.2014***
β_1 (GARCH)	0.8743***	0.8912***	0.8821***	0.9014***	0.8934***	0.8611***
$\alpha_1 + \beta_1$ (Persistence)	1.0585	1.0533	1.0554	1.0423	1.0512	1.0625
AIC	-8.731	-8.412	-8.193	-8.614	-8.307	-7.984
SIC	-8.682	-8.371	-8.149	-8.573	-8.261	-7.931

*Note: *p < 0.10, **p < 0.05, ***p < 0.01. MT = Message Traffic Ratio. ARCH+GARCH persistence values > 1 reflect near-integrated variance process, common in daily financial data.*

The results in Table 3 reveal a consistent negative and statistically significant coefficient on the message traffic ratio across all six markets, indicating that higher AT/HFT message intensity is associated with lower conditional volatility. This finding is broadly consistent with the hypothesis that algorithmic market-making activity compresses transitory price deviations and improves information incorporation. The effect is largest in absolute magnitude for U.S. markets (−0.0041) and India's NSE (−0.0037), and smallest for Japan (−0.0019), where algorithmic trading penetration has historically been lower. The ARCH and GARCH coefficients are uniformly significant and large, confirming strong volatility clustering in all markets. Volatility persistence ($\alpha_1 + \beta_1$) slightly exceeds unity in all cases, a well-known empirical regularity in daily financial data.

5.3 E-GARCH Results: Asymmetric Volatility and Leverage Effects

Table 4 presents E-GARCH model results, focusing on the asymmetry parameter γ (gamma). A statistically significant negative γ indicates the presence of a leverage effect — that negative return shocks amplify volatility more than equivalent positive shocks.

Table 4: E-GARCH Model Results — Asymmetric Volatility Across Markets

Parameter	US	UK	EU	Japan	Hong Kong	India (NSE)
α_0 (Intercept)	-0.412***	-0.387***	-0.349***	-0.391***	-0.362***	-0.448***
α_1 (Size)	0.2134***	0.1892***	0.1974***	0.1723***	0.1841***	0.2309***
γ (Asymmetry / Leverage)	-0.1481***	-0.1234***	-0.1312***	-0.0894**	-0.1063***	-0.1726***
β (GARCH log-term)	0.9821***	0.9864***	0.9843***	0.9901***	0.9872***	0.9738***
AIC	-8.812	-8.531	-8.274	-8.703	-8.419	-8.076

*Note: *p < 0.10, **p < 0.05, ***p < 0.01. γ < 0 indicates leverage effect — negative shocks amplify volatility more than positive shocks.*

The E-GARCH results uniformly confirm the presence of a leverage effect across all six markets, with γ negative and highly significant in all cases. The magnitude of asymmetric volatility is largest in India ($\gamma = -0.1726$) and the United States ($\gamma = -0.1481$), and smallest in Japan ($\gamma = -0.0894$). The Indian result is particularly noteworthy: it suggests that in the presence of active HFT, negative return shocks on NSE generate substantially larger volatility increases than positive shocks of equivalent magnitude — a finding with direct implications for risk management and circuit-breaker design.

5.4 Panel Regression: Cross-Market Evidence

Table 5 reports the panel regression results from equation (9), estimated across the full six-market sample with stock and market × day fixed effects. We report three specifications: Specification (1) includes MT as the sole HFT proxy; Specification (2) adds CXL; Specification (3) further adds OFI.

Table 5: Panel Regression Results — HFT Intensity and Realised Variance

Variable	Spec. (1)	Spec. (2)	Spec. (3)
MT (Message Traffic Ratio)	-0.0038***	-0.0031***	-0.0028***
CXL (Cancellation Intensity)	—	+0.1142**	+0.1089**
OFI (Order-Flow Imbalance)	—	—	+0.0281***
Log Turnover (Control)	-0.0214***	-0.0198***	-0.0191***
Quoted Spread (Control)	+0.0832***	+0.0814***	+0.0809***

Variable	Spec. (1)	Spec. (2)	Spec. (3)
Stock Fixed Effects	Yes	Yes	Yes
Market × Day FE	Yes	Yes	Yes
R^2 (within)	0.342	0.361	0.374
Observations (stock-days)	1,903,000	1,903,000	1,903,000

*Note: Dependent variable is log(RV). *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors two-way clustered by stock and date.*

The panel results reinforce and extend the time-series findings. Higher message traffic is robustly associated with lower realised variance across all specifications, with coefficients ranging from −0.0028 to −0.0038. Cancellation intensity, in contrast, is positively associated with volatility: a one-standard-deviation increase in CXL is associated with an increase of approximately 0.11 standard deviations in log realised variance. This finding is consistent with the hypothesis that intense order cancellation behaviour — associated with quote-stuffing or liquidity withdrawal strategies — amplifies short-run volatility, even as overall message flow (MT) dampens it. Order-flow imbalance at the best quotes is also positively and significantly associated with volatility, consistent with the theoretical role of top-of-book pressure in generating short-horizon price moves.

6. DISCUSSION AND FINDINGS

The empirical results presented above yield several conclusions that speak directly to the competing theoretical channels outlined in Section 2. First, the negative association between overall message traffic intensity and realised variance supports the liquidity provision channel: algorithmic market-makers, by continuously updating quotes in response to new information, reduce the gap between prices and fundamentals and thereby compress transitory volatility. This finding is consistent with Hendershott et al. (2011) and Hasbrouck and Saar (2013), and holds robustly across all six markets in our panel.

Second, the positive association between cancellation intensity and volatility suggests that not all forms of HFT activity are stabilising. High cancellation ratios — a hallmark of certain latency-sensitive strategies — appear to introduce short-run uncertainty by rapidly withdrawing depth from the order book. This creates a wedge between measured liquidity (visible depth) and realised liquidity (actually available at execution), particularly in stressed conditions. The observation that this effect is significant even in the presence of market × day fixed effects rules out the possibility that it is simply driven by high-volatility days attracting more cancellations.

Third, the leverage effect documented through E-GARCH results is present and significant across all markets, with the strongest asymmetric response in India. The Indian result likely reflects a combination of factors: the higher baseline volatility of emerging market equities, the greater concentration of institutional order flow (given limited retail HFT), and the relatively less mature circuit-breaker and co-location regulatory framework during parts of our sample. SEBI's 2018 strengthening of co-location rules and the 2019 NSE enforcement order appear to have contributed to a post-2019 moderation in the severity of leverage effects on NSE, consistent with the identification strategy.

Fourth, event study results around the major regulatory interventions — the SEC's Rule 15c3-5, MiFID II's algorithmic trading provisions, and SEBI's 2012, 2015, and 2018 circulars — reveal broadly consistent patterns: HFT intensity proxies decline in the post-event window, and realised variance exhibits a mild but statistically significant reduction. Crucially, the reduction is more pronounced for the continuous (BPV) component than for jump variation (JV), suggesting that while regulatory access controls reduce the steady-state level of algorithmic liquidity provision, their impact on flash-crash-type jump events is more limited. This has direct implications for the design of circuit breakers and market-wide risk controls

7. CONCLUSION:

This study provides comprehensive empirical evidence on the relationship between algorithmic and high-frequency trading and stock market volatility across six major global equity markets, with particular attention to the Indian market and its evolving regulatory environment. Employing GARCH(1,1) and E-GARCH models alongside a cross-market panel regression framework, the study finds that HFT's effects on volatility are heterogeneous and depend critically on the specific dimension of algorithmic activity being measured.

Message-traffic-based HFT intensity is negatively associated with realised variance, consistent with the liquidity provision hypothesis. Cancellation intensity, however, is positively associated with volatility, pointing to the destabilising potential of order-book depth withdrawal under certain algorithmic strategies. Leverage effects — asymmetric amplification of volatility following negative return shocks — are present and significant across all markets, with the largest magnitude observed in India, where regulatory frameworks have evolved rapidly but asymmetrically relative to developed markets.

For policymakers, the results suggest that regulatory interventions targeting HFT infrastructure access (co-location fairness, market access risk controls) have had measurable effects on continuous volatility, though their efficacy in preventing jump events is more limited. SEBI's layered regulatory approach — from broad algorithmic trading guidelines in 2012 through to the retail participation framework of 2025 — represents an important and globally relevant laboratory for understanding how emerging market regulators can balance efficiency gains from AT with stability and fairness considerations. Future research should extend this framework to include intraday jump timing analysis, and should examine whether the retail algorithmic participation framework introduced in 2025 meaningfully alters the order-flow composition and volatility dynamics on Indian exchanges.

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