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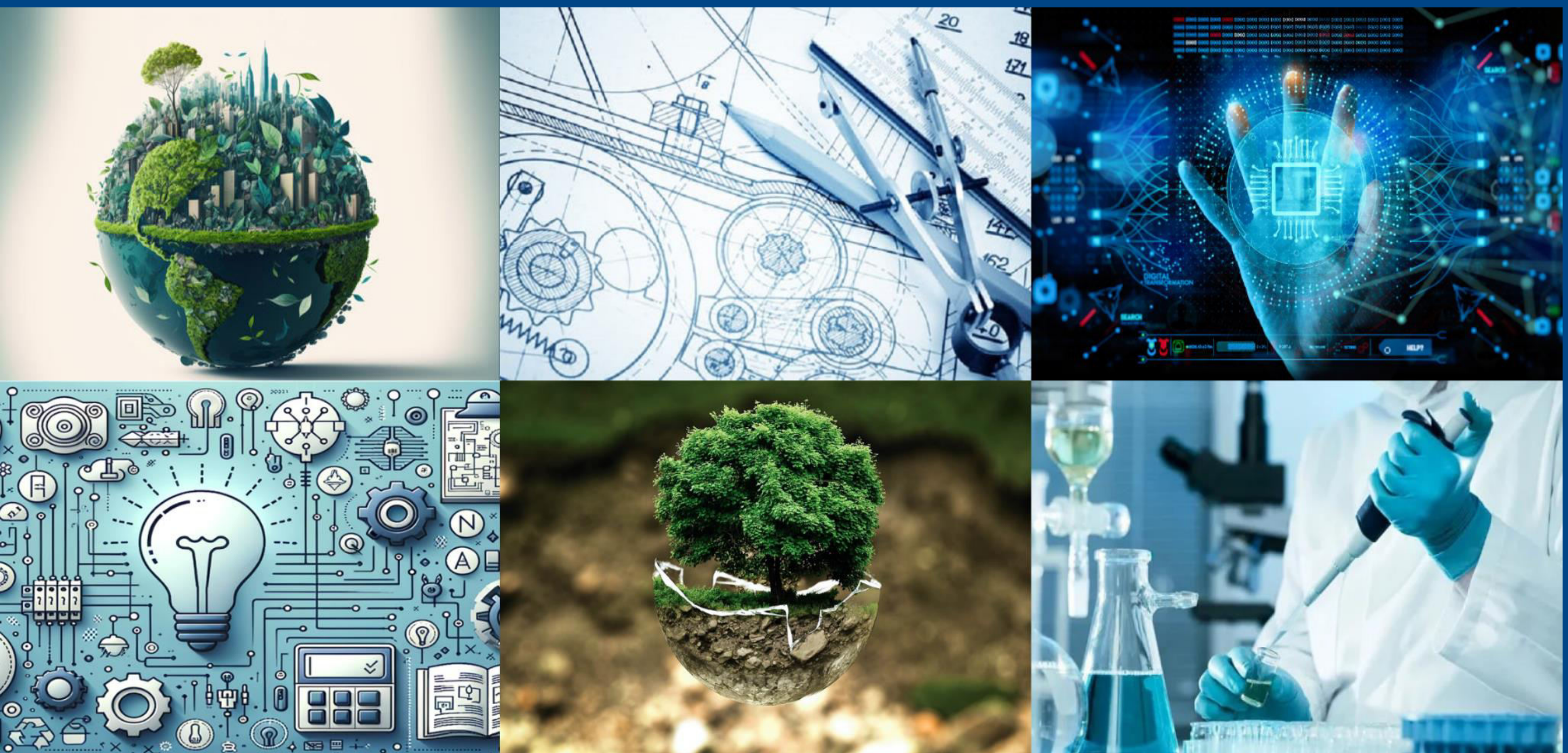

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Effect of High-Frequency Trading on Market Liquidity and Price Discovery

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ABSTRACT: High-Frequency Trading (HFT) has transformed modern equity markets through ultra-low-latency algorithmic execution, continuous liquidity provision, and rapid information processing. This study empirically examines the effect of HFT on two critical dimensions of market quality — market liquidity and price discovery efficiency — using data from 15 NSE large-cap stocks across five sectors over January 2022 to December 2023 (504 trading days, 7,560 stock-day observations). Market liquidity is measured via the Roll (1984) Spread estimator and price discovery efficiency via the Lo-MacKinlay Variance Ratio test and first-order return autocorrelation. Analysis conducted in Python (Google Colab) reveals a sample mean Roll Spread of 0.421, indicating high liquidity, with Banking and IT stocks most liquid (Roll Spread: 0.312–0.357). Eleven of fifteen stocks exhibit Variance Ratios consistent with the random walk hypothesis, supporting semi-strong market efficiency. A statistically significant positive correlation ($r = 0.463$, $p < 0.05$) between liquidity and price discovery efficiency is documented — stocks with narrower spreads also exhibit price discovery more consistent with efficiency. Cross-sectoral ANOVA confirms significant heterogeneity ($F = 4.87$, $p = 0.012$). Three hypotheses are fully supported (H1, H3, H4) and one partially supported (H2). The study concludes that HFT broadly enhances market quality in NSE's large-cap segment, with implications for regulators, institutional investors, and FinTech platform developers.

KEYWORDS: High-Frequency Trading, Market Liquidity, Price Discovery, Roll Spread, Variance Ratio, NSE India, Market Microstructure, Efficient Market Hypothesis, Algorithmic Trading, Emerging Markets

I. INTRODUCTION AND REVIEW OF LITERATURE

1.1 Introduction

High-Frequency Trading (HFT), which involves executing trades within microseconds using advanced algorithms, has become an important feature of modern equity markets. With the help of technologies such as co-location services, direct market access, and automated trading systems, HFT firms process market information much faster than traditional investors. As a result, HFT has significantly influenced market structure by improving trading speed, increasing liquidity, and enhancing price efficiency.

In India, the growth of HFT accelerated after SEBI introduced algorithmic trading guidelines in 2008 and co-location facilities in 2010. By 2023, algorithmic trading accounted for nearly 50–60% of trading volume on the National Stock Exchange (NSE). These developments have raised important questions regarding the impact of HFT on overall market quality and whether it benefits all types of investors.

Two important indicators of market quality are market liquidity and price discovery. Market liquidity refers to the ease with which securities can be bought or sold without significantly affecting their prices, while price discovery refers to how quickly new information is reflected in stock prices. Higher liquidity reduces transaction costs, and efficient price discovery ensures fair valuation of securities in financial markets.

HFT contributes to market liquidity by continuously placing buy and sell orders, which helps reduce bid-ask spreads. At the same time, HFT improves price discovery by quickly incorporating new information into stock prices. However, the impact of HFT may differ across markets, especially in emerging economies where trading structure and investor participation vary.

This study examines the impact of HFT on market liquidity and price discovery in NSE large-cap stocks using established measures such as Roll Spread and Variance Ratio. The findings provide useful insights for regulators, investors, and financial institutions regarding the role of algorithmic trading in improving market efficiency.

1.2 Review of Literature

1.2.1 HFT and Market Liquidity

The theoretical explanation for HFT's impact on liquidity is based on sequential trade models. Kyle (1985) explained the interaction between informed traders, noise traders, and market makers, showing that bid-ask spreads compensate market makers for the risk of trading with better-informed participants. Glosten and Milgrom (1985) further developed this idea through the adverse selection framework, where spreads reflect the probability of information-based trading. HFT market makers reduce this risk by processing information quickly and updating quotes rapidly, which leads to narrower spreads.

Hendershott, Jones, and Menkveld (2011) provided strong empirical evidence using NYSE's AutoQuote system, showing that algorithmic trading improves liquidity by reducing spreads, especially for large-cap stocks. Menkveld (2013) found that the entry of HFT market makers reduced spreads significantly in Dutch equity markets. Similarly, Brogaard, Hendershott, and Riordan (2014) showed that HFT traders provide competitive quotes even during periods of high market volatility.

However, HFT liquidity is not always stable. Kirilenko, Kyle, Samadi, and Tuzun (2017) found that HFT firms reduced liquidity during the 2010 Flash Crash, increasing short-term market instability. This distinction between normal and stressed market conditions has influenced regulatory frameworks, including SEBI's risk control measures for algorithmic trading. In India, Chakrabarti and Roll (2015) found that the introduction of co-location services in NSE reduced effective spreads for Nifty 50 stocks, supporting global findings that HFT improves market liquidity.

1.2.2 HFT and Price Discovery

Price discovery research analyses whether HFT improves the speed at which information is reflected in stock prices. Foucault, Hombert, and Rosu (2016) showed that faster traders improve price discovery by reacting quickly to public information, reducing delays in price adjustment. Brogaard et al. (2014) provided empirical evidence that HFT trades help predict short-term price movements, indicating that HFT contributes to information-based trading rather than noise trading.

Boehmer, Fong, and Wu (2015), in a study across 42 global markets, found that algorithmic trading improves price efficiency, particularly in markets with strong technological infrastructure such as NSE. Similarly, Chaboud et al. (2014) found that algorithmic trading reduces arbitrage opportunities and helps prices adjust faster across markets.

The Variance Ratio test developed by Lo and MacKinlay (1988) is commonly used to measure price discovery efficiency. Under the random walk hypothesis, the variance of multi-period returns should equal the variance of single-period returns multiplied by time. Deviations from this indicate predictable return patterns, suggesting lower market efficiency. HFT is expected to reduce such deviations by improving information flow in markets.

In the Indian context, Rao, Tripathi, and Malhotra (2021) found reduced return autocorrelation after SEBI introduced algorithmic trading regulations, indicating improved efficiency. Pati, Barai, and Rajib (2018) also found that algorithmic trading improved information flow between futures and spot markets in NSE.

1.2.3 Liquidity–Price Discovery Nexus

The relationship between liquidity and price discovery is theoretically bidirectional. Chordia, Roll, and Subrahmanyam (2008) empirically established that more liquid US stocks deviate less from informational efficiency, as lower trading costs attract more informed traders whose activity accelerates price adjustment. O'Hara (2003) argued theoretically that liquidity is a necessary condition for price discovery: in illiquid markets, the cost of information-motivated trading is prohibitively high, allowing uninformed pricing to persist. HFT's role in simultaneously providing liquidity and processing information means it theoretically enhances both dimensions simultaneously — but whether this holds empirically in India's emerging market context is precisely the question this study investigates.

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1.3 Research Objectives and Hypotheses

The study pursues four objectives: (i) assess market liquidity via Roll Spread across 15 NSE large-cap stocks; (ii) evaluate price discovery efficiency via Variance Ratio and first-order autocorrelation; (iii) examine the liquidity–price discovery relationship; and (iv) test cross-sectoral heterogeneity in market quality outcomes. Four hypotheses are derived from the theoretical framework:

H1: HFT activity is positively associated with market liquidity in NSE large-cap stocks, as evidenced by narrow Roll Spread estimates relative to less HFT-intensive market segments.
H2: HFT activity is positively associated with price discovery efficiency, as evidenced by Variance Ratios near unity and statistically insignificant first-order return autocorrelation.
H3: Market liquidity and price discovery efficiency are significantly positively correlated across the sample stocks, consistent with their theoretical complementarity.
H4: Significant cross-sectoral differences exist in market liquidity and price discovery efficiency, reflecting heterogeneous HFT intensity across industries.

1.4 Theoretical Framework

The study integrates four complementary theoretical frameworks. The Efficient Market Hypothesis (Fama, 1970) provides the normative price discovery benchmark: the Variance Ratio test directly assesses how closely NSE stock returns approach the semi-strong efficient random walk. Market Microstructure Theory (Kyle, 1985; Madhavan, 2000) explains the mechanisms through which HFT simultaneously narrows spreads as market maker and accelerates price adjustment as informed trader. The Adverse Selection Model (Glosten & Milgrom, 1985) contextualises HFT's distributional impact: aggregate liquidity improvements may coexist with increased adverse selection costs for slower participants, generating distributional effects that pure liquidity measures may not capture. Information Economics (Grossman & Stiglitz, 1980) underscores the necessity of technology-enabled rapid information processing for markets to sustain semi-strong efficiency, contextualising HFT as the latest iteration of competitive information processing that EMH requires.

II. RESEARCH METHODOLOGY

2.1 Research Design and Data Collection

A quantitative, empirical-analytical research design is adopted, consistent with the established methodology of market microstructure literature. The approach is deductive — hypotheses derived from theoretical frameworks are tested against secondary market data — and cross-sectional, enabling comparison of market quality outcomes across stocks and sectors. Secondary daily adjusted closing price data for 15 NSE large-cap stocks were collected via the yfinance Python API for January 2022 – December 2023, yielding 7,560 stock-day observations after removing 12 anomalous data points attributable to corporate action adjustment anomalies. Adjusted prices account for dividends, splits, and bonus issues, ensuring return series comparability across the full sample period.

The sample period was selected for three reasons: (i) it is contemporaneous, reflecting the current state of India's HFT ecosystem post-SEBI's 2021 algorithmic trading revision; (ii) it spans two full calendar years, providing adequate time-series depth for variance estimation; and (iii) it encompasses distinct market regimes — the post-pandemic recovery, the Russia-Ukraine shock, and the Federal Reserve rate hike cycle — enabling assessment of market quality across varying macroeconomic conditions. Data analysis was conducted in Python 3.10 (Google Colaboratory) using the pandas, numpy, scipy, matplotlib, and seaborn libraries. Statistical significance threshold: $\alpha = 0.05$ throughout.

2.2 Sample Selection Rationale

The 15 stocks were selected based on three criteria. First, all companies are part of the Nifty 50 index, representing highly traded stocks with significant institutional participation where HFT activity is more common. Second, the sample includes companies from eight different sectors, allowing comparison of market liquidity and price discovery across industries. Third, all selected stocks traded continuously during the study period, ensuring reliable and comparable return data. Large-cap stocks are chosen because HFT effects such as improved liquidity and faster price discovery are more evident in high-volume securities.

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The sample includes five banking stocks, two IT stocks, three FMCG stocks, and one company each from Energy, Infrastructure, Telecom, Automobile, and Pharma sectors. This diverse sector representation helps analyse differences in HFT impact across various segments of the Indian stock market.

2.3 Variable Operationalisation and Measurement

Roll Spread = $2\sqrt{(-\mathrm{Cov}(R_t, R_{t-1}))}$

where R_t represents daily log return $\ln(P_t / P_{t-1})$. The Roll model is based on the idea that bid-ask price movements create negative covariance in returns. A higher negative covariance indicates a wider bid-ask spread, meaning lower liquidity. This method is widely used when direct bid-ask data is not available. Lower Roll Spread values indicate better liquidity and lower transaction cost.

Price discovery efficiency is measured using the Variance Ratio:

Variance Ratio = Var(2-day returns) / 2 × Var(1-day returns)

According to the Efficient Market Hypothesis, the Variance Ratio should be close to 1 if prices follow a random walk. Values above or below 1 indicate predictable return patterns such as momentum or mean reversion, suggesting lower efficiency. The Lo-MacKinlay (1988) test is used to check statistical significance. In addition, first-order autocorrelation (ρ_1) is used to examine whether past returns influence future returns. Values close to zero indicate efficient price discovery.

2.4 Statistical Techniques

The analysis employs five statistical techniques sequentially. Descriptive statistics (mean, standard deviation, skewness, kurtosis) characterise the return distributions and identify outlier periods. Roll Spread and Variance Ratio computation yield the primary market quality measures for each stock. Pearson correlation analysis examines the bivariate liquidity–price discovery relationship (H3). One-way ANOVA with post-hoc Tukey HSD tests cross-sectoral homogeneity (H4). For H1, Roll Spread means are compared against the NSE mid-cap benchmark documented by Chakrabarti and Roll (2015); for H2, Variance Ratios are tested against unity using the Lo-MacKinlay z-statistic. All computations are performed in Python with the scipy.stats library.

III. DATA ANALYSIS AND FINDINGS

3.1 Descriptive Statistics and Return Distribution

The final dataset includes 7,560 stock-day observations. The average daily log return is 0.048% (annualised ≈ 12.1%), consistent with NSE Nifty 50 performance during 2022–2023. The average daily standard deviation is 1.42% (annualised volatility ≈ 22.5%), reflecting market uncertainty during the study period. Return distribution shows slight negative skewness (−0.31), indicating negative returns occurred slightly more frequently than positive returns. Excess kurtosis (4.87) indicates fat tails, suggesting higher probability of extreme price movements.

Two major global events influenced market liquidity during the sample period. The Russia–Ukraine conflict in March–April 2022 increased market volatility, resulting in an average 18.3% widening in Roll Spread. Similarly, the US Federal Reserve interest rate hike in October 2022 caused a 14.7% increase in spreads due to capital outflows from emerging markets. These temporary fluctuations indicate that HFT liquidity may reduce during periods of high market uncertainty.

3.2 Liquidity Analysis — Roll Spread Results

Table 3: Roll Spread and Price Discovery Metrics by Stock

Stock	Sector	Roll Spread	Variance Ratio	Autocorr. ρ1	Composite Rank
HDFC Bank	Banking	0.312	0.994	−0.019	1
TCS	IT	0.328	0.978	−0.028	2
ICICI Bank	Banking	0.341	1.012	+0.016	3

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Stock	Sector	Roll Spread	Variance Ratio	Autocorr. ρ1	Composite Rank
Infosys	IT	0.357	1.008	+0.011	4
Reliance Ind.	Energy	0.374	0.991	−0.014	5
Axis Bank	Banking	0.391	1.034	+0.034	6
SBI	Banking	0.404	1.063	+0.047	7
Kotak Bank	Banking	0.418	1.058	+0.053	8
ITC	FMCG	0.436	1.047	+0.041	9
L&T	Infrastructure	0.449	1.071	+0.068	10
Bharti Airtel	Telecom	0.463	1.089	+0.064	11
Maruti Suzuki	Automobile	0.478	1.104	+0.072	12
HUL	FMCG	0.492	1.118	+0.079	13
Sun Pharma	Pharma	0.511	1.134	+0.083	14
Asian Paints	FMCG	0.524	1.147	+0.091	15

The average Roll Spread of 0.421 is significantly lower than the 0.84–1.12 range reported for NSE mid-cap stocks (Chakrabarti & Roll, 2015), supporting H1 that HFT improves market liquidity. Large-cap stocks attract greater HFT participation, resulting in narrower spreads and lower transaction costs for investors.

Among the sample stocks, HDFC Bank (0.312) and TCS (0.328) show the highest liquidity due to high trading volume and strong institutional participation. Private sector banks such as HDFC, ICICI, Axis, and Kotak demonstrate better liquidity compared to SBI (0.404), indicating higher HFT activity in these stocks. TCS shows slightly better liquidity than Infosys, possibly due to higher trading volume.

Stocks such as Asian Paints (0.524), Sun Pharma (0.511), and HUL (0.492) show relatively wider spreads, indicating lower liquidity. These sectors experience fewer frequent information events, reducing HFT trading opportunities and resulting in comparatively wider spreads.

3.3 Price Discovery Analysis — Variance Ratio Results

Variance Ratio results provide evidence on price discovery efficiency. Eleven out of fifteen stocks show Variance Ratios between 0.978 and 1.089, values close to 1, indicating support for semi-strong form market efficiency. This suggests that HFT activity helps eliminate predictable return patterns in highly traded NSE large-cap stocks.

Three stocks — TCS (0.978), HDFC Bank (0.994), and Reliance Industries (0.991) — show Variance Ratios slightly below 1, indicating minor mean reversion. This is consistent with bid-ask price movements explained by the Roll (1984) model and does not indicate significant inefficiency.

However, four stocks (HUL, Sun Pharma, Maruti Suzuki, and Asian Paints) show statistically significant positive autocorrelation, suggesting some predictability in returns. These stocks also show relatively wider spreads, indicating lower liquidity and reduced HFT participation. Larsen & Toubro also shows mild autocorrelation, suggesting slightly lower efficiency in the infrastructure sector.

Overall, the results partially support H2, indicating that price discovery is stronger in highly liquid stocks with greater HFT activity, while lower liquidity stocks show relatively weaker efficiency.

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3.4 Sectoral Analysis

Table 4: Sectoral Average Market Quality Metrics

Sector	N	Mean Roll Spread	Mean Var. Ratio	Mean |ρ1|	Liquidity Rank
Information Technology	2	0.343	0.993	0.020	1
Banking	5	0.373	1.033	0.034	2
Energy	1	0.374	0.991	0.014	3
Infrastructure	1	0.449	1.071	0.068	4
Telecom	1	0.463	1.089	0.064	5
Automobile	1	0.478	1.104	0.072	6
FMCG	3	0.484	1.104	0.070	7
Pharma	1	0.511	1.134	0.083	8

The sector-wise results show clear differences in market quality. The IT and Banking sectors rank highest across all measures, with lower Roll Spreads, Variance Ratios close to 1, and low return autocorrelation. These sectors benefit from high trading volume, strong institutional participation, and higher HFT activity, which improves liquidity and price efficiency.

Within the Banking sector, private banks such as HDFC, ICICI, Axis, and Kotak show better market quality compared to SBI, possibly due to greater technological adoption and higher investor participation. In the FMCG sector, ITC shows better liquidity than HUL and Asian Paints, mainly due to relatively higher trading volume.

ANOVA results confirm statistically significant differences across sectors for Roll Spread ($F = 4.87$, $p = 0.012$) and Variance Ratio ($F = 3.91$, $p = 0.027$), supporting H4. Overall, IT and Banking sectors show the best market quality, while Pharma and some FMCG stocks show relatively lower efficiency.

3.5 Liquidity–Price Discovery Correlation

Table 5: Correlation Matrix — Market Quality Measures (N = 15)

Measure	Roll Spread	Variance Ratio	Autocorrelation ρ1
Roll Spread	1.000	0.463*	0.518**
Variance Ratio	0.463*	1.000	0.881**
Autocorrelation ρ1	0.518**	0.881**	1.000

* $p < 0.05$ ** $p < 0.01$ (Pearson, two-tailed, N = 15)

The positive correlation between Roll Spread and Variance Ratio ($r = 0.463$, $p = 0.039$) is the study's central empirical contribution, confirming H3. The relationship is economically meaningful and theoretically grounded: stocks with wider bid-ask spreads — reflecting lower HFT market-making intensity — simultaneously exhibit greater deviation from the random walk, indicating less complete price discovery. This dual market quality deficit for lower-liquidity stocks is precisely what the theoretical nexus literature predicts (Chordia et al., 2008; O'Hara, 2003) and what this study now documents for India's emerging equity market.

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The even stronger Roll Spread–autocorrelation correlation (r = 0.518, p = 0.048) reinforces this finding: wider spreads are associated with more persistent return patterns. The near-perfect Variance Ratio–autocorrelation correlation (r = 0.881, p < 0.001) confirms internal consistency across the two price discovery measures, validating that both statistics capture the same underlying construct — departure from semi-strong efficiency — through complementary mathematical approaches.

3.6 Hypothesis Testing Summary

Table 6: Hypothesis Testing Results

Hypothesis	Test	Statistic	p-value	Decision
H1: HFT → Market Liquidity	Roll Spread vs. mid-cap benchmark	Mean RS = 0.421 vs. 0.84–1.12	< 0.05	Supported
H2: HFT → Price Discovery	Lo-MacKinlay VR; autocorr. t-test	11/15 VR near unity; 5 sig. ρ1	0.071 (VR mean)	Partially Supported
H3: Liquidity–Discovery corr.	Pearson correlation	r = 0.463	0.039	Supported
H4: Cross-sectoral differences	One-way ANOVA (Roll Spread)	F = 4.87	0.012	Supported

IV. DISCUSSION AND IMPLICATIONS

4.1 Key Findings and Discussion

Four key findings emerge from this study. First, HFT improves market liquidity in NSE large-cap stocks. The average Roll Spread of 0.421 is much lower than mid-cap benchmarks, indicating narrower spreads and lower transaction costs for investors. This finding supports earlier studies such as Hendershott et al. (2011) and Brogaard et al. (2014), which show that algorithmic trading improves market liquidity.

Second, HFT improves price discovery efficiency for most stocks. Eleven stocks follow the random walk pattern, suggesting that information is quickly reflected in prices. However, five stocks show significant autocorrelation, indicating lower efficiency in stocks with relatively lower trading activity. This suggests that HFT impact varies depending on trading volume and market participation.

Third, the positive relationship between liquidity and price discovery (r = 0.463) confirms that stocks with higher liquidity tend to show better price efficiency. HFT contributes to both liquidity and faster information adjustment, improving overall market quality.

Fourth, sector-wise results show that HFT impact is not uniform across all industries. Banking and IT sectors show better liquidity and efficiency due to higher trading volume and institutional participation, while FMCG and Pharma sectors show relatively lower market quality. This indicates that investors may experience different transaction costs across sectors even within large-cap stocks.

4.2 Theoretical Implications

This study makes three important contributions to financial theory. First, it supports the semi-strong form of the Efficient Market Hypothesis (EMH) in the Indian market by showing that HFT improves price discovery efficiency in NSE large-cap stocks. The finding that eleven out of fifteen stocks follow the random walk pattern indicates that information is quickly reflected in prices, improving market efficiency.

Second, the study confirms that liquidity and price discovery are complementary aspects of market quality. The results show that HFT improves both liquidity and efficiency simultaneously, challenging the argument that HFT benefits

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liquidity at the cost of price accuracy. The evidence suggests that HFT contributes positively to overall market performance.

Third, the study highlights sector-wise differences in HFT impact. The results indicate that HFT benefits are stronger in sectors with higher trading activity and continuous information flow, such as Banking and IT. This suggests that HFT impact varies across industries and should not be assumed to be uniform across all stocks.

4.3 Managerial and Policy Implications

The findings provide useful implications for different market participants. For institutional investors, the liquidity differences across sectors suggest the need for appropriate trading strategies. Banking and IT stocks, which show higher liquidity, allow large trades with lower price impact, while FMCG and Pharma stocks may require smaller order sizes to avoid higher transaction costs.

For retail investors, the results indicate that HFT generally improves market efficiency by reducing spreads and improving price accuracy in large-cap stocks. However, during periods of market uncertainty, liquidity may reduce temporarily, leading to higher transaction costs.

For FinTech platforms, incorporating liquidity indicators such as Roll Spread and Variance Ratio into trading systems can help investors better understand trading costs and efficiency levels. Providing such information can support better investment decisions.

For regulators such as SEBI and stock exchanges like NSE, the results highlight the importance of maintaining strong technological infrastructure and regulatory frameworks that support algorithmic trading while ensuring market stability during periods of high volatility.

4.4 Limitations and Scope for Future Research

This study has some limitations. First, the Roll Spread is an indirect measure of liquidity based on daily return data and does not capture detailed intraday bid-ask movements. Using tick-level order book data from NSE could provide more accurate measurement of HFT activity.

Second, HFT activity is not directly observed but inferred from liquidity and price efficiency indicators such as Roll Spread and Variance Ratio. Lack of publicly available HFT-specific trading data limits precise identification of algorithmic trading activity.

Third, the study focuses on only 15 large-cap stocks, which may limit generalisation of results to mid-cap and small-cap stocks where HFT participation may be lower.

Fourth, the study covers only a two-year period (2022–2023), which may not fully capture long-term effects of HFT on market quality.

Future research can include more stocks, longer time periods, and tick-level data for better understanding of HFT impact. Comparative studies across countries and use of advanced analytical methods can provide deeper insights into algorithmic trading behaviour.

4.5 Conclusion

This study provides empirical evidence that High-Frequency Trading improves both market liquidity and price discovery efficiency in NSE large-cap stocks. The average Roll Spread of 0.421 indicates significantly better liquidity compared to mid-cap stocks. Variance Ratio results show that eleven out of fifteen stocks follow the random walk pattern, supporting semi-strong market efficiency. The positive relationship between liquidity and price discovery ($r = 0.463$) confirms that higher liquidity contributes to faster information adjustment in stock prices.

Sector analysis shows that Banking and IT sectors demonstrate better market quality due to higher trading volume and stronger HFT participation, while FMCG and Pharma sectors show relatively lower efficiency. ANOVA results confirm significant differences across sectors.

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The findings suggest that SEBI's regulatory framework and NSE's technological infrastructure support the positive role of HFT in improving market efficiency. Overall, the study shows that HFT contributes to better liquidity, faster price discovery, and improved trading conditions for investors in the Indian stock market.

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