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ANALYSIS OF HIGH- FREQUENCY TRADING AT NATIONAL STOCK EXCHANGE OF INDIA

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ABSTRACT
The main objective of this research article is to analyze the impact of High Frequency Trading (HFT) on price formation and liquidity in the National Stock Exchange(NSE) market in India. Analysis revealed that HFT firms tended to place more orders than non-HFT firms during auction trading sessions, most HFT orders could be classified as "make" orders, the ratio of HFT orders which hold back pricemovements is higher than that of conventional orders, and the carrying out of HFT orders tended to hold down directional price movements. These observations suggest that HFT firms at NSE adopt a market making strategy known as electronic liquidity provision.

KEYWORDS : *Financial markets, HFT, Orders, non-HFT, price movement, NSE*

INTRODUCTION
Recently financial markets have felt an increase in millisecond trading strategies aimed atgarnering profit from repeatedly trading at high speeds to accumulate small margins. This High Frequency Trading (HFT) according to TABB Group (2013a) ("US Equities Market 2013 State of the Industry", Tabb Group Report), (2013b) ("European Equities Market 2013 State of the Industry", Tabb Group Report), respectively accounted for 52% and 35% of all equity trading in the US and Europe in 2012. HFT is increasing in India after the National Stock Exchange (NSE) replaced its equity trading system in January 2000, and executions are becoming increasingly frequent and in smaller lots, As a new trading technique whose presence is gradually increasing in the securities market, many aspects of HFT continue to remain unclear, and this has given rise to criticism that HFT is responsible for sudden volatility in the market. This research article seeks to analyze the effect of HFT on price formation and liquidity in the NSE market based on actual data.

LITERATURE REVIEW:
1. The financial industry does not offer a clear definition of HFT, and the authorities in various jurisdictions are also currently attempting to define it. In the report by Ferber, M. (2012a), which was submitted to the European Parliament Committee on Economic and Monetary Affairs, an HFT firm is defined as one that satisfies at least four of the six conditions below:
   1) Uses co-location service
   2) Daily trading value is at least 50% of the portfolio
   3) Order execution rate is less than 25%
   4) Order cancellation rate is more than 20%
   5) More than half of positions are offset by intraday positions
   6) Receives rebates on more than 50% of transactions or orders.

2. The strategies employed by HFT firms are based on a diverse range of algorithms, making it difficult to classify them under a certain trading pattern. ASIC (2010), categorizes HFT activity strategies into three elements – (1) electronic liquidity provision, (2) statistical arbitrage, and (3)liquidity detection. Electronic liquidity provision involves displaying both bid and asks quotes in a role similar to that of a market maker. Gomber et. al. (2011), further defines this category into (a) spread capturing and (b) rebate-driven strategies. Strategies that accumulate gains from the spread of executed quotes would fall under(a), while (b) would be those that center on garnering profit from rebates on executed trades.
3. Empirical Analysis of Impact of HFT on stock market is increasing in the US and Europe, with many studies indicating that HFT supplies liquidity. Brogaard et. al. (2013), point out that HFT has contributed to improved price discovery and market efficiency by, for instance, providing liquidity in the form of orders that sought to address temporary mispricing in times of high volatility. Hasbrouck et. al. (2012) also suggests that HFT contributed to narrower spreads and increased depth, and could alleviate short term volatility.

RESEARCH GAP:

While studies on high speed trading and HFT may be considered to overlap, there are no past studies of the impact of HFTon the NSEIndia market that differentiates between HFT and non-HFT, or conventional, orders. This research article is an attempt at an empirical analysis of the impact on price formation and liquidity on the NSE market using NSE intraday data.

(1) Data Analysis and discussion:

This research article analyzed NSE intraday data for order book reproduction.The data is more detailed and includes details on individual orders (order timestamp, order price, quantity, execution conditions and category flags) and executions (timestamp, execution price and quantity)

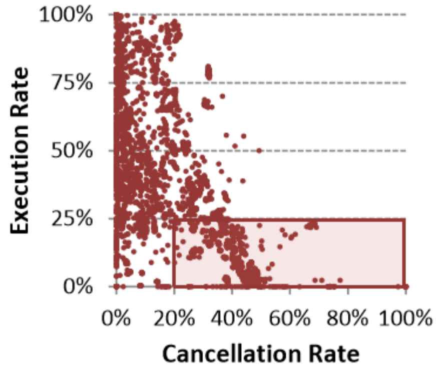
To cover different market conditions, the following data periods were selected for analysis

- 1st April 2017 to 31st March 2018
- 1st April 2018 to 30th April 2018
- National Stock Exchange of India Limited April 2018- Cash Market mode of Trading
- National Stock Exchange of India Limited April 2018 - Equity Derivatives mode of Trading

2. Estimates of HFT orders

Since NSE does not identify the originating investor for each order, the data used in analysis does not contain information on investor attributes. Hence it was difficult to identify whether the HFT order was placed by the originating investor or not. As such, for the purpose of identifying HFT orders, this research article applied the definition suggested in Ferber,M. (2012a) – orders that were placed by virtual servers and had execution rates of less than 25%, and cancellation rates of more than 20% (Figure 1). Virtual servers refer to logical devices set up in trading participant systems to send and receive data/messages to and from the NSE matching engine. Trading participants set up multiple virtual servers for trading, each virtual server is subject to an upper limit on the number of orders it can place per second,. In addition, while the corresponding relationships and interactions between end-investors and trading participant virtual servers are dependent on the trading participant's system configuration and cannot be fully understood from exchange data. Trading participants are capable to decide to set up or remove virtual servers at any time based on their needs. Trading participants are expected to accommodate the needs of new investors, particularly those engaged in HFT, by setting up dedicated virtual servers. Therefore, this article assumes a corresponding relationship between applications by trading participants to set up virtual servers with HFT end –investors.

Figure 1: Distribution of Virtual Servers



(Source: https://www.nseindia.com)

(2) Stocks selected for Analysis:

Stocks for analysis were limited to NIFTY50 listed on the NSE. For the purpose of analyzing the impact of HFT on price formation and liquidity, stocks that met any of the following conditions were excluded from analysis to avoid light HFT activity and impact of corporate actions on trading activity.

- Stocks that were newly listed, delisted or transferred to other market sections between 1st April 2017 to 30th April 2018
- Stocks that recorded HFT trading value of INR 50 lakhs or less on any single day during the periods for analysis.

❖ Stocks were selected, covering about 80% of the trading value and market capitalization.As Stock Exchange uses the 80-15-5 rule to classify the companies in large cap, mid cap or small cap. The largest market capitalization which covers up to 80% of the total market cap of all the listed company on the NSE is categorized as large cap company.

(3) Share of HFT Orders / Trading

The share of HFT and trading value was arrived at after differentiating between HFT and non-HFT orders. The results are shown in Table 1(a) and 1(b). The HFT share rose from 28.34% to 30.14% in terms of order value (% of Shares Deliverable to Total Shares Traded)and from 29.78% to 32.08% in terms of trading values(% of Delivery to Value of Shares Traded) betweenApril 2016 and March 2017 but declined from 29.05% to 24.12% in terms of% of Shares Deliverable to Total Shares Traded and from 30.29% to 25.54 in terms of % of Delivery to Value of Shares Traded

Table 1(a): HFT Share of Orders and Trading (April 2016- April 2018)

Period	% of Shares Deliverable to Total Shares Traded	% of Delivery to Value of Shares Traded	% of Short Delivery (Auction) to Delivery
Apr-16	28.34	29.78	0.18
May-16	27.92	28.77	0.17
Jun-16	26.35	29.52	0.19
Jul-16	25.62	29.14	0.19
Aug-16	27.99	28.56	0.16
Sep-16	27.99	29.73	0.21
Oct-16	28.45	29.16	0.15
Nov-16	28.36	29.06	0.16
Dec-16	28.8	30.01	0.19

Jan-17	28.71	29.13	0.14
Feb-17	28.65	29.88	0.13
Mar-17	30.01	32.08	0.13
Apr-17	29.05	30.29	0.12
May-17	27.2	28.6	0.13
Jun-17	26.15	29.28	0.15
Jul-17	27.03	29.03	0.23
Aug-17	25.73	26.84	0.34
Sep-17	26.45	27.86	0.14
Oct-17	27.05	29.11	0.19
Nov-17	26.12	27.84	0.11
Dec-17	25.22	28.4	0.16
Jan-18	23.3	26.83	0.11
Feb-18	23.78	26.3	0.12
Mar-18	23.1	27.61	0.13
Apr - 18	24.12	26.54	0.14

Source: https://www.nseindia.com/live_market/dynaContent/live_watch/equities_stock_watch.htm

1. Empirical Analysis:

HFT order patterns and trading tendencies, and impact on liquidity and price discovery based on empirical data are analysed. Analysis has been conducted to test hypotheses regarding liquidity and stock price movement. Since price discovery and liquidity are considered to be based on the given conditions (ie, size of the bid/ask spread and amount of orders quoted in the order book) and ultimately determined by the flow of order matching, matched orders have also be analyzed.

(1) Hypotheses Regarding HFT Activity

Based on the results of earlier studies, the following two hypotheses are set regarding the impact of HFT on the market.

H1: HFT supplies liquidity to the market.
H2: HFT contributes to smoother stock price movement

Hypothesis 1 is based on the idea that liquidity allows investors to easily buy or sell stocks when they want to. As such, as a precondition for creating a situation where trading can occur smoothly, the hypothesis asks that HFT improves liquidity by supplying quotes that do not execute immediately ("make" orders).
Hypothesis 2 was set to validate claims made in earlier studies that HFT reduces volatility and pricing error. Since volatility was understood to be dependent on market conditions rather than HFT activity, analysis was conducted from the prespective of whether HFT exacerbated price moves or involved orders that allowed prices to move in smaller increments and curbed large jumps in stock price.

Table 2 (a): National Stock Exchange of India Limited April 2018
Equity Derivatives mode of Trading Data

Particulars	Percentage
Non Algo	34.30
Algo	3.76
Direct Market Access (DMA)	7.76

Co-location	34.33
Internet Based Trading (IBT)	16.95
Mobile	2.88
Smart Order Routing	0.00

Source: https://www.nseindia.com/content/equities/ed_mode_of_trading.pdf

Note: The above figures are computed on the basis of gross turnover (for options traded value i.e. premium was considered) and the terminal identification as provided by the trading members at the time of order entry.

Table 2(b): NATIONAL STOCK EXCHANGE OF INDIA LIMITED April 2018
Cash Market mode of Trading Data

Particulars	Percentage
Non Algo	33,52
Algo	14.58
Direct Market Access (DMA)	1.11
Co-location	25.78
Internet Based Trading (IBT)	16.35
Mobile	7.70
Smart Order Routing	0.96

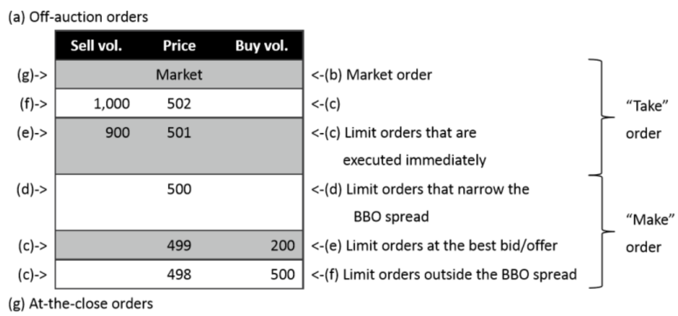
Source: https://www.nseindia.com/content/equities/cm_mode_of_trading.pdf

Note: The above figures are on the basis of the terminal identification as provided by the Trading members at the time of order entry.

(2) HFT Order Tendencies

Order tendencies between HFT and conventional orders were analyzed by comparing the time of a new order and its relationship with the best bid/offer (BBO) price to identify the price bands atwhich HFT orders are placed. First, orders were classified into auction and off-auction based on their timestamps. Orders placed during auction sessions were further classified based on their relationship with the price of the best bid (in the case of a buy order, or the best offer in the case of a sell order) to create seven categories ((a) –(g)) as shown in Figure 2 below

Fig. 2 Categorization by Order Price



*Prices and sell/buy volumes are indicated as examples.

Source: https://www.investopedia.com

The distribution of the quoted value of the various order categories across the three analysis periods is shown in Table 3. The ratios in Table 3 are indicated by investor type, HFT or non-HFT, for each order category by quoted value of all orders placed. As a result of the chi-square test of independence of the ratios of HFT and conventional orders, the null hypothesis that the ratios over the analysis periods were the same was rejected at the 0.1% significance level. As such, we can conclude that HFT and conventional orders exhibit different tendencies.

An evaluation of the distribution of HFT and non-HFT orders over the analysis periods showed several common characteristics . First, in terms of order time period, off-auction HFT orders only reached .34%, less than conventional orders. Thus orders that were placed in the auction session In other words, orders placed in the auction sessions made up an overwhelming majority of both HFT and conventional orders. Furthermore, for orders placed in auction sessions, low ratios of (g) at-the-close orders, which are not shown in the order book immediately, for HFT and conventional one's were observed at 3-6% and 13-18% respectively. This trend in HFT orders can be attributed to algorithms favoring order placement that respond to real-time conditions instead of off-auction or at-the-close orders, which involve uncertainties in price movement until execution.

The ratio of auction orders that took liquidity with immediate execution ((b) market orders and (c) limit orders that are executed immediately)was low at about 5% and 13-20% for HFT and non-HFT orders over the analysis periods. In particular, market orders accounted for only 0.2-0.3%, Strong HFT aversion to market orders can be attributed to algorithms favoring limit orders to avoid pricing risk that accompanies market orders between order placement and execution due to their nature to execute at the best price in the market. Among HFT order, there was also a higher ratio of "make" orders ((d) to (f)), which remained in the order book, than "take" orders, which executed immediately. This finding in the NSE market concurs with suggestion by Brogaard et. al. (2013) and ASIC(2010) that HFT firms in effect conduct market making.

The above findings indicate that HFT firms tend to place orders in the auction market that increase the depth of the order book and that HFT order pattern exhibit features that can be strongly identified with liquidity provision. As such, the findings support Hypothesis 1. Returning to the trading techniques defined by earlier studies in 2(2), a large portion of HFT in the NSE market can be considered to fall under (1) electronic liquidity provision.

Table 3: Order Categories and distribution of Quoted Value

Order Category		Sept 2017		Jan 2018		April 2018	
		HFT	Conventional	HFT	Conventional	HFT	Conventional
a	Off-auction orders	3.5%	12.1%	4.2%	13.4%	0.85%	10.5%
b	Market orders	0.35%	1.8%	0.25%	2.1%	0.45%	4.6%
c	Limit orders that are executed immediately	6.5%	13.6%	5.8%	17.5%	5.6%	20.5%
d	Limit orders that narrow BBO spread	2.1%	3.1%	3.4%	3.3%	4.8%	3.9%
e	Limit orders at the best bid/offer	19.8%	19.6%	21.5%	19.2%	17.6%	17.8%
f	Limit orders outside BBO spread	68.8%	42.2%	65.8%	30.6%	72.1%	28.6%
g	At-the-close orders	4.9%	15.4%	2.8%	18.5%	1.8%	17.6%
Results of chi-square test of independence		7,750		19,776		9,308	

Source: www.nseindia.com

(1) Resting Time of Orders Near the BBO

Based on the order categories defined in Figure 2, the two types of orders that improved liquidity, that is increased depth or narrowed spreads, were (d) limit orders that narrow the BBO spread and (e) limit orders at the best bid/order.

Analysis revealed that the volume of orders was almost the same for both HFT and conventional orders. The behavior of orders near the BBO that were cancelled with a focus on their resting times, which was defined as the time from order placement to the time of order cancellation was also analysed. The quartiles and averages of the resting times of HFT orders and conventional orders in each price range were calculated. Analysis results are shown in Table 5. Orders spanning both the morning and afternoon sessions were excluded from this analysis.

For (d) limit orders that narrow the BBO spread, while maximum and minimum order resting times for both HFT and conventional orders were almost the same, 1st quartile values were lower for HFT orders. The median values for both HFT and conventional orders, with the exception of September 2017, were around one second. As such, the resting times of HFT orders were not exceptionally short. Meanwhile, 3rd quartile values for both HFT and conventional orders also fell within a similar range. The resting times of € limit orders at the best bid/offer were also similarly calculated for comparison. The results revealed a similar distribution pattern among (e) limit orders at the best bid/offer but longer resting times than (d) limit orders that narrow the BBO spread.

Based on these findings, we can conclude that while the resting times of HFT near the BBO exhibited a trend of being cancelled within a short period of time, this trend was not unique to HFT orders since it was also observed in conventional orders.

Table 5: Resting Times of Orders Near BBO (to cancellation) (Units: milliseconds)

	HFT			Conventional		
	Sept 2017	Jan 2018	April 2018	Sept 2017	Jan 2018	April 2018
Min. Value	0	0	0	0	0	1
1st Quartile	48	98	67	205	223	243
Median	1,230	2,120	1,080	4,224	1,606	1,486
3rd Quartile	12,361	9,090	6,980	12,786	14,044	8,098
Max. Value	859,131	859,876	858,989	768,681	769,235	769,468

Source: www.nseindia.com

(4) Trading Value by order Type

After analyzing whether HFT and conventional orders contributed to market liquidity, this section will analyze matched orders to determine whether HFT provided or took liquidity. First, the trading value of all auction orders falling under (b) market orders and (c) limit orders that are executed immediately was considered “take” trading value, and the trading value of orders that were matched by such orders was considered “make” trading values. The ratio of “make” trading value for HFT trading was obtained by dividing HFT “make” trading value by overall HFT trading value, likewise for conventional trading. The ratios are shown in Table 6.

Therefore, based on the observation that not only were there many HFT orders that provided liquidity, but also that, in terms of actual trading values, there were more ‘make” orders, we can conclude that HFT contributed to improving market liquidity. This conclusion can be considered to support Hypothesis 1

Table 6: ratio of “Make” Orders in HFT and Conventional Trading

	Sept 2017		Jan 2018		April 2018	
	HFT	Conventional	HFT	Conventional	HFT	Conventional
“Take” Trading Value	38.2%	54.2%	33.3%	52.2%	38.4%	55.8%
“Make” Trading Value	61.8%	45.8%	66.7%	47.8%	61.6%	44.2%
z-score	2.160		4.280		3.654	

Source: Stock Reports compiled from National Stock Exchange

Table 6 shows the ratios of the “make” or “take” HFT/conventional orders to all HFT/conventional trading. Figures were obtained after differentiating HFT and conventional trading, and figures for “make” and “take” add up to 100%

Based on the above results, even though the majority of HFT and non-HFT orders involved directional trading, an investment pattern that follows price trends, since the ratio of counter-directional “take” orders in HFT was higher than in conventional trading, we can consider HFT to exhibit a higher tendency toward opposing price trends. Such HFT activity contributes to smoother stock price movement and supports Hypothesis 2. Furthermore, since similar tendencies were found in HFT “take order ratios under different market conditions, we can conclude that HFT is not easily influenced by market conditions.

Figure 3: Nifty Top 50 monthly volume traded

Source: www.nseindia.com

CONCLUSION

This paper used NSE intraday data to analyze the impact of HFT on price discovery and liquidity in the NSE market based on orders that were thought to be due to HFT. The analysis set out to validate the following two hypotheses:

Hypothesis 1: HFT supplies liquidity to the market.

Hypothesis 2: HFT contributes to smoother stock price movement.

First, with regards to Hypothesis 1, analysis of HFT order tendencies revealed that auction sessions saw a greater number of HFT orders than conventional orders, and also involved a greater number of HFT “make” orders, which remained in the order book. The resting times of orders near the BBO before they were cancelled were similar for both HFT and conventional trading. Meanwhile, in terms of contribution to price discovery, a higher proportion of HFT “make” orders were matched than conventional trading. These findings support the hypothesis and establish the conclusion that HFT firms provide liquidity to the market. It also suggests that HFT firms generally adopt a trading strategy similar to market making, thereby falling under the category of electronic liquidity provision.

As for Hypothesis 2, analysis revealed that HFT orders had a greater tendency toward being counter-directional (i.e., opposing price trends) and contributed to smoother price moves. This behavior was seen across all three sets of data from periods that were subject to different market conditions, and suggests that HFT activity is not easily influenced by market conditions.

This paper analyzed the general tendency of HFT orders but did not examine the differences between order tendencies for each issue or execution costs, which directly impact user convenience. This paper only begins to study the impact of HFT on price discovery and liquidity, and recognizes that the above areas remain to be addressed in future research. Furthermore, since algorithms can be expected to be modified constantly, their behavior will need to be continually analyzed.

REFERENCES

Arai, R (2012) "Changes in stock market liquidity and trading costs due to introduction of arrowhead – Analysis from perspective of institutional investors", Securities Analysts Journal 50.(9),pp17-24 (In Japanese).

ASIC (2010) "Australian equity market structure", Australian Securities and Investments Commission Report 215.

Brogaard, J.A., T. Hendershott, and R Riordan 92013) "High Frequency Trading and Price Discovery"', ECB Working Paper Series No. 1602.

Ferber, M (2012a) "DRAFT REPORT on the proposal for a directive of the European Parliament and of the Council on markets in financial instruments repealing Directive 2004/39/EC of the European Parliament and of the Council (recast)", EUROPEAN PARLIAMENT, pp35-36.

Ferber, M (2012b) "REPORT on the proposal for a directive of the European Parliament and of the Council on markets in financial instruments repealing Directive 2004/39/EC of the European Parliament and of the Council (recast)", EUROPEAN PARLIAMENT, pp43-44.

Gamber, P., B,. Arndt, M, Lutat, and T. Uhle (2011) "High-Frequency Trading", working paper.

Hasbrouck, J (2012) "Low-Latency Trading", New York University Stern School Working Paper Ota, W (2013) "Long-term effect of increased speed of trading systems on liquidity"' Proceedings of the 21st Annual Meeting of Nippon Finance Association (In Japanese).

https://deutsche-boerse.com/dbg/dispatch/en/binary/gdb content pool/imported files/public files/10 downlods/11 about us/Public Affairs/High Frequencytrading.pdf

Tabb Group (2013a) "US Equities Market 2013 State of the Industry", Tabb Group Report.

Tabb Group (2013b) "European Equities Market 2013 State of the Industry", Tabb Group Report.

Uno, J. and M Shibata (2012) "Trading speed and liquidity: the case of arrowhead", Gendai Finance 31, pp87-107 (In Japanese).www.nseindia.com

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