How Does High Frequency Trading Affect Low Frequency Trading?

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Running Head: **How Does HFT Affect LFT?**

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Abstract

High frequency trading dominates trading in financial markets. How it affects the low frequency trading, however, is still unclear. Using NASDAQ order book data, we investigate this question by categorizing orders as either high or low frequency, and examining several measures. We find that high frequency trading enhances liquidity by increasing the trade frequency and quantity of low frequency orders. High frequency trading also reduces the waiting time of low frequency limit orders and improves their likelihood of execution. Our results indicate that high frequency trading has a liquidity provision effect and improves the execution quality of low frequency orders.

Key words: high frequency trading, limit order book, liquidity, order execution quality

JEL: G10, G14

I. INTRODUCTION

High frequency trading (HFT) dominates volume in financial markets. However, how HFT affects low frequency trading (LFT) is less well understood. Previous papers have studied how HFT impacts the market overall. This paper attempts to characterize the mechanism by which HFT impacts the market experience of LFT participants by testing seven hypotheses regarding the interaction between these segments of the market.

One difficulty in any analysis of HFT is the method of differentiating between HFT and LFT activity. Some studies [e.g. Kirilenko, et al. 2011; Menkveld, 2013] assign messages based on individual trading accounts or broker IDs data without distinguishing marks on HFT firms. Others use datasets only including transaction records generated by HFT firms, as in Brogaard [2010] and Brogaard, et al. [2013]. In order to accurately test the hypotheses, this paper use the order identification field of the NASDAQ ITCH feed and develops a unique methodology of differentiation. Using the order identification field, we categorize orders as 1) high frequency limit orders (HFT limit orders), 2) low frequency limit orders (LFT limit orders), or 3) market orders, which we consider to be all LFT. Once categorized, we are able to proceed with the tests of the various hypotheses.

This paper makes three contributions. First, we present evidence that HFT improves the market for LFT. We find that an increase in HFT activity is associated with an increase in the frequency and trade size of LFT limit orders, implying that HFT activity improves the liquidity of LFT orders. HFT's order book imbalance has much smaller impact, implying that the volume inequality caused by HFT does not largely affect the liquidity of LFT. Besides examining the impact of HFT activity on LFT, we implement a Granger causality test by estimating a vector auto-regression model (VAR) model, and prove that our independent variables regard to HFT activity display causality to the dependent variables regard to the liquidity of LFT.

Second, we examine the order execution quality of LFT limit orders using four measures related to likelihoods of execution and waiting time for execution or cancellation. We find that HFT activity improves the order execution quality as well as the liquidity of LFT orders. An increase in HFT activity reduces both the waiting time for cancelation or execution, and improves the likelihoods of execution of LFT limit order. This type of analysis is new. Previous studies measure how overall market liquidity is affected by HFT, mainly using the bid-ask spread and volatility. They do not examine how HFT precisely affects the order execution quality of LFT. Through a Granger causality test, we confirm that our independent variables regard to HFT activity display causality to the dependent variables regard to the execution quality of LFT limit orders. Additionally, we find evidence that the realized spread paid by market orders is lower in the presence of high frequency traders because they require a smaller adverse selection premium. This corroborates previous research from the Dutch markets by Menkveld [2013].

Furthermore, we find evidence that HFT contributes to liquidity provision for LFT. We use measures related to the willingness to pay of HFT and find that the increasing liquidity taking by HFT improves the liquidity and execution quality of LFT orders. The results indicate that HFT is not only a liquidity taker but also provides liquidity that it takes for LFT limit orders.

The remainder of this paper is organized as follows. Section II presents background information and a review of the relevant literature. Section III describes the data. Section IV presents the differentiation methodology. Section V describes measures and statistics. Section VI discusses the liquidity provision effects and hypotheses. Section VII presents regression tests and results. Section VIII concludes.

II. BACKGROUND

Several studies state that HFT now dominates trading volume in financial markets [Brogaard, 2010 and 2011; Hendershott and Riordan, 2013; Castura, et al., 2010]. Angel, et al. [2010] describe the increasing use of computer-based automation as one of the most important characteristics of the equity market, and conclude that it helps fulfill investors' demands for better solutions. More studies relate HFT and algorithmic trading (AT) to market quality, especially focusing on liquidity and trading efficiency. Cvitanic and Kirilenko [2010] find that the presence of HFT makes the distribution of transaction prices have thinner tails with greater concentration near the mean. Hasbrouck and Saar [2013] analyze two NASDAQ data samples in 2007 and 2008. They find that low latency AT is associated with lower quoted and effective spreads, lower volatility and greater liquidity. Through analyzing common stocks between 2001 and 2005, Hendershott, et al. [2011] states that for all stocks, and particularly for large-cap stocks, AT increases liquidity, narrows bid-ask spreads and reduces adverse selection.

However, the development of HFT is accompanied with controversy. Kang and Shin [2012] point out a tag-along effect of HFTs when they study HFT behavior in South Korean markets. They state that the HFT's large-scale use of impatient limit orders may potentially have negative effects on the market by lowering the informativeness of the limit order book. Syn [2014] states that systematic instabilities in market dominated by HFT has become the principal concerns on regulating HFT activity since the 2010 Flash Crash. In addition, many studies discuss "fleeting orders" or "flickering orders", the rapid cancelation of limit orders after submission has been considered as the symbolic characteristic of HFT and explored by many studies, including Baruch and Glosten [2013], Biais and Woolley [2011], Gai, et al. [2013], Hasbrouck and Saar [2009]. They state that such fleeting orders are submitted by HFT and may purposely generate congestion in the market.

This paper, however, is less concerned with the specific activities of HFT, and more concerned with a direct analysis of the effect of HFT activity on LFT executions. We add, for example, to the trajectory of the literatures that focuses on HFT and adverse selection as a component of the bid-ask spread. This literature includes Menkveld [2013], who shows that HFT market making leads to a reduction of adverse selection by 23%. Riordan et al. [2012] conclude that HFT's ability to update quotes more quickly leads to a reduction in their adverse selection. Jovanovic and Menkveld [2012] present a model that shows that HFT's are able to avoid adverse selection. Brogaard [2012] finds that HFT liquidity suppliers incur lower adverse selection than traditional liquidity suppliers.

In 2000 the U.S. Securities and Exchange Commission (SEC) adopted Rule 605 (formerly Rule 11Ac1-5), which requires the equity market centers to make monthly public disclosure of execution quality[1]. Since then, order execution quality has become an important aspect of evaluating equity markets. Cho and Nelling [2000] examine the likelihood that a limit order will execute. They find that the probability of execution (as opposed to cancelation) is higher if 1) the limit price is closer to the prevailing top-of-book quote, 2) the trade size is smaller, and 3) the spread is wider. Boehmer [2005] adds the execution speed[2] as another dimension of the order execution quality. He examines a negative relationship between the order execution speed and execution cost by examining identical stocks traded in different venues. Such relationship reverses as the order size increases. Boehmer, et al. [2007] further find that the market's future share of order flow increases when either execution costs decline or execution speed increases. Relevant studies including Battalio, et al. [2003], Chordia, et al. [2005], Zhao and Chung [2007] analyze order speed as an important component of market efficiency and order quality.

These studies essentially argue that order execution quality is as important as liquidity in the evaluation of an equity market. However, studies on HFT have not involved order execution quality in their investigations. We examine how HFT affects the order execution quality of LFT limit orders through an array of HFT measures.

III. DESCRIPTION OF DATA

Our dataset consists of NASDAQ ITCH feed data with all top-of-book time-sequenced messages about order additions, cancelations and executions. Each message is time-stamped to microsecond resolution and contains a Token ID which uniquely identifies an order. This gives us the ability to track orders from their addition to their removal from the limit order book. For example, a message that adds an order to the limit order book has a Token ID. When this order is finalized (i.e. executed or cancelled), the resulting message will use the same Token ID value. Thus, we are able to match additions with finalizations. For a more detailed presentation of the raw data set, see Appendix A.

Using our matching of Token IDs, we categorize each message as containing information about either a market order or a limit order. Token IDs associated with two (or more) messages we categorize as limit orders. Transaction messages for executions (or partial executions) are market orders, since market orders execute against the limit orders on the top of the book[3]. We categorize those pairs of limit order messages with a time difference less than ten seconds as HFT limit orders. Those pairs of limit order messages with a time difference greater than ten seconds, we categorize as LFT limit orders.

We take the thirty Dow Jones Industrial Average (DJIA) stocks as an example, and the observation period contains for 134 trading days from November 1, 2010 to May 12, 2011. For each of the three categories—HFT limit orders, LFT limit orders and LFT market orders—we group the messages by minute so that each stock has 390 message groups for each trading day[4]. The total number of one minute periods over the 134 days is 52,260. For each minute group, we calculate the minute-based average values of liquidity and order execution quality measures. As special cases, we calculate transaction-cost-related liquidity measures and waiting time measures by including only execution messages or cancelation messages. For the remaining measures, we include the overall messages.

IV. DIFFERENTIATION METHODOLOGY

We take 10.5 seconds as a time frame short enough to differentiate computer-controlled algorithmic electronic trading from manual trading for establishing and liquidating positions[5]. The choice of 10.5-second threshold is not arbitrary. According to SEC [2010], a symbolic characteristic of HFT activity is "the submission of numerous orders that are cancelled shortly after submission". They report that the cancelation probability of HFT-submitted limit orders can reach over 80% or even 90% on occasion.

To find the boundary between HFT and LFT by way of resting time, we follow the intuition that short term forecasts decay with time [Li, 2015; Cooper and Van Vliet, 2015]. HFTs add and cancel in order to obtain queue position that fosters quicker execution and to avoid adverse selection. We test the hypothesis that HFT abandons a queue position when the forecast decay reaches some threshold amount of time. If this hypothesis is true, then the probability of cancellation should peak at some time. We call this the maximum average duration of HFT-submitted limit orders.

In order to detect the peak of order cancelation, we observe the cancelation ratio. It is the proportion of canceled limit orders to the total of finalized limit orders (canceled or executed) over the time interval [*t*, *t* + *dt*).

$$Cancelation\ Ratio_{[t,t\,+\,dt)} = \frac{Number\ of\ canceled\ limit\ orders_{[t,t\,+\,dt)}}{Number\ of\ finalized\ limit\ orders_{[t,t\,+\,dt)}} \tag{1}$$

This methodology of differentiation finds that the cumulative probability of cancelation reaches around 85% within 10.5 seconds after submission. Figure 1 depicts the declining value of the cancellation ratio in half second intervals. As can be seen, there is a pronounced peak at the 10-10.5 second interval occurs. This suggests that HFTs profitability forecasts cross a threshold at this time and they capitulate. When the time decay overwhelms the value of their queue position, they cancel their limit orders in order to avoid adverse selection.

The 10.5 second threshold is in line with the SEC's compilation. It is also in line with Brogaard's [2010] compilation where HFT participates in around 77% of all trades. The 10.5 second threshold categorizes as HFT limit orders around 79% of the volume.

V. MARKET MEASURES AND STATISTICS

Having differentiated the activity in the data into the three categories, we are able to pursue various analyses. To begin, we define several variables to categorize the current state of the market for a given stock.

5.1 Market State Measures

We use average values across the DJIA thirty stocks of five measures—the order book imbalance, the effective half-spread, the realized spread, the price impact, and the trade quantity for each of the three categories (HFT limit orders, LFT limit orders, and market orders). In addition, we count the trade frequency in each minute for the three categories.

1. For each message i received, we calculate the **order book imbalance** (*BI*) in stock j as defined in equation (2), as an extension to the order imbalance by Chordia et al. [2002].

$$BI_{j,i} = \frac{quoted\ bid\ volume - quoted\ ask\ volume}{quoted\ ask\ volume + quoted\ bid\ volume} \tag{2}$$

   We group $BI_{j,i}$ in the same minute T, and then calculate $\boldsymbol{BI_T}$ as the average value of $BI_{j,T}$ for messages in T across the DJIA thirty stocks.

2. We measure the **effective half-spread** (*espread*), which represents the transaction cost. It is the difference between the mid-point of the bid-ask spread and the actual transaction price. According to Bessembinder [2003] and Hendershott, et al. [2011], for an execution message i in stock j, the proportional effective half-spread is as defined in equation (3).

$$espread_{j,i} = \frac{q_{j,i}(p_{j,i} - M_{j,i})}{M_{j,i}} \tag{3}$$

   where $q_{j,i}$ is an indicator variable that equals +1 for buyer-initiated trades and -1 for seller-initiated trades, following the standard trade-signing approach of Lee and Ready [1991], where $p_{j,i}$ is the transaction price, and $M_{j,i}$ is the midpoint prevailing at the time the execution message i is received. In similar fashion to the calculation of $\boldsymbol{BI_T}$ above, we calculate $\boldsymbol{espread_T}$ as the average value across the DJIA thirty stocks for minute T.

   We follow Glosten [1987] and explore the components of the bid-ask spread to determine the manner in which HFT affects the price paid in the market to trade. In order to calculate the actual transaction cost components, we pick up the executed limit orders and calculate the realized spread and the price impact.

3. We estimate the revenue to the liquidity providers using the **realized spread** (*rspread*). For each execution message i in stock j, the proportional realized spread is defined in equation (4) [Bessembinder, 2003; Hendershott, et al., 2011].

$$rspread_{j,i} = \frac{q_{j,i}(p_{j,i} - MF_{j,i})}{M_{j,i}} \tag{4}$$

where $q_{j,i}$ is an indicator variable that equals +1 for buyer-initiated trades and -1 for seller-initiated trades, and $p_{j,i}$ is the transaction price, $M_{j,i}$ is the quoted midpoint prevailing at the time of the trade is executed, and $MF_{j,i}$ is the quoted midpoint one minute after the execution of this trade. We then calculate $\boldsymbol{rspread_T}$ as the average value across the DJIA thirty stocks in minute *T*.

4. We measure the **price impact** (*Adv_selection*) to indicate the revenue to the informed traders due to adverse selection, which is defined in equation (5) [Bessembinder, 2003; Hendershott, et al., 2011].

$$Adv\_selection_{j,i} = \frac{q_{j,i}(MF_{j,i} - M_{j,i})}{M_{j,i}} \tag{5}$$

We calculate $\boldsymbol{Adv\_selection_T}$ as the average value across the DJIA thirty stocks in minute *T*. Note the arithmetic identity in equation (6).

$$espread_{j,i} = rspread_{j,i} + Adv\_selection_{j,i} \tag{6}$$

5. For each of the three categories of orders, we calculate the **average trade quantity** $\boldsymbol{Avg\_qty_T}$ as the average value across the DJIA thirty stocks in minute *T*.

6. For each of the three categories of orders—HFT limit orders, LFT limit orders and LFT market orders—of one stock *j*, we count the **trade frequency** ($Freq_{j,T}$) as the number of messages as counted by Token ID in minute *T*. We sum the trade frequencies for the overall DJIA thirty stocks as $Freq_T = \sum_{j=1}^{30} Freq_{j,T}$.

5.2 Order Execution Quality Measures

Using the data, we also measure the order execution quality of LFT limit orders. We calculate the waiting time till finalization (i.e. execution or cancelation) for each order, and two ratios that measure likelihood of execution for each order.

1. Similar to Boehmer [2005], we define the time gap of one limit order as the interval between order receipt and finalization counted in seconds. The average time gap in minute *T* is the mean of time gaps of LFT limit orders added in the same minute. The finalization of LFT limit orders can be either execution or cancelation. So we calculate the average time gap for executed LFT limit orders and canceled LFT limit orders respectively. For minute *T*, we calculate $Time\_E_T$, the average time gap for execution, as the average value across the DJIA thirty stocks, and $Time\_C_T$, the average time gap for cancelation, as the average value across the DJIA thirty stocks.
2. The **frequency ratio** (*FR*) of execution evaluates the probability of execution in terms of the frequency. It is the ratio of trade frequencies between executed orders and all added orders in minute *T* across the DJIA thirty stocks, as calculated in equation (7).

$$FR_T = \frac{\sum_{j=1}^{30} frequency\ of\ executed\ orders_{j,T}}{\sum_{j=1}^{30} Freq_{j,T}} \tag{7}$$

3. The **quantity ratio** (*QR*) of execution evaluates the probability of execution in terms of quantity. It is the ratio of total trading volumes between executed orders and all added orders in minute *T* across the DJIA thirty stocks. *QR* is defined as in equation (8).

$$QR_T = \frac{\sum_{j=1}^{30} volume\ of\ executed\ orders_{j,T}}{\sum_{j=1}^{30} volume\ of\ all\ orders_{j,T}} \tag{8}$$

5.3 Summary Statistics

In this section, we show the values of the descriptive statistics for the nine types of liquidity and execution quality measures for the DJIA stocks. Table 1 presents these statistics arranged by the type of order—HFT limit order, LFT limit order, or market order. The variables shown in Table 1 are the cross-sectional averages by minute, with the exception of *Freq*, *FR* and *QR* as discussed in the previous section.

Looking at the rows labeled $Freq_{HFT}$, $Freq_{LFT}$, and $Freq_{MO}$ in Table 1, there are on average 8,430 HFT transaction messages, 1,025 LFT market order messages and 2,060 LFT limit order messages of the DJIA index stocks in each minute. Each HFT order contains an average (Avg_qty_{HFT}) of 235 shares, whereas each LFT limit order (Avg_qty_{LFT}) and market order (Avg_qty_{MO}) contain 288 shares and 180 shares respectively on average. Thus, we calculate that HFT limit orders account for 73% of messages. LFT limit orders account for 18% of messages. Market orders account for 9% of messages. Additionally, the maximum number of HFT limit order messages in one minute is 214,778. By comparison, the maximum number of market orders in one minute is 14,391, and the number of LFT limit order is 10,171. Clearly, HFT activity far exceeds that of LFT. The summary statistics on trade frequency and quantity measures are consistent with several existing studies [Angel, et al., 2010; Brogaard, 2010 and 2011; Castura, et al., 2010; Hendershott and Riordan, 2013] and show the dominant status of HFT in the equity market.

The *rspread* measures the revenue to liquidity providers for their service and the price that liquidity demanders pay for that service. A negative *rspread* indicates that demanders are in fact earning the *rspread*. Because HFTs also generate revenue from (price direction or arbitrage) information and exchanges rebates, they are able to earn profits from smaller, even negative *rspread*s. Considering market orders, those executed against HFT limit orders ($rspread_{HFT}$) have a realized spread of -0.1, while those executed against LFT limit orders ($rspread_{LO}$) have a realized spread of -0.11 basis points (bps). These amounts are approximately the same on average for both groups. Following this inference from *rspread*, we observe the price impact measures for HFT limit orders ($Adv\_selection_{HFT}$) and LFT limit orders ($Adv\_selection_{LO}$). Their average values are higher, 0.35 and 0.42 bps respectively. Thus, we can see that HFTs charge a lower adverse selection premium. Together, this is a new result. With HFTs in the market, all liquidity providers now on average now suffer a negative *rspread*, which HFTs incur in order to obtain the order flow necessary to increase their revenues from information (either price movement or arbitrage), avoid adverse selection, and earn rebates.

This result implies that executions against HFT limit orders pay 17% less adverse selection fee, which is roughly similar to that shown by Menkveld [2013]. But the range of $Adv\_selection_{HFT}$ (-0.34 and 2.54 bps) is narrower than that of $Adv\_selection_{LO}$ (-0.66 and 7.83 bps). This result suggests that HFT can better avoid extreme adverse selection because of their speed. This corroborates Jovanovic and Menkveld [2012], and Brogaard [2012]. This discussion leads to two formal hypotheses.

Hypothesis 1: When HFT is in the market, Adv_selection$_{LO}$ *is lower.*

Hypothesis 2: When HFT is in the market, rspread$_{LO}$ *is lower.*

Based upon the extremely large sample size of these summary statistics, both of these hypotheses cannot be rejected.

5.4 Univariate Analysis of LFT Activity Sorted on the Activeness of HFT

In order to see the impact of HFT on LFT, we compare the performances of LFT in periods with different "activenesses" of HFT. To measure the activeness of HFT, we use $\boldsymbol{Freq_{HFT}}$ and sort all the trading periods (52,260 minutes) in ascending order. Then, we equally divide the trading periods into three groups by their values of $\boldsymbol{Freq_{HFT}}$. Each group contains 17,420 minutes. We categorize the 17,420 minutes with the smallest numbers of $\boldsymbol{Freq_{HFT}}$ as the

Low HFT group, where $\boldsymbol{Freq_{HFT}}$ ranges between zero and 5,206 per minute; we categorize the 17,420 minutes with the largest numbers of $\boldsymbol{Freq_{HFT}}$ as the High HFT group, where $\boldsymbol{Freq_{HFT}}$ ranges between 9,142 and 214,778 per minute. The remaining is the Medium HFT group. To distinguish how the LFT activity differs with different activeness of HFT, we only need to compare how those LFT measures behave between the Low HFT group and the High HFT group. We omit the Medium HFT group.

Table 2 presents the summary statistics for the eight LFT limit order measures in the Low HFT group and the High HFT group. As shown in Panel A, in the periods with Low HFT activity, the trade frequency of LFT limit orders $Freq_{LO}$ has a mean of 1,527 and ranges between zero and 5,022. Whereas in the periods with High HFT activity (Panel B), the mean rises to 2,540 and the range is between 447 and 9,065. Therefore, when the activeness of HFT is higher, the simultaneous LFT activity is more active and frequent.

Similarly, results of the other seven measures also show the higher activeness of LFT accompanied by the higher activeness of HFT. In Panel A, the means of *FR* and *QR* are 0.15 and 0.11, while those means increase to 0.18 and 0.12 respectively in Panel B. This implies that the execution quality of LFT limit orders improves as the prevalence of HFT gets higher. Shown in Panel A, the waiting times, *Time_C* and *Time_E*, are 164 and 102 seconds on average in the Low HFT group, while they decrease to 110 and 81 seconds on average in the High HFT group. These results indicate that higher HFT activity reduces the waiting time and thus improves market efficiency. The paired *t*-test results are also provided in Panel C. They show that the means of the eight measures between the High HFT and Low HFT groups are not equal to each other.

Therefore, by comparing the univariate results between the Low HFT and High HFT groups, we observe that as HFT becomes more active, LFT performs with higher frequencies, larger quantities, shorter waiting times, and higher likelihoods of execution.

VI. LIQUIDITY PROVISION EFFECT OF HFT ON LFT

In this section, we explore how HFT contributes to the liquidity provision for LFT. Several papers claim that HFT contributes to liquidity provision by discussing HFT's position in the market. Jovanovic and Menkveld [2012], and Menkveld and Zhou [2013] model HFT as a middleman liquidity provider in limit order markets. Gerig and Michayluk [2013] suggest that traditional market makers[6] are losing their importance and that HFT now dominates in liquidity provision. Huh [2013] confirms that HFT acts as both liquidity providers and takers and its liquidity provision is associated with information asymmetry. Weller [2013] shows that HFT takes liquidity from slower market makers, and then provides fast liquidity for fundamental traders in lower-frequency.

Following these prior studies, we explore evidence on the liquidity provision effect of HFT activity on LFT, which requires a breakdown of the bid-ask spread. Glosten [1987] decomposes the bid-ask spread into two components — *rspread* and *Adv_selection*. Traders that can exploit this second component with transitory asymmetric information are informed traders [Harris, 1998], because they have skills in assessing immediate market situations in high-frequency [Aldridge, 2009]. Since these statistics are calculated from messages of executed limit orders, they represent the actual (negative) revenue to liquidity providers and (negative) cost to informed traders. For HFT limit orders, the component $rspread_{HFT}$ evaluates the revenue that HFT attains through order executions. $Adv\_selection_{HFT}$ evaluates HFT's actual revenue premium for losses incurred by informed trading. To confirm HFT's liquidity provision on LFT, we infer that the increase of both $rspread_{HFT}$ and $Adv\_selection_{HFT}$ should have positive effects on LFT by improving their order execution quality and liquidity. The reason is that as $rspread_{HFT}$ increases, the increasing actual revenue potential will attract HFTs to participate in the market with more activity and higher trade frequency. This benefits the liquidity provision to LFTs.

Therefore, together with the other measures, we use these spread measures to state five additional, formal hypotheses.

Hypothesis 3: HFT activity increases the trade frequency of LFT limit orders.

Hypothesis 4: HFT activity increases the average trade quantity of LFT limit orders.

Hypothesis 5: HFT activity reduces the average time gap of LFT limit orders.

Hypothesis 6: HFT activity increases the frequency ratio of execution of LFT limit orders.

Hypothesis 7: HFT activity increases the quantity ratio of execution of LFT limit orders.

Table 3 summarizes these five hypotheses. These hypotheses fall into two categories: those relating to the liquidity of LFT limit orders (measured by $Freq_{LO}$ and Avg_qty_{LO}), and those relating to the execution quality of LFT limit orders (*Time_E, FR,* and *QR*). Table 3 lists independent and dependent variables involved in each regression corresponding to each hypothesis. We will test them in the next section.

VII. REGRESSION TESTS AND RESULTS

We have stated five new hypotheses. To test these hypotheses, we use the regression model in (9) to examine HFT's impact on LFT liquidity and order execution quality. In order to compare the importance across the independent variables, we use standardized β coefficients. We note that BI_{HFT} is included to control for market conditions—up or down. Given the nature of equation (5), we also note that some correlations between the variables are significant. We use a variance inflation factor (*VIF*) test to check for multicollinearity in the regressions in (9). The test results indicate that there are no multicollinearity problems among the independent variables. For the results of our variance inflation factor test, see Appendix B.

$$DV_T = \alpha_T + \beta_1 \cdot Freq_{HFT,T} + \beta_2 \cdot Avg_{qty_{HFT,T}} + \beta_3 \cdot BI_{HFT,T} + \beta_4 \cdot rspread_{HFT,T} + \beta_5 \cdot Adv_{selection_{HFT,T}} + \varepsilon_T$$

$T = 1, \ldots, 52{,}260$ (9)

On the left hand side, DV_T represents the six dependent variables, one for each regression: $Freq_{LO}$, Avg_qty_{LO}, *Time_E*, *Time_C*, *FR* and *QR*. $Freq_{LO}$ and Avg_qty_{LO} measure the liquidity of LFT limit orders. *Time_E*, *Time_C*, *FR* and *QR* measure the order execution quality of LFT limit orders.

7.1 Impact of HFT on Liquidity

With respect to the impact of HFT on the liquidity of LFT limit orders, we first examine Hypothesis 3, that HFT activity increases the trade frequency of LFT limit orders. Table 4 reports the standardized ordinary least squares (OLS) coefficients for the two dependent variables $Freq_{LO}$ and Avg_qty_{LO}. $Freq_{HFT}$, Avg_qty_{HFT} and $BI_{HFT,T}$ display positive relationships to LFT limit orders' trade frequency ($Freq_{LO}$) by 0.2402, 0.2581 and 0.0164. To be clear, as these regressions have been normalized, this result shows that an increase in HFT's trade frequency ($Freq_{HFT}$) by one standard deviation raises the LFT limit orders' trade frequency ($Freq_{LO}$) by 0.2402 of its standard deviation. These coefficients are significant at the 1% level. Therefore, we cannot reject Hypothesis 3.

Second, we examine Hypothesis 4, that HFT activity increases the average trade quantity of LFT limit orders. Table 4 reports that both $Freq_{HFT}$ and Avg_qty_{HFT} also display positive relationships with Avg_qty_{LO}, 0.0317 and 0.2540 respectively. These coefficients are significant at the 1% level. Therefore, we cannot reject Hypothesis 4. In summary, these results show that HFT activity increases the trade frequency of LFT limit orders, and that HFT activity increases the average trade quantity of LFT limit orders.

Our results in Table 4 show that HFT activity increases the trade frequency of LFT limit orders, and that HFT activity increases the average trade quantity of LFT limit orders. As an implication, a negative "spillover" effect does not appear, and the coexistence of HFT brings positive effects to LFT by improving liquidity. These results are consistent with the SEC literature review [2014], showing that HFT serves as market makers with liquidity for counterparties including LFT.

7.2 Impact of HFT on Order Execution Quality

With respect to the impact of HFT on the order execution quality of LFT limit orders, we first examine Hypothesis 5, that HFT activity reduces the average time gap of LFT limit orders. Table 5 reports that $Freq_{HFT}$ and Avg_qty_{HFT} both decrease the time to execution ($Time\_E$) of LFT limit orders. The coefficients are -0.1525 and -0.0118 respectively. These coefficients are both significant at the 1% level. Therefore, we cannot reject Hypothesis 5.

Second, we examine Hypothesis 6, that HFT activity increases the frequency ratio of execution of LFT limit orders. Table 5 shows that $Freq_{HFT}$ increases the FR of LFT limit orders (0.0495), but that Avg_qty_{HFT} slightly decreases it (-0.0095). This means that more HFT transactions increases the probability an LFT limit order is executed, but that higher quantities in these HFT executions slightly reduce this probability. These coefficients are both significant at the 1% level. Therefore, we cannot reject Hypothesis 6.

Third, we examine Hypothesis 7, that HFT activity increases the quantity ratio of execution of LFT limit orders. Table 5 shows that $Freq_{HFT}$ slightly increases the QR of LFT limit orders (0.0055), but that Avg_qty_{HFT} slightly decreases it (-0.0558). This means that more HFT transactions increases the average quantity of executed LFT limit order, but that higher quantities in these HFT executions slightly reduce this average quantity. These coefficients are both significant at the 1% level. Therefore, we cannot reject Hypothesis 7.

In summary, these results show that HFT activity reduces the average time gap of LFT limit orders, that HFT activity increases the frequency ratio of execution of LFT limit orders, and that HFT activity increases the quantity ratio of execution of LFT limit orders. These results suggest that HFT activity improves the order execution quality of LFT limit orders. HFT reduces the waiting time and improves the likelihoods of execution of LFT limit orders. These results are in line with previous studies by Castura, et al. [2010], Cvitanic and Kirilenko [2010], Hasbrouck and Saar [2010], and Hendershott, et al. [2011], which suggest that HFT improves liquidity and market efficiency.

In summary, these results show that HFT activity reduces the average time gap of LFT limit orders, that HFT activity increases the frequency ratio of LFT limit orders, and that HFT activity increases the quantity ratio of execution of LFT limit orders. Like the results in Section 7.1, our results give evidence that HFT reduces the waiting time and improves the likelihoods of execution of LFT limit orders, which confirms that negative “spillover” effects of HFT on LFT do not exist. These results suggest that HFT activity improves the order execution quality of LFT limit orders, consistent to Castura et al. [2010], Cvitanic and Kirilenko [2010], Hasbrouck and Saar [2010], and Hendershott et al. [2011].

7.3 Liquidity Provision Effect of HFT

The results of the regressions in Tables 4 and 5 provide additional information about the interaction between HFT and LFT beyond the five hypotheses. First, shown in Table 5, an increase in HFT's trade frequency ($Freq_{HFT}$) by one standard deviation reduces the time gap for execution (*Time_E*) by 0.1525 of its standard deviation, and increases the frequency ratio of execution (*FR*) by 0.0495 of its standard deviation. By improving the likelihoods of execution and reducing the waiting time of execution, HFT improves the order execution quality of LFT limit orders. This suggests that increased order execution consequently increases the rate at which fundamental information is incorporated into the price. Increasing HFT activity accelerates the rates of execution of information-laden LFT limit orders.

Second, in Table 5 an increase in $rspread_{HFT}$ or $Adv\_selection_{HFT}$ reduces the time gap for execution (*Time_E*) of LFT limit orders by 0.1924 or 0.3219 respectively, indicating that higher willingness to pay of HFT improves the execution speed for LFT limit orders and consequently suggesting the existence of HFT's liquidity provision effect. HFT's liquidity provision effect also appears in the regressions of the likelihoods of execution. The increase in $rspread_{HFT}$ or $Adv\_selection_{HFT}$ will raise the frequency ratio of execution (*FR*) by 0.2324 or 0.3267 respectively, whereas will raise the quantity ratio of execution (*QR*) by 0.2476 or 0.3556 respectively. All the coefficients above are significant at 1‰ level. The results suggest that when the willingness to pay by HFT is higher, it will improve the order execution quality of LFT limit orders.

The improvement of execution quality by HFT activity also benefits LFT with respect to the fundamental information acquisition. An increase in $rspread_{HFT}$ and $Adv\_selection_{HFT}$ reduces the time gap for cancelation (*Time_C*) of LFT limit orders by 0.1274 and 0.1650 respectively. This result indicates that the more HFT activity incurred by higher willingness to pay improve LFT's efficiency to acquire the fundamental information, and such improvement accelerates LFT's decision making on canceling limit orders with tiny execution probabilities. Thus, HFT's liquidity provision effect improves the execution quality and efficiency of LFT limit orders. These results confirm the importance of HFT with respect to the liquidity provision for LFT. Our finding empirically supports the previous studies by Gerig and Michayluk [2013], Huh [2013], Jovanovic and Menkveld [2012], Menkveld and Zhou [2013], and Weller [2013].

7.4. Granger Causality Tests

We have examined HFT's instantaneous impact on LFT liquidity and order execution quality. As a supplement, we further examine whether the past HFT activity affects the liquidity and order execution quality of LFT. Following Hiemstra and Jones [1994], we implement a Granger causality test on the linear reduced-form VAR in (10).

$$DV_T = \boldsymbol{\beta'_1} \cdot \boldsymbol{Freq_{HFT,(T-1,T-5)}} + \boldsymbol{\beta'_2} \cdot \boldsymbol{Avg\_qty_{HFT,(T-1,T-5)}} + \boldsymbol{\beta'_3} \cdot \boldsymbol{BI_{HFT,(T-1,T-5)}} + \boldsymbol{\beta'_4} \cdot \boldsymbol{rspread_{HFT,(T-1,T-5)}} + \boldsymbol{\beta'_5} \cdot \boldsymbol{Adv\_selection_{HFT,(T-1,T-5)}} + \varepsilon_T$$

$$T = 6, \ldots, 52{,}260 \qquad (10)$$

On the left side, DV_T still represents the six dependent variables for each regression. The variables on the right side are 5-length lagged vectors for each corresponding measure. For example, $\boldsymbol{Freq_{HFT,(T-1,T-5)}}$ represents the 5-by-1 vector $[Freq_{HFT,T-1}, Freq_{HFT,T-2}, Freq_{HFT,T-3}, Freq_{HFT,T-4}, Freq_{HFT,T-5}]^2$. Similarly, $\boldsymbol{\beta'_i}$ is a 1-by-5 coefficient vector. To determine the appropriate lag length, we use Akaike's [1974] information criterion (AIC). Then the selected lag length is also verified by the final prediction error (FPE), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC). Thus, the VAR model in (10) involves measures during the past five minutes and consequently captures the past 5-minute influence of HFT activity on the current liquidity and order execution quality of LFT.

To test for strict Granger causality in (10), we employ a standard joint test (F-test or χ^2-test) of exclusion restrictions to determinewhether lagged measure vectors have significant linear predictive power for dependent variables (DV_T). The null hypothesis is that lagged measure vectors do not strictly Granger cause DV_T. It is rejected if the coefficients on the elements in $\boldsymbol{\beta}_i'$s are jointly significantly different from zero. Then the knowledge of past 5-minute values of measures helps predict current DV_T.

Table 6 reports the results of Granger causality test on the liquidity of LFT limit orders. Lag lengths on the independent variables are five. Computed χ^2-statistics with their marginal significance levels are also reported. Focusing on rejections of the null hypothesis of Granger non-causality at the 5% nominal significance level, the Granger test shows evidence of unidirectional causality from lagged independent variables to all the four dependent variables regarding the liquidity of LFT with respect to both order types. The results suggest that the lagged independent variables Granger cause the dependent variables, and confirm that the knowledge from measures in the past helps predict current liquidity of LFT. The only individual exception is the causality from the order book imbalance of HFT (BI_{HFT}) to the average trade quantity of LFT limit orders. The significance level is 0.11, suggesting that the null hypothesis of Granger non-causality from BI_{HFT} to Avg_qty_{LO}cannot be rejected at the 5% nominal significance level.

Table 7 reports the results of Granger causality test on the execution quality of LFT limit orders. Lag lengths on the independent variables are still five. According to the χ^2-statistics and their marginal significance levels, the null hypotheses of Granger non-causality can be rejected at the 5% nominal significance level across all the four dependent variables. The results confirm that the knowledge from measures in the past helps predict current execution quality of LFT limit orders.

As the only individual exception in Table 7, a very important finding is the causality from the order book imbalance of HFT (BI_{HFT}) to the four dependent variables. The significance levels of BI_{HFT} are extremely high across all the four tests, suggesting that the null hypotheses of Granger non-causality on BI_{HFT} cannot be rejected at the 5% nominal significance level. Shown in Tables 6 and 7, the non-causality cases on BI_{HFT} indicate that the past order book imbalance does not significantly affect the current liquidity or execution quality of LFT. This finding is in line with our previous finding in Section 7.1 and 7.2, suggesting that the volume inequality caused by HFT does not prevent the liquidity and execution quality of LFT. Therefore, our finding differs from Baruch and Glosten [2013], Biais and Woolley [2011], Gai, et al. [2013], Hasbrouck and Saar [2009], Kang and Shin [2012], and Syn [2014], which state that HFT activity may incur systematic instability and generate intentional congestions on market liquidity. We find that HFT activity and the volume inequality caused by HFT's fleeting orders neither incur the systematic instability nor generate intentional congestions in markets.

In summary, as a supplemental causality analysis, our Granger causality test results further strengthen HFT's instantaneous impact and intermediary effect on LFT liquidity and order execution quality. The selected independent variables display causality to dependent variables. The only exception is the order book imbalance, suggesting that the volume inequality caused by HFT does not hurt the liquidity or execution quality of LFT.

VIII. CONCLUSION

This paper examines how HFT activity affects LFT in different dimensions and thus answers a long-term question: does HFT harm LFT on its liquidity and execution quality? We have been able to overcome the difficulty of differentiating between HFT and LFT activity with a new dataset based upon the NASDAQ feed, which gives us the ability to track orders from their addition to their removal from the limit order book. We match messages into orders, and then categorize orders as HFT limit orders, LFT limit orders, or market orders.

First, we present results from our comprehensive analyses of HFT activity and its impact LFT. We use HFT top-of-book message data for DJIA thirty stocks in a 134-day period, and generate liquidity measures for the three types of orders above. Besides, we examine order execution quality of LFT limit orders by three additional measures. We state seven hypotheses. Our finding shows that HFT activity improves both the liquidity and order execution quality for LFT limit orders. HFT increases the trade frequency and trade quantity of LFT orders, reduces the waiting time and improves the likelihoods of execution of LFT limit orders. HFT's trade frequency has larger impacts on LFT limit orders' execution quality than LFT's direct cost. HFT's order book imbalance has much smaller coefficients in all tables, implying that the volume inequality caused by HFT does not largely affect the liquidity of LFT limit orders.

Furthermore, we find evidence that HFT contributes to liquidity provision for LFT. We use measures related to the willingness to pay of HFT and find that the increasing liquidity taking by HFT improves the liquidity and execution quality of LFT orders. The results indicate that HFT is not only a liquidity taker but also provides liquidity that it takes for LFT limit orders.

As a supplemental causality analysis, we implement a Granger causality test by estimating a VAR model using the same independent variables and dependent variables. Our results further strengthen HFT's instantaneous impact and intermediary effect on LFT liquidity and order execution quality. The selected independent variables display causality to dependent variables. The only exception is the order book imbalance, suggesting that the volume inequality caused by HFT does not hurt the liquidity or execution quality of LFT.

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Table 1: Summary Statistics of the DJIA Index

This table presents the summary statistics of the measures in three types of orders (denoted by subscripts, *HFT* as HFT limit orders, *LO* as LFT limit orders and *MO* as market orders) across the Dow Jones Industrial Index thirty stocks. The measures of the order book imbalance (*BI*), the effective half-spread (*espread*), the realized spread (*rspread*), and the price impact (*Adv_selection*) are expressed in basis points (henceforth bps).

Variable	Mean	Std. Dev.	Min	Max	Description
Panel A: HFT Measures					
$Freq_{HFT}$	8430.33	6273.20	0.00	214,778	minute-based trade frequency of HFT orders
BI_{HFT}	15.05	752.10	-2892.82	3248.30	average minute-based order book imbalance of HFT orders (bps)
$rspread_{HFT}$	-0.10	0.10	-1.5	1.17	average minute-based realized spread of HFT orders (bps)
$Adv\_selection_{HFT}$	0.35	0.17	-0.34	2.54	average minute-based price impact of HFT orders (bps)
Avg_qty_{HFT}	235.92	53.39	0.00	3205.81	average minute-based trade quantity per HFT order
Panel B: Market Order (*MO*) Measures					
$Freq_{MO}$	1025.93	701.97	0.00	14391	minute-based trade frequency of LFT market orders
$espread_{MO}$	0.34	0.08	0.00	2.44	average minute-based effective spread of LFT market orders (bps)
Avg_qty_{MO}	180.53	42.05	0.00	1167.14	average minute-based trade quantity per LFT market order
Panel C: LFT Limit Order (*LO*) Measures					
$Freq_{LO}$	2060.51	704.39	0.00	10171	minute-based trade frequency of LFT limit orders
$rspread_{LO}$	-0.11	0.21	-7.12	1.39	average minute-based realized spread of LFT limit orders (bps)
$Adv\_selection_{LO}$	0.42	0.24	-0.66	7.83	average minute-based price impact of LFT limit orders (bps)
Avg_qty_{LO}	288.21	82.11	0.00	3973.66	average minute-based trade quantity per LFT limit order
$Time\_E$	137.80	88.59	0.00	1336.06	average minute-based time gap in seconds of executed LFT limit orders
$Time\_C$	93.17	49.56	0.00	808.86	average minute-based time gap in seconds of canceled LFT limit orders
FR	0.17	0.04	0.00	1.00	frequency ratio of execution
QR	0.11	0.05	0.00	1.00	quantity ratio of execution
Number of Observations = 390 × 134 (minute per day × day)					

Table 2: Summary Statistics for the LFT Limit Order Measures Sorted on the Activeness of HFT

This table presents the summary statistics for the LFT Limit Order Measures sorted on the activeness of HFT. The trading periods (52,260 minutes) are sorted by the trade frequency of HFT ($Freq_{HFT}$) and then equally divided into three sections: Low HFT activity ($Freq_{HFT}$ ranges between zero and 5,206 per minute), Medium HFT activity, and High HFT activity ($Freq_{HFT}$ ranges between 9,412 and 214,778 per minute). Panel A presents the summary statistics of LFT Limit Order Measures from Low HFT activity periods. Panel B presents the summary statistics of LFT Limit Order Measures from High HFT activity periods. Panel C presents the paired t-test results for these measures between Low HFT and High HFT activity periods.

Panel A: Periods with Low HFT activity								
	$Freq_{LO}$	Avg_qty_{LO}	$rspread_{LO}$	$Adv\_selection_{LO}$	*FR*	*QR*	*Time_E*	*Time_C*
Mean	1527	278	-0.01	0.28	0.15	0.11	164	102
Std. Dev.	396	91	0.11	0.12	0.04	0.05	91	48
Min	0	0	-0.83	-0.04	0.00	0.00	0	0
Max	5022	3663	1.28	1.18	1.00	1.00	1163	676
t	509	403	-11	320	456	265	238	281
Panel B: Periods with High HFT Activity								
	$Freq_{LO}$	Avg_qty_{LO}	$rspread_{LO}$	$Adv\_selection_{LO}$	*FR*	*QR*	*Time_E*	*Time_C*
Mean	2540	299	-0.21	0.57	0.18	0.12	110	81
Std. Dev.	769	87	0.29	0.30	0.04	0.03	82	50
Min	447	159	-7.12	-0.66	0.04	0.00	14	13
Max	9065	3974	1.39	7.83	0.42	0.36	1250	809
t	436	451	-97	254	647	454	177	217
Panel C: Paired *t*-test for LFT Variables between Periods with Low and High HFT Activity								
	$Freq_{LO}$	Avg_qty_{LO}	$rspread_{LO}$	$Adv\_selection_{LO}$	*FR*	*QR*	*Time_E*	*Time_C*
t	-150	-22	86	-114	-57	-30	58	40

Table 3: Hypotheses

This table presents the hypotheses examining the impact of HFT on LFT in terms of the liquidity and order execution quality, categorized by three sections: the liquidity of LFT limit orders (measured by $Freq_{LO}$ and Avg_qty_{LO}), the execution quality of LFT limit orders ($Time\_E$,$Time\_C$, FR and QR).

<table>
<tr><th colspan="2"></th><th>Dependent Variables</th><th>Independent Variables</th></tr>
<tr><td colspan="2">Section 1: The liquidity of LFT Limit orders:</td><td></td><td rowspan="8">$Freq_{HFT}$
BI_{HFT}
Avg_qty_{HFT}
$rspread_{HFT}$
$Adv\_selection_{HFT}$
$rspread_{LO}$
$Adv\_selection_{LO}$</td></tr>
<tr><td>Hypothesis 3:</td><td>HFT activity increases the trade frequency of LFT limit orders.</td><td>$Freq_{LO}$</td></tr>
<tr><td>Hypothesis 4:</td><td>HFT activity increases the average trade quantity of LFT limit orders.</td><td>Avg_qty_{LO}</td></tr>
<tr><td colspan="2">Section 2: The execution quality of LFT limit orders:</td><td></td></tr>
<tr><td>Hypothesis 5:</td><td>HFT activity reduces the average time gap of LFT limit orders.</td><td>Time_E, Time_C</td></tr>
<tr><td>Hypothesis 6:</td><td>HFT activity increases the frequency ratio of execution of LFT limit orders.</td><td>FR</td></tr>
<tr><td>Hypothesis 7:</td><td>HFT activity increases the quantity ratio of execution of LFT limit orders.</td><td>QR</td></tr>
</table>

Table 4: OLS estimates for the liquidity of LFT limit orders

This table presents the standard OLS estimates for the liquidity of LFT limit orders (measured by $Freq_{LO}$ and Avg_qty_{LO}). The independent variables are across the three types of orders (denoted by subscripts, *HFT* as HFT limit orders, *LO* as LFT limit orders and *MO* as market orders). *Freq* represents the trade frequency in one minute. *BI* represents the average order book imbalance in one minute. *espread* represents the average effective half-spread in one minute. *rspread* represents the average realized spread in one minute. *Adv_selection* represents the average price impact in one minute. *Avg_qty* represents the average trade quantity in one minute.

LFT Limit Orders	Dependent Variables			
	$Freq_{LO}$		Avg_qty_{LO}	
Independent Variables	β	*t*-stat	β	*t*-stat
$Freq_{HFT}$	0.2402	53.53	0.0317	5.57
Avg_qty_{HFT}	0.2581	76.88	0.254	59.62
BI_{HFT}	0.0164	4.95	-0.0012	-0.29
$rspread_{HFT}$	0.326	34.26	-0.0273	-2.26
$Adv\_selection_{HFT}$	0.6752	49.59	-0.0758	-4.39

Table 5: OLS estimates for the order execution quality of LFT limit orders

This table presents the standard OLS estimates for the order execution of LFT limit orders (*Time_E*, *Time_C*, *FR* and *QR*). *Time_E* represents the average time gap for execution in one minute (counted in seconds) calculated from the LFT executed limit orders. *Time_C* represents the average time gap for cancelation in one minute (counted in seconds) calculated from the LFT canceled limit orders. *FR* represents the ratio of the trade frequency of executed messages over the trade frequency of all messages in one minute. *QR* represents the ratio of the trade quantity of executed messages over the trade quantity of all messages in one minute. The independent variables are across the three types of orders (denoted by subscripts, *HFT* as HFT limit orders). *Freq* represents the trade frequency in one minute. *BI* represents the average order book imbalance in one minute. *espread* represents the average effective half-spread in one minute. *rspread* represents the average realized spread in one minute. *Adv_selection* represents the average price impact in one minute. *Avg_qty* represents the average trade quantity in one minute.

LFT Limit Orders		**Dependent Variables**											
		Time_E			***Time_C***			***FR***			***QR***		
Independent Variables		β	Std. Err.	*t*-stat	β	Std. Err.	*t*-stat	β	Std. Err.	*t*-stat	β	Std. Err.	*t*-stat
HFT Related	$\boldsymbol{Freq_{HFT}}$	-0.1525	0.00	-26.56	-0.1646	0.00	-28.57	0.0495	0.00	8.86	0.0055	0.00	0.95
	$\boldsymbol{Avg\_qty_{HFT}}$	-0.0118	0.01	-2.76	-0.0054	0.00	-1.25	-0.0095	0.00	-2.27	-0.0558	0.00	-12.83
	$\boldsymbol{BI_{HFT}}$	-0.0020	0.00	-0.47	0.0004	0.00	0.09	-0.0061	0.00	-1.49	-0.0168	0.00	-3.93
	$\boldsymbol{rspread_{HFT}}$	-0.1924	10.60	-15.81	-0.1274	5.95	-10.42	0.2324	0.00	19.62	0.2476	0.01	20.09
	$\boldsymbol{Adv\_selection_{HFT}}$	-0.3219	9.27	-18.48	-0.1650	5.21	-9.44	0.3267	0.00	19.27	0.3556	0.00	20.15

Table 6: Granger Causality Test Results on the Liquidity of LFT

This table presents the results of the Granger causality test for the liquidity of LFT limit orders (measured by $Freq_{LO}$ and Avg_qty_{LO}). *df* denotes the lag lengths on the independent variables, set with Akaike's [1974] information criterion (AIC). *Sig* denotes the marginal significance level of the computed χ^2-statistic used to test the zero restrictions implied by the null hypothesis of Granger non-causality.

H_0: Independent variables do not cause the trade frequency of LFT limit orders.					**H_0: Independent variables do not cause the average trade quantity of LFT limit orders.**				
Dependent	**Independent**	χ^2	***df***	***Sig***	**Dependent**	**Independent**	χ^2	***df***	***Sig***
$\boldsymbol{Freq_{LO}}$	$\boldsymbol{Freq_{HFT}}$	67.94	5	0	$\boldsymbol{Avg\_qty_{LO}}$	$\boldsymbol{Freq_{HFT}}$	91.17	5	0
	$\boldsymbol{BI_{HFT}}$	37.79	5	0		$\boldsymbol{BI_{HFT}}$	8.87	5	0.11
	$\boldsymbol{rspread_{HFT}}$	979.74	5	0		$\boldsymbol{rspread_{HFT}}$	380.92	5	0
	$\boldsymbol{Adv\_selection_{HFT}}$	956.53	5	0		$\boldsymbol{Adv\_selection_{HFT}}$	648.78	5	0
	$\boldsymbol{Avg\_qty_{HFT}}$	13.378	5	0.02		$\boldsymbol{Avg\_qty_{HFT}}$	1369.7	5	0
	ALL	5110.3	40	0		**ALL**	6085.6	40	0

Table 7: Granger Causality Test Results on the Execution Quality of LFT Limit Orders

This table presents the results of the Granger causality test for the execution quality of LFT limit orders (measured by *Time_E*, *Time_C*, *FR* and *QR*). *df* denotes the lag lengths on the independent variables, set with Akaike's [1974] information criterion (AIC). *Sig* denotes the marginal significance level of the computed χ^2-statistic used to test the zero restrictions implied by the null hypothesis of Granger non-causality.

H_0: Independent variables do not cause the average time gap for execution.					**H_0: Independent variables do not cause the average time gap for cancelation.**				
Dependent	**Independent**	χ^2	***df***	***Sig***	**Dependent**	**Independent**	χ^2	***df***	***Sig***
Time_E	$\boldsymbol{Freq_{HFT}}$	38.702	5	0	***Time_C***	$\boldsymbol{Freq_{HFT}}$	30.69	5	0
	$\boldsymbol{BI_{HFT}}$	9.2224	5	0.101		$\boldsymbol{BI_{HFT}}$	2.38	5	0.795
	$\boldsymbol{rspread_{HFT}}$	56.907	5	0		$\boldsymbol{rspread_{HFT}}$	74.15	5	0
	$\boldsymbol{Adv\_selection_{HFT}}$	206.18	5	0		$\boldsymbol{Adv\_selection_{HFT}}$	255.99	5	0
	$\boldsymbol{Avg\_qty_{HFT}}$	80.63	5	0		$\boldsymbol{Avg\_qty_{HFT}}$	25.06	5	0
	ALL	3421	40	0		**ALL**	4010.40	40	0
H_0: Independent variables do not cause the frequency ratio of execution.					**H_0: Independent variables do not cause the quantity ratio of execution.**				
Dependent	**Independent**	χ^2	***df***	***Sig***	**Dependent**	**Independent**	χ^2	***df***	***Sig***
FR	$\boldsymbol{Freq_{HFT}}$	272.16	5	0	***QR***	$\boldsymbol{Freq_{HFT}}$	101.68	5	0
	$\boldsymbol{BI_{HFT}}$	5.36	5	0.374		$\boldsymbol{BI_{HFT}}$	3.99	5	0.551
	$\boldsymbol{rspread_{HFT}}$	819.71	5	0		$\boldsymbol{rspread_{HFT}}$	324.94	5	0
	$\boldsymbol{Adv\_selection_{HFT}}$	1036.50	5	0		$\boldsymbol{Adv\_selection_{HFT}}$	447.65	5	0
	$\boldsymbol{Avg\_qty_{HFT}}$	59.66	5	0		$\boldsymbol{Avg\_qty_{HFT}}$	14.81	5	0.011
	ALL	3332.40	40	0		**ALL**	4183.90	40	0

Appendix A: Example of the Data

SYM	DATE	TIME	BID	ASK	BQ	AQ	TOKEN	ACT	QTY	B/A	PRICE
AAPL	20101101	34868960292	304.38	304.4	55	100	17901758	E	45	B	304.38
AAPL	20101101	34868975609	304.38	304.4	155	100	17894646	A	100	B	304.38
AAPL	20101101	34869029978	304.38	304.4	100	100	17894646	D	55	B	304.38

Table A1: Data Sample

Table A1 shows three rows from our data set for Apple, Inc. (AAPL) stock, where each row represents a limit order book event, or message. The columns include the symbol (SYM), the date (DATE), the time represented in integer format (TIME), the bid (BID) and ask (ASK) prices along with the bid quantity (BQ) and ask quantity (AQ). The TOKEN column is a unique identifier for each order. The action type (ACT) has five valid types for messages: 1) the addition of a displayed order to the book (as A); 2) the cancellation of an order (as D); 3) the partial cancellation of an order (as X); 4) the execution of an order (as E); and, 5) the partial execution of an order (as C). The QTY column is the quantity. The B/A column indicates whether the event occurred on the bid side (as B) or ask side (as A). The PRICE column shows the price of the event.

Appendix B: Multicollinearity Diagnostics

In order to examine the possibility of multicollinearity among the independent variables, we employ a variance inflation factor (*VIF*) test. For independent variable *j*, its *VIF* is defined as in equation (B1).

$$VIF_j = \frac{1}{1 - R_j^2} \tag{B1}$$

Where R_j^2 denotes the R^2 of the regression of independent variable *j* on the remaining independent variables. Using Stata, we calculate the R^2s and *VIF*s for each independent variable. A *VIF* of 10 or above would indicate a multicollinearity problem [see Heij et al., 2004]. However, the *VIF* results in Table B1 are all smaller than 10, with a mean *VIF* of 2.21. Therefore, multicollinearity is not an issue among the independent variables and the regressions in our paper.

Variable	***VIF***	$\boldsymbol{R^2}$
$\boldsymbol{Freq_{HFT}}$	1.71	0.42
$\boldsymbol{BI_{HFT}}$	1.00	0.00
$\boldsymbol{rspread_{HFT}}$	3.07	0.67
$\boldsymbol{Adv\_selection_{HFT}}$	4.25	0.76
$\boldsymbol{Avg\_qty_{HFT}}$	1.02	0.02
Mean	**2.21**	

Table B1: VIF Test Results

[1] In this paper, the term "execution quality" refers to several components, including the time length between limit order receipt and finalization, and the probability of execution in one unit of time length (e.g. 1 minute).
[2] Boehmer [2005] defines his "order execution speed" as the time between the order receipt and execution, which is equivalent to our term "execution quality".
[3] A very small percentage of market orders may occasionally come from HFT firms which execute immediately at a loss to eliminate risk positions. But HFT firms that trade across the bid-ask spread frequently do not stay in business long.
[4] Each trading day, 9:30 AM to 4:00 PM EST consists of 390 minutes.
[5] Additionally, we generated all results with threshold time frames ranging from 10.5 seconds to one minute and the results were little changed.
[6] HFT behaves differently from market makers who are required to maintain limit orders on both sides of the market continuously. HFT rarely carries positions. It has "very short time frames for establishing and liquidating positions" and "ends the trading day in as close to a flat position as possible" [SEC, 2010].