A Blessing or a Curse? The Impact of High Frequency Trading on Institutional Investors

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Abstract

The rapid growth of high frequency trading (HFT) has aroused considerable public attention and policy interests in its impact on institutional investors. Previous studies show that HFT decreases the average bid-ask spread. However, the major component of institutional trading costs is the price impact, as measured by the execution shortfall. Combining data on institutional trades and HFT trades, I find that HFT increases traditional institutional investors' trading costs. Specifically, one standard deviation increase in the intensity of HFT activities increases institutional execution shortfall costs by a third. I also perform various tests to rule out an alternative explanation that high frequency traders are attracted to stocks that have high trading costs. Further analysis suggests that HFT represents a short-lived and expensive source of liquidity provision when demand and supply among institutional investors are imbalanced, and that the impact on institutional trading costs is most pronounced when high frequency traders engage in directional strategies. Additionally, I find that institutional trading skills can alleviate the adverse impact of HFT.

Keywords: High frequency trading, Institutional investors, Trading costs, Execution shortfall

I. Introduction

Fueled by rapid technology advances, financial markets have undergone tremendous changes in the last decade. Stock trades are now exclusively placed and executed electronically, with over a dozen for-profit exchanges, as well as alternative trading venues competing for volume and liquidity. Notably, high frequency trading (HFT) has grown from being virtually non-existent in the market to being a dominant force. As of 2014, HFT firms accounted for 50% of the U.S. stock trading volume according to TABB Group. The fast development of HFT has led to considerable media attention and policy interests in its impact on market quality and on the welfare of other market participants. The recent book "Flash Boys" by Michael Lewis (2013), for example, has highlighted some of the related issues.

This study examines how the recent explosion of HFT activities affects a particularly important class of market participants, namely, institutional investors including mutual funds, pensions, insurance firms, hedge funds, etc. These traditional institutional investors play a critical role in financial markets. They account for over 50% of the public equity ownership in the U.S. (see French (2008)), and a considerable number of retail investors invest their savings/retirement money through such institutions (e.g., mutual funds and pension funds).[1] Institutional investors help improve price efficiency by trading based on new information or in response to price deviations from fundamentals. They generate substantial trading volume and their trading costs are critical determinants of their performance. Hence, institutional trading costs are often viewed as an important yardstick for measuring the quality and liquidity of a financial market. For this reason, facilitating efficient execution of institutional trades has been a core objective in the design and regulation of securities markets.

Whether HFT is good or bad for traditional institutional investors has been widely discussed and debated in public media, and the debate remains open. Some institutional investors have expressed serious concerns that high frequency (HF) traders may adversely

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[1]According to the 2014 Investment Company Fact Book, 46% of all U.S. households owned mutual funds.

impact their trading profits.[2] Such concerns are also echoed by regulators. For example, the former SEC Chairperson, Mary Shapiro, noted in a 2010 speech that "Institutional investors, also have expressed serious reservations about the current equity market structure. ... Institutional investors questioned whether our market structure meets their need to trade efficiently and fairly, in large size." In fact, institutional investors' concerns about HFT have led to the growing popularity of off-exchange trading venues, e.g., "dark pools".

In contrast to the above concerns by investment professionals and regulators, several empirical studies document that HFT activities actually reduce the bid-ask spread (e.g., Hasbrouck and Saar (2013), Menkveld (2013), and Brogaard, Hagströmer, Nordèn, and Riordan (2015)) and improve price efficiency (see Brogaard, Hendershott, and Riordan (2014b)).[3] Such evidence is consistent with the view that HF traders are the modern-day version of market makers with highly engineered computer systems. If technology expedites the execution of trades and/or improves the efficiency of market making, HFT should benefit other market participants, including institutional investors.

This study is distinguished from previous works in the following three aspects. First, this paper directly targets HFT's impact on the trading costs of institutional investors. By contrast, previous studies predominantly looked at general market quality measures such as the average bid-ask spread. In fact, institutional investors' trading costs consist of the bid-ask spread, trading commissions, price impact, and the timing delay cost. Because institutions usually trade in large quantities, the major component of their trading costs is

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[2]See, for example, "Institutional Investors Air HFT Concerns." Financial Times, September 12, 2011, "Wealth Fund Cautions against Costs Exacted by High-Speed Trading." New York Times, October 20, 2013, and "Berkshire's Munger: High-Frequency Trading 'Basically Evil'." Berkshire Munger, May 3, 2013.

[3]Some researchers have focused on Algorithm Trading (AT), which refers to the general use of computer algorithms to manage orders and execute trades. For example, Hendershott, Jones, and Menkveld (2011), Boehmer, Fong, and Wu (2014), and Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) find that the prevalence of AT reduces the bid-ask spread and improves market efficiency. However, it is worth noting that HFT is a particular subset of AT that requires low latency (see Hasbrouck and Saar (2013)). AT may also refer to the algorithms used by institutional investors when placing their trades, which is different from HFT. There is also mixed evidence on HFT's effect on short-term volatility and crashes: among others, Hasbrouck and Saar (2013) and Chaboud et al. (2014) find that HFT activity lowers short-term volatility whereas Ye, Yao, and Gai (2013), Boehmer et al. (2014), and Kirilenko, Kyle, Samadi, and Tuzun (2014) document a positive relationship between HFT activity and short-term volatility/price movements during the Flash Crash. See Jones (2013) for a comprehensive survey of the HFT literature.

the price impact, which can be five to ten times the magnitude of the bid-ask spread. Thus, the impact of HFT on institutional trading costs can be different from its impact on the average bid-ask spread.

Second, this work investigates how several types of popular HFT strategies affect institutional trading costs, while existing studies have mainly focused on the market making role of HFT. However, certain directional HFT strategies, such as order anticipation and momentum ignition, appear to explicitly increase the price impact cost of institutional investors.[4] Since institutions usually split a large order into small trades and execute them in sequence, a successful order anticipation strategy enables HFT firms to detect such order sequences and "front-run" them.[5] Further, using momentum ignition strategies, HF traders may ignite rapid price movements along one direction through a series of order submissions and cancellations to trigger institutional investors' order execution and profit by establishing an early position. These directional HFT strategies may increase intraday price volatility and drive up the institutional investors' trading costs. However, such strategies do not necessarily increase the bid-ask spread in the market.

Third, this paper examines whether HF traders provide a reliable source of liquidity when liquidity is most demanded by institutional investors. Some researchers have raised the concern that the liquidity provided by HF traders may be illusory. Since HF traders have no affirmative obligation to provide liquidity, their trading is opportunistic in nature, and the liquidity they create may disappear quickly when it is most needed on the market. For example, Kirilenko et al. (2014) and Easley, de Prado, and O'Hara (2011a) both document that during the Flash Crash of May 6, 2010, many HF traders withdrew from the market while others turned into liquidity demanders. Considering these issues, this work analyzes

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[4]Several popular HFT strategies are discussed in the Concept Release on Equity Market Structure by the SEC (2010). In addition to directional trading strategies, other popular strategies include electronic market making and rebate capturing, etc. Electronic market making and rebate capturing strategies may result in narrowed bid-ask spreads for small orders, which is consistent with the findings in aforementioned studies.

[5]Korajczyk and Murphy (2015) and van Kervel and Menkveld (2015) find that HF traders initially trade against large institutional orders and then switch to compete with them later on. Hirschey (2013) also uncovers that HF traders can anticipate order flow from non-HF traders and trade ahead of their order flow.

the time horizon of HFT liquidity provision and the impact of HFT on institutional trading costs when institutional trades are imbalanced.

This study combines the NASDAQ HFT dataset and the Ancerno institutional trading dataset to provide complete trading information for 120 stocks during the period of 2008 and 2009. The main measure of institutional trading cost is the execution shortfall, which captures the bid-ask spread, the market impact, and the drift in price during order execution (following, e.g., Anand, Irvine, Puckett, and Venkataraman (2012) and Anand, Irvine, Puckett, and Venkataraman (2013)).

The relationship between HFT and institutional trading costs is assessed using both sorted portfolios and multivariate regressions. The results of the sorted portfolios reveal an intriguing contrast in the relations between HFT activity intensity, stock liquidity (measured by the Amihud (2002) illiquidity measure), and institutional trading costs – HFT is positively correlated with stock liquidity and the latter is negatively correlated with institutional trading costs; however, the correlation between HFT and institutional trading costs is positive. The multivariate panel regressions confirm the significant positive impact of HFT activity on institutional trading costs after controlling for various stock characteristics and institutional trading characteristics. The regression coefficients suggest that one standard deviation increase in HFT activity is associated with an increase in average execution shortfall by one third. Considering the fact that on average an institution in the sample has a daily trading volume of $20.5 million for the sample stocks, a one-third increase in execution shortfall cost implies additional transaction costs of more than $10,000 per day.

This paper also carefully examines the alternative explanations for the positive relation between HFT and institutional trading costs. To begin with, there may be omitted variables causing both HFT activity and institutional trading costs to increase at the same time. I seek to rule out this alternative interpretation through the following approaches. First, beyond controlling for the variables documented to affect both institutional trading costs and HFT, I also include firm- and day-fixed effects in the multivariate regression specification, which

ensures that the observed positive relation between HFT activity and trading costs is not driven by unobserved stock-specific characteristics and time-specific factors. Second, since days with news releases may also affect both HFT and trading costs, I control for major corporate events such as earnings and mergers and acquisitions announcements, and continue to find similar results.

Another possibility could be that HF traders find it more attractive to trade stocks that have high trading costs. However, this is less likely because anecdotal evidence suggests that HF traders tend to trade in large and liquid stocks that allow them to "turn around" quickly.[6] I further rule out this possibility through the following tests. First, the sorted portfolio analysis indicates that HF traders are indeed most active in large and liquid stocks, rather than illiquid stocks which have high trading costs. Second, I study the short selling ban on financial stocks instituted on September 19, 2008. The results reveal that, as expected, the execution shortfall increases sharply on that day due to the ban. Under the alternative hypothesis that HF traders choose to be more active when execution shortfall is high, one would expect an increase in HFT activity after the implementation of the ban. However, HFT activity drops sharply subsequent to the ban's implementation. This evidence suggests that when liquidity is low, HF traders withdraw from the market.[7] Third, Granger causality tests provide further evidence that intensive HFT activity contributes to an increase in trading costs, but not vice versa.

Aside from the above tests, further analysis is also performed to understand the nature of HFT liquidity provision to institutional investors. Specifically, I examine whether HF traders profit from providing liquidity when institutional investors exhibit large buy-sell imbalance, i.e., when institutional investors on the net are either large buyers or sellers of a stock. The results suggest that on days with large institutional buy-sell imbalance on a given stock, HFT activities are more intense, but at market close HF traders manage to keep virtually

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[6]See "Top Stocks High-Frequency Traders (HFTs) Pick," http://www.investopedia.com/.

[7]A recent study by Brogaard, Hendershott, and Riordan (2014c) also looks at the short selling ban and finds that HFT short-selling decreases liquidity and price efficiency.

no open positions on the stock. Therefore, HFT at best represents a short-lived source of liquidity. Importantly, the impact of HFT on institutional trading costs is most pronounced when institutions exhibit large trade imbalances on the buy side. This finding suggests that the liquidity provided by HFT is expensive to institutional investors.

It is also of great interest to further study the impact of specific HFT strategies. Based on the non-randomness of HF trade directions, one may infer whether directional trading, reversal trading, and other types of HFT strategies are in present in the market and assess their different effects on institutional trading costs. In the case of directional strategies such as order anticipation and momentum ignition, one would observe long sequences of HF trades in the same direction.[8] Such directional strategies are designed to take advantage of large institutional trades. By contrast, when HF traders engage in reversal strategies, they buy and sell the same stocks very quickly to keep near-zero inventories, so that one should observe rapid reversals of HF trade directions.[9] The present analysis shows that both directional trading and reversal trading are pervasively employed by HF traders. More importantly, the impact of HFT on institutional trading costs is most pronounced when HF traders engage in directional trading. This evidence supports institutional investors' various anecdotal observations that their trades are anticipated and taken advantage of by HF traders.

The final part of this work investigates the heterogeneity across institutions in terms of HFT's impact on their trading costs. Anand et al. (2012) find substantial heterogeneity as well as short-term persistence in the performance of institutional trading desks, indicating differences in institutional trading skills. The results show that when trades are executed by institutions with better previous trading-desk performance, the positive relation between HFT activity and execution shortfall cost is substantially lower in magnitude. This suggests

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[8] "Front-running" trades by HF traders are more likely in the form of a sequence of small trades in the same direction than a few large trades, because in recent years both institutions and HF traders split large orders into sequences of small orders with the same direction for execution.

[9] HF trades may exhibit rapid reversals when HF traders engage in electronic market making or rebate-capturing strategies.

that some skillful institutional investors are able to alleviate the adverse impact of HFT on their trading costs.

One closely related work is Brogaard, Hendershott, Hunt, Latza, Pedace, and Ysusi (2014a). The authors study the relation between HFT and institutional trading costs in the UK market during the speed increase episodes at the London Stock Exchange (LSE). They find that, although LSE speed change increases HFT, this increase does not impact institutional trading costs significantly. My work, on the other hand, examines a different market where HFT is most prevalent,[10] during a different time period (2008 and 2009), and reaches different conclusions.[11] Also, I looks further into the illusory nature of HFT liquidity provision to institutional investors and the impact of specific HFT strategies, while neither has been investigated in Brogaard et al. (2014a).

Following the initial circulation of my paper, there are two papers which also examine the nature of HFT liquidity provision and the impact of specific HFT trading strategies. Using data from Toronto Stock Exchange, Korajczyk and Murphy (2015) find that HF traders initially trade against institutional investors' large orders and quickly turn to competing with them by trading in the same direction later. They also report that HF traders reduce liquidity provision when institutional trades are too large. Using Swedish data, van Kervel and Menkveld (2015) find that institutional investors' trading costs are higher when HF traders trade in the same direction with institutions. The findings from both studies, albeit from different stock markets, are by and large consistent with the findings of my paper.

The rest of the paper is organized as follows: Section II describes the data. Section III presents the baseline results and analyses on the causal relation between HFT and insti-

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[10]According to TABB Group, HFT generates 52% and 61% of the trading volume in 2008 and 2009, respectively, in the U.S. equity market, which is more than double their participation rate in Europe of 21% and 29% during the same period.

[11]Brogaard et al. (2014a) use speed increases at LSE as an instrument to examine the relation between HFT and institutional trading costs. Although exchange speed increases represent exogenous shocks to HFT, it is unclear how institutional investors respond to LSE speed increases when they place trades, and whether such speed increases change the competition among HFT traders. If exchange speed increases improve the order execution ability of institutional investors (which appears to be the main purpose of such speed increases) or intensify the competition among HF traders, then such speed increases do not necessarily result in extra rents that HF traders can extract from institutional investors.

tutional trading costs. Section IV provides further analysis on how and when HFT affects institutional trading costs, the heterogeneity of HFT's impact across institutions with different trading skills, as well as the robustness of the results. Section V concludes this work.

II. Data and Descriptive Statistics

A. Measuring HFT

The HFT dataset is provided by NASDAQ under a non-disclosure agreement. The dataset contains all exchange trades from 2008 and 2009 on a sample of 120 randomly selected stocks listed on NASDAQ or the New York Stock Exchange (NYSE). The time-stamps for trades in the dataset are to the millisecond. For each trade, a variable named "Type" identifies the liquidity demander and supplier as an HF trader or a non-high frequency (non-HF) trader based on NASDAQ's knowledge of its customers and analysis of the firm's trading, such as how often its net trading in a day crosses zero, its order duration, and its order to trade ratio.

NASDAQ identifies a total of 26 HFT firms in the data. However, HFT firms that route their orders through large integrated firms such as Goldman Sachs and Morgan Stanley cannot be identified and thus are excluded. As noted in Brogaard et al. (2014b), even though the 26 HFT firms represent a significant amount of HFT activity, it is impossible to completely identify all HF trades. Despite this limitation, this dataset is by far the most suitable data for the purpose of this study. Previous academic studies that use this dataset include Brogaard et al. (2014b) and Carrion (2013).

The dataset categorizes 120 stocks into three market capitalization groups: large, medium and small. Each size group contains 40 stocks, with 20 stocks listed on NYSE and the other 20 listed on NASDAQ. The top 40 stocks are from the largest market capitalization stocks. The medium-size category consists of stocks around the 1000th largest stocks in the Russell 3000, and the small-size category contains stocks around the 2000th largest stock in the Russell 3000. For each stock, the dataset contains the following fields: Ticker Symbol, Date,

Time (in milliseconds), Shares, Price, Buy/Sell Indicator, and Type (HH, HN, NH, NN). The Type variable identifies whether the two participants in a trade are HFT firms (H) or not (N). For example, "HN" means that an HF firm demands liquidity and a non-HF firm supplies liquidity in the trade. A trader may supply liquidity by posting limit orders on the order book and demand liquidity by executing market orders against existing limit orders.

This paper focuses on the aggregate HFT intensity on a stock on a given day. To construct a measure of HFT activity, I first calculate the dollar size of each trade in the dataset by multiplying Price and Shares traded. Each day, the aggregate dollar size of all trades that HFT firms participate in (i.e., HH*2+HN+NH) for a particular stock captures the total HFT volume on that stock. The measure of HFT daily activity on stock i, denoted as HFT Intensity$_{it}$, is defined as the aggregate HFT volume for stock i on day t divided by the stock's average daily trading volume in the past 30 days.

It is potentially interesting to divide HFT trading volume into liquidity demand volume (total of HN and HH volume) and liquidity supply volume (total of HH and NH volume). A logical conjecture is that liquidity-supplying trades by HF traders would benefit other investors while liquidity-demanding trades may hurt other investors instead. However, a particular HFT strategy may involve both liquidity supplying and demanding trades. For example, an HF trader who anticipates buying pressure from an institutional investor could first use market buy orders to take existing liquidity and then post limit orders at a higher price to sell back to the institution. This type of directional trading strategy will increase the institutional investor's trading costs, but it involves both liquidity supplying and liquidity demanding trades by HF traders. For this reason, this work chooses to focus on the total trading volume by HF traders to measure the intensity of HFT activity.[12]

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[12]In untabulated tests, I also explore the potential difference in the impact of HFT liquidity demand activity and HFT liquidity supply activity on institutional investors' trading costs. The results based on separate measures of liquidity demand and liquidity supply activities turn out to be qualitatively similar to each other and to those based on the total HFT activity.

B.   *Measuring institutional trading costs*

The NASDAQ dataset is merged with a proprietary database of institutional investors' equity transactions compiled by Ancerno Ltd. (formerly known as Abel/Noser). The measure of institutional trading costs is constructed from the Ancerno dataset. There are 204 institutions in the Ancerno dataset that are involved in trading the 120 sample stocks during 2008 and 2009. Their average trading volume on these stocks is $20.5 million per institution per day. Previous academic studies that use Ancerno's data include Anand et al. (2012), Anand et al. (2013), Goldstein, Irvine, Kandel, and Weiner (2009), Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2010), and Puckett and Yan (2011), among others.

A typical order from a buy-side institution is large in size and usually has high information content. To reduce market impact, the trading desk of the buy-side institution may split the large order and place them with several brokers. In the dataset, the allocation to each broker is defined as a "ticket" (used interchangeably with "order" throughout the paper) and each ticket may further result in several distinct trades or executions. For each execution, the database reports identity codes for the institution, the CUSIP and ticker for the stock, the stock price at the placement time, date of execution, execution price, number of shares executed, the direction of the execution (buy or sell), and the commissions paid. See Anand et al. (2012) for additional details on this dataset.

Following Anand et al. (2012), I measure the cost of each ticket by execution shortfall, which is defined as:

$$\text{Execution Shortfall} = \frac{P_1 - P_0}{P_0} \times D, \tag{1}$$

where P_1 is the value-weighted execution price of the ticket, P_0 is the price at the time when the broker receives the ticket, and D is a dummy variable that equals 1 for a buy trade and -1 for a sell trade. I calculate the volume-weighted average of the execution shortfall of all trading tickets for stock i on day t and denote it as Execution Shortfall$_{it}$.

In this study, most of the tests are conducted at the stock level using the daily measures of

HFT intensity and execution shortfall.[13] As a robustness check, I also examine the relation between HFT activity and execution shortfall at the trading ticket level. For this latter analysis, HFT activity is calculated at stock-day level while execution shortfall is calculated for each ticket.

Another component of institutional trading costs is the execution timing delay cost, which refers to the difference between the market-open price and the price at the time the order is placed with the broker:[14]

$$\text{Timing Delay} = \frac{P_0 - \text{Open Price}}{\text{Open Price}} \times D, \tag{2}$$

where Open Price is the opening price on the execution day. This timing delay cost can be thought as the cost of seeking liquidity (e.g., ITG (2009)). This measure is constructed for each trading ticket in the sample. I calculate the volume-weighted average of the timing delay cost of all trading tickets for stock i on day t and denote it as Timing Delay$_{it}$. While the main focus of this paper is to investigate the impact of HFT on execution shortfall, a major component of institutional investors' trading costs, it is also of interest to examine if HFT helps reduce the timing delay cost.

C. Sample descriptive statistics

As mentioned above, the sample covers 120 stocks from 2008 and 2009. To minimize data errors, I impose two filters following Anand et al. (2012): 1) tickets with execution shortfall greater than an absolute value of 10% are excluded; 2) tickets with trade size larger than the stock's total trading volume on the execution date are excluded. I obtain data on stock daily trading volume, daily returns, close price, and total shares outstanding from $CRSP$. In addition, I identify earnings announcement dates from $I/B/E/S$ and $COMPUSTAT$

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[13]Even though the Ancerno data provide time-stamps for trades, these time-stamps are not reliable; see, e.g., Anand et al. (2012). Thus, I cannot match the Ancerno data with the NASDAQ data at the individual trade level.

[14]A traditional institution typically decides on a list of stocks to trade before the market opens (e.g., at 8AM fund manager meetings) and then places the orders during the trading day.

and obtain information on mergers and acquisitions from SDC Platinum.

Table I reports the descriptive statistics of HFT and institutional trades. Panel A presents descriptive statistics of the NASDAQ dataset. These numbers reveal a notable pattern in HFT: the HF traders are most active in large stocks. The average daily HFT volume on large stocks, medium stocks and small stocks is \$158.23, \$3.65 and \$0.38 million, respectively.

Panel B reports the descriptive statistics of the Ancerno dataset. In the merged sample, there is a total of 204 institutions trading on the 120 stocks during 2008 and 2009. As reported in Anand et al. (2012), the total number of institutions in the full sample of the Ancerno dataset is 223 in 2008. Thus my sample covers the majority of the institutions in the Ancerno dataset. The average execution shortfall for large, medium, or small stocks is 0.15%, 0.16%, or 0.20%, respectively. In addition, the size of an average trading ticket is 14,823 shares and it takes more than two executions to implement the ticket.

D.   Determinants of HFT

Before an examining on the relation between HFT and institutional trading costs, it is helpful to understand the firm characteristics that may be associated with HFT intensity. These characteristics may also relate to trading costs and serve as control variables in the main analysis.

I consider the following characteristics: 1) firm size (Log Market Cap), measured by the logarithm of a stock's daily market capitalization; 2) Book-to-Market Ratio, measured using information available at the beginning of each calendar quarter; 3) Event Dummy, a dummy variable that equals one for a stock on a given day if there is a corporate event (earnings announcement or mergers and acquisitions announcement), and equals zero otherwise; 4) Daily Return Volatility, i.e. a stock's range-based estimate of daily volatility (annualized), following Parkinson (1980); 5) Prior One-Day Return, Prior One-Month Return, and Prior 12-Month Return, i.e. a stock's lagged daily return, lagged monthly return, and lagged 12 months return, respectively; 6) stock illiquidity as measured by the Amihud illiquidity ratio,

i.e., the daily absolute return divided by the dollar trading volume on that day; 7) Daily Dollar Turnover, a stock's daily dollar trading volume scaled by the stock's total shares outstanding; 8) Average Institutional Order Size, the average dollar volume of all tickets placed on a stock, scaled by the average trading volume of that stock in prior 30 days; 9) Absolute Institutional Imbalance, the absolute value of the daily total dollar volume of all institutional buy tickets minus that of all sell tickets on a stock, scaled by the average trading volume of that stock in the past 30 days; 10) Average Trades Per Order, defined as the average number of trades to complete a trading ticket on a stock; 11) Prior One-Month Market Volatility, annualized daily return volatility of the CRSP value-weighted index in the prior month; 12) Prior One-Day Market Return, the return of the CRSP value-weighted index during the previous day.

I estimate a panel regression model by regressing daily stock HFT intensity on these firm characteristics. The estimated coefficients and two-way clustered t-statistics are reported in Table II. The results suggest that HFT intensity is positively related to firm size and return volatility and is negatively related to illiquidity. HF traders are also more active in stocks with high daily dollar turnover, high absolute institutional trading imbalance, and a large number of trades per order, as well as on days with event announcements. Taken together, the results in this table indicate that HF traders favor large and liquid stocks, which allow them to make round-trip trades fast and at low costs. It is also worth pointing out that they are more active when a large institutional order is split into more trades. The reason could be that longer sequences of institutional trades give HF traders a better chance to figure out the order flow pattern. In the subsequent analysis of this paper, I pay particular attention to HFT activities at corporate events days and when institutional trades are imbalanced.

III. HFT's Impact on Institutional Trading Costs

A. *HFT, liquidity, and trading costs: sorted portfolios*

I begin with a sorted portfolio analysis to present an intuitive picture of the relations between HFT activity, a conventional measure of liquidity, and institutional investors' trading costs.

First of all, I examine the relation between HFT and the conventional measure of stock liquidity, the Amihud illiquidity ratio (detailed in Section II.D). Since the 120 stocks are in three distinctive size categories, I further divide the stocks in each size group into terciles based on the Amihud illiquidity ratio on each day. I calculate the average HFT Intensity of all stock days in each of the nine (3×3) groups. Figure 1 plots the average HFT intensity against the Amihud illiquidity ratio across the nine groups. It shows a positive relation between HFT and liquidity within each size group. This finding is consistent with those reported by the existing literature on HFT. However, we cannot infer the direction of the causality from such a simple statistical association. It could well be the case that HF traders choose to trade more in liquid stocks, considering their reliance on rapid-fire trading strategies.

Then, I investigate the relation between stock liquidity and institutional trading costs as measured by execution shortfall. I continue to rely on the nine groups of stocks sorted on size and Amihud illiquidity ratio. Figure 2 plots the average execution shortfall across the nine groups. It shows a negative relation between execution shortfall and liquidity within each size group. That is, trading costs are lower for liquid stocks.

Combining the patterns from Figure 1 and 2, one may expect a negative relation between HFT intensity and execution shortfall. However, Figure 3 shows that the opposite holds. In this plot, I sort stocks into terciles based on HFT intensity within each size group to form nine portfolios and compute the average execution shortfall within each portfolio. The plot shows that within each size group, when HFT is more intense, the average institutional investors' execution shortfall is also higher. In other words, the HFT activity is positively

correlated with institutional trading costs.

Figure 1 to 3 present somewhat intriguing contrasts on the relations among HFT activity, liquidity, and institutional execution shortfall. If HFT activity improves liquidity, then why does execution shortfall increase when HFT activity is more intense? The contrast suggests that the conventional notion of liquidity and institutional trading costs may be quite different in nature. First of all, the liquidity provided by HFT may be illusory and disappear when institutional investors need it most. Moreover, the large order sizes and potentially high information content make institutional trades most vulnerable to HFT strategies such as order anticipation (see Hirschey (2013), Korajczyk and Murphy (2015), and van Kervel and Menkveld (2015)). Such strategies can dramatically increase the price drifts and market impact during the execution of a large order. These adverse effects of HFT on institutional investors may not be captured by the conventional measure of liquidity.

B. Multivariate analysis

In order to control for other relevant factors that may affect trading costs, I perform the following multivariate panel regression, controlling for various firm characteristics:

$$\text{Execution Shortfall}_{it} = \alpha_i + y_t + a \times \text{HFT Intensity}_{it} + b \times X_{it} + \epsilon_{it}, \tag{3}$$

where HFT Intensity$_{it}$ is the measure of daily HFT activity on stock i. Execution Shortfall$_{it}$ is the volume-weighted average execution shortfall of all trading tickets on stock i at day t. X_{it} represents a set of firm characteristics that have been considered in Table II when I examine the determinants of HFT activity. They include firm size, book-to-market ratio, stock returns during the prior one day, one month, and 12 months, the Amihud illiquidity ratio, a range-based daily stock volatility measure, daily trading turnover, average institutional order size, absolute institutional trade imbalance, and average number of trades per order. α_i and y_t represent the firm- and time(day)-fixed effects, respectively. For statistical inference I use two-way clustered standard errors (by stock and by day) that are robust to

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cross-sectional and time-series heteroscedasticity and within-group autocorrelation based on Petersen (2009).

Table III presents estimates of coefficients and the two-way clustered t-statistics. The first two columns report the estimates of the model without controlling for the time-fixed and firm-fixed effects. However, to control for market conditions, I also include the prior one-day market return and prior one-month market volatility as control variables. In the last two columns, the linear regression model in Equation (3) is estimated with both time-fixed and firm-fixed effects, but without the two market condition variables.

In both sets of tests, the coefficient on HFT Intensity is positive and significant at the 1% level. This result suggests that after controlling for other economic determinants of trading costs, HFT activity has an *increasing* effect on institutional investors' execution shortfall. In particular, the result from the fixed-effects regression indicates that one standard deviation increase in HFT activity leads to $0.309 \times 0.16\% = 5bp$ increase in execution shortfall, which is about 30% of the average execution shortfall ($16.7bp$) in the sample. Considering that an average institution in the sample generates a daily trading volume of $20.5 million on the 120 sample stocks, a 5bp increase in execution shortfall means an additional cost of more than $10,000 per day.

To better evaluate the effects of the control variables on institutional execution shortfall, I focus on the estimation results of the model without the time-fixed and firm-fixed effects, i.e., those reported in the first two columns in Table III. For example, the coefficients for the control variables are of expected signs. The coefficient of the illiquidity measure is also positive and significant, which is consistent with the intuition that higher illiquidity leads to higher execution shortfall. The coefficient of the absolute value of institutional buy-sell imbalance is positive and significant at the 1% level. This is because that higher imbalance leads to more competition for liquidity in one direction. Moreover, similar to prior studies, I find that execution shortfall increases with stock volatility.

In sum, the results from the multivariate panel regression indicate that when HFT ac-

tivity is more intense, institutional investors' execution shortfall is higher. This positive relationship holds after controlling for various stock and institutional trading characteristics, as well as the unobservable time-invariant firm characteristics and pervasive factors affecting all stocks during a given day (captured by the time-fixed and firm-fixed effects).

C. Direction of causality

There are two alternative explanations for the multivariate test results. First, there may be some omitted variables that cause both HFT activity and execution shortfall to increase at the same time. Second, it could also be that high execution shortfall attracts more HF traders.

The tests conducted in previous subsections have already helped rule out the alternative interpretations to a certain degree. The sorted portfolio analysis indicates that HF traders are most active in liquid stocks, rather than illiquid stocks. Second, I include firm and time-fixed effects in the multivariate regression specification, which helps ensure that unobserved slow-moving stock characteristics and time-specific factors do not cause the positive relationship between HFT activity and execution shortfall.

In this subsection, I conduct further analysis to address these alternative hypotheses.

C.1. Controlling for corporate events

Although the results in the previous subsection established the increasing effect of HFT activity on execution shortfall for institutional investors after controlling for time-fixed and firm-fixed effects, there may be certain special events that cause an increase in both HFT activity and execution shortfall. To rule out this possibility, I control for two types of important corporate events: earnings and mergers and acquisitions (M&A) announcements. I identify earnings announcement dates from *COMPUSTAT* (and augmented with *I/B/E/S* data in the case of missing earnings announcement dates in *COMPUSTAT*). The M&A announcement dates are identified from SDC Platinum database. In total, during the two-

year period, there are 960 quarterly earnings announcements and 323 M&A announcements where the 120 firms in my sample are either candidate acquirers or candidate targets.

In order to observe the different impact of HFT on execution shortfall on event days and non-event days, I create a dummy variable Event Dummy that equals one for a stock-day observation falling within a 5-day window of a corporate event for that stock. It is zero otherwise. No-Event Dummy is a dummy variable that equals one for a stock day not in any 5-day corporate event window for that firm. I then interact HFT Intensity with Event Dummy and No-Event Dummy, respectively, and use the interaction terms in place of HFT Intensity in the panel regression analysis. The Event Dummy is also included in the regression. Other variables in the regression remain the same as those reported in Table III.

Table IV presents estimates of the coefficients and the two-way clustered t-statistics. The coefficient of the interaction between HFT Intensity and Event Dummy is positive but not significant. However, the interaction between HFT Intensity and No-Event Dummy is positive and significant at the 1% level. The results indicate that the increasing effect of HFT activity on execution shortfall mainly occurs on days without corporate events. This finding is inconsistent with the particular alternative hypothesis that certain corporate events drive both HFT intensity and execution shortfall higher.

C.2. Short selling ban

In this subsection, I examine a special event in my sample period – the short selling ban of 2008 – in order to rule out the alternative explanation of reverse causality, i.e., HF traders choose to be more active when institutional trading costs are high.

I study the behavior of HF traders and the pattern of execution shortfall around the short selling ban from September 19, 2008 to October 8, 2008. On September 19, 2008, the SEC released an emergency order prohibiting short selling in a group of 799 financial stocks. The initial list of securities covered 13 stocks in the sample. On September 22, the list expanded to cover 16 stocks in the sample, and one more stock was added to the

banned list on September 23.[15] The prohibition on short selling has an immediate impact on institutional investors' execution shortfall cost in the banned stocks. This ban, however, does not by itself impact HF traders directly, because short-selling is not a necessary strategy for HF traders.

Figure 4 presents the time-series pattern of the average execution shortfall of the banned and unbanned stocks around the short selling ban. As expected, the execution shortfall of the banned stocks increases sharply when the ban is imposed on September 19. Figure 5 plots the time-series of the average HFT intensity for the banned and unbanned stocks around the same period. On September 19, when execution shortfall reaches its highest level in the picture, I observe a sharp decrease in HFT activity. If the increasing effect of HFT activity on execution shortfall is because HF traders choose to participate more when trading costs are high, one should observe an increase in HFT activity instead. This pattern also raises a question on HF traders' role in providing liquidity. Clearly when liquidity is most needed and trading becomes difficult, HF traders appear to withdraw from the market altogether (e.g., Carrion (2013)).

In conclusion, through observations of institutional trading costs and the behavior of HF traders during the short selling ban, I further rule out the alternative explanation that the positive relation between HFT and institutional trading costs is due to a reverse-causality effect, i.e., HF traders choose to be more active when trading costs are high.

C.3. Granger causality

Lastly, I use the Granger causality test to further establish the direction of causality. The Granger causality test enables one to infer, in a statistical sense, whether a lagged variable (e.g., lagged HFT Intensity) bears a causal effect on another variable (e.g., Execution Shortfall). Specifically, for a given stock, the Granger causality test is performed under the following VAR(1) framework:

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[15]The trading symbols of the sample stocks in the initial short-selling ban list are: AINV, BXS, CB, CRVL, DCOM, EWBC, FFIC, FMER, FULT, MIG, PNC, PTP, SF. The list is expanded to cover GE, AXP, and CSE on 9/22/2008 and ARCC on 9/23/2008.

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$$\begin{pmatrix} ES_{i,t} \\ HFT_{i,t} \end{pmatrix} = \begin{pmatrix} a_{1,i} \\ a_{2,i} \end{pmatrix} + \begin{pmatrix} b_{11,i} & b_{12,i} \\ b_{21,i} & b_{22,i} \end{pmatrix} \begin{pmatrix} ES_{i,t-1} \\ HFT_{i,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,i,t} \\ \epsilon_{2,i,t} \end{pmatrix}, \qquad (4)$$

where $ES_{i,t}$ and $HFT_{i,t}$ represent the Execution Shortfall and HFT Intensity for stock i on day t, respectively. $a_{1,i}$, $a_{2,i}$, $b_{11,i}$, $b_{12,i}$, $b_{21,i}$, $b_{22,i}$ are parameters. $\epsilon_{1,i,t}$ and $\epsilon_{2,i,t}$ are innovation terms.

I examine the following two null hypotheses: (1) HFT Intensity does not Granger cause Execution Shortfall; (2) Execution Shortfall does not Granger cause HFT Intensity. If $b_{12,i} \neq 0$ then null hypothesis (1) is rejected, indicating that HFT Intensity Granger causes Execution Shortfall. On the other hand, if $b_{21,i} \neq 0$ then null hypothesis (2) is rejected, which means that Execution Shortfall Granger causes HFT Intensity.

A statistical issue here is that inference has to be made jointly on 120 stocks. Take the inference on the first hypothesis (i.e., HFT Intensity does not Granger cause Execution Shortfall) for example. Even when the true values of $b_{12,i}$s are all zero across the 120 stocks, by statistical randomness the sample estimates of some of the $b_{12,i}$s will be significantly different from zero. Therefore, in the presence of a relatively large cross-section of stocks, inference in a stock-by-stock fashion is likely problematic. Instead, I focus on the distribution of the estimated coefficients (i.e., $b_{12,i}$ and $b_{21,i}$) across the 120 stocks, and assess whether the sample distribution of the coefficients is different from what one would observe under the null hypothesis of no causality. To do so, a further complication is that the variables of interest, $b_{12,i}$s or $b_{21,i}$s, are correlated across stocks.[16]

I take a bootstrap approach to perform statistical inference jointly on the 120 stocks, in a way similar to the bootstraps performed by Kosowski, Timmermann, White, and Wermers (2005) and Jiang, Yao, and Yu (2007) in their studies of mutual fund performance. In the context of this study, the bootstrap procedure generates randomized observations of $ES_{i,t}$ and $HFT_{i,t}$ under the null of no causality (i.e., $b_{12,i}=0$ and $b_{21,i}=0$ for all i), while at the same

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[16]In addition to inference based on the cross-sectional distribution of the coefficients, one can also use more conventional Wald-type test on the hypothesis that the coefficients $b_{12,i}$s (or $b_{21,i}$s) are jointly zero across all 120 stocks. However, in the presence of a large cross-section relative to the length of the time series, the power and size of the conventional test are likely an issue.

time keep the time-series persistence parameters of $ES_{i,t}$ and $HFT_{i,t}$ per se, the correlation between $\epsilon_{1,i,t}$ and $\epsilon_{2,i,t}$ for any given stock, as well as the correlations among $\epsilon_{1,i,t}$ and $\epsilon_{2,i,t}$ across 120 stocks.[17] For each bootstrap, I estimate the cross-sectional statistics, including the mean, median, and 1st and 3rd quartiles of the t-statistics, for the estimated coefficients. The bootstraps are performed 2,000 times, and the sample cross-sectional statistics (e.g., the mean of the t-statistics) are compared with the corresponding bootstrapped statistics to assess statistical significance. Specifically, the bootstrapped p-value is computed as the percentage of bootstrapped statistics that exceed the sample statistics. A bootstrapped p-value close to 1 indicates that the sample statistic is abnormally low relative to the distribution under the null hypothesis of no causality. A bootstrapped p-value close to 0 indicates that the sample statistic is abnormally high relative to what one would expect under the null of no causality.

Table V presents the results of the Granger causality test. As shown in Panel A, across the 120 stocks, $b_{12,i}$, the coefficient related to the causality of HFT on ES, has a positive mean of 0.317, and its corresponding t-statistic has a positive mean of 0.311. The bootstrapped p-value is 0.002, indicating that the mean of the sample t-statistic is abnormally high relative to what is expected under the null of no causality. Note that the p-values for other cross-sectional statistics, i.e., median, 1st and 3rd quartiles, are all very low. Therefore, I infer that across the 120 stocks, there is a pervasive pattern: the HFT intensity Granger causes institutional trading costs.

On the other hand, as shown in Panel B of the table, the coefficient related to the

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[17]Specifically, the procedure involves the following steps. Across the 120 stocks, I compute the cross-sectional distribution statistics such as the mean, median, 1st and 3rd quartiles of the t-statistics. First, I estimate the VAR(1) model described in (4) using the sample data, and obtain the coefficients, corresponding t-statistics, and the estimated residuals for all stocks. Second, I bootstrap (i.e., resampling with replacements) the residuals to reconstruct the bootstrapped time series of $ES_{i,t}$ and $HFT_{i,t}$, using the bootstrapped residuals and the estimated parameters from the model (4) but restricting $b_{12,t}$ and $b_{21,i}$ to be zero. Third, I estimate the model (4) using the bootstrapped $ES_{i,t}$ and $HFT_{i,t}$, and obtain a new set of coefficients and the corresponding t-statistics. Across 120 stocks, I obtain the cross-sectional distribution statistics of the bootstrapped t-statistics. Step 2 and 3 are repeated for 2,000 times to obtain 2,000 bootstrapped observations of the cross-sectional statistics (i.e., mean, median, 1st and 3rd quartiles of the t-statistics). Note that I bootstrap t-statistics rather than the coefficients per se, because the t-statistics are pivotal statistics that have a better convergence property.

causality of ES on HFT, $b_{21,i}$, has a small mean of 0.001; the corresponding t-statistic has a small mean of 0.039, with a bootstrapped p-value of 0.341. These results suggest that the mean of the sample t-statistic is within the normal range of what one would expect under the null of no causality. In addition, the p-values for the median and 1st and 3rd quartiles are in the range of 0.14 to 0.70. Overall, this suggests that there is no pervasive support of the hypothesis that institutional execution shortfall Granger-causes HFT.

In sum, the Granger causality tests provide further confirmation that more intensive HFT activities lead to an increase in institutional trading costs, but not vice-versa.

IV.   Further Analysis of HFT activities

The analysis in this section consists three parts. The first part includes two sets of robustness results based on the timing delay component of trading costs and trade-level regression analysis. The second part contains results on the specific mechanisms through which HFT impacts institutional trading costs. The third part examines the heterogeneity of institutional trading skills and the related heterogeneity in HFT's impact on execution shortfall across institutions.

A.   Robustness: Timing delay cost and trade-level regressions

A.1.   Timing delay cost

This study has provided evidence that intensive HFT activities lead to an increase in institutional investors' execution shortfall. This finding suggests that even though HFT improves general measures of market quality, as documented in current literature, it induces additional trading costs for institutional investors. A reasonable question to ask is whether HFT may benefit institutional investors in some other ways and, to some extent, offset the increase in trading costs. Considering the large amount of quotes sent by HF traders, one possible benefit to institutional investors may be that the costs incurred while waiting for liquidity could decrease. Here, I perform analysis to address this possibility.

The cost incurred while seeking liquidity is known as timing delay cost in the literature.

The specific measure of the timing delay cost is defined in Equation (2). To study the impact of HFT on timing delay cost, I estimate the following panel regression model:

$$\text{Timing Delay}_{it} = \alpha_i + y_t + a \times \text{HFT Intensity}_{it} + b \times X_{it} + \epsilon_{it}, \tag{5}$$

where α_i and y_t are the firm- and day-fixed effects; HFT Intensity$_{it}$ is the measure of daily HFT activity on stock i as described in subsection II.A; Timing Delay$_{it}$ is the volume-weighted average timing delay cost of all institutional trades on stock i at day t defined in subsection II.B; X_{it} represents the same set of control variables as in Equation (3).

Table VI presents the estimates of the coefficients, with t-statistics computed using the two-way (by stock and by day) clustered standard errors. The regression model is estimated with both day- and firm-fixed effects. The coefficient of HFT Intensity is insignificant, which suggests that after controlling for other economic determinants of trading costs, HFT activity has no effect on institutional investors' timing delay cost. Thus, while HFT activity increases institutional investors' execution shortfall, it does not provide the benefit of reduced timing delay cost.

A.2. Trade-level analysis

So far, all the multivariate panel regression analyses are conducted at the stock-day level, where execution shortfall cost is aggregated for each stock on each trading day. The aggregation at the stock-day level provides a strong indication that HFT increases institutional trading costs. However, one factor may be missing in the analysis of the data at the stock-day level, which is the difference in the trading skills of institutional investors.[18] As pointed out by Anand et al. (2012), some institutions consistently execute trades at lower execution shortfall than the others. If trades are executed by different institutions at different days on different stocks, the heterogeneity of institutional trading skills likely influences the aggregated measure of trading costs at stock-day level. To control for this factor, I estimate the following regression model based on trade-level observations:

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[18]The impact of HFT on execution shortfall when institutional trading desks are highly skilled is examined in detail in section IV.C.

$$\text{Execution Shortfall}_{i,j,t} = \alpha_j + \gamma_m + a \times \text{HFT Intensity}_{it} + b \times X_{it} + \epsilon_{it}, \qquad (6)$$

where Execution Shortfall$_{i,j,t}$ is the execution shortfall of each trade (referred to as a "ticket" in the Ancerno data) for stock i on day t by institution j. α_j represents the institution-fixed effects, and γ_m represents the time(month)-fixed effects. X_{it} represents the same set of control variables as in Equation (3).

Table VII presents the estimates of coefficients, with the t-statistics computed using the two-way clustered standard errors. The coefficient of HFT Intensity is 0.115 and significant at the 1% level. This suggests that after controlling for heterogeneous institutional trading skills, HFT increases execution shortfall at the trade level, consistent with the conclusion drawn from the stock-day level analysis.

B.   When and how does HFT impact institutional trading costs

In this subsection, I investigate two specific conjectures related to the mechanisms through which HFT affects institutional trading costs. The first possibility is that HFT may profit from providing liquidity to institutions when the latter have large buy-sell imbalance among themselves. The second one is that HF traders anticipate and trade ahead of institutional investors' large trades.

B.1.   HFT and institutional buy-sell imbalance

I first investigate the possibility that HF traders profit from providing liquidity to traditional institutional investors when the latter have large trade imbalances. If this notion of liquidity provision turns out to be true in the data, then the profits made by HF traders in a way resemble the profits made by traditional market makers. After all, electronic market making is an important form of HF strategies. However, even in this case, it is important to question whether the liquidity provision by HF traders comes with extra costs to institutional investors.

To begin with, I compare the daily buy-sell imbalance of the two types of investors –

institutional investors and HF traders. For each of them, I define their daily imbalance on each stock as the buy dollar volume minus the sell dollar volume normalized by the stock's average daily trading volume over the prior 30 days. Panel A of Table VIII presents the distribution of such buy-sell imbalances for the sample stocks in 2008 and 2009. The table shows that while the daily imbalance by traditional institutional investors exhibits large variations, the daily imbalance for HF traders is very close to zero. This contrast is consistent with the notion that institutional investors trade on information or mispricing that may pay off over a relatively long horizon, while HF traders profit mostly from price swings at very short horizons. Both anecdotal evidence and academic studies have suggested that holding overnight positions can be very costly for HF traders (e.g., Menkveld (2013)).

Next, I use sorted portfolios to examine the relation between institutional buy-sell imbalance with both HFT activity and HFT buy-sell imbalance. Specifically, within each of the three-size groups, I sort stocks into terciles based on institutional buy-sell imbalance, and I examine the average HFT intensity and average HFT buy-sell imbalance across the nine groups. Panel B and C of Table VIII report the average institutional buy-sell imbalance and HFT buy-sell imbalance in each of the nine groups, respectively. The numbers suggest that, despite the large swings of institutional imbalances, the imbalances of HF traders tend to be very small. This pattern is consistent with the statistics reported in Panel A on HF trade imbalances. Finally, Panel D shows that when institutions exhibit buy-sell imbalance on either the buy or sell side, HFT intensity becomes higher relative to when institutional trades are balanced.

Combining results from all panels of Table VIII, one can make the following inferences. First, HFT becomes more active when institutions encounter large trade imbalances; presumably this is consistent with a liquidity provision role played by HF traders. However, the results in Panel C suggest that HF traders have minimum trade imbalances at the end of a trading day. Thus, if they provide liquidity to institutions, such liquidity provision is short-lived, i.e., within a day. Therefore, a more accurate description of the liquidity pro-

vision role of HF traders is that they serve as intraday intermediaries and quickly pass the imbalances from institutions to other market participants.

I then investigate another important question regarding the liquidity provision role of HF traders. The analysis in Table III shows that institutional trading costs are higher when institutions face large trade imbalances. If the presence of HFT reduces institutional trading costs on such occasions, then liquidity provision by HFT has a socially beneficial element. On the other hand, if the presence of HFT increases trading costs on such occasions, it is likely that HF traders are successful in taking advantage of institutional investors when the latter face large trade imbalances.

To address this question, I examine the differential impact of HFT on execution shortfall when institutions are net sellers, net buyers, or have relatively balanced buys and sells. Specifically, I divide all stock days into three groups based on institutional buy-sell imbalance, and then estimate the panel regression model specified in Equation (3) within each group. The results are reported in Table IX. The first two columns of the table report results when institutions have relatively large net sell imbalance. The coefficient of HFT Intensity is -0.178 but it is not significant at the 5% level, suggesting that HFT activity does not hurt institutional investors when the latter are net selling. The middle two columns report results when institutional trading is relatively balanced. The coefficient of HFT Intensity is 0.524 and significant at the 5% level, suggesting that HFT activity significantly increases institutional investors' trading costs when their trading is balanced. The most striking results are reported in the last two columns, in the case when institutional investors are net buyers. The coefficient of HFT Intensity is 0.612 and significant at the 1% level, which suggests that the impact of HFT activity on execution shortfall is most pronounced when institutional investors have relatively large net buy imbalance. Overall, there is no evidence that HFT helps reduce trading costs when institutional investors have large trade imbalances; rather, HF traders appear to have successfully taken advantage of institutions when the latter are net buyers on a stock, making their trades extra costly.

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In sum, the evidence presented in this part of the analysis suggests that HF traders serve as a type of intraday liquidity providers to institutions when the latter have large buy-sell imbalance among themselves; however, such liquidity provision is costly to institutions, especially when they are net buyers of a stock.

B.2. Impact of HFT strategies on institutional trading costs

I now turn to the second conjecture that HF traders use certain strategies (e.g., directional trading) to take advantage of institutional investors and increase the latter's trading costs. Here, I rely on the non-randomness (i.e., sequences and reversals) of HF trade directions to detect the presence of HF strategies. For example, directional trading strategies, such as momentum ignition and order anticipation for large institutional orders, typically involve long sequences of trades in the same direction. By definition, HF directional trading strategies are designed to take advantage of large institutional trades and thus are most costly to institutional investors. In contrast, HF traders' trading directions may also display a reversal pattern, i.e., one trade immediately followed by another trade in opposite direction.[19] In fact, reversal strategies can either reduce or increase the trading costs of institutional investors depending on whether HF traders trade against or compete with institutional orders.

The non-randomness of HFT is tested using the runs test on all trades made by HF traders on a stock on a given day, excluding trades when both parties are HF traders (i.e., type HH). The runs test has been used in early studies on the random walk properties of stock prices (e.g., Fama (1965) and Campbell, Lo, and MacKinlay (1970)). In the context of this study, I create a trading direction variable that equals 1 if an HF trader is on the buy side of a trade and -1 otherwise. I then use the runs statistic to test the null hypothesis of randomness in the sequence of HF trade directions at the stock-day level.[20] A negative and

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[19]HF trades may exhibit rapid reversals when HF traders engage in electronic market making or rebate-capturing strategies.

[20]Runs test is also known as the Wald-Wolfowitz test and is used to test the hypothesis that a series of numbers is random. A run is a series of numbers below or above the benchmark. The test statistic is: $Z = (R - E(R))/\sqrt{V(R)}$, where R is the number or runs, $E(R)$ and $V(R)$ are the expectation and variance of R. The test statistic is asymptotically normally distributed; see Wald and Wolfowitz (1940).

significant runs test statistic for a given day suggests frequent reversals in trade directions, while a positive and significant test statistic means the presence of sequential trades in the same direction, an indication that directional trading strategies dominate that day. If the null hypothesis of random trading directions cannot be rejected on a particular day, I then infer that random HF strategies dominate that day.

Based on the one-way critical value at the 2.5% level (i.e., -1.96 and 1.96), I identify 18,506 cases at the stock-day level where the runs statistics are significantly positive, 18,195 cases where the runs statistics are significantly negative, and 18,262 cases of insignificant runs statistics. This translates into approximately one-third of stock-day cases where directional HF strategies are detected and approximately one-third of cases where reversal strategies are detected. Such high frequencies are striking; if HF trades are random, one would expect the significant cases to be only 2.5% in each direction. Therefore, both reversal and directional trading are important strategies employed by HF traders.

The important question is what these strategies mean to institutional investors' trading costs. To address this question, I perform panel regressions following the model specified in Equation (3) separately for the cases where the runs test statistics at the stock-day level are significantly positive, significantly negative, and insignificant. The results are presented in Table X. First, as shown in the first two columns of the table, when HF trades exhibit significant directional sequences (i.e., when the runs statistics are significantly positive), the coefficient of HFT Intensity is 0.409, significant at the 1% level. This result indicates that HF traders' use of directional trading strategies significantly increases the execution shortfall of institutional investors. Second, as shown in the middle two columns of the table, when HF trades exhibit frequent reversals, the coefficient of HFT Intensity is 0.291 and not significant at the conventional 5% level. Finally, the results reported in the last two columns of the table show that when neither directional trading nor reversal strategies are detected (i.e., when the runs statistics are insignificant), HFT intensity does not have a significant impact on institutional trading costs (with a coefficient of 0.196 and a t-statistic of 1.64). In sum,

the results suggest that the adverse impact of HFT on institutional trading costs is most pronounced when HF trades are directional.

C. Heterogeneity of HFT's impact on execution shortfall across institutions with different trading skills

In Section IV.A.2, I show that HFT increases institutional investors' execution shortfall after controlling for the heterogeneity of institutions' trading skills. In this subsection, I further examine whether the heterogeneity of institutional trading skills makes a difference in the impact of HFT. The trading desks of institutional investors are responsible for the execution of trades. The trading desks that execute trades at low execution shortfall are considered skillful. Anand et al. (2012) find that there is economically substantial heterogeneity in the performance of trading desks. More importantly, they find that institutional trading desks can sustain relative performance over adjacent periods (up to four months). Therefore, it is reasonable to conjecture that institutional investors with skillful trading desks have a better understanding of the market conditions and thus are able to alleviate the impact of HFT on their trading costs.

I investigate the above hypothesis in the following way. Each month, the trading-desk performance of an institution is measured by its average monthly execution shortfall over the previous three months.[21] For each institution, its monthly execution shortfall is calculated as the volume-weighted average execution shortfall across all tickets for the month. Lower execution shortfall indicates better trading skills. For each stock day, I then calculate the volume-weighted trading-desk performance of all institutions that trade on that stock as a measure of the aggregate trading skill of institutions trading on the given stock.

In order to observe the impact of HFT on institutions with high trading skills, I create a dummy variable labeled High Trading Skill Dummy. This High Trading Skill Dummy equals

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[21]I choose the rolling three month period to measure trading skills because Anand et al. (2012) documented that the trading-desk performance is persistent up to four months.

one if the aggregate trading-desk performance on a given stock day is ranked in the top tercile in the sample, and zero otherwise. I then interact HFT Intensity with High Trading Skill Dummy and use the interaction term in the panel regression analysis. Other variables in the regression remain the same as those reported in Table III.

Table XI presents estimates of the coefficients and the two-way clustered t-statistics. The coefficient of the interaction between HFT Intensity and High Trading Skill Dummy is negative and significant at the 1% level. The results indicate that institutional investors with better trading skills are able to alleviate the impact of HFT on their execution shortfall.

V.   Conclusions

This paper fills a gap in the literature by directly examining the impact of HFT on the trading costs of institutional investors in the U.S. market. To establish the relation between the two, I first construct daily measures of trading costs and HFT activity during 2008 and 2009 from two datasets. I obtain daily measures of HFT activity from a dataset of 120 stocks, representing a subset of HFT activity, which NASDAQ makes available to academics. To measure trading costs I use a proprietary database of institutional investors' equity transactions compiled by Ancerno.

Using direct measures of institutional trading costs and daily HFT activity on each of the 120 sample stocks, I conduct a sorted portfolio test and a panel regression with controls for various firm characteristics. I find strong evidence that an increase in HFT is associated with an increase in the trading costs of institutional investors. The regression result suggests that one standard deviation increase of HFT activity leads to an additional trading cost of more than $10,000 per day for an average institution in the dataset.

I adopt a variety of approaches to rule out the alternative interpretation that it is precisely when execution shortfall is high that it is more profitable for HF traders to trade more aggressively. First, the sorted portfolio analysis indicates that HF traders are most active in liquid stocks, rather than illiquid stocks which tend to have high trading costs. Second, I

include firm- and time-fixed effects in the multivariate regression specification, which helps ensure that unobserved slow-moving stock characteristics and time-invariant factors do not cause the positive relationship between HFT activity and execution shortfall. Third, I control for corporate events such as earnings announcements and M&A announcements, and the results still hold. Fourth, I study the short selling ban imposed on financial stocks on September 19, 2008. I find that for the stocks in my sample that are subject to the short selling ban, HF traders' market participation rate declined while institutional trading costs rose sharply. Fifth, I apply the Granger causality test to establish the direction of causality between HFT activity and execution shortfall. The results provide further evidence that intensive HFT activity contributes to an increase in trading costs, but not vice-versa.

I perform further analysis to understand the mechanisms through which HFT affects institutional trading costs. The analysis shows that HFT provides liquidity to the market when institutions have large trade imbalances. However, the liquidity provision by HFT is short-lived, as HF traders maintain zero open positions at market close. Moreover, such liquidity provision proves particularly expensive for institutions in terms of their trading costs. The analysis also shows the prevalence of directional strategies used by HF traders. The presence of directional strategies results in increased institutional trading costs. This supports institutional investors' anecdotal observations that their trades have been anticipated by HF traders. Lastly, I find heterogeneity in the impact of HFT. Institutions with better trading skills are able to reduce the adverse impact of HFT on their trading costs.

In sum, the evidence provided in this paper suggests a significant impact of HFT on traditional institutional investors. An increase in HF traders' participation rate is associated with higher trading costs for institutional investors. This finding underscores the need for further investigation into the broader impact of the rapid growth in HFT, particularly in terms of its implications for long-term investors.

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Table I Descriptive Statistics

This table reports the equal-weighted averages of stock and trading characteristics across stock days, as well as the averages by market capitalization, for 120 stocks traded on NASDAQ during the period of 2008 and 2009. All variables are measured on a daily basis. Panel A presents the descriptive statistics of the NASDAQ dataset. Market Capitalization is a stock's market value. HFT (Non-HFT) Total Trading Volume is the total daily dollar trading volume by HF (non-HF) traders on a given stock. HFT (Non-HFT) Liquidity Demand (Supply) Trading Volume is the total dollar volume of all trades in which an HF (non-HF) trader demands (supplies) liquidity. An HF (non-HF) trader may supply liquidity by posting limit orders on the order book and demand liquidity by executing market orders against existing limit orders. Panel B presents the descriptive statistics of the Ancerno dataset. The analysis is conducted by using institutional tickets, which could be executed through multiple trades. Execution Shortfall is the volume-weighted average execution shortfall of all institutional tickets on a given stock on a given day. A ticket's execution shortfall is measured for buy tickets as the percentage difference between the execution price and the market price at the time of ticket placement (for sell tickets it is multiplied by -1). Institutional Ticket Size is the average share volume of all institutional tickets placed on a given stock on a given day. Number of Executions Per Ticket is the average number of executions to complete a ticket on a given stock on a given day. Total Number of Tickets is the total number of tickets in the sample. Total Number of Institutions is the total number of institutions in the sample.

Panel A: NASDAQ Dataset Descriptive Statistics				
	All	Large	Mid	Small
Market Capital ($billion)	17.500	46.780	1.590	0.400
HFT Total Trading Volume ($million)	54.439	158.231	3.654	0.378
HFT Liquidity Demand Trading Volume ($million)	27.582	79.532	2.401	0.259
HFT Liquidity Supply Trading Volume ($million)	26.857	78.699	1.253	0.119
Non-HFT Total Trading Volume ($million)	80.882	219.233	9.449	1.817
Non-HFT Liquidity Demand Trading Volume ($million)	40.076	109.201	4.155	0.833
Non-HFT Liquidity Supply Trading Volume ($million)	40.806	110.032	5.294	0.984
Panel B: Ancerno Dataset Descriptive Statistics				
Execution Shortfall (%)	0.167	0.146	0.163	0.196
Institutional Ticket Size (share)	14,823	16,854	7,570	5,287
Number of Executions Per Ticket	2.303	3.126	1.861	1.850
Total Number of Tickets	1,708,108	1,358,225	252,742	97,141
Total Number of Institutions	204	204	195	170

Table II Determinants of HFT

This table reports the determinants of HFT intensity based on panel regressions. The dependent variable is HFT Intensity, the total daily trading volume of HFT on a stock for a trading day scaled by the average trading volume of that stock in the prior 30 days. The explanatory variables include the following. Log Market Cap is the logarithm of a stock's daily market capitalization. Book-to-Market Ratio is the quarterly book-to-market ratio. Event Dummy is a dummy variable that equals one for a stock within a 5-day window of corporate events (earnings announcements or M&A announcements), and zero otherwise. Daily Return Volatility is a stock's annualized range based daily volatility. Prior 1-Day Return is a stock's lagged daily return. Prior 1-Month Return is a stock's lagged monthly return. Prior 12-Month Return is a stock's lagged 12 months return. Amihud illiquidity ratio is the ratio of the daily absolute return to the dollar trading volume on a trading day. Daily Dollar Turnover is a stock's daily dollar trading volume scaled by the stock's total shares outstanding. Average Institutional Order Size is the average dollar volume of all tickets placed on a stock on a trading day, scaled by the average trading volume of that stock in prior 30 days. Absolute Institutional Imbalance is the absolute value of the daily total dollar volume of all institutional buy trades minus that of all sell trades on a stock on a trading day, scaled by the average trading volume of that stock in the past 30 days. Average Trades Per Order is the average number of trades to complete a trading ticket on a stock for a trading day. Prior 1-Month Market Volatility is the market's annualized monthly return volatility in prior month. Prior 1-Day Market Return is the market return in prior day. The t-statistics are computed using two-way (by stock and by day) clustered standard errors. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	HFT Intensity	
	Coefficient	t-value
Intercept	-0.179***	(-3.65)
Log Market Cap	0.022***	(6.75)
Book-to-Market Ratio	-3.080*	(-1.92)
Event Dummy	0.058***	(10.89)
Daily Return Volatility	0.098**	(1.98)
Prior 1-Day Return	0.192***	(6.83)
Prior 1-Month Return	-0.003	(-0.36)
Prior 12-Month Return	-0.010***	(-2.69)
Amihud Illiquidity Ratio	-0.570***	(-3.20)
Daily Dollar Turnover	0.036***	(3.18)
Average Institutional Order Size	-0.161*	(-1.69)
Absolute Institutional Imbalance	0.132***	(3.80)
Average Trades Per Order	0.000**	(2.06)
Prior 1-Month Market Volatility	-0.003	(-0.24)
Prior 1-Day Market Return	-0.376***	(-3.98)
Day-fixed Effects	No	
Stock-fixed Effects	No	
Two-way Clustered Standard Deviations	Yes	
Adjusted R-squared (%)	29.2	
Number of Observations	52809	

Table III HFT's Impact on Execution Shortfall

This table reports the results of panel regressions that examine the impact of HFT intensity on the execution shortfall cost of institutional investors. The dependent variable is Execution Shortfall, the volume-weighted average execution shortfall of all institutional trades on a stock for a trading day. The main explanatory variable, HFT Intensity, is the total daily trading volume of HFT on a stock for a trading day scaled by the average trading volume of that stock in the prior 30 days. The control variables include the following. Log Market Cap is the logarithm of a stock's daily market capitalization. Book-to-Market Ratio is the quarterly book-to-market ratio. Stock Volatility is a stock's annualized range based daily volatility. Prior 1-Day Return is a stock's lagged daily return. Prior 1-Month Return is a stock's lagged monthly return. Prior 12-Month Return is a stock's lagged 12 months return. Amihud Illiquidity Ratio is the daily absolute return to the dollar trading volume on that day. Dollar Turnover is a stock's daily dollar trading volume scaled by the stock's total shares outstanding. Average Institutional Order Size is the average dollar volume of all tickets placed on a stock, scaled by the average trading volume of that stock in prior 30 days. Absolute Institutional Imbalance is the absolute value of the daily total dollar volume of all institutional buy tickets minus that of all sell tickets on a stock, scaled by the average trading volume of that stock in the past 30 days. Average Trades Per Order is the average number of trades to complete a trading ticket on a stock. Prior 1-Month Market Volatility is the market's annualized monthly return volatility in prior month. Prior 1-Day Market Return is the market return in prior day. The first two columns report the panel regression results with no day- or stock-fixed effects. The last two columns report the panel regression results with both day- and stock-fixed effects. The t-statistics are computed using two-way (by stock and by day) clustered standard errors. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Execution Shortfall		Execution Shortfall	
	Coefficient	t-value	Coefficient	t-value
Intercept	0.025	(0.24)	-1.144*	(-1.77)
HFT Intensity	0.336***	(4.48)	0.309***	(3.37)
Log Market Cap	-0.004	(-0.66)	0.043	(1.08)
Book-to-Market Ratio	-5.978	(-0.95)	6.303	(1.23)
Prior 1-Day Return	-0.072	(-0.24)	-0.178	(-0.64)
Prior 1-Month Return	0.017	(0.25)	-0.037	(-0.69)
Prior 12-Month Return	0.013	(0.92)	-0.004	(-0.26)
Amihud Illiquidity Ratio	3.955***	(3.14)	4.687***	(3.36)
Daily Return Volatility	0.324	(1.42)	0.046	(0.30)
Daily Dollar Turnover	-0.007*	(-1.66)	-0.001	(-0.19)
Average Institutional Order Size	0.743	(1.37)	0.735	(1.42)
Absolute Institutional Imbalance	0.271**	(2.56)	0.281***	(2.67)
Average Trades Per Order	0.000	(0.16)	0.000	(-0.44)
Prior 1-Month Market Volatility	0.285***	(3.24)		
Prior 1-Day Market Return	-0.031	(-0.05)		
Day-fixed Effects	No		Yes	
Stock-fixed Effects	No		Yes	
Two-way Clustered Standard Deviations	Yes		Yes	
Adjusted R-squared (%)	0.69		3.47	
(Number of Observations)	54963		54963	

Table IV HFT's Impact on Execution Shortfall on Event Days and No-event Days

This table reports the results of panel regressions that examine the differential impact of HFT activity on the execution shortfall on days with and without corporate events. Event Dummy is a dummy variable that equals one for a stock within a 5-day corporate event window (earnings announcement or M&A announcement), and zero otherwise. No-Event Dummy is a dummy variable that equals zero for a stock not within a corporate event window, and zero otherwise. All other variables are defined in Table III. The regression model is estimated with both day and stock-fixed effects. The t-statistics are computed using two-way (by stock and by day) clustered standard errors. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Execution Shortfall	
	Coefficient	t-value
Intercept	-1.129*	(-1.74)
HFT Intensity × Event Dummy	0.155	(1.29)
HFT Intensity × No-Event Dummy	0.375***	(3.88)
Event Dummy	0.058	(1.39)
Log Market Cap	0.041	(1.03)
Book-to-Market Ratio	6.284	(1.23)
Prior 1-Day Return	-0.181	(-0.65)
Prior 1-Month Return	-0.037	(-0.70)
Prior 12-Month Return	-0.005	(-0.31)
Amihud Illiquidity Ratio	4.711***	(3.37)
Daily Return Volatility	0.039	(0.26)
Daily Dollar Turnover	0.002	(0.24)
Average Institutional Order Size	0.725	(1.40)
Absolute Institutional Imbalance	0.285***	(2.69)
Average Trades Per Order	0.000	(-0.49)
Day-fixed Effects	Yes	
Stock-fixed Effects	Yes	
Two-way Clustered Standard Deviations	Yes	
Adjusted R-squared (%)	3.49	
Number of Observations	54963	

Table V Granger Causality

This table reports the results of the Granger causality test on the relation between HFT Intensity and Execution Shortfall. The following VAR(1) model is estimated for each stock:

$$
\begin{pmatrix} ES_{i,t} \\ HFT_{i,t} \end{pmatrix} = \begin{pmatrix} a_{1,i} \\ a_{2,i} \end{pmatrix} + \begin{pmatrix} b_{11,i} & b_{12,i} \\ b_{21,i} & b_{22,i} \end{pmatrix} \begin{pmatrix} ES_{i,t-1} \\ HFT_{i,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,i,t} \\ \epsilon_{2,i,t} \end{pmatrix},
$$

where $ES_{i,t}$ and $HFT_{i,t}$ are the Execution Shortfall and HFT Intensity for stock i on day t, respectively. The table reports the cross-sectional distribution (mean, median, the 1st and 3rd quartiles) of the coefficients $b_{12,i}$ and $b_{21,i}$ across 120 stocks, and the cross-sectional distribution of the t-statistics for these two coefficients. The p-values reported in the table are obtained via a bootstrapping procedure to assess the statistical significance of these cross-sectional statistics. The bootstraps are performed under the null of no causality (i.e., $b_{12,i} = b_{21,i} = 0$) but retain the time-series persistence of each variables in the sample, the correlations of the residuals $\epsilon_{1,i,t}$ and $\epsilon_{2,i,t}$ for a given stock, as well as the cross-stock correlations of these residuals. The bootstrapped p-values are calculated as the percentages of bootstrapped distributional statistics (e.g., mean, median, Q1 and Q3) of the t-statistics for the estimated coefficients exceed the corresponding sample distributional statistics. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Distribution of $b_{12,i}$				
	Q1	Mean	Median	Q3
Sample Coefficients	-0.215**	0.317***	0.117***	0.486***
Sample t-statistic	(-0.456)	(0.311)	(0.265)	(0.977)
Bootstraped p-value	[0.043]	[0.002]	[0.010]	[0.008]

Panel B: Distribution of $b_{21,i}$				
	Q1	Mean	Median	Q3
Sample Coefficients	-0.002	0.001	0.000	0.002
Sample t-statistic	(-0.725)	(0.039)	(-0.031)	(0.793)
Bootstraped p-value	[0.695]	[0.341]	[0.583]	[0.141]

Table VI HFT's Impact on Timing Delay Cost

This table reports the results of panel regressions that examine the impact of HFT activity on the timing delay cost of institutional investors. The dependent variable, Timing Delay Cost, is the volume-weighted average timing delay cost of all institutional trades on a stock for a trading day. All the other variables are defined in Table III. The regression model is estimated with both day and stock-fixed effects. The t-statistics are computed using two-way (by stock and by day) clustered standard errors. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Timing Delay Cost	
	Coefficient	t-value
Intercept	-0.022	(-0.04)
HFT Intensity	0.013	(0.19)
Log Market Cap	0.032	(0.82)
Book-to-Market Ratio	2.455	(0.99)
Prior 1-Day Return	-0.349	(-1.32)
Prior 1-Month Return	0.062	(1.63)
Prior 12-Month Return	-0.051**	(-2.39)
Amihud Illiquidity Ratio	1.167**	(2.11)
Daily Return Volatility	-0.360	(-1.34)
Daily Dollar Turnover	0.014***	(2.74)
Institutional Order Size	-0.747**	(-1.96)
Absolute Institutional Imbalance	0.241**	(2.49)
Trades Per Order	-0.001	(-1.44)
Day-fixed Effects	Yes	
Stock-fixed Effect	Yes	
Two-way Clustered Standard Deviations	Yes	
Adjusted R-squared (%)	1.2	
Number of Observations	54963	

Table VII Trade-level Analysis of HFT's Impact on Execution Shortfall

This table reports the results of trade-level panel regressions that examine the impact of HFT activity on institutional execution shortfall. The dependent variable, Execution Shortfall, is measured for each order. Institutional Order Size is the dollar volume of an institutional trading ticket, scaled by the average trading volume of that stock in the past 30 days. Trades Per Order is number of executions used to complete a ticket. All the other variables are the same as described in Table III. The linear regression model is estimated with both month- and institution-fixed effects. The t-statistics are computed using two-way clustered standard errors. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Execution Shortfall	
	Coefficient	t-value
Intercept	-0.127	(-0.96)
HFT Intensity	0.115***	(2.90)
Log Market Cap	-0.005	(-1.35)
Book-to-Market Ratio	-0.617	(-0.08)
Prior 1-Day Return	0.165	(0.55)
Prior 1-Month Return	-0.020	(-0.28)
Prior 12-Month Return	0.003	(0.27)
Amihud Illiquidity Ratio	2.543**	(2.16)
Daily Return Volatility	-0.073	(-0.60)
Daily Dollar Turnover	-0.002	(-1.26)
Institutional Order Size	1.467***	(6.58)
Absolute Institutional Imbalance	0.037	(0.57)
Trades Per Order	0.000	(0.01)
Month-fixed Effects	Yes	
Institution-fixed Effect	Yes	
Two-way Clustered Standard Deviations	Yes	
Adjusted R-squared (%)	1.13	
Number of Observations	1689919	

Table VIII HFT and Institutional Buy-sell Imbalance

This table reports the results of analysis on the relations among institutional trade imbalances, HFT intensity, and HFT trade imbalances. Institutional (HFT) trade imbalances are the buy volume minus sell volume of all institutions (HF traders) normalized by the stock's average daily trading volume over the prior 30 days. HFT Intensity is the total daily trading volume of HFT on a stock for a trading day scaled by the average trading volume of that stock in the prior 30 days. Panel A reports the sample distribution of institutional trade imbalances and HFT trade imbalances. Panel B reports the institutional trade imbalances for nine groups of stocks classified by size and institutional trade imbalances. Panel C reports the HFT Intensity for the same nine groups of stocks. Panel D reports the HFT trade imbalances for the same nine groups of stocks.

Panel A: Distribution of HFT and Institution Buy-sell Imbalance				
	Q1	Mean	Median	Q3
HFT Buy-sell Imbalance	-0.009	0.000	0.000	0.009
Institution Buy-sell Imbalance	-0.022	0.003	0.001	0.024

Panel B: Institutional Buy-sell Imbalance		
	Institutions net selling	Institutions balanced	Institutions net buying
Large Stocks	-0.062	0.000	0.060
Mid Stocks	-0.104	0.002	0.106
Small Stocks	-0.116	0.002	0.138

Panel C: HFT Intensity		
	Institutions net selling	Institutions balanced	Institutions net buying
Large Stocks	0.246	0.226	0.255
Mid Stocks	0.171	0.151	0.166
Small Stocks	0.093	0.082	0.095

Panel D: HFT Buy-sell Imbalance		
	Institutions net selling	Institutions balanced	Institutions net buying
Large Stocks	0.001	0.000	-0.001
Mid Stocks	0.003	0.000	-0.002
Small Stocks	0.002	-0.001	-0.002

Table IX HFT's Impact on Execution Shortfall when Institutional Trading is Imbalanced

This table reports the results of panel regressions that examine the differential impact of HFT on execution shortfall when institutions are net selling, net buying, or trading with balance. All stock days are divided into three groups based on Institutional Buy-Sell Imbalance. The baseline regression model (as described in Table III) is estimated within each group, respectively. The linear regression model is estimated with both day- and firm-fixed effects. The t-statistics are computed using two-way (by stock and by day) clustered standard errors. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Execution Shortfall					
	Institutions net selling		Institutions balanced		Institutions net buying	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Intercept	3.176***	(2.82)	-1.525	(-1.37)	-2.473***	(-2.86)
HFT Intensity	-0.178*	(-1.77)	0.524**	(2.24)	0.612***	(4.78)
Log Market Cap	-0.198***	(-2.79)	0.083	(1.18)	0.177**	(2.36)
Book-to-Market Ratio	32.267***	(2.72)	1.584	(0.34)	24.048**	(2.41)
Prior 1-Day Return	0.594	(1.50)	-0.603	(-0.99)	-0.438	(-1.01)
Prior 1-Month Return	0.157	(1.40)	-0.041	(-0.45)	-0.172	(-1.22)
Prior 12-Month Return	0.065*	(1.76)	0.019	(0.61)	-0.054	(-1.31)
Amihud Illiquidity Ratio	3.236	(1.38)	2.657	(0.96)	6.167**	(2.25)
Daily Return Volatility	0.312	(0.89)	-0.174	(-0.75)	0.043	(0.20)
Daily Dollar Turnover	0.024**	(2.36)	-0.009	(-1.05)	-0.015**	(-2.14)
Average Institutional Order Size	0.528	(1.04)	0.531	(0.30)	0.858	(1.11)
Absolute Institutional Imbalance	0.359***	(3.12)	7.783**	(2.02)	0.258**	(2.09)
Average Trades Per Order	0.000	(0.12)	-0.003	(-1.28)	0.000	(0.23)
Day-fixed Effects	Yes		Yes		Yes	
Stock-fixed Effects	Yes		Yes		Yes	
Two-way Clustered Std.	Yes		Yes		Yes	
Adjusted R-squared (%)	12.2		16.1		8.96	
Number of Observations	18362		18398		18203	

Table X Impact of HFT Strategies on Execution Shortfall

This table reports the results of panel regressions that examine the differential impact of HFT on execution shortfall when different types of HF strategies are detected. Stock-day observations are divided into three groups based on the non-randomness of HF trades. The non-randomness of HF trades is measured by runs test statistics obtained from all HF trades on a stock on a given day. The regression model (as described in Table III) is estimate within each group, respectively, with both day- and stock-fixed effects. The t-statistics are computed using two-way (by stock and by day) clustered standard errors. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Execution Shortfall					
	Directional		Reversal		Random Walk	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Intercept	0.143	(0.14)	-0.217	(-0.18)	-1.371	(-1.44)
HFT Intensity	0.409***	(2.60)	0.291*	(1.94)	0.196	(1.64)
Log Market Cap	-0.019	(-0.30)	0.054	(0.69)	0.093	(1.63)
Book-to-Market Ratio	10.538**	(2.49)	2.742	(0.42)	-2.678	(-0.15)
Prior 1-Day Return	0.075	(0.21)	-0.339	(-0.65)	-0.316	(-0.66)
Prior 1-Month Return	-0.019	(-0.20)	0.046	(0.38)	-0.130	(-1.48)
Prior 12-Month Return	0.038	(1.38)	0.001	(0.03)	-0.026	(-0.85)
Amihud Illiquidity Ratio	9.170***	(4.61)	5.798**	(2.43)	2.208	(1.09)
Daily Return Volatility	-0.213	(-1.41)	0.172	(0.69)	0.223	(0.62)
Daily Dollar Turnover	-0.024*	(-1.70)	0.004	(0.43)	0.010	(0.92)
Average Institutional Order Size	1.275	(0.95)	-0.903	(-1.45)	1.525***	(2.95)
Absolute Institutional Imbalance	0.220	(1.18)	0.595***	(3.83)	0.135	(0.88)
Average Trades Per Order	-0.000	(-0.53)	-0.000	(-0.20)	-0.001	(-0.39)
Day-fixed Effects	Yes		Yes		Yes	
Stock-fixed Effects	Yes		Yes		Yes	
Two-way Clustered Std.	Yes		Yes		Yes	
Adjusted R-squared (%)	3.45		4.02		3.98	
Number of Observations	18506		18195		18262	

## Table XI Heterogeneity of HFT's Impact on Execution Shortfall

This table reports the results of a panel regression that examines the heterogeneous impact of HFT on execution shortfall when institutional investors have varying trading skills. The dependent variable is Execution Shortfall, the volume-weighted average execution shortfall of all institutional trades on a stock for a trading day. The explanatory variable HFT Intensity is the total daily trading volume of HFT on a stock for a trading day scaled by the average trading volume of that stock in the prior 30 days. The High Trading Skill Dummy is a dummy variable that equals one if the aggregate previous trading-desk performance measure of a stock day is ranked in the top tercile in the sample, and zero otherwise. The aggregate trading-desk performance of the stock day is the volume-weighted average trading-desk performance during the previous three months of all institutions that trade on the stock. Each month, the trading-desk performance of an institution is measured by its average monthly execution shortfall over the previous three months. For each institution, the monthly execution shortfall is calculated as the volume-weighted execution shortfall across all tickets for the month. HFT Intensity × High Trading Skill Dummy is the interaction term between HFT Intensity and the dummy variable High Trading Skill Dummy. All the other control variables are the same as described in Table III. The regression model is estimated with both day- and stock-fixed effects. The t-statistics are computed using two-way (by stock and by day) clustered standard errors. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

| Dependent Variable	Execution Shortfall	
	Coefficient	t-value
Intercept	-0.365	(-0.55)
HFT Intensity	0.514***	(4.01)
HFT Intensity × High Trading Skill Dummy	-0.308**	(-2.55)
High Trading Skill Dummy	-0.006	(-0.19)
Log Market Cap	0.035	(0.88)
Book-to-Market Ratio	5.326	(0.99)
Prior 1-Day Return	-0.209	(-0.81)
Prior 1-Month Return	-0.053	(-0.98)
Prior 12-Month Return	-0.005	(-0.32)
Amihud Illiquidity Ratio	5.509***	(3.72)
Daily Return Volatility	0.089	(0.51)
Daily Dollar Turnover	0.002	(0.35)
Average Institutional Order Size	0.505	(0.96)
Absolute Institutional Imbalance	0.286***	(2.74)
Average Trades Per Order	-0.000	(-0.85)
Day-fixed Effects	Yes	
Stock-fixed Effects	Yes	
Two-way Clustered Standard Deviations	Yes	
Adjusted R-squared (%)	4.80	
Number of Observations	53661	

Figure 1. Relation between HFT Intensity and Liquidity

This figure plots the HFT Intensity for different levels of liquidity in each of the three size groups. Liquidity is measured by Amihud Illiquidity Ratio. HFT Intensity is the total daily trading volume that HF traders involve on a stock scaled by the average trading volume of that stock in the prior 30 days. Each day, I sort all stocks into three portfolios based on their size. Then each portfolio is further divided into three groups based on Amihud Illiquidity Ratio. The columns in the figure represent the average HFT Intensity in each group.
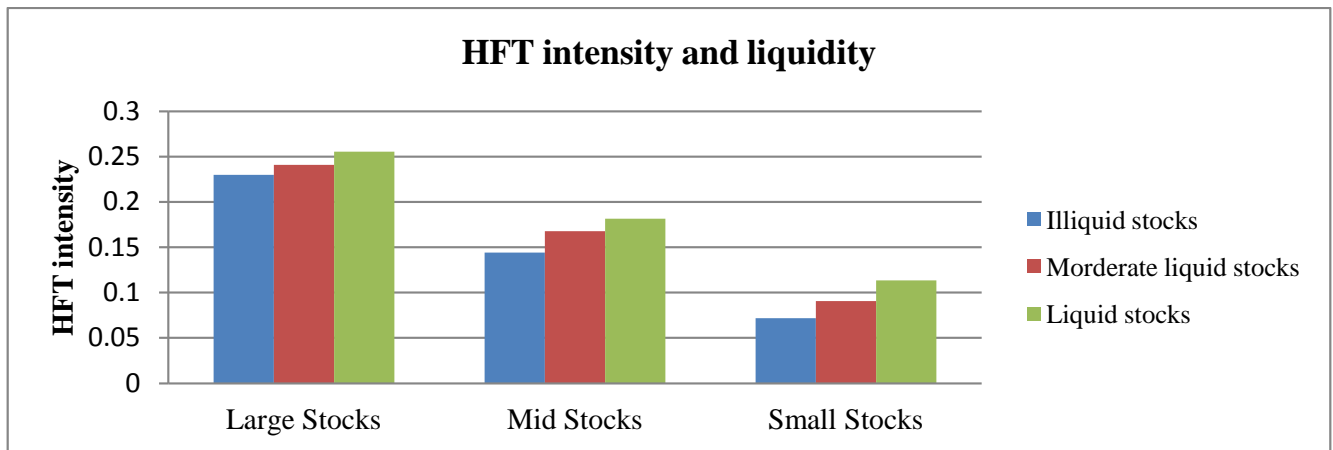
Figure 2. Relation between Liquidity and Execution Shortfall

This figure plots the Execution Shortfall for different levels of liquidity in each of the three size groups. Liquidity is measured by Amihud Illiquidity Ratio. Execution Shortfall is the volume-weighted average execution shortfall of all institutional trading tickets on a stock. Each day, I sort all stocks into three portfolios based on their size. Then each portfolio is further divided into three groups based on the Amihud Illiquidity Ratio. The columns in the figure represent the average Execution Shortfall in each group.
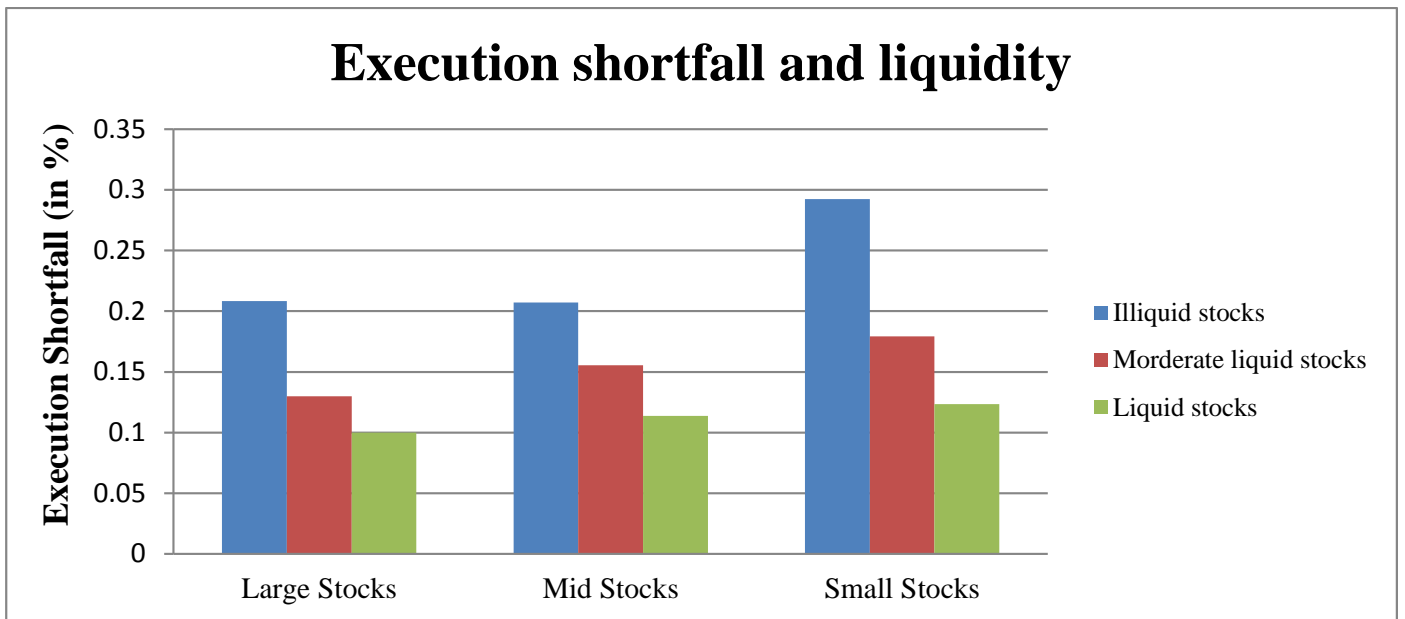
Figure 3. Relation between HFT Intensity and Execution Shortfall

This figure plots the Execution Shortfall for different levels of HFT Intensity in each of the three size groups. Execution Shortfall and HFT Intensity are defined the same as in Figure 1 and 2. Each day, I sort all stocks into three portfolios based on their size. Then each portfolio is further divided into three groups based on HFT Intensity. The columns in the figure represent the average Execution Shortfall in each group.

Figure 4. Execution Shortfall around the Short-selling Ban of September 18, 2008

This figure plots the time-series of the average Execution Shortfall for banned and unbanned stocks around the short selling ban period from September 18, 2008 to October 8, 2008. Execution Shortfall is the volume-weighted average execution shortfall of all institutional trading tickets on a stock. There are 13 stocks in my sample in the initial short selling ban list on 9/18/2008. On 9/22/2008, the list expanded to cover 16 stocks in the sample, and one more stock was added to the list on 9/23/2008.

Execution shorfall (in %) for banned and unbanned stocks

Legend: Banned execution shortfall; Unanned execution shortfall
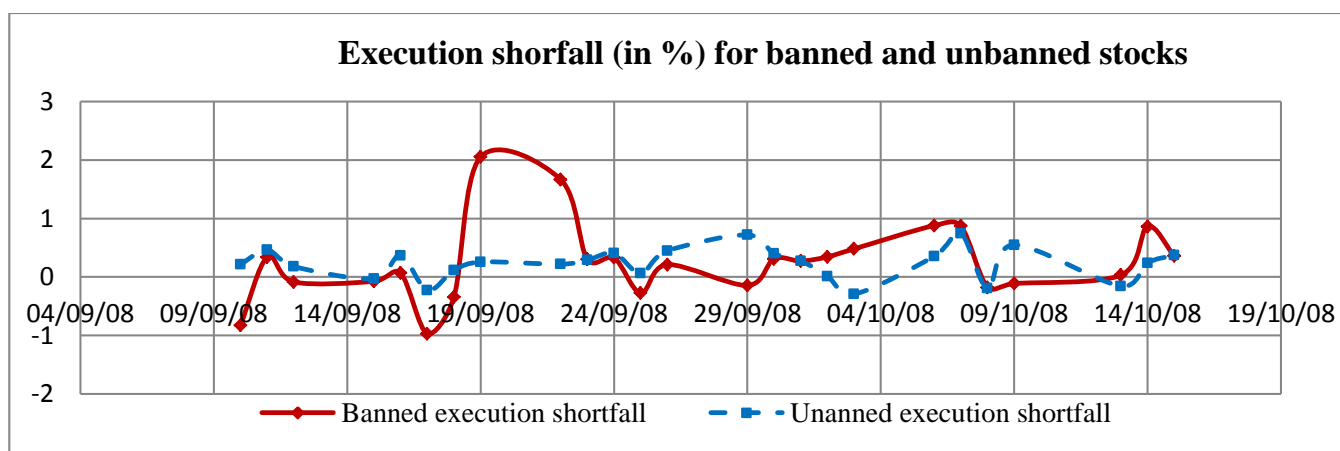
Figure 5. HFT Activity around the Short-selling Ban of the September 18, 2008

This figure plots the time-series of the average HFT Intensity for banned and unbanned stocks around the Short-selling Ban period from September 18, 2008 to October 8, 2008.

HFT Activity for Banned and Unbanned Stocks