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

Lin Tong*

November 2013

*Department of Finance, Henry B. Tippie College of Business, University of Iowa. Email: lin-tong@uiowa.edu. I thank Wei Li, Erik Lie, Andy Puckett, Yiming Qian, Ashish Tiwari, Tong Yao, and seminar participants at Fordham University, Georgia State University, Iowa State University, University of Arkansas, University of Iowa, Stevens Institute of Technology for helpful comments. I thank NASDAQ OMX (and especially Frank Hatheway) for providing the HFT data and Ancerno Ltd. for providing the institutional trading data. NASDAQ makes the data freely available to academics providing a project description and signing a non-disclosure agreement. All errors are my own.

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


## Abstract

Combining data on high frequency trading (HFT) activities of a randomly selected sample of 120 stocks and data on institutional trades, I find that HFT increases the trading costs of traditional institutional investors. One standard deviation increase in the intensity of HFT activities increases institutional execution shortfall costs by a third. Further analysis suggests that HFT represents as an ephemeral and extra-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 (HF) traders engage in directional strategies (e.g., front-running). I perform various analyses to rule out an alternative explanation that HF traders are attracted to stocks that have high trading costs. First, HFT is most active on liquid stocks. Second, the results are robust to the controls for stable stock liquidity characteristics and events that might jointly affect HFT and trading costs. Third, an analysis of the HFT behavior around the temporary short selling ban in September 2008 highlights the opportunistic nature of liquidity provision by HF traders. Finally, Granger causality tests show that intensive HFT activity significantly contributes to institutional trading costs, but not vice versa.



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

# I. Introduction

In recent years, financial markets have undergone tremendous changes with the adoption of new technology. Trades are now mostly placed and executed electronically, while there are over a dozen for-profit exchanges as well as alternative trading venues competing for volume and liquidity. Equally prominently, computer-based high frequency trading (HFT) has grown from being virtually non-existent, to becoming a dominant force in the market. By some statistics, HFT firms account for 70% of the U.S. stock trading volume in 2009.[1] The rapid growth of HFT has led to considerable media attention and policy interest in the issue of the impact of HFT on market quality and on the welfare of other market participants. Despite this interest, there is so far scant evidence on the question of how the recent explosion in HFT has affected a particularly important class of market participants, namely, institutional investors. The goal of this study is to provide evidence regarding the impact of HFT activity on the trading costs of institutional investors.

Traditional institutional investors such as mutual funds, pensions, insurance firms, and hedge funds account for over 50% of the public equity ownership in the U.S. (French (2008)). They play a critical role in price discovery by trading based on new information or in response to price deviations from fundamentals. Moreover, they generate a huge volume of trading and trading costs are a critical determinant of their performance. Hence, institutional trading costs are often viewed as an important yardstick for measuring the quality and liquidity of the financial markets. For this reason, facilitating efficient execution of institutional trades has been a key objective of the securities markets design and regulation. Whether HFT is good news or bad news for traditional institutional investors has been extensively discussed and debated in public media. Some institutional investors have expressed serious concerns that high frequency (HF) traders may negatively impact their trading profits (e.g., Arnuk and Saluzzi (2009)). Such concerns are apparently heard by regulators, as noted in the 2010 speech by Mary Schapiro, the former SEC Chairperson, "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, asset managers' concerns regarding HFT have led to the growing popularity

[1] See, e.g., "High-frequency trading under scrutiny," Financial Times, July 28, 2009.

of off-exchange trading venues, e.g., "dark pools".[2]

Interestingly, the widespread concerns about the negative impact of HFT on institutional trading costs are in sharp contrast to the findings of a few recent academic studies. Academic evidence so far seems to suggest that, predominantly, HFT is associated with improved market liquidity, reduced volatility, and increased price efficiency/discovery; see, for example, Chaboud *et al.* (2009), Brogaard (2010), Hendershott *et al.* (2011), Boehmer *et al.* (2012), Menkveld (2012), Hasbrouck and Saar (2013), Brogaard *et al.* (2013), and Malinova, Park and Riordan (2013). The evidence produced by these studies is consistent with the view that HFT firms are the modern day version of market makers with enhanced technology. If technology expedites the execution of trades and/or improves the efficiency of market making, HFT should benefit market participants, including institutional investors.[3]

However, some researchers have raised the concern that the liquidity provided by HF traders may be illusory. Since HF traders do not have an 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. Kirilenko *et al.* (2011) and Easley *et al.* (2011a) both note that during the Flash Crash of May 6, 2010, many HF traders withdrew from the market while others turned into liquidity demanders. In the context of institutional trading, an open question is whether HFT is a reliable source of liquidity when liquidity is most demanded by institutional investors.

The illusory nature of liquidity created by HFT may also be understood in the context of specific HFT strategies. Two particular types of directional HFT strategies appear to directly take advantage of the large trades made by institutional investors – order anticipation (front running) and momentum ignition.[4] An HF trader following an order anticipation strategy detects large orders from institutional investors and trades in front of them. For example, a HF trader who buys

[2]The trading volume in dark pools has grown by almost one-half between the years 2009-2012; see "U.S. 'dark pool' trades up 50%," Financial Times, November 19, 2012.

[3]A study perhaps most related to mine is Brogaard *et al.* (2012). Using UK data, they find no clear evidence that increases in HFT activities due to speed changes at London Stock Exchange affect institutional trading costs. However, to my knowledge, so far there is no study on the impact of HFT on institutional trading cost in the context of the U.S. market.

[4]Several popular types of HFT strategies are discussed in the Concept Release on Equity Market Structure by SEC (2010). In addition to directional trading strategies, three other broad types of strategies include passive market making, arbitrage, and structural trading.

in front of a large buy order will subsequently attempt to sell to the large buyer at a higher price or to hold on to the position in case of a permanent price increase. The institutional investor who submits the large buy order is adversely impacted in either case. With momentum ignition, HF traders may ignite rapid price movement along one direction through a series of submissions and cancelations of orders, and profit by establishing an early position. Such strategies may increase intraday price volatility and drive up the trading costs of institutional investors.

In this study, I combine two sources of data to examine the relationship between HFT and institutional trading costs. Data on institutional trading costs are from Ancerno (formerly Abel/Noser). The main measure of trading cost is execution shortfall, defined as the percentage difference between the execution price and a benchmark price that is prevailing in the market when the ticket is placed with the broker. The execution shortfall captures the bid-ask spread, the market impact, and the drift in price while the ticket is executed. Data on HFT is provided by NASDAQ. This dataset contains all trades on NASDAQ for a randomly selected sample of 120 stocks during 2008 and 2009, with identification of trades executed by HFT firms.

I assess the relation between HFT and institutional trading costs using both sorted portfolios and multivariate regressions. Using sorted portfolios, I show that while HFT is positively associated with stock liquidity and the latter is negatively associated with institutional trading costs, the relation between HFT and institutional trading costs is positive. The multivariate panel regressions confirm this relation by controlling for various stock characteristics and institutional trading characteristics. The regression coefficient suggests that one standard deviation increase in HFT activity is associated with an increase in average execution shortfall by one third. Considering that an average institution in the sample has a daily trading volume of $20.5 million for the sample stocks, one third increase in execution shortfall cost implies an additional transaction cost of more than $10,000 per day. I also find that the impact of HFT on institutional trading costs is stronger for both small-cap and large-cap stocks, relative to mid-cap stocks.[5]

[5]The main measure of trading cost in this study is execution shortfall, which captures the bid-ask spread as well as the price impact (e.g., Anand *et al.* (2012)). I have also examined the timing delay component of trading cost to test a hypothesis that HFT reduces delays in trade execution. However I do not find evidence in favor of this hypothesis. In addition, the main regressions performed in the study are based on stock-day observations. I have also obtained similar results using regressions at individual trade level that control for heterogeneity in institutional trading skills.

I consider alternative explanations for the positive relation between HFT and institutional trading cost. These include the possibility of omitted variables causing both HFT activity and institutional trading costs to increase at the same time. Alternatively, it could be that HF traders find it more attractive to trade on stocks that have high trading costs. I seek to rule out the alternative interpretations through several approaches.

First, the sorted portfolio analysis indicates that HF traders are most active in liquid stocks, rather than illiquid stocks which have high trading costs. Second, I include firm- and time-fixed effects in the multivariate regression specification, which helps to ensure that unobserved slow-moving stock characteristics and time-invariant factors do not cause the positive relationship between HFT activity and trading costs. Third, since days with news releases may also affect both HFT and trading costs, I control for earnings announcements and mergers and acquisitions events in the sample and the results still hold. Fourth, I study the short selling ban on financial stocks instituted on September 19, 2008, which is an exogenous shock to execution shortfall. I find that, as expected, the execution shortfall increases sharply on that day due to the ban. If HF traders choose to be more active when the execution shortfall is high, we would expect an increase in HFT after the implementation of the ban. However, I find that the HFT activity drops sharply subsequent to the ban being implemented. This evidence also suggests that when liquidity is low, HF traders withdraw from the market. Fifth, Granger causality tests provide further evidence that intensive HFT activity contributes to an increase in trading costs, but not vice versa.

Finally, I perform two sets of analysis to understand the specific mechanisms through which HFT may increase the costs of traditional institutional investors. First, 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. I find 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 no open positions on the stock. Further, the impact of HFT on institutional trading costs is more pronounced when institutions exhibit large imbalance on the buy side. Therefore, if anything, HFT represents an ephemeral and expensive source of liquidity provision to institutional investors.

Second, I use the non-randomness of HF trades to test whether directional trading, electronic marketing making, and other types of HFT strategies have different impact on institutional trading costs. In the case of directional strategies such as momentum ignition and front running, one would observe long sequences of HF trades in the same direction.[6] As for electronic market making, HF traders have to buy and sell the same stocks very fast so that one should observe rapid reversals of HF trade directions. I use the runs test to detect non-randomness in HF trade directions on each stock on a given day. The runs tests detect the pervasive use of directional trading and market making strategies by HF traders. More importantly, the impact of HFT on institutional trading costs is most pronounced when HF traders engage in directional trading strategies. This lends support to the anecdotal observations made by institutional investors that their trades are front-run by HF traders.

The rest of the paper is organized as follows: Section II. discusses the literature related to HFT. Section III. describes the data. Section IV. presents the baseline results and analyses on causality between HFT and institutional trading costs. Section V. provides further analysis on how and when HFT affects institutional trading costs as well as the robustness of the results. Section VI. concludes.

# II. Related Literature

This paper fits in the growing literature on algorithmic trading and HFT. Theoretical models in this area focus primarily on the interaction between HF traders and traditional investors. Such studies generally predict undesirable impacts of HFT and a wealth transfer from slow traders to HF traders. Hoffman (2009) finds that algorithmic traders suffer less from adverse selection because of their speed advantage and that they decrease the profits of human traders. Cartea and Penalva (2011) present a model with a liquidity trader, a market maker and a HF trader. Their model predicts an increase in volatility and price impact of the liquidity trader. In the model built by

[6]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 small sizes for execution.

McInish and Upson (2011), HF traders use their speed advantage to learn quote updates quicker than slow traders, which allows the former to profit from trading at stale prices with the latter. Jarrow and Protter (2011) find that HF traders create temporary mispricing and profit from it. Biais, Foucault, and Moinas (2011) document that multiple equilibriums can arise for a given level of algorithmic trading and some of them are associated with a sharp increase in the price impact of trades. Jovanovic and Menkveld (2011) model HF traders as middlemen between the buyers and sellers. Their model suggests that HF traders can exert positive or negative effects depending on their informational advantage stemming from their speed.

In contrast to the overall negative predictions of theoretical models, most empirical studies document a positive impact of HFT. Using the same dataset as in this study, Brogaard *et al.* (2013) provide evidence that HF traders facilitate price efficiency by placing marketable orders in the direction of permanent price changes and in the opposite direction of transitory pricing errors on average days and the days with highest volatility. Their limit orders are adversely selected but are compensated by liquidity rebates. With the same dataset, Brogaard (2010) finds no evidence that HF traders withdrawing from markets in bad times or that they front run large non-HFT trades. Using message counts as a proxy for algorithmic trading (AT), Hendershott *et al.* (2011) find that AT improves liquidity and brings about more efficient price discovery. With the same proxy, Boehmer *et al.* (2012) document that on average AT improves liquidity and informational efficiency. Another study by Chaboud *et al.* (2009) also documents that algorithmic traders increase their supply of liquidity over the hour following macroeconomic data releases, even though they restrict activity in the minute following each release. Also, Hasbrouck and Saar (2013) find improved spreads, depth and volatility associated with HFT. Menkveld (2012) finds that the bid-ask spreads of a new market for Dutch stocks, Chi-X, were reduced by about 30% within a year with the entry of a new HF trader on the market.

There are also some empirical studies that document negative effects of HFT. The major concerns are the quality of the liquidity provided by HF traders and whether they increase volatility. Kirilenko *et al.* (2011) find evidence that instead of supplying liquidity, some HF traders withdrew from the market and some demanded liquidity during the Flash Crash on May 6, 2010. Hasbrouck and Saar (2009) document the "fleeting" nature of many limit orders in electronic markets and point out the liquidity provided by HF traders is short-lived. Similarly, Egginton *et al.* (2011) question the degraded quality of liquidity and elevated volatility caused by HFT. Easley *et al.* (2011) find that extraordinary flow toxicity, i.e., market makers being adversely selected without knowing, in the hours leading up to the Flash Crash causes HF traders to withdraw from the market.

Overall, even though theoretical models predict the shift in wealth from slow traders to HF traders, there is limited empirical evidence along this direction. In fact, most empirical evidence suggests an improvement in market quality with the occurrence of HFT. However, this improvement does not immediately lead to more efficient trading for traditional investors. A related study by Malinova *et al.* (2013) examines the impact of HFT on retail investors. They find that a reduction of HFT causes a decline in market liquidity and trading profits of retail traders. In a recent study, Brogaard *et al.* (2012) use data from the London Stock Exchange and find no clear evidence of change in trading costs caused by increases in HFT activities due to speed changes at the exchange. However, in the U.S. market, there is so far no direct analysis on whether HFT increases institutional investors' trading costs. This paper fills the gap.

## III. Data and Descriptive Statistics

### III.A. Measuring HFT

The HFT dataset is provided by NASDAQ under a non-disclosure agreement. The dataset contains trading data from 2008 and 2009 for a sample of 120 randomly selected stocks listed on NASDAQ or the New York Stock Exchange (NYSE). The timestamp for trades in the dataset is to the millisecond. For each trade in the dataset, a variable named "Type" identifies the liquidity demander and supplier as a high-frequency (HF) trader or non-high-frequency (nHF) 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.* (2013), even though the 26 HFT firms represent a significant amount of HFT activity, it is not possible to completely identify all HF trades. Despite this limitation, this dataset is by far the most suitable for this study. Previous academic studies that use this dataset include Brogaard (2010), Brogaard, Hendershott and Riordan (2013), 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 an nHF (non-HF) firm supplies liquidity in the trade. See Brogaard, Hendershott, and Riordan (2013) for additional details on this dataset.

In this paper, I focus on the total HFT activity on a stock. To construct the measure of HFT activity, I first calculate the trading volume of each trade in the dataset by multiplying Price and Shares traded. Each day, the aggregate trading volume of all trades that HFT firms participate in (with Type of HH, HN or 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 .

## III.B. Measuring institutional trading cost

The NASDAQ dataset is merged with a proprietary database of institutional investors' equity transactions compiled by Ancerno Ltd., from which I construct the measure of institutional trading cost. There are 204 institutions in the Ancerno dataset that are involved in trading the 120 sample stocks during 2008 and 2009, with an average trading volume of $20.5 million per institution per day.

Previous academic studies that use Ancerno's data include Anand *et al.* (2010, 2012), Goldstein et al. (2009), Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2010), and Puckett and Yan (2011).

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 splits the large order to several brokers. The allocation to each broker is defined as a ticket and each ticket may 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 placement time, date of execution, execution price, number of shares executed, whether the execution is a buy or sell, and the commissions paid. See Anand *et al.* (2012) for additional details on this dataset.

Following Anand *et al.* (2012), the cost of each trade (referred to as "ticket" in the Ancerno data) is defined in terms of execution shortfall:

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

where $P_1$ measures 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, I conduct most of the tests at the stock level using the daily measures of HFT Intensity$_{it}$ and Execution Shortfall$_{it}$. As a robustness test, I also examine the relationship between HFT activity and execution shortfall at the trading ticket level.

Another aspect of institutional trading costs is the execution timing delay cost incurred between the initial trading decision point (market open) and the price at the time the order is placed with the broker:

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

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

## III.C. Sample descriptive statistics

I obtain data on institutional trading and HFT from 2008 to 2009 on a sample of 120 stocks. To minimize observations with errors I impose several data screens. I delete tickets with execution shortfall greater than an absolute value of $10\%$. Also, I delete tickets with ticket volume larger than the stock's total trading volume on the execution date. 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 $COMPUSTAT$. I obtain information on mergers and acquisitions from SDC Platinum.

Table 1 reports the summary statistics of HFT and the institutional trading. These numbers reveal some notable patterns 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. This pattern raises a natural question about the role of HF traders. If, as the proponents of HFT typically advocate, HF traders play a role in providing liquidity, they should be more active in small stocks where liquidity is scarce. The average Execution Shortfall for large, medium and small stocks is 0.15%, 0.16%, and 0.20%, respectively. The results indicate that trading tickets placed on small stocks are more difficult to execute, as shown by the larger execution shortfall. This observation is consistent with the findings of Anand $et\ al.$ (2012). The size of an average trading ticket placed on large stocks is \$487,871 and it takes more than three executions to implement the ticket. The average ticket size on small stocks is only \$63,943 and it takes about $1.8$ executions to implement the ticket.

## III.D. Determinants of HFT

Before an examination on the relation between HFT and institutional trading cost, it is useful to understand the firm characteristics that may be associated with the intensity of HFT. These characteristics may also be related to trading costs and serve as control variables in my main analysis.

I consider the following characteristics. 1) firm size (Log Market Cap), 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; 2) Event Dummy, a dummy variable that equals one for a stock on a given day if there is a corporate event (earnings announcement or merger and acquisition announcement), and equals zero otherwise; 3) Daily Return Volatility, which is a stock's range-based estimate of daily volatility (annualized), following Parkinson (1980); 4) Prior 1-day Return, Prior 1-month Return, and Prior 12-month Return, which are a stock's lagged daily return, lagged monthly return, and lagged 12 months return, respectively; 5) stock illiquidity as measured by the Amihud Illiquidity Ratio, i.e., the daily absolute return divided by the dollar trading volume on that day; 6) Daily Dollar Turnover, a stock's daily dollar trading volume scaled by the stock's total shares outstanding; 7) 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; 8) 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; 9) Average Trades Per Order, defined as the average number of trades to complete a trading ticket on a stock; 10) Prior 1-month Market Volatility, annualized daily return volatility of the CRSP value-weighted index in prior month; 11) Prior 1-day Market Return, the return of the CRSP value-weighted index during the previous day.

A panel regression model is estimated by regressing daily stock HFT Intensity on these firm characteristics. The estimated coefficients and two-way clustered t-statistics are reported in Table 2. The results suggest that HFT intensity is positively related to firm size, return volatility, and negatively related to illiquidity. HF trading is also more active in stocks with high daily dollar turnover and high absolute institutional trading imbalance, stocks with large number of institutional trades per order, and on days with event announcements.

# IV. Impact of HFT on Institutional Trading Costs

## IV.A. HFT, liquidity, and trading costs: sorted portfolios

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

First, I look at the relation between HFT and the conventional measure of stock liquidity, the Amihud Illiquidity Ratio. Since that the 120 stocks are in three distinctive size categories, I first sort all stocks into three groups based on size. Within each size group stocks are further divided into three groups based on the Amihud Illiquidity Ratio on each day. I calculate the average HFT Intensity of all stock-days in each of the nine ($3\times3$) groups. Figure 1 plots the average HFT Intensity against the Amihund Illiquidity Ratio across the nine groups; it shows clearly a positive relation between HFT and liquidity, within each size group. This finding complements those reported by the existing literature. However, we cannot infer the direction of the causality from such a simple statistical association. It may be the case that HF traders choose to trade more in liquid stocks, given their reliance on rapid-fire trading strategies.

Next, I look at the relation between stock liquidity and institutional trading costs 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 clear negative relation between execution shortfall and liquidity within each size group. That is, trading costs are lower for liquid stocks.

Combining the patterns from the first two panels of 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 active, the average Execution Shortfall for institutional investors is also higher. In other words, the HFT activity is positively correlated with institutional trading costs.

Figure 1-3 present rather intriguing relationship among HFT activity, liquidity, and institutional execution shortfall. If HFT activity could improve liquidity, as documented in the extant literature, why does execution shortfall increase when HFT activity is more intensive? Considering the distinctive features of institutional trading, HFT may indeed bring more harm than good to institutional investors. First of all, the liquidity provided by HFT may be illusory and may disappear when institutional investors most need it. Moreover, the large order sizes and potentially high information content make institutional trades most vulnerable to HFT strategies such as front running (see Hirschey (2011)). Such strategies can dramatically increase the price drifts and market impact during the execution of a large order.

## IV.B. Multivariate analysis

In order to control for other relevant factors that may affect trading costs, I move on to conduct the following tests in a multivariate panel regression setting with controls of various firm characteristics. Specifically, I estimate a panel regression model of the form:

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

where $\alpha_i$ and $y_t$ represent firm-fixed effects and time(day)-fixed effects, respectively. HFT Intensity$_{it}$ is the measure of daily HFT activity on stock $i$. Execution Shortfall$_{it}$ is 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 2 when I examine the determinants of HFT activity. These include firm size, book-to-market ratio, stock returns during 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. For inference I use standard errors that are robust to cross-sectional and time-series heteroskedasticity and within-group autocorrelation based on Petersen (2009).

Table 3 presents estimates of coefficients and the two-way clustered t-statistics. The first two columns report the estimates of the model without controlling for day- and firm-fixed effects.

However, to control for market conditions I additionally include the prior 1-day market return and prior 1-month market volatility as control variables. In the last two columns, the linear regression model in Equation (3) is estimated with both day dummies 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 positive coefficient suggests that after controlling for other economic determinants of trading costs, HFT activity has an *increasing* effect on execution shortfall of institutional investors. In particular, the coefficient from the fixed-effects regression indicates that a one standard deviation increase in HFT activity leads to a 5bp increase in execution shortfall. Considering that an average institution in my sample generates a daily trading volume of $20.5 million, a 5bp increase in execution shortfall means an additional cost of more than $10,000 per day on the sample stocks.

To better evaluate the effects of control variables on execution shortfall, I focus on the estimation results of the model without day- and firm-fixed effects, as shown in the first two columns of Table 3. The coefficients for the control variables are of expected signs. The coefficient of the illiquidity measure is positive and significant since a higher illiquidity measure means lower liquidity which leads to a 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 the higher imbalance leads to more competition for liquidity in one direction, thus execution shortfall is higher. 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 activity is more intense, institutional investors' execution shortfall is higher. More importantly, this positive relationship holds when I control for various firm characteristics as well as the time- and firm-fixed effects.

## IV.C. Impact of HFT across firm size

I further examine the differential effects of HFT on execution shortfall for stocks with different sizes. To do this, I estimate the baseline model in Equation (3) within each size group. I expect the impact of HFT on execution shortfall to be stronger for small stocks. This is because it is more costly for HF traders to participate in small stocks and they will charge a higher premium to do so. In fact, in order to make profit, HFT strategies require such traders to be able to buy and sell in a timely manner, yet this is harder to accomplish in the case of small stocks (e.g., Arnuk and Saluzzi (2008)).

Table 4 reports the estimates of coefficients and the two-way clustered t-statistics. The regression model is estimated with both day dummies and firm-fixed effects. From left to right, the table reports the estimation results in the subsamples of large, mid, and small stocks. The coefficient of HFT Intensity suggests that, as expected, the increasing effect of HFT activity on execution shortfall is strongest on small stocks. Thus, HF traders charge a high premium when they trade small stocks. It is further noted that the coefficient for HFT Intensity is also significantly positive for large-cap stocks, suggesting an important impact by HFT on the trading costs of such stocks. Finally, the coefficient for HFT Intensity is insignificantly positive in the subsample of midcap stocks.

## IV.D. Direction of causality

There are two alternative explanations for the multivariate test results. This includes the possibility of some omitted variables that cause both HFT activity and execution shortfall to increase at the same time. Alternatively, it could be that it is precisely when execution shortfall is high that it is more profitable for HF traders to trade actively.

In fact, the tests conducted in the previous subsections have already help to rule out the alternative interpretations to certain degree. First, the sorted portfolio analysis indicates that HF traders are most active in liquid stocks, rather than illiquid stocks featured with 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.

In this subsection, I conduct further analysis on this issue.

#### IV.D.1. Controlling for corporate events

The above results establish the increasing effect of HFT activity on execution shortfall for institutional investors after controlling for time- and firm-fixed effects. However, 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 announcements and mergers and acquisitions (M&A). I identify earnings announcement days from $COMPUSTAT$ (and augmented with $I/B/E/S$ data in the case of missing earnings announcement dates in $COMPUSTAT$). The M&A dates are identified from SDC. 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 acquirers or 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. Other variables in the regression remain the same as those reported in Table 3.

Table 5 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 is inconsistent with the hypothesis that certain corporate events drive both HFT Intensity and Execution Shortfall higher.

#### IV.D.2. Short selling ban

In the previous subsection, I find that when HF traders participate more, institutional investors encounter a higher execution shortfall. Alternatively, it could also be that HF traders choose to be more active when execution shortfall is high. In this subsection, I will rule out this possibility through analysis of an exogenous event - the short selling ban.

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 covers 13 stocks in my sample. On September 22, the list expanded to cover 16 stocks in my sample, and one more stock was added to the banned list on September 23.[7] This short selling ban was instituted immediately without any advance notice, and thus can be viewed as an exogenous event. 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.

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 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 that the 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 the HF trader' role in providing liquidity. Clearly when liquidity is most needed, they 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 shore selling ban, I further rule out the alternative explanation that the positive relation between HFT and trading cost is due to a selection effect, i.e. HF traders choose to be more active when trading cost is high.

[7] 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.

### IV.D.3. Granger causality

I use the Granger causality test to further establish the direction of causality. The Grander 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:

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

where $ES_{i,t}$ and $HFT_{i,t}$ are 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 to take into account is that the variables of interest, $b_{12,i}$s or $b_{21,i}$s, are correlated across stocks.[8]

I take a bootstrap approach to perform statistical inference jointly on the 120 stocks, in a way

[8]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 120 $b_{21,i}$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.

similar to the bootstraps performed by Kosowski, et al. (2006) and Jiang et al. (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 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.[9] For each bootstrap, I estimate the cross-sectional statistics including the mean, median, 1st and 3rd qunitiles 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 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 indicating that the sample statistic is abnormally low relative to the distribution under the null hypothesis of no causality; and a bootstrapped p-value of 0 indicating that the sample statistic is abnormally high relative to what one would expect under the null of no causality.

Table 6 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 quintiles, are all very low. Therefore, we infer that across the 120 stocks, there is a pervasive pattern that the intensity of HFT Granger-causes institutional trading cost.

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

[9] Specifically, the procedure involves the following steps. Across the 120 stocks, I compute the cross-sectional distribution statistics such as mean, median, 1st and 3rd quintiles 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 quintiles 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.

ES on HFT, $b_{21,i}$, has a small mean of 0.001; and the corresponding t-statistic has a small mean of 0.039, with a bootstrapped p-value of 0.341. This suggests 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 quintiles are in the range of 0.14 to 0.70. Overall, this suggests that there is no pervasive support to the hypothesis that institutional trading cost 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.

# V. Further Analysis of HFT activities

The analysis in this section consists two parts. The first part includes two sets of robustness results, based on the timing delay component of trading costs and on trade-level regression analysis. The second part includes two sets of results on the specific mechanisms through which HFT impacts institutional trading costs.

## V.A. Robustness: Timing delay costs and trade-level regressions

### V.A.1. Timing delay costs

I have provided evidence that intensive HFT activities lead to an increase in institutional investors' execution shortfall. This finding suggests that even though HFT improves the overall market quality, as documented in current literature, it causes additional trading costs for institutional investors. A natural question to ask is whether improved market quality 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 may go down. Here, I perform analysis to address this possibility.

The cost incurred while seeking liquidity is known as timing delay 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, 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 $\alpha_i$ are the firm-fixed effects, the $y_t$ are day dummies, and HFT Intensity$_{it}$ is the measure of daily HFT activity on stock $i$ as describe in subsection III.A., Timing Delay$_{it}$ is the volume-weighted average timing delay of all institutional trades on stock $i$ at day $t$, and $X_{it}$ represents the same set of control variables as in Equation (3).

Table 7 presents the estimates of 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 dummies 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 the timing delay costs of institutional investors. Thus, while HFT activity increases institutional investors' execution shortfall, it does not provide the benefit of reduced timing delay costs.

#### V.A.2. Trade-level analysis

So far, I conduct all the multivariate panel regression analyses at the stock-day level, where execution shortfall costs are aggregated for each stock on each trading day. The aggregation at 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. As pointed out by Anand *et al.* (2012), some institutions consistently execute trades with lower execution shortfalls 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:

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

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 $j$. $\alpha_j$ represents the institution-fixed effects, and

$\gamma_m$ represents the time(month)-fixed effects. $X_{it}$ represents the same set of control variables as in Equation (3).

Table 8 presents the estimates of coefficients, with the t-statistics computed using the two-way clustered standard errors. The coefficient of HFT Intensity is positive and significant at the $1\%$ level. This suggests that after controlling for heterogenous institutional trading skills, HFT increases execution shortfall at the trade level, consistent with the conclusion drawn from stock-day level analysis.

## V.B. When and how does HFT impact institutional trading costs

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

### V.B.1. HFT and institutional buy-sell imbalance

I first investigate the possibility that HFT profits 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 HFT comes with extra costs to institutional investors, given the same level of trade imbalances among the institutions.

To begin with, I compare the daily buy-sell imbalance of the two types of investors–institutional investors and HF traders. I define the daily institutional imbalance on each stock as the buy dollar volume minus sell dollar volume of all institutions (HF traders) normalized by the stock's average daily trading volume over the prior 30 days. Panel A of Table 9 presents the distribution of such buy-sell imbalances for the sample stocks from 2008 to 2009. The table shows that while the daily imbalance by traditional institutional investors exhibits large variations, the daily imbalance for

HF traders is mostly 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 researchers have suggested that holding overnight positions can be very costly for HF traders (e.g., Menkveld (2010)).

Next, I use sorted portfolios to examine the relation of institutional buy-sell imbalance with both HFT activity and HFT buy-sell imbalance. Specifically, within each of the three size group, I sort stocks into terciles based on institutional buy-sell imbalance, and examine the average HFT Intensity and average HF buy-sell imbalance across the nine groups.

Panel B and C of Table 9 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 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 the case when institutional trades are balanced.

Combining results from all panels of Table 9, 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 quite ephemeral – within a day, literally. Therefore, a more accurate description of the liquidity provision role of HF traders is that they serve as intra-day intermediaries and quickly pass the imbalances from institutions to other market participants.

We then investigate another important question regarding the liquidity provision role of HF traders. Our analysis in Table 3 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 trading with relative balance. 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 10. The first two columns of the table report results when institutions are net selling. The coefficient of HFT Intensity is negative but not significant at the 5% level, suggesting that HFT activity does not hurt institutional investors significantly 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, for 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 are net buyers. 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.

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

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

I now turn to the second conjecture, that is, HF traders use certain strategies (e.g., front-running) to take advantage of institutional investors and increase the latter's trading costs. Here, I rely on the non-randomness, or sequences and reversals, of HF trade directions to detect the presence of HF strategies. For example, if HF traders engage in electronic market making, a type of HFT strategy considered to provide liquidity to the market, they have to buy and sell the same stocks very fast so that one should observe rapid reversals of trade directions. In contrast, directional trading strategies such as momentum ignition and front-running large institutional orders typically involve long sequences of trades in the same direction.

The non-randomness of HF trading is tested using the runs test on all trades made by HF traders on a stock on a given day. 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 (1997)). 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.[10] A negative and significant runs test statistic indicates frequent reversals in trade directions, an indication of market making strategies in play. A positive and significant test statistic means the popularity of sequential trades in the same direction, an indication directional trading strategies in use.

Based on the one-way critical value at the 2.5% level (i.e., -1.96 and 1.96), I identify 18506 cases at the stock-day level where the runs statistics are significantly positive, 18195 cases where the runs statistics are significantly negative, and 18262 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 market making 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 market making and directional trading are important strategies employed by HF traders.

The important question is what these strategies mean to the trading costs of institutional investors. To address this question, I perform panel regressions following the model specified in Equation (3), but separately for the cases where the runs tests at stock-day level are significantly positive, significantly negative, and insignificant. The results are presented in Table 11. First, as shown in the first two columns of the table, when HF trades exhibit directional sequences (i.e., when the runs statistics are significantly positive), the coefficient of HFT Intensity is 0.409, sig-

[10] 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 expectation and variance of $R$. The test statistic is asymptotically normally distributed; see Wald and Wolfowitz (1940).

nificant 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, significant at the 5% level. This suggests that the electronic market making strategies employed by HF traders also increases institutional trading costs, although at a smaller magnitude relative to the case when HF traders engage in direction trading. Finally, the results reported in last two columns of the table show that when neither directional trading nor market making 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).

# VI. 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, 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 120 sample stocks, I conduct a sorted portfolio test and a panel regression with control 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 a 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 also find that this incremental effect of HFT on execution shortfall is stronger on smaller stocks.

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 in 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 holds. Fourth, I use the short selling ban imposed on financial stocks on September 19, 2008 as an exogenous shock to execution shortfall. 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 via which HFT affects institutional trading costs. My 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. And such liquidity provision proves particularly expensive for institutions in terms of their trading costs. My analysis also shows the prevalence of both directional strategies and market making strategies used by HF traders. The presence of either type of strategies results in increased institutional trading costs; but the impact is most pronounced when the directional trading strategies are in use. This lends support to the anecdotal observations among institutional investors that their trades have been front-run by HF traders.

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 high frequency trading, particularly in terms of its implications for long term investors.

# Reference


Amihud, Y., 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets 5*, 31-56.

Anand, Amber, Paul Irvine, Andy Puckett and Kumar Venkataraman, 2010, Market crashes and institutional trading, Working Paper, University of Georgia.

Anand, Amber, Paul Irvine, Andy Puckett, and Kumar Venkataraman, 2012, Performance of institutional trading desks: An analysis of persistence in trading costs, *Review of Financial Studies 25*, 557-598.

Arnuk, Sal L. and Joseph Saluzzi, 2008, Toxic equity trading order flow on Wall Street, White Paper, Themis Trading LLC.

Biais, B., T. Foucault, and S. Moinas, 2010, Equilibrium algorithmic trading, Working paper, IDEI Toulouse.

Boehmer, E., K. Fong, and J. Wu, 2012, International evidence on algorithmic trading, Working paper, University of Georgia.

Brogaard, J., 2010, High frequency trading and its impact on market quality, Working paper, University of Washington.

Brogaard, J., Hendershott, T.J., S. Hunt, T. Latza, L. Pedace, and C. Ysusi, 2012, High frequency trading and the execution costs of institutional investors, UK Government's Foresight Project: The future of computer trading in financial markets, Foresight Driver Review 21.

Brogaard, J., Hendershott, T.J., and Riordan, R., 2013, High frequency trading and price discovery, Working paper, University of Washington.

Brunnermeier, M., and L. H. Pedersen, 2005, Predatory trading, *Journal of Finance 60*, 1825 -1863.

Campbell, J., A. Lo, and C. MacKinlay, 1997, The econometrics of financial markets, Princeton University Press, Princeton, NJ.

Carrion, A., 2013, Very fast money: High-frequency trading on NASDAQ, *Journal of Financial Markets*, forthcoming.

Cartea, A. and J. Penalva, 2011, Where is the value in high frequency trading? Working paper, Universidad Carlos III de Madrid.

Chaboud, A., B. Chiquoine, E. Hjalmarsson, and C. Vega, 2009, Rise of the machines: Algorithmic trading in the foreign exchange market, Working paper, Federal Reserve Board.

Chemmanur, T., S. He, and G. Hu, 2009, The role of institutional investors in seasoned equity offerings, *Journal of Financial Economics 94*, 384-411.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance 52*, 1035-1058.

Easley, D., Lopez de Prado, M. and O'Hara, M., 2011a, The microstructure of the 'Flash Crash': low toxicity, liquidity crashes and the probability of informed trading, *The Journal of Portfolio Management 37*, 118-128.

Easley, D., Lopez de Prado, M. and O'Hara, M., 2012, Flow toxicity and liquidity in a high-frequency world, *The Review of Financial Studies 25*, 1457-1493.

Egginton, J., B. F. VanNess, and R. A. VanNess, 2011, Quote stuffing, Working paper, University of Mississippi.

Fama, E., 1965, The behavior of stock market prices, *Journal of Business 38*, 34-105.

Goldstein, M., P. Irvine, E. Kandel, and Z. Weiner, 2009, Brokerage commissions and institutional trading patterns, *Review of Financial Studies 22*, 5175-5212.

Goldstein, M., P. Irvine, and A. Puckett., 2010, Purchasing IPOs with Commissions, *Journal of Financial and Quantitative Analysis 46*, 1193-1225.

Hasbrouck, J., Saar, G., 2013, Low-Latency Trading, *Journal of Financial Markets*, Forthcoming.

Hendershott, T., C. Jones, and A.J. Menkveld, 2011, Does algorithmic trading increase liquidity? *Journal of Finance 66*, 1-33.

Hirschey, N., 2011, Do high-frequency traders anticipate buying and selling pressure? Working paper, London Business School.

Hoffmann, P., 2010, Algorithmic trading in a dynamic limit order market, Working Paper, Universitat Pompeu Fabra.

Hu, G., 2009, Measures of implicit trading costs and buy-sell asymmetry, *Journal of Financial Markets 12*, 418-437.

ITG Investment Technology Group, 2009, ITG's Global Cost Review, White paper.

Jarrow, R. and P. Protter, 2011, A dysfunctional role of high frequency trading in electronic Markets, Working paper, Cornell University.

Jiang, G., T. Yao, and T. Yu, 2007, Do mutual funds time the market? Evidence from portfolio holdings, *Journal of Financial Economics 86*, 724-758.

Kosowski, R., A. Timmermann, H. White, and R. Wermers, 2005, Can mutual fund stars really pick stocks? New evidence from a bootstrap analysis, *Journal of Finance 51*, 2551-2595.

Kirilenko, A., A. S. Kyle, M. Samadi, and T. Tuzun., 2011, The Flash Crash: The impact of high frequency trading on an electronic market, Working Paper, University of Maryland.

Malinova, K., A. Park, and R. Riordan, 2013, Do retail traders suffer from high frequency traders? Working paper, University of Toronto.

McInish, T. and J. Upson, 2011, Strategic liquidity supply in a market with fast and slow traders, Working paper, University of Memphis.

Menkveld, A., 2010, High frequency trading and the new-market makers, Working paper, Free University of Amsterdam.

O'Hara, M., 2003, Liquidity and price discovery, *Journal of Finance 58*, 1335-1354.

Parkinson, M., 1980, The extreme value method for estimating the variance of the rate of return, *Journal of Business 53*, 61-65.

Peterson, Mitchell A., 2009, Estimating standard errors in panel data sets, *Review of Financial Studies 22*, 435-480.

Puckett, A., and S. Yan, 2011, The interim trading skills of institutional investors, *Journal of Finance 66*, 601-633.

UK Government's Foresight Project, 2012, The future of computer trading in financial markets.

US Securities & Exchange Commission, 2010, Concept release on equity market structure, Release No. 34-61458, File No. S7-02-10.

Wald, A. and Wolfowitz, J., 1940, On a test whether two samples are from the same population, *Annals of Mathematical Statist 11*, 147-162.

## Table 1: Summary statistics

This table reports the averages of stock characteristics, HFT activity, and execution shortfall of all stock-days, as well as the averages by market capital, during the periods of 2008 and 2009. All the variables are measured on a daily basis. Market Capitalization is a stock's market value. HFT Total Trading Volume is the daily total trading volume of HFT on a stock. Average Execution Shortfall is the volume-weighted average execution shortfall of all institutional trades on a stock. Amihud Illiquidity Ratio is the daily absolute return divided by the dollar trading volume on that day. Average Institutional Order Size is the average dollar volume of all institutional trades placed on a stock. Average Trades Per Order is the average number of trades to complete an order ("ticket") on a stock.

| | All | Large Cap | Mid Cap | Small Cap |
|---|---|---|---|---|
| Average Market Capital ($billion) | 17.500 | 46.780 | 1.590 | 0.400 |
| Average HFT Total Trading Volume (million) | 54.570 | 158.230 | 3.650 | 0.380 |
| Average Execution Shortfall (%) | 0.167 | 0.146 | 0.163 | 0.196 |
| Amihud Illiquidity Ratio | 0.006 | 7.6E-05 | 0.002 | 0.019 |
| Average Institutional Order Size | 244,286 | 487,871 | 154,823 | 63,943 |
| Average Trades Per Order | 2.303 | 3.126 | 1.861 | 1.850 |

## Table 2: 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 announcement or M&A announcement), 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.

| 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 3: 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 costs 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 only day-fixed effects but no 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.

| 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 4: HFT's impact on execution shortfall across stock sizes

This table report the results of panel regressions that examine the differential impact of HFT activity on execution shortfall for different stock size groups. The 120 stocks are divided into three groups based on their market capitalizations. The baseline regression model (as described in Table 3) is estimate within the three size groups, respectively. 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.

| Dependent Variable | Execution Shortfall | | | | | |
|---|---|---|---|---|---|---|
| | Large Stocks | | Mid Stocks | | Small Stocks | |
| | Coefficient | t-value | Coefficient | t-value | Coefficient | t-value |
| Intercept | -1.078 | (-1.97) | -1.101 | (-1.32) | -2.125 | (-2.16) |
| HFT Intensity | 0.188 | (1.99) | 0.152 | (1.56) | 0.622 | (2.49) |
| Log Market Cap | 0.063 | (1.90) | 0.059 | (0.92) | 0.145 | (1.76) |
| Book-to-Market Ratio | 114.861 | (1.33) | -46.562 | (-0.97) | 9.820 | (1.75) |
| Prior 1-day Return | -0.098 | (-0.30) | -0.402 | (-1.23) | -0.060 | (-0.10) |
| Prior 1-month Return | 0.083 | (1.51) | -0.105 | (-1.33) | -0.086 | (-0.79) |
| Prior 12-month Return | -0.012 | (-0.41) | 0.028 | (1.06) | -0.018 | (-0.68) |
| Amihud Illiquidity Ratio | 648.124 | (4.25) | 24.085 | (4.19) | 4.771 | (3.32) |
| Daily Return Volatility | -0.055 | (-2.81) | 0.203 | (0.40) | 0.157 | (0.30) |
| Daily Dollar Turnover | 0.004 | (0.56) | -0.002 | (-0.07) | -0.016 | (-0.17) |
| Average Institutional Order Size | 14.595 | (2.26) | 2.848 | (1.86) | 0.909 | (1.72) |
| Absolute Institutional Imbalance | 1.064 | (5.26) | 0.126 | (0.81) | 0.163 | (1.05) |
| Average Trades Per Order | -0.005 | (-1.87) | 0.007 | (1.87) | -0.007 | (-1.39) |
| Day-fixed Effects | Yes | | Yes | | Yes | |
| Stock-fixed Effects | Yes | | Yes | | Yes | |
| Two-way Clustered Std. | Yes | | Yes | | Yes | |
| Adjusted R-squared (%) | 4.54 | | 4 | | 5.79 | |
| Number of Observations | 20119 | | 18981 | | 15863 | |

## Table 5: 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 3. 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.

| Dependent Variable | Execution Shortfall | |
|---|---|---|
| | Coefficient | t-value |
| Intercept | -1.129 | -(1.74) |
| HFT Intensity $\times$ Event Dummy | 0.155 | (1.29) |
| HFT Intensity $\times$ 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 6: Granger causality

This table reports the result 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.

| 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 7: HFT's impact on timing delay costs

This table reports the results of panel regressions that examine the impact of HFT activity on the timing delay costs of institutional investors. The dependent variable, Timing Delay Cost, is the volume-weighted average timing delay costs of all institutional trades on a stock for a trading day. All the other variables are defined in Table 3. 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.

| 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 8: 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 trade. 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 3. The linear regression model is estimated with both month- and institution-fixed effects. The t-statistics are computed using two-way clustered standard errors.

| 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 9: HFT and institutional buy-sell imbalances

This table reports the results of analysis on the relations among institutional trade imbalances, HFT intensity, and HFT trade imbalances. Institutional (HFT) trade imbalance is 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 report 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 10: 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 3) is estimate 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.

| 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) | -0.054 | (-1.31) |
| 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 11: 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 in 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 tests on all HF trades on a stock on a given day. The regression model (as described in Table 3) 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.

| Dependent Variable | Execution Shortfall | | | | | |
|---|---|---|---|---|---|---|
| | Directional | | Market Making | | 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 | |

**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 HFT involves 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.

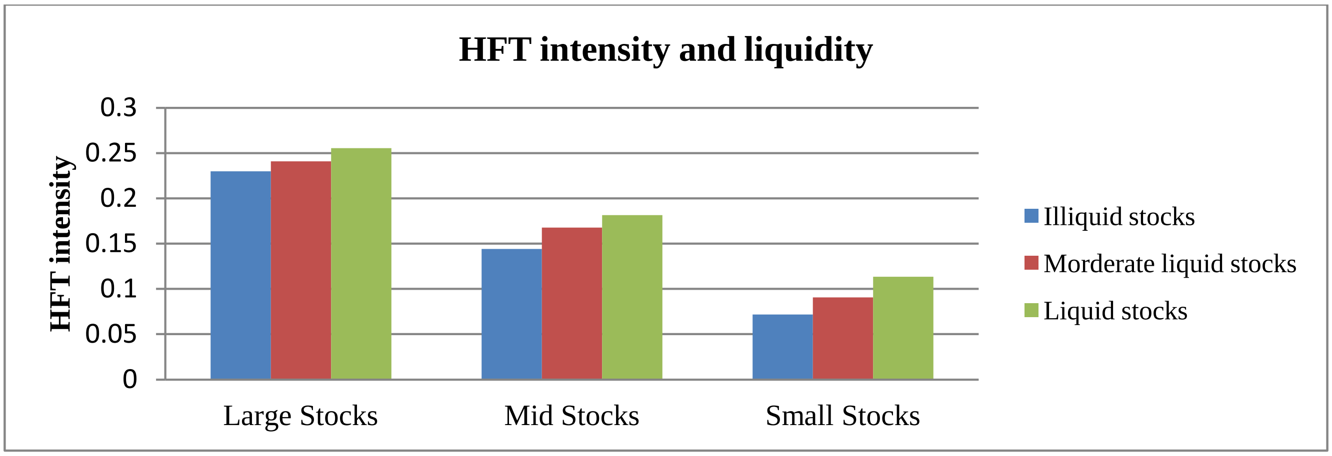

**Figure 2: Relation between liquidity and execution shortfall**

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.

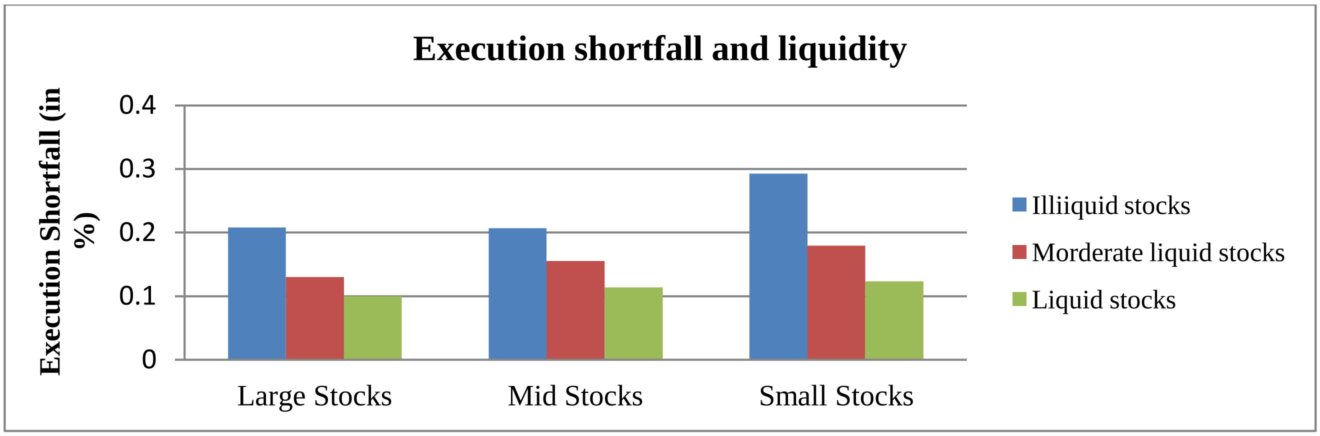

**Figure 3: Relation between HFT intensity and execution shortfall**

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 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.

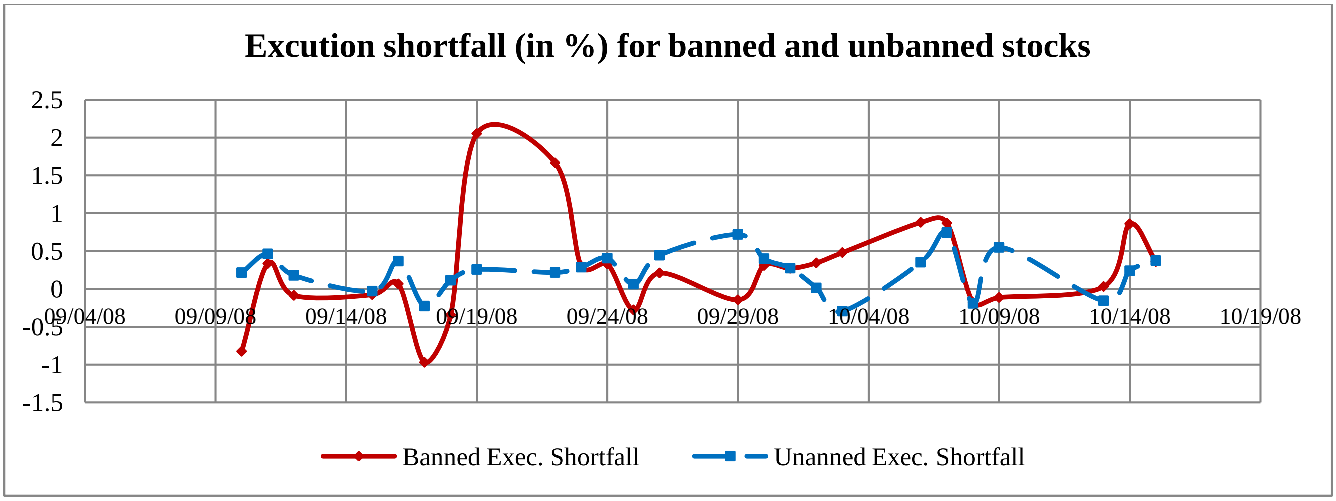

**Figure 5: HFT activity around the Short-selling Ban of the September 18, 2008**

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.