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# HIGH FREQUENCY TRADING AND PRICE DISCOVERY

Jonathan Brogaard,
Terrence Hendershott
and Ryan Riordan


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**Jonathan Brogaard**
University of Washington

**Terrence Hendershott**
University of California at Berkeley

**Ryan Riordan (corresponding author)**
University of Ontario Institute of Technology; e-mail: ryan.riordan@uoit.ca



| | |
|---|---|
| **Address** | Kaiserstrasse 29, 60311 Frankfurt am Main, Germany |
| **Postal address** | Postfach 16 03 19, 60066 Frankfurt am Main, Germany |
| **Telephone** | +49 69 1344 0 |
| **Internet** | http://www.ecb.europa.eu |
| **Fax** | +49 69 1344 6000 |



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# ABSTRACT

We examine empirically the role of high-frequency traders (HFTs) in price discovery and price efficiency. Based on our methodology, we find overall that HFTs facilitate price efficiency by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors, both on average and on the highest volatility days. This is done through their liquidity demanding orders. In contrast, HFTs' liquidity supplying orders are adversely selected. The direction of buying and selling by HFTs predicts price changes over short horizons measured in seconds. The direction of HFTs' trading is correlated with public information, such as macro news announcements, market-wide price movements, and limit order book imbalances.



## Keywords

high frequency trading, price formation, price discovery, pricing errors

## JEL codes

G12


(for internet appendix click: http://goo.gl/vyOEB)

# NON-TECHNICAL SUMMARY

Financial markets have undergone a dramatic transformation. Traders no longer sit in trading pits buying and selling stocks with hand signals, today these transactions are executed electronically by computer algorithms. Stock exchanges' becoming fully automated (Jain (2005)) increased the number of transactions a market executes and this enabled intermediaries to expand their own use of technology. Increased automation reduced the role for traditional human market makers and led to the rise of a new type of electronic intermediary (market-maker or specialist), typically referred to as high frequency traders (HFTs).

This paper examines the role of HFTs in the stock market using transaction level data from NASDAQ that identifies the buying and selling activity of a large group of HFTs. The data used in the study are from 2008-09 for 120 stocks traded on NASDAQ. Of the 120 stocks 60 are listed on the New York Stock Exchange and 60 from NASDAQ. The stocks are also split into three groups based on market capitalization. To understand the impact of HFT on the overall market prices we use national best-bid best-offer prices that represent the best available price for a security across all markets.

The substantial, largely negative media coverage of HFTs and the "flash crash" on May 6, 2010 raise significant interest and concerns about the fairness of markets and HFTs' role in the stability and price efficiency of markets. Our analysis suggests that HFTs impose adverse selection costs on other investors, by trading with them when they (HFTs) have better information. At the same time, HFTs being informed allows them to play a beneficial role in price efficiency by trading in the opposite direction to transitory pricing errors and in the same direction as future efficient price movements.

To obtain our results we follow Hendershott and Menkveld's (2011) approach, and use a state space model to decompose price movements into permanent and temporary components and to relate changes in both to HFTs. The permanent component is normally interpreted as information and the transitory component as pricing errors, also referred to as transitory volatility or noise. Transitory price movements, also called noise or short-term volatility make it difficult for unsophisticated investors to determine the true price. This may cause them to buy when they should be selling or sell when they should be buying. HFTs appear to reduce this risk. The state space model incorporates the interrelated concepts of price discovery (how information is impounded into prices) and price efficiency (the informativeness of prices). We also find that HFTs' trading is correlated with public information, such as macro news announcements, market-wide price movements, and limit order book imbalances.

Our results have implications for policy makers that are contemplating the introduction of measures to curb HFT. Our research suggests, within the confines of our methodological approach, that HFT provide a useful service to markets. They reduce the noise component of prices and acquire and trade on different types of information, making prices more efficient overall. Introducing measures to curb their activities without corresponding measures to that support price discovery and market efficiency improving activities could result in less efficient markets.

HFTs are a type of intermediary by standing ready to buy or sell securities. When thinking about the role HFTs play in markets it is natural to compare the new market structure to the prior market structure. Some primary differences are that there is free entry into becoming an HFT, HFTs do not have a designated role with special privileges, and HFTs do not have special obligations. When considering the best way to organize securities markets and particularly the intermediation sector, the current one with HFT more resembles a highly competitive environment than traditional a market structure. A central question is whether there were possible benefits from the old more highly regulated intermediation sector, e.g., requiring continuous liquidity supply and limiting liquidity demand that outweigh lower innovation and monopolistic pricing typically associated with regulation.

# I INTRODUCTION

Financial markets have two important functions for asset pricing: liquidity and price discovery for incorporating information in prices (O'Hara (2003)). Historically, financial markets relied on intermediaries to facilitate these goals by providing immediacy to outside investors. Stock exchanges' becoming fully automated (Jain (2005)) increased markets' trading capacity and enabled intermediaries to expand their use of technology. Increased automation reduced the role for traditional human market makers and led to the rise of a new class of intermediary, typically referred to as high frequency traders (HFTs). This paper examines the role of HFTs in the price discovery process using transaction level data from NASDAQ that identifies the buying and selling activity of a large group of HFTs.

Like traditional intermediaries HFTs have short holding periods and trade frequently. Unlike traditional intermediaries, however, HFTs are not granted privileged access to the market unavailable to others.[1] Without such privileges, there is no clear basis for imposing the traditional obligations of market makers (e.g., see Panayides (2007)) on HFTs. These obligations were both positive and negative. Typically, the positive obligations required intermediaries to always stand ready to supply liquidity and the negative obligations limited intermediaries' ability to demand liquidity. Restricting traders closest to the market from demanding liquidity mitigates the adverse selection costs they impose by possibly having better information about the trading process and being able to react faster to public news.

The substantial, largely negative media coverage of HFTs and the "flash crash" on May 6, 2010 raise significant interest and concerns about the fairness of markets and HFTs' role in the stability and price efficiency of markets.[2] Our analysis suggests that HFTs impose adverse selection costs on other investors. At the same time, HFTs being informed allows them to play a beneficial role in price efficiency by trading in the opposite direction to transitory pricing errors and in the same direction as future efficient price movements. In addition, HFTs supply liquidity in stressful times such as the most volatile days and around macroeconomic news announcements.

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[1] Traditional intermediaries were often given special status and located on the trading floor of exchanges. The "optional value" inherent in providing firm quotes and limit orders allows faster traders to profit from picking off stale quotes and orders (Foucault, Roell, and Sandas (2003). This makes it difficult for liquidity suppliers to not be located closest to the trading mechanism. HFT firms typically utilize colocated servers at exchanges and purchase market data directly from exchanges. These services are available to other investors and their brokers, although at nontrivial costs.

[2] For examples of the media coverage, see Duhigg (2009) and the October 10, 2010 report on CBS News' 60 Minutes. See Easley, Lopez de Prado, and O'Hara (2011, 2012) and Kirilenko, Kyle, Samadi, and Tuzun (2011) for analysis of order flow and price dynamics on May 6, 2010.

We use a dataset NASDAQ makes available to academics that identifies a subset of HFTs. The dataset includes information on whether the liquidity demanding (marketable) order and liquidity supplying (nonmarketable) side of each trade is from a HFT. The dataset includes trading data on a stratified sample of stocks in 2008 and 2009. Following Hendershott and Menkveld's (2011) approach, we use a state space model to decompose price movements into permanent and temporary components and to relate changes in both to HFTs. The permanent component is normally interpreted as information and the transitory component as pricing errors, also referred to as transitory volatility or noise. The state space model incorporates the interrelated concepts of price discovery (how information is impounded into prices) and price efficiency (the informativeness of prices).

HFTs' trade (buy or sell) in the direction of permanent price changes and in the opposite direction of transitory pricing errors. This is done through their liquidity demanding (marketable) orders and is true on average and on the most volatile days. In contrast, HFTs' liquidity supplying (non-marketable) limit orders are adversely selected. The informational advantage of HFTs' liquidity demanding orders is sufficient to overcome the bid-ask spread and trading fees to generate positive trading revenues. For liquidity supplying limit orders the costs associated with adverse selection are smaller than revenues from the bid-ask spread and liquidity rebates.

In its concept release on equity market structure one of the Securities and Exchange Commission's (SEC (2010)) primary concerns is HFTs. On p.36-37, the SEC expresses concern regarding short-term volatility, particularly "excessive" short-term volatility. Such volatility could result from long-term institutional investors' breaking large orders into a sequence of small individual trades that result in a substantial cumulative temporary price impact (Keim and Madhavan (1995, 1997)). While each trade pays a narrow bid-ask spread, the overall order faces substantial transaction costs. The temporary price impact of large trades causes noise in prices due to price pressure arising from liquidity demand by long-term investors. If HFTs trade against this transitory pricing error, they can be viewed as reducing long-term investors' trading costs. If HFTs trade in the direction of the pricing error, they can be viewed as increasing the costs to those investors.

HFTs trading in the direction of pricing errors could arise from risk management, predatory trading, or attempts to manipulate prices while HFTs following various arbitrage strategies could lead to HFTs trading in the opposite direction of pricing errors. We find that overall HFTs benefit price efficiency suggesting that the efficiency-enhancing activities of HFTs play a greater role. Our data represent an equilibrium outcome in the presence of HFTs, so the counterfactual of how other market participants would behave in the absence of HFTs is not known.

We compare HFTs' and non-HFTs' role in the price discovery process. Because of the adding up constraint in market clearing, overall non-HFTs' order flow plays the opposite role in price discovery relative to HFTs: non-HFTs' trade in the opposite direction of permanent price changes and in the direction of transitory pricing errors. Non-HFTs' liquidity demanding and liquidity supplying trading play the same corresponding role in price discovery as HFT's liquidity demand and liquidity supply. While HFTs' overall trading is negatively correlated with past returns, commonly referred to as following contrarian strategies, non-HFTs' trading is positively correlated with past returns, implying they follow momentum strategies with respect to recent past returns.

The beneficial role of HFTs in price discovery is consistent with theoretical models of informed trading, e.g., Kyle (1985). In these models informed traders trade against transitory pricing errors and trade in the direction of permanent price changes. Balanced against the positive externalities from greater price efficiency are the adverse selection costs to other traders. Regulation FD and insider trading laws attempt to limit certain types of informed trading due to knowledge of soon-to-be public information and "unfairly" obtained information. Given that HFTs are thought to trade based on market data, regulators try to ensure that all market participants have equal opportunity in obtaining up-to-date market data. Such an objective is consistent with the NYSE Euronext's $5 million settlement over claimed Reg NMS violations from market data being sent over proprietary feeds before the information went to the public consolidated feed (SEC File No. 3-15023).

HFTs differ from other traders due to their use of technology for processing information and trading quickly.[3] A number of theoretical models use HFTs to motivate their informational structure. Martinez and Rosu (2013) and Foucault, Hombert, and Rosu (2013) model HFTs receiving information slightly ahead of the rest of the market. Consistent with these modeling assumptions we find that HFTs predict price changes over horizons of less than 3 to 4 seconds. In addition, HFTs trading is related to two sources of public information: macroeconomic news

[3] Biais, Foucault, and Moinas (2011) and Pagnotta and Philippon (2011) provide models where investors and markets compete on speed. Hasbrouck and Saar (2010) study low-latency trading—substantial activity in the limit order book over very short horizons—on NASDAQ in 2007 and 2008 and find that increased low-latency trading is associated with improved market quality.

announcements (Andersen, Bollerslev, Diebold, and Vega (2003)) and imbalances in the limit order book (Cao, Hansch, and Wang (2009)).[4]

HFTs are a subset of algorithmic traders (ATs). Biais and Woolley (2011) survey research on ATs and HFTs. ATs have been shown to increase liquidity (Hendershott, Jones, and Menkveld (2011) and Boehmer, Fong, and Wu (2012)) and price efficiency through arbitrage strategies (Chaboud, Chiquoine, Hjalmarsson, and Vega (2013)).[5] Our results are consistent with HFTs playing a role in ATs improving price efficiency.

One of the difficulties in empirically studying HFTs is the availability of data identifying HFTs. Markets and regulators are the only sources of these and HFTs and other traders often oppose releasing identifying data.[6] Hirschey (2013) uses data similar to ours from NASDAQ. Hirschey also finds that HFTs' liquidity demand predicts future returns. Hirschey explores in detail one possible information source for liquidity demanding HFTs: the ability to forecast non-HFTs' liquidity demand. He finds that liquidity demand by HFTs in one second predicts subsequent liquidity demand by non-HFTs. Given that liquidity demand by non-HFTs has information about subsequent returns, then such predictability is consistent with our findings that HFTs' liquidity demand helps incorporate information into prices. In addition to HFTs' liquidity demanding trades our paper analyzes the role of HFTs' overall trading and liquidity supplying trading in price discovery and the relation of HFTs' trading to the transitory pricing error. We also provide evidence on different sources of HFTs' information such as information in the limit order book and macroeconomic news announcements.

Several papers use data on HFTs and specific events to draw causal inferences. Hagströmer and Norden (2012) use data from NASDAQ-OMX Stockholm. They find that HFTs tend to specialize in either liquidity demanding or liquidity supplying. Using events where share price declines result in tick size changes, they conclude that HFTs mitigate intraday price volatility. This finding is consistent with our result on HFTs trading against transitory volatility. Malinova, Park, and Riordan (2012) examine a change in exchange message fees that leads HFTs to significantly reduce their market activity. The reduction of HFTs' message traffic causes an increase in spreads and an increase in the trading costs of retail and other traders.

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4 Jovanovic and Menkveld (2011) show that one HFT is more active when market-wide news increases and this HFT allows for a reduction in the related adverse selection costs.

5 Menkveld (2011) studies how one HFT firm improved liquidity and enabled a new market to gain market share. Hendershott and Riordan (2012) focus on the monitoring capabilities of AT and study the relationship between AT and liquidity supply and demand dynamics. They find that AT demand liquidity when it is cheap and supply liquidity when it is expensive smoothing liquidity over time.

6 A number of papers use CME Group data from the Commodity Futures Trading Commission that identifies trading by different market participants. Access by non-CFTC employees was suspended over concerns about the handling of such confidential trading data: http://www.bloomberg.com/news/2013-03-06/academic-use-of-cftc-s-private-derivatives-data-investigated-1-.html. We omit reference to papers that are currently not publically available.

The paper is structured as follows. Section 2 describes the data, institutional details, and descriptive statistics. Section 3 examines the lead-lag correlation between HFTs' trading and returns and uses a state space model to decompose prices into their permanent/efficient component and transitory/noise component and examines the role of HFTs' and non-HFTs' trading in each component. It also relates HFTs' role in price discovery to HFTs' profitability. Section 4 focuses on HFTs' trading during high permanent volatility day. Section 5 analyzes the different sources of information used by HFTs. Section 6 discusses the implications of our findings in general and with respect to social welfare. Section 7 concludes.

# 2 DATA, INSTITUTIONAL DETAILS, AND DESCRIPTIVE STATISTICS

NASDAQ provides the HFT data used in this study to academics under a non-disclosure agreement. The data is for a stratified sample of 120 randomly selected stocks listed on NASDAQ and the New York Stock Exchange (NYSE). The sample contains trading data for all dates in 2008 and 2009. Trades are time-stamped to the millisecond and identify the liquidity demander and supplier as a high-frequency trader or non-high-frequency trader (nHFT). Firms are categorized as HFT based on NASDAQ's knowledge of their customers and analysis of firms' trading such as how often their net trading in a day crosses zero, their order duration, and their order to trade ratio.

One limitation of the data is that NASDAQ cannot identify all HFT. Possible HFT firms excluded are those that also act as brokers for customers and engage in proprietary lower-frequency trading strategies, e.g., Goldman Sachs, Morgan Stanley, and other large integrated firms. HFTs who route their orders through these large integrated firms cannot be clearly identified so they are also excluded. The 26 HFT firms in the NASDAQ data are best thought of as independent proprietary trading firms.[7] If these independent HFT firms follow different strategies than the large integrated firms, then our results may not be fully generalizable. While we are unaware of any evidence of independent HFT firms being different, the definition of HFTs themselves is subject to debate.

The sample categorizes stocks into three market capitalization groups, high, medium and low. Each size group contains 40 stocks. Half of the firms in each size category are NASDAQ-listed the other half NYSE-listed. The top 40 stocks are composed of 40 of the largest market capitalization stocks, such as Apple and GE. The medium-size category consists of stocks around the 1000$^{th}$ largest stock in the Russell 3000, e.g., Foot Locker, and the small-size category contains stocks around the 2000$^{th}$ largest stock in the Russell 3000.[8]

The HFT dataset is provided by NASDAQ and contains the following data fields:

1. Symbol
2. Date

[7] Some HFT firms were consulted by NASDAQ in the decision to make data available. No HFT firm played any role in which firms were identified as HFT and no firms that NASDAQ considers HFT are excluded. While these 26 firms represent a significant amount of trading activity and according to NASDAQ fit the characteristics of HFT, determining the representativeness of these firms regarding total HFT activity is not possible. Hirschey (2013) has access to more detailed data and uses the same classification approach.

[8] See the internet appendix for a complete list of sample stocks and size categories.

3. Time in milliseconds
4. Shares
5. Price
6. Buy Sell indicator
7. Type (HH, HN, NH, NN)

Symbol is the NASDAQ trading symbol for a stock. The Buy-Sell indicator captures whether the trade was buyer or seller initiated. The type flag captures the liquidity demanding and liquidity supplying participants in a transaction. The type variable can take one of four values, HH, HN, NH or NN. HH indicates that a HFT demands liquidity and another HFT supplies liquidity in a trade; NN is similar with both parties in the trade being nHFTs. HN trades indicate that an HFT demands and a nHFT supplies liquidity, the reverse is true for NH trades. The remainder of the paper denotes HFT-demanding trades as $HFT^{D}$ (HH plus HN) and HFT-supplying trades as $HFT^{S}$ (NH plus HH). Total HFT trading activity ($HFT^{D}$ + $HFT^{S}$) is labeled as $HFT^{All}$. The nHFT trading variables are defined analogously. We use this notation for HFT trading volume (buy volume plus sell volume) and HFT order flow (net trading: buy volume minus sell volume).

The NASDAQ HFT dataset is supplemented with the National Best Bid and Offer (NBBO) from TAQ and the NASDAQ Best Bid and Best Offer (NASDAQ BBO) from NASDAQ. The NBBO measures the best prices prevailing across all markets to focus on market-wide price discovery and is available for all of 2008 and 2009. The NASDAQ BBO is available for a subsample for the first week in every quarter of 2008 and 2009 and measures the best available price on NASDAQ. When combining the NASDAQ HFT and NBBO data sets two small-cap firms do not appear in TAQ at the beginning of the sample period: Boise Inc. (BZ) and MAKO Surgical Corp. (MAKO). To maintain a balanced panel we drop these stocks. While the HFT trading data and the NBBO do not have synchronized time stamps, the HFT trading data and NASDAQ BBO are synchronized. Market capitalization data is year-end 2009 data retrieved from Compustat. We focus on continuous trading during normal trading hours by removing trading before 9:30 or after 16:00 and the opening and closing crosses, which aggregate orders into an auction.

Table 1 reports the descriptive statistics overall and by market capitalization size category. The average market capitalization of sample firms is \$18.23 billion. The range across size categories is high with an average of \$52.47 billion in large and \$410 million in small. We report average closing prices and daily volatility of returns. As is typical prices are highest and return volatility is lowest in large stocks with the reverse holding for small stocks.

**Table 1**

We report time-weighted bid-ask spreads in dollars and as a percentage of the prevailing quoted midpoint using the TAQ NBBO and NASDAQ BBO data sampled at one second frequencies. Spreads increase in both dollar and percentage terms from large to small stocks. Percentage spreads in small stocks are roughly eight times higher than for large stocks. Spreads likely play an important role in decisions to demand or supply liquidity. However, spreads calculated based on displayed liquidity may overestimate the effective spreads actually paid or received due to non-displayed orders. On NASDAQ non-displayed orders are not visible until they execute. NASDAQ matches orders based on price, time, display priority rules, meaning that hidden orders lose time priority to displayed orders at the same price.

Trading volume is highest in large stocks at $186.61 million traded per stock-day and lowest in small stocks with roughly $1.18 million traded per stock-day. Trading volume is similar in the NASDAQ BBO subsample with $205.2 million traded in large and $1.42 million traded in small stocks. $HFT^D$ makes up 42% of trading volume in large stocks and 25% of trading volume in small stocks. $HFT^S$ makes up 42% of trading volume in large stocks and only 11% of trading volume in small stocks. $HFT^{All}$ is the average of $HFT^D$ and $HFT^S$ and demonstrates that HFTs are responsible for roughly 42% of trading volume in large stocks and 18% in small stocks. These numbers show that HFT is concentrated in large liquid stocks and less in small less liquid stocks. The reasons for this are not obvious. One conjecture is that for risk management reasons HFTs value the ability to exit positions quickly in calendar time, making more frequently traded stocks more attractive. Other possibilities include trading frequency increasing the value of faster reaction times and narrower bid-ask spreads in large stock facilitating liquidity demanding statistical arbitrage strategies.

nHFTs' total trading volume is simply the difference between twice total trading volume and HFT trading volume. In Table 1 the overall HFT variable measures total trading volume by summing HFT buying and selling. For the remainder of the paper the HFT trading variables are order flow (net trading): buy volume minus sell volume. For market clearing every transaction must have both a buyer and a seller, implying for order flow that $HFT^{All} = - nHFT^{All}$. Therefore, we do not analyze both $HFT^{All}$ and $nHFT^{All}$. The HH and NN trades add to zero in $HFT^{All}$ and $nHFT^{All}$, so $HFT^{All}$ equals the HN order flow plus NH order flow. Because of the HH and NN trades, HFT liquidity demand and liquidity supply do not have such a simple correspondence to nHFT liquidity demand and supply. Hence, we analyze $HFT^D$, $HFT^S$, $nHFT^D$ and $nHFT^S$, although we cannot study all four variables simultaneously because they are collinear as they always sum to zero.

The SEC (2010) concept release lists a number of characteristics of HFTs. One important characteristic is the mean reversion of their trading positions. NASDAQ reports that their internal analysis finds evidence of mean reversion in individual HFTs' positions. However, the aggregation of all 26 HFT firms on one of many market centers may not clearly exhibit mean reversion.[9] See the Internet Appendix for the results of augmented Dickey-Fuller (ADF) test for each stock-day. If HFTs' inventory positions are close to zero overnight, then their inventories can be measured by accumulating their buying and selling activity in each stock from the opening up to each point in time. The results of the ADF test do not suggest that the inventories aggregated across HFTs are stationary in our data. Therefore, we use order flow rather than inventory levels in the statistical analysis of HFT trading behavior.

9 See Menkveld (2011) for evidence on cross-market inventory management by one HFT firm and how its trading position mean reverts quickly across markets, but slowly in each individual markets.

# 3 TRADING AND RETURNS

Correlations between HFTs' and nHFTs' trading and returns relate trading to price changes at different horizons. Figures 1-3 plots the correlation between returns and HFT and nHFT trading with returns over the prior five seconds, contemporaneous returns, and returns over the next ten seconds.

**Figure 1**

Figure 1 shows that the correlations between $HTF^{All}$ and subsequent returns are positive, die out quickly, and are essentially zero after two seconds. This is consistent with HFT's overall information being short-lived. 1-second lagged returns are statistically significantly positively correlated with $HTF^{All}$ while -5 to -2 second returns are statistically significantly negatively correlated with $HTF^{All}$. Looking across all five lags $HTF^{All}$ is negatively correlated with past returns, which implies HFTs overall follow contrarian strategies. Aggregate nHFTs must therefore be trend followers.

While Figure 1 illustrates the relation between $HTF^{All}$ and returns, Figure 2 shows these relations for $HTF^{D}$ and $nHTF^{D}$. $HTF^{D}$ is positively correlated with contemporaneous and subsequent returns and falls to zero three to four seconds in the future. $nHTF^{D}$ is more positively correlated with contemporaneous and subsequent returns with the relation dying out to zero eight to nine seconds in the future. These results suggest that while the direction of liquidity demand by both HFTs and nHFTs predicts future returns, information in $HTF^{D}$ is more short-lived than in $nHTF^{D}$.

**Figure 2**

The relation between lagged returns and $HFT^{D}$ is negative and significant for lags five through two. The opposite is the case for $nHFT^{D}$ where all lags are positively and significantly correlated. Consistent with the $HFT^{All}$ correlations, this suggests that on average liquidity demanding HFTs follow contrarian strategies while liquidity demanding nHFTs are trend followers. If price changes have both a permanent and temporary component, the HFT correlations with returns are consistent with liquidity demanding HFTs trading to correct transitory price movements (prices overshooting). The nHFT correlations are consistent with liquidity demanding nHFTs trading on lagged price adjustment to information (prices undershooting).

Figure 3 graphs the correlations between returns and $HFT^{S}$ and $nHFT^{S}$. The correlations are similar in that they die out quickly, but they are of the opposite sign as those for $HFT^{D}$. The negative $HFT^S$ correlations with returns are consistent with HFTs' liquidity supply being adversely selected. $nHFT^S$ also negatively correlates with contemporaneous and subsequent returns, although more so. HFTs' and nHFTs' liquidity supply correlate with lagged returns in the opposite way, with $nHFT^S$ being negatively correlated and $HFT^S$ being positively correlated. The nHFTs' negative correlation is consistent with nHFTs' limit orders being stale and adversely selected due to both the contemporaneous and lagged price impact of liquidity demand. Positive correlation between lagged returns and $HFT^S$ suggests HFTs avoid this lagged price adjustment to trading and possibly benefit from it. The $HFT^{All}$ correlations with returns have the same sign as $HFT^D$, suggesting that HFTs' liquidity demanding trades dominate HFTs' trading relations to returns.

**Figure 3**

The HFT and nHFT trading variables have the same correlations with respect to contemporaneous and subsequent returns. However, they have the opposite correlation with lagged returns. HFTs follow contrarian strategies with respect to past prices changes with their liquidity demanding trading. nHFTs follow momentum strategies when demanding liquidity. The simple correlations provide useful information. However, contrarian and momentum strategies can be associated with permanent and transitory price movements. Therefore, a more complex model is required to disentangle the relation between HFT and nHFT and price discovery and efficiency.

## 3.1 STATE SPACE MODEL OF HFT AND PRICES

The results of the correlation analysis suggest that liquidity demanding and liquidity supplying trades have distinct relations with prices. To better understand the relation between the trading variables, permanent price changes, and transitory price changes we estimate a state space model.[10] The state space model assumes that a stock's price can be decomposed into a permanent component and a transitory component (Menkveld, Koopman, and Lucas (2007)):

$$p_{i,t} = m_{i,t} + s_{i,t}.$$

[10] Hendershott and Menkveld (2011) provide several reasons why the state space methodology is preferable to other approaches such as autoregressive models. First, maximum likelihood estimation is asymptotically unbiased and efficient. Second, the model implies that the differenced series is an invertible moving average time series model which implies an infinite lag autoregressive model. When estimating in a vector autoregression Hasbrouck (1991) and following work must truncate the lag structure. Third, after estimation, the Kalman smoother (essentially a backward recursion after a forward recursion with the Kalman filter) facilitates a series decomposition where at any point in time the efficient price and the transitory deviation are estimated using all observations, i.e., past prices, the current price, and future prices.

where $p_{i,t}$ is the (log) midquote at time interval $t$ for stock $i$ and is composed of a permanent component $m_{i,t}$ and a transitory component $s_{i,t}$. The permanent (efficient) component is modeled as a martingale:

$$m_{i,t} = m_{i,t-1} + w_{i,t}$$

The permanent process characterizes information arrivals where $w_{i,t}$ represents the permanent price increments. To capture the overall impact of HFTs and the individual impacts of $HFT^D$, $nHFT^D$, $HFT^S$ and $nHFT^S$ we formulate and estimate three models. One model incorporates $HFT^{All}$, a second includes $HFT^D$ and $nHFT^D$, and a third includes $HFT^S$ and $nHFT^S$. Following Hendershott and Menkveld (2011) and Menkveld (2011) we specify $w_{i,t}$ for the aggregate model as:

$$w_{i,t} = \kappa_i^{All} \widetilde{HFT}_{i,t}^{All} + \mu_{i,t},$$

where $\widetilde{HFT}_{i,t}^{All}$ is the surprise innovation in $HFT^{All}$, which is the residual of an autoregressive model to remove autocorrelation. For the disaggregated model $w_{i,t}$ is formulated as:

$$w_{i,t} = \kappa_{i,HFT}^{D} \widetilde{HFT}_{i,t}^{D} + \kappa_{i,nHFT}^{D} n\widetilde{HFT}_{i,t}^{D} + \mu_{i,t},$$

where $\widetilde{HFT}_{i,t}^{D}$ and $n\widetilde{HFT}_{i,t}^{D}$ are the surprise innovations in the corresponding variables. The surprise innovations are the residuals of a vector auto-regression of HFT and nHFT on lagged HFT and nHFT. A lag length of 10 (10 seconds) is used as determined by standard techniques.[11] The same disaggregate model is estimated for HFT and nHFT liquidity supply, resulting in three models. The trading variables are designed to allow for measurement of informed trading and its role in the permanent component of prices. The changes in $w_{i,t}$ unrelated to trading are captured by $\mu_{i,t}$.

The state space model assumes that the transitory component of prices (pricing error) is stationary. To identify the transitory component of prices we include an autoregressive component and the raw trading variables in the equation. We formulate $s_{i,t}$ for the aggregate model as:

$$s_{i,t} = \phi s_{i,t-1} + \psi_i^{All} HFT_{i,t}^{All} + \upsilon_{i,t},$$

and the disaggregate model as:

$$s_{i,t} = \phi s_{i,t-1} + \psi_{i,HFT}^{D} HFT_{i,t}^{D} + \psi_{i,nHFT}^{D} nHFT_{i,t}^{D} + \upsilon_{i,t}.$$

[11] The optimal lag length is chosen that minimizes the Akaike Information Criterion (AIC). We present the results of a model estimated with lag lengths of 20 and 50 seconds in the internet appendix.

$HFT^{All}_{i,t}$ enables measurement of the aggregate role HFTs play in transitory price movements. The inclusion of $HFT^{D}_{i,t}$, $HFT^{S}_{i,t}$, $nHFT^{D}_{i,t}$, and $nHFT^{S}_{i,t}$ allow for analysis of the role of liquidity supplying and demanding trading by both HFTs and nHFTs as well as relative comparisons between the two types of traders. As is standard, the identification assumption is that conditional on the trading variables the innovations in the permanent and transitory components are uncorrelated: $Cov(\mu_t, \upsilon_t) = 0$.[12] The intuition behind the identification is that liquidity demand can lead to correlation between the innovations in the two components of price. The inclusion of the trading variables eliminates the correlation, allowing for decomposition of the permanent and transitory components of price. See Chapters 8 and 9 of Hasbrouck (2007) for a detailed discussion.

## 3.2 STATE SPACE MODEL ESTIMATION

To estimate the state space model for each of the 23,400 1-second time intervals in a trading day for each stock we use the NBBO midquote price or the NASDAQ BBO, the HFT/nHFT liquidity demanding order flow (dollar buying volume minus selling volume), the HFT/nHFT liquidity supplying order flow, and overall HFT order flow (sum of liquidity demand and liquidity supply order flows). The state space model is estimated on a stock-day-by-stock-day basis using maximum likelihood via the Kalman filter.

The NBBO sample contains 118 stocks on 510 trading days and the NASDAQ BBO sample contains 45 trading days. The NASDAQ BBO is market specific, as opposed to the market-wide NBBO, and is available for less than one-tenth of the sample period. The advantage of the NASDAQ BBO is that it does not suffer from potential time-stamp discrepancies between the trading data and quoted prices.

The estimation of the state space model for the NBBO is calculated in calendar time (1-second) and the NASDAQ BBO is calculated in event time. For the NBBO sample we require at least 10 seconds with price changes and trading. For the NASDAQ BBO we require at least 10 trading events, for each trading variable, that result in price changes. For example, for the aggregate ($HFT^{All}$) NASDAQ BBO model, we require at least 10 $HFT^{All}$ trades associated with at least 10 prices changes. This results in 503 days for which we have adequate data, for at least one stock, for the NBBO and all 45 days for the NASDAQ BBO. We estimate the SSM by stock and by day. The Kalman filter, and the subsequent numerical optimization, converges fairly reliably. For large stocks the model converges over 99% of the time (19,932 of the 20,120 potential

[12] See the internet appendix for additional implementation details.

stock-days). For medium and small stocks the convergence rate is 98.7% and 97.4%, respectively. In most cases the SSM fails to converge on days when trading volume is extremely low.

The starting values for Kappa and Psi are diffuse, meaning the covariance matrix is set arbitrarily large. We allow $\sigma(v)$ to range from 0 to a maximum of 90% of the unconditional variance for that stock on that day. We use these stock days for the analysis in the remainder of the paper. Statistical inference is conducted on the average stock-day estimates by calculating standard errors controlling for contemporaneous correlation across stocks and time series correlation within stocks using the clustering techniques in Petersen (2009) and Thompson (2011).

Table 2 reports the results of the $HFT^{All}$ state space model estimation for each size category for the calendar time (NBBO) and event time (NASDAQ BBO) samples. Overall we see that $HFT^{All}$ is positively related to efficient price changes and negatively related to pricing errors. It seems that HFTs are able to predict both permanent price changes and transitory price changes, suggesting a positive role in incorporating information into prices for HFTs.

The $\kappa$ and $\psi$ coefficients are in basis points per $10,000 traded. The 0.21 large stock $\kappa$ coefficient implies that $10,000 of positive surprise HFT order flow (buy volume minus sell volume) is associated with a 0.21 basis point increase in the efficient price. The negative $\psi$ coefficients show that HFTs are generally trading in the opposite direction of the pricing error. The pricing errors are persistent with an AR(1) coefficient between 0.46 and 0.50.

**Table 2**

Table 3 reports the results of the disaggregated model of HFTs' and nHFTs' liquidity demanding trades. We include both the $HFT^D$ and $nHFT^D$ trading variables to better understand their different impacts and to provide insight into the trading strategies employed. Consistent with the correlation results for the liquidity demanding trading variables and subsequent returns, Panel A shows that $HFT^D$ and $nHFT^D$ are both positively correlated with the permanent price movements. A positive $\kappa$ is associated with informed trading. The more positive $\kappa$ on $HFT^D$ suggests that on a per dollar basis HFT is more informed when they trade. When both HFT and nHFT variables are included we use an asterisk to denote where the coefficients are statistically significantly different from each other at the 1% level. In Table 3 this is true for large and medium stocks in the NBBO sample and for all market capitalization groups in the NASDAQ BBO sample.

**Table 3**

Panel B of Table 3 reports results for the transitory price component and finds that $HFT^D$ and $nHFT^D$ are both negatively correlated with transitory price movements. This negative correlation arises from liquidity demanders trading to reduce transitory pricing errors. The transitory component captures noise in the observed midquote price process as well as longer lived private information which is not yet incorporated into the price.

The natural way to separate which effect dominates is to examine how trading is related to past price changes. Lagged adjustment to informed trading is associated with momentum trading while trading against overshooting in prices is associated with contrarian trading. Therefore, HFTs' liquidity demanding trades are characterized as informed about future prices due to predicting both the elimination of transitory pricing errors and the incorporation of new information. This type of trading is typically associated with both getting more information into prices and reducing the noise in the price process. nHFTs' liquidity demanding trades are characterized as informed about future prices due to the incorporation of information both immediately and with a lag.

Table 4 reports the results of the SSM estimation on HFTs' and nHFTs' liquidity supplying trades. Panel A shows that HFTs' and nHFTs' liquidity supplying trades are adversely selected as they are negatively correlated with changes in the permanent price component. This finding follows from $\kappa^{HFT}$ and $\kappa^{nHFT}$ being negative in each size category. The negative coefficients show that HFT and nHFT passive trading occurs in the direction opposite to permanent price movements. This relation exists in models of uninformed liquidity supply where suppliers earn the spread but lose to informed traders.

**Table 4**

Panel B of Table 4 show that both HFT and nHFT liquidity supplying trades are positively associated with transitory price movements. This follows from the positive coefficient on $\psi^{HFT}$ and $\psi^{nHFT}$. $HFT^S$ is more positively associated with transitory price movements than is $nHFT^S$. The opposite ordering holds for $HFT^D$ and $nHFT^D$. The overall state space model shows that $HFT^{All}$ is negatively related to transitory price movements.

Tables 2-4 characterize the role of HFTs and nHFTs in the permanent and transitory components of the price process. It is important to interpret these relations in the context of economic models and in the context of the HFT strategies outlined in SEC (2010). Kyle (1985) style models of informed trading have informed traders trading to move prices in the direction of the fundamental value. In the state space model this results in a positive $\kappa$ and a negative $\psi$. These match the estimates for liquidity demand by both HFTs and nHFTs. In this way HFTs' liquidity demanding strategies are consistent with the SEC's (2010) arbitrage and directional strategies, which are types of informed trading.

Hirschey (2013) provides evidence consistent with part of HFTs' ability to predict future returns stemming from HFTs' ability to anticipate future nHFT liquidity demand. The $\widehat{HFT}^D$ variable used in the state space model's efficient price estimate is the unexpected HFT liquidity demand based on past HFTs' and nHFTs' liquidity demand. This implies that HFTs' liquidity demand contains information about the efficient price above and beyond anticipating future nHFTs' liquidity demand.

While not based on an economic model, the SEC's (2010) momentum ignition strategies would presumably stem from liquidity demanding trading causing transitory price effects. The liquidity traders in informed trading models are also positively correlated with transitory price effects. We find no evidence that on average HFTs' liquidity demand or HFTs' overall trading are associated with such pricing errors. This does not establish that HFTs never follow any sort of manipulative strategies, but the model's estimates are inconsistent with this being their predominant role in price discovery.

In informed trading models liquidity is typically supplied by risk neutral market makers. These are adversely selected by the informed trades and consequently should have a negative $\kappa$ and a positive $\psi$. These match the estimates for liquidity supply by both HFT and nHFT. This is consistent with HFTs' liquidity supplying trades containing market making strategies discussed in SEC (2010).

The SEC concept release provides little discussion of risk management that is essential to short-horizon trading strategies. Risk management typically involves paying transaction costs to reduce unwanted positions. The costs are directly observable for liquidity demanding trades in terms of the bid-ask spread and any transitory price impact. For liquidity supplying limit orders risk management involves adjusting quotes upwards or downwards to increase the arrival rate of buyers or sellers, e.g., lowering the price on a limit order to sell when a firm has a long position (see Amihud and Mendelson (1980), Ho and Stoll (1981), and others).[13] HFTs applying price pressure either by demanding or supplying liquidity to reduce risk would result in HFTs' order flow being positively associated with transitory pricing errors. Therefore, the positive $\psi$ for HFTs' liquidity supply is consistent with risk management.

[13] See Madhavan and Sofianos (1998) for an analysis of trading and risk management strategies by designated market makers on the New York Stock Exchange (specialists).

Hirshleifer, Subrahmanyam, and Titman (1994) provide a two-trading period model where some risk-averse traders receive information before others. In the first period the early informed trades buy or sell based on their information. In the second period, the early informed traders consciously allow themselves to be adversely selected by the later informed traders because the benefits of risk reduction exceed the adverse selection costs. Hirshleifer, Subrahmanyam, and Titman refer to this as profit taking. The model integrates an interesting informational structural together with risk management. Our findings are consistent with a component of HFTs' liquidity demand and liquidity supply being part of an integrated strategy by which the HFTs demand liquidity when initially informed and subsequently supply liquidity when profit taking. The profit taking behavior is similar to risk management in the above models of market making where the market maker is risk averse.

Foucault, Hombert, and Rosu (2013) also model some agents, which they refer to as news traders, receiving information before the news is revealed to the market as a whole. In their model the news traders are risk neutral so there is no risk management or profit taking. Foucault, Hombert, and Rosu derive news trading's role in the permanent and temporary price components. As is standard in informed trading models, news traders' order flow is positively correlated with innovations in the efficient price and negatively correlated with the transitory pricing error. However, the negative relation of news trading with pricing errors is solely due to lagged price adjustment to information.

Models of informed trading, including Hirshleifer, Subrahmanyam, and Titman (1994) and Foucault, Hombert, and Rosu (2013), typically show zero correlation between past trading and returns. With risk neutral competitive market makers, prices follow a martingale and all information revealed in trading is immediately impounded into prices. The correlations between past returns and order flow in Figures 1-3 are inconsistent with this prediction.

In dynamic risk-averse market-making models (e.g., Nagel (2012)) the midquote price process contains a transitory component where prices overshoot due to the market maker's risk management. For example, when the market maker has a long position prices are too low to induce other investors to be more likely to buy than sell. This leads to prices mean reverting as the market maker's inventory position mean reverts. The pricing error is often referred to as price pressure. Amihud and Mendelson (1980) obtain a similar result due to position limits instead of risk aversion. Price pressures also arise conditional on liquidity traders' actions in models with risk neutral market makers (see Colliard (2013) for an example with discussion of HFTs). Our findings for HFTs overall and HFTs' liquidity demand show a contrarian strategy which is negatively correlated with pricing errors. A natural interpretation is that there are times when prices deviate from their fundamental value due to price pressure and some HFTs demand liquidity to help push prices back to their efficient levels. This reduces the distance between quoted prices and the efficient/permanent price of a stock.

Overall and liquidity demanding HFTs are associated with more information being incorporated into prices and smaller pricing errors. It is unclear whether or not the liquidity demanding HFTs know which role any individual trade plays. HFTs' strategies typically focus on identifying predictability, something we focus on in later sections. Whether that predictability arises from the permanent or transitory component of prices is less important to HFTs.

### 3.3 HFT REVENUES

The state space model characterizes the role of HFTs in the price process. $HFT^D$ gain by trading in the direction of permanent price changes and against transitory pricing errors. $HFT^S$ lose due to adverse selection and trading in the direction of pricing errors. Because the state space model is estimated using midquote prices, these possible gains and losses are before taking into account trading fees and the bid-ask spread. Liquidity suppliers earn the spread that liquidity demanders pay. In addition, NASDAQ pays liquidity rebates to liquidity suppliers and charges fees to liquidity demanding trades.

Using the stock-day panel from the state space model we analyze revenues of overall, liquidity demanding and liquidity supplying HFTs. Given that HFTs engage in short-term speculation, it must be profitable or it should not exist. We observe neither all of HFTs' trading nor all their costs, e.g., investments in technology, data and collocation fees, salaries, clearing fees, etc. Hence, we focus on HFT trading revenues incorporating NASDAQ trading maker/taker fees and rebates.

We assume that HFTs are in the highest volume categories for liquidity demand and supply. NASDAQ fees and rebates are taken from the NASDAQ Equity Trader Archive on NasdaqTrader.com. In 2008 and 2009 we identify six fee and rebate changes affecting the top volume bracket.[14] Fees for liquidity demanding trades range from \$0.0025 to \$0.00295 per share and rebates for passive trades from \$0.0025 to \$0.0028 per share. For comparability, we use the same fee schedule for nHFTs. Given that most nHFTs have lower trading volume, they pay higher fees and earn lower rebates, making our estimates for nHFTs' revenues an upper bound.

[14] It is difficult to ensure that every fee and rebate change was identified in the archive. However, discrepancies are likely small and on the order of 0.5 to 1 cent per 100 shares traded.

We estimate HFT revenues following Sofianos (1995) and Menkveld (2011). Both analyze primarily liquidity supply trading. We decompose total trading revenue into two components, revenue attributable to $HFT^D$ and $nHFT^D$ trading activity and revenue associated with $HFT^S$ and $nHFT^S$ trading activity. We assume that for each stock and each day in our sample, HFTs and nHFTs start and end the day without inventories. $HFT^D$ trading revenue for an individual stock for one day is calculated as (each of the *N* transactions within each stock day is subscripted by *n*):

$$\overline{\pi}^{*HFT,D} = \sum\nolimits_{n}^{N} -(HFT_n^D) + INV\_HFT_N^D * P_T,$$

where $INV\_HFT_N^D$ is the daily closing inventory in shares and $P_T$ is the closing quote midpoint. The first term captures cash-flows throughout the day and the second term values the terminal inventory at the closing midquote.[15] $nHFT^D$ revenues are calculated in the same manner. $\overline{\pi}^{*S,HFT}$ is calculated analogously.

$$\overline{\pi}^{*HFT,S} = \sum\nolimits_{n}^{N} -(HFT_n^S) + INV\_HFT_N^S * P_T,$$

nHFT liquidity supplying revenues are calculated in the same manner, with nHFT variables replacing the HFT variables. Total HFTs' revenue, $\overline{\pi}^{*HFT,All}$, is:

$$\overline{\pi}^{*HFT,All} = \overline{\pi}^{*HFT,D} + \overline{\pi}^{*HFT,S}.$$

Trading revenues without fees are zero sum in the aggregate so in that case $\overline{\pi}^{*nHFT,All} = -\overline{\pi}^{*HFT,All}$.

Table 5 presents the stock-day average revenue results overall and for liquidity demanding and supplying trading with and without NASDAQ fees. Panel A provides the average revenue per stock day across size categories for overall HFTs and nHFTs.

**Table 5**

$HFT^{All}$ is profitable overall and more profitable after NASDAQ fees and rebates are taken into account. $nHFT^{All}$ is unprofitable overall. HFTs are net receivers of NASDAQ fees in large stocks and net payers in small stocks. The reverse is true for nHFTs. In most size categories HFT and nHFT total trading revenues differ substantially. HFTs earn over 200 times more in

[15] Because we do not observe HFTs' trading across all markets and HFTs likely use both liquidity demanding and liquidity supplying orders in the same strategy, the end-of-day inventory could be an important factor in revenues. For large stocks the end-of-day inventories are roughly five to seven percent of trading volume. For smaller stocks the end-of-day inventories are closer to 30 percent of volume. For robustness we calculate but do not report, profitability using a number of alternative prices for valuing closing inventory: the volume-weighted average price, time-weighted average price, and average of open and close prices. All of these prices yielded similar results. If HFTs' revenues are different on NASDAQ versus other trading venues then our calculations are only valid for their NASDAQ trading.

large stocks than in small stocks. For one HFT firm Menkveld (2011) also finds significantly higher revenues in larger stocks.

Panel B shows that both $HFT^D$ and $nHFT^D$ have positive revenues in each size category before NASDAQ fees and rebates. After NASDAQ fees and rebates only HFTs continue to have positive trading revenues. HFTs' liquidity demanding trading's informational advantage is sufficient to overcome the bid-ask spread and fees. Because the revenue estimates are fairly noisy, the differences between HFTs' and nHFTs' revenues are generally statistically insignificant. Panel C reports trading revenues for HFTs' and nHFTs' liquidity supplying trades. Before NASDAQ rebates both are negative consistent with liquidity suppliers being adversely selected. After the inclusion of NASDAQ rebates HFTs' liquidity supply revenues becomes statistically significantly positive in large stocks and nHFTs' revenues remains negative.

Another concern highlighted by the SEC (2010) is that HFTs supply liquidity to earn fee rebates. Our revenue results are consistent with this. However, if liquidity supply is competitive then liquidity rebates should be incorporated in the endogenously determined spread (Colliard and Foucault (2012)). Our revenue results also show that HFTs' liquidity supplying revenues are negative without fee rebates, consistent with some of the rebates are being passed on to liquidity demanders in the form of tighter spreads. If some of HFTs' liquidity supply is Hirshleifer, Subrahmanyam, and Titman style profit taking as part of an integrated liquidity supplying and demanding strategy, overall, the informational disadvantage is overcome by revenues from the bid-ask spread and fees.

Multiplying the HFTs' revenues net of fees from Panel A of Table 5 times the 40 stocks in each size category yields roughly $275,000 per trading day. Dividing this by the corresponding HFTs' average trading volume in Table 1 suggests that HFTs' have revenues of approximately $0.43 per $10,000 traded. Given HFTs' revenues in small stocks are minimal and approximately four percent of stocks in the Russell 3000 are in our sample, we can multiply $275,000 by 25 to obtain an estimate of HFTS' daily NASDAQ revenues of $6.875 million. If HFTs' revenues per dollar traded are similar for off NASDAQ trading then adjusting for NASDAQ's market share implies HFTs' daily revenues are approximate $20 million. Multiplying this by 250 trading days yields $5 billion per year. Dividing across the 26 HFT firms in our sample would imply revenues of almost $200 million per firm if the firms are of equal size.

HFTs' revenues are typically only estimated. Getco's recent merger announcement with Knight Trading provides one of the few audited HFT's financial data. In our 2008 and 2009 sample, Getco, a large market-making HFT, had revenues across all U.S. asset classes of close to one billion dollar per year and Getco's equity trading represented about 20 percent of its trading volume.[16] This suggests that our estimate of HFTs' equity revenues appear to be of the right order of magnitude. Revenues for HFTs not in our sample, e.g., large integrated firms, could differ if these HFTs follow different strategies and/or if these HFTs have access to information from other parts of the firm, e.g., the order flow of other strategies.

Determining the profitability of HFTs is difficult. Without knowledge of the capital employed and technology costs using the revenue figures provide a rough estimate of industry profitability. One approximation of the capital employed by HFT is to use their maximum inventory position on a given day. Assuming that HFTs' are able to offset long positions in one stock with short positions in other stocks, in our data the maximal capital usage is roughly $318 million.[17] Using the $275,000 per trading day HFTs' revenue from above together with the maximum inventory suggests that for every $100 dollars of capital they earn roughly 8.6 cents. Adding this across days translates into an annualized return of almost 22%. However, the Getco S-4 filing shows that for 2008 and 2009 its costs were roughly 2/3 of revenues.

The revenue analysis suggests that HFTs have positive revenues, but these are small compared to their trading volume and estimate of capital employed. This suggests reasonable competition between HFTs for attractive trading opportunities. Getco's decline in revenues after our sample period could indicate HFTs becoming increasingly competitive, although the revenue decline could also be due to declining market volatility or be Getco specific.

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16 The financial information for Knight Trading and Getco can be found here: Form S-4.

17 Depending on a HFT's clearing broker the netting of positions across assets may not be possible. This maximal inventory estimate does not account for possible netting of trading in the same security across markets. Therefore, the $318 million estimate of HFTs' capital employed may be significantly too high or too low.

# 4 STATE SPACE MODEL ON HIGH PERMANENT VOLATILITY DAYS

The SEC (2010, p.48) and others express concern about market performance during times of stress. To better understand HFTs' and nHFTs' relative roles in price discovery during such times we analyze the subsample of the highest-permanent volatility days. The underlying assumption is that high permanent volatility is associated with market stress. To identify high-permanent volatility days we place stocks based on the level of $\sigma^2$ ($w_{i,t}$) into percentiles and examine the stock days above the $90^{th}$ percentile. We then compare those days to the remaining 90% of days.

Table 6 reports descriptive statistics as for high-permanent volatility days. Statistical inference is conducted on the difference between high-permanent volatility days and other days. The volatility of returns is considerably higher which is expected as total volatility is simply the sum of permanent and transitory volatility. Both dollar and relative spreads are higher on high permanent volatility days, consistent with inventory and adverse selection costs being higher for liquidity suppliers on high-permanent volatility days.

**Table 6**

Trading volume is higher both in total and for HFTs and nHFTs on high information days. Overall total trading volume increases by $47.41 million and by $54.89 for HFTs and $39.94 for nHFTs. As a percentage of total trading volume $HFT^D$ and $HFT^S$ slightly increase their participation. The fact that $HFT^S$ increases their participation on high-permanent volatility days shows that at a daily frequency HFTs do not reduce their liquidity supply in times of market stress.

Table 7 reports the state space model estimates on high-permanent volatility days for the aggregate model. As in Table 2, Panel A reports results for the permanent price component and Panel B for the transitory price component. In columns 3 – 5 of Table 7 we report the mean coefficients on high permanent volatility days and in columns 6 – 8 we report the means on other days. Statistical inference is conducted on the difference between high-permanent volatility days and other days. The t-statistics are calculated by regressing each set of the stock-day coefficient estimates on a constant and a dummy variable that is one on high permanent volatility days and zero otherwise. The T-statistics are calculated using standard errors double clustered on stock and day.

**Table 7**

Comparing Tables 2 and 7 shows that the coefficients in the state space model on high-permanent volatility days all have the same signs and are generally of larger magnitudes than on other days. The differences between high-permanent volatility days and other days are statically significant for most coefficients.

Table 8 presents the results of the disaggregate liquidity demand model's estimates structured as in Table 3. Similar to the aggregate model results we find that the coefficients have the same signs and are larger in magnitude on high-permanent volatility days. The coefficients on $HFT^D$ and $nHFT^D$ for the permanent component of prices are both higher on permanent volatility days than on other days, with the exception of small stocks for HFTs. Table 8 also shows that HFTs contribute more to price discovery overall and that the difference is statistically significantly higher on high permanent volatility days. The results also show that HFT is more negatively related to pricing errors overall and more so on high permanent volatility days. These show that HFT's role in price discovery is qualitatively similar on high-permanent volatility days which are generally associated with heightened market stress.[18]

**Table 8**

Table 9 reports results for $HFT^S$ and $nHFT^S$ in the same format as Table 8. We find that the coefficients on $\kappa$ and $\psi$ show similar patterns as those for liquidity demand. That is the coefficients are of the same sign on high permanent volatility and other days and the differences between the HFT and nHFT coefficients become more pronounced on high permanent volatility days. The differences between HFTs' and nHFTs' coefficients are generally statistically significant.

**Table 9**

[18] Revenue analysis as in Table 5 for high permanent volatility days is available in the internet appendix.

# 5 SOURCES OF PUBLIC INFORMATION

The preceding sections suggest that HFTs are informed about subsequent short-term price movements and more so on high information (permanent volatility) days than on other days. However, these analyses provide little insight into what sources of information drive HFTs' trading. In this section we look closer at publicly available information that HFTs may use to predict subsequent price movements.

Information comes from many sources and in many forms. It can be market-wide or firm specific, long-term or short-term, soft or hard or distinguished among numerous other dimensions.[19] We focus on three types of information identified in prior literature: macroeconomic news announcements, market-wide returns, and imbalances in the limit order book.[20]

## 5.1 MACRO NEWS ANNOUNCEMENTS

Macroeconomic news receives significant attention as a source of market-wide information, e.g, Andersen, Bollerslev, Diebold, and Vega (2003). To examine this we analyze eight key macro announcements that occur during trading hours from Bloomberg: Construction Spending, Consumer Confidence, Existing Home Sales, Factory Orders, ISM Manufacturing Index, ISM Services, Leading Indicators, and Wholesale Inventories.

While the expected date and time of a report are announced in advance, the announcements occasionally occur slightly before or after the designated time. For instance, many announcements are reported to be made at 10:00:00 A.M. EST However, the actual announcement may be made at 10:00:10 A.M. EST. Therefore, instead of using the anticipated report time, we use the time stamp of the first news announcement from Bloomberg. While this usually matches the anticipated report time, there are several occasions where it differs.

Figures 4 and 5 plot the HFT order flow summed across stocks and the return on a value-weighted portfolio of the stocks in our sample around positive and negative macroeconomic news, respectively. A macro announcement is considered a positive announcement if the announced value is greater than the average analyst's forecast as reported by Bloomberg, and a negative announcement if it is below the forecasted average.

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[19] See Jovanovic and Menkveld (2011) for a discussion of the differences in types of information employed by HFT and non-HFT investors.

[20] We also obtained the Thompson Reuters News Analytics database to examine HFT and idiosyncratic news. However, the accuracy of the time stamps does not correspond to when news reaches the market and is incorporated into prices (Groß-Klußmann and Hautsch (2010)).

### Figures 4 and 5

Both figures show that at time t = 0 prices begin to move in the direction of the macro economic announcement. As expected, when the announcement is negative prices fall and when the announcement is positive prices rise. The figures also show that $HFT^{D}$ buy on positive and sell on negative macroeconomic news; the reverse is true for $HFT^{S}$. Overall, $HFT^{S}$ trading in the opposite direction of macroeconomic news is larger, which results in overall HFTs' ($HFT^{All}$) trading in the opposite direction of macroeconomic news. We cannot determine whether HFTs trade on the news directly or trade on the price movements in other related securities, e.g., the index futures.

The figures show that macroeconomic announcements contain information and that HFTs' trading relates to this information. HFTs' liquidity demanding trades impose adverse selection. As with trading around public news announcements, the social value of such trading depends on how much of the trading is simply being able to react faster to news that all investors interpret in the same way versus trading related to better interpretation of the public news. HFTs' liquidity supplying trades are adversely selected. The fact that the HFTs' liquidity supply is greater than their liquidity demand shows HFTs are actively supplying liquidity under the stressful market conditions surrounding macroeconomic announcements.

Figures 4 and 5 show that information is not fully incorporated into prices immediately as returns continue to drift for a number of seconds after the announcement. HFT demand follows a similar drift, but, given the graphs are aggregates across all the stocks and announcements in the sample, this does not directly establish that HFTs' trading improves price discovery. For example, it could be the case that higher HFT is associated with prices overshooting in the cross-section of stocks.

For HFTs to push prices beyond their efficient level following announcements HFT's liquidity demand would need to have a transitory price impact. If this is the case, past HFTs' order flow should negatively predict subsequent returns. To test this possibility we estimate the following regression for HFT liquidity demanding and supplying order flow as well as overall HFT order flow:

$$Ret_{i,t+2,t+10} = \alpha + \beta \, HFT^{D,S,All}_{i,t-1,t+1} + \varepsilon_{i,t},$$

where $HFT^{D,S,All}_{i,t-1,t+1}$ is the cumulative HFT order flow imbalance from 1 second before to 1 second after a macro economic announcement becomes publicly available; $Ret_{i,t+2,t+10}$ is the cumulative return in basis points from two seconds after the macro economic announcement through 10 seconds afterwards. The regression pools all 209 announcements for all stocks. Statistical significance is calculated controlling for contemporaneous correlation across stocks by clustering on announcement days.

The coefficients in Table 10 capture whether HFTs are associated with the incorporation of information into prices or transitory price movements. Positive coefficients imply HFTs improve the price discovery process while negative coefficients suggest HFTs exacerbate inefficient price movements. Panel A reports the $HFT^D$ results, Panel B the $HFT^S$ results, and Panel C the results for $HFT^{All}$.

**Table 10**

Consistent with the state space model HFTs' demand liquidity in the same direction as subsequent price movements, suggesting that they are trading on information in the announcement and that HFTs' profit from lagged price adjustment. This is consistent with the view that at least some component of HFTs' liquidity demand relates to soon to be public information as for the news traders in the Foucault, Hombert, and Rosu (2013) model.

HFTs supply liquidity in the opposite direction to subsequent price changes suggesting they are adversely selected on lagged price adjustment. The negative coefficient on HFT liquidity supply is consistent with a positive association with pricing errors, as in the state space model. The coefficient on $HFT^{All}$ is positive, although the statistical significance is weak.

## 5.2 MARKET WIDE RETURNS

The prior section shows that macroeconomic news announcements impact HFTs' trading. Jovanovic and Menkveld (2011) find that one HFT trades more when there is higher market-wide volatility. To examine this market-wide interaction between the trading of our larger set of HFTs and returns, Figure 6 extends the stock-specific cross autocorrelations between HFTs' order flows and returns in Figures 1-3 to market-wide order flows and returns. The market-wide HFT variables are the sum of the corresponding HFT order flows across all stocks. The market-wide return variables are calculated with value-weighted returns.

**Figures 6**

As in the individual stock correlations in Figures 2 and 3 there is a large positive contemporaneous correlation between $HFT^D$ and returns and a negative correlation between $HFT^S$ and returns. Also like the individual stock results, the liquidity demand effect is greater than the liquidity supply effect so $HFT^{All}$ is positively correlated with contemporaneous returns.

An interesting difference in the market-wide results is that the correlations with subsequent returns die out less quickly than for the individual stocks. This suggests that HFT plays a somewhat more important and longer lasting role in market-wide price discovery, although still over short time horizons. This is also consistent with the Jovanovic and Menkveld (2011) finding that one HFT is more active when there is more market-wide volatility.

Figure 6 also graphs the correlations of market-wide HFTs' order flow and lagged returns. Here the market-wide correlations have the opposite signs as the individual stock correlations in Figures 1-3: HFTs' liquidity demand follows a momentum strategy and HFTs' liquidity supply follows a contrarian strategy with the demand effect dominant for overall HFTs' order flow. This is consistent with index returns leading the underlying stock returns and HFTs' liquidity demand capitalizing on this predictability.

## 5.3 LIMIT ORDER BOOK

Macroeconomic news announcements and market returns are examples of publicly available information that HFTs may use to predict short-term price movements. Another source of information is the state of the limit order book. Cao, Hansch, and Wang (2009) find that imbalances between the amount of liquidity available for buying and selling predict short-run price movements. To test the hypothesis that HFTs use order book information to predict short-term subsequent price movements we calculate limit order book imbalances (LOBI) using the NBBO TAQ best bid and best offer size:

$$LOBI_{i,t} = (Size^{Offer}_{i,t} - Size^{Bid}_{i,t})/(Size^{Offer}_{i,t} + Size^{Bid}_{i,t}),$$

where *Size* is the dollar volume of orders available at the NBBO. *LOBI* is scaled by 10,000. To test if HFTs are trading in the direction of limit order book imbalances we estimate the following regressions:

$$HFT^{D,S,All}_{i,t} = \alpha + \beta_1\, LOBI_{i,t-1} + \beta_2\, Ret_{i,t} + \varepsilon_{i,t},$$

where $HFT^{D,S,All}_{i,t}$ is the HFTs' order flow in period $t$ for HFT's liquidity demand, liquidity supply, and overall order flow, respectively, for stock $i$. We include the contemporaneous return for stock $i$, $Ret_{i,t}$, to control for the correlation between HFT and returns. Panel A of Table 11 reports the mean stock-day coefficient estimates for large, medium, and small stocks. The results show that HFTs' order flow is correlated with information imbedded in the limit order book. Negative coefficients represent HFTs' trading in the direction of the imbalance, e.g., buying when there are fewer shares offered to buy than shares offered to sell. Positive coefficients indicate HFTs supplying liquidity on the thin side of the book or HFTs demanding liquidity on the thicker side of the book. As with the state space model, the regressions are estimated for each stock-day and statistical significance is based on the averages of these stock-day estimates clustering on day and stock.

**Table 11**

The negative coefficients in the $HFT^{D}$ and $HFT^{All}$ regressions in Panel A suggest that HFTs use information in the limit order book to demand liquidity. The positive coefficient in the $\mathrm{HFT}^{\mathrm{S}}$ regression suggests that HFTs often supply liquidity on the thin side of the limit order book. This involves possibly incurring adverse selection costs by supplying liquidity in the direction where less liquidity is available. Such liquidity supply is generally interpreted as beneficial if it reduces transitory volatility.

Overall *LOBI* predicts liquidity demand more than liquidity supply, so HFTs trade on the thinner side of the book. HFTs' liquidity demand appears to use the easily interpretable public information in limit order books to trade. It is possible that limit order submitters are aware of this, but prefer placing aggressive limit orders rather than paying the spread. In this case, the adverse selection is limit order submitters' conscious payment to liquidity demanders to avoid paying the spread.

The state space model and the correlation coefficients in Figures 1 – 4 show that HFTs' order flow predicts future price movements. Next we confirm that LOBI predicts future returns and test whether HFTs' trading exhibits return predictability beyond the predictability in LOBI. We estimate the following regression with the dependent variable being the next period stock return:

$$Ret_{i,t} = \alpha + \beta_1\, HFT_{i,t-1}^{D,S,All} + \beta_2\, HFT_{i,t-2}^{D,S,All} + \beta_3 LOBI_{i,t-1} + \beta_4\, Ret_{i,t-1} + \varepsilon_{i,t}.$$

We include two lags of HFTs' order flows along with the LOBI variable and lagged returns. The analysis is performed for each type of order flow: $HFT^{D}$, $HFT^{S}$, and $HFT^{All}$. Panel B of Table 11 reports the mean coefficient estimates for large, medium, and small stocks. As in Cao, Hansch, and Wang (2009), LOBI predicts subsequent returns. HFTs' trading has information for subsequent returns beyond LOBI. However, it is short lived. Only the first lag coefficient is statistically significant for $HFT^{D}$ and $HFT^{S}$ and only for large and medium size stocks. As with the correlations and state-space model, $\mathrm{HFT}^{\mathrm{D}}$ positively predicts future returns and $HFT^{S}$ negatively predicts future returns. The $HFT^{All}$ analysis shows that the $HFT^{D}$ results dominate.

# 6 DISCUSSION

Overall HFTs have a beneficial role in the price discovery process in terms of information being impounded into prices and smaller pricing errors. Traditionally this has been viewed positively as more informative stock prices can lead to better resource allocation in the economy. However, the information HFTs use is short-lived at less than 3-4 seconds. If this information would become public without HFTs, then the potential welfare gains may be small or negative if HFTs impose significant adverse selection on longer-term investors.[21] Our evidence on HFTs' liquidity demand immediately following macroeconomic announcements may fall into this category. However, HFTs' liquidity supply at this time is greater than HFT liquidity demand so overall HFTs are not imposing net adverse selection on others around macroeconomic news.

The fact that HFTs predict price movements for mere seconds does not demonstrate that the information would inevitably become public. It could be the case that HFTs compete with each other to get information not obviously public into prices. If HFTs were absent, it is unclear how such information would get into prices unless some other market participant played a similar role. This is a general issue in how to define what information is public and how it gets into prices, e.g., the incentives to invest in information acquisition in Grossman and Stiglitz (1980). As Hasbrouck (1991, p. 190) writes "the distinction between public and private information is more clearly visible in formal models than in practice."

Reducing pricing errors improves the efficiency of prices. Just as with the short-term nature of HFTs' informational advantage, it is unclear whether or not intraday reductions in pricing errors facilitate better financing decisions and resource allocations by firms and investors. One important positive role of smaller pricing errors would be if these corresponded to lower implicit transaction costs by long-term investors. Examining non-public data from long-term investors' trading intentions would help answer this.

The negative association of overall HFT order flow with pricing errors shows that HFTs are generally not associated with price manipulation behavior. However, liquidity supplying HFTs are positively associated with pricing errors. This could be due to risk management, order anticipation, or manipulation. The SEC (2010, p. 53) suggests one manipulation strategy based on liquidity supply: "A proprietary firm could enter a small limit order in one part of the market to set up a new NBBO, after which the same proprietary firm triggers guaranteed match trades

21 Jovanovic and Menkveld (2011) show how HFT trading on soon-to-be public information can either enhance welfare by increasing gains from trade or lower welfare by imposing adverse selection costs on other investors. They focus largely on HFT liquidity supply.

in the opposite direction."[22] If the limit order is executed before being cancelled, it could result in HFTs' liquidity supply being positively associated with pricing errors.

As is often the case, one can argue whether the underlying problem in possible manipulation would lie with the manipulator or the market participant who is manipulated. In the SEC example if there is no price matching the liquidity supply manipulation could not succeed. While we think risk management is a more plausible explanation for the positive relation between HFT's liquidity supply and pricing errors, further investigation is warranted. Cartea and Penalva (2011) present a scenario in which HFTs' intermediation leads to increased price volatility. The risk management and manipulation stories are testable with more detailed data identifying each market participant's orders, trading, and positions in all markets.

[22] This is the basic behavior that the Financial Industry Regulatory Authority (FINRA) fined Trillium Brokerage Services for in 2010 (http://www.finra.org/Newsroom/NewsReleases/2010/P121951). Trillium is not one of the 26 firms identified as HFT in this paper.

# 7 CONCLUSION

We examine the role of HFTs in price discovery. Overall HFTs increase the efficiency of prices by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. This is done through their marketable orders. In contrast, HFTs' liquidity supplying non-marketable orders are adversely selected. HFTs' marketable orders' informational advantage is sufficient to overcome the bid-ask spread and trading fees to generate positive trading revenues. For non-marketable limit orders the costs associated with adverse selection are less than the bid-ask spread and liquidity rebates. HFTs predict price changes occurring a few seconds in the future. The short-lived nature of HFTs' information raises questions about whether the informational efficiency gains outweigh the direct and indirect adverse selection costs imposed on non-HFTs.[23]

One important concern about HFTs is their role in market stability.[24] Our results provide no direct evidence that HFTs contribute directly to market instability in prices. To the contrary, HFTs overall trade in the direction of reducing transitory pricing errors both on average days and on the most volatile days during a period of relative market turbulence (2008-2009). The fact that HFTs impose adverse selection costs on liquidity suppliers, overall and at times of market stress, could lead non-HFT liquidity suppliers to withdraw from the market as discussed in Biais, Foucault, and Moinas (2011). This could indirectly result in HFTs reducing market stability despite the fact that HFT liquidity suppliers remain active during these stressful periods.

Our results are one step towards better understanding how HFTs trade and affect market structure and performance. We identify different types of public information related to HFTs: macroeconomic announcements and limit order book imbalances (see Hirschey (2013) for evidence on HFTs predicting the behavior of non-HFTs). Studies examining HFTs around individual firm news announcements, firm's earnings, and other events could provide further identification and understanding. Our analysis is for a single market for a subset of HFTs. Better data for both HFTs and long-term investors may enable more general conclusions. The cross-stock, cross-market, and cross-asset behavior of HFTs are also important areas of subsequent research.

[23] HFT adverse selection due to marginally faster reaction can lead other investors to make significant technology investments. Another related cost for exchanges, investors and brokers of HFT activity is the significant flow of market data generated.

[24] See, for example, the speech "Race to Zero" by Andrew Haldane, Executive Director, Financial Stability, of the Bank of England, at the International Economic Association Sixteenth World Congress, Beijing, China, on July 8, 2011.

HFTs are a type of intermediary. When thinking about the role HFTs play in markets it is natural to compare the new market structure to the prior market structure. Some primary differences are that there is free entry into becoming an HFT, HFTs do not have a designated role with special privileges, and HFTs do not have special obligations. When considering the optimal industrial organization of the intermediation sector, HFTs more resembles a highly competitive environment than traditional market structures. A central question is whether there were possible benefits from the old more highly regulated intermediation sector, e.g., requiring continuous liquidity supply and limiting liquidity demand that outweigh lower innovation and higher entry costs typically associated with regulation.

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# 9 TABLES AND FIGURES

**Table 1 Descriptive statistics**

| | | | Calendar Time (TAQ NBBO) | | | Event Time (NASDAQ BBO) | | |
|---|---|---|---|---|---|---|---|---|
| **Summary Statistics** | **Units** | **Source** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| **Market Capitalization** | $ Billion | Compustat | 52.47 | 1.82 | 0.41 | 52.47 | 1.82 | 0.41 |
| **Price** | $ | TAQ | 56.71 | 30.03 | 17.93 | 57.24 | 30.22 | 17.31 |
| **Daily Midquote Return Volatility** | bps. | TAQ | 3.58 | 9.93 | 24.09 | 2.26 | 9.35 | 24.41 |
| **Bid-Ask Spread** | $ | NASDAQ | 0.03 | 0.04 | 0.07 | 0.05 | 0.1 | 0.23 |
| **Relative Bid-Ask Spread** | bps. | TAQ | 4.72 | 14.61 | 38.06 | 9.96 | 34.4 | 85.75 |
| **NASDAQ Trading Volume** | $ Million | NASDAQ | 186.61 | 6.52 | 1.18 | 205.33 | 7.02 | 1.42 |
| $HFT^{All}$ **Trading Volume** | $ Million | NASDAQ | 157.76 | 3.61 | 0.43 | 172.40 | 4.23 | 0.52 |
| $HFT^{D}$ **Trading Volume** | $ Million | NASDAQ | 79.24 | 2.37 | 0.30 | 85.10 | 2.84 | 0.36 |
| $HFT^{S}$ **Trading Volume** | $ Million | NASDAQ | 78.52 | 1.24 | 0.13 | 87.30 | 1.39 | 0.16 |
| $nHFT^{All}$ **Trading Volume** | $ Million | NASDAQ | 215.46 | 9.44 | 1.92 | 238.25 | 9.80 | 2.32 |
| $nHFT^{D}$ **Trading Volume** | $ Million | NASDAQ | 107.37 | 4.15 | 0.88 | 120.15 | 4.90 | 1.06 |
| $nHFT^{S}$ **Trading Volume** | $ Million | NASDAQ | 108.09 | 5.29 | 1.04 | 118.10 | 4.90 | 1.26 |

This table reports descriptive statistics that are equal weighted averages across stock days for 118 stocks traded on NASDAQ for 2008 and 2009. Each stock is in one of three market capitalization categories: large, medium, and small. The closing midquote price is the average bid and ask price at closing. Trading volume is the average dollar trading volume and is also reported for HFTs and nHFTs.

## Table 2 State space model of $HFT^{All}$ and prices

| **Panel A: Permanent Price Component** | | **Calendar Time** | | | **Event Time** | | |
|---|---|---|---|---|---|---|---|
| | **Units** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| $\kappa^{All}$ | **bps. / $10000** | 0.21 | 5.16 | 1.02 | 0.21 | 6.89 | -16.62 |
| **(t-stat)** | | (28.83) | (30.61) | (0.31) | (4.37) | (7.16) | (-0.62) |
| $\sigma^2(\widehat{HFT^{All}})$ | **$10000** | 3.07 | 0.54 | 0.19 | 0.77 | 0.26 | 0.12 |
| $(\kappa^{All} * \sigma(\widehat{HFT^{All}}))^2$ | ***bps.***$^2$ | 0.54 | 13.81 | 75.42 | 0.16 | 11.35 | 83.43 |
| **(t-stat)** | | (7.76) | (8.52) | (18.77) | (1.59) | (2.13) | (3.86) |
| $\sigma^2(w_{i,t})$ | ***bps.***$^2$ | 14.97 | 115.63 | 665.23 | 5.44 | 81.49 | 609.57 |

| **Panel B: Transitory Price Component** | | **Calendar Time** | | | **Event Time** | | |
|---|---|---|---|---|---|---|---|
| | **Units** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| $\phi$ | | 0.49 | 0.50 | 0.46 | 0.43 | 0.39 | 0.38 |
| $\psi^{All}$ | **bps. / $10000** | -0.01 | -2.08 | -2.60 | -0.04 | -5.72 | 10.16 |
| **(t-stat)** | | (-3.83) | (-25.30) | (-1.45) | (-0.87) | (-6.13) | (-0.67) |
| $\sigma^2(HFT^{All})$ | **$10000** | 3.08 | 0.55 | 0.20 | 0.80 | 0.27 | 0.13 |
| $(\psi^{All} * \sigma(HFT^{All}))^2$ | ***bps.***$^2$ | 0.09 | 3.69 | 27.11 | 0.13 | 6.54 | 40.41 |
| **(t-stat)** | | (4.68) | (6.53) | (8.58) | (2.10) | (4.28) | (4.55) |
| $\sigma^2(s_{i,t})$ | ***bps.***$^2$ | 0.77 | 8.36 | 78.04 | 1.27 | 21.98 | 208.75 |

The model is estimated for each stock each day using HFT trading variables to decompose the observable price (log midquote) $p_{i,t}$ for stock $i$ at time $t$ into two components: the unobservable efficient price $m_{i,t}$ and the transitory component $s_{i,t}$:

$$p_{i,t} = m_{i,t} + s_{i,t}$$
$$m_{i,t} = m_{i,t-1} + w_{i,t}$$
$$w_{i,t} = \kappa_i^{All}\widehat{HFT}_{i,t}^{All} + \mu_{i,t}$$
$$s_{i,t} = \phi s_{i,t-1} + \psi_i^{All} HFT_{i,t}^{All} + \upsilon_{i,t}$$

$HFT_{i,t}^{All}$ is HFTs; overall order flow; $\widehat{HFT}_{i,t}^{All}$ is the surprise component of the order flow. Each stock is in one of three market capitalization categories: large, medium, and small. Columns 3-5 report coefficients for the entire sample at 1-second frequencies using the NBBO. Columns 6-8 report coefficients for a 50 day subsample in event time using the Nasdaq BBO. T-statistics are calculated using standard errors double clustered on stock and day.

## Table 3: State space model of liquidity demand, HFT$^D$ and nHFT$^D$, and prices

| **Panel A: Permanent Price Component** | | **Calendar Time** | | | **Event Time** | | |
|---|---|---|---|---|---|---|---|
| | **Units** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| $\kappa^D_{HFT}$ | **bps. / \$10000** | 0.55* | 9.26* | 43.51 | 0.22* | 11.91* | 69.59* |
| **(t-stat)** | | (35.21) | (39.03) | (3.11) | (7.07) | (11.24) | (10.77) |
| $\kappa^D_{nHFT}$ | **bps. / \$10000** | 0.34 | 6.21 | 41.20 | 0.11 | 6.69 | 40.78 |
| **(t-stat)** | | (31.26) | (39.83) | (18.36) | (6.02) | (13.86) | (13.66) |
| $\sigma^2(\widetilde{HFT}^D)$ | **\$10000** | 3.02 | 0.52 | 0.17 | 0.68 | 0.23 | 0.11 |
| $\sigma^2(n\widetilde{HFT}^D)$ | **\$10000** | 3.95 | 0.72 | 0.33 | 0.98 | 0.36 | 0.22 |
| $(\kappa^D_{HFT} * \sigma(\widetilde{HFT}^D))^2$ | ***bps.***$^2$ | 1.80 | 13.15 | 57.65 | 0.15 | 8.14 | 50.41 |
| **(t-stat)** | | (23.06) | (23.39) | (18.49) | (2.48) | (5.82) | (8.24) |
| $(\kappa^D_{nHFT} * \sigma(n\widetilde{HFT}^D))^2$ | ***bps.***$^2$ | 1.83 | 15.40 | 113.00 | 0.15 | 13.03 | 77.23 |
| **(t-stat)** | | (3.24) | (10.42) | (18.33) | (1.75) | (2.25) | (5.41) |
| $\sigma^2 (w_{i,t})$ | ***bps.***$^2$ | 16.61 | 122.28 | 701.03 | 5.61 | 92.14 | 563.64 |

| **Panel B: Transitory Price Component** | | **Calendar Time** | | | **Event Time** | | |
|---|---|---|---|---|---|---|---|
| | **Units** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| $\phi$ | | 0.59 | 0.54 | 0.45 | 0.36 | 0.37 | 0.36 |
| $\psi^D_{HFT}$ | **bps. / \$10000** | -0.05* | -3.40* | -76.17 | -0.62* | -15.30* | -77.53* |
| **(t-stat)** | | (-12.30) | (-33.25) | (-1.18) | (-9.59) | (-13.27) | (-12.70) |
| $\psi^D_{nHFT}$ | **bps. / \$10000** | -0.03 | -2.11 | -14.04 | -0.41 | -9.51 | -54.81 |
| **(t-stat)** | | (-9.84) | (-34.85) | (-28.19) | (-12.07) | (-17.47) | (-15.37) |
| $\sigma^2(HFT^D)$ | **\$10000** | 3.05 | 0.54 | 0.18 | 0.73 | 0.25 | 0.12 |
| $\sigma^2(nHFT^D)$ | **\$10000** | 4.03 | 0.75 | 0.36 | 1.02 | 0.39 | 0.24 |
| $(\kappa^D_{HFT} * \sigma(HFT^D))^2$ | ***bps.***$^2$ | 0.20 | 2.80 | 16.95 | 0.31 | 11.53 | 50.29 |
| **(t-stat)** | | (7.93) | (16.09) | (19.22) | (4.61) | (7.28) | (9.76) |
| $(\kappa^D_{nHFT} * \sigma(nHFT^D))^2$ | ***bps.***$^2$ | 0.22 | 4.42 | 31.55 | 0.26 | 15.58 | 108.47 |
| **(t-stat)** | | (4.81) | (4.15) | (15.79) | (4.12) | (3.73) | (10.98) |
| $\sigma^2 (s_{i,t})$ | ***bps.***$^2$ | 1.03 | 10.01 | 94.14 | 1.62 | 32.19 | 237.19 |

The model is estimated for each stock each day using HFT trading variables to decompose the observable price (log midquote) $p_{i,t}$ for stock $i$ at time $t$ (in 1 second increments) into two components: the unobservable efficient price $m_{i,t}$ and the transitory component $s_{i,t}$:

$$p_{i,t} = m_{i,t} + s_{i,t}$$

$$m_{i,t} = m_{i,t-1} + w_{i,t}$$

$$w_{i,t} = \kappa^D_{i,HFT}\widetilde{HFT}^D_{i,t} + \kappa^D_{i,nHFT}n\widetilde{HFT}^D_{i,t} + \mu_{i,t}$$

$$s_{i,t} = \phi s_{i,t-1} + \psi^{D}_{i,HFT} HFT^{D}_{i,t} + \psi^{D}_{i,nHFT} nHFT^{D}_{i,t} + \upsilon_{i,t}$$

$HFT^{D}_{i,t}$ and $nHFT^{D}_{i,t}$ are HFTs' and nHFTs' liquidity demanding order flow; $\widetilde{HFT}^{D}_{i,t}$ and $\widetilde{nHFT}^{D}_{i,t}$ are the surprise components of those order flows. Each stock is in one of three market capitalization categories: large, medium, and small. Columns 3-5 report coefficients for the entire sample at 1-second frequencies using the NBBO. Columns 6-8 report coefficients for a 50 day subsample in event time using the Nasdaq BBO. T-statistics are calculated using standard errors double clustered on stock and day. * denotes significance at the 1% level on the difference between $\kappa^{D}_{HFT}$ - $\kappa^{D}_{nHFT}$ and $\psi^{D}_{HFT}$ - $\psi^{D}_{nHFT}$.

## Table 4 State Space Model of liquidity supply, HFT$^S$ and nHFT$^S$, and prices

| Panel A: Permanent Price Component | | Calendar Time | | | Event Time | | |
|---|---|---|---|---|---|---|---|
| | Units | Large | Medium | Small | Large | Medium | Small |
| $\kappa^S_{HFT}$ | bps. / $10000 | -0.55* | -10.71* | -100.42* | -0.06* | -11.09* | -55.42* |
| (t-stat) | | (-31.03) | (-22.16) | (-6.97) | (-1.10) | (-6.84) | (-1.10) |
| $\kappa^S_{nHFT}$ | bps. / $10000 | -0.43 | -6.82 | -42.28 | -0.18 | -7.30 | -49.08 |
| (t-stat) | | (-32.61) | (-39.66) | (-29.93) | (-4.12) | (-7.64) | (-5.50) |
| $\sigma^2(\widetilde{HFT^S})$ | $10000 | 2.31 | 0.26 | 0.08 | 0.53 | 0.14 | 0.07 |
| $\sigma^2(\widetilde{nHFT^S})$ | $10000 | 4.04 | 0.86 | 0.37 | 1.07 | 0.41 | 0.23 |
| $(\kappa^S_{HFT} * \sigma(\widetilde{HFT^S}))^2$ | $bps.^2$ | 0.96 | 6.94 | 47.24 | 0.23 | 5.11 | 48.99 |
| (t-stat) | | (23.93) | (9.62) | (22.85) | (1.44) | (3.75) | (3.19) |
| $(\kappa^S_{nHFT} * \sigma(\widetilde{nHFT^S}))^2$ | $bps.^2$ | 3.73 | 21.61 | 111.80 | 0.15 | 14.51 | 101.06 |
| (t-stat) | | (2.78) | (13.30) | (22.45) | (3.29) | (3.13) | (5.12) |
| $\sigma^2(w_{i,t})$ | $bps.^2$ | 17.78 | 121.49 | 693.95 | 5.59 | 86.87 | 613.56 |

| Panel B: Transitory Price Component | | Calendar Time | | | Event Time | | |
|---|---|---|---|---|---|---|---|
| | Units | Large | Medium | Small | Large | Medium | Small |
| $\phi$ | | 0.56 | 0.54 | 0.45 | 0.38 | 0.39 | 0.36 |
| $\psi^S_{HFT}$ | bps. / $10000 | 0.08* | 3.94* | 29.18* | 0.92* | 18.27* | 140.51* |
| (t-stat) | | (14.86) | (33.80) | (13.41) | (5.98) | (7.58) | (3.89) |
| $\psi^S_{nHFT}$ | bps. / $10000 | 0.03 | 2.33 | 13.32 | 0.37 | 9.70 | 63.86 |
| (t-stat) | | (10.27) | (34.15) | (24.92) | (5.28) | (8.24) | (6.78) |
| $\sigma^2(HFT^S)$ | $10000 | 2.32 | 0.26 | 0.09 | 0.56 | 0.14 | 0.07 |
| $\sigma^2(nHFT^S)$ | $10000 | 4.14 | 0.89 | 0.40 | 1.13 | 0.44 | 0.25 |
| $(\kappa^S_{HFT} * \sigma(HFT^S))^2$ | $bps.^2$ | 0.14 | 2.01 | 19.71 | 0.34 | 5.69 | 45.21 |
| (t-stat) | | (10.42) | (6.01) | (12.45) | (3.09) | (4.36) | (4.17) |
| $(\kappa^S_{nHFT} * \sigma(nHFT^S))^2$ | $bps.^2$ | 0.31 | 4.76 | 32.49 | 0.30 | 19.03 | 134.12 |
| (t-stat) | | (9.08) | (8.76) | (15.45) | (3.10) | (4.63) | (6.13) |
| $\sigma^2(s_{i,t})$ | $bps.^2$ | 0.96 | 9.69 | 90.07 | 1.55 | 32.90 | 262.08 |

The model is estimated for each stock each day using HFT trading variables to decompose the observable price (log midquote) $p_{i,t}$ for stock $i$ at time t (in 1 second increments) into two components: the unobservable efficient price $m_{i,t}$ and the transitory component $s_{i,t}$:

$$p_{i,t} = m_{i,t} + s_{i,t}$$
$$m_{i,t} = m_{i,t-1} + w_{i,t}$$
$$w_{i,t} = \kappa^S_{i,HFT}\widetilde{HFT}^S_{i,t} + \kappa^S_{i,nHFT}n\widetilde{HFT}^S_{i,t} + \mu_{i,t}$$
$$s_{i,t} = \phi s_{i,t-1} + \psi^S_{i,HFT}HFT^S_{i,t} + \psi^S_i nHFT^S_{i,t} + \upsilon_{i,t}$$

$HFT^S_{i,t}$ and $nHFT^S_{i,t}$ are HFTs' and nHFTs' liquidity demanding order flow; $\widetilde{HFT}^S_{i,t}$ and $n\widetilde{HFT}^S_{i,t}$ are the surprise components of those order flows. Each stock is in one of three market capitalization categories: large, medium, and small. Columns 3-5 report coefficients for the entire sample at 1-second frequencies using the NBBO. Columns 6-8 report coefficients for a 50 day subsample in event time using the Nasdaq BBO. T-statistics are calculated using standard errors double clustered on stock and day. * denotes significance at the 1% level on the difference between $\kappa^S_{HFT}$ - $\kappa^S_{nHFT}$ and $\psi^S_{HFT}$ - $\psi^S_{nHFT}$.

## Table 5 HFT revenues

| Panel A: All | Trading Revenues | | | Trading Revenues Net of Fees | | |
|---|---|---|---|---|---|---|
| | Large | Medium | Small | Large | Medium | Small |
| $HFT^{All}$ | $5,642.27 | $272.80 | $55.23 | $6,651.03 | $173.77 | $29.86 |
| **(t-stat)** | (3.99) | (3.07) | (2.18) | (4.68) | (1.96) | (1.18) |
| $nHFT^{All}$ | -$5,642.27 | -$272.80 | -$55.23 | -$7,624.71 | -$234.45 | -$44.96 |
| **(t-stat)** | (3.99) | (3.07) | (2.18) | (-5.35) | (-2.64) | (-1.78) |
| $HFT^{All} - nHFT^{All}$ | $11,284.53 | $545.60 | $110.46 | $14,275.74 | $408.22 | $74.82 |
| **(t-stat)** | (3.99) | (3.07) | (2.18) | (5.02) | (2.30) | (1.48) |

| Panel B: Demand | Trading Revenues | | | Trading Revenues Net of Fees | | |
|---|---|---|---|---|---|---|
| | Large | Medium | Small | Large | Medium | Small |
| $HFT^{D}$ | $7,467.26 | $377.37 | $64.43 | $1,990.85 | $75.05 | $15.63 |
| **(t-stat)** | (6.71) | (4.54) | (3.23) | (1.80) | (0.91) | (0.78) |
| $nHFT^{D}$ | $4,393.94 | $379.56 | $230.26 | -$4,247.97 | -$198.02 | $60.21 |
| **(t-stat)** | (1.16) | (1.75) | (2.66) | (-1.12) | (-0.91) | (0.70) |
| $HFT^{D} - nHFT^{D}$ | $3,073.32 | -$2.19 | -$165.83 | $6,238.82 | $273.07 | -$44.58 |
| **(t-stat)** | (0.88) | (-0.01) | (-2.07) | (1.79) | (1.39) | (-0.56) |

| Panel C: Supply | Trading Revenues | | | Trading Revenues Net of Fees | | |
|---|---|---|---|---|---|---|
| | Large | Medium | Small | Large | Medium | Small |
| $HFT^{S}$ | -$1,824.99 | -$104.57 | -$9.21 | $4,660.18 | $98.72 | $14.23 |
| **(t-stat)** | (-1.99) | (-1.78) | (-0.52) | (5.01) | (1.68) | (0.82) |
| $nHFT^{S}$ | -$10,036.21 | -$652.35 | -$285.49 | -$3,376.74 | -$36.43 | -$105.17 |
| **(t-stat)** | (-2.26) | (-2.75) | (-3.11) | (-0.76) | (-0.15) | (-1.15) |
| $HFT^{S} - nHFT^{S}$ | $8,211.21 | $547.79 | $276.28 | $8,036.92 | $135.15 | $119.40 |
| **(t-stat)** | (1.75) | (2.45) | (3.08) | (1.71) | (0.60) | (1.34) |

This table presents results on HFTs' trading revenue with and without NASDAQ trading fees and rebates. Revenues are calculated for all, liquidity demand, and liquidity supplying HFT and nHFT: $HFT^{All}$, $HFT^{D}$, $HFT^{S}$, $nHFT^{All}$, $nHFT^{D}$, and $nHFT^{S}$. Each stock is in one of three market capitalization categories: large, medium, and small. Columns 2-4 of all panels report results per stock day and columns 5-7 report per stock and day net of fees. *T*-statistics are calculated using standard errors double clustered on stock and day.

## Table 6 Descriptive Statistics on High Permanent Volatility Days

| | | | High Permanent Volatility | | | Other Days | | |
|---|---|---|---|---|---|---|---|---|
| **Summary Statistics** | **Units** | **Source** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| **Price** | $ | TAQ | 45.22 | 24.77 | 12.24 | 58.23 | 30.44 | 16.88 |
| **Daily Midquote Return Volatility** | bps. | TAQ | 6.39 | 19.05 | 46.63 | 3.27 | 8.93 | 21.61 |
| **Bid-Ask Spread** | $ | NASDAQ | 0.04 | 0.06 | 0.08 | 0.03 | 0.04 | 0.07 |
| **Relative Bid-Ask Spread** | bps. | TAQ | 7.29 | 25.20 | 62.31 | 4.44 | 13.45 | 35.38 |
| **NASDAQ Trading Volume** | $ Million | NASDAQ | 231.58 | 6.24 | 0.71 | 181.6 | 6.64 | 1.15 |
| $HFT^A$ **Trading Volume** | $ Million | NASDAQ | 207.15 | 3.63 | 0.26 | 152.25 | 3.66 | 0.42 |
| $HFT^D$ **Trading Volume** | $ Million | NASDAQ | 106.24 | 2.50 | 0.18 | 76.23 | 2.39 | 0.29 |
| $HFT^S$ **Trading Volume** | $ Million | NASDAQ | 100.91 | 1.13 | 0.08 | 76.02 | 1.27 | 0.13 |
| $nHFT^A$ **Trading Volume** | $ Million | NASDAQ | 256.01 | 8.85 | 1.16 | 210.95 | 9.62 | 1.88 |
| $nHFT^D$ **Trading Volume** | $ Million | NASDAQ | 125.34 | 3.74 | 0.53 | 105.37 | 4.25 | 0.86 |
| $nHFT^S$ **Trading Volume** | $ Million | NASDAQ | 130.67 | 5.11 | 0.63 | 105.58 | 5.37 | 1.02 |

This table reports descriptive statistics for high permanent volatility ($\sigma(w_{i,t})$) and other days that are equal weighted averages across stock days for 118 stocks traded on NASDAQ for 2008 and 2009. High permanent volatility days are categorized for each stock when $\sigma(w_{i,t})$ is in the 90$^{th}$ percentile for that stock. Each stock is in one of three market capitalization categories: large, medium, and small. The closing midquote price is the average bid and ask price at closing. Trading volume is the average dollar trading volume and is also reported for HFTs and nHFTs.

## Table 7 State space model of $HFT^{All}$ and prices on high-permanent volatility days

| Panel A: Permanent Price Component | | High Permanent Volatility | | | Other Days | | |
|---|---|---|---|---|---|---|---|
| | Units | Large | Medium | Small | Large | Medium | Small |
| $\kappa^{All}$ | bps. / $10000 | 0.57 | 12.57 | -11.18 | 0.17 | 4.35 | 2.37 |
| (t-stat) | | (11.14) | (8.54) | (-0.56) | (43.03) | (42.35) | (1.02) |
| $\sigma^2(\widehat{HFT}^{All})$ | $10000 | 2.45 | 0.46 | 0.14 | 3.13 | 0.55 | 0.20 |
| $(\kappa^{All} * \sigma(\widehat{HFT}^{All}))^2$ | $bps.^2$ | 2.80 | 72.15 | 373.78 | 0.29 | 7.43 | 42.50 |
| (t-stat) | | (3.87) | (4.15) | (9.36) | (35.40) | (52.19) | (43.34) |
| $\sigma^2(w_{i,t})$ | $bps.^2$ | 46.40 | 431.85 | 2662.65 | 11.46 | 81.04 | 444.85 |

| Panel B: Transitory Price Component | | High Permanent Volatility | | | Other Days | | |
|---|---|---|---|---|---|---|---|
| | Units | Large | Medium | Small | Large | Medium | Small |
| $\phi$ | | 0.50 | 0.45 | 0.40 | 0.49 | 0.51 | 0.46 |
| $\psi^{All}$ | bps. / $10000 | -0.11 | -5.53 | -12.29 | 0.00 | -1.70 | -1.53 |
| (t-stat) | | (-9.38) | (-7.43) | (-0.73) | (-2.69) | (-35.73) | (-1.41) |
| $\sigma^2(HFT^{All})$ | $10000 | 2.47 | 0.47 | 0.14 | 3.15 | 0.56 | 0.20 |
| $(\psi^{All} * \sigma(HFT^{All}))^2$ | $bps.^2$ | 0.58 | 20.06 | 154.32 | 0.04 | 1.68 | 13.08 |
| (t-stat) | | (2.77) | (3.68) | (4.66) | (13.79) | (43.65) | (34.07) |
| $\sigma^2(s_{i,t})$ | $bps.^2$ | 1.69 | 30.05 | 248.98 | 0.67 | 5.33 | 59.19 |

This table reports the estimates for the state space model for high permanent volatility ($\sigma^2(w_{i,t})$) days. High permanent volatility days are categorized for each stock when $\sigma^2(w_{i,t})$ is in the 90th percentile for that stock. The model is estimated for each stock each day using HFT trading variables to decompose the observable price (log midquote) $p_{i,t}$ for stock i at time t (in 1 second increments) into two components: the unobservable efficient price $m_{i,t}$ and the transitory component $s_{i,t}$:

$$p_{i,t} = m_{i,t} + s_{i,t}$$
$$m_{i,t} = m_{i,t-1} + w_{i,t}$$
$$w_{i,t} = \kappa_i^{All}\widehat{HFT}_{i,t}^{All} + \mu_{i,t}$$
$$s_{i,t} = \phi s_{i,t-1} + \psi_i^{All} HFT_{i,t}^{All} + \upsilon_{i,t}$$

$HFT_{i,t}^{All}$ is HFTs' overall order flow; $\widehat{HFT}_{i,t}^{All}$ is the surprise component of the order flow. Each stock is in one of three market capitalization categories: large, medium, and small. Columns 3-5 report the mean of the coefficient when the permanent volatility for that day is above the 90% percentile for that stock. Columns 6-8 report the mean of the coefficients on other days. T-statistics are calculated using standard errors double clustered on stock and day. T-statistics in columns 3-5 are from a regression of the coefficient on a dummy that takes the value one on high permanent volatility days and zero otherwise. T-statistics for columns 6-8 are from the constant in the previous regression.

## Table 8 State space model of liquidity demand, $HFT^D$ and $nHFT^D$, and prices on high-permanent volatility days

| **Panel A: Permanent Price Component** | | **High Permanent Volatility** | | | **Other** | | |
|---|---|---|---|---|---|---|---|
| | **Units** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| $\kappa^D_{HFT}$ | **bps. / \$10000** | 1.37*† | 22.77*† | -28.95 | 0.46* | 7.77* | 51.66* |
| **(t-stat)** | | (17.57) | (14.20) | (-0.60) | (47.79) | (52.97) | (14.67) |
| $\kappa^D_{nHFT}$ | **bps. / \$10000** | 0.89 | 16.12 | 118.53 | 0.28 | 5.11 | 32.51 |
| **(t-stat)** | | (12.72) | (14.76) | (11.42) | (43.38) | (55.73) | (15.31) |
| $\sigma^2(\widetilde{HFT^D})$ | **\$10000** | 2.52 | 0.45 | 0.11 | 3.08 | 0.53 | 0.17 |
| $\sigma^2(\widetilde{nHFT^D})$ | **\$10000** | 3.11 | 0.58 | 0.24 | 4.04 | 0.74 | 0.34 |
| $(\kappa^D_{HFT} * \sigma(\widetilde{HFT^D}))^2$ | **bps.²** | 7.01 | 48.41 | 253.42 | 1.22 | 9.26 | 35.65 |
| **(t-stat)** | | (9.30) | (9.08) | (8.44) | (47.25) | (59.01) | (41.47) |
| $(\kappa^D_{nHFT} * \sigma(\widetilde{nHFT^D}))^2$ | **bps.²** | 12.03 | 73.11 | 511.18 | 0.70 | 9.02 | 68.25 |
| **(t-stat)** | | (1.98) | (4.55) | (8.00) | (41.90) | (59.22) | (48.78) |
| $\sigma^2(w_{i,t})$ | **bps.²** | 58.27 | 450.10 | 2784.39 | 11.99 | 86.06 | 466.89 |
| **Panel B: Transitory Price Component** | | **High Permanent Volatility** | | | **Other** | | |
| | **Units** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| $\phi$ | | 0.63 | 0.47 | 0.38 | 0.58 | 0.54 | 0.46 |
| $\psi^D_{HFT}$ | **bps. / \$10000** | -0.29*† | -9.26*† | 1.69 | -0.03* | -2.76* | -84.92 |
| **(t-stat)** | | (-14.19) | (-13.05) | (0.86) | (-12.13) | (-46.64) | (-1.18) |
| $\psi^D_{nHFT}$ | **bps. / \$10000** | -0.19 | -6.33 | -39.94 | -0.01 | -1.64 | -11.13 |
| **(t-stat)** | | (-11.89) | (-14.14) | (-10.17) | (-7.84) | (-51.45) | (-34.59) |
| $\sigma^2(HFT^D)$ | **\$10000** | 2.54 | 0.46 | 0.13 | 3.10 | 0.54 | 0.19 |
| $\sigma^2(nHFT^D)$ | **\$10000** | 3.19 | 0.61 | 0.27 | 4.12 | 0.77 | 0.37 |
| $(\kappa^D_{HFT} * \sigma(HFT^D))^2$ | ***bps.²*** | 1.15 | 12.35 | 71.68 | 0.10 | 1.75 | 10.79 |
| **(t-stat)** | | (4.15) | (7.27) | (8.65) | (21.16) | (43.59) | (31.37) |
| $(\kappa^D_{nHFT} * \sigma(nHFT^D))^2$ | **bps.²** | 1.29 | 27.87 | 144.08 | 0.10 | 1.83 | 18.90 |
| **(t-stat)** | | (2.53) | (2.45) | (7.00) | (27.43) | (37.62) | (37.33) |
| $\sigma^2(s_{i,t})$ | **bps.²** | 3.37 | 39.59 | 315.00 | 0.78 | 6.74 | 69.32 |

This table reports the estimates for the state space model for high permanent volatility ($\sigma^2$ ($w_{i,t}$)) days. High permanent volatility days are categorized for each stock when ($\sigma^2$ ($w_{i,t}$)) is in the 90th percentile for that stock. The model is estimated for each stock each day using HFT trading variables to decompose the observable price (log midquote) $p_{i,t}$ for stock $i$ at time t (in 1 second increments) into two components: the unobservable efficient price $m_{i,t}$ and the transitory component $s_{i,t}$:

$$p_{i,t} = m_{i,t} + s_{i,t}$$

$$m_{i,t} = m_{i,t-1} + w_{i,t}$$

$$w_{i,t} = \kappa^D_{i,HFT}\widetilde{HFT}^D_{i,t} + \kappa^D_{i,nHFT}n\widetilde{HFT}^D_{i,t} + \mu_{i,t}$$

$$s_{i,t} = \phi s_{i,t-1} + \psi^D_{i,HFT}HFT^D_{i,t} + \psi^D_i nHFT^D_{i,t} + \upsilon_{i,t}$$

$HFT^D_{i,t}$ and $nHFT^D_{i,t}$ are HFTs' and nHFTs' liquidity demanding order flow; $\widetilde{HFT}^D_{i,t}$ and $\widetilde{nHFT}^D_{i,t}$ are the surprise components of those order flows. Each stock is in one of three market capitalization categories: large, medium, and small. Columns 3-5 report the mean of the coefficient when the permanent volatility for that day is above the 90% percentile for that stock. Columns 6-8 report the mean of the coefficient on other days. T-statistics are calculated using standard errors double clustered on stock and day. T-statistics in columns 3-5 are from a regression of the coefficient on a dummy that takes the value one on high permanent volatility days and zero otherwise. T-statistics for columns 6-8 are from the constant in the previous regression. * denotes significance at the 1% level on the difference between $\kappa^S_{HFT}$ - $\kappa^S_{nHFT}$ and $\psi^S_{HFT}$ - $\psi^S_{nHFT}$. † denotes significance at the 1% level on the difference between $\kappa/\psi^D_{HFT}$ - $\kappa/\psi^D_{nHFT}$ on high permanent volatility days and $\kappa/\psi^D_{HFT}$ - $\kappa/\psi^D_{nHFT}$ on other days.

## Table 9 State space model of liquidity supply, HFT$^S$ and nHFT$^S$, and prices on high-permanent volatility days

| Panel A: Permanent Price Component | | High Permanent Volatility | | | Other | | |
|---|---|---|---|---|---|---|---|
| | **Units** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| $\kappa^S_{HFT}$ | bps. / \$10000 | -1.42* | -27.66* | -205.64 | -0.46* | -8.85* | -88.83* |
| (t-stat) | | (-13.32) | (-4.45) | (-2.92) | (-42.90) | (-44.99) | (-6.27) |
| $\kappa^S_{nHFT}$ | bps. / \$10000 | -1.16 | -17.49 | -114.54 | -0.35 | -5.65 | -34.33 |
| (t-stat) | | (-11.75) | (-15.86) | (-10.36) | (-45.53) | (-55.73) | (-39.48) |
| $\sigma^2(\widetilde{HFT}^S)$ | \$10000 | 1.81 | 0.20 | 0.07 | 2.36 | 0.26 | 0.09 |
| $\sigma^2(\widetilde{nHFT}^S)$ | \$10000 | 3.36 | 0.72 | 0.26 | 4.11 | 0.87 | 0.38 |
| $(\kappa^S_{HFT} * \sigma(\widetilde{HFT}^S))^2$ | $bps.^2$ | 3.77 | 30.94 | 208.70 | 0.65 | 4.30 | 29.46 |
| (t-stat) | | (10.06) | (3.75) | (10.74) | (41.45) | (51.24) | (39.06) |
| $(\kappa^S_{nHFT} * \sigma(\widetilde{nHFT}^S))^2$ | $bps.^2$ | 26.33 | 94.24 | 458.27 | 1.22 | 13.63 | 73.64 |
| (t-stat) | | (1.85) | (5.46) | (9.23) | (47.92) | (61.04) | (49.25) |
| $\sigma^2(w_{i,t})$ | $bps.^2$ | 69.37 | 448.49 | 2726.17 | 12.06 | 85.57 | 470.15 |

| Panel B: Transitory Price Component | | High Permanent Volatility | | | Other | | |
|---|---|---|---|---|---|---|---|
| | **Units** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** |
| $\phi$ | | 0.61 | 0.47 | 0.38 | 0.56 | 0.54 | 0.46 |
| $\psi^S_{HFT}$ | bps. / \$10000 | 0.34*† | 9.29* | 57.03 | 0.05* | 3.35* | 26.11* |
| (t-stat) | | (11.40) | (10.20) | (1.96) | (16.55) | (38.57) | (15.95) |
| $\psi^S_{nHFT}$ | bps. / \$10000 | 0.23 | 6.97 | 37.74 | 0.01 | 1.82 | 10.63 |
| (t-stat) | | (15.20) | (15.27) | (8.31) | (7.03) | (50.70) | (32.64) |
| $\sigma^2(HFT^S)$ | \$10000 | 1.82 | 0.21 | 0.08 | 2.38 | 0.27 | 0.10 |
| $\sigma^2(nHFT^S)$ | \$10000 | 3.45 | 0.74 | 0.29 | 4.21 | 0.91 | 0.41 |
| $(\kappa^S_{HFT} * \sigma(HFT^S))^2$ | $bps.^2$ | 0.62 | 10.75 | 92.71 | 0.09 | 1.05 | 11.67 |
| (t-stat) | | (4.06) | (2.90) | (5.70) | (29.12) | (37.37) | (25.73) |
| $(\kappa^S_{nHFT} * \sigma(nHFT^S))^2$ | $bps.^2$ | 1.59 | 25.65 | 156.81 | 0.17 | 2.46 | 18.79 |
| (t-stat) | | (4.18) | (4.51) | (7.34) | (23.84) | (47.80) | (40.50) |
| $\sigma^2(s_{i,t})$ | $bps.^2$ | 3.11 | 36.91 | 286.39 | 0.72 | 6.70 | 68.45 |

This table reports the estimates for the state space model for high permanent volatility ($\sigma^2(w_{i,t})$) days. High permanent volatility days are categorized for each stock when $\sigma^2(w_{i,t})$ is in the 90$^{th}$ percentile for that stock. The model is estimated for each stock each day using HFT trading variables to decompose the observable price (log midquote) $p_{i,t}$ for stock i at time t (in 1 second increments) into two components: the unobservable efficient price $m_{i,t}$ and the transitory component $s_{i,t}$:

$$p_{i,t} = m_{i,t} + s_{i,t}$$
$$m_{i,t} = m_{i,t-1} + w_{i,t}$$
$$w_{i,t} = \kappa^S_{i,HFT}\widetilde{HFT}^S_{i,t} + \kappa^S_{i,nHFT}\widetilde{nHFT}^S_{i,t} + \mu_{i,t}$$
$$s_{i,t} = \phi s_{i,t-1} + \psi^S_{i,HFT}HFT^S_{i,t} + \psi^S_i nHFT^S_{i,t} + \upsilon_{i,t}$$

$HFT^S_{i,t}$ and $nHFT^S_{i,t}$ are HFTs' and nHFTs' liquidity supplying order flow; $\widetilde{HFT}^S_{i,t}$ and $\widetilde{nHFT}^S_{i,t}$ are the surprise components of those order flows. Each stock is in one of three market capitalization categories: large, medium, and small. Columns 3-5 report the mean of the coefficient when the permanent volatility for that day is above the 90% percentile for that stock. Columns 6-8 report the mean of the coefficient on other days. T-statistics are calculated using standard errors double clustered on stock and day. T-statistics in columns 3-5 are from a regression of the coefficient on a dummy that takes the value one on high permanent volatility days and zero otherwise. T-statistics for columns 6-8 are from the constant in the previous regression. * denotes significance at the 1% level on the difference between $\kappa^S_{HFT}$ - $\kappa^S_{nHFT}$ and $\psi^S_{HFT}$ - $\psi^S_{nHFT}$. † denotes significance at the 1% level on the difference between $\kappa/\psi^D_{HFT}$ - $\kappa/\psi^D_{nHFT}$ on high permanent volatility days and $\kappa/\psi^D_{HFT}$ - $\kappa/\psi^D_{nHFT}$ on other days.

## Table 10 HFT and returns around macro economic news announcements

| | Large | Medium | Small |
|---|---|---|---|
| $\boldsymbol{HFT^{D}_{t-1,t+1}}$ | 0.08 | 1.06 | 1.35 |
| **(t-stat)** | (2.03) | (2.26) | (1.99) |
| $\boldsymbol{HFT^{S}_{t-1,t+1}}$ | -0.14 | 0.23 | -4.30 |
| **(t-stat)** | (-4.30) | (0.24) | (-1.36) |
| $\boldsymbol{HFT^{All}_{t-1,t+1}}$ | 0.04 | 1.00 | 1.15 |
| **(t-stat)** | (1.27) | (2.27) | (1.85) |

This table presents results on HFTs' trading and future returns around macroeconomic announcements. We report the coefficients from a regression of cumulative returns from time t+2 to time t+10 on HFTs' liquidity demand, liquidity supply, and overall order flow: $HFT^D$, $HFT^S$ and $HFT^{All}$ from time t-1 to time t+1 after a macroeconomic announcement becomes publicly available. Time t is the second in which a macro economic news announcement is publicly available. $HFT^{D,S,All}_{i,t-1,t+1}$ is scaled by 10,000 and $Ret_{i,t+2,t+10}$ is the cumulative return in basis points from two seconds after the macroeconomic announcement to 10 seconds afterwards.

$$Ret_{i,t+2,t+10} = \alpha + \beta\, HFT^{D,S,All}_{i,t-1,t+1} + \varepsilon_{i,t}.$$

Each stock is in one of three market capitalization categories: large, medium, and small. The first row reports the $HFT^D$ results, the second row the $HFT^S$ results, and the third row the $HFT^{All}$ results. T-statistics are calculated using standard errors clustered by announcement day.

## Table 11 Limit Order Book Imbalance and Subsequent HFT

**Panel A: HFT regressed on lagged Limit Order Book Imbalance**

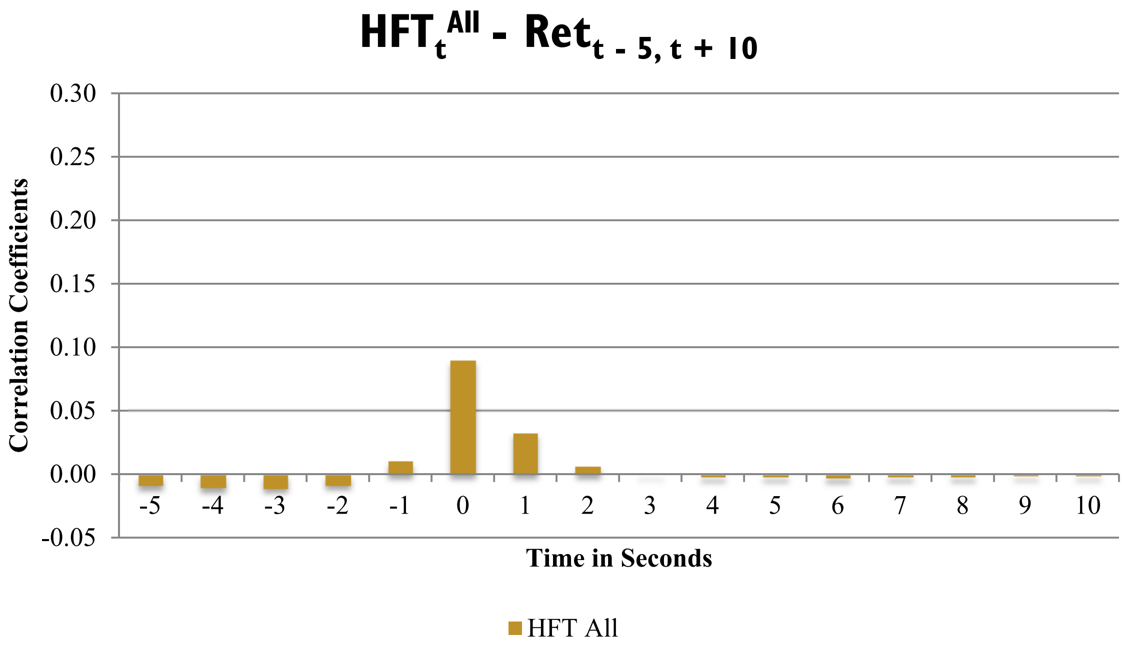
| | | Large | Medium | Small |
|---|---|---|---|---|
| **HFT All** | $LOBI_{t-1}$ | -54.20 | -284.07 | -104.24 |
| | **(t-stat)** | (-7.30) | (-14.08) | (-1.06) |
| **HFT Demand** | $LOBI_{t-1}$ | -108.44 | -434.89 | -512.15 |
| | **(t-stat)** | (-11.52) | (-17.52) | (-4.32) |
| **HFT Supply** | $LOBI_{t-1}$ | 31.81 | 192.02 | 462.06 |
| | **(t-stat)** | (4.93) | (8.57) | (4.96) |

**Panel B: Returns regressed on lagged HFT and LOBI**

| | | Large | Medium | Small |
|---|---|---|---|---|
| **HFT All** | $HFT_{t-1}^{All}$ | 0.20 | 4.33 | -32.98 |
| | **(t-stat)** | (1.65) | (9.32) | (-0.59) |
| | $HFT_{t-2}^{All}$ | -0.01 | 0.56 | 15.65 |
| | **(t-stat)** | (-0.26) | (2.84) | (0.91) |
| | $LOBI_{t-1}$ | -0.01 | -0.01 | -0.02 |
| | **(t-stat)** | (-16.55) | (-18.61) | (-17.20) |
| **HFT Demand** | $HFT_{t-1}^{D}$ | 0.52 | 7.84 | 2.88 |
| | **(t-stat)** | (2.70) | (10.34) | (0.15) |
| | $HFT_{t-2}^{D}$ | 0.03 | 0.29 | -65.96 |
| | **(t-stat)** | (0.46) | (0.20) | (-1.15) |
| | $LOBI_{t-1}$ | -0.01 | -0.01 | -0.02 |
| | **(t-stat)** | (-16.45) | (-18.51) | (-16.51) |
| **HFT Supply** | $HFT_{t-1}^{S}$ | -1.43 | -11.96 | -50.57 |
| | **(t-stat)** | (-4.56) | (-8.17) | (-1.40) |
| | $HFT_{t-2}^{S}$ | -0.58 | -2.98 | 5.45 |
| | **(t-stat)** | (-4.93) | (-8.57) | (-4.96) |
| | $LOBI_{t-1}$ | -0.01 | -0.01 | -0.02 |
| | **(t-stat)** | (-16.59) | (-18.99) | (-17.70) |

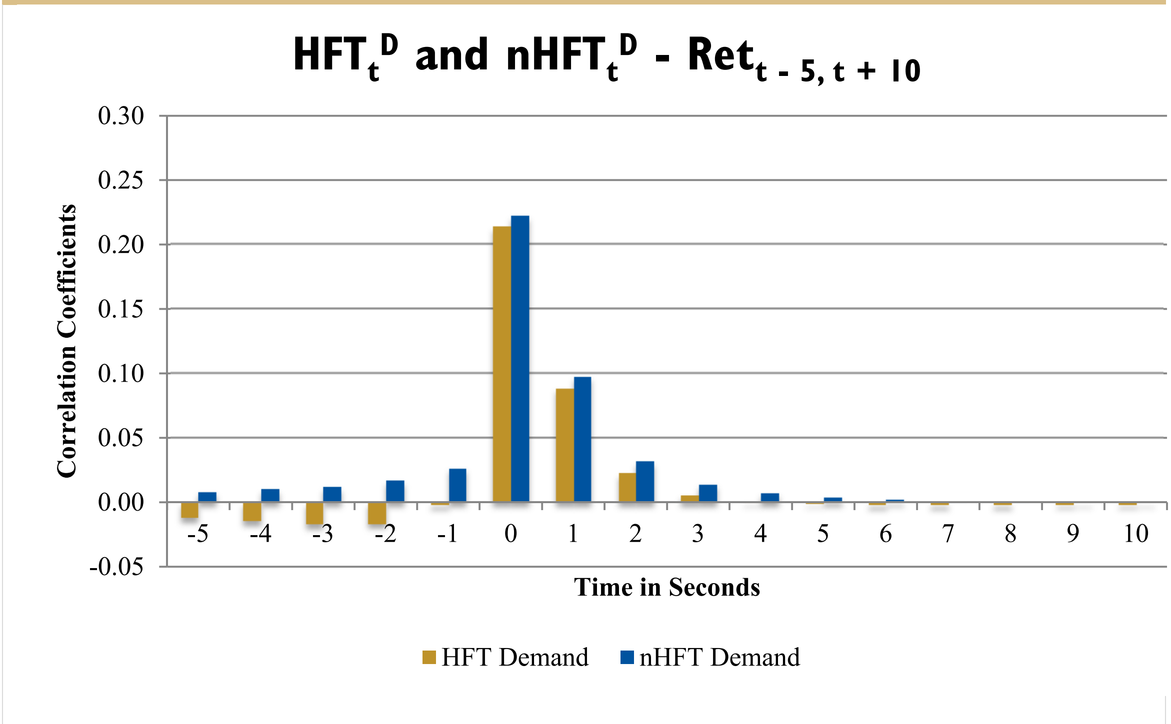
This table presents results on HFTs' trading, limit order book imbalances (LOBI), and returns. LOBI is defined as: $LOBI_{i,t} = (Size_{i,t}^{Offer} - Size_{i,t}^{Bid}) / (Size_{i,t}^{Offer} + Size_{i,t}^{Bid})$ where *Size* is the dollar volume of orders available at the NBBO scaled by 10,000. Panel A regresses HFTs' order flows in period *t* on $Ret_{t-1}$ and $LOBI_{t-1}$: $HFT_{i,t}^{D,S,All} = \alpha + \beta_1 LOBI_{i,t-1} + \beta_2 Ret_{i,t} + \varepsilon_{i,t}$, where $HFT_{i,t+1}^{D,S,All}$ is HFTs' dollar volume order flow scaled by 10,000. Panel B reports returns regressed on prior HFTs' order flows and LOBI: $Ret_{i,t} = \alpha + \beta_1 HFT_{i,t-1}^{D,S,All} + \beta_2 HFT_{i,t-2}^{D,S,All} + \beta_3 LOBI_{i,t-1} + \beta_4 Ret_{i,t-1} + \varepsilon_{i,t}$. We report the mean coefficient from regressions conducted for each stock on each trading day. T-statistics are calculated using standard errors double clustered on stock and day. Each stock is in one of three market capitalization categories: large, medium, and small.

**Figure 1 Overall correlation of HFT and Returns**



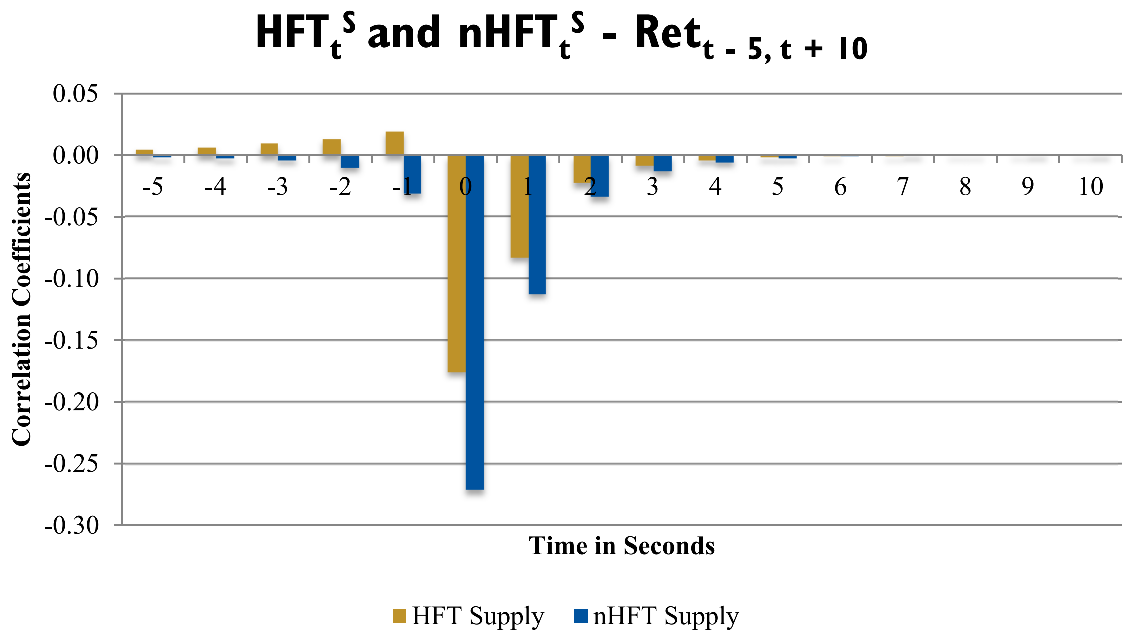

This figure plots an equal weighted average of the stock-day correlations between and returns 5 seconds prior, contemporaneously, and up to 10 seconds into the future in 1 second increments.

**Figure 2  Correlation of returns with HFT and nHFT liquidity demand**



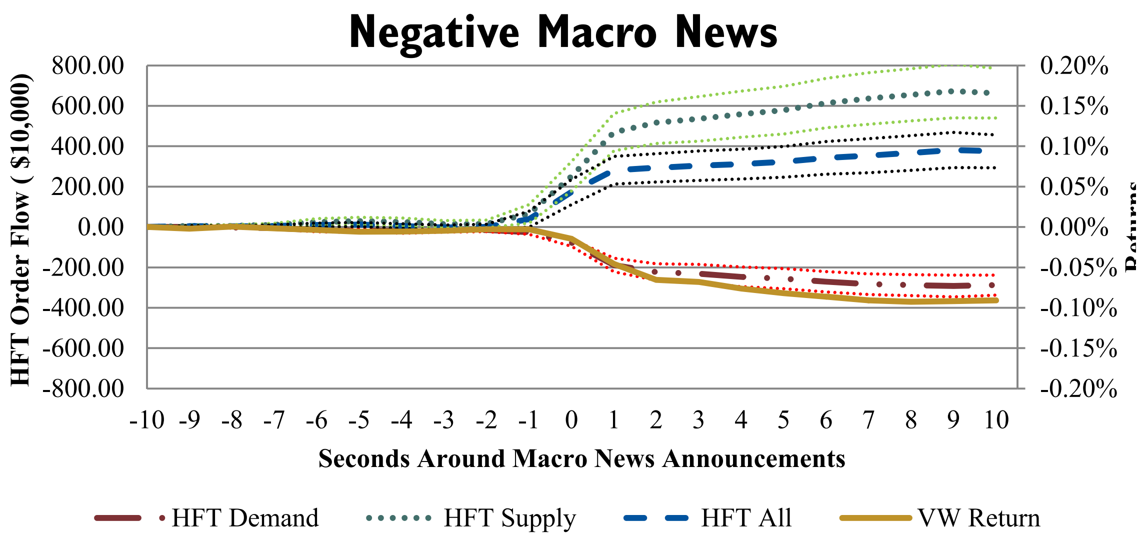

This figure plots an equal weighted average of the stock-day correlations between , and returns 5 seconds prior, contemporaneously, and up to 10 seconds into the future in 1 second increments.

**Figure 3 Correlation of returns with HFT and nHFT liquidity supply**



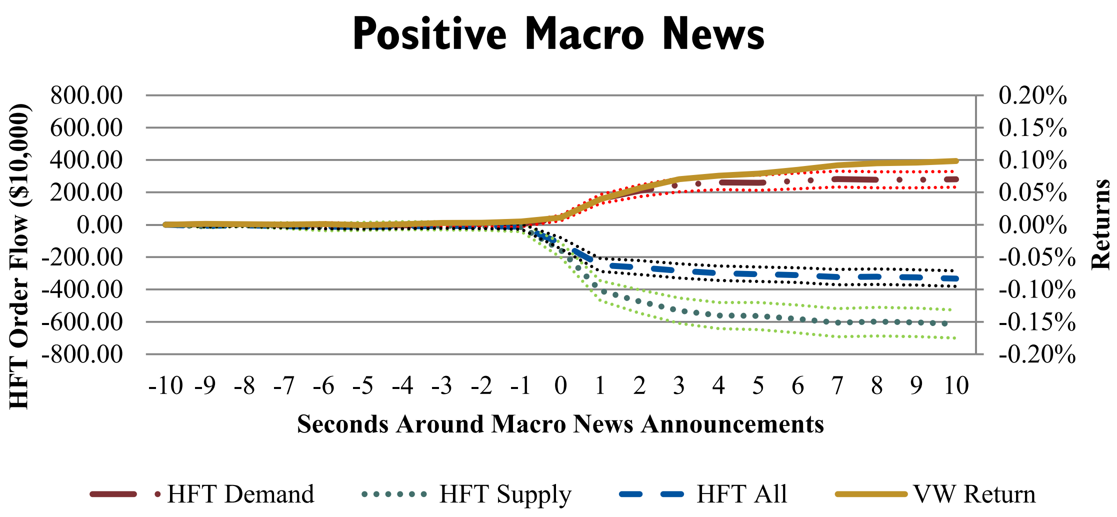

This figure plots an equal weighted average of the correlation between , and returns 5 seconds prior, contemporaneously, and up to 10 seconds into the future in 1 second increments.

## Figure 4 HFT trading and portfolio returns for positive macro announcements



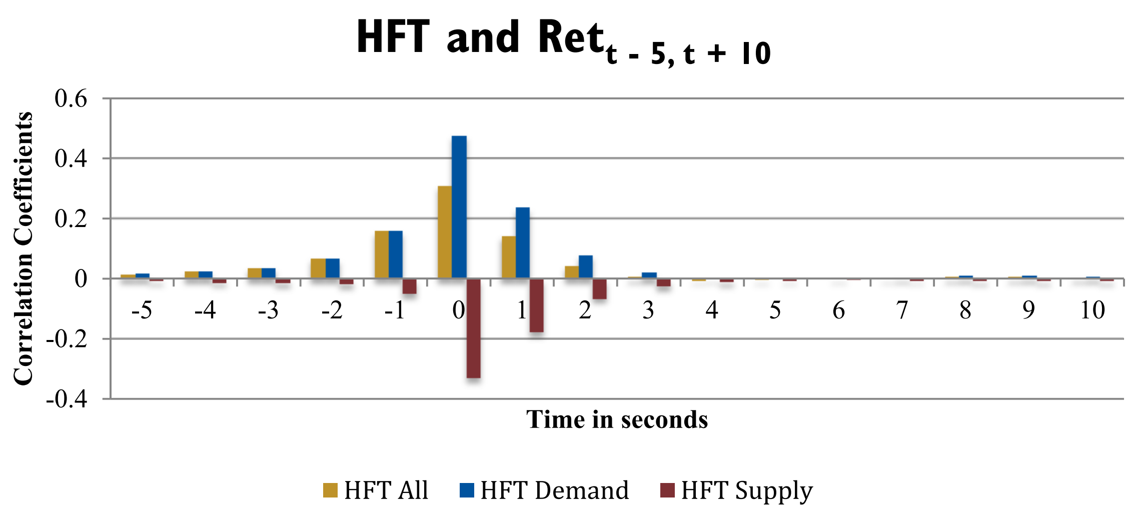

This figure plots the value-weighted sample portfolio return, and ⟦HFT⟧^D, ⟦HFT⟧^S, and ⟦HFT⟧^All around negative macro economic news announcements. Time is in seconds, at time t = 0 news is made publicly available. Positive announcements are those below the average analyst forecast. 5% and 95% confidence intervals denoted with dotted lines.

## Figure 5 HFT trading and portfolio returns for negative macro announcements




This figure plots the value-weighted sample portfolio return, and $HFT^D$, $HFT^S$, and $HFT^{All}$ around positive macro economic news announcements. Time is in seconds, at time $t$ = 0 news is made publicly available. Negative announcements are those below the average analyst forecast. 5% and 95% confidence intervals denoted with dotted lines.

**Figure 6 Correlation of market wide returns with *HFT***




This figure plots the correlation between aggregated across all stocks and value-weighted portfolio returns 5 seconds prior, contemporaneously, and up to 10 seconds into the future in 1 second increments.