High-Frequency Trading and Price Discovery

Author(s): Jonathan Brogaard, Terrence Hendershott and Ryan Riordan

Source: *The Review of Financial Studies*, August 2014, Vol. 27, No. 8 (August 2014), pp. 2267-2306

Published by: Oxford University Press. Sponsor: The Society for Financial Studies.

Stable URL: http://www.jstor.com/stable/24465658

High-Frequency Trading and Price Discovery

Jonathan Brogaard
University of Washington

Terrence Hendershott
University of California at Berkeley

Ryan Riordan
University of Ontario Institute of Technology

We examine the role of high-frequency traders (HFTs) in price discovery and price efficiency. Overall 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 HFTs' trading 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. (*JEL* G12, G14)

Financial markets have two important functions for asset pricing: liquidity and price discovery for incorporating information in prices (O'Hara 2003). Historically, financial markets have relied on intermediaries to facilitate these goals by providing immediacy to outside investors. Fully automated stock exchanges (Jain 2005) have increased markets' trading capacity and enabled intermediaries to expand their use of technology. Increased automation has 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). Using transaction level data from NASDAQ that identifies the buying and selling activity of a large group of HFTs, this paper examines the role of HFTs in the price discovery process.

Like traditional intermediaries HFTs have short holding periods and trade frequently. Unlike traditional intermediaries, however, HFTs are not granted

We thank Frank Hatheway and Jeff Smith at NASDAQ OMX for providing data. NASDAQ makes the data freely available to academics who provide a project description and sign a nondisclosure agreement. For helpful comments, we thank participants at the Fifth Erasmus Liquidity Conference, University of Notre Dame & NASDAQ OMX Conference on Current Topics in Financial Regulation, and Workshop on High-Frequency Trading: Financial and Regulatory Implications, as well as Álvaro Cartea, Frank de Jong, Richard Gorelick, Charles Jones, Andrei Kirilenko, Charles Lehalle, Albert Menkveld, Adam Nunes, Roberto Pascual, Gideon Saar, Stephen Sapp, and Cameron Smith. All errors are our own. Supplementary data can be found on *The Review of Financial Studies* web site. Send correspondence to Jonathan Brogaard, Foster School of Business, University of Washington, Box 353226, Seattle, WA 98195, USA; telephone: (206) 685-7822. E-mail: brogaard@uw.edu.

doi:10.1093/rfs/hhu032 Advance Access publication May 14, 2014

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 are both positive and negative. Typically, the positive obligations require intermediaries to always stand ready to supply liquidity and the negative obligations limit 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 reacting faster to public news. The absence of these obligations allows HFTs to follow a variety of strategies beyond traditional market making.

The substantial, largely negative media coverage of HFTs and the "flash crash" on May 6, 2010, raised significant interest and concerns about the fairness of markets and the role of HFTs in the stability and price efficiency of markets.[2] We show that HFTs impose adverse selection costs on other investors.[3] Informed HFTs 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 moves. In addition, HFTs supply liquidity in stressful times such as the most volatile days and around macroeconomic news announcements.

We use a data set NASDAQ makes available to academics that identifies a subset of HFTs. The data set includes information on whether the liquidity demanding (marketable) order and liquidity supplying (nonmarketable) side of each trade is from a HFT. The data set includes trading data on a stratified sample of stocks in 2008 and 2009. Following Hendershott and Menkveld's (Forthcoming) approach, we use a state space model to decompose price movements into permanent and temporary components and to relate changes in both to HFTs and non-HFTs. The permanent component is normally interpreted as information, and the transitory component is interpreted 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

[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 et al. (2011) for analysis of order flow and price dynamics on May 6, 2010.

[3] This contrasts with traditional intermediaries. See Hasbrouck and Sofianos (1993) and Hendershott and Menkveld (Forthcoming) for evidence on NYSE specialists being adversely selected.

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 was HFTs. On pages 36 and 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). Although 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 because of 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, whereas 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 the roles of 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. HFTs' overall trading is negatively correlated with past returns, commonly referred to as following contrarian strategies.

The beneficial role of HFTs in price discovery is consistent with theoretical models of informed trading, for example, Kyle (1985). In these models informed traders trade against transitory pricing errors and trade in the direction of permanent price changes. The adverse selection costs to other traders are balanced against the positive externalities from greater price efficiency. Regulation FD and insider trading laws attempt to limit certain types of informed trading because of the 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 because of their use of technology for processing information and trading quickly.[4] Foucault, Hombert, and Rosu (2013) use HFTs to motivate their informational structure. They 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 announcements (Andersen et al. 2003) and imbalances in the limit order book (Cao, Hansch, and Wang 2009).[5]

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; Boehmer, Fong, and Wu 2012) and price efficiency through arbitrage strategies (Chaboud et al. forthcoming).[6] 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.[7] Carrion (2013) and Hirschey (2013) use data, similar to ours, from NASDAQ. Carrion (2013) and Hirschey (2013) also find that HFTs can forecast short horizon price movements. Carrion (2013) finds that HFTs are more likely to trade when liquidity is dear and when market efficiency is higher. Carrion (2013) finds revenue results that are similar to our overall level of revenues. However, he finds that HFT liquidity demanding revenues are negative if one excludes HFT-to-HFT trades and positive if one includes HFT-to-HFT trades. Excluding HFT-to-HFT trades focuses revenue calculations on transfers between HFTs

---

4 Biais, Foucault, and Moinas (2011) and Pagnotta and Philippon (2011) provide models in which investors and markets compete on speed. Hasbrouck and Saar (2013) 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.

5 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.

6 Menkveld (2011) studies how one HFT firm improved liquidity and enabled a new market to gain market share. Hendershott and Riordan (2013) 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.

7 A number of papers use CME Group data from the Commodity Futures Trading Commission that identify trading by different market participants. Access by non-CFTC employees was suspended over concerns about the handling of such confidential trading data: 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.

and non-HFTs. Because our goal is to examine the overall economics of HFTs and HFTs cannot choose their counterparty, we include HFT-to-HFT trades.

Hirschey (2013) explores in detail a 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 provides an explanation for how HFTs' liquidity demand helps incorporate information into prices. 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 (2013) use data from NASDAQ-OMX Stockholm. They find that HFTs tend to specialize in either liquidity demanding or liquidity supplying. Using events in which 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.

The paper is structured as follows. Section 1 describes the data, institutional details, and descriptive statistics. Section 2 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 3 focuses on HFTs' trading during high permanent volatility day. Section 4 analyzes the different sources of information used by HFTs. Section 5 discusses the implications of our findings in general and with respect to social welfare. Section 6 concludes.

1. Data, Institutional Details, and Descriptive Statistics

NASDAQ provides the HFT data used in this study to academics under a nondisclosure agreement. The data are for a stratified sample of 120 randomly selected stocks listed on NASDAQ and the NYSE. The sample contains trading data for all dates in 2008 and 2009. The data include trades executed against either displayed or hidden liquidity on the NASDAQ exchange, but not trades that were executed on other markets, including those that report on NASDAQ's trade reporting facility. 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 a firm's net trading in a day crosses zero, its order duration, and its order-to-trade ratio.

One limitation of the data is that NASDAQ cannot identify all HFT. Possible excluded HFT firms are those that also act as brokers for customers and engage in proprietary lower-frequency trading strategies, for example, Goldman Sachs, Morgan Stanley, and other large and 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.[8] If these independent HFT firms follow different strategies than the large integrated firms, then our results may not be fully generalizable. Although 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: large, medium, and small. Each size group contains forty stocks. Half of the firms in each size category are listed on NASDAQ, and the other half are listed on NYSE. The top forty 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, for example, Foot Locker, and the small-size category contains stocks around the 2000th largest stock in the Russell 3000.[9]

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

1. symbol,
2. date,
3. time in milliseconds,
4. shares,
5. price,
6. buy-sell indicator, and
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

8 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. Although 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.

9 See the Internet Appendix for a complete list of sample stocks and size categories.

a trade; NN is similar with both parties in the trade being nHFTs. HN trades indicate that a 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 data set 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. Although 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 are 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.

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, compared with 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, nondisplayed orders are not visible until executed. NASDAQ matches orders based on price, time, and 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

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, or small. The closing midquote price is the average bid and ask price at the close. Trading volume is the average dollar trading volume and is also reported for HFTs and nHFTs. Columns 4–6 report values for the calendar time (one-second) data, and Columns 7–9 report value for the event time (trade-by-trade) subsample.

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 so 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, narrower bid-ask spreads in large stock facilitating liquidity demanding statistical arbitrage strategies, and higher execution risk for liquidity supplying orders in smaller stocks.

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.[10] 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 opening 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.

2. Trading and Returns

Correlations between HFTs' and nHFTs' trading and returns relate trading to price changes at different horizons. Figures 1–3 plot 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 shows that the correlations between HFT^{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. One-second lagged returns are statistically significantly positively correlated with HFT^{All}, whereas -5- to -2-second returns are statistically significantly negatively correlated with HFT^{All}. Looking across all five lags, HFT^{All} is negatively correlated with past returns, implying HFTs overall follow contrarian strategies with respect to past price changes. Aggregate nHFTs must therefore trade in the direction of past price changes. This can arise from nHFTs, including investors with large orders that are split into a series of smaller transactions over time. Such positively autocorrelated order flow having a price impact can result in past returns predicting future order flow for nHFTs. HFTs' ability to anticipate trading from order splitting is Hirschey's focus (2013).

Figure 1 illustrates the relation between HFT^{All} and returns, whereas Figure 2 shows these relations for HFT^D and $nHFT^D$. HFT^D is positively correlated with contemporaneous and subsequent returns and falls to zero three to four seconds in the future. $nHFT^D$ is more positively correlated with

[10] 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 does so slowly in each individual market.

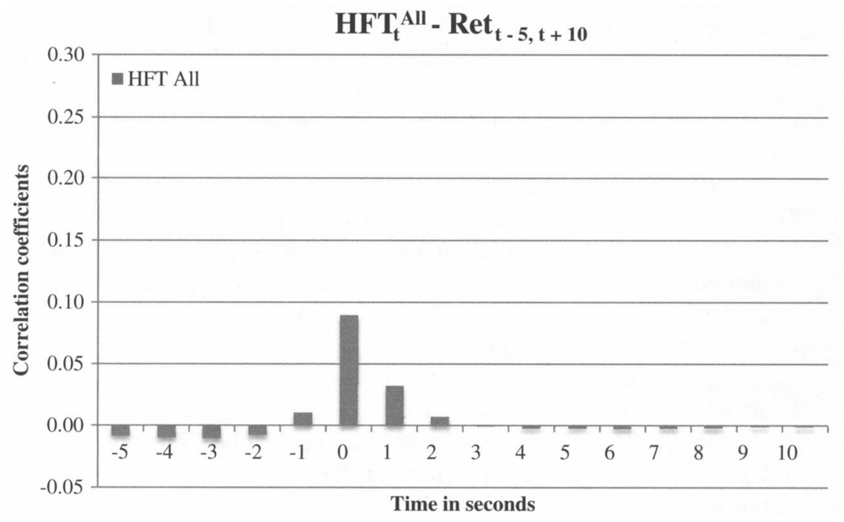

Figure 1
Overall correlation of *HFT* and returns
This figure plots an equal-weighted average of the stock-day correlations between HFT^{All} and returns five seconds prior to the future, contemporaneously, and up to ten seconds into the future in one-second increments.

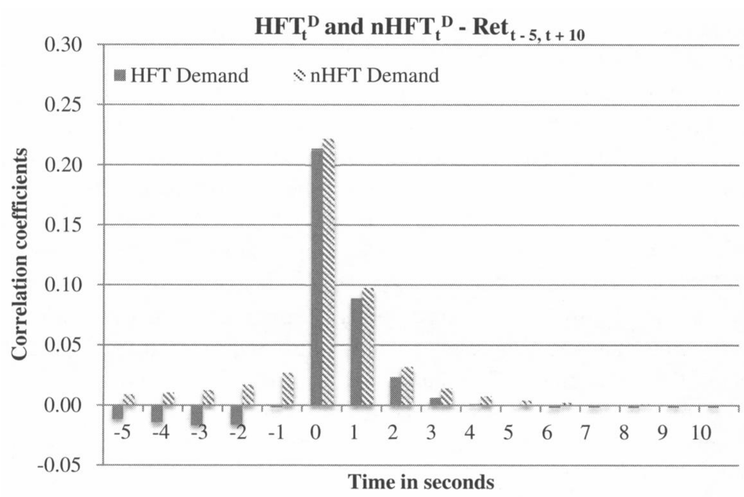

Figure 2
Correlation of returns with HFT and nHFT liquidity demand
This figure plots an equal-weighted average of the stock-day correlations between HFT^D, $nHFT^D$ and returns 5 seconds prior to the future, contemporaneously, and up to ten seconds into the future in one-second increments.

contemporaneous and subsequent returns with the relation approaching 0 eight to nine seconds in the future. These results suggest that although the direction of liquidity demand by both HFTs and nHFTs predicts future returns, information in HFT^D is more short lived than in $nHFT^D$.

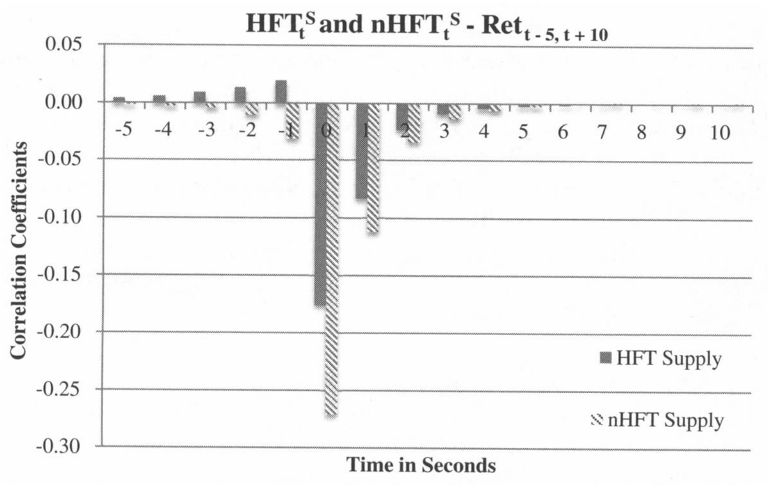

Figure 3
Correlation of returns with HFT and nHFT liquidity supply
This figure plots an equal-weighted average of the correlation between HFT^S, $nHFT^S$ and returns five seconds prior to the future, contemporaneously, and up to ten seconds into the future in one-second increments.

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, whereas 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.

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's trading overall positive correlation with past returns is driven by their liquidity demanding traded. The simple correlations provide useful information. However, strategies positively and negative related to past returns 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.

2.1 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.[11] The state space model assumes that the price of a stock can be decomposed into a permanent component and a transitory component (Menkveld, Koopman, and Lucas 2007):

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

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's (Forthcoming) 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

[11] Hendershott and Menkveld (Forthcoming) 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 the 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, that is, past prices, the current price, and future prices.

$w_{i,t}$ is formulated as

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

where $\widetilde{HFT}^D_{i,t}$ and $\widetilde{nHFT}^D_{i,t}$ are the surprise innovations in the corresponding variables. The surprise innovations are the residuals of a vector autoregression of HFT and nHFT on lagged HFT and nHFT. A lag length of ten (ten seconds) is used as determined by standard techniques.[12] 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

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

and the disaggregate model as

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

$HFT^{All}_{i,t}$ 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: $\mathrm{Cov}(\mu_t, \upsilon_t) = 0$. 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 (2006) for a detailed discussion.

2.2 State space model estimation

To estimate the state space model for each of the 23,400 one-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

[12] The optimal lag length is chosen that minimizes the Akaike information criterion (AIC). In the Internet Appendix, we present the results of a model estimated with lag lengths of 20 and 50 seconds.

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 (trade-by-trade). The NBBO estimation uses the sum of the signed order flow recorded in a particular second, whereas the NASDAQ BBO estimation uses each trade to estimate the model. For the NBBO sample, we require at least ten seconds with price changes and trading. For the NASDAQ BBO, we require at least ten 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 ten HFT^{All} trades associated with at least ten prices changes. This results in 503 days, for which we have adequate data, for at least one stock, for the NBBO (calendar time), and all 45 days for the NASDAQ BBO (event time).[13] We estimate the state space model 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 stock days). For medium and small stocks, the convergence rate is 98.7% and 97.4%, respectively. In most cases, the state space model 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 $\sigma(\upsilon)$ to range from zero 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 of 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.

[13] Out of the possible 23,400 seconds during the trading day the calendar time sample has the following daily average of the number seconds with trading: 4,690 for large stocks, 1,003 for medium stocks, and 341 for small stocks. The event time sample has the following daily average of the number of trades: 29,804 in large stocks, 2,587 in medium stocks, and 671 in small stocks.

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

Panel A: Permanent price component		Calendar time			Event time		
	Units	Large	Medium	Small	Large	Medium	Small
κ^{All}	bps/\$10,000	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)
$\sigma^2(\widetilde{HFT}^{All})$	\$10,000	3.07	0.54	0.19	0.77	0.26	0.12
$(\kappa^{All} * \sigma(\widetilde{HFT}^{All}))^2$	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
ϕ		0.49	0.50	0.46	0.43	0.39	0.38
ψ^{All}	bps/\$10,000	−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 $s_{i,t}$:

$$
\begin{aligned}
p_{i,t} &= m_{i,t} + s_{i,t}, \\
m_{i,t} &= m_{i,t-1} + w_{i,t}, \\
w_{i,t} &= \kappa_i^{All} \widetilde{HFT}_{i,t}^{All} + \mu_{i,t}, \\
s_{i,t} &= \phi s_{i,t-1} + \psi_i^{All} HFT_{i,t}^{All} + \upsilon_{i,t}.
\end{aligned}
$$

$HFT_{i,t}^{All}$ is HFTs; overall order flow; $\widetilde{HFT}_{i,t}^{All}$ is the surprise component of the order flow. Each stock is in one of three market capitalization categories: large, medium, or small. Columns 3–5 report coefficients for the entire sample at one-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.

The κ and ψ coefficients are in basis points per \$10,000 traded. The 0.21 large stock κ 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 ψ 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 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 κ is associated with informed trading. The more positive κ on HFT^D suggests that on a per dollar basis HFT is more informed

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
κ^D_{HFT}	bps/$10,000	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)
κ^D_{nHFT}	bps/$10,000	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)
$\sigma^2(\widetilde{HFT}^D)$	$10,000	3.02	0.52	0.17	0.68	0.23	0.11
$\sigma^2(\widetilde{nHFT}^D)$	$10,000	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)
$(\kappa^D_{nHFT} * \sigma(\widetilde{nHFT}^D))^2$	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
ϕ		0.59	0.54	0.45	0.36	0.37	0.36
ψ^D_{HFT}	bps/$10,000	−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)
ψ^D_{nHFT}	bps/$10,000	−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)
$\sigma^2(HFT^D)$	$10,000	3.05	0.54	0.18	0.73	0.25	0.12
$\sigma^2(nHFT^D)$	$10,000	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 and 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 $s_{i,t}$:

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

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

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

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

$HFT^D_{i,t}$ 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, or small. Columns 3–5 report coefficients for the entire sample at one-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 $\psi^D_{HFT} - \psi^D_{nHFT}$.

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.

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 and in longer-lived private information, which is not yet incorporated into the price. Whereas the corresponding coefficients for HFTs and nHFTs have the same sign, the HFT coefficients are larger in magnitude, consistent with HFTs' liquidity demand playing a larger role in improving price efficiency and imposing adverse selection.

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 state space model 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 κ^{HFT} and κ^{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 in which suppliers earn the spread but lose to informed traders.

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 ψ^{HFT} and ψ^{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.

Table 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 by the SEC (2010). Kyle-style (1985) 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 κ and a negative ψ. 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.

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
κ^S_{HFT}	bps/\$10,000	−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)
κ^S_{nHFT}	bps/\$10,000	−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)
$\sigma^2(\widetilde{HFT}^S)$	\$10,000	2.31	0.26	0.08	0.53	0.14	0.07
$\sigma^2(\widetilde{nHFT}^S)$	\$10,000	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
ϕ		0.56	0.54	0.45	0.38	0.39	0.36
ψ^S_{HFT}	bps/\$10,000	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)
ψ^S_{nHFT}	bps/\$10,000	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)
$\sigma^2(HFT^S)$	\$10,000	2.32	0.26	0.09	0.56	0.14	0.07
$\sigma^2(nHFT^S)$	\$10,000	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 one-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 demanding 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, or small. Columns 3–5 report coefficients for the entire sample at one-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 $\psi^S_{HFT} - \psi^S_{nHFT}$.

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 $\widetilde{HFT}^D$ 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.

Although 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 is 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 κ and a positive ψ. 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 by the 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 upward or downward to increase the arrival rate of buyers or sellers, for example, 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).[14] 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 ψ for HFTs' liquidity supply is consistent with risk management. The fact that coefficients on HFTs' liquidity supplying trades have more negative κ and more positive ψ than the corresponding coefficients for nHFTs' liquidity supplying trades is consistent with market-making-type strategies being a larger component of HFTs' order flow than for nHFTs. The ordering of these HFT and nHFT coefficients is also consistent with HFTs being worse than nHFTs at protecting themselves from adverse selection when supplying liquidity (inconsistent with Jovanovic and Menkveld's 2011 model). We view the risk management explanation as more plausible, but data on individual HFTs' inventory position are needed to be certain.

Hirshleifer, Subrahmanyam, and Titman (1994) provide a two-trading period model in which 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

[14] 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).

to be adversely selected by the later-informed traders because the benefits of risk reduction exceed the adverse selection costs. Hirshleifer, Subrahmanyam, and Titman (1994) 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 in which 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 (2013) derive the role of news trading 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 those by 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 in which prices overshoot because of 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 to 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 that 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.[15]

2.3 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, for example, investments in technology, data and collocation fees, salaries, or clearing fees. 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. For 2008 and 2009, we identify six fee and rebate changes affecting the top volume bracket.[16] 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.

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)

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

[15] In untabulated results we repeat the analysis in Tables 3, 4, 8, and 9 with only HN and NH trades for the large stocks. The coefficients are of similar magnitude across types of counterparty.

[16] 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.

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.[17] $nHFT^D$ revenues are calculated in the same manner. $\bar{\pi}^{*S,HFT}$ is calculated analogously,

$$\bar{\pi}^{*HFT,S} = \sum_{n}^{N} -(HFT_n^S) + INV\_HFT_N^S * P_T.$$

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

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

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

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.

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 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

[17] 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% 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. Carrion (2013) uses a benchmark price for the imbalance based on HFTs' trades. This primarily impacts the breakdown of revenues between supplying and demanding trades. Our methodology of using a posttrade benchmark is consistent with standard trading cost measures, such as realized spread. This ex post benchmark incorporates the price dynamics associated with a trade. Carrion's approach of using transaction prices of HFTs both before and after the relevant transaction is appropriate when the missing trades are randomly selected. The benchmark price is not important for overall revenue calculations but does impact the revenue decomposition between liquidity demand and liquidity supply.

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, or small. Columns 2–4 for 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.

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 become statistically significantly positive in large stocks, and nHFTs' revenues remain negative.[18]

Another concern highlighted by the SEC (2010) is 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 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

18 Using a different benchmark price for HFTs' end of day order flow imbalance Carrion (2013) finds that HFTs' liquidity supplying trades have positive revenues before the inclusion of NASDAQ's liquidity rebates.

of an integrated liquidity supplying and demanding strategy, then 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 forty 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 4% 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% of its trading volume.[19] 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, for example, large and 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, for example, the order flow of other strategies.

Determining the profitability of HFTs is difficult. Without knowledge of the capital employed and technology costs, the revenue figures provide only a rough estimate of industry profitability. The Getco S-4 filing shows that for 2008 and 2009 costs were roughly two-thirds of revenues.

The revenue analysis suggests that HFTs have positive revenues, but these are small compared with their trading volume. 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.

3. State Space Model on High Permanent Volatility Days

The SEC (2010, 48) and others express concern about market performance during times of stress. To better understand HFTs' and nHFTs' relative roles

[19] The financial information for Knight Trading and Getco can be found at http://services.corporate-ir.net/SEC/Document.Service?id=P3VybD1hSFIwY0RvdkwyRndhUzUwWlc1cmQybDZZWEprTG1OdmJTOWtiM2R1Ykc5aFpDNXdhSEEvWVdOMGFXOXVQVkJFUmlacGNHRm5aVDA0TnpFMk56QTVKbk4xWW5OcFpEMDFOdz09JnR5cGU9MiZmbj04NzE2NzA5LnBkZg==.

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 90th percentile for that stock. Each stock is in one of three market capitalization categories: large, medium, or small. The closing midquote price is the average bid-and-ask price at the close. Trading volume is the average dollar trading volume and is also reported for HFTs and nHFTs.

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 90th percentile. We then compare those days to the remaining 90% of days.

Table 6 reports descriptive statistics 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.

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

Panel A: Permanent price component		High permanent volatility			Other		
	Units	Large	Medium	Small	Large	Medium	Small
κ^{All}	bps/\$10,000	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)
$\sigma^2(\widetilde{HFT}^{All})$	\$10,000	2.45	0.46	0.14	3.13	0.55	0.20
$(\kappa^{All} * \sigma(\widetilde{HFT}^{All}))^2$	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		
	Units	Large	Medium	Small	Large	Medium	Small
ϕ		0.50	0.45	0.40	0.49	0.51	0.46
ψ^{All}	bps/\$10,000	−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)
$\sigma^2(HFT^{All})$	\$10,000	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 one-second increments) into two components: the unobservable efficient price $m_{i,t}$ and the transitory component $s_{i,t}$:

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

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

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

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

$HFT_{i,t}^{All}$ is HFTs' overall order flow; $\widetilde{HFT}_{i,t}^{All}$ is the surprise component of the order flow. Each stock is in one of three market capitalization categories: large, medium, or 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 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. t-statistics are calculated using standard errors double clustered on stock and day.

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 impose more adverse selection 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 the role of HFTs in price discovery is qualitatively similar on high permanent volatility days, which are generally associated with heightened market stress.[20] If one believes that HFTs can create information and permanent volatility, then Table 7 suggests that HFTs play a role in creating higher permanent volatility days. We think it more likely that HFTs simply incorporate existing higher volatility into prices on these days.

Table 9 reports results for HFT^S and $nHFT^S$ in the same format as Table 8. We find that the coefficients on κ and ψ how 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.

4. 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.[21] We focus on three types of information

---

20 Revenue analysis as in Table 5 for high permanent volatility days is available in the Internet Appendix.

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

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
κ^D_{HFT}	bps/\$10,000	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)
κ^D_{nHFT}	bps/\$10,000	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)
$\sigma^2(\widetilde{HFT}^D)$	\$10,000	2.52	0.45	0.11	3.08	0.53	0.17
$\sigma^2(\widetilde{nHFT}^D)$	\$10,000	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
ϕ		0.63	0.47	0.38	0.58	0.54	0.46
ψ^D_{HFT}	bps/\$10,000	−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)
ψ^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)
$\sigma^2(HFT^D)$	\$10,000	2.54	0.46	0.13	3.10	0.54	0.19
$\sigma^2(nHFT^D)$	\$10,000	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 one-second increments) into two components: the unobservable efficient price $m_{i,t}$ and the transitory component $s_{i,t}$:

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

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

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

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

$HFT^D_{i,t}$ 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, or 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
κ^S_{HFT}	bps/$10,000	−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)
κ^S_{nHFT}	bps/$10,000	−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)
$\sigma^2(\widetilde{HFT}^S)$	$10,000	1.81	0.20	0.07	2.36	0.26	0.09
$\sigma^2(\widetilde{nHFT}^S)$	$10,000	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
ϕ		0.61	0.47	0.38	0.56	0.54	0.46
ψ^S_{HFT}	bps/$10,000	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)
ψ^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)
$\sigma^2(HFT^S)$	$10,000	1.82	0.21	0.08	2.38	0.27	0.10
$\sigma^2(nHFT^S)$	$10,000	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$^{\text{th}}$ 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 one-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, or 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.

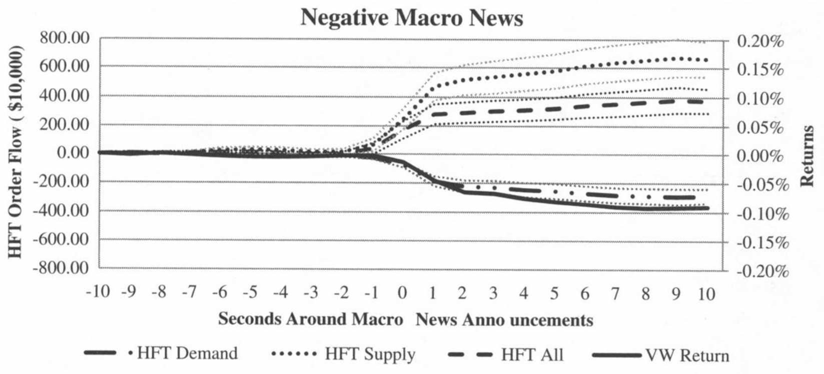

Figure 4
HFT trading and portfolio returns for positive macro announcements
This figure plots the value-weighted sample portfolio return and HFT^D, HFT^S, and HFT^{All} around negative macroeconomic news announcements. Time is in seconds, and at time $t=0$ news is made publicly available. Positive announcements are those below the average analyst forecast. Five percent and 95% confidence intervals are denoted with dotted lines.

identified in prior literature: macroeconomic news announcements, market-wide returns, and imbalances in the limit order book.[22]

4.1 Macro news announcements

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

Although 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. Although this usually matches the anticipated report time, there are several occasions for which 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

[22] 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).

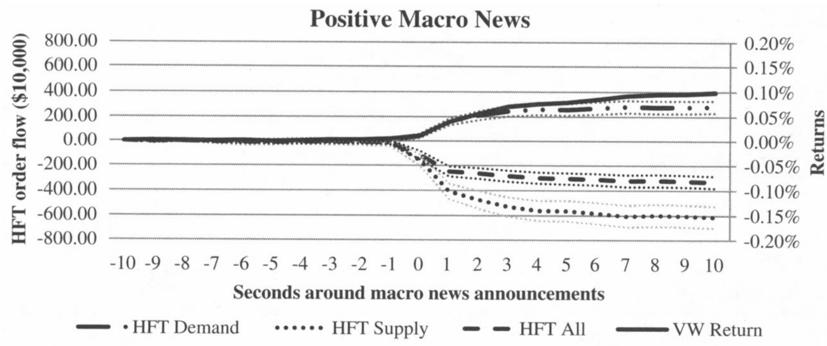

Figure 5
HFT trading and portfolio returns for negative macro announcements
This figure plots the value-weighted sample portfolio return and HFT^D, HFT^S, and HFT^{All} around positive macroeconomic news announcements. Time is in seconds, and at time $t = 0$ news is made publicly available. Negative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

the average analyst's forecast as reported by Bloomberg and is considered a negative announcement if it is below the forecasted average.

Both figures show that at time $t = 0$, prices begin to move in the direction of the macroeconomic 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, resulting 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, for example, 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

Table 10
HFT and returns around macroeconomic news announcements

	Large	Medium	Small
$HFT^{\prime D}_{t-1,t+1}$	0.08	1.06	1.35
(t-stat.)	(2.03)	(2.26)	(1.99)
$HFT^{\prime S}_{t-1,t+1}$	−0.14	0.23	−4.30
(t-stat.)	(−4.30)	(0.24)	(−1.36)
$HFT^{\prime All}_{t-1,t+1}$	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. $HFT^{\prime D,S,All}_{i,t-1,t+1}$ 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 ten seconds afterward.

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

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

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 $HFT^{\prime D,S,All}_{i,t-1,t+1}$ is the cumulative HFT order flow imbalance from one second before to one second after a macroeconomic announcement becomes publicly available; $Ret_{i,t+2,\ t+10}$ is the cumulative return in basis points from two seconds after the macroeconomic announcement through ten seconds afterward. The regression pools all 209 announcements for all stocks. Statistical significance is calculated by controlling for contemporaneous correlation across stocks and 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. Results are reported for HFT^D, HFT^S, and HFT^{All}.

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

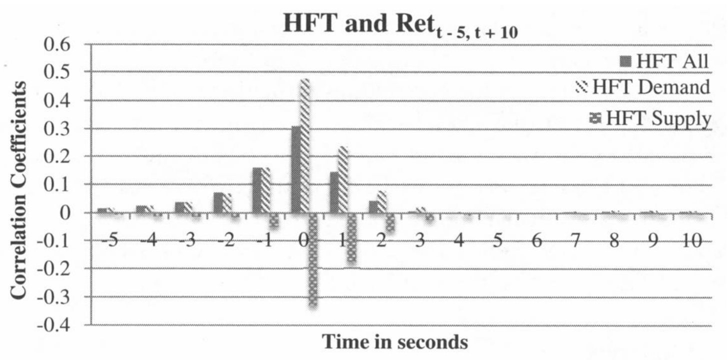

Figure 6
Correlation of market-wide returns with *HFT*
This figure plots the correlation between $HFT^{All,D,S}$ aggregated across all stocks and value-weighted portfolio returns five seconds prior to the future, contemporaneously, and up to ten seconds into the future in one-second increments.

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 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.

4.2 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.

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 HFTs play a somewhat more important and longer-lasting role in market-wide price discovery, although still over short time horizons. This is also consistent with 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.

4.3 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:

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

where *Size* is the dollar volume of orders available at the NBBO. *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:

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

where $HFT_{i,t}^{D,S,All}$ 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, for example, buying when there are fewer shares offered to buy than there are 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 by stock.

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 HFT^S regression suggests that HFTs often supply liquidity on the thin side of the limit order book. This involves possibly

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}_{t-1}	0.20	4.33	−32.98
	(t-stat.)	(1.65)	(9.32)	(−0.59)
HFT All	HFT^{All}_{t-2}	−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^{D}_{t-1}	0.52	7.84	2.88
	(t-stat.)	(2.70)	(10.34)	(0.15)
HFT Demand	HFT^{D}_{t-2}	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^{S}_{t-1}	−1.43	−11.96	−50.57
	(t-stat.)	(−4.56)	(−8.17)	(−1.40)
HFT Supply	HFT^{S}_{t-2}	−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: $LOBI_{i,t} = (Size^{Offer}_{i,t} - Size^{Bid}_{i,t})/(Size^{Offer}_{i,t} + Size^{Bid}_{i,t})$ where *Size* is the dollar volume of orders available at the NBBO scaled by 10,000. Panel A regresses HFTs' order flows in period t on Ret_{t-1} and $LOBI_{t-1}$: $HFT^{D,S,All}_{i,t} = \alpha + \beta_1 LOBI_{i,t-1} + \beta_2 Ret_{i,t} + \varepsilon_{i,t}$, where $HFT^{D,S,All}_{i,t+1}$ is HFTs' dollar volume order flow scaled by 10,000. Panel B reports returns regressed on prior HFTs' order flows and LOBI: $Ret_{i,t} = \alpha + \beta_1 HFT^{D,S,All}_{i,t-1} + \beta_2 HFT^{D,S,All}_{i,t-2} + \beta_3 LOBI_{i,t-1} + \beta_4 Ret_{i,t-1} + \varepsilon_{i,t}$. 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, or small.

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 the coefficient on the second lag of HFT^S is much smaller than the first lag coefficient. As with the correlations and state-space model, HFT^D positively predicts future returns and HFT^S negatively predicts future returns. The HFT^{All} analysis shows that the HFT^D results dominate.

5. 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.[23] 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 which information is public and how it gets into prices, for example, the incentives to invest in information

[23] 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 largely focus on HFT liquidity supply.

acquisition in Grossman and Stiglitz (1980). As Hasbrouck (1991, 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 nonpublic 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, 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 in the opposite direction."[24] 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 (2012) 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.

6. 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 nonmarketable 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

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

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.[25]

One important concern about HFTs is their role in market stability.[26] 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 by 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 toward 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 behaviors of HFTs are also important areas of subsequent research.

HFTs are a type of intermediary different from traditional market makers. 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, for example, requiring continuous liquidity supply and limiting liquidity demand, that outweigh lower innovation and higher entry costs typically associated with regulation.

---

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

[26] 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.

References

Amihud, Y., and H. Mendelson. 1980. Dealership market: Market-making with inventory. *Journal of Financial Economics* 8:31–53.

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega. 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review* 93:38–62.

Biais, B., T. Foucault, and S. Moinas. 2011. Equilibrium high frequency trading. Working Paper.

Biais, B., and P. Woolley. 2011. High frequency trading. Working Paper.

Boehmer, E., K. Fong, and J. Wu. 2012. International evidence on algorithmic trading. Working Paper.

Cao, C., O. Hansch, and X. Wang. 2009. The information content of an open limit-order book. *Journal of Futures Markets* 29:16–41.

Carrion, A. 2013. Very fast money: 'High-frequency trading on the NASDAQ.' *Journal of Financial Markets* 16:680–711.

Cartea, A., and J. Penalva. 2012. Where is the value in high frequency trading? *Quarterly Journal of Finance* 2.

Chaboud, A., B. Chiquoine, E. Hjalmarsson, and C. Vega. (Forthcoming) Rise of the machines: Algorithmic trading in the foreign exchange market. *Journal of Finance*.

Colliard, J.-E. 2013. Catching falling knives: Speculating on market overreaction. Working Paper.

Colliard, J.-E., and T. Foucault. 2012. Trading fees and efficiency in limit order markets. *Review of Financial Studies* 25:3389–421.

Duhigg, C. "Stock traders find speed pays, in milliseconds." *New York Times*, July 25, 2009.

Easley, D., M. M. Lopez de Prado, and M. O'Hara. 2011. The microstructure of the 'flash crash': Flow toxicity, liquidity crashes, and the probability of informed trading. *Journal of Portfolio Management* 37:118–28.

———. 2012. Flow toxicity and liquidity in a high frequency world. *Review of Financial Studies* 25:1457–93.

Foucault, T., J. Hombert, and I. Rosu. 2013. News trading and speed. Working Paper.

Foucault, T., A. Roell, and P. Sandas. 2003. Market making with costly monitoring: An analysis of the SOES controversy. *Review of Financial Studies* 16:345–84.

Groß-Klußmann, A., and N. Hautsch. 2010. When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. *Journal of Empirical Finance* 18:321–40.

Grossman, S., and J. Stiglitz. 1980. On the impossibility of informationally efficient markets. *American Economic Review* 70:393–408.

Hagströmer, B., and L. Norden. 2013. The diversity of high frequency traders. *Journal of Financial Markets* 16:741–70.

Hasbrouck, J. 1991. The information content of stock trades. *Journal of Finance* 46:179–207.

———. Empirical market microstructure: The institutions, economics, and econometrics of securities trading. Oxford University Press, 2006.

Hasbrouck, J., and G. Saar. 2013. Low latency trading. *Journal of Financial Markets* 16:646–79.

Hasbrouck, J., and G. Sofianos. 1993. The trades of market makers: An empirical analysis of NYSE specialists. *Journal of Finance* 48:1565–93.

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

Hendershott, T., and A. Menkveld. Forthcoming. Price pressures. *Journal of Financial Economics*.

Hendershott, T., and R. Riordan. 2013. Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis* 48:1001–24.

Hirschey, N. 2013. Do high-frequency traders anticipate buying and selling pressure? Working Paper.

Hirshleifer, D., A. Subrahmanyam, and S. Titman. 1994. Security analysis and trading patterns when some investors receive information before others. *Journal of Finance* 49:1665–98.

Ho, T., and H. Stoll. 1981. Optimal dealer pricing under transaction cost and return uncertainty. *Journal of Financial Economics* 9:47–73.

Jain, P. 2005. Financial market design and the equity premium: Electronic vs. floor trading. *Journal of Finance* 60:2955–85.

Jovanovic, B., and A. Menkveld. 2011. Middlemen in limit-order markets. Working Paper.

Keim, D., and A. Madhavan. 1995. Anatomy of the trading process empirical evidence on the behavior of institutional traders. *Journal of Financial Economics* 37:371–98.

———. 1997. Transactions costs and investment style: An inter-exchange analysis of institutional equity trades. *Journal of Financial Economics* 46:265–92.

Kirilenko, A., A. Kyle, M. Samadi, and T. Tuzun. 2011. The flash crash: The impact of high frequency trading on an electronic market. Working Paper.

Kyle, A. 1985. Continuous auctions and insider trading. *Econometrica* 53:1315–35.

Madhavan, A., and G. Sofianos. 1998. An empirical analysis of NYSE specialist trading. *Journal of Financial Economics* 48:189–210.

Malinova, K., A. Park, and R. Riordan. 2012. Do Retail Traders Suffer from High Frequency Traders? Working Paper.

Menkveld, A. 2011. High frequency trading and the new-market makers. Working Paper.

Menkveld, A., S. J. Koopman, and A. Lucas. 2007. Modeling around-the-clock price discovery for cross-listed stocks using state space models. *Journal of Business & Economic Statistics* 25:213–25.

Nagel, S. 2012. Evaporating liquidity. *Review of Financial Studies* 25:2005–39.

O'Hara, M. 2003. Liquidity and price discovery. *Journal of Finance* 58:1335–54.

Pagnotta, E., and T. Philippon. 2011. Competing on speed. Working Paper.

Panayides, M. 2007. Affirmative obligations and market making with inventory. *Journal of Financial Economics* 8:513–42.

Petersen, M. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22:435–80.

Securities and Exchange Commission. 2010. Concept release on equity market structure, Release No. 34-61358. File No. S7-02-10.

Sofianos, G. 1995. Specialist gross trading revenues at the New York Stock Exchange. Working Paper.

Thompson, S. 2011. Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics* 99:1–10.