Liquidity Provision of High Frequency Traders in Stressful States: Evidence from the KOSPI 200 Futures Market

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Abstract

We study high frequency traders' (HFTs) trading activity during stressful states and normal states. From the high-quality intraday transaction data of the KOSPI 200 futures market, we find that HFTs demand liquidity in normal times, and demand even more in extreme price movements (EPMs). Among the HFTs, foreign HFTs demand liquidity the most and earn the highest profits. Foreign HFTs take liquidity in advance of EPMs, which implies their timing ability (quote-sniping). We argue that HFTs in the KOSPI futures market exploit low-frequency traders by taking the liquidity both in normal and extreme states.

JEL classification: G14

Keywords: liquidity provision; high frequency traders; extreme price movements; market quality

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Abstract

We study high frequency traders' (HFTs) trading activity during stressful states and normal states. From the high-quality intraday transaction data of the KOSPI 200 futures market, we find that HFTs demand liquidity in normal times, and demand even more in extreme price movements (EPMs). Among the HFTs, foreign HFTs demand liquidity the most and earn the highest profits. Foreign HFTs take liquidity in advance of EPMs, which implies their timing ability (quote-sniping). We argue that HFTs in the KOSPI futures market exploit low-frequency traders by taking the liquidity both in normal and extreme states.

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1 Introduction

As technology has advanced considerably over recent decades, modern markets encounter a new type of traders called "High-frequency traders (HFTs)". The U.S. Securities and Exchange Commission (SEC) referred to this newly emerged traders as "professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis" and identified their characteristics as follows: (i) the use of high speed and sophisticated programs for generating, routing, and executing orders; (ii) use of co-location services and individual data feeds offered by exchanges and others to minimize network and other types of latencies; (iii) very short time-frames for establishing ad liquidating positions; (iv) the submission of numerous orders that are cancelled shortly after submission and (v) ending the trading day in as close to a flat position as possible.[1] At present, HFTs become dominant traders in the current market structure, and their trading activity is likely to have crucial effects on its performance. Thus, understanding the effects of HFTs on market quality is important to researchers, practitioners, and policy makers.

HFTs with speed advantage are able to implement various strategies that may cause mixed effects on markets. On the one hand, fast reaction to market condition enables HFTs to avoid "being picked off", and to provide more attractive quotes and then narrower bid-ask spread. For example, Hendershott, Jones, and Menkveld (2011) and Hasbrouck and Saar (2013) show that quoted and effective bid-ask spreads are decreased as HFTs trade more actively in the U.S. stock market. Boehmer, Fong, and Wu (2015), Benos and Sagade (2012), Malinova, Park, and Riordan (2013), Menkveld (2013), and Riordan and Storkenmaier (2012) find similar results in international equity markets. Other than equity markets, HFTs are reported to be beneficial to market quality in foreign exchange market (Chaboud, Chiquoine, Hjalmarsson, & Vega, 2014), in the Korean ELW market (Chae, Khil, & Lee, 2013), and in the KOSPI 200 option market (Jeon, Kang, & Kang, 2013).

On the other hand, HFTs use their fast access to the markets in order to make profit at the expense of

[1] See SEC Concept Release on Equity Market Structure, 75 Fed. Reg. 3603, January 21, 2010

low-frequency traders. This adverse selection cost can induce the low-frequency traders to participate less in the markets, which is detrimental to market liquidity. Biais, Foucault, and Moinas (2015) find the socially optimal level of investment in fast trading technologies with consideration for adverse selection cost which gives rise to negative externality to the social welfare. Brogaard, Hendershott, and Riordan (2017) indicate that HFTs' trading and HFTs' short selling decreases liquidity by adversely selecting liquidity suppliers during the short-sale ban period. In addition, HFTs can manipulate markets by exploiting their fast market access. Egginton, Van Ness, and Van Ness (2016) and Ye, Yao, and Gai (2013) find empirical evidence consistent with "quote stuffing", which is to slow down other traders by sending a huge number of messages. Besides, many manipulation plots, such as "smoking", "spoofing" and "momentum ignition strategies", are employed by HFTs in the markets. It is hard to say that those HFTs' trading activities enhance market quality. Collectively, it is not clear how HFTs affect market quality. The empirical evidences are reported conflictingly depending on sample periods, markets, and empirical methodologies.

On May 6, 2010, the U.S. financial markets experienced "the Flash Crash" where the E-mini S&P 500 stock index price declined rapidly and rebounded during 36 minutes after a large automated selling program was rapidly executed. Subsequently to this systematic intraday event, it is important to investigate whether HFTs, who do not have any obligation to provide liquidity in stressful states, are actually reliable. Kirilenko, Kyle, Samadi, and Tuzun (2017) use audit trail transaction-level data for the E-mini S&P 500 stock index futures market and conclude that HFTs' trading pattern did not change when price dropped during the Flash Crash. Brogaard et al. (2016) deal with this issue by seeing HFTs' activity around extreme price movements (EPMs) in the NASDAQ market. They show that HFTs provide liquidity during EPMs except for co-EPMs when multiple stocks simultaneously go though EPMs. However, except for these two papers, empirical works on HFTs' activity during stressful states are rare.

This paper examines HFTs' trading activity during stressful states as well as during normal states in the KOSPI 200 index futures market from January 2010 to June 2014. We use the high-quality data that records all transaction-by-transaction trade data for the KOSPI 200 futures. The use of our dataset has a number of advantages. First, the data includes encrypted account information that enables us to measure HFTs directly. Without any HFT identifier, we define the HFTs from their pure trading activities. Second, thanks to the data, we further classify the HFTs by different investor groups (individual, institutional, and foreign) from the investor group identifier. We study the behavior of different investors around the extreme events to see the clear picture during intervals near extreme events. Third, in contrast to the NASDAQ HFT data, the KOSPI 200 futures market does not suffer from any market fragmentation. Therefore, we do not worry about the HFTs who behave differently in other fragmented markets. For trading activity, we mainly focus on whether HFTs provide liquidity or take liquidity. When we measure liquidity provision, we do not use traditional liquidity measures, such as bid-ask spreads and depth, since in the era of HFTs they are no longer good proxies for liquidity. Instead, we compute directional trade imbalances, which indicate whether traders trade in the direction of price movement or in the opposite direction. We also compute HFTs' profitability and check whether HFTs' trading activity during stressful states can bring profit to themselves.

The main results can be summarized as follows. First, HFTs take market liquidity during normal states and take even more during in states of extreme price movements (EPMs). We argue that it is consistent not only with their price impact but also with their timing ability (quote-sniping). Compared to Brogaard et al. (2016) and Kirilenko et al. (2017), this paper provides the conflicting evidence that HFTs do not act as liquidity suppliers in the Korean index futures market. Second, we show that the overall behavior of HFTs are mostly from foreign HFTs. They trade in direction of extreme price changes in advance without changing the price much, and individual and institutional traders do not make significant movement before the EPMs. Therefore, we argue that foreign HFTs exploit the market with their speed, algorithmic, and informational advantage. Third, foreign HFTs earn the highest profit from their liquidity-demanding strategy. Individual and institutional HFTs do not earn high profit compared to foreign HFTs. Finally, we observe that foreign HFTs earn higher profit with more extreme price movement events. In conclusion, the liquidity-demanding behavior of (foreign) HFTs is even stronger in extreme times, and by doing so they earn more profit.

We contribute to the literature in the following aspects. First, we add empirical evidence to the debate about the role of HFTs in market quality. Our results indicate that the HFTs trading direction is the same direction as price movements, and they even more in the events of extreme movement of prices. This is consistent with the conclusion of Brogaard, Hendershott, and Riordan (2014) and E. J. Lee (2015) and is in a sharp contrast to the results in Kirilenko et al. (2017) and Brogaard et al. (2016) in the U.S. stock and futures market. Second, by looking at the behavior of HFTs closer in intervals around the events, we show that HFTs take liquidity in advance to big swings of prices. This behavior is consistent of the view that HFTs exploit the market. Third, since our evidence suggests that foreign HFTs drive most of our results, we contribute to the literature about foreigners' relative informativeness and superiority in the trading strategies. For example, Ahn, Kang, and Ryu (2008), Chakravarty (2001), and Kang, Kang, and Lee (2016) argue that foreginers are more informative, whereas Chan, Menkveld, and Yang (2007) and Cho, Kho, and Stulz (2005) show that foreign investors are informationally inferior. Our work show that in some way, foreign HFTs have an edge relative to domestic individuals and institutions.

The rest of the paper is organized as follows. Section 2 explains the environment of the KOSPI 200 index futures market. Section 3 describes our dataset. In Section 4, we present our empirical methodology: trader categorization, EPM identification, and measure of liquidity provision. Section 5 shows the main empirical results and Section 6 deals with robustness checks. In Section 7, we summarize the paper and leave concluding remarks.

2 Market Environment

Since the Korea Exchange (KRX) listed the KOSPI 200 index futures and options on May 1996 and July 1997, respectively, the markets have achieved outstanding development albeit short histories. The Futures Industry Association (FIA) reported that in 2011 the KOSPI 200 index derivatives were the most actively traded derivative contracts in the world.[1] After the Korean authorities decided to put restrictions on individual investors' accounts and increase the option multiplier in March 2012, however, the trading volume of the KOSPI 200 index derivatives has collapsed sharply. During our sample period spanning before and after the structural change, the KOSPI 200 index futures and options markets were one of the major derivative markets in the world.

The KOSPI 200 index futures are traded exclusively on the KRX trading platform. Therefore, in contrast to the studies that focus on the U.S. financial markets, our results do not suffer from market fragmentation. The KOSPI 200 index futures market is a fully electronic limit order market without floor traders and designated market makers. The market opens at 9:00 a.m. and closes at 3:15 p.m., 15 minutes after the closing time of the stock market. The opening price is determined by a batch auction at a one-hour pre-opening session (8:00 a.m. to 9:00 a.m.), and for the last ten minutes until the market closes (3:05 p.m. to 3:15 p.m.) orders are executed in the closing batch auction. The market adopts the price-time priority, a rule that orders which offer better prices will be firstly executed, and if the prices are the same orders which come first will be executed. The minimum tick size of the market is 0.05 index point, and one index point had its value of KRW500,000 during our sample period, implying the minimum tick value was $0.05 \times \text{KRW}500{,}000 = \text{KRW}25{,}000$.

One notable feature of the KOSPI 200 index futures market is that it requires negligible transaction cost and no tax, which is a crucial advantage to (foreign) HFTs. The KRX imposes 0.3% tax of transaction on the sale of equity. However, for exchange-traded derivatives, investors are not required to pay capital gains tax as well as tax of transaction.

[1] According to the FIA Annual Volume Survey in 2011, the KOSPI 200 options took the 1st rank of global equity index futures & options contracts with 3,671,662,258 cumulative contracts during 2011. And the KOSPI 200 futures took the 15th rank with 86,214,025 cumulative contracts during 2011. After the increase in the option multiplier in March 2012, the number of contracts traded and/or cleared in the KOSPI 200 futures and options in 2012 were declined by 28.5% and 57.1%, respectively, compared to 2011. Still, the KOSPI 200 options and futures took the 1st and 20th rank of global equity index futures & options contracts in 2012.

3 Data Description

Offered from the KRX, our high-quality data encompasses all transaction-by-transaction trade records for all trading days from January 2010 to June 2014 (1,115 trading days). Our sample period is very long relative to other studies related to HFTs. Each transaction is time-stamped in a millisecond unit, and has data fields including encrypted account information, investor group identifier (foreign, individual, and institutional), buyer-seller identifier and order acceptance number. The encrypted account information enables us to look into trading activities account-by-account. Therefore, after we collectively see the trading activity of each account, we can categorize each investor into some investor groups such as HFT and fundamental buyer. Based on the investor group identifier, we further classify HFTs as foreign, individual, and institutional HFTs. The buyer-seller identifier and the time-ordered order acceptance number allow us to determine exactly whether each transaction is buyer-initiated or seller-initiated without depending on C. Lee and Ready (1991) algorithm. For example, if the seller has larger order acceptance number, it means that the seller initiates the trade and takes the existing order of the buyer. We use only the front-month futures contracts since longer-maturity futures contracts are rarely traded. We focus on continuous normal trading hours, from 9:00 am. to 3:05 pm. Also, to avoid frictions in the beginning and ending the market, we discard the first and the last five minutes in our sample. The resulting trading hour in our sample is from 9:05 am to 3:00 pm. To calculate dollar volume, we use the fixed exchange rate of 1,153.3 (1,014.4) KRW/USD for January 2010 to December 2011 (January 2012 to June 2014) which was the exchange rate on December 30, 2011 (June 30, 2014).

4 Empirical Methodology

4.1 Trader categorization

The KOSPI 200 index futures market does not have traders with formal designation such as floor traders and market makers. We classify accounts as intraday intermediaries using a data-driven approach based on trading activity and inventory patterns. Specifically, following Kirilenko et al. (2017), for each day

d, an account i is defined as an intraday intermediary if the account i meets the following three criteria:

(i) The account i should trade 10 or more contracts.

$$VOL_{i,d} \geq 10$$

(ii) The absolute value of the ratio of the account i's end-of-day net position to its daily trading volume do not exceed 5%.

$$\frac{\left|NP_{i,d,t=365}\right|}{VOL_{i,d}} \leq 5\%$$

(iii) The square root of the account i's daily mean of squared end-of-minute net position deviations from its end-of-day net position over its daily trading volume do not exceed 1%.

$$\sqrt{\frac{1}{365}\sum_{t=1}^{365}\left(\frac{NP_{i,d,t} - NP_{i,d,t=365}}{VOL_{i,d}}\right)^2} \leq 1\%$$

where $VOL_{i,d}$ is trading volume of the account i on day d, and $NP_{i,d,t}$ is a net inventory position of the account i in minute t of day d. The criteria (i)-(iii) capture that intraday intermediaries trade significant amount of contracts, end a trading day with near-zero position relative to their daily trading volume, and have mean-reverting inventories at high-frequency, respectively. Note that these cutoff levels are specific to the KOSPI 200 index futures market. Among intraday intermediaries, for each day, we further classify the 20 most active accounts in terms of daily trading volume as high-frequency traders (HFTs) and the remaining accounts as market makers (MMs).

Following Kirilenko et al. (2017), on each day, we classify all other accounts as small traders (STs), fundamental buyers (FBs), fundamental sellers (FSs), and opportunistic traders (OTs). Specifically, if an account trades less than 10 contracts, it is classified as a ST. If an account trades 10 or more contracts and accumulates a net long end-of-day position equal to at least 15% of its total trading volume for the day, then it is classified as a FB. If an account trades 10 or more contracts and accumulates a net short end-of-day position equal to at least 15% of its total trading volume for the day, then it is classified as a FS. Finally, all the remaining accounts are classified as OTs.

Our trader classification is carried out in a daily basis. Since we adopt the data-driven approach to identify HFTs, one may concern that some account is classified as a HFT on one day but is classified as a non-HFT on another day. Since HFTs and MMs are differentiated only by trading volume, we admit the possibility that an account identified as a HFT yesterday may act as a MMs today in our classification, *i.e.*, the account trades less than yesterday for some reason. However, we want to emphasize that the transition between intraday intermediaries and non-intraday intermediaries is unusual.

Figure 1 provides the visual indication of trader categorization on selected days.[1] Each account is scattered in a plane where the y-axis is its daily trading volume and the x-axis is its end-of-day position divided by the daily trading volume. For all panels of Figure 1, HFTs are spread out vertically around zero net end-of-day position and are distinct from MMs who are near the origin. FBs (FSs) are located to the right (left) of the origin. STs are spread out close to the x-axis due to their small number of contracts. OTs are located around the origin and overlap with other trader categories. Therefore, on extreme trading days as well as normal trading days, our trader classification suits consistently well to our purpose.

Table 1 reports summary statistics for all trader categories. According to Panel A of Table 1, HFTs who consist of 20 accounts on each day account for the most significant trading volume over the trader types during our sample period. They are involved in about 38% of total dollar volume and share volume, and trade 2.41 contracts per each transaction which are chosen out of 19.15 contracts they send to the market. Almost all portion of their trading volume is transacted by limit orders. One notable thing is that HFTs are more aggressive than fundamental buyers and sellers, which is measured by "Aggressiveness", defined by the percentage of trading volume that resulted from marketable orders

[1] The first panel of Figure 1 is the case for March 31, 2010 which was a normal trading day. The second panel of Figure 1 represents the case for August 8, 2011, the day when the U.S. credit rating is downgraded. On that day, the KOSPI 200 index futures price was extremely volatile, which leads to the highest number of EPMs occurred (See Figure 2). The third and fourth panel of Figure 1 shows the cases for maturity dates of the futures contracts.

(market orders and marketable limit orders). It implies that HFTs trade aggressively via marketable limit orders.

We further classify HFTs by investor groups, and summary statistics for each HFTs investor group are shown in Panel C of Table 1. Foreign HFTs consist of about 8 traders per day and occupy more than half of total HFTs trading volume. They use limit orders exclusively and are much more aggressive than individual and institutional HFTs. Individual HFTs negligibly participate in the market. Institutional HFTs have similar statistics to foreign, except that they are relatively passive.

4.2 EPM identification

Our focus is to examine HFTs' trading activity during stressful states. Following (Brogaard et al. (2016)), we define stressful states as the intervals of extreme price movements (EPMs). Specifically, we identify EPMs as extreme changes in the best bid and offer midquotes to exclude the bid-ask bounce effect. To avoid the possibility that the price may be dislocated in the market opening and closing procedures, we consider trading activity between 9:05 a.m. and 3:00 p.m. that removes five minutes in both ends.

We compute EPMs for various time intervals: 1-, 5-, 10-, 30-, and 60-second intervals. Except for 1-second EPMs, the empirical results for 5-, 10-, 30- and 60-second EPMs are qualitatively similar. The results for an extremely high-frequency time interval, one second, provides us more intuition on HFTs' trading activity. Therefore, in the main empirical results of this paper, we report 1-second and 10-second results and compare with each other.

We adopt two approaches to identify EPMs. First, we identify EPMs as all intervals that belong to the 99.9th percentile of absolute midquote returns. Second, we identify EPMs as all intervals that belong to the 99.9th percentile of absolute midquote return residuals from the following a short-term market model:

$$r_t = \hat{a}_1 r_{t-1} + \cdots + \hat{a}_5 r_{t-5} + e_t$$

where $\hat{a}_i$'s are OLS estimators in the previous day. Throughout the empirical results, we use the second approach since it captures unpredictable changes in the price level. The first approach of EPM identification produces the similar results.

Figure 2 shows the daily frequency of EPMs over sample dates and the intraday frequency over trading times for 10-second and 1-second EPMs. In both of 10-second and 1-second EPMs (the left two panels), the largest number of EPMs can be found on August 9, 2011, the day after the U.S. credit rating was downgraded. The right two panels of Figure 2 indicate that most EPMs occur early in the morning (9:05 a.m. ~ 9:35 a.m.) and are evenly distributed after that time. Note that both daily and intraday frequencies for 10-second EPMs are similarly distributed as those for 1-second EPMs.

Table 2 reports summary statistics for EPM intervals in Panel A and for all intervals in Panel B. As expected, price changes, trading intensity, and bid-ask spreads are substantially higher during EPMs than during all intervals. The average absolute returns during 10-second and 1-second EPMs are 0.15% and 0.05%, respectively, while nearly zero during average 10-second and 1-second intervals. When an interval undergoes an EPM, total trades as well as HFT trades intensifies, and share volume and dollar volume also increase sharply. Since the KOSPI 200 index futures market is extremely liquid, volume-weighted quoted spread and effective spread are nearly zero or one minimum tick size during normal intervals. However, the spreads widen during EPMs, implying that liquidity becomes worse while the price changes extremely.

4.3 Measure of liquidity provision

Traditional measures of liquidity, such as bid-ask spreads and trading volume, may no longer be good proxies for liquidity after the emergence of HFTs. Hence, we do not adopt VAR approach that take bid-ask spread or trading volume as a dependent variable and HFT measure as an independent variable. Instead, to investigate whether HFTs provide liquidity or not during intervals, we calculate directional trade imbalances, defined by the difference between trading activity in the direction of returns and trading activity in the opposite direction.

Specifically, directional trade imbalance measures are computed as follows: for each *Type = HFT, MM, FB, FS, OT, ST,*

$$Type^{M} = Type^{M+} - Type^{M-}$$

$$Type^{L} = Type^{L+} - Type^{L-}$$

$$Type^{NET} = Type^{M} + Type^{L}$$

where the superscript M and L represent market orders and limit orders respectively, and the superscript + and − represent trading activity in the direction of returns and trading activity in the opposite direction respectively. For example, during positive EPMs, HFT^{M} is calculated by HFTs' share volumes via market buy orders minus HFTs' share volumes via market sell orders. Similarly, HFT^{L} is calculated by HFTs' share volumes via limit buy orders minus HFTs' share volumes via limit sell orders. HFT^{NET} is the sum of HFT^{M} and HFT^{L}. If $HFT^{M} < 0$ during an interval, then HFTs trade in the opposite direction of the return during the interval with market orders, *i.e.*, they provide liquidity during the interval with market orders. We can similarly interpret $HFT^{L} < 0$ or $HFT^{NET} < 0$.

5 Empirical Results

5.1 Liquidity provision during EPMs and non-EPMs

Table 3 reports liquidity provision during EPMs and non-EPMs by each trader category. Panel A of Table 3 shows that HFTs take liquidity in normal states and take even more during EPMs, primarily with the use of limit orders. They trade, on average, 12.66 contracts in the same direction of returns for 10-second non-EPMs. In contrast, during 10-second EPMs, they take 76.01 contracts, which are more than six times of contracts in usual intervals. These liquidity-consuming activities of HFTs during EPMs are more severe for the case of 1-second intervals; they take liquidity during 1-second EPMs ten times more than the normal level. OTs supply liquidity in normal times. However, OTs take liquidity during 10-second EPMs primarily with market orders while providing liquidity during 1-second EPMs. It indicates that OTs can detect 10-second EPMs and trade accordingly, but, at extremely high-frequency, 1-second EPMs, they may not detect EPMs and trade in the opposite direction of returns against HFTs. Other trader types, MMs, FBs, FSs, and STs, are liquidity providers in the market during EPMs as well as non-EPMs. They absorb volume imbalances created by HFTs. Finally, it is noteworthy that all trader types use market orders to trade in the direction of returns.

In Panel B of Table 3, foreign HFTs take more liquidity during both 10-second and 1-second EPMs than non-EPMs. The liquidity-demanding behavior of HFTs in Panel A of Table 3 mostly comes from that of foreign HFTs, especially during 1-second EPMs. They take 16.37 contracts in EPMs whereas they take 1.06 contracts in usual intervals. Institutional HFTs trade similarly to foreign HFTs during 10-second EPMs, but they trade much less during 1-second EPMs. They take 1.72 contracts in 1-second EPMs while taking 0.35 contracts in normal times. Compared to the trading patterns of foreign HFTs, the evidence implies that they may not detect 1-second EPMs. Individual HFTs provide liquidity in all intervals, although the magnitude of their trading activity is negligible compared to the other HFTs.

Our empirical results in Table 3 are in a sharp contrast to those in Brogaard et al. (2016) who document that the HFTs provide liquidity in EPMs in the NASDAQ stock market. The HFTs in the KOSPI 20 futures market worsen the liquidity even more in extremely stressful times, by taking the quotes from the other types of traders. The argument of Brogaard et al. (2016) that the HFTs act as endogenous liquidity providers (ELPs) by their sophiscated trading algorithm in EPMs is not the case in the KOSPI 200 futures market. We also document that a small number of foreign HFTs, who consist of significant amount of trading volume, mainly drives the behavior of HFTs in normal times and especially in EPMs. Although the empirical methodology for the definition of the HFTs and the liquidity measure is different, our results for normal times are consistent with those in Lee (2015) who study the trading patterns of HFTs in the same market. However, we emphasize that our results for the EPMs are our main interest, and we discuss more details about them in next subsections.

5.2 Further classifications of EPMs

To examine that HFTs may supply liquidity in various subtypes of EPMs, we further classify EPMs as follows: (i) positive and negative EPMs, (ii) EPMs divided into quartiles by the magnitude of absolute return, and (iii) permanent and transitory EPMs. For the classification (iii), we identify EPMs as permanent if EPMs do not revert by more than 2/3 by the end of a 30-minute period and as transitory if EPMs revert by more than 1/3 by the end of a 30-minute period.

HFTs' trading activity during each subtype of EPMs is essentially the same as the aggregated EPMs. That is, HFTs demand liquidity during positive/negative EPMs, return magnitude quartile EPMs, and permanent/transitory EPMs. For brevity, tables for detailed results are relegated to Appendix.

5.3 Liquidity provision around EPMs

In this subsection, we look into the trade imbalances around EPMs to observe the average sequential patterns. To investigate how each trader category behaves before and after EPMs, we compute trade imbalances in several intervals around EPMs. Table 4 provides trading activity around 10-second EPMs for each trader category. In Panel A of Table 4, until 20 seconds before EPMs, HFTs do not generate significant amount of trade imbalances in the any direction of returns. From 10 seconds before EPMs, HFTs start to trade 6.91 contracts significantly in the direction of returns, and during EPMs they take a huge number of contracts as shown in Table 3. Following EPMs, they trade against the return direction up to 50 seconds after EPMs, which leads to accelerate reversal process. OTs also take liquidity during the interval $t-10$ and during EPMs. However, unlike HFTs, they continue to take liquidity until the interval $t+50$. Although our definition of MMs follow Kirilenko et al. (2017) and does not mean the designated market makers, MMs act as traditional market makers; they absorb trade imbalances during EPMs and then demand liquidity until 20 seconds after EPMs to maintain appropriate inventory levels. The remaining market participants, FBs, FSs, and STs, absorb trade imbalances around EPMs caused by HFTs and/or OTs.

Panel B of Table 4 indicates that HFTs' trading activity around EPMs are mainly driven by foreign HFTs. Foreign HFTs take liquidity of more than 50 contracts during EPMs and provide liquidity after EPM. Institutional HFTs take liquidity less than half of the amounts consumed by foreigners, but their liquidity provision after EPMs is weaker than foreigners. Individual HFTs do not behave significantly during EPMs and demand the small amount of liquidity at the interval $t+10$.

To see HFTs' trading activity at extremely high-frequency around EPMs, we look over trading activity around 1-second EPMs in a second-by-second view, reported in Table 5. According to Panel A of Table 5, HFTs trade 17.29 contracts in the same direction of returns one second before EPMs that are the same amount of contracts taken during EPMs. We demonstrate that their trading activity is consistent with quote-sniping; extremely short time before EPMs, they snipe stale quotes ahead of EPMs using speed advantage. All other traders supply liquidity during the interval $t-1$ and during the EPM intervals. Noticeably, OTs' trading activity are relatively flat around 1-second EPMs in contrast to the case of 10-second EPMs.

Panel B of Table 5 reveals that only foreign HFTs exploit speed advantage to trade ahead of EPMs. Actually, trade imbalances by HFTs during the interval $t-1$ are mostly incurred by foreign HFTs. Institutional and individual HFTs do not trade ahead of EPMs. Compared to 10-second results in Table 4, institutional HFTs demand negligible amount of liquidity during 1-second EPMs, which shows that they may not detect price changes at extremely high-frequency. Figure 3 and Figure 4 summarize graphically trading imbalances in Table 4 and Table 5 with the cumulative returns from the interval $t-50$ marked as dashed lines.[1] In both figures, we note that (foreign) HFTs trade ahead of EPMs without significant price impacts during one time interval before EPMs.

Considering that the HFTs trade in milliseconds, the results shown in Table 5 and Figure 4 are of our

[1] In Figure 3 and 4, for negative EPMs, we invert share imbalance and cumulative return for exposition purposes.

main focus. HFTs demand liquidity one second ahead of EPMs, while they don't ten second ahead of EPMs since they don't need to. After they take the liquidity without generating big price movement one second before EPMs, the price moves rapidly in the direction of their trades. This might come from the superior information of HFTs or their speed advantage from trading algorithm. Strikingly, those who take liquidity in advance are only foreign HFTs, meaning that other HFTs do not show significant moves or even exploited by foreign HFTs in EPMs.

5.4 Regression: Net HFT trade imbalances and Returns

To empirically examine the co-movement between HFTs' net trading imbalances and price levels, we employ the following multivariate regression without making any causal inference:

$$HFT_t^{NET} = \beta_0 + \beta_1 1_{EPM,t} + \beta_2 |r_t| + \beta_3 VOL_t + \beta_4 ESPRD_t + \beta_5 PRCHL_t + \boldsymbol{\gamma}' \boldsymbol{Lags_{t-\sigma}} + \epsilon_t$$

where HFT_t^{NET} denotes net HFT trade imbalances during the interval t; $|r_t|$ denotes the absolute return at the interval t; $1_{EPM,t}$ denotes EPM dummy variable that is equal to one if the interval t is an EPM and is equal to zero otherwise; VOL_t denotes share volume at the interval t; $ESPRD_t$ denotes volume-weighted effective spread at the interval t; $PRCHL$ denotes the difference between maximum price and minimum price during the interval t; and $\boldsymbol{Lags_{t-\sigma}}$ denotes a vector of lagged independent and dependent variables with $\sigma = 1, \ldots, 10$.

The estimation results for 10-second EPMs are reported in Table 6. Panel A of Table 6 shows that HFTs' net trade imbalances are positively related to contemporaneous returns, which is different from traditional market maker's pattern. As the price rises by one basis point, HFTs trade, on average, 11.44 contracts contemporaneously in the direction of the price change. Their liquidity-taking trades are more active when total trading volume is higher, the effective spread is narrower, and the price volatility is higher. All other traders trade in opposite to the price movement. Especially, OTs, who demand liquidity during 10-second EPMs, do not trade in the same direction of the returns on average. Therefore, we show that the positive relation between net trade imbalance and return is the distinctive feature of HFTs' trading behavior.

Notably, the negative coefficient of the EPM dummy indicates that the normal positive relation between net HFT trade imbalances and returns is decreased during EPMs. This result is attributed to the risk-bearing capacity of intermediaries; as the price rises by 0.15% on average during 10-second EPMs, HFTs trade 171.6 contracts $(= 15 \times 11.44)$ in the direction of returns according to the coefficient of $|r_t|$, which exceeds their risk-bearing capacity. Thus, to keep the appropriate level of the capacity, they reduce the number of trades during EPMs.

Panel B of Table 6 confirms that foreign HFTs are the main drivers of HFTs' trading directionality on returns; most of the positive relation between net HFT trade imbalances and returns stems from foreigners' trading activity. Institutional HFTs' trading activity is similar to foreign HFTs' but the pattern is much weaker. Individual HFTs behave like non-HFTs according to the regression coefficients.

Table 7 reports the regression results for 1-second intervals and produces the similar results with 10-second intervals in Table 6. In addition, we estimate the regression coefficients for several subtypes of EPMs, which are presented in Appendix. The regression results are essentially the same as the results for the aggregated EPMs.

5.5 Logistic regression

We have shown that HFTs trade ahead of EPMs extremely short time before EPMs, which is consistent with quote-sniping. They make a move one second before huge price movement in one second. Then it is natural to suspect that HFT may predict the EPM and increase the probability of EPM occurrence. To investigate this issue, we estimate the following logistic regression:

$$log\left(\frac{P(EPM_t = 1)}{1 - P(EPM_t = 1)}\right) = \beta_0 + \beta_1 HFT_{t-i}^{NET} + \beta_2 |r_{t-i}| + \beta_3 VOL_{t-i} + \beta_4 ESPRD_{t-i} + \beta_5 PRCHL_{t-i}$$

where $|r_t|$ denotes the absolute return at the interval t; $1_{EPM,t}$ denotes EPM dummy variable that is equal to one if the interval t is an EPM and is equal to zero otherwise; VOL_t denotes share volumes at the interval t; $ESPRD_t$ denotes volume-weighted effective spread at the interval t; and $PRCHL$ denotes the difference between maximum price and minimum price during the interval t. The time lag i is set to 20 or 10 seconds for 10-second intervals and one or two seconds for 1-second intervals.

Table 8 reports the estimation results. The result for 10-second intervals is provided in Panel A of Table 8 and the result for 1-second intervals in Panel B of Table 8. According to Panel A of Table 8, HFTs' trading activity 10 seconds or 20 seconds before 10-second EPMs reduces the probability that EPMs occur. Both foreign and institutional HFTs let EPMs not to take place. This is consistent with Table 4 and Figure 3 that the HFTs do not make significant liquidity demand or provision before 10-second EPMs. In contrast, in Panel B of Table 8, (foreign) HFTs elevate the probability of EPM occurrence one or two seconds before EPMs. This result is consistent with their timing ability in Table 5 and Figure 4; trading ahead of EPMs in the direction of returns has positive correlation with EPM occurrence. Although this positive correlation is natural from Figure 4, however, we are cautious about the interpretation of the results as HFTs "cause" the EPMs. Instead, we argue that the (foreign) HFTs predict big swings in price and make moves in advance.

5.6 Profitability

In previous subsections, we see that HFTs demand liquidity in normal times, and demand more liquidity in EPMs. Considering that most of the HFTs in the KOSPI 200 futures market are proprietary traders, the strategy should be profitable. Therefore, in this subsection, we focus on HFTs' profitability to examine whether HFTs are profitable in normal states and more profitable during EPMs. We estimate HFTs' daily trading profits as follows: for each day d and for each account i,

$$\pi_{id} = \sum_{n=1}^{N_{id}} (1_S P_S V_S - 1_B P_B V_B) + Inv_{idT} P_T$$

where $1_S(1_B)$ is a sell- (buy-) indicator which has value one for sell (buy) trade and zero otherwise; $P_S(P_B)$ is a sell (buy) trade price; Inv_{idT} is the ending inventory position of account i on day d; and

P_T is a clearing price that is the closing price of KOSPI 200 on day d. In this calculation, we assume that all traders start and end with zero inventory and that all inventory accumulated by the end of the day is sold at the closing price. For HFTs' trading profits, we aggregate profits earned by accounts identified as HFTs.

Table 9 reports summary statistics for HFTs' daily trading profits. From January 2010 to June 2014, HFTs earn $375,317 on each day on average. We decompose total HFT profits into profits by each HFT investor type. Most of HFTs' trading profits are earned by foreign HFTs. Individual HFTs lose their money. Institutional HFTs are profitable but their profits are not comparable to foreign HFTs' trading profits. Therefore, foreign HFTs are the most successful trader group in the KOSPI 200 index futures market relative to other investor groups of HFTs. We plot daily time series of HFTs' trading profits in Panel A of Figure 5. Except for few days, HFTs are consistently profitable over the period. Panel B of Figure 5 shows daily time series of trading profits for each HFTs investor type. Until 2011, foreign HFTs and institutional HFTs made similar amount of money. However, the gap between them started to widen after 2011. Particularly, on August 8, 2011, the day after the downgrade of the U.S. credit rating, institutional HFTs made a substantial loss of $1,038,260 while foreign HFTs earned $2,727,087. After that day, the daily profits of institutional HFTs are close to zero, whereas foreign HFTs are consistently profitable over the sample period.

To evaluate the effect of EPMs on HFTs' daily trading profits, we investigate whether HFTs are more profitable on the day with more EPMs. Table 10 and Figure 6 show the pattern that as EPMs occur more in a day, HFTs earn more profits on that day for both 10-second and 1-second EPMs. This increasing pattern mostly stems from foreign HFTs' profit pattern. Individual HFTs have rather a deceasing pattern, and institutional HFTs have no clear pattern.

To see this issue in the entire sample, we estimate the following regression:

$$\pi HFT_d = \beta_0 + \beta_1 nEPM_d + \epsilon_d$$

where πHFT_d is the aggregated HFTs' trading profits on day d, and $nEPM_d$ is the number of EPMs on day d. If HFTs' trading activity during EPMs are more profitable, the coefficient β_1 should be positive. Table 11 reports the estimation results. As expected, HFTs are more profitable when EPMs occur more. Specifically, they earn $365,385 on an average day, and earn $4,936 more with each 10-second EPM and $793 more with each 1-second EPM. Again, this relation between HFTs' profits and EPMs can be seen clearly in the foreign HFT case. On the contrary, individual and institutional HFTs lose money in days with more EPMs.

6 Robustness Checks

To examine whether our results are concrete, we have performed some types of robustness checks. For the sake of brevity, we do not report the whole results, and summarize the tests we have done in this section. All the detailed results can be obtained from the authors upon request.

6.1 Subsample period analysis

After the increase in the option multiplier in March 2012, trading activities in the KOSPI 200 index futures market as well as options market evened out. In order to take into consideration of this possible structural break in the early 2012, we divide the full sample period into two subsample periods, January 2010 to December 2011 for the first and January 2012 to June 2014 for the second, and repeat the empirical analysis for both periods. The main results are unchanged except for two notable things: (i) before 2012 OTs trade in the opposite direction of price change during EPMs and non-EPMs, but after 2012 they trade in the same direction of price change mostly with market orders; (ii) Institutional HFTs' trading activity has become less active after 2012, possibly because they lost massive money.

6.2 EPM identification by absolute return

In this paper, we identify EPMs as all intervals that belong to the 99.9th percentile of absolute midquote return residuals from the short-term market model. Alternatively, EPMs can be identified as all intervals that belong to the 99.9th percentile of the absolute returns. We employ the same empirical analysis with EPMs identified by the magnitude of returns. The corresponding empirical results are remained to be unchanged.

6.3 Alternative return intervals: 5-second, 30-second, 60-second intervals

We are able to choose several alternative interval lengths: 5 seconds, 30 seconds, and 60 seconds. We repeat the main analyses for these interval lengths and confirm that the results are qualitatively similar to those for 10 seconds.

7 Concluding Remarks

In recent years, HFTs account for the largest trading volume in modern markets by using sophisticated computer algorithms. Hence, in the area of market microstructure, the effect of HFTs on market quality is one of the major issues for researchers and practitioners. Particularly, the Flash Crash in 2010 raised a further important consideration that HFTs, who do not have any obligation to provide liquidity, may not be reliable traders during stressful states in the markets. Using all transaction-by-transaction trade records for all trading days from January 2010 to June 2014, we examine HFTs' trading activity during unusually large price changes in the KOSPI 200 index futures market.

Our finding indicates that HFTs trade in the direction of returns in normal states, and this trading activity is stronger in stressful states, which implies that they take more liquidity in stressful states than they normally do. This empirical evidence is in contrast to the case of the U.S. financial markets. We also find that, extremely short time before stressful states, HFTs trade ahead of price changes, which is consistent with quote-sniping. Therefore, it is difficult to say that these trading activities are helpful to the market.

HFTs earn massive profits normally in the KOSPI 200 index futures market. They earn even more profits in stressful states from their liquidity-taking strategies. We further categorize HFTs into foreign, individual, and institutional HFTs, and investigate their trading activity and profitability respectively. As a result, foreign HFTs drive overall features of trading activity, and most of HFTs' trading profits are actually made by foreigners. Therefore, the foreign HFTs exploit the other HFTs and low-frequency traders by aggressive trading strategies that takes liquidity.

Although the results in this study raise hands to the argument that HFTs worsen the market quality and exploit other traders, as Brogaard et al. (2014) show, they contribute to price discovery and enhance market efficiency in modern financial markets. On the other hand, if HFTs (especially foreign HFTs in this paper) are "predatory" in the market, other traders would be ruled out from the market after losses. This issue would be more important in futures and options market since derivatives markets are zero-sum market where stock markets are not. Studies on the role of HFTs in options market and on some appropriate restriction and incentive system would be important questions for researchers and policy makers.

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Table 1. Summary statistics of trader categories

Table 1 reports summary statistics of trader categories from January 2010 to June 2014, spanning 1,115 trading days. Panel A shows the statistics for all trader types: high-frequency traders (HFT), market makers (MM), fundamental buyers (FB), fundamental sellers (FS), opportunistic traders (OT), and small traders (ST). Panel B shows the statistics for all investor types: foreign (FOR), individual (IND), and institutional (INS) traders. Panel C shows the statistics of HFTs by investor group: foreign HFTs (HFT_FOR), individual HFTs (HFT_IND), and institutional HFTs (HFT_INS). The summary statistics include a time-series average of the daily number of traders (# Traders), a proportion of dollar volume to total dollar volume in percentages (% Dollar Volume), a proportion of share volume to total share volume in percentages (% Share Volume), an average number of contracts traded across all transactions (Trade Size), an average number of contracts ordered across all transactions (Order Size), a proportion of share volumes executed by limit orders (Limit orders, % Volume), and a proportion of share volumes executed by marketable orders (Aggressiveness, % Volume).

Panel A. Traders by trader type

	# Traders	% Dollar Volume	% Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
HFT	20.00	37.72%	37.97%	2.41	19.15	99.70%	52.89%
MM	100.43	9.96%	10.03%	2.41	18.96	96.71%	38.07%
FB	277.87	6.52%	6.41%	2.51	30.42	95.07%	48.68%
FS	274.32	6.49%	6.39%	1.69	4.74	95.20%	49.05%
OT	1,495.76	37.10%	37.05%	2.01	17.53	95.07%	51.38%
ST	2,908.63	2.21%	2.15%	1.09	1.19	91.54%	37.69%
	# Traders	Dollar Volume	Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
All	5,077.00	$ 62,709,223,833,144	550,505,976	2.14	19.57	96.93%	50.00%

Panel B. Traders by investor group

	# Traders	% Dollar Volume	% Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
FOR	201.28	35.83%	35.31%	2.29	21.53	99.17%	63.17%
IND	4,280.42	28.84%	28.80%	1.69	11.01	92.20%	42.68%
INS	595.30	35.33%	35.89%	2.51	27.66	98.50%	42.92%
	# Traders	Dollar Volume	Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
All	5,077.00	$ 62,709,223,833,144	550,505,976	2.14	19.57	96.93%	50.00%

Panel C. HFTs by investor group

	# Traders	% Dollar Volume	% Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
HFT_FOR	8.25	53.42%	52.36%	2.40	25.31	100.00%	64.81%
HFT_IND	1.74	2.23%	2.23%	1.36	3.10	90.49%	37.32%
HFT_INS	10.77	44.34%	45.41%	2.77	39.93	99.80%	39.90%

Table 2. Summary statistics for EPMs and for all intervals

Table 2 reports summary statistics for the intervals of extreme price movements (EPMs) in Panel A and for all intervals in Panel B. Absolute Return (%) is the average of absolute returns during the interval. Total Trades are the average number of trades during the interval. Total HFT Trades are the average number of HFT trades during the interval. Share Volume and Dollar Volume are the total share volume and dollar volume during the interval. Quoted Spread (index point) is the share volume-weighted average quoted spread in index points during the interval. Effective Spread (%) is the share volume-weighted average effective spread during the interval. Price High-Low is the difference between maximum price and minimum price level during the interval. All statistics are averaged over the sampling intervals.

Panel A: Extreme price movements (EPM)

	10-second		1-second	
	Mean	Std. Dev.	Mean	Std. Dev.
Absolute Return (%)	0.15	0.06	0.05	0.02
Total Trades	444.34	217.91	51.16	36.82
Total HFT Trades	203.44	90.68	28.28	20.53
Share Volume	903.23	489.95	105.68	87.33
Dollar Volume	$ 105,442,128	$ 63,339,557	$ 12,173,457	$ 10,520,146
Quoted Spread (index point)	0.058	0.013	0.056	0.018
Effective Spread (%)	0.024	0.006	0.023	0.008
Price High-Low	0.42	0.17	0.09	0.07
Number of Intervals	2,360		23,667	

Panel B: All intervals

	10-second		1-second	
	Mean	Std. Dev.	Mean	Std. Dev.
Absolute Return (%)	0.01	0.01	0.00	0.01
Total Trades	50.28	68.50	5.05	12.44
Total HFT Trades	29.11	40.65	2.92	8.25
Share Volume	107.27	158.37	10.77	29.58
Dollar Volume	$ 12,210,418	$ 17,795,125	$ 1,225,644	$ 3,352,721
Quoted Spread (index point)	0.049	0.010	0.028	0.025
Effective Spread (%)	0.000	0.000	0.011	0.010
Price High-Low	0.05	0.05	0.01	0.02
Number of Intervals	2,361,723		23,667,423	

Table 3. Net trade imbalances during EPMs and during non-EPMs

Table 3 reports net trade imbalances of trader categories during EPMs and during non-EPMs. Panel A shows the net trade imbalances of all trader types: high-frequency traders (HFT), market makers (MM), fundamental buyers (FB), fundamental sellers (FS), opportunistic traders (OT), and small traders (ST). Panel B shows the net trade imbalances of HFT by investor group: foreign HFTs (HFT_FOR), individual HFTs (HFT_IND), and institutional HFTs (HFT_INS). HFT^M is the difference between HFT volume with market orders in the direction of returns and HFT volume with market orders in the opposite direction of returns. HFT^L is the difference between HFT volume with limit orders in the direction of returns and HFT volume with limit orders in the opposite direction of returns. HFT^{NET} is the sum of HFT^M and HFT^L. All variables for other trader categories are similarly computed.

Panel A. Net trade imbalances by trader type

	10-second interval						1-second interval					
	EPMs			non-EPMs			EPMs			non-EPMs		
	Mean	Std. Dev.	t-Value	Mean	Std. Dev.	t-Value	Mean	Std. Dev.	t-Value	Mean	Std. Dev.	t-Value
HFT^{NET}	76.01	136.96	26.96	12.66	47.83	406.72	17.26	45.42	58.46	1.37	12.46	534.72
HFT^M	3.70	11.08	16.21	0.10	1.57	98.57	0.30	2.88	16.12	0.01	0.41	95.13
HFT^L	72.32	136.94	25.65	12.56	47.75	404.18	16.96	45.40	57.46	1.36	12.45	531.89
MM^{NET}	-7.81	62.64	-6.06	-1.72	14.00	-188.50	-5.96	17.68	-51.87	-0.21	3.95	-253.06
MM^M	12.49	13.51	44.89	0.30	2.35	194.28	0.84	2.77	46.34	0.02	0.53	222.34
MM^L	-20.30	61.96	-15.92	-2.02	13.95	-221.83	-6.80	17.51	-59.70	-0.23	3.93	-284.94
FB^{NET}	-40.84	93.74	-21.16	-2.25	23.30	-148.62	-2.95	27.72	-16.38	-0.22	5.18	-210.18
FB^M	3.18	20.76	7.44	0.18	5.49	50.71	0.42	6.48	9.96	0.02	1.35	55.78
FB^L	-44.02	89.43	-23.91	-2.44	22.58	-165.72	-3.37	26.86	-19.31	-0.24	5.02	-231.76
FS^{NET}	-44.39	99.24	-21.73	-2.21	23.19	-146.07	-3.36	27.24	-18.97	-0.22	5.15	-206.00
FS^M	2.68	18.44	7.05	0.17	5.35	49.39	0.44	7.03	9.72	0.02	1.32	55.93
FS^L	-47.06	96.51	-23.69	-2.38	22.51	-162.20	-3.80	26.14	-22.38	-0.23	5.00	-227.10
OT^{NET}	41.20	180.14	11.11	-4.93	42.79	-176.82	-1.84	48.84	-5.80	-0.57	10.69	-260.84
OT^M	33.21	46.48	34.71	1.33	11.43	178.79	2.79	12.01	35.81	0.11	2.58	203.01
OT^L	7.99	169.84	2.29	-6.26	42.29	-227.20	-4.64	48.04	-14.85	-0.68	10.63	-311.59
ST^{NET}	-24.17	26.91	-43.64	-1.56	5.19	-462.02	-3.15	5.90	-82.02	-0.15	1.22	-591.35
ST^M	2.14	4.20	24.80	0.07	1.11	92.38	0.12	0.91	19.76	0.00	0.24	90.30
ST^L	-26.32	28.15	-45.41	-1.63	5.21	-480.48	-3.26	5.94	-84.56	-0.15	1.21	-617.08

Panel B. Net trade imbalances by HFT investor group

	10-second interval						1-second interval					
	EPMs			non-EPMs			EPMs			non-EPMs		
	Mean	Std. Dev.	t-Value	Mean	Std. Dev.	t-Value	Mean	Std. Dev.	t-Value	Mean	Std. Dev.	t-Value
HFT_FOR^{NET}	51.45	105.35	23.72	10.61	41.62	391.55	16.37	39.08	64.44	1.06	10.73	482.30
HFT_FOR^M	0.00	0.14	1.64	0.00	0.07	4.50	0.00	0.04	0.00	0.00	0.02	4.75
HFT_FOR^L	51.44	105.35	23.72	10.61	41.62	391.54	16.37	39.08	64.44	1.06	10.73	482.30
HFT_IND^{NET}	-0.20	16.34	-0.60	-0.43	3.82	-171.06	-0.83	5.74	-22.20	-0.05	1.02	-221.72
HFT_IND^M	2.52	5.22	23.44	0.07	1.09	104.26	0.17	1.15	22.84	0.01	0.27	106.32
HFT_IND^L	-2.72	16.06	-8.23	-0.50	3.72	-206.04	-1.00	5.65	-27.22	-0.05	0.99	-258.23
HFT_INS^{NET}	24.77	103.90	11.58	2.48	34.43	110.66	1.72	32.01	8.26	0.35	9.25	185.52
HFT_INS^M	1.17	9.87	5.78	0.03	1.08	37.63	0.13	2.63	7.62	0.00	0.30	33.14
HFT_INS^L	23.59	103.63	11.06	2.45	34.41	109.54	1.59	31.91	7.66	0.35	9.24	184.50

Table 4. Net trade imbalances around 10-second EPMs

Table 4 reports net trade imbalances around 10-second EPMs. We calculate the net trade imbalances for the five time intervals preceding EPMs and the net trade imbalances for the five time intervals following EPMs. Panel A and Panel B show the results for each trader type and the results for each HFT investor group, respectively. HFT^{M} is the difference between HFT volume with market orders in the direction of returns and HFT volume with market orders in the opposite direction of returns. HFT^{L} is the difference between HFT volume with limit orders in the direction of returns and HFT volume with limit orders in the opposite direction of returns. HFT^{NET} is the sum of HFT^{M} and HFT^{L}. All variables for other trader categories are similarly computed.

Panel A. Net trade imbalances around EPMs by trader type

		t-50	t-40	t-30	t-20	t-10	t	t+10	t+20	t+30	t+40	t+50
HFT^{NET}	Mean	3.83	-1.48	0.67	0.93	6.91	76.01	-15.93	-10.75	-7.33	-3.41	-1.95
	t-Value	2.62	-1.01	0.43	0.53	3.81	26.96	-7.51	-6.15	-4.56	-2.12	-1.34
HFT^{M}	Mean	-0.14	0.47	0.18	-0.07	0.16	3.70	1.35	0.23	-0.26	-0.28	0.03
	t-Value	-1.05	3.09	1.34	-0.43	0.97	16.21	7.29	1.90	-1.49	-2.00	0.19
HFT^{L}	Mean	3.97	-1.95	0.49	1.00	6.75	72.32	-17.28	-10.98	-7.08	-3.13	-1.98
	t-Value	2.74	-1.34	0.31	0.57	3.76	25.65	-8.19	-6.31	-4.42	-1.95	-1.37
MM^{NET}	Mean	0.02	-1.00	-0.88	-0.44	-3.14	-7.81	10.25	2.26	-0.12	0.39	1.80
	t-Value	0.03	-1.39	-1.16	-0.54	-3.74	-6.06	10.63	2.67	-0.15	0.55	2.65
MM^{M}	Mean	0.55	0.34	0.39	0.59	1.14	12.49	3.72	0.58	0.00	-0.07	-0.09
	t-Value	3.07	2.02	2.18	3.26	5.62	44.89	18.03	3.29	-0.01	-0.47	-0.57
MM^{L}	Mean	-0.54	-1.34	-1.27	-1.03	-4.28	-20.30	6.53	1.68	-0.12	0.46	1.89
	t-Value	-0.85	-1.91	-1.70	-1.31	-5.15	-15.92	6.83	2.02	-0.15	0.65	2.84
FB^{NET}	Mean	0.03	0.77	-0.38	-1.75	-4.01	-40.84	-8.27	-2.24	-1.03	-3.15	-3.17
	t-Value	0.03	0.71	-0.35	-1.55	-3.24	-21.16	-6.00	-2.08	-0.98	-3.12	-3.40
FB^{M}	Mean	0.28	0.04	0.13	0.61	0.84	3.18	1.67	1.53	0.76	0.47	0.14
	t-Value	1.28	0.20	0.58	2.25	3.06	7.44	4.41	4.58	2.46	1.44	0.56
FB^{L}	Mean	-0.26	0.73	-0.50	-2.36	-4.85	-44.02	-9.93	-3.78	-1.78	-3.61	-3.31
	t-Value	-0.26	0.68	-0.48	-2.17	-4.05	-23.91	-7.59	-3.69	-1.79	-3.78	-3.68
FS^{NET}	Mean	-0.74	-0.91	-2.39	-0.68	-4.20	-44.39	-8.82	-2.21	-0.90	-3.08	-2.79
	t-Value	-0.75	-0.86	-2.18	-0.55	-3.16	-21.73	-6.23	-1.92	-0.80	-3.10	-3.00
FS^{M}	Mean	0.38	0.58	0.02	0.19	0.31	2.68	1.16	0.57	0.00	0.15	0.28
	t-Value	2.09	2.72	0.09	0.83	1.13	7.05	4.14	1.80	0.02	0.62	1.24
FS^{L}	Mean	-1.11	-1.49	-2.41	-0.87	-4.51	-47.06	-9.98	-2.78	-0.91	-3.23	-3.07
	t-Value	-1.15	-1.45	-2.25	-0.72	-3.50	-23.69	-7.29	-2.55	-0.84	-3.40	-3.47
OT^{NET}	Mean	-2.16	3.89	4.30	3.73	8.34	41.20	26.42	15.34	11.19	10.75	7.77
	t-Value	-1.33	2.25	2.40	1.90	3.92	11.11	11.30	7.95	6.37	6.16	4.97
OT^{M}	Mean	0.95	1.33	1.37	1.84	3.73	33.21	11.02	3.61	2.03	0.86	1.60
	t-Value	2.01	2.76	2.89	3.58	6.43	34.71	16.41	6.32	3.73	1.68	2.93
OT^{L}	Mean	-3.11	2.57	2.94	1.89	4.61	7.99	15.40	11.72	9.16	9.88	6.17
	t-Value	-1.97	1.53	1.68	0.99	2.22	2.29	6.81	6.18	5.40	5.88	4.06
ST^{NET}	Mean	-0.98	-1.28	-1.32	-1.80	-3.90	-24.17	-3.65	-2.39	-1.80	-1.51	-1.66
	t-Value	-4.28	-5.49	-5.07	-6.30	-11.73	-43.64	-12.56	-10.32	-8.54	-7.40	-8.51
ST^{M}	Mean	0.09	0.16	0.07	0.13	0.27	2.14	0.74	0.09	-0.02	-0.08	-0.09
	t-Value	2.20	3.99	1.42	3.00	5.33	24.80	11.24	1.82	-0.56	-2.11	-1.46
ST^{L}	Mean	-1.07	-1.44	-1.39	-1.94	-4.17	-26.32	-4.40	-2.48	-1.77	-1.42	-1.57
	t-Value	-4.54	-5.84	-5.14	-6.51	-12.06	-45.41	-14.65	-10.34	-8.12	-6.74	-8.18

Table 4. Net trade imbalances around 10-second EPMs (continued)

Panel B. Net trade imbalances around EPMs of HFTs by investor group

		t-50	t-40	t-30	t-20	t-10	t	t+10	t+20	t+30	t+40	t+50
HFT_FOR^{NET}	Mean	3.48	0.83	3.81	2.47	8.54	51.45	-20.29	-6.08	-3.64	-2.00	-1.83
	t-Value	3.22	0.79	3.36	2.05	6.38	23.72	-13.42	-4.82	-3.03	-1.71	-1.66
HFT_FOR^{M}	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
	t-Value	.	.	.	-1.00	.	1.64	1.09	.	-1.00	.	.
HFT_FOR^{L}	Mean	3.48	0.83	3.81	2.47	8.54	51.44	-20.30	-6.08	-3.64	-2.00	-1.83
	t-Value	3.22	0.79	3.36	2.05	6.38	23.72	-13.43	-4.82	-3.03	-1.71	-1.66
HFT_IND^{NET}	Mean	0.28	-0.42	-0.06	-0.19	-0.31	-0.20	1.34	-0.27	-0.48	-0.07	-0.16
	t-Value	1.25	-1.65	-0.27	-0.79	-1.24	-0.60	4.59	-0.91	-1.99	-0.29	-0.70
HFT_IND^{M}	Mean	0.08	0.12	0.13	0.13	0.30	2.52	0.93	0.12	0.08	0.02	0.09
	t-Value	1.82	2.66	2.88	2.65	4.94	23.44	11.33	2.40	1.78	0.42	2.18
HFT_IND^{L}	Mean	0.20	-0.54	-0.19	-0.32	-0.61	-2.72	0.42	-0.39	-0.56	-0.09	-0.25
	t-Value	0.89	-2.16	-0.84	-1.35	-2.45	-8.23	1.47	-1.32	-2.36	-0.37	-1.09
HFT_INS^{NET}	Mean	0.07	-1.89	-3.08	-1.35	-1.32	24.77	3.02	-4.40	-3.22	-1.34	0.04
	t-Value	0.07	-1.58	-2.55	-1.00	-1.00	11.58	1.68	-3.08	-2.47	-1.10	0.04
HFT_INS^{M}	Mean	-0.22	0.35	0.05	-0.20	-0.14	1.17	0.42	0.12	-0.34	-0.30	-0.06
	t-Value	-1.84	2.47	0.41	-1.28	-0.95	5.78	2.52	1.05	-2.04	-2.27	-0.41
HFT_INS^{L}	Mean	0.30	-2.24	-3.13	-1.16	-1.18	23.59	2.60	-4.52	-2.88	-1.04	0.10
	t-Value	0.27	-1.88	-2.59	-0.87	-0.90	11.06	1.46	-3.18	-2.22	-0.86	0.10

Table 5. Net trade imbalances around 1-second EPMs: A second-by-second view

Table 5 reports net trade imbalances around 1-second EPMs. We calculate the net trade imbalances second-by-second for ten seconds preceding EPMs and for ten seconds following EPMs. Panel A and Panel B show the results for each trader type and the results for each HFT investor group, respectively. HFT^M is the difference between HFT volume with market orders in the direction of returns and HFT volume with market orders in the opposite direction of returns. HFT^L is the difference between HFT volume with limit orders in the direction of returns and HFT volume with limit orders in the opposite direction of returns. HFT^{NET} is the sum of HFT^M and HFT^L. All variables for other trader categories are similarly computed.

Panel A. Net trade imbalances around EPMs by trader type

		t-10	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
HFT^{NET}	Mean	-0.47	-0.39	-0.57	-0.69	-0.44	-0.37	-0.27	-0.16	2.00	17.29	17.26	3.47	0.89	0.26	0.21	0.20	0.02	-0.17	0.12	0.05	0.01
	t-Value	-3.48	-2.85	-4.08	-4.55	-3.08	-2.49	-1.83	-1.05	11.36	56.81	58.46	19.26	5.69	1.83	1.53	1.43	0.18	-1.35	0.90	0.42	0.06
HFT^M	Mean	0.01	-0.01	-0.01	0.00	-0.02	0.00	-0.01	0.00	0.03	0.14	0.30	0.24	0.17	0.09	0.07	0.07	0.05	0.04	0.06	0.05	0.02
	t-Value	0.74	-1.16	-1.03	0.42	-2.09	0.20	-0.49	-0.16	2.08	8.31	16.12	16.28	12.12	9.35	6.56	7.00	4.97	4.73	5.38	4.84	2.24
HFT^L	Mean	-0.47	-0.38	-0.56	-0.69	-0.42	-0.37	-0.27	-0.16	1.97	17.15	16.96	3.23	0.73	0.17	0.15	0.13	-0.03	-0.21	0.06	0.01	-0.02
	t-Value	-3.56	-2.77	-4.02	-4.59	-2.94	-2.51	-1.80	-1.04	11.24	56.39	57.46	17.98	4.65	1.18	1.06	0.92	-0.20	-1.64	0.43	0.05	-0.13
MM^{NET}	Mean	0.04	0.01	-0.05	-0.07	-0.04	-0.02	0.03	0.02	-0.58	-6.39	-5.96	1.38	1.36	0.71	0.72	0.51	0.42	0.37	0.36	0.20	0.19
	t-Value	0.65	0.08	-0.78	-1.07	-0.56	-0.35	0.49	0.35	-7.71	-58.40	-51.87	15.05	17.60	9.96	10.41	7.72	6.75	5.99	5.85	3.28	3.22
MM^M	Mean	0.00	-0.02	-0.01	0.00	-0.01	-0.01	0.00	-0.01	0.07	0.26	0.84	0.85	0.55	0.32	0.23	0.19	0.14	0.14	0.12	0.11	0.10
	t-Value	-0.38	-1.50	-0.48	0.13	-1.02	-0.86	-0.44	-1.16	5.37	19.00	46.34	49.90	37.77	26.44	21.05	18.00	13.33	13.78	12.17	10.80	9.55
MM^L	Mean	0.05	0.02	-0.04	-0.07	-0.02	-0.01	0.04	0.04	-0.65	-6.65	-6.80	0.53	0.81	0.39	0.49	0.32	0.28	0.23	0.23	0.09	0.10
	t-Value	0.73	0.35	-0.70	-1.10	-0.39	-0.21	0.57	0.55	-8.70	-60.94	-59.70	5.89	10.73	5.57	7.15	4.86	4.56	3.74	3.85	1.51	1.62
FB^{NET}	Mean	0.13	0.09	0.22	0.23	0.12	0.24	0.09	-0.27	-0.77	-3.48	-2.95	-1.94	-1.03	-0.70	-0.55	-0.36	-0.31	-0.32	-0.29	-0.26	-0.24
	t-Value	1.75	1.17	2.81	2.81	1.58	3.07	1.07	-3.27	-8.99	-20.51	-16.38	-21.42	-13.74	-9.80	-8.21	-5.25	-4.46	-4.80	-4.30	-4.03	-3.66
FB^M	Mean	0.00	0.00	0.00	0.00	0.00	0.03	0.04	0.03	0.02	0.41	0.42	0.11	0.05	0.05	0.08	0.06	0.03	0.05	0.07	0.05	0.03
	t-Value	-0.03	0.10	-0.10	0.01	0.14	1.28	1.84	1.41	0.67	8.48	9.96	4.36	2.13	2.28	3.31	2.55	1.51	2.08	3.76	2.55	1.49
FB^L	Mean	0.13	0.09	0.23	0.23	0.12	0.22	0.04	-0.30	-0.79	-3.89	-3.37	-2.04	-1.07	-0.75	-0.63	-0.43	-0.34	-0.38	-0.36	-0.31	-0.27
	t-Value	1.80	1.19	2.91	2.91	1.59	2.83	0.55	-3.85	-9.56	-23.85	-19.31	-23.22	-15.15	-11.02	-10.09	-6.54	-4.99	-6.06	-5.53	-5.13	-4.49

Table 5. Net trade imbalances around 1-second EPMs: A second-by-second view (continued)

Panel A. Net trade imbalances around EPMs by trader type (continued)

		t-10	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
FS^{NET}	Mean	-0.02	0.00	0.16	0.19	0.03	0.13	-0.11	-0.22	-0.88	-3.71	-3.36	-2.06	-1.10	-0.68	-0.65	-0.47	-0.38	-0.23	-0.40	-0.33	-0.29
	t-Value	-0.26	0.03	2.15	2.51	0.45	1.73	-1.39	-2.80	-10.40	-22.86	-18.97	-23.75	-14.87	-9.92	-9.68	-6.91	-5.72	-3.33	-6.44	-5.29	-4.33
FS^{M}	Mean	-0.02	-0.01	0.00	-0.01	-0.03	-0.01	-0.03	0.00	0.00	0.34	0.44	0.13	0.06	0.03	0.00	0.06	0.04	0.04	0.01	0.02	0.00
	t-Value	-1.08	-0.48	0.19	-0.73	-1.63	-0.86	-1.36	-0.17	0.22	7.20	9.72	4.82	3.40	2.09	0.12	3.43	1.99	2.78	0.34	1.62	-0.03
FS^{L}	Mean	0.00	0.01	0.16	0.21	0.06	0.14	-0.08	-0.21	-0.89	-4.05	-3.80	-2.18	-1.17	-0.71	-0.66	-0.53	-0.42	-0.26	-0.40	-0.35	-0.29
	t-Value	-0.01	0.14	2.16	2.72	0.84	1.95	-1.07	-2.83	-10.74	-25.99	-22.38	-26.23	-16.21	-10.65	-10.06	-8.12	-6.43	-3.93	-6.79	-5.75	-4.42
OT^{NET}	Mean	0.26	0.25	0.20	0.27	0.27	-0.01	0.24	0.71	0.66	-1.34	-1.84	0.08	0.30	0.68	0.47	0.33	0.41	0.49	0.33	0.46	0.44
	t-Value	1.79	1.80	1.40	1.92	1.89	-0.07	1.55	4.70	3.74	-4.48	-5.80	0.41	1.97	4.83	3.47	2.48	3.18	3.86	2.60	3.59	3.73
OT^{M}	Mean	-0.06	-0.05	-0.02	-0.14	-0.11	-0.11	-0.13	-0.11	0.31	1.97	2.79	1.87	1.16	0.85	0.56	0.49	0.39	0.37	0.30	0.29	0.33
	t-Value	-1.73	-1.39	-0.50	-3.41	-2.90	-2.83	-3.44	-2.48	6.25	23.99	35.81	33.84	26.29	19.25	14.58	13.13	11.02	10.59	8.81	8.20	9.57
OT^{L}	Mean	0.32	0.30	0.21	0.41	0.38	0.10	0.37	0.82	0.35	-3.30	-4.64	-1.80	-0.85	-0.16	-0.09	-0.16	0.02	0.12	0.03	0.17	0.11
	t-Value	2.23	2.20	1.56	2.92	2.70	0.73	2.44	5.47	2.02	-11.28	-14.85	-9.95	-5.65	-1.18	-0.67	-1.23	0.18	0.99	0.24	1.35	0.94
ST^{NET}	Mean	0.05	0.05	0.04	0.06	0.05	0.02	0.02	-0.09	-0.42	-2.37	-3.15	-0.93	-0.43	-0.28	-0.20	-0.21	-0.16	-0.14	-0.12	-0.12	-0.12
	t-Value	2.34	2.49	2.16	3.27	2.82	1.23	0.89	-4.32	-15.72	-64.79	-82.02	-37.06	-22.54	-17.01	-13.58	-13.61	-11.45	-10.22	-8.10	-8.93	-8.32
ST^{M}	Mean	0.00	-0.01	0.00	-0.01	0.00	-0.01	-0.01	-0.01	0.01	0.05	0.12	0.14	0.10	0.06	0.05	0.03	0.03	0.02	0.02	0.02	0.02
	t-Value	-1.10	-1.59	-0.81	-1.67	-0.80	-2.00	-2.37	-1.85	1.38	10.93	19.76	26.58	21.63	15.69	14.24	10.03	8.58	6.14	6.53	6.66	3.50
ST^{L}	Mean	0.05	0.05	0.04	0.07	0.06	0.03	0.03	-0.08	-0.42	-2.42	-3.26	-1.07	-0.52	-0.34	-0.25	-0.24	-0.19	-0.16	-0.14	-0.14	-0.13
	t-Value	2.51	2.81	2.30	3.59	2.98	1.65	1.27	-3.99	-15.90	-65.98	-84.56	-42.53	-27.60	-20.99	-17.16	-15.99	-13.51	-12.20	-9.84	-10.95	-10.10

Table 5. **Net trade imbalances around 1-second EPMs: A second-by-second view (continued)**

Panel B. Net trade imbalances around EPMs of HFTs by investor group

		t-10	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
HFT_FOR^{NET}	Mean	-0.25	-0.29	-0.24	-0.58	-0.47	-0.30	-0.12	0.12	1.68	17.79	16.37	1.94	-0.45	-0.74	-0.69	-0.57	-0.64	-0.56	-0.39	-0.33	-0.21
	t-Value	-2.23	-2.56	-2.13	-4.60	-4.09	-2.48	-0.99	0.92	11.32	68.05	64.44	12.67	-3.51	-6.17	-5.91	-4.99	-5.76	-5.10	-3.65	-3.03	-1.98
HFT_FOR^{M}	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	t-Value	-0.33		-1.00		-1.00	-1.18	-2.00	-1.00	-1.00	1.18	0.00	1.50	1.00	1.00			1.18				
HFT_FOR^{L}	Mean	-0.25	-0.29	-0.24	-0.58	-0.47	-0.30	-0.12	0.12	1.68	17.79	16.37	1.94	-0.45	-0.74	-0.69	-0.57	-0.64	-0.56	-0.39	-0.33	-0.21
	t-Value	-2.23	-2.56	-2.13	-4.60	-4.09	-2.48	-0.99	0.92	11.32	68.05	64.44	12.67	-3.51	-6.17	-5.91	-4.99	-5.76	-5.10	-3.65	-3.03	-1.98
HFT_IND^{NET}	Mean	0.01	0.01	-0.01	-0.03	0.01	0.00	0.00	-0.01	-0.07	-0.69	-0.83	0.08	0.23	0.21	0.12	0.07	0.07	0.07	0.05	0.03	0.01
	t-Value	0.37	0.37	-0.57	-1.36	0.44	0.09	0.01	-0.35	-2.60	-18.77	-22.20	4.00	10.59	8.65	5.49	3.32	3.58	3.06	2.66	1.34	0.45
HFT_IND^{M}	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.06	0.17	0.16	0.12	0.07	0.06	0.04	0.04	0.03	0.02	0.02	0.02
	t-Value	0.93	-0.29	-0.45	0.29	-0.38	1.06	1.23	0.86	4.10	8.82	22.84	24.43	19.91	15.94	11.33	10.13	9.55	8.45	5.01	6.27	4.77
HFT_IND^{L}	Mean	0.00	0.01	-0.01	-0.03	0.01	0.00	0.00	-0.01	-0.09	-0.75	-1.00	-0.08	0.10	0.14	0.07	0.03	0.03	0.04	0.03	0.00	-0.01
	t-Value	0.21	0.45	-0.50	-1.43	0.52	-0.10	-0.21	-0.59	-3.25	-20.60	-27.22	-4.00	5.02	5.82	3.06	1.29	1.63	1.65	1.62	0.14	-0.51
HFT_INS^{NET}	Mean	-0.23	-0.11	-0.31	-0.08	0.02	-0.06	-0.15	-0.27	0.39	0.19	1.72	1.45	1.12	0.80	0.78	0.70	0.60	0.32	0.45	0.35	0.21
	t-Value	-2.41	-1.13	-3.30	-0.79	0.20	-0.63	-1.46	-2.64	3.39	0.98	8.26	10.85	9.22	7.20	7.52	6.86	6.22	3.28	4.59	3.65	2.30
HFT_INS^{M}	Mean	0.00	-0.01	-0.01	0.00	-0.02	0.00	-0.01	-0.01	0.01	0.08	0.13	0.08	0.04	0.02	0.01	0.03	0.01	0.00	0.04	0.02	0.01
	t-Value	0.46	-1.20	-0.92	0.33	-2.12	-0.21	-0.98	-0.60	0.93	5.36	7.62	5.83	3.37	2.57	1.21	3.01	1.10	0.65	3.75	2.69	0.67
HFT_INS^{L}	Mean	-0.23	-0.10	-0.31	-0.08	0.04	-0.06	-0.14	-0.27	0.37	0.11	1.59	1.38	1.07	0.77	0.77	0.67	0.59	0.31	0.41	0.33	0.20
	t-Value	-2.47	-1.04	-3.22	-0.82	0.39	-0.61	-1.36	-2.59	3.30	0.55	7.66	10.33	8.91	7.02	7.43	6.62	6.15	3.24	4.21	3.42	2.24

Table 6. Net trade imbalances and Returns: 10-second intervals

Table 6 reports the estimation results of the regression as follows: for 10-second intervals t,

$$HFT_t^{NET} = \beta_0 + \beta_1 1_{EPM,t} + \beta_2 |r_t| + \beta_3 VOL_t + \beta_4 ESPRD_t + \beta_5 PRCHL_t + \boldsymbol{\gamma}' \boldsymbol{Lags_{t-\sigma}} + \epsilon_t$$

where HFT_t^{NET} denotes net HFT trade imbalances during the interval t; $|r_t|$ denotes the absolute return at the interval t; $1_{EPM,t}$ denotes EPM dummy variable that is equal to one if the interval t is an EPM and is equal to zero otherwise; VOL_t denotes share volumes at the interval t; $ESPRD_t$ denotes volume-weighted effective spread at the interval t; $PRCHL$ denotes the difference between maximum price and minimum price during the interval t; and $\boldsymbol{Lags_{t-\sigma}}$ denotes a vector of lagged independent and dependent variables with $\sigma = 1, \ldots, 10$. The regression is repeated for all other trader categories. Panel A and Panel B show the results for each trader type and the results for each HFT investor group, respectively.

Panel A. Net trade imbalances and Returns by trader type

Trader		1_{EPM}	|Return| (1bp, 0.01%)	Share Vol. (1000 shares)	Eff. Spread (1bp, 0.01%)	Price High-Low (1 index point)
HFT	Mean	-110.09	11.44	42.64	-2.00	23.20
	Std. Dev.	0.96	0.03	0.27	0.08	0.97
MM	Mean	21.32	-1.96	3.34	0.33	-11.25
	Std. Dev.	0.30	0.01	0.08	0.02	0.31
FB	Mean	-4.83	-1.53	-26.45	0.63	3.93
	Std. Dev.	0.50	0.01	0.14	0.04	0.51
FS	Mean	-9.08	-1.53	-25.46	0.51	6.51
	Std. Dev.	0.50	0.01	0.14	0.04	0.51
OT	Mean	104.05	-5.39	19.71	0.28	-23.82
	Std. Dev.	0.93	0.03	0.26	0.08	0.94
ST	Mean	-1.71	-1.05	-13.21	0.23	1.50
	Std. Dev.	0.10	0.00	0.03	0.01	0.10

Panel B. Net trade imbalances and Returns by HFT investor group

Trader		1_{EPM}	|Return| (1bp, 0.01%)	Share Vol. (1000 shares)	Eff. Spread (1bp, 0.01%)	Price High-Low (1 index point)
HFT_FOR	Mean	-103.64	10.04	15.47	-1.35	44.83
	Std. Dev.	0.85	0.02	0.24	0.07	0.86
HFT_IND	Mean	5.65	-0.37	-0.18	0.09	-2.64
	Std. Dev.	0.08	0.00	0.02	0.01	0.08
HFT_INS	Mean	-11.90	1.77	27.40	-0.75	-18.88
	Std. Dev.	0.75	0.02	0.21	0.06	0.76

Table 7. Net imbalances and Returns: 1-second intervals

Table 7 reports the estimation results of the regression as follows: for 1-second intervals t,

$$HFT_t^{NET} = \beta_0 + \beta_1 1_{EPM,t} + \beta_2 |r_t| + \beta_3 VOL_t + \beta_4 ESPRD_t + \beta_5 PRCHL_t + \boldsymbol{\gamma}' \boldsymbol{Lags_{t-\sigma}} + \epsilon_t$$

where HFT_t^{NET} denotes net HFT trade imbalances during the interval t; $|r_t|$ denotes the absolute return at the interval t; $1_{EPM,t}$ denotes EPM dummy variable that is equal to one if the interval t is an EPM and is equal to zero otherwise; VOL_t denotes share volumes at the interval t; $ESPRD_t$ denotes volume-weighted effective spread at the interval t; $PRCHL$ denotes the difference between maximum price and minimum price during the interval t; and $\boldsymbol{Lags_{t-\sigma}}$ denotes a vector of lagged independent and dependent variables with $\sigma = 1, \ldots, 10$. The regression is repeated for all other trader categories. Panel A and Panel B show the results for each trader type and the results for each HFT investor group, respectively.

Panel A. Net trade imbalances and Returns by trader type

Trader		1_{EPM}	$\lvert Return_t \rvert$ (1bp, 0.01%)	Share Vol. (1000 shares)	Eff. Spread (1bp, 0.01%)	Price High-Low (1 index point)
HFT	Mean	-10.96	4.30	133.72	-0.32	-23.75
	Std. Dev.	0.08	0.00	0.10	0.00	0.14
MM	Mean	0.33	-1.24	-17.90	0.09	-0.30
	Std. Dev.	0.03	0.00	0.03	0.00	0.05
FB	Mean	0.94	-0.28	-28.36	0.10	2.64
	Std. Dev.	0.03	0.00	0.04	0.00	0.06
FS	Mean	0.54	-0.32	-27.64	0.10	2.80
	Std. Dev.	0.03	0.00	0.04	0.00	0.06
OT	Mean	9.57	-2.16	-42.59	-0.01	17.18
	Std. Dev.	0.07	0.00	0.09	0.00	0.13
ST	Mean	-0.42	-0.31	-17.09	0.04	1.51
	Std. Dev.	0.01	0.00	0.01	0.00	0.01

Panel B. HFT net liquidity and EPMs by investor group

Trader		1_{EPM}	|Return| (1bp, 0.01%)	Share Vol. (1000 shares)	Eff. Spread (1bp, 0.01%)	Price High-Low (1 index point)
HFT_FOR	Mean	-6.45	3.82	92.93	-0.15	-11.18
	Std. Dev.	0.07	0.00	0.09	0.00	0.13
HFT_IND	Mean	0.29	-0.19	-4.35	0.01	0.25
	Std. Dev.	0.01	0.00	0.01	0.00	0.01
HFT_INS	Mean	-4.81	0.67	45.17	-0.19	-12.85
	Std. Dev.	0.06	0.00	0.08	0.00	0.11

Table 8. HFTs' trading activity and EPM occurrence

Table 8 reports the estimation results of the following logistic regression:

$$log\left(\frac{P(EPM_t = 1)}{1 - P(EPM_t = 1)}\right) = \beta_0 + \beta_1 HFT_{t-i}^{NET} + \beta_2|r_{t-i}| + \beta_3 VOL_{t-i} + \beta_4 ESPRD_{t-i} + \beta_5 PRCHL_{t-i}$$

where $|r_t|$ denotes the absolute return at the interval t; $1_{EPM,t}$ denotes EPM dummy variable that is equal to one if the interval t is an EPM and is equal to zero otherwise; VOL_t denotes share volumes at the interval t; $ESPRD_t$ denotes volume-weighted effective spread at the interval t; and $PRCHL$ denotes the difference between maximum price and minimum price during the interval t. The time lag i is set to 20 or 10 seconds for 10-second intervals and one or two seconds for 1-second intervals. Panel A and Panel B shows the results for 10-second intervals and the results for 1-second intervals, respectively.

Panel A. HFTs' trading activity and EPM occurrence for 10-second intervals

			HFT_NET	|Return| (1bp, 0.01%)	Share Vol. (1000 shares)	Eff. Spread (1bp, 0.01%)	Price High-Low (1 index point)
HFT	t-10	Coeff.	-0.00073	-0.0349	0.918	0.6588	11.5389
		p-Value	0.0043	0.0001	<.0001	<.0001	<.0001
	t-20	Coeff.	-0.00088	-0.0318	0.6589	0.9537	10.3807
		p-Value	0.0015	0.0007	<.0001	<.0001	<.0001
HFT_FOR	t-10	Coeff.	-0.00036	-0.0377	0.8982	0.6689	11.5773
		p-Value	0.2644	<.0001	<.0001	<.0001	<.0001
	t-20	Coeff.	-0.00073	-0.0341	0.6334	0.9589	10.4264
		p-Value	0.034	0.0003	<.0001	<.0001	<.0001
HFT_IND	t-10	Coeff.	0.00692	-0.039	0.903	0.6684	11.5756
		p-Value	0.0006	<.0001	<.0001	<.0001	<.0001
	t-20	Coeff.	0.005	-0.0365	0.6398	0.9688	10.4264
		p-Value	0.0219	<.0001	<.0001	<.0001	<.0001
HFT_INS	t-10	Coeff.	-0.00098	-0.0366	0.9285	0.6746	11.5215
		p-Value	0.0026	<.0001	<.0001	<.0001	<.0001
	t-20	Coeff.	-0.00079	-0.0347	0.6596	0.972	10.3872
		p-Value	0.0269	0.0002	<.0001	<.0001	<.0001

Panel B. HFTs' trading activity and EPM occurrence for 1-second intervals

			HFT_NET	|Return| (1bp, 0.01%)	Share Vol. (1000 shares)	Eff. Spread (1bp, 0.01%)	Price High-Low (1 index point)
HFT	t-1	Coeff.	0.000451	-0.0436	6.9649	0.3165	29.2403
		p-Value	0.0048	<.0001	<.0001	<.0001	<.0001
	t-2	Coeff.	0.000141	0.2827	1.2389	0.4842	17.2872
		p-Value	0.5787	<.0001	<.0001	<.0001	<.0001
HFT_FOR	t-1	Coeff.	0.00233	-0.0499	6.8731	0.3184	29.3161
		p-Value	<.0001	<.0001	<.0001	<.0001	<.0001
	t-2	Coeff.	0.000388	0.282	1.2283	0.4843	17.2951
		p-Value	0.2076	<.0001	<.0001	<.0001	<.0001
HFT_IND	t-1	Coeff.	0.0056	-0.0408	7.0332	0.3156	29.2015
		p-Value	0.0005	<.0001	<.0001	<.0001	<.0001
	t-2	Coeff.	0.013	0.2848	1.3082	0.4836	17.2556
		p-Value	<.0001	<.0001	<.0001	<.0001	<.0001
HFT_INS	t-1	Coeff.	-0.0014	-0.0413	7.0742	0.3162	29.1694
		p-Value	<.0001	<.0001	<.0001	<.0001	<.0001
	t-2	Coeff.	-0.00052	0.2831	1.2767	0.4842	17.2659
		p-Value	0.1099	<.0001	<.0001	<.0001	<.0001

Table 9. Summary statistics of HFTs' daily profits

Table 9 reports summary statistics of a time-series of HFTs' daily profits. To calculate dollar volume, we use the fixed exchange rate of 1,153.3 (1,014.4) KRW/USD for the first (second) sub-period which was the exchange rate on December 30, 2011 (June 30, 2014), the last day of the first (second) sub-period, where the first (second) sub-period spans from January 2010 to December 2012 (from January 2012 to June 2014), respectively.

	Mean	Median	Std. Dev.	Max	Min
HFT	$ 375,317	$ 315,911	$ 307,816	$ 2,012,323	$ -358,233
HFT_FOR	$ 317,451	$ 255,983	$ 278,537	$ 2,727,087	$ -331,427
HFT_IND	$ -47,741	$ -25,115	$ 86,589	$ 214,051	$ -943,007
HFT_INS	$ 84,798	$ 58,010	$ 161,284	$ 1,443,293	$ -1,038,260

Table 10. HFTs' daily profits and the number of EPMs

Table 10 reports HFTs' daily profits aggregated and averaged according to the number of EPMs occurred on each day. Panel A and Panel B shows the results for 10-second EPMs and the results for 1-second EPMs, respectively. # of EPMs is the number of EPMs occurred on each day. # of days is the number of sample days in which the corresponding number of EPMs are occurred. HFT denotes the average daily profits of high-frequency traders over the corresponding samples. HFT_FOR, HFT_IND, and HFT_INS denotes the average daily profits of foreign, individual, and institutional HFTs over the corresponding samples, respectively.

Panel A. 10-second EPMs

# of EPMs	# of days	HFT	HFT_FOR	HFT_IND	HFT_INS
0	633	$ 341,543	$ 257,806	$ -38,428	$ 106,381
1	164	$ 346,465	$ 307,828	$ -55,694	$ 67,503
2	101	$ 352,767	$ 328,633	$ -38,315	$ 37,790
3	51	$ 448,450	$ 409,871	$ -34,225	$ 55,356
4	48	$ 403,996	$ 377,803	$ -38,723	$ 52,008
5	27	$ 462,825	$ 421,126	$ -31,611	$ 65,115
6	22	$ 452,329	$ 485,646	$ -91,741	$ 25,063
7~9	30	$ 551,381	$ 542,736	$ -88,060	$ 58,546
>10	37	$ 768,205	$ 795,225	$ -153,317	$ 76,572

Panel B. 1-second EPMs

# of EPMs	# of days	HFT	HFT_FOR	HFT_IND	HFT_INS
0	228	$ 314,432	$ 220,754	$ -32,467	$ 113,472
1	99	$ 366,836	$ 250,564	$ -30,253	$ 134,302
2	48	$ 378,630	$ 314,079	$ -61,260	$ 110,495
3	47	$ 373,847	$ 304,143	$ -40,176	$ 97,913
4	31	$ 307,659	$ 285,272	$ -49,938	$ 57,826
5	39	$ 337,235	$ 300,086	$ -54,862	$ 66,691
6	36	$ 283,930	$ 208,639	$ -30,850	$ 89,859
7	34	$ 338,733	$ 277,618	$ -52,447	$ 90,423
8	35	$ 305,044	$ 261,288	$ -62,949	$ 72,532
9	31	$ 333,225	$ 325,798	$ -39,720	$ 18,959
10~19	183	$ 345,947	$ 293,741	$ -38,104	$ 71,362
20~29	110	$ 384,573	$ 359,892	$ -60,189	$ 56,417
30~39	64	$ 484,202	$ 462,275	$ -70,187	$ 54,827
40~49	33	$ 506,070	$ 480,805	$ -46,642	$ 46,465
50~99	67	$ 504,754	$ 450,703	$ -53,345	$ 84,306
>100	28	$ 786,276	$ 836,538	$ -130,169	$ 56,663

Table 11. Regression: HFT profits and the number of EPMs

Table 11 reports the estimation results of the following regression:

$$\pi HFT_d = \beta_0 + \beta_1 nEPM_d + \epsilon_d$$

where πHFT_d is the aggregated HFTs' trading profits on day d, and $nEPM_d$ is the number of EPMs on day d. The regression is repeated for foreign HFTs (HFT_FOR), individual HFTs (HFT_IND), and institutional HFTs (HFT_INS). Panel A and Panel B show the results for 10-second EPMs and the results for 1-second EPMs, respectively.

Panel A. 10-second EPMs

		Const.	# of EPMs
HFT	Mean	$ 365,385	$ 4,936
	t-Value	39.33	5.63
HFT_FOR	Mean	$ 302,788	$ 7,060
	t-Value	36.79	9.09
HFT_IND	Mean	$ -44,695	$ -1,083
	t-Value	-12.88	-4.30
HFT_INS	Mean	$ 86,916	$ -971
	t-Value	17.63	-2.09

Panel B. 1-second EPMs

		Const.	# of EPMs
HFT	Mean	$ 358,994	$ 793
	t-Value	38.15	6.59
HFT_FOR	Mean	$ 293,796	$ 1,127
	t-Value	35.52	10.65
HFT_IND	Mean	$ -42,944	$ -180
	t-Value	-12.29	-5.23
HFT_INS	Mean	$ 87,881	$ -142
	t-Value	17.51	-2.22

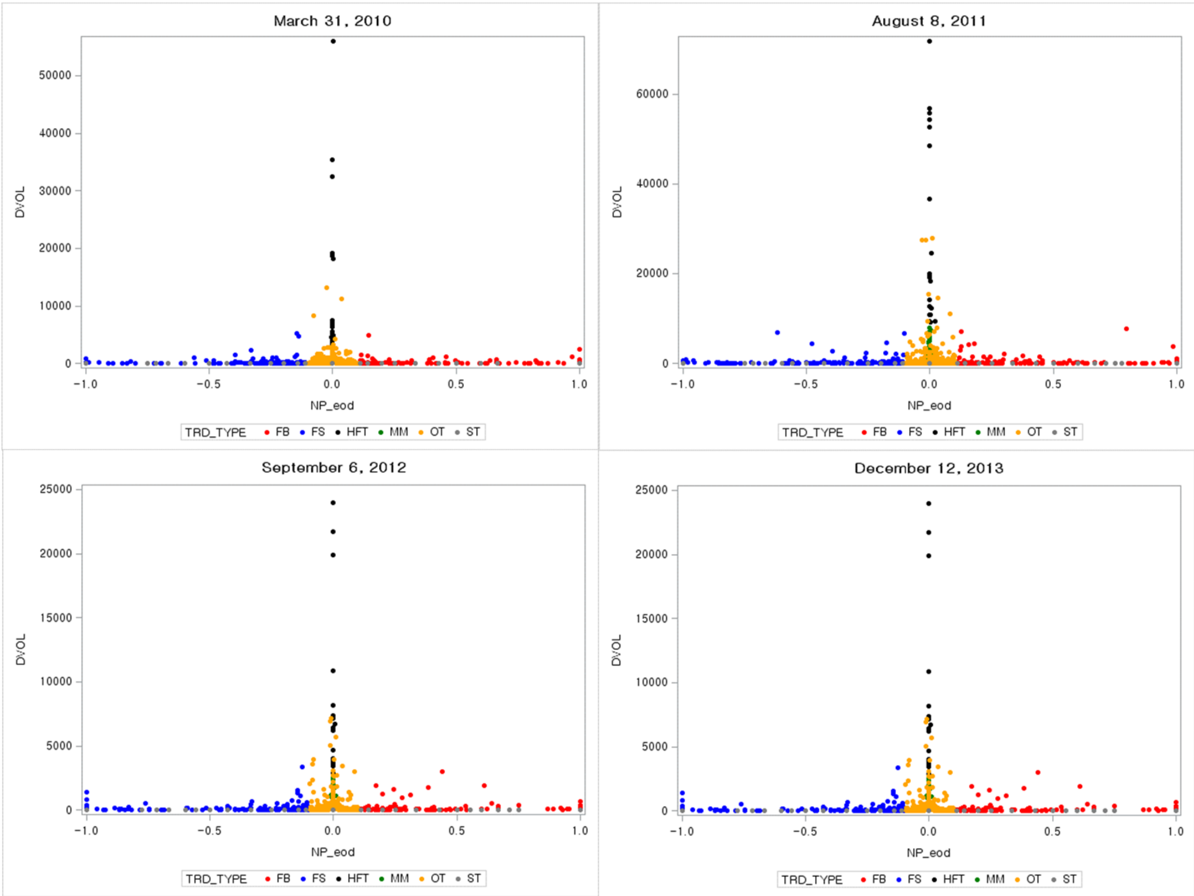

Figure 1. Scatter plots of trading accounts for selected days

Each account is scattered in two dimensional plane where the y-axis is its daily trading volume and the x-axis is its end-of-day position divided by the daily trading volume. The first panel of Figure 1 is the case for March 31, 2010 which was a normal trading day. The second panel of Figure 1 represents the case for August 8, 2011, the day when the downgrade of the U.S. credit rating occurred. On that day, the KOSPI 200 index futures price was extremely volatile, which leads to the highest number of EPMs occurred (See Figure 2). The third and fourth panel of Figure 1 shows the cases for maturity dates of the futures contracts.

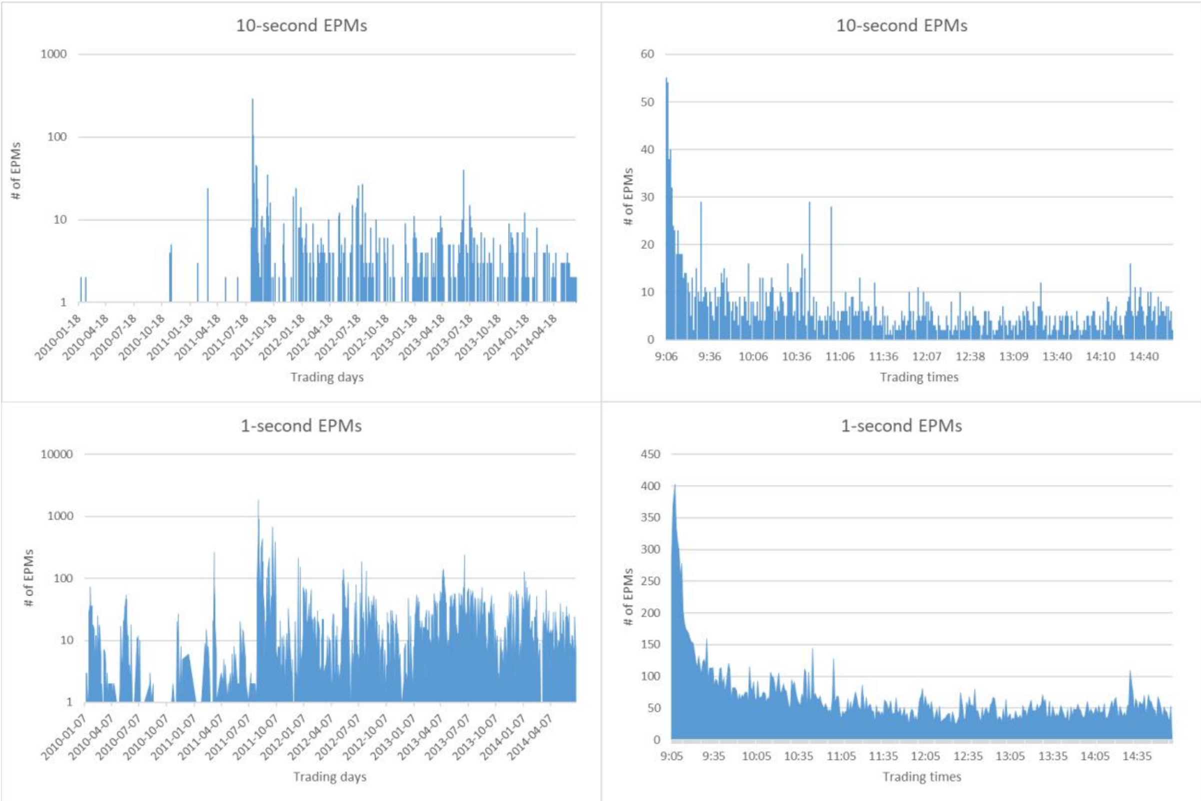

Figure 2. Daily and intraday distribution of EPMs for 10-second and 1-second EPMs

Figure 2 shows the daily frequency of EPMs over sample dates (the left two panels) and the intraday frequency over trading times (the right two panels) for 10-second and 1-second EPMs.

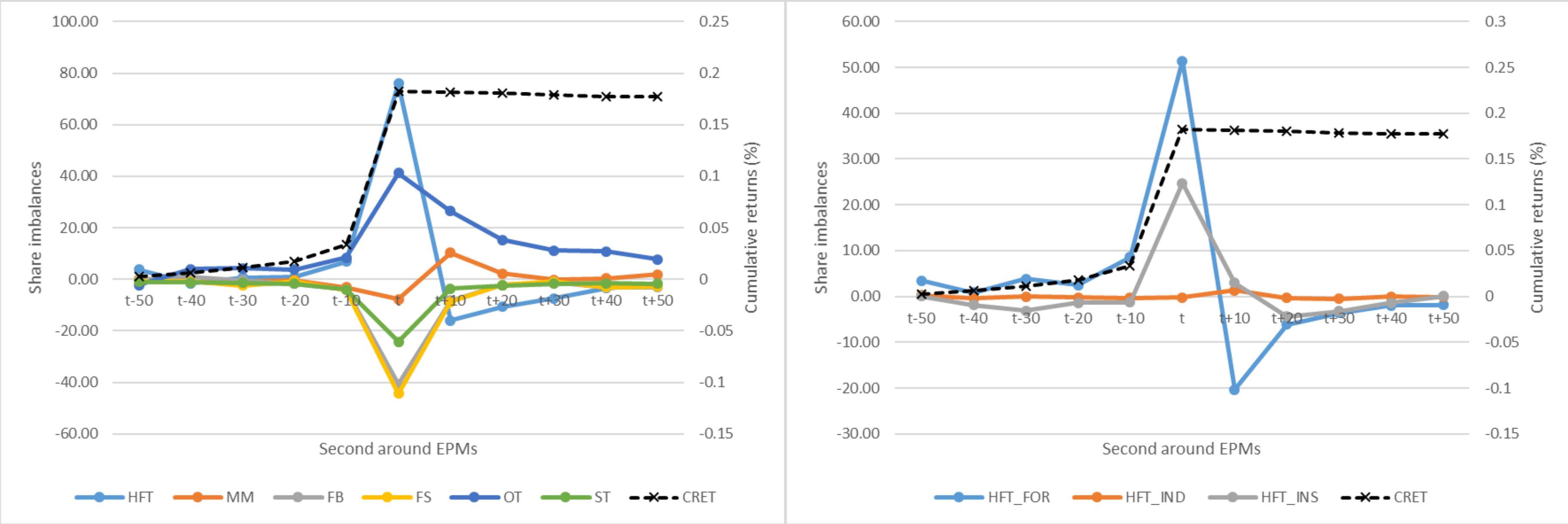

Figure 3. Liquidity supply and demand around 10-second EPMs

Figure 3 summarizes graphically net trade imbalances around 10-second EPMs in Table 3 with the cumulative returns from the interval $t-50$ marked as dashed lines. The first panel and the second panel show net trade imbalances for each trader type and net trade imbalances for each HFT investor group. For negative EPMs, we invert net trade imbalances and cumulative returns for exposition purposes.

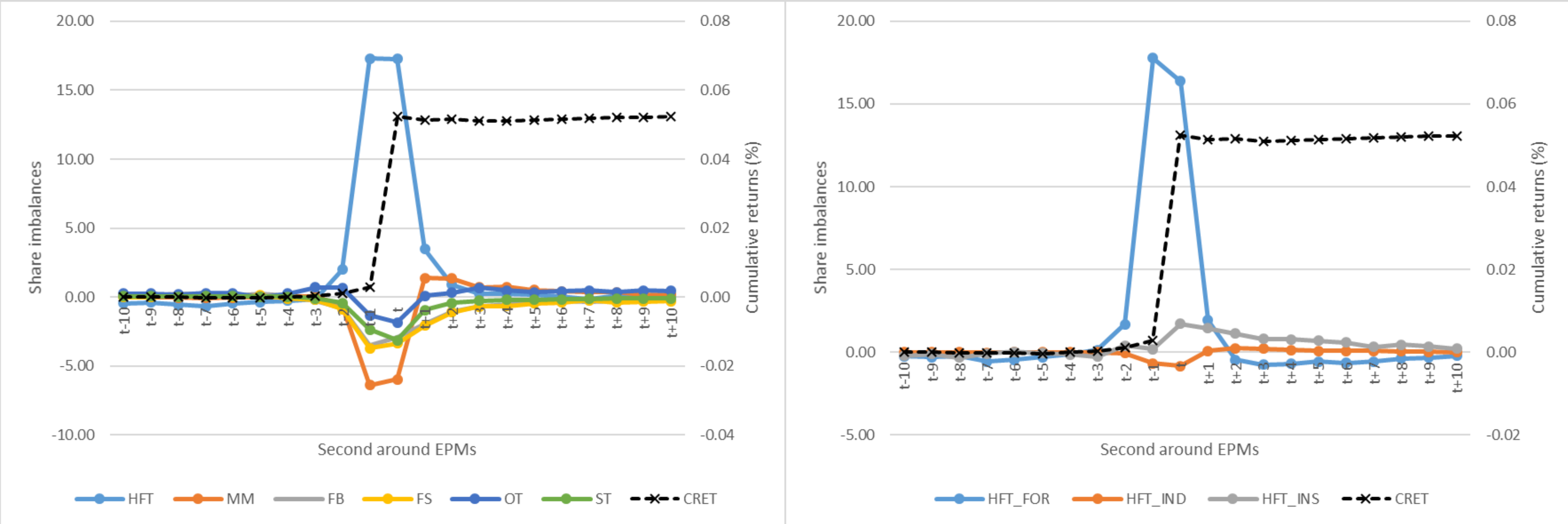

Figure 4. Liquidity supply and demand around 1-second EPMs

Figure 4 summarizes graphically net trade imbalances around 1-second EPMs in Table 4 with the cumulative returns from the interval $t-10$ marked as dashed lines. The first panel and the second panel show net trade imbalances for each trader type and net trade imbalances for each HFT investor group. For negative EPMs, we invert net trade imbalances and cumulative returns for exposition purposes.

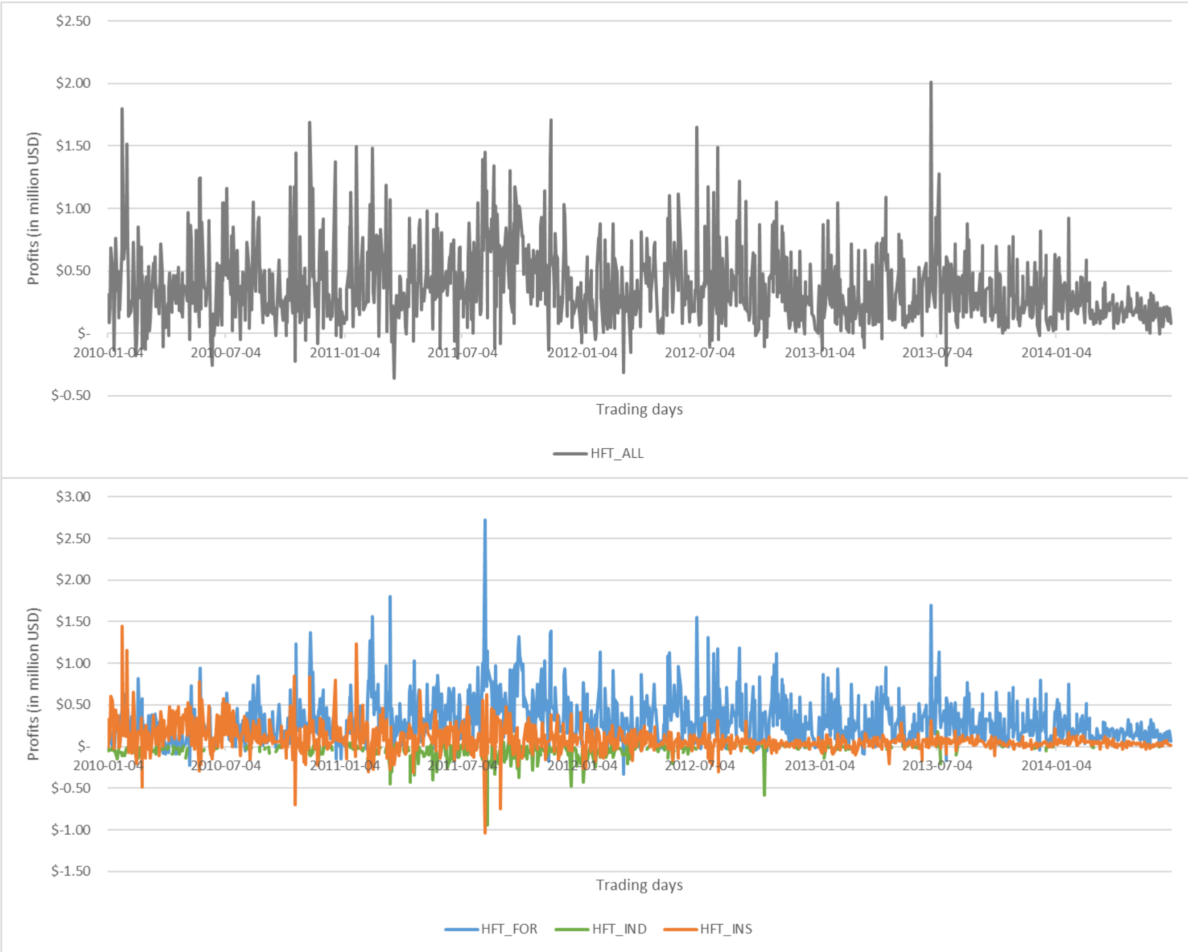

Figure 5. Daily time series of HFT profits

Figure 5 shows a time-series of daily profits for high-frequency traders (HFTs) and for each investor type of high-frequency traders. The upper panel presents a time-series of HFTs' daily profits. The bottom panel presents time-series of foreign HFTs (blue line), individual HFTs (green line), and institutional HFTs (orange line).

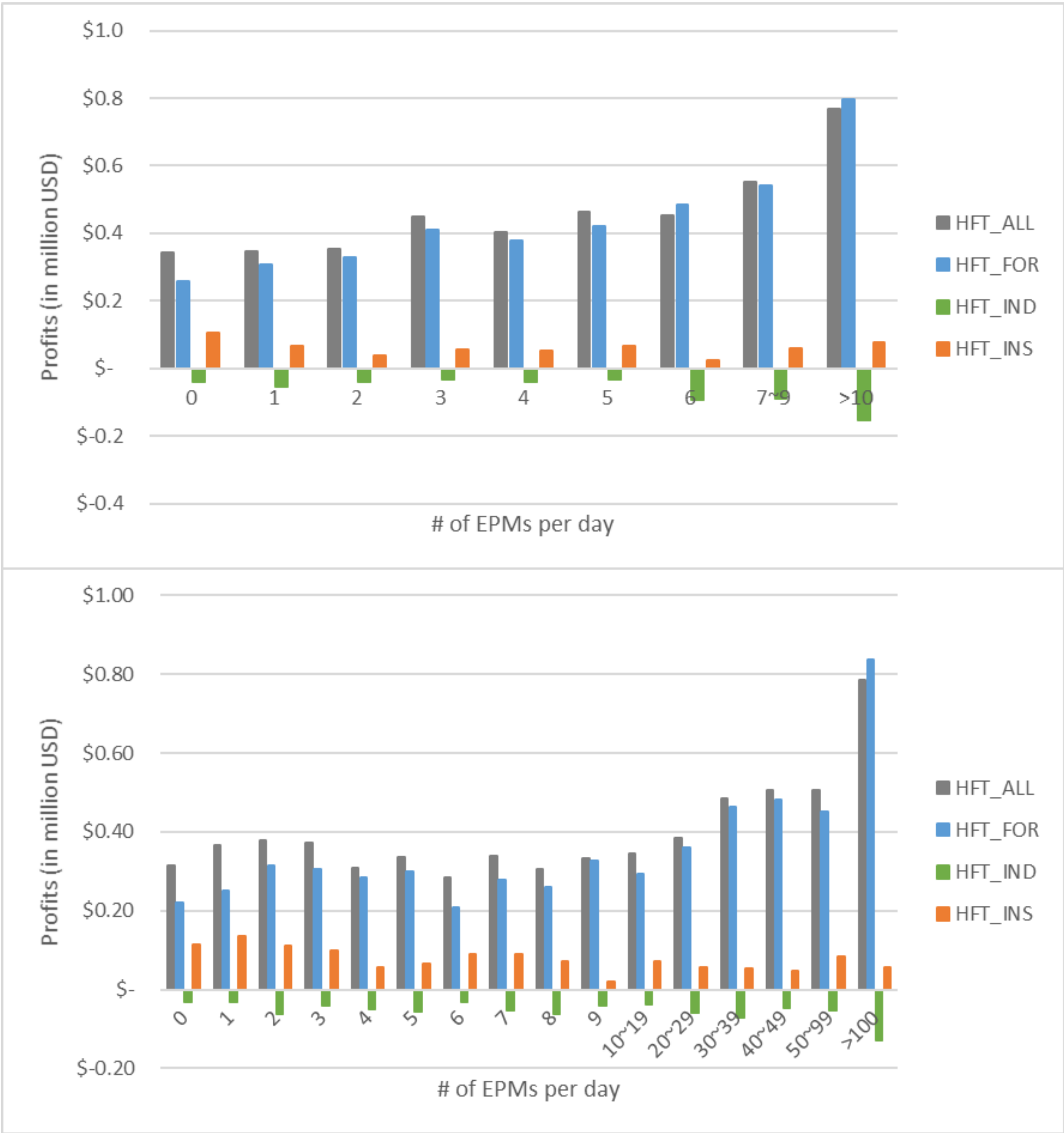

Figure 6. HFT profits and the number of EPMs

Figure 6 shows the histogram of an average daily profits aggregated and averaged according to the number of EPMs occurred on each day. The upper panels and bottom panels presents the results for 10-second EPMs and the results for 1-second EPMs, respectively.

Appendix

Table A1. Positive and negative EPMs

Table A1 reports the results for robustness check with positive and negative EPMs. Panel A shows summary statistics for positive and negative EPMs. Absolute Return (%) is the average of absolute returns during the interval. Total Trades are the average number of trades during the interval. Total HFT Trades are the average number of HFT trades during the interval. Share Volume and Dollar Volume are the total share volume and dollar volume during the interval. Quoted Spread (index point) is the share volume-weighted average quoted spread in index points during the interval. Effective Spread (%) is the share volume-weighted average effective spread during the interval. Price High-Low is the difference between maximum price and minimum price level during the interval. All statistics in Panel A are averaged over the sampling intervals. Panel B shows net trade imbalances of high-frequency traders (HFTs) and each HFT investor group for positive and negative EPMs.

Panel A. Summary statistics								
	10-second EPMs				1-second EPMs			
	Positive		Negative		Positive		Negative	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Absolute Return (%)	0.15	0.07	0.15	0.06	0.05	0.02	0.05	0.02
Total Trades	444.58	219.33	444.10	216.51	50.89	36.69	51.45	36.96
Total HFT Trades	202.61	90.51	204.31	90.89	28.24	20.38	28.33	20.69
Share Volume	907.54	495.77	898.72	483.97	104.65	86.61	106.76	88.07
Dollar Volume	$ 105,838,269	$ 63,665,223	$ 105,028,137	$ 63,022,352	$ 12,063,411	$ 10,442,761	$ 12,288,846	$ 10,599,908
Quoted Spread ($)	0.058	0.011	0.059	0.015	0.056	0.017	0.056	0.018
Effective Spread (%)	0.024	0.006	0.024	0.007	0.023	0.008	0.023	0.008
Price High-Low	0.43	0.19	0.42	0.16	0.09	0.07	0.09	0.07
Number of intervals	1,206		1,154		12,114		11,553	

Table A1. Positive and negative EPMs (continued)

Panel B. Net trade imbalances of HFT for positive and negative EPMs

	10-second EPMs				1-second EPMs			
	Positive		Negative		Positive		Negative	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
HFT^{NET}	75.44	141.54	76.62	132.06	17.69	44.44	16.81	46.41
HFT^{M}	3.77	10.60	3.62	11.57	0.30	2.79	0.30	2.97
HFT^{L}	71.67	141.49	73.00	132.07	17.38	44.43	16.51	46.40
HFT_IND^{NET}	53.83	109.23	48.95	101.12	16.94	39.32	15.77	38.81
HFT_IND^{M}	0.00	0.00	0.01	0.20	0.00	0.01	0.00	0.06
HFT_IND^{L}	53.83	109.23	48.95	101.11	16.94	39.32	15.77	38.81
HFT_INS^{NET}	-0.61	16.31	0.23	16.38	-0.82	5.13	-0.83	6.32
HFT_INS^{M}	2.34	4.92	2.71	5.52	0.18	1.26	0.17	1.03
HFT_INS^{L}	-2.95	16.14	-2.48	15.97	-1.00	5.01	-1.00	6.25
HFT_FOR^{NET}	22.22	107.60	27.43	99.86	1.57	30.85	1.87	33.19
HFT_FOR^{M}	1.43	9.52	0.90	10.22	0.13	2.48	0.14	2.78
HFT_FOR^{L}	20.78	107.12	26.53	99.81	1.45	30.74	1.74	33.09

Table A2. EPM magnitude quartiles

Table A2 reports the results for robustness check with EPM quartiles divided by the magnitude of absolute returns. Panel A shows summary statistics for each EPM quartile. Absolute Return (%) is the average of absolute returns during the interval. Total Trades are the average number of trades during the interval. Total HFT Trades are the average number of HFT trades during the interval. Share Volume and Dollar Volume are the total share volume and dollar volume during the interval. Quoted Spread (index point) is the share volume-weighted average quoted spread in index points during the interval. Effective Spread (%) is the share volume-weighted average effective spread during the interval. Price High-Low is the difference between maximum price and minimum price level during the interval. All statistics in Panel A are averaged over the sampling intervals. Panel B shows net trade imbalances of high-frequency traders (HFTs) and each HFT investor group for each EPM quartile.

Panel A. Summary statistics

	10-second EPMs							
	Q1		Q2		Q3		Q4	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Absolute Return (%)	0.09	0.01	0.12	0.01	0.16	0.01	0.22	0.07
Total Trades	438.29	183.00	523.33	196.01	395.65	209.77	420.10	254.98
Total HFT Trades	198.51	81.08	219.34	87.99	192.79	89.65	203.11	100.95
Share Volume	894.64	405.86	1076.33	442.43	791.00	472.69	850.95	576.28
Dollar Volume	$ 112,883,699	$ 52,227,551	$ 133,464,508	$ 57,094,677	$ 84,690,407	$ 57,637,591	$ 90,729,898	$ 72,582,235
Quoted Spread ($)	0.052	0.003	0.053	0.005	0.060	0.011	0.068	0.020
Effective Spread (%)	0.020	0.001	0.021	0.002	0.026	0.005	0.029	0.009
Price High-Low	0.28	0.05	0.34	0.08	0.45	0.08	0.61	0.21
Number of intervals	590		590		590		590	

	1-second EPMs							
	Q1		Q2		Q3		Q4	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Absolute Return (%)	0.04	0.00	0.04	0.00	0.05	0.00	0.07	0.02
Total Trades	52.17	34.73	56.12	37.79	44.08	31.12	52.28	41.78
Total HFT Trades	29.48	20.98	29.33	21.56	26.25	19.80	28.08	19.58
Share Volume	106.78	80.29	113.67	85.85	94.66	79.00	107.60	101.29
Dollar Volume	$ 13,677,162	$ 10,339,813	$ 13,911,439	$ 10,659,556	$ 9,677,839	$ 8,391,033	$ 11,427,640	$ 11,820,930
Quoted Spread ($)	0.051	0.004	0.052	0.004	0.058	0.015	0.065	0.030
Effective Spread (%)	0.020	0.002	0.021	0.002	0.025	0.007	0.028	0.013
Price High-Low	0.06	0.04	0.07	0.04	0.10	0.06	0.14	0.10
Number of intervals	5,916		5,917		5,917		5,917	

Table A2. EPM magnitude quartiles

Panel B. Liquidity supply and demand of HFT for EPM magnitude quartiles

	10-second EPMs							
	Q1		Q2		Q3		Q4	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
HFT^{NET}	64.62	128.96	83.72	155.81	80.43	129.75	75.28	131.05
HFT^{M}	1.24	4.19	2.41	6.16	4.54	11.95	6.60	16.63
HFT^{L}	63.38	129.05	81.31	155.87	75.89	129.64	68.68	131.02
HFT_FOR^{NET}	58.41	107.71	54.75	107.94	50.32	100.14	42.32	105.01
HFT_FOR^{M}	0.01	0.12	0.01	0.25	0.00	0.00	0.00	0.00
HFT_FOR^{L}	58.40	107.69	54.74	107.94	50.32	100.14	42.32	105.01
HFT_IND^{NET}	-1.18	11.72	-1.05	11.14	0.37	20.58	1.05	19.53
HFT_IND^{M}	1.23	3.86	2.39	5.31	3.18	5.49	3.28	5.78
HFT_IND^{L}	-2.41	11.49	-3.44	11.03	-2.81	20.26	-2.23	19.18
HFT_INS^{NET}	7.39	87.75	30.02	132.30	29.73	98.22	31.92	89.30
HFT_INS^{M}	0.00	1.63	0.01	3.16	1.36	10.65	3.32	16.01
HFT_INS^{L}	7.39	87.69	30.01	132.63	28.37	97.80	28.59	88.38

	1-second EPMs							
	Q1		Q2		Q3		Q4	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
HFT^{NET}	18.17	43.99	15.81	45.56	21.19	47.85	13.87	43.84
HFT^{M}	0.13	2.25	0.13	1.01	0.30	2.62	0.65	4.48
HFT^{L}	18.04	43.97	15.68	45.57	20.89	47.90	13.22	43.70
HFT_FOR^{NET}	17.93	39.18	15.10	38.77	17.69	41.02	14.76	37.15
HFT_FOR^{M}	0.00	0.08	0.00	0.02	0.00	0.00	0.00	0.00
HFT_FOR^{L}	17.93	39.18	15.10	38.77	17.69	41.02	14.76	37.15
HFT_IND^{NET}	-0.58	3.80	-0.56	4.04	-0.81	6.25	-1.36	7.84
HFT_IND^{M}	0.08	0.98	0.13	1.01	0.21	1.32	0.26	1.27
HFT_IND^{L}	-0.66	3.72	-0.70	3.97	-1.01	6.13	-1.63	7.74
HFT_INS^{NET}	0.82	29.72	1.28	32.18	4.31	36.35	0.47	29.16
HFT_INS^{M}	0.05	2.02	0.00	0.05	0.09	2.25	0.38	4.30
HFT_INS^{L}	0.77	29.67	1.28	32.18	4.22	36.30	0.09	28.81

Table A3. Permanent and Transitory EPMs

Table A1 reports the results for robustness check with permanent and transitory EPMs. We identify EPMs as permanent if EPMs do not revert by more than 2/3 by the end of a 30-minute period and as transitory if EPMs revert by more than 1/3 by the end of a 30-minute period. Panel A shows summary statistics for permanent and transitory EPMs. Absolute Return (%) is the average of absolute returns during the interval. Total Trades are the average number of trades during the interval. Total HFT Trades are the average number of HFT trades during the interval. Share Volume and Dollar Volume are the total share volume and dollar volume during the interval. Quoted Spread (index point) is the share volume-weighted average quoted spread in index points during the interval. Effective Spread (%) is the share volume-weighted average effective spread during the interval. Price High-Low is the difference between maximum price and minimum price level during the interval. All statistics in Panel A are averaged over the sampling intervals. Panel B shows net trade imbalances of high-frequency traders (HFTs) and each HFT investor group for permanent and transitory EPMs.

Panel A. Summary statistics

	10-second EPMs				1-second EPMs			
	Permanent		Transitory		Permanent		Transitory	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Absolute Return (%)	0.15	0.06	0.14	0.05	0.05	0.02	0.05	0.01
Total Trades	446.02	232.06	462.61	198.86	50.33	36.91	52.70	36.89
Total HFT Trades	203.96	94.07	210.24	81.80	28.23	20.36	28.87	20.89
Share Volume	900.51	518.35	935.07	459.83	103.22	87.50	108.68	86.43
Dollar Volume	$ 105,194,119.09	$ 67,575,687.67	$ 109,728,443.83	$58,852,890.42	$11,865,424	$10,571,793	$12,597,924	$10,403,687
Quoted Spread ($)	0.059	0.015	0.056	0.009	0.056	0.018	0.055	0.014
Effective Spread (%)	0.025	0.007	0.023	0.005	0.024	0.008	0.023	0.007
Price High-Low	0.43	0.18	0.39	0.13	0.09	0.07	0.09	0.06
Number of intervals	1,241		727		12,664		7,325	

Table A3. Permanent and Transitory EPMs (continued)

Panel B. Liquidity supply and demand of HFT for permanent and transitory EPMs

	10-second EPMs				1-second EPMs			
	Permanent		Transitory		Permanent		Transitory	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
HFT^{NET}	72.89	136.60	80.44	140.33	17.14	44.83	17.48	45.94
HFT^{M}	4.05	11.58	3.37	8.96	0.34	3.26	0.23	1.89
HFT^{L}	68.84	136.68	77.07	140.16	16.80	44.82	17.25	45.92
HFT_FOR^{NET}	51.46	106.20	56.55	104.02	16.52	38.46	16.88	39.77
HFT_FOR^{M}	0.00	0.06	0.01	0.23	0.00	0.01	0.00	0.07
HFT_FOR^{L}	51.46	106.20	56.54	104.01	16.52	38.46	16.88	39.77
HFT_IND^{NET}	-0.07	16.27	-1.46	15.32	-0.85	6.28	-0.86	5.17
HFT_IND^{M}	2.54	5.35	2.65	5.27	0.17	1.16	0.17	1.19
HFT_IND^{L}	-2.61	16.02	-4.11	15.26	-1.02	6.19	-1.04	5.09
HFT_INS^{NET}	21.51	100.88	25.35	111.48	1.47	31.58	1.47	31.57
HFT_INS^{M}	1.51	10.34	0.71	7.33	0.17	3.04	0.06	1.46
HFT_INS^{L}	20.00	100.79	24.64	111.02	1.30	31.44	1.41	31.54

Table A4. Net trade imbalances and Returns during subtypes of EPMs: 10-second intervals

Trader A4 reports the estimation results of the regression in Table 6, with dummy variables for subtypes of EPMs instead EPM dummy. We replace EPM dummy with permanent EPM dummy and transitory EPM dummy in Model (1), with four EPM quartile dummies in Model (2), and with positive EPM dummy and negative EPM dummy in Model (3).

Trader	Model		$1_{\text{EPM-PERMANENT}}$	$1_{\text{EPM-TRANSITORY}}$	$1_{\text{EPM-Q1}}$	$1_{\text{EPM-Q2}}$	$1_{\text{EPM-Q3}}$	$1_{\text{EPM-Q4}}$	1_{POSITIVE}	1_{NEGATIVE}	$\lvert\text{Return}\rvert$	Share Vol.	Eff. Spread	Price H-L
HFT	(1)	Mean	-113.88	-96.23							11.32	42.87	-1.95	21.72
		Std. Dev.	1.30	1.68							0.03	0.27	0.08	0.97
	(2)	Mean			-73.41	-85.58	-109.94	-175.27			11.53	41.73	-2.00	24.54
		Std. Dev.			1.86	1.86	1.86	1.88			0.03	0.27	0.08	0.97
	(3)	Mean							-111.56	-108.58	11.44	42.64	-2.00	23.20
		Std. Dev.							1.32	1.34	0.03	0.27	0.08	0.97
HFT_FOR	(1)	Mean	-104.10	-88.51							9.91	15.70	-1.31	43.30
		Std. Dev.	1.15	1.49							0.02	0.24	0.07	0.86
	(2)	Mean			-51.02	-79.44	-112.23	-176.54			10.15	14.38	-1.36	46.42
		Std. Dev.			1.64	1.64	1.64	1.66			0.02	0.24	0.07	0.86
	(3)	Mean							-102.06	-105.28	10.04	15.47	-1.35	44.82
		Std. Dev.							1.16	1.18	0.02	0.24	0.07	0.86
HFT_IND	(1)	Mean	5.70	4.08							-0.36	-0.19	0.09	-2.55
		Std. Dev.	0.11	0.15							0.00	0.02	0.01	0.08
	(2)	Mean			2.76	4.02	6.58	9.51			-0.38	-0.12	0.09	-2.73
		Std. Dev.			0.16	0.16	0.16	0.16			0.00	0.02	0.01	0.08
	(3)	Mean							5.22	6.11	-0.37	-0.18	0.09	-2.64
		Std. Dev.							0.11	0.12	0.00	0.02	0.01	0.08
HFT_INS	(1)	Mean	-15.25	-11.70							1.77	27.42	-0.75	-18.92
		Std. Dev.	1.02	1.31							0.02	0.21	0.06	0.76
	(2)	Mean			-25.22	-10.15	-4.02	-7.73			1.76	27.52	-0.75	-19.05
		Std. Dev.			1.45	1.45	1.45	1.47			0.02	0.21	0.06	0.76
	(3)	Mean							-14.53	-9.18	1.77	27.40	-0.75	-18.87
		Std. Dev.							1.03	1.05	0.02	0.21	0.06	0.76

Table A5. Net trade imbalances and Returns during subtypes of EPMs: 1-second intervals

Trader A5 reports the estimation results of the regression in Table 7, with dummy variables for subtypes of EPMs instead EPM dummy. We replace EPM dummy with permanent EPM dummy and transitory EPM dummy in Model (1), with four EPM quartile dummies in Model (2), and with positive EPM dummy and negative EPM dummy in Model (3).

Trader	Model		$1_{EPM\text{-}PERMANENT}$	$1_{EPM\text{-}TRANSITORY}$	$1_{EPM\text{-}Q1}$	$1_{EPM\text{-}Q2}$	$1_{EPM\text{-}Q3}$	$1_{EPM\text{-}Q4}$	$1_{POSITIVE}$	$1_{NEGATIVE}$	$\lvert Return \rvert$	Share Vol.	Eff. Spread	Price H-L
HFT	(1)	Mean	-10.75	-10.44							4.27	133.77	-0.31	-23.95
		Std. Dev.	0.11	0.14							0.00	0.10	0.00	0.14
	(2)	Mean			-7.25	-10.74	-4.92	-21.52			4.32	133.52	-0.32	-23.46
		Std. Dev.			0.15	0.15	0.15	0.15			0.00	0.10	0.00	0.14
	(3)	Mean							-10.38	-11.58	4.30	133.72	-0.32	-23.75
		Std. Dev.							0.11	0.11	0.00	0.10	0.00	0.14
HFT_FOR	(1)	Mean	-6.13	-5.57							3.80	92.97	-0.14	-11.32
		Std. Dev.	0.09	0.12							0.00	0.09	0.00	0.13
	(2)	Mean			-2.03	-5.74	-3.61	-14.96			3.84	92.74	-0.15	-10.93
		Std. Dev.			0.13	0.13	0.13	0.14			0.00	0.09	0.00	0.13
	(3)	Mean							-5.77	-7.17	3.82	92.93	-0.15	-11.18
		Std. Dev.							0.09	0.10	0.00	0.09	0.00	0.13
HFT_IND	(1)	Mean	0.26	0.23							-0.19	-4.35	0.01	0.26
		Std. Dev.	0.01	0.01							0.00	0.01	0.00	0.01
	(2)	Mean			0.37	0.41	0.24	0.14			-0.19	-4.36	0.01	0.26
		Std. Dev.			0.01	0.01	0.01	0.01			0.00	0.01	0.00	0.01
	(3)	Mean							0.29	0.29	-0.19	-4.35	0.01	0.25
		Std. Dev.							0.01	0.01	0.00	0.01	0.00	0.01
HFT_INS	(1)	Mean	-4.88	-5.12							0.66	45.19	-0.19	-12.91
		Std. Dev.	0.08	0.11							0.00	0.08	0.00	0.11
	(2)	Mean			-5.57	-5.44	-1.57	-6.69			0.67	45.16	-0.19	-12.82
		Std. Dev.			0.12	0.12	0.12	0.12			0.00	0.08	0.00	0.11
	(3)	Mean							-4.91	-4.70	0.67	45.17	-0.19	-12.85
		Std. Dev.							0.09	0.09	0.00	0.08	0.00	0.11