High-Frequency Trading in an Options Market: Evidence from the KOSPI 200 Options Market

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ABSTRACT

We examine the trading activity of high-frequency traders (HFTs) and their impact on market quality in an options market. We use a unique dataset of the KOSPI 200 options market from January 2, 2012, to June 30, 2014, that not only contains detailed information about every trade and quote but also enables us to directly identify HFTs' accounts. On average, 39 HFTs trade each day, and HFTs account for 37% of the transactions on the options market. We find that high-frequency trading is profitable in the KOSPI 200 options market, especially for HFTs who aggressively use marketable orders. HFTs trade on information and execute their trades at advantageous prices when they take liquidity. The price impact is higher in their liquidity taking transactions, one of the sources for the high profitability of aggressive HFTs. We also find that spreads are tighter when HFTs participate in trades and HFTs do not harm market quality compared to non-HFTs. HFTs tend to reduce trading costs and do not significantly affect short-term volatility, while non-HFTs increase it. Overall, the evidence indicates that HFTs enhance the market quality of the options market compared to non-HFTs.

Keywords: High-frequency trading; Options market; Trading cost; Market quality; Volatility

JEL classification: G10, G20

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ABSTRACT

We examine the trading activity of high-frequency traders (HFTs) and their impact on market quality in an options market. We use a unique dataset of the KOSPI 200 options market from January 2, 2012, to June 30, 2014, that not only contains detailed information about every trade and quote but also enables us to directly identify HFTs' accounts. On average, 39 HFTs trade each day, and HFTs account for 37% of the transactions on the options market. We find that high-frequency trading is profitable in the KOSPI 200 options market, especially for HFTs who aggressively use marketable orders. HFTs trade on information and execute their trades at advantageous prices when they take liquidity. The price impact is higher in their liquidity taking transactions, one of the sources for the high profitability of aggressive HFTs. We also find that spreads are tighter when HFTs participate in trades and HFTs do not harm market quality compared to non-HFTs. HFTs tend to reduce trading costs and do not significantly affect short-term volatility, while non-HFTs increase it. Overall, the evidence indicates that HFTs enhance the market quality of the options market compared to non-HFTs.

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1. Introduction

Recent advances in technology and electronic trading employed in financial markets allow traders to process information and submit orders extremely quickly. These developments in financial market have led to the rise of a new type of traders, referred to as high-frequency traders (HFTs). The U.S. Securities and Exchange Commission (SEC) defines these traders as “professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis.” HFTs have come to play a significant role in financial markets. For example, Zhang (2010) reports that HFTs account for over 70% of the dollar trading volume in the U.S. capital market. High-frequency trading is not only dominant in the U.S. equity market but also pervasive throughout the world financial markets. Zook and Grote (2014) report that HFTs account for about half of trades at stock exchanges worldwide. However, concerns about the impact of high-frequency trading on market quality have been growing. Especially since the 2010 Flash Crash, the belief that HFTs exploit other investors and destabilize markets has spread among the public. On the other hand, others believe that high-frequency trading is nothing more than a tool that results in improved liquidity. Whether HFTs enhance market quality or reduce it and whether high-frequency trading should be regulated are still controversial matters.

This paper provides empirical evidence on these issues by examining high-frequency trading and its impact on market quality in an options market. We use a unique dataset for KOSPI 200 options that enable us to directly identify HFTs. We can also exactly identify who initiates trades, buyers or sellers. Direct identification is not possible in most markets, so this feature elevates the accuracy of the analysis for high-frequency trading.

We are particularly interested in the impact of HFTs in one options market, the KOSPI 200 options market, with the following reasons. First, as documented by Lo and MacKinlay (1990), an out-of-sample experiment can provide additional evidence whether findings in developed markets should be generalized as a worldwide phenomenon. Previous literature on HFTs primary focuses on the U.S. market. Investigating HFTs in the Korean market may provide different empirical results compared to the evidence on the U.S. market due to difference in market structures and regulatory environment. Second, the KOSPI 200 options market, one of the most active derivatives markets in the world, is proper for studying high frequency trading. A crucial advantage of the KOSPI 200 options market in carrying out high-frequency trading is the negligible transaction costs and lack of taxes. In addition, highly leveraged trading and easy short selling are also advantages for HTFs in the options market. Thus, it is natural that HFTs who are interested in financial markets focus more on the options market than the stock markets. To our best knowledge, our paper is the first to study HFTs on an options market. Examining high-frequency trading on the options market will therefore enhance the understanding of HFTs and contribute to the literature.

There has been a growing body of theoretical and empirical literature on high-frequency trading. Several recent theoretical papers provide models to determine the impact of high-frequency trading on markets. Gerig and Michayluk (2013) extend Glosten and Milgrom's (1985) model including multiple securities and an automated market maker, arguing that the automated market maker makes markets more efficient and lowers transaction costs. Rosu (2014) extends Kyle's (1985) model with multiple informed traders who may have different speeds and with changing fundamental values, suggesting that competition among fast informed traders improves market efficiency and liquidity. On the contrary, Jarrow and Protter (2012) suggest that HFTs gain profits at the expense of other traders and may reduce market efficiency. Han, Khapko, and Kyle (2014) develop a model in which low-frequency traders may suffer due to the actions of HFTs, claiming that restrictions on HFTs may be needed. There are also models in which the impact of HFTs depends on the market environment. Jovanovic and Menkveld (2012) provide a model in which HFTs can mitigate or exacerbate the adverse selection problem, depending on market conditions. Their calibration implies that HFTs may raise welfare. Hoffmann (2014) develops a model based on Foucault's (1999) dynamic limit order market. In the model, fast traders can reduce inefficiency, but it is possible that they also decrease the welfare of slow traders and the arms race for speed is triggered. Biais, Foucault, and Moinas (2014), in line with Grossman and Stiglitz (1980), consider the fraction of fast institutions and the costs of becoming faster an important element. Fast trading is beneficial in dealing with market fragmentation but also results in adverse selection and overinvestment in speed. These studies provide useful implications but do not cover the overall effects of diverse and complicated HFT strategies.

Unlike theoretical works in the field, empirical works mainly show the positive effects of HFTs. Several empirical studies on the NASDAQ examine whether HFTs generally play a positive role. Brogaard (2010) reports that HTFs contribute to the price discovery process, lower transaction costs, and may decrease volatility. Brogaard, Hendershott, and Riordan (2014) find that HFTs improve price efficiency and do not seem to destabilize the market, even if the market is volatile. Carrion (2013) argues that HFTs reduce transaction costs and make the market more efficient. A study on the London Stock Exchange also suggests that HFTs tend to enhance market liquidity (Jarnecic and Snape, 2014). Malinova, Park, and Riordan (2013) show that introducing a per-message fee in Canada, which constricts HFTs' trading activity, is not helpful to retail traders. However, a few studies have negative views on HFTs. Kirilenko, Kyle, Samadi, and Tuzun (2014) claim that HFTs did not cause the 2010

Flash Crash but exacerbated it by absorbing liquidity. Breckenfelder (2013) argues that competition among HFTs eventually reduces liquidity and raises short-term volatility in the Swedish equity market. Lee (2013) reports that HFTs impede the price discovery process and do not improve market quality in the KOSPI 200 futures market, which directly contrasts with studies on the NASDAQ.

Our main findings are consistent with the positive views on HFTs. We study HFTs' profits and then analyze their relation with trading costs and impact on market quality. Generally, HFTs gain profits but the profits are distributed in a wide range. In general, there are three ways to make money in a financial market. The first way is to bear systematic risk. However, because HFTs tend to change their positions every minute and end trading days with negligible inventory positions, they do not bear any significant systematic risk. The second way is to provide liquidity. Although passive HFTs basically act like market-makers and supply liquidity, they do not earn substantial trading profits. The third way is to trade on private information. Our empirical results show that the main source of profits for HFTs is private information. Aggressive HFTs seem to trade on information and earn much more profit than passive HFTs. On the other hand, HFTs tend to demand liquidity when it is relatively plentiful and are associated with lower trading costs. Our estimation through a vector autoregression (VAR) model also shows that HFTs significantly reduce effective spreads, while the effect of non-HFTs is small. Furthermore, it is surprising that HFTs do not affect or may even reduce short-term volatility while non-HFTs significantly increase it. Understanding the effect of HFT is important for the analysis of modern financial markets, and it is essential for addressing policy issues about regulation on HFTs. These empirical results indicate that regulators' concerns seem misplaced. HFTs enhance market liquidity and do not harm market quality.

The remainder of the paper is organized as follows. Section 2 describes the structure of the KOSPI 200 options market and data. Section 3 reports the trading activity of HFTs. Section 4 examines the profitability of HFTs. Section 5 investigates the trading execution costs when HFTs are liquidity providers and when they are liquidity takers. Section 6 presents evidence regarding HFTs' impact on market quality. Finally, Section 7 summarizes and concludes the paper.

2. Description of the Market and Data

We use intraday trade and quote data for KOSPI 200 options on the Korea Exchange (KRX) from January 2, 2012 to June 30, 2014. Our dataset comprises detailed information of all trades and quotes in the KOSPI 200 options market. The data include a millisecond timestamp denoting when trades occur and quotes arrive at the exchange.

The KOSPI 200 options market was launched on the KRX in July 1997. Despite its short history, the KOSPI 200 options market is one of the most active derivatives markets in the world. According to the Futures Industry Association report, the KOSPI 200 options market was the most active derivatives market in terms of trading volumes until 2012. After an option multiplier change that raised the multiplier for KOSPI 200 options from KRW 100,000 to KRW 500,000 in March 9, 2012, there were substantial drops in trading volumes. However, the KOSPI 200 options market still remains one of the top three more active derivatives markets in the world.[1]

KOSPI 200 options are European options, exercisable only at expiration, where the contract months are three consecutive months plus the one month nearest to the quarterly cycle (March, June, September, or December). The last trading day is the second Thursday of the contract month. Each option contract month has at least five strike prices, with an interval of 2.5 points. There are no floor traders, market makers, or specialists in this market. This market is a completely electronic order-driven market. The KOSPI 200 options market opens at 9:00 a.m. and closes at 15:15 p.m.[2] Trading runs continuously from 9:00 a.m. to 3:05 p.m., with the opening price determined by a batch auction at a one-hour pre-opening session. For the last 10 minutes until the market closes, there is a closing batch auction. All order prices are required to be a multiple of a fixed tick size. When option premiums are below (above or equal to) three points, the tick size is 0.01 (0.05) point.

A crucial advantage of the KOSPI 200 options market carrying out high-frequency trading is that this market requires negligible transaction costs and no tax. For equity trading in the KRX, investors pay 0.3% taxes on their sales. By contrast, for option trading in the KRX, investors do not pay any tax and often do not pay commissions either. In addition, options are highly leveraged instruments and it is easy to carry out short selling in an options market. Thus, it is natural for HFTs interested in the Korean markets to focus on options markets rather than stock markets. Moreover, our data for the KOSPI 200 options market are appropriate for investigating high-frequency

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[1] According to the Futures Industry Association Annual Volume Survey (http://www.futuresindustry.org), the KOSPI 200 options market was the highest ranked among all derivative markets in terms of trading volume until 2012. The cumulative trading volume consisted of 1,575,394,249 contracts during 2012. However, the trading volume dropped to 580,460,364 contracts during 2013, but the KOSPI 200 options market still ranked as the third largest derivatives market in 2013.

[2] The sample period contains some irregular trading days. On the last trading day, the options market closes at 2:50 p.m. On the first trading day of the year, the market opens one hour late, at 10:00 a.m. On the day of the national college scholastic ability examination, the market not only opens one hour late but also closes one hour late.

trading. Our intraday dataset contains not only high-quality information about every order and transaction, but also the encoded accounts of each trader. The encoded account information enables us to directly identify HFTs. In addition, since the data include buy–sell indicators and detailed millisecond time stamps, we can determine exactly whether each trade is buyer or seller initiated at the transaction level, without depending on econometric methods such as Lee and Ready (1991) algorithm.

The categorization of traders used in this paper is based on capturing the common characteristics of HFTs. According to the SEC (2010), HFTs submit numerous orders at extraordinarily high speeds, cancel orders shortly after their original submission, and end the trading day at or as close to a neutral inventory position as possible. Specifically, we select traders who satisfy the following four conditions as HFTs: (1) They submit more than 1,000 limit orders in the day, (2) they have a median order duration of less than one second, (3) they have a median cancellation duration of less than two seconds, and (4) they have an end-of-day inventory position of no more than 1% of the total volume traded that day. We also decompose two different subcategories of HFTs based on how frequently they initiate transactions. To be considered a liquidity taking (aggressive, marketable) HFT, a trader must initiate more than half of his or her total transactions; to be considered a liquidity providing (passive, non-marketable) HFT, a trader must initiate fewer than half of his or her total transactions.

We classify non-HFTs into two different subcategories: algorithmic traders (ATs) and normal traders (NTs). The AT category is meant to capture "the use of computer algorithms to automatically make trading decisions" (Hendershott, Terrence, and Riordan, 2013) . HFTs can be considered included in ATs, but since we want to observe the interaction between HFTs and non-HFT ATs, we define ATs as non-HFT accounts that submit more than 1,000 limit orders a day. If a human trader, who does not use computer-generated decision making technology, tries to submit 1,000 orders a day, the trader must submit orders once every 20 seconds during the entire trading day, which is far from realistic. We classify all remaining accounts that do not belong to ATs as NTs. They comprise the majority of traders.

3. Trading activity of HFTs

From the above categorization of HFTs, on average, we identify 39 accounts as HFTs a trading day. We also identify 157 ATs and 15,317 NTs a trading day, on average. HFTs comprise only 0.25% of daily traders' accounts. However, despite the very small number of accounts, they make up 44% of order submissions (on average, 2,479,679 orders out of 5,655,292 orders a day), 37% of transactions (on average, 320,431 transactions out of 875,306 transactions a day), and 31% of the total trading volume (on average, 2,134,967 contracts out of 6,904,488 contracts a day) of the overall options market. In addition, ATs are also responsible for a large portion of the option market. Although only 1.01% of traders are ATs, they account for 44%, 25%, and 28% of order submissions, transactions, and trading volumes, respectively. In other words, the participation of HFTs and ATs comprises a rather large portion in the KOSPI 200 index options market.

< Insert Figure 1 >

Figure 1 shows the number of HFT accounts each day. The number of HFTs tends to decrease and this tendency is due to domestic HFTs. Especially in the case of domestic individual HFTs, there is a big difference between before and after the change of the option multiplier in June 2012.[3] Specifically, there were 19.0 domestic individual HFTs, on average, before June 14, 2012; however, after, only 4.4 domestic individual HFTs participate in the market. For domestic institutional HFTs, the number of accounts declined from 9.2 to 5.9 after the option multiplier change; on the other hand, the number of foreign HFT accounts slightly increased, from 22.8 to 26.6. Thus, the downward trend of the entire HFT is completely caused by the decrease in domestic HFTs.

< Insert Table 1 >

Table 1 presents a summary of the average daily trading behavior of our three trader categories for the sample period from January 2, 2012, to June 30, 2014. Panel A summarizes the daily trading activities by the three trader groups. The table describes the daily mean of order and cancellation activities, such as *Number of Order Submitted, Order Duration, Cancellation Rate,* and *Cancellation Duration*. It also provides the mean of transaction activities such as *Number of Transactions, Volume, Order to Trade Ratio,* and *|Net Position| to Volume*. All variables in Panel A show substantial differences in the characteristics of trading activities among the three trader groups. First, HFTs exhibit very fast and frequent order activity. On average, one HFT submits 62,827 orders per day, including order submissions, revisions, and cancellations. They submit one order every 0.21 seconds. On average, per day, ATs submit 15,854 orders and NTs submit 45 orders per person. Their order duration is longer than that of HFTs: ATs submit one order every 4.31 seconds and NTs have an order duration of 994 seconds. We can also

[3] The multiplier for KOSPI 200 Options was increased to KRW 500,000, five times the prior multiplier since March 9, 2012, step by step, across contract months. Both multipliers of 100,000 and 500,000 were used for about three months after the effective date of March 9, 2012, but the use of the multiplier of 100,000 gradually decreased and only the multiplier of 500,000 has been used since June 15, 2012.

find similar differences in cancellation orders: HFTs cancel about two-thirds of their limit orders in just a few seconds. The variable *Cancellation Rate*, defined as the ratio of the number of limit order cancellations to the number of limit order submissions (including revisions), is 63.7% and the *Cancellation Duration*, defined as the median value of the time to cancellation for cancelled limit orders, is only 0.36 seconds. ATs also cancel fairly large amounts of their orders (49.1%), but *Cancellation Duration* for ATs is relatively long; it takes 475 seconds to cancel a limit order. This finding suggests that ATs also actively participate in the options market but their strategies may be different from those of HFTs in determining cancellations. On the other hand, it is unusual for NTs to cancel limit orders; their *Cancellation Rate* is just 18% and *Cancellation Duration* is very long (1,230 seconds). Second, in terms of transaction activity, HFTs also show distinguishable features. On average, an HFT is involved in 8,119 transactions per day. This is about 5.7 times greater than an AT's number of transactions and the dollar amount of transactions is more than 369 times larger than that of NTs. In addition, HFTs have a very low execution rate. Their *Order to Trade Ratio,* defined as the ratio of the number of limit order submissions to the number of executed transactions, is 8.73. This means that HFTs submit 8.73 orders to execute one transaction. However, ATs and NTs have a relatively low value of *Order to Trade Ratio,* so they have a high rate of execution. The trading volume exhibits a pattern similar to that of the number of transactions, but the volume per transaction of HFTs is 6.66 contracts, while ATs and NTs trade 8.6 contracts in a transaction. It seems that HFTs use many small trades compared to the other traders. Finally, although HFTs are involved in a significant portion of the total trading volume, their end-of-day inventory is close to zero. The most important feature of HFTs is that they hold their positions for a very short time and try to close a day with a zero inventory position. In fact, HFTs' ratio of the absolute value of their net position to trading volume is 0.08%. Moreover, 76% of HFTs end the day with an inventory position of exactly zero.

Next, we examine the trading activity of HFTs regarding liquidity provision. Each day, we classify HFTs into two groups based on how frequently they initiate trades. Aggressive (passive) HFTs are traders who initiate trades for more (fewer) than half of their trades that day. Panel B in Table 1 reports the daily trading activity of these two HFT subgroups. There are slightly more aggressive HFTs than passive HFTs. On average, there are 22 aggressive and 17 passive HFTs active in a day. We can find differences between the two groups. Passive HFTs' order and transaction activity is more active than aggressive HFTs'. They have the greatest number of orders and transactions and are the fastest traders in terms of order duration. Although aggressive HFTs cancel orders more quickly and more frequently, their trading volume is large. As a result, aggressive HFTs' volume per transaction is 8.98, similar to that for ATs and NTs. However, the volume per transaction of passive HFTs is only 4.45. It seems that small trades are usually executed by passive HFTs rather than by aggressive HFTs.

4. Profitability of HFTs

In this section, we examine the profitability of HFTs. Given their huge trading activity, it is natural to ask how profitable their trading behavior is. We follow Baron, Brogaard, and Kirilenko (2012) to calculate daily profits. We assume that every HFT starts each day with a zero inventory position. With this assumption, we calculate the daily profits for each HFT *i* for each trading day *t* according to marked to market accounting. Since about three-fourths of HFTs end the day with a zero inventory position and most of the other HFTs in our sample also end the day near a zero inventory, we believe that marking to market at the end of the trading day affects profits little. We calculate the daily profits for each HFT *i* for each trading day *t* as

$$profit_{i,t} = \sum_{n=1}^{N_{i,t}} [1_{sell} p_n y_n - 1_{buy} p_n y_n] + \sum_{k=1}^{K_{i,t}} p_{c,k} y_{c,k}$$

where $n = 1 \ldots N_{i,t}$ indexes the transaction for HFT *i* on trading day *t*, 1_{sell} is an indicator that has a value of one if the HFT sold in transaction *n* and zero otherwise, 1_{buy} is similarly defined for HFT buying, p_n is the transaction price of the *n*th transaction, y_n is the number of contracts traded in transaction *n*, *k* indexes an option that has any outstanding position at the end of the day, $y_{c,k}$ is the number of outstanding positions, and $p_{c,k}$ is the closing price of option *k*. This formula means that *profit* is measured as the cumulative cash received from selling options minus the cash paid from buying options, plus the market value of any remaining positions at the end of the day.

<Insert Table 2>

Table 2 presents the results of the profitability of HFTs. Panel A reports summary statistics such as the mean, median, standard deviation, skewness, and kurtosis for daily profits per account. We use the daily profits of all account-day observations in this panel. Our results show that HFTs earn profits, on average. The mean of HFTs' daily profits is $12,897 and HFTs who trade aggressively earn much more profit. Aggressive HFTs earn a mean of \$19,394, while passive HFTs earn only \$4,255 per day.[4] The variable *Total Cumulative Profits* represents overall profits during our sample period. The HFTs earn an aggregate of \$311.1 million, aggressive HFTs accounting for 85.8% of this. Since HFTs' trading frequency is very large, we need to consider trading fees to see whether HFTs result in positive net profits. Because we cannot obtain their exact amount of fees and trading fees differ across traders, we assume that the trading fee is 2 bps.[5] Considering that fees paid to the exchange are 1.09 bps of trading amounts and the other additional trading fees for HFTs are not high, our assumption about the size of the fees is reasonably conservative. Under this assumption, the mean daily net profit for HFTs remains positive after considering trading fees. Daily net profits are \$8,581 for one HFT and \$336,088 for all HFTs. However, the same cannot be said for passive HFTs. The net profits of passive HFTs are quite small and the mean of their time-series net profits is not statistically significantly different from zero.

To investigate the relation between profitability and liquidity provision further, we employ an alternative methodology. We calculate the time-series mean profits of HFTs by creating three different subcategories of HFTs based on their aggressiveness. Each day, we sort all HFTs' accounts into three groups based on the intra-day liquidity taking ratio, which is defined as the ratio of the number of trades an HFT initiates to the number of trades the HFT participates in a day. The top 30% of HFTs, who have the largest liquidity taking ratio, are classified as *High*, the bottom 30% of HFTs are *Low*, and the remaining HFTs are *Mid*. Next, we calculate average profits across traders for each day and each group.[6] We report the equally weighted daily average profits and *t*-values of each group. Panel B in Table 2 presents the results, revealing that HFTs who trade more aggressively earn higher returns. The gross mean profits are \$38,693 for the *High* HFT group and monotonically drop to -\$4,213 for the *Low* HFT group. The *High* HFT group has huge positive profits that are statistically significant, even after transaction fees, while the *Mid* HFT group has only tiny profits that are completely wiped out after trading fees are considered. The profits of *Mid* HFTs are not statistically different from zero. Interestingly, *Low* HFTs who trade passively lose money. Traders in the *Low* HFT group lose \$7,852 per day net of expenses on average and this loss is statistically significant. The overall results indicate that aggressive HFTs earn much more profit and the profitability of all HFTs is derived from the aggressive HFTs' superior performance. The results are consistent

[4] Dollar-based figures are calculated at the exchange rate of 1,011.5 KRW to \$1, which was the exchange rate in effect on June 30, 2014, the last date of the sample period.

[5] The exchange fees are 0.010944% for trading and 0.00171% for settlement. The membership fees for institutional investors are 0.000684%. The fees are from the KRX's homepage (www.krx.co.kr).

[6] We also sort HFT accounts into quintile groups based on their liquidity taking ratio. We find qualitatively similar results.

with those of Baron, Brogaard, and Kirilenko (2012), who also show that aggressive HFTs earn more profit in the E-mini S&P 500 futures contracts, which have no liquidity rebates. Our results suggest the possibility that liquidity taking activity is related to strong trade motivation or superior trading skill rather than liquidity providing behavior. We examine the source of profitability by investigating trading costs in the next section.

While profits are positive on average, they are distributed in a wide range. Moreover, the profits of aggressive HFTs exhibit higher variation than those of passive HFTs. The skewness and kurtosis in Panel A of Table 2 show that the distribution deviates greatly from the normal distribution, especially in the sense that the tails have heavy excess weight. This means some HFTs have very large gains, but others suffer incredibly huge losses, too. Panel A in Figure 2 shows more detailed results about the variation of profitability across HFT accounts. It presents the distribution of HFTs across the range of profits. The result shows that 65.6% of HFTs have positive gains, while 34.4% of all HFTs have profits less than zero; 11.5% of HFTs earn more than $25,000 per day and their mean profit is $128,671 per day. On the other hand, 8.3% of HFTs lose more than $25,000 and their mean loss is $118,446 a day. The result implies that, even though average HFTs earn positive profits, profitability varies greatly across traders.

< Insert Figure 2 >

Next, we look at the time variation in profitability of HFTs. Panel B of Figure 2 shows the time series of daily profits for aggregate HFTs. The profits also vary substantially across time. HFTs as a whole earn $505,103 a day, with a high of $23.9 million in August 9, 2012, and low of -$13.4 million in March 12, 2014. They have occasionally lost in aggregate, but they earn positive profits more than 69.0% of the days over the 616 trading days. In sum, there is evidence that HFTs make profits on average, but there is also substantial variation of profitability across trading days.

5. Trading costs

Trading execution costs are not only one of the important determinants of trading profits but also a crucial indicator of market liquidity. To search for the source of HFTs' profits and the relation between HFTs and liquidity, we analyze the trading costs of the transactions of liquidity providing and liquidity taking HFTs. In this paper, we use three simple and common measures of trading costs: effective spreads, price impacts, and realized spreads. These measures are widely used in several studies, including those of Lee, Mucklow, and Ready (1993), Bessembinder and Kaufman (1997), Huang and Stoll (1997), and Madhavan and Cheng (1997). Effective spreads are estimated as the deviation between transaction prices and an estimate of the true value of securities, as follows:

$$Effective\ spread = D(P - V)/V$$

where D is a trade indicator variable that equals one for buyer-initiated trades and -1 for seller-initiated trades, P is the transaction price, and V is the true value of the security. We use the bid–ask midpoint at the time of the transaction as a proxy for the pre-trade benchmark price V. Effective spreads can be decomposed into informational and non-informational components, based on the price movement subsequent to a trade. The informational component, the price impact, can be measured by the change in the true value process of the security, while the non-informational component, the realized spread, can be measured by the reversal from the transaction price to the post-trade value. We estimate the price impact and the realized spread as follows:

$$Price\ impact = \frac{D(V_T - V)}{V}$$

$$Realized\ spread = \frac{D(P - V_T)}{V}$$

$$= Effective\ spread - Price\ impact$$

where V_T is the true value of the security T periods after the transaction. Here, we use the first transaction price five minutes after the trade as a proxy for the post-trade benchmark price V_T, following Huang and Stoll (1997).[7]

We suggest some testable implications from the interpretation of this decomposition. If HFTs have private information, the price impact is expected to be higher when they take liquidity than when non-HFTs take liquidity. In other words, we will observe high price impacts on their liquidity taking transactions if they are trading on information. On the other hand, we expect that the realized spreads on HFTs' liquidity supplying trades are higher than those on the liquidity of non-HFTs if HFTs have timing skill to decide when to supply liquidity. Traditionally, the realized spreads represent compensation to liquidity suppliers for adverse selection. For this section's analysis, we use all the transactions for which both pre- and post-trade benchmark prices are available. As a result, our sample consists of all transactions executed from 9:00 a.m. to 3:00 p.m., for a total of 442,787,602 transactions.

[7] Werner (2003) shows that the choice of the post-benchmark price barely affects the price impact and the realized spread in a large sample. Because our sample is large, we believe that the measures are relatively insensitive to the choice of the post-trade benchmark price.

Table 3 summarizes the means of the spreads and price impacts. Panel A reports the means of each trading execution cost measure for the overall sample and for groups that are classified by trading counterparty type, that is, HFTs and non-HFTs. Panel B divides non-HFTs into ATs and NTs.

< Insert Table 3 >

We can capture preliminary evidence from this summary table. First, the mean price impacts are high on trades where HFTs take liquidity. When HFTs take liquidity from non-HFTs (row 3, HFT–nHFT), the mean price impact is 1.156%, which is the largest among the four transaction categories in Panel A. If we set the liquidity providers of trades as HFTs, the price impact is 0.534% for transactions with HFTs taking liquidity (row 2, HFT–HFT) but only 0.384% for transactions with non-HFTs taking liquidity (row 4, nHFT–HFT). Similarly, if we set the liquidity providing side of transactions as non-HFTs, we observe a higher value of the mean price impact on trades where HFTs take liquidity. Overall, the mean price impacts are greater on trades where HFTs take liquidity than on trades where non-HFTs take liquidity. This evidence is consistent with the hypothesis that HFTs have superior skill in using private information and are trading on information when they take liquidity. Second, the realized spread is not very high on trades where HFTs provide liquidity. The mean realized spread is 26.8 bps when HFTs provide liquidity to non-HFTs (row 4, nHFT–HFT) and it is smaller than the mean realized spread on all transactions, 42.7 bps (row 1, All). If we set the liquidity takers of trades as non-HFTs, the realized spread is 26.8 bps for transactions with HFTs providing liquidity (row 4, nHFT–HFT), but the value is 98.0 bps for transactions with non-HFTs providing liquidity (row 5, nHFT–nHFT). Similarly, if we set the liquidity taking side of transactions as HFTs, we observe a smaller value of the mean realized spread on trades where an HFT provides liquidity. Moreover, if an HFT provides liquidity to an HFT, we observe a negative realized spread, -2.6 bps. Overall, it is hard to find evidence that HFTs are good at providing liquidity from the results in this table. This may be one of the reasons for the underperformance of passive HFTs. Finally, spreads are tighter when HFTs participate in trades, regardless of their trading side. For example, the mean effective spread is 2.03% on trades between non-HFTs but just 0.51% on trades between HFTs.

Another interesting finding is that, if you look at Panel B of Table 3, there are differences in price impacts (realized spreads), depending on the counterparty that provides liquidity to (takes liquidity from) the HFTs. When HFTs take liquidity, the largest price impact is due to NTs, ATs, and HFTs as liquidity providers, in that order. When HFTs take liquidity from NTs, the mean price impact is 1.2% (row 2 in Panel B, HFT–NT), which is the largest impact. When HFTs take liquidity from HFTs, the mean price impact is 0.53% (row 2 in Panel A, HFT–

HFT), which is the smallest. Similarly, when HFTs provide liquidity, the realized spread is largest for NTs, ATs, and HFTs as liquidity takers, in that order. Thus, when trading with HFTs, HFTs are the best traders and NTs are the worst in terms of trading execution costs.

However, inferences about skills from Table 3 require further tests, since we do not adjust any other characteristics that affect trading costs. To investigate trading costs rigorously, we conduct a regression analysis following Carrion (2013). Specifically, we regress trading cost measures on dummy variables that capture whether an HFT participates in a transaction. To control for option-specific characteristics and market conditions, we estimate regressions using option half-hour fixed effects. We also include control variables related to transaction characteristics, such as transaction size and buy–sell direction. We apply the following model for the regression analysis:

$$Spread_{itn} = \alpha_{it} + \beta_1 HFT_{itn} + \beta_2(HFT_{itn} \times Medium_{itn}) + \beta_3(HFT_{itn} \times Large_{itn})$$
$$+\beta_4(HFT_{itn} \times Buy_{itn}) + \beta_5 Medium_{itn} + \beta_6 Large_{itn} + \beta_7 Buy_{itn} + \varepsilon$$

where *i* indexes options, *t* indexes half hours, and *n* indexes transactions. We use the effective spread, price impact, or realized spread as *Spread*. The variable *HFT* is a dummy that has a value of one if an HFT participates in the trade and zero otherwise. We separately analyze HFT participation by the liquidity taking and the liquidity providing sides. *Medium* and *Large* are indicator variables that control for transaction size; *Medium* indicates transaction sizes between 10 and 100 contracts and *Large* indicates transaction sizes greater than 100 contracts. *Buy* is a dummy variable that takes a value of one if the trade is initiated by a buyer and zero otherwise. At the first stage, we estimate regression models using the fixed effects estimator with pooled OLS using option transaction-level observations each day and cluster standard errors within half-hour intervals, following Petersen (2009). Then, at the second stage, we calculate the time-series means of estimates, Newey–West (1994) *t*-statistics for the time-series means, and the percentage of days with statistically significant coefficients.

The coefficient of *HFT* is of primary interest. It indicates the difference in the spreads or price impact between trades with and without HFT participation after controlling for the other relevant variables. In specifications including all interaction terms, the coefficient of *HFT* indicates the trading cost difference for sell trades of fewer than 10 contracts and the coefficients of the interaction terms are additional differences in HFT participation in medium, large, or buy trades.

< Insert Table 4 >

Table 4 reports the results of the regressions when the HFT participation indicator is defined based on the liquidity taking side of trades. The dependent variable is the effective spread in Panel A, the price impact in Panel B, and the realized spread in Panel C. Model 1 in each panel includes only the HFT participation indicator and option half-hour fixed effects, while the other models include trade characteristic controls. Model 2 omits the interaction terms, while Models 3 and 4 allow the effect of HFT participation to vary with trade size or trade direction. Model 1 in Panel A shows that the effective spread is 4.4 bps tighter for trades where HFTs take liquidity. Moreover, this result comes from buy-side trades. The estimation results in Model 4 show that the effective spread is 10.4 bps tighter on trades where HFTs take liquidity through buys than on trades where non-HFTs do, while the difference is statistically insignificant in selling. These findings suggest that HFTs aggressively buy options when the market is relatively liquid and do not harm market liquidity compared to non-HFTs.

Panels B and C of Table 4 report the results for the price impact and realized spread, respectively, which are strongly statistically significant. Evidence suggests that HFTs trade on information when they take liquidity, consistent with our preliminary results in Table 3. The price impact is more than 30 bps greater and the realized spread is more than 35 bps tighter on trades where HFTs take liquidity than trades where non-HFTs take liquidity. The price impact of HFTs is 24.6 bps higher in seller-initiated trades and 40.7 bps higher in buyer-initiated trades due to the buy interaction term. This implies HFTs have an informational advantage on both trading sides when taking liquidity and the adverse selection costs of liquidity providers are larger for trades with HFTs. This is consistent with Hirschey (2013), who documents that HFTs' liquidity taking trades anticipate non-HFTs' trades. In addition, the size interaction terms show that this effect is smaller for medium and large trades. HFTs are likely to trade on information in small liquidity taking trades.

< Insert Table 5 >

Table 5 presents the results of the regressions when the HFT participation indicator is defined based on the liquidity providing side of trades. The dependent variable is the effective spread in Panel A, the price impact in Panel B, and the realized spread in Panel C. Here, we find the same results on the effective spread as in Table 4. Model 1 in Panel A shows that the effective spread is 4.6 bps tighter on trades where HFTs provide liquidity. Combined with the results in Table 4, these results suggest that HFTs trade when liquidity is plentiful, regardless of the direction of liquidity provision. Overall, trading costs are low when HFTs participate in transactions.

Panels B and C of Table 5 report the results for the price impact and the realized spread. Here, after controlling for option half-hour fixed effects, we obtain the opposite results to Table 3. Model 1 in Panel C shows that the realized spread is 9.6 bps wider on trades where HFTs provide liquidity than on trades where non-HFTs provide liquidity. This implies that HFTs have better skill at deciding when to provide liquidity than non-HFTs do. The result remains unchanged after adding other control variables. We observe significantly positive coefficients for *HFT* and interaction terms with trade size in Models 2 and 3 in Panel C. However, we are not sure that HFTs have enough market timing skill in providing liquidity. Although the coefficient of *HFT* is positive in Table 5, the magnitude 9.6 bps is relatively small compared to the corresponding coefficient of *HFT* in Table 4, -35 bps. This means that HFTs' adverse selection costs may be large relative to their compensation when they provide liquidity to other HFTs, although HFTs do better than non-HFTs.

Overall, the results from the regressions confirm our testable implications. Trading cost measures exhibit statistically significant differences, depending on HFT participation. HFTs have an informational advantage, so they execute their trades at better prices when they take liquidity, which can be one of the sources for the profitability of aggressive HFTs. On the other hand, when HFTs provide liquidity, they are better able to avoid adverse selection costs than non-HFTs are. Nevertheless, this ability may not be good enough to compensate for the adverse selection from the liquidity taking trades of HFTs. The poor performance of passive HFTs may be due to trading against aggressive HFTs. In addition, HFTs are associated with low trading costs and do not seem to harm market liquidity in terms of trading costs. We examine HFTs' impact on market quality more thoroughly in the next section.

6. Market quality

In the previous section, we addressed issues related to HFTs' activity, profitability, and trading costs. In this section, we investigate their impact on market quality, whether HFTs affects liquidity and generate or dampen volatility.

We apply empirical methods from Lee (2013) to investigate the relation between HFTs' trading and market quality. However, we apply a multivariate VAR model rather than a bivariate VAR model unlike Lee. Our VAR model is motivated by concerns about the correlation between HFTs' and non-HFTs' trading volumes. The HFTs' and non-HFTs' trading volumes are contemporaneously correlated because HFTs and non-HFTs trade simultaneously. Moreover, if there is a serial correlation between these trading volumes, then non-HFTs' lagged trading volumes will predict HFTs' trading volumes because they are correlated with lagged HFTs' trading volumes. Thus, the relation between HFTs' trading volumes and market quality may be attributed to non-HFTs' trading volumes and may change after controlling for them. We therefore modify Lee's (2013) bivariate VAR model. We control for non-HFTs' trading volumes using the trading volumes of ATs and NTs. Thus, our VAR is a system of four equations in which lags of HFTs', ATs', and NTs' trading volumes and market quality variables are used to explain each other. Specifically, we use the following VAR model with six lags for each option–day:

$$HFT_t = \alpha_1 + \sum_{k=1}^{6} \beta_{1,k} HFT_{t-k} + \sum_{k=1}^{6} \gamma_{1,k} AT_{t-k} + \sum_{k=1}^{6} \delta_{1,k} NT_{t-k} + \sum_{k=1}^{6} \theta_{1,k} MQ_{t-k} + \sum_{k=1}^{5} \pi_{1,k} TimeDummy_k + \epsilon_{1,t}$$

$$AT_t = \alpha_2 + \sum_{k=1}^{6} \beta_{2,k} HFT_{t-k} + \sum_{k=1}^{6} \gamma_{2,k} AT_{t-k} + \sum_{k=1}^{6} \delta_{2,k} NT_{t-k} + \sum_{k=1}^{6} \theta_{2,k} MQ_{t-k} + \sum_{k=1}^{5} \pi_{2,k} TimeDummy_k + \epsilon_{2,t}$$

$$NT_t = \alpha_3 + \sum_{k=1}^{6} \beta_{3,k} HFT_{t-k} + \sum_{k=1}^{6} \gamma_{3,k} AT_{t-k} + \sum_{k=1}^{6} \delta_{3,k} NT_{t-k} + \sum_{k=1}^{6} \theta_{3,k} MQ_{t-k} + \sum_{k=1}^{5} \pi_{3,k} TimeDummy_k + \epsilon_{3,t}$$

$$MQ_t = \alpha_4 + \sum_{k=1}^{6} \beta_{4,k} HFT_{t-k} + \sum_{k=1}^{6} \gamma_{4,k} AT_{t-k} + \sum_{k=1}^{6} \delta_{4,k} NT_{t-k} + \sum_{k=1}^{6} \theta_{4,k} MQ_{t-k} + \sum_{k=1}^{5} \pi_{4,k} TimeDummy_k + \epsilon_{4,t}$$

where *HFT* is the total trading volume of HFTs during the period, *AT* is the total trading volume of ATs during the period, *NT* is the total trading volume of NTs during the period, *MQ* is the market quality variable, and *TimeDummy* is a dummy variable that takes a value of one or zero for each respective hour periods. The variable *TimeDummy* is used to control for market conditions. We use three measures as proxies for *MQ*: *Effective spread, DEPTH*, and *HL*. *Effective spread* is calculated by the time-weighted average of the effective spreads during the interval and *DEPTH* is the time-weighted average of the number of contracts in the book at the best posted prices during the interval. These two measures capture liquidity. *HL* is defined as the highest transaction price minus the lowest transaction price divided by the midpoint of the highest and lowest prices during the interval. The variable *HL* is a proxy for short-term volatility. Each day, we partition normal trading times into 2,160 10-second intervals and conduct the above VAR analysis for each option–day.

To conduct the VAR analysis, we need sufficient variation in the variables. Unless each variable has sufficient variation, the VAR model cannot be identified. Therefore, we filter the sample to choose actively traded options each day. Specifically, we require at least 1,000 intervals where non-zero transactions take place among 2,160 10-second intervals for each option–day, which reduces the sample to 10,190 option–day observations.

Table 6 summarizes our option–day sample for the VAR estimation. Since this subsample makes up more than 95% of the total trading volume of the entire options market, the results of the analysis are not caused by specific parts of the options market.

< Insert Table 6 >

Panel A in Table 7 reports the means of the coefficients across all option–day estimations and also shows the percentage of significantly positive (negative) coefficients, as is commonly done in the literature to summarize VAR results. We also calculate the average of the coefficients each day and report the *t*-statistics for the time-series means in Panel B. We can check the consistency of estimated coefficients across days from the time-series *t*-test. Since our primary interest is the impact of HFTs on market quality, we focus on the results of the fourth equation. Thus, we only report the estimation results of the fourth equation in the table.

The estimation results provide evidence that HFTs improve liquidity. Panel B in Table 7 supports this argument, showing that a 1,000-contract increase in the trading volume of HFTs results in a 0.23% decrease in the effective spread after 10 seconds at the 1% significance level. Noting that 0.23% is quite a large portion of the mean value of the effective spread, 1.72% for our VAR sample, this effect is not only statistically but also economically significant. On the other hand, ATs do not reduce the effective spread and the coefficients for lagged NTs' trading volume are also positive, except the first one, which is small. In sum, HFTs reduce the effective spread, whereas ATs and NTs do not. We also study HFTs' impact on depth. Panel D shows that a 1,000-contract increase in the trading volume of HFTs results in a 326-contract decrease in depth after 10 seconds, which is statistically insignificant. The mean coefficients of the first lagged trading volumes of ATs and NTs are small compared to that of HFTs but statistically significant. Thus, it is difficult to determine the impact of traders on depth.

It is surprising that ATs and NTs increase volatility while HFTs do not increase or may reduce volatility. Panel F in Table 7 shows that a 1,000-contract increase in the trading volume of HFTs will result in a 0.22% decrease in the short-term volatility after 10 seconds. Although this is statistically insignificant, all the coefficients for HFTs are negative. On the contrary, a 1,000-contract increase in the trading volume of ATs (NTs) results in a

0.65% (0.97%) increase in volatility, which is both statistically and economically significant. The mean of *HL* is 0.74% for our VAR sample.[8]

< Insert Table 7 >

In line with the previous sections, we conduct VAR analysis for liquidity demanding and supplying volumes, separately. Table 8 shows the VAR results, where *HL* is a dependent variable. In the liquidity demanding case, most coefficients for each trader type's lagged trading volumes are positive, but the *t*-statistics for HFTs are much less than the *t*-statistics for the others. In the liquidity providing case, most coefficients for HFTs' lagged trading volumes are even negative, while the coefficients for the others are positive, with high *t*-statistics. These results also indicate that HFTs do not harm market quality in terms of short-term volatility.

< Insert Table 8 >

Overall, HFTs enhance market quality compared to non-HFTs, consistent with Brogaard (2010). These results counter the findings from the KOSPI 200 futures market. Lee (2013) reports that HFTs increase intraday volatility in the KOSPI 200 futures market. However, Lee's VAR model does not consider contemporaneous correlation between HFTs' and non-HFTs' trading volumes, unlike the other research such as Hirschey's (2013) VAR models including both HFT and non-HFT components. We run the bivariate VAR of HFTs' trading volumes and the market quality variables following Lee (2013) and obtain similar results to her. In this estimation, a 1,000-contract increase in the trading volume of HFTs will result in a 0.94% increase in short-term volatility after 10 seconds at the 1% significance level. Higher levels of HFT activity correspond to higher levels of short-term volatility, but this is not true after controlling for non-HFTs' trading volumes. Nevertheless, because of different sample periods and different markets in Lee's (2013) study, it is not certain whether her results are solely attributable to misspecification. Future research needs to integrate the analysis of options and futures markets.

[8] We also conduct the same analysis using the other proxy for short-term volatility. We define the short-term volatility measure as the highest mid-quote during the interval minus the lowest mid-quote during the same interval. The results from this definition are consistent with those in Table 7. The results of this analysis are not presented here for brevity.

7. Conclusion

High-frequency trading is prevalent throughout the world financial markets. We investigate the profitability, trading costs, and impact on market quality of HFTs, using complete trade and quote data from the KOSPI 200 options market. We can directly identify HFTs and who initiates trades from the high-quality data. The KOSPI 200 options market is attractive to HFTs and we find 39 HFT accounts each trading day, on average. Overall, HFTs earn profits and the profits are closely related to their aggressiveness. Aggressive HFTs earn much more profit than passive HFTs do. Analysis of trading costs reveals that HFTs take liquidity on information. HFTs seem better than non-HFTs in selecting when to provide liquidity, but providing liquidity to other HFTs may damage their profits. HFTs tend to demand liquidity when it is abundant and are associated with lower trading costs. Our VAR model including the non-HFT component shows that HFTs improve market quality compared to non-HFTs. Specifically, HFTs reduce effective spreads and do not significantly affect short-term volatility, while non-HFTs increase volatility. Our research contributes to the understanding of HFTs with a unique data on the options market. However, our study has some limitations. Investors tend to trade on options and futures markets simultaneously. Thus, studying the interaction between options and futures markets can provide better insight into HFTs. In addition, it is necessary to investigate more thoroughly the role of passive HFTs, whose performance is worse than that of aggressive HFTs.

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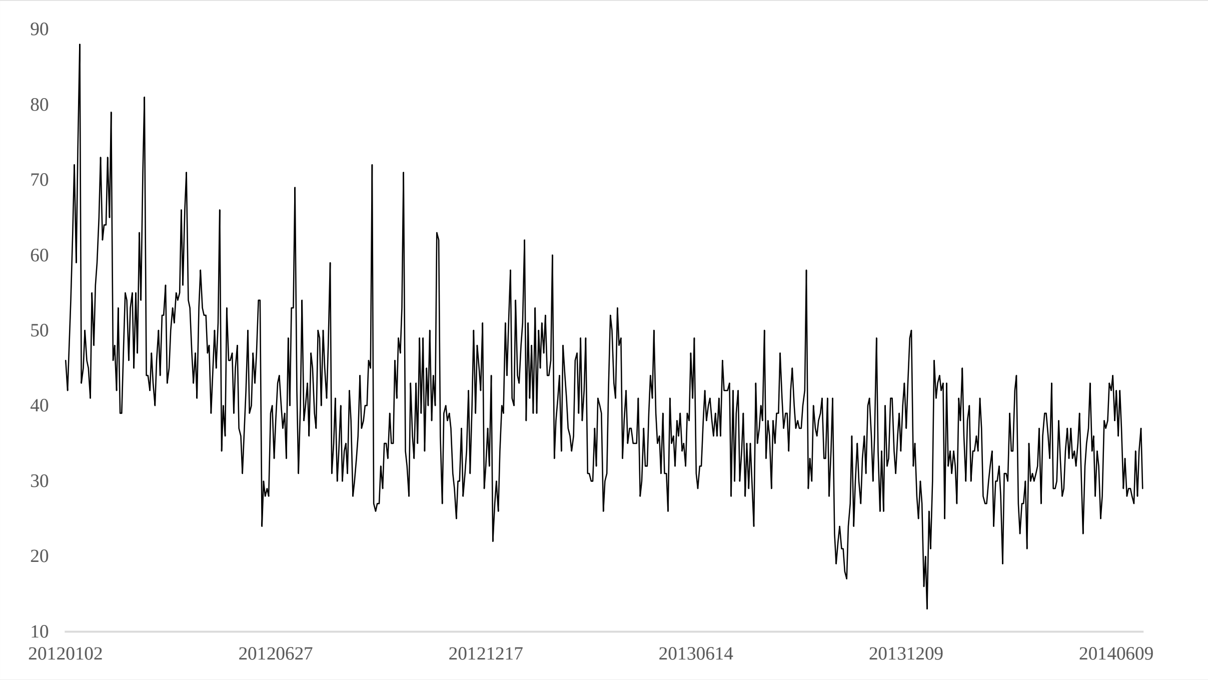
Figure 1. Number of HFT accounts

This figure shows the time series of the daily number of HFT accounts. Each day, there are four conditions a trader must satisfy to be considered an HFT: The trader must (1) submit more than 1,000 limit orders that day, (2) have a median order duration of less than one second, (3) have a median cancellation duration of less than two seconds, and (4) have an end-of-day inventory position, scaled by the total volume the trader traded that day, of no more than 1%.

Panel A: Daily number of HFT accounts



Panel B: Daily number of HFT accounts by investor type

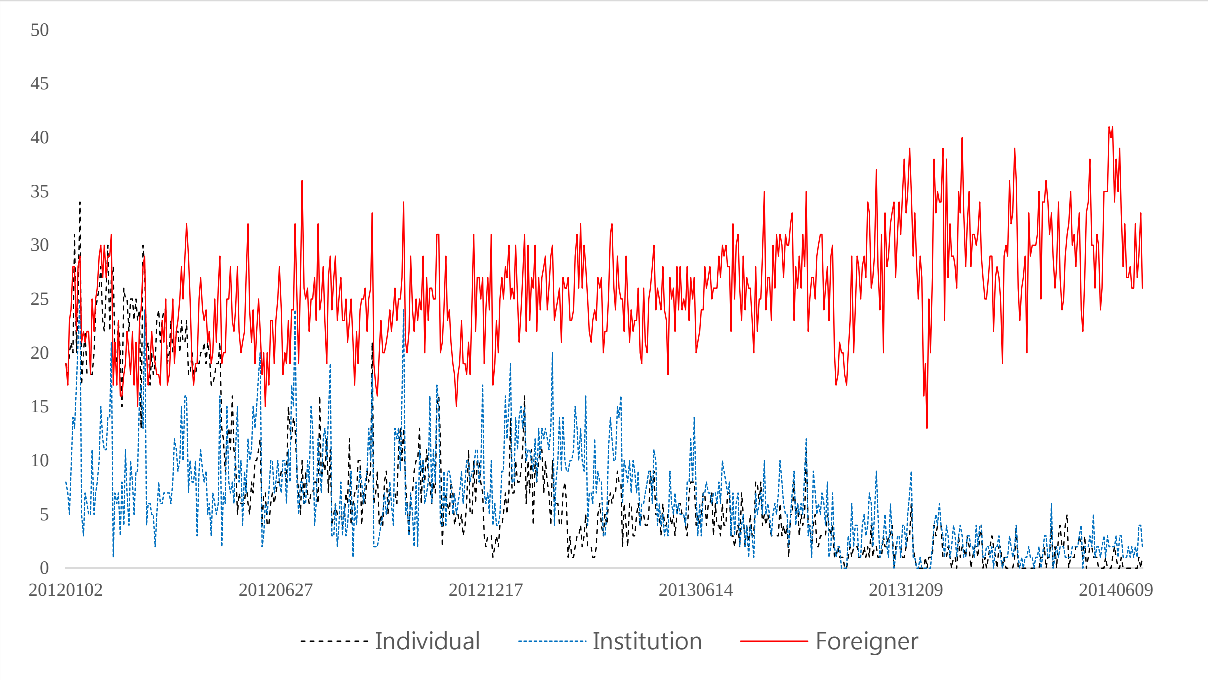
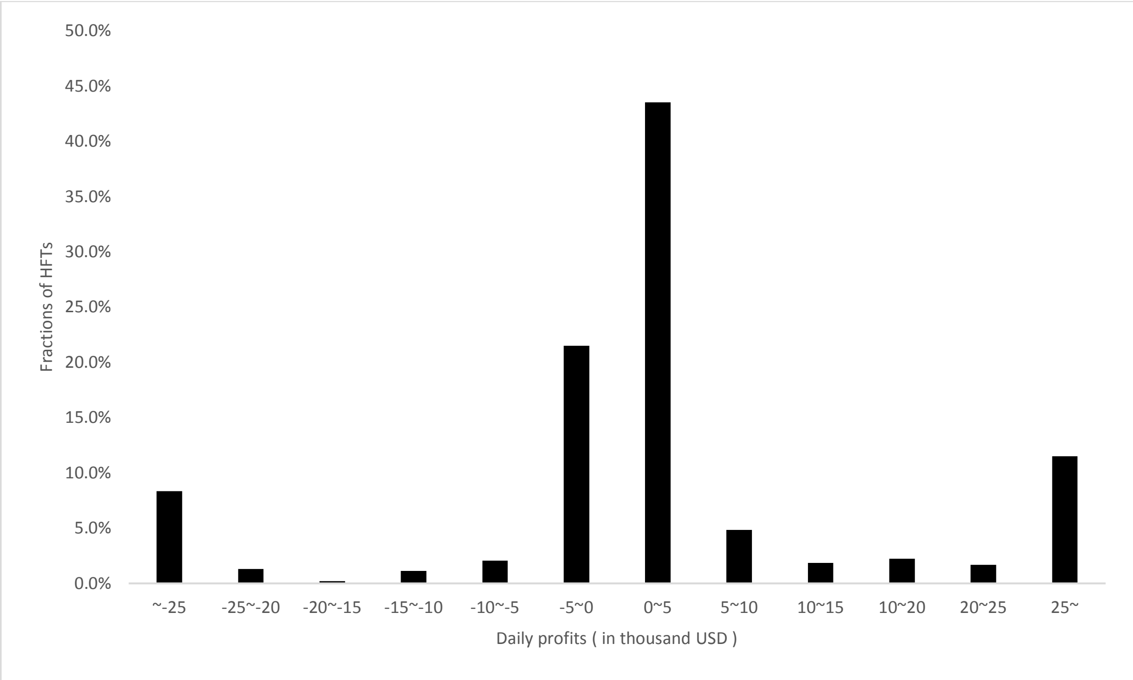


Figure 2. Distribution of HFT profits

This figure shows the distribution of each HFT account's daily profits (Panel A) and the daily time series of aggregate HFTs' profits (Panel B). In Panel A, there are 540 distinct HFT accounts in the sample period from January 2, 2012, to June 30, 2014. We calculate each HFT account's mean daily profits from high-frequency trading and plot the distribution of daily profits. In Panel B, each day, we combine all HFT accounts' profits and plot the time series of the aggregate HFTs' profits.

Panel A: Distribution of each HFT account's daily profits



Panel B. Daily time series of aggregate HFT profits

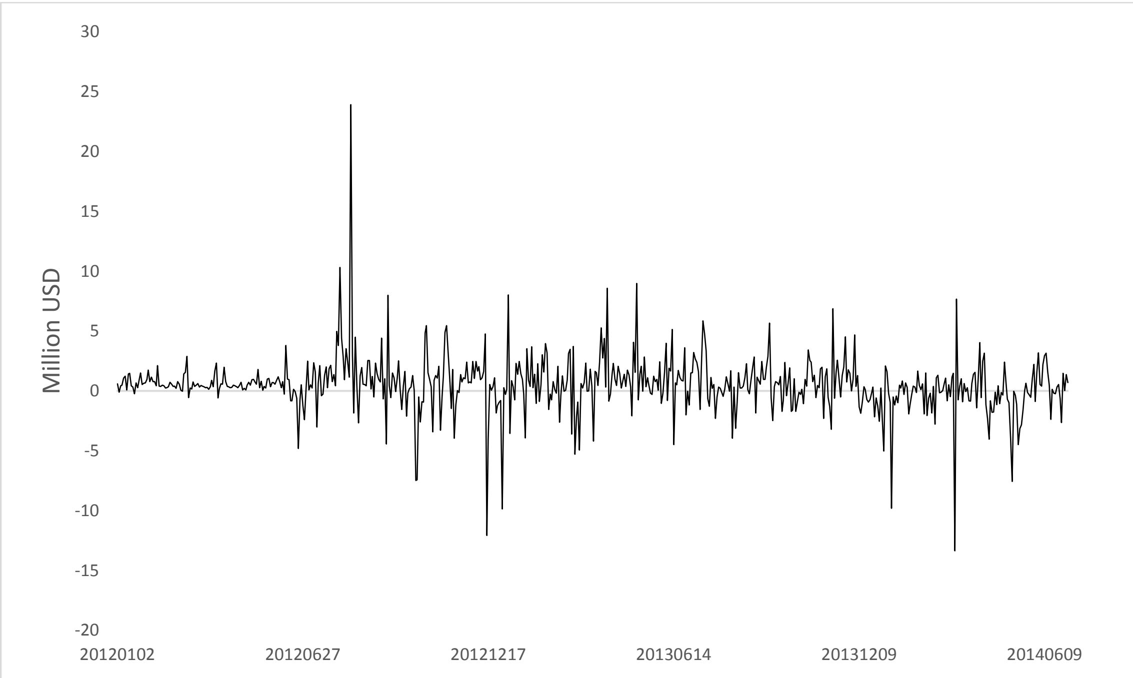


Table 1. Summary statistics of trading activity

This table shows summary statistics for the trading and quoting activity of HFTs and non-HFTs in the KOSPI 200 options from January 2, 2012, to June 30, 2014. Our sample contains 616 trading days. Panel A presents summary statistics for the three trader groups: HFTs, ATs, and NTs. Panel B reports summary statistics for HFTs by aggressiveness, for aggressive HFTs and passive HFTs. Panel C reports the distribution of HFTs' end-of-day net positions. All statistics are calculated per trader on a daily basis. The variable *Number of Traders* is the daily time-series average of the number of accounts classified in each trader category; *Number of Order Submitted* is the total number of order submissions, including modification and cancellation orders; *Order Duration* is the median inter-order duration, measured in seconds; *Cancellation Rate* is calculated as the number of limit order cancellations divided by the number of limit order submissions, as a percentage; *Cancellation Duration* is the median value of the lifetime of cancelled limit orders, measured in seconds; *Number of Transactions* is the total number of trades executed; *Volume* is the total number of contracts traded by each trader; *Order to Trade Ratio* is the aggregate number of orders divided by the aggregate number of executions; *|Net Position| to Volume* is the absolute value of the end-of-day position, scaled by the total trading volume; and *Liquidity taking ratio* is the fraction of transactions that were initiated.

Panel A: Trader groups

	HFTs	ATs	NTs
Number of Traders	39	157	15,317
Number of Order Submitted	62,827	15,854	45
Order Duration	0.21	4.31	994.39
Cancellation Rate	63.7	49.1	18.0
Cancellation Duration	0.36	475.00	1230.74
Number of Transactions	8,119	1,409	22
Volume	54,122	12,099	187
Order to Trade Ratio	8.73	4.26	1.66
|Net Position| to Volume	0.08	3.73	25.13

Panel B: HFTs by aggressiveness

	All HFTs	Aggressive HFTs	Passive HFTs
Number of Traders	39	22	17
Number of Order Submitted	62,827	56,596	74,842
Order Duration	0.21	0.24	0.19
Cancellation Rate	63.7	64.2	60.8
Cancellation Duration	0.36	0.18	0.63
Number of Transactions	8,119	7,999	9,497
Volume	54,122	71,827	42,258
Order to Trade Ratio	8.73	6.28	14.47
|Net Position| to Volume	0.08	0.10	0.04
Liquidity taking ratio	59.8	81.1	28.9

Panel C: HFTs' net positions

	~ -1000	-1000 ~ -500	-500 ~ 0	0	0 ~ 500	500 ~ 1000	1000 ~
mean	-2,079	-680	-90	0	92	705	1,797
%	0.3	0.5	10.6	76.3	11.2	0.7	0.3

Table 2. Daily profits of HFTs

This table shows the daily profits of HFTs. We report both gross profits and net profits. Dollar-based figures are calculated at the exchange rate of 1011.5 KRW to $1, in effect on June 30, 2014, the last date of the sample period. Panel A presents the daily profits by each HFT account. All statistics in this panel are calculated by using all day account-level profits. The variable *Total Cumulative Profits* is overall profits during our sample period for the HFTs. There are three rows, *All, Aggressive,* and *Passive,* for the results of all HFTs, aggressive HFTs, and passive HFTs, respectively. If an HFT initiates more (less) than half of his or her transactions each day, we consider the trader an aggressive HFT (passive HFT). Panel B reports the mean daily profits for three groups based on liquidity provision. Each day, we sort HFTs by the ratio of liquidity taking transactions. The top 30% of HFTs are classified as *High,* the bottom 30% are *Low,* and those HFTs classified as neither are *Mid*. For each day and each group, we calculate the mean profits across traders and calculate the times-series mean. Newey–West (1994) *t*-statistics are reported in parentheses.

Panel A: Summary of daily profits (in USD)

	N	Mean	Median	Std. dev	Skew.	Kurt.	Min	Max	Total cumulative profits
Gross profits									
ALL	24,126	12,897	1,671	332,865	-4.99	307.82	-11,381,874	9,677,761	311,143,629
Aggressive	13,772	19,394	2,773	403,735	-4.85	238.09	-11,381,874	9,677,761	267,092,428
Passive	10,354	4,255	949	203,080	-0.87	222.52	-4,732,999	5,519,413	44,051,201
Net profits									
ALL	24,126	8,581	876	332,360	-5.21	309.97	-11,398,044	9,634,170	207,030,293
Aggressive	13,772	14,449	1,706	403,103	-5.01	239.84	-11,398,044	9,634,170	198,997,165
Passive	10,354	776	429	202,880	-1.39	222.38	-4,774,828	5,443,985	8,033,128

Panel B: Mean daily profits by three groups based on liquidity provision (in USD)

	Gross profits		Net profits		Liquidity taking ratio
All	10,444	(3.47)	6,114	(2.06)	0.598
High	38,693	(8.45)	32,251	(7.05)	0.923
Mid	3,059	(0.54)	-469	(-0.08)	0.639
Low	-4,213	(-1.25)	-7,852	(-2.30)	0.248

Table 3. Mean spread and price impact summary

This table presents the mean spreads and price impacts. The following formulas are used for every transaction:

$$Effective\ spread = D(P - V)/V$$

$$Price\ impact = D(V_T - V)/V$$

$$Realized\ spread = D(P - V_T)/V$$

where *D* is an indicator variable that equals one for buyer-initiated orders and -1 for seller-initiated orders, *P* is the transaction price, *V* is the quote midpoint at the time of the trade, and V_T is the first trade price five minutes after the trade. All spreads are measured as percentages of the midpoint quote prior to the trade and half-spreads. In Panel A, we categorize the trades according to the counterparty type, HFTs and non-HFTs. The first term in each trade category indicates the liquidity taker and the second refers to the liquidity provider, with HFT denoting HFTs and nHFT denoting non-HFTs. In Panel B, we divide non-HFTs' trade categories into ATs and NTs.

Panel A: Mean spreads and price impacts

Category	N	Effective spread	Price impact	Realized spread
All	442,787,602	1.346	0.919	0.427
HFT–HFT	53,980,757	0.508	0.534	-0.026
HFT–nHFT	146,214,603	1.167	1.156	0.011
nHFT–HFT	68,703,430	0.652	0.384	0.268
nHFT–nHFT	173,888,812	2.030	1.050	0.980

Panel B: Mean spreads and price impacts by non-HFT subcategory

Category	N	Effective spread	Price impact	Realized spread
HFT–AT	53,366,751	1.095	1.072	0.023
HFT–NT	92,847,852	1.208	1.204	0.004
AT–HFT	29,110,330	0.555	0.455	0.100
NT–HFT	39,593,100	0.723	0.331	0.392

Table 4. Regression estimates of spreads and price impacts on HFT demand participation variables

For each day, the following regression is estimated with option half-hour fixed effects and standard errors clustered within half-hour intervals:

$$\text{Spread}_{itn} = \alpha_{it} + \beta_1 HFT_D + \beta_2(HFT_D \times Medium) + \beta_3(HFT_D \times Large) + \beta_4(HFT_D \times Buy) + \beta_5 Medium + \beta_6 Large + \beta_7 Buy + \varepsilon$$

where *i* indexes options, *t* is half hours, and *n* is transactions; *Spread* is an effective spread (Panel A), price impact (Panel B), or realized spread (Panel C); HFT_D is a dummy variable that has a value of one if an HFT participated in the trade as a liquidity taker and zero otherwise; *Medium* and *Large* are indicator variables that control for transaction size, where *Medium* indicates a transaction size between 10 and 100 contracts and *Large* indicates a transaction size greater than 100 contracts; *Buy* is a dummy variable that takes a value of one if the trade is initiated by a buyer and zero otherwise. The averages of the coefficients are reported in the *estimate* column. The percentages of positive (negative) coefficients that are significantly different from zero at the 5% confidence level are reported in the column *%+* (*%-*). Parentheses indicate Newey–West (1994) *t*-statistics for the mean estimates.

Panel A: Effective spread

Model	(1)				(2)				(3)				(4)			
	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-
HFT	-0.044	(-15.85)	1.3	68.8	-0.048	(-16.58)	0.6	74.2	-0.044	(-18.77)	0.6	75.2	0.002	(0.59)	12.3	40.7
*HFT*MEDIUM*									-0.003	(-0.33)	37.3	8.1				
*HFT*LARGE*									-0.052	(-1.35)	21.3	7.6				
*HFT*BUY*													-0.104	(-13.99)	11.4	39.0
MEDIUM					-0.023	(-6.19)	2.8	48.9	-0.024	(-3.68)	3.7	45.9	-0.023	(-6.31)	2.8	49.5
LARGE					-0.008	(-0.28)	6.2	23.1	-0.003	(-0.10)	5.7	22.9	-0.009	(-0.30)	6.2	23.1
BUY					0.131	(19.85)	91.1	0.3					0.178	(18.40)	83.9	0.8

Table 4 – continued

Panel B: Price impact

Model	(1)				(2)				(3)				(4)			
	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-
HFT	0.306	(53.87)	70.5	0.0	0.324	(54.41)	73.2	0.0	0.329	(54.35)	75.2	0.0	0.246	(20.26)	36.2	0.0
*HFT*MEDIUM*									-0.218	(-13.87)	1.6	17.7				
*HFT*LARGE*									-1.987	(-18.37)	0.5	39.4				
*HFT*BUY*													0.161	(6.98)	7.8	0.8
MEDIUM					0.222	(21.64)	46.4	0.0	0.313	(19.89)	40.1	0.3	0.222	(21.73)	46.8	0.0
LARGE					2.349	(25.90)	78.6	0.0	2.696	(26.87)	73.5	0.0	2.351	(25.92)	78.6	0.0
BUY					-0.366	(-16.41)	0.3	4.4					-0.437	(-14.78)	0.2	4.5

Panel C: Realized spread

Model	(1)				(2)				(3)				(4)			
	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-
HFT	-0.350	(-54.77)	0.0	78.2	-0.373	(-54.06)	0.0	81.0	-0.373	(-55.03)	0.0	83.1	-0.244	(-19.80)	0.0	36.9
*HFT*MEDIUM*									0.216	(15.60)	18.8	0.8				
*HFT*LARGE*									1.935	(19.98)	42.0	0.3				
*HFT*BUY*													-0.266	(-11.58)	0.8	12.8
MEDIUM					-0.245	(-25.39)	0.0	52.4	-0.337	(-23.74)	0.0	45.5	-0.246	(-25.50)	0.0	52.8
LARGE					-2.357	(-29.89)	0.0	81.7	-2.699	(-31.08)	0.0	79.7	-2.360	(-29.91)	0.0	81.7
BUY					0.497	(21.47)	8.9	0.2					0.615	(20.38)	10.1	0.2

Table 5. Regression estimates of spreads and price impacts on HFT supply participation variables

For each day, the following regression is estimated with option half-hour fixed effects and standard errors clustered within half-hour intervals:

$$\text{Spread}_{itn} = \alpha_{it} + \beta_1 HFT_S + \beta_2 (HFT_S \times Medium) + \beta_3 (HFT_S \times Large) + \beta_4 (HFT_S \times Buy) + \beta_5 Medium + \beta_6 Large + \beta_7 Buy + \varepsilon$$

where *i* indexes options, *t* is half hours, and *n* is transactions; *Spread* is an effective spread (Panel A), price impact (Panel B), or realized spread (Panel C); HFT_S is a dummy variable that has a value of one if an HFT participated in the trade as a liquidity provider and zero otherwise; *Medium* and *Large* are indicator variables that control for transaction size, where *Medium* indicates a transaction size between 10 and 100 contracts and *Large* indicates a transaction size greater than 100 contracts; *Buy* is a dummy variable that takes a value of one if the trade is initiated by a buyer and zero otherwise. The averages of the coefficients are reported in the *estimate* column. The percentages of positive (negative) coefficients that are significantly different from zero at the 5% confidence level are reported in the column *%+* (*%-*). Parentheses indicate Newey–West (1994) *t*-statistics for the mean estimates.

Panel A: Effective spread

Model	(1)				(2)				(3)				(4)			
	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-
HFT	-0.046	(-15.74)	1.5	85.7	-0.048	(-16.10)	1.6	85.6	-0.041	(-15.88)	1.9	80.4	0.033	(10.52)	34.1	11.9
*HFT*MEDIUM*									-0.090	(-12.61)	5.5	43.5				
*HFT*LARGE*									-0.366	(-5.31)	9.1	12.8				
*HFT*BUY*													-0.167	(-20.11)	0.0	92.4
MEDIUM					-0.024	(-6.72)	2.3	51.9	-0.007	(-1.38)	4.4	39.3	-0.024	(-6.54)	2.3	51.6
LARGE					-0.002	(-0.08)	5.8	23.9	0.015	(0.51)	6.5	19.8	-0.002	(-0.08)	6.0	24.0
BUY					0.130	(19.83)	89.8	0.3					0.179	(19.97)	91.6	0.3

Table 5 – continued

Panel B: Price impact

Model	(1)				(2)				(3)				(4)			
	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-
HFT	-0.143	(-22.60)	0.5	21.8	-0.136	(-21.75)	0.6	18.5	-0.130	(-21.12)	0.5	17.5	-0.200	(-16.67)	0.3	13.5
*HFT*MEDIUM*									-0.197	(-16.87)	1.1	19.2				
*HFT*LARGE*									-1.411	(-12.17)	1.6	29.5				
*HFT*BUY*													0.133	(6.39)	5.0	0.6
MEDIUM					0.223	(22.94)	48.4	0.0	0.258	(22.20)	48.5	0.0	0.222	(22.87)	48.2	0.0
LARGE					2.295	(25.68)	77.4	0.0	2.402	(26.15)	76.6	0.0	2.294	(25.68)	77.6	0.0
BUY					-0.354	(-15.91)	0.3	4.4					-0.389	(-14.77)	0.0	3.9

Panel C: Realized spread

Model	(1)				(2)				(3)				(4)			
	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-	Estimate	*t*-Stat	%+	%-
HFT	0.096	(18.97)	10.9	1.0	0.088	(17.18)	10.2	1.3	0.088	(17.06)	9.3	1.1	0.233	(19.53)	16.1	0.2
*HFT*MEDIUM*									0.106	(10.72)	11.2	1.9				
*HFT*LARGE*									1.045	(8.69)	26.9	1.6				
*HFT*BUY*													-0.300	(-13.81)	0.5	14.0
MEDIUM					-0.247	(-27.32)	0.0	56.3	-0.265	(-25.29)	0.0	51.1	-0.246	(-27.26)	0.0	56.2
LARGE					-2.297	(-29.72)	0.0	80.0	-2.387	(-29.93)	0.0	80.4	-2.297	(-29.73)	0.0	80.0
BUY					0.484	(21.01)	8.6	0.2					0.568	(20.81)	9.1	0.0

Table 6. Option–day sample summary statistics

This table reports summary statistics of the trading volumes for the intra-day VAR sample and subsamples by calls and puts, moneyness, and time to maturity. We require at least 1,000 non-zero transaction intervals among 2,160 10-second intervals for each option–day, which reduces the sample to 10,190 option–day observations. The variables *%HFT*, *%AT*, and *%NT* are the mean percentages of each trader group's trading volume to total trading volume, respectively. The variables *%HFT DEMAND*, *%AT DEMAND*, and *%NT DEMAND* are the mean percentages of each trader group's liquidity taking trading volume to each trader group's trading volume. Moneyness is defined for calls as DITM, ITM, ATM, OTM, and DOTM as K/S in $[-\infty,0.93]$, $(0.93,0.97]$, $(0.97,1.03]$, $(1.03,1.07]$, and $(1.07,\infty]$, respectively. Moneyness is defined for puts as DOTM, OTM, ATM, ITM, and DITM as K/S in $[-\infty,0.93]$, $(0.93,0.97]$, $(0.97,1.03]$, $(1.03,1.07]$, and $(1.07,\infty]$, respectively.

		N	Volume	%HFT	%AT	%NT	%HFT DEMAND	%AT DEMAND	%NT DEMAND
All options	Mean	10,190	408,256	35.7	26.8	37.5	66.2	47.7	36.7
	Median		217,755	38.2	25.2	35.1	64.9	47.3	36.6
Call options	Mean	4,825	457,978	33.9	26.7	39.4	67.1	48.9	36.4
	Median		239,108	36.4	25.3	36.3	65.9	48.4	36.0
Put options	Mean	5,365	363,540	37.3	26.9	35.9	65.4	46.6	37.0
	Median		197,372	39.5	25.2	34.0	64.1	46.1	37.0
Moneyness									
DITM	Mean	0							
	Median								
ITM	Mean	28	60,974	38.8	32.3	28.8	72.4	47.2	24.5
	Median		49,493	37.6	32.0	30.3	73.9	49.9	24.3
ATM	Mean	5,330	446,430	40.5	25.3	34.2	64.1	48.7	35.1
	Median		223,398	42.1	23.6	33.3	62.6	48.4	35.5
OTM	Mean	3,911	377,381	31.8	27.5	40.7	67.9	46.3	38.4
	Median		218,568	33.3	26.4	37.6	67.3	45.8	37.7
DOTM	Mean	921	329,007	24.1	32.2	43.7	71.2	47.6	39.7
	Median		167,146	24.2	30.5	41.2	70.8	47.0	38.8
Time to maturity									
$T - t \leq 10$	Mean	3,415	676,712	33.6	26.4	40.0	66.1	47.5	37.8
	Median		385,824	37.2	25.4	36.1	64.9	47.4	37.9
$10 < T - t \leq 20$	Mean	2,649	338,843	36.8	25.7	37.5	65.7	47.9	36.5
	Median		227,630	38.8	24.3	35.5	64.7	47.6	36.3
$20 < T - t \leq 30$	Mean	3,338	253,983	37.6	26.8	35.6	65.9	47.7	36.0
	Median		159,005	39.5	24.8	34.2	64.4	47.3	35.8
$30 < T - t$	Mean	788	131,687	32.7	32.0	35.3	70.2	47.4	35.9
	Median		59,487	33.2	31.8	33.6	68.8	46.2	35.6

Table 7. Intra-day VAR estimate: HFT trading volumes and market quality

This table presents intra-day VAR results. For each option–day observation, the following VAR is estimated:

$$\mathrm{HFT_t} = \alpha_1 + \sum_{k=1}^{6} \beta_{1,k} HFT_{t-k} + \sum_{k=1}^{6} \gamma_{1,k} AT_{t-k} + \sum_{k=1}^{6} \delta_{1,k} NT_{t-k} + \sum_{k=1}^{6} \theta_{1,k} MQ_{t-k} + \sum_{k=1}^{5} \pi_{1,k} TimeDummy_k + \epsilon_{1,t} \quad (1)$$

$$\mathrm{AT_t} = \alpha_2 + \sum_{k=1}^{6} \beta_{2,k} HFT_{t-k} + \sum_{k=1}^{6} \gamma_{2,k} AT_{t-k} + \sum_{k=1}^{6} \delta_{2,k} NT_{t-k} + \sum_{k=1}^{6} \theta_{2,k} MQ_{t-k} + \sum_{k=1}^{5} \pi_{2,k} TimeDummy_k + \epsilon_{2,t} \quad (2)$$

$$\mathrm{NT_t} = \alpha_3 + \sum_{k=1}^{6} \beta_{3,k} HFT_{t-k} + \sum_{k=1}^{6} \gamma_{3,k} AT_{t-k} + \sum_{k=1}^{6} \delta_{3,k} NT_{t-k} + \sum_{k=1}^{6} \theta_{3,k} MQ_{t-k} + \sum_{k=1}^{5} \pi_{3,k} TimeDummy_k + \epsilon_{3,t} \quad (3)$$

$$\mathrm{MQ_t} = \alpha_4 + \sum_{k=1}^{6} \beta_{4,k} HFT_{t-k} + \sum_{k=1}^{6} \gamma_{4,k} AT_{t-k} + \sum_{k=1}^{6} \delta_{4,k} NT_{t-k} + \sum_{k=1}^{6} \theta_{4,k} MQ_{t-k} + \sum_{k=1}^{5} \pi_{4,k} TimeDummy_k + \epsilon_{4,t} \quad (4)$$

where *HFT* is the total trading volume of HFTs during the 10-second period (in thousands of contracts), *AT* is the total trading volume of ATs during the 10-second period (in thousands of contracts), *NT* is the total trading volume of NTs during the 10-second period (in thousands of contracts), and *MQ* is the market quality variable. We use three measures of market quality: *Effective spread* is calculated by the time-weighted average of the effective spread in the interval; *DEPTH* is the time-weighted average of the number of contracts in the book at the best posted prices in the interval; *HL* is defined as the highest transaction price minus the lowest transaction price divided by the midpoint of the highest and lowest prices in the interval; and *TimeDummy* is a dummy variable that takes a value of one or zero for each respective hour period. For example, $TimeDummy_1$ has a value of one from 9:00 a.m. to 10:00 a.m. and zero otherwise. We require at least 1,000 non-zero trading volume intervals among 2,160 10-second intervals for each option–day, reducing the sample to 10,190 option–day observations. In the table, we only report estimation results for equation (4). Panels A and B report the estimation result when we use *Effective spread* as *MQ*. Panels C and D present the estimation results when we using *DEPTH* as *MQ*. Panels E and F show the estimation results when we use *HL* as *MQ*. Panels A, C, and E report the average coefficients in the *estimate* column. The percentages of option–days with positive (negative) coefficients that are significantly different from zero at the 5% confidence level are reported in the column *%+* (*%-*). In Panels B, D, and F, the coefficients are averaged across all options for each day and the mean of the daily time series is reported in the *estimate* column. Parentheses indicate Newey–West (1994) *t*-statistics for the time-series means.

Panel A: MQ = effective spread, summary of option–day observations

Lag	HFT			AT			NT			ESP		
	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-
1	-0.0025	2.3	11.9	0.0001	5.8	4.5	-0.0002	4.7	6.3	0.3369	99.9	0.0
2	-0.0008	2.5	5.8	0.0001	4.2	3.5	0.0002	4.5	3.6	0.0586	56.3	1.5
3	-0.0004	2.8	4.8	0.0001	3.4	3.4	0.0003	3.9	2.7	0.0356	34.9	2.1
4	-0.0004	2.2	4.3	0.0001	3.1	3.3	0.0002	4.1	3.1	0.0246	26.3	3.0
5	-0.0006	2.4	3.9	0.0001	2.8	3.0	0.0002	3.6	2.6	0.0236	25.0	2.3
6	-0.0001	2.1	3.8	0.0001	2.9	3.0	0.0002	4.0	2.6	0.0254	28.0	2.6
Time dummy	Included											
R^2	0.3368											

Panel B: MQ = effective spread, time-series average of mean daily coefficients

Lag	HFT		AT		NT		ESP	
	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat
1	-0.0023	(-3.53)	0.0002	(3.07)	-0.0002	(-6.00)	0.3331	(191.66)
2	-0.0007	(-2.53)	0.0002	(3.06)	0.0002	(5.34)	0.0587	(82.09)
3	-0.0004	(-2.21)	0.0001	(2.67)	0.0003	(7.85)	0.0352	(50.47)
4	-0.0004	(-2.53)	0.0001	(2.59)	0.0002	(7.15)	0.0245	(39.25)
5	-0.0005	(-1.08)	0.0001	(3.64)	0.0002	(5.95)	0.0236	(37.35)
6	-0.0001	(-0.56)	0.0001	(1.61)	0.0002	(6.39)	0.0253	(38.72)

Table 7 – continued

Panel C: MQ = depth, summary of option–day observations

Lag	HFT			AT			NT			DEPTH		
	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-
1	-0.3926	5.7	12.5	-0.0114	7.4	10.3	-0.0212	6.2	22.6	0.6105	100	0.0
2	0.2443	4.9	6.1	0.0062	7.8	5.3	0.0052	7.8	5.2	0.0390	49.9	8.0
3	0.0262	4.2	5.2	0.0032	6.1	4.5	0.0018	6.3	5.3	0.0402	39.8	2.1
4	0.0007	3.9	4.6	0.0030	5.9	4.2	0.0049	6.2	4.1	0.0257	25.8	3.1
5	0.0611	4.1	4.2	0.0024	5.5	4.4	0.0042	6.1	4.2	0.0228	22.6	3.1
6	-0.0116	3.7	4.6	0.0022	5.2	4.0	0.0084	6.4	3.6	0.0339	38.6	1.7
Time dummy	Included											
R^2	0.6391											

Panel D: MQ = depth, time-series average of mean daily coefficients

Lag	HFT		AT		NT		DEPTH	
	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat
1	-0.3260	(-0.92)	-0.0115	(-4.84)	-0.0200	(-15.89)	0.6116	(245.37)
2	0.1866	(1.18)	0.0065	(3.24)	0.0054	(6.03)	0.0396	(42.22)
3	0.0201	(0.40)	0.0040	(2.64)	0.0021	(2.44)	0.0404	(81.78)
4	0.0001	(0.00)	0.0035	(2.15)	0.0046	(5.29)	0.0254	(59.42)
5	0.0503	(1.31)	0.0028	(1.87)	0.0044	(4.97)	0.0226	(53.46)
6	-0.0088	(-0.72)	0.0028	(2.18)	0.0080	(9.92)	0.0334	(82.09)

Panel E: MQ = HL, summary of option–day observations

Lag	HFT			AT			NT			HL		
	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-
1	-0.0026	9.9	11.2	0.0065	29.5	2.3	0.0088	50.6	2.0	0.1328	96.1	0.0
2	-0.0026	7.0	7.6	0.0020	12.8	4.4	0.0040	23.5	2.2	0.0581	58.8	0.3
3	-0.0030	6.9	6.7	0.0016	10.5	4.5	0.0028	15.6	2.8	0.0451	44.7	0.3
4	-0.0016	5.5	7.4	0.0007	8.4	5.4	0.0022	13.0	2.6	0.0345	33.8	0.8
5	-0.0042	5.8	7.2	0.0007	8.2	5.7	0.0019	12.2	3.2	0.0357	34.9	0.6
6	-0.0039	7.0	8.0	0.0020	12.2	4.3	0.0028	17.5	2.8	0.0471	47.4	0.4
Time dummy	Included											
R^2	0.2146											

Panel F: MQ = HL, time-series average of mean daily coefficients

Lag	HFT		AT		NT		HL	
	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat
1	-0.0022	(-0.68)	0.0065	(28.10)	0.0097	(40.89)	0.1326	(134.06)
2	-0.0022	(-0.74)	0.0020	(11.47)	0.0044	(32.42)	0.0572	(88.09)
3	-0.0024	(-1.23)	0.0017	(9.90)	0.0030	(22.91)	0.0450	(75.62)
4	-0.0016	(-0.83)	0.0006	(4.31)	0.0024	(21.99)	0.0341	(57.57)
5	-0.0037	(-1.24)	0.0007	(4.84)	0.0021	(18.82)	0.0356	(59.83)
6	-0.0032	(-1.07)	0.0020	(12.12)	0.0032	(21.12)	0.0465	(63.39)

Table 8. Intra-day VAR estimate: HFTs' demand (supply) volume and short-term volatility

This table presents intra-day VAR) results. For each option–day observation, the following VAR is estimated:

$$\mathrm{HFT_t} = \alpha_1 + \sum_{k=1}^{6}\beta_{1,k}HFT_{t-k} + \sum_{k=1}^{6}\gamma_{1,k}AT_{t-k} + \sum_{k=1}^{6}\delta_{1,k}NT_{t-k} + \sum_{k=1}^{6}\theta_{1,k}MQ_{t-k} + \sum_{k=1}^{5}\pi_{1,k}TimeDummy_k + \epsilon_{1,t} \quad (1)$$

$$\mathrm{AT_t} = \alpha_2 + \sum_{k=1}^{6}\beta_{2,k}HFT_{t-k} + \sum_{k=1}^{6}\gamma_{2,k}AT_{t-k} + \sum_{k=1}^{6}\delta_{2,k}NT_{t-k} + \sum_{k=1}^{6}\theta_{2,k}MQ_{t-k} + \sum_{k=1}^{5}\pi_{2,k}TimeDummy_k + \epsilon_{2,t} \quad (2)$$

$$\mathrm{NT_t} = \alpha_3 + \sum_{k=1}^{6}\beta_{3,k}HFT_{t-k} + \sum_{k=1}^{6}\gamma_{3,k}AT_{t-k} + \sum_{k=1}^{6}\delta_{3,k}NT_{t-k} + \sum_{k=1}^{6}\theta_{3,k}MQ_{t-k} + \sum_{k=1}^{5}\pi_{3,k}TimeDummy_k + \epsilon_{3,t} \quad (3)$$

$$\mathrm{MQ_t} = \alpha_4 + \sum_{k=1}^{6}\beta_{4,k}HFT_{t-k} + \sum_{k=1}^{6}\gamma_{4,k}AT_{t-k} + \sum_{k=1}^{6}\delta_{4,k}NT_{t-k} + \sum_{k=1}^{6}\theta_{4,k}MQ_{t-k} + \sum_{k=1}^{5}\pi_{4,k}TimeDummy_k + \epsilon_{4,t} \quad (4)$$

where *HFT* is HFTs' liquidity taking (or liquidity providing) trading volume during the 10-second period (in thousands of contracts); *AT* is ATs' liquidity taking (or liquidity providing) trading volume during the 10-second period (in thousands of contracts); *NT* is NTs' liquidity taking (or liquidity providing) trading volume during the 10-second period (in thousands of contracts); *MQ* is short-term volatility, *HL*, where *HL* is defined as the highest transaction price minus the lowest transaction price divided by the midpoint of the highest and lowest prices in the interval; and *TimeDummy* is a dummy variable that takes a value of one or zero for each respective hour period. For example, $TimeDummy_1$ has a value of one from 9:00 a.m. to 10:00 a.m. and zero otherwise. We require at least 1,000 non-zero trading volume intervals among 2,160 10-second intervals for each option–day, which filters the sample down to 10,190 option–day observations. In the table, we only report estimation results for equation (4). In Panels A and B (Panels C and D), *HFT, AT,* and *NT* are liquidity taking (liquidity providing) trading volumes. Panels A and C report the average coefficients in the *estimate* column. The percentages of option–days with positive (negative) coefficients that are significantly different from zero at the 5% confidence level are reported in the column *%+* (*%-*). In Panels B and D, the coefficients are averaged across all options for each day and the mean of the daily time series is reported in the *estimate* column. Parentheses indicate Newey–West (1994) *t*-statistics for the time-series means.

Panel A: Demand trading volume and volatility, summary of option–day observations

Lag	HFT			AT			NT			HL		
	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-
1	0.0213	28.7	1.6	0.0131	37.3	1.2	0.0148	46.8	1.2	0.1318	96.0	0.0
2	-0.0001	11.2	3.7	0.0046	15.3	3.2	0.0070	22.1	1.8	0.0566	57.6	0.3
3	0.0132	9.5	3.9	0.0037	12.1	3.3	0.0056	17.1	2.0	0.0444	44.2	0.4
4	0.0125	6.6	5.3	0.0020	10.0	4.0	0.0037	13.1	2.6	0.0339	33.7	0.9
5	-0.0042	6.7	5.7	0.0021	9.4	4.3	0.0036	12.2	2.9	0.0351	34.4	0.6
6	0.0108	7.7	6.2	0.0043	13.8	3.1	0.0072	22.0	1.7	0.0467	46.9	0.4
Time dummy	Included											
R^2	0.2138											

Panel B: Demand trading volume and volatility, time-series average of mean daily coefficients

Lag	HFT		AT		NT		HL	
	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat
1	0.0187	(1.60)	0.0135	(37.20)	0.0160	(42.57)	0.1314	(129.88)
2	0.0004	(0.15)	0.0047	(18.84)	0.0075	(31.16)	0.0555	(83.17)
3	0.0113	(1.13)	0.0038	(16.75)	0.0061	(25.46)	0.0443	(73.11)
4	0.0102	(1.08)	0.0020	(9.72)	0.0040	(20.16)	0.0334	(55.99)
5	-0.0035	(-0.87)	0.0021	(10.78)	0.0039	(18.54)	0.0349	(58.31)
6	0.0091	(1.00)	0.0045	(19.54)	0.0079	(27.27)	0.0461	(62.21)

Table 8 – continued

Panel C: Supply trading volume and volatility, summary of options-day observation

Lag	HFT			AT			NT			HL		
	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-	Estimate	%+	%-
1	-0.0368	13.7	6.8	0.0109	29.8	2.0	0.0128	57.1	0.9	0.1325	96.1	0.0
2	-0.0384	9.2	5.4	0.0040	13.2	3.9	0.0058	26.3	1.2	0.0588	59.3	0.3
3	-0.0759	9.5	4.7	0.0036	10.8	4.4	0.0041	17.6	1.9	0.0455	45.3	0.3
4	-0.0324	7.1	5.7	0.0015	8.5	5.2	0.0028	13.1	2.3	0.0349	34.0	0.9
5	0.0497	8.0	5.0	0.0001	7.9	5.6	0.0025	11.7	2.8	0.0361	35.0	0.6
6	-0.1468	12.0	3.7	0.0042	10.2	5.1	0.0031	14.4	2.5	0.0473	47.5	0.4
Time dummy	Included											
R^2	0.2136											

Panel D: Supply trading volume and volatility, time-series average of mean daily coefficients

Lag	HFT		AT		NT		HL	
	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat	Estimate	*t*-Stat
1	-0.0301	(-0.82)	0.0111	(18.49)	0.0138	(46.92)	0.1322	(135.49)
2	-0.0319	(-0.88)	0.0041	(7.32)	0.0062	(38.75)	0.0578	(90.18)
3	-0.0619	(-1.00)	0.0036	(3.90)	0.0043	(28.57)	0.0454	(76.00)
4	-0.0271	(-0.86)	0.0014	(2.76)	0.0030	(24.37)	0.0344	(58.21)
5	0.0407	(1.03)	0.0002	(0.32)	0.0026	(20.71)	0.0360	(59.99)
6	-0.1199	(-0.92)	0.0038	(2.02)	0.0034	(22.06)	0.0466	(62.46)