High Frequency Trading in an Options Market: Evidence from the KOSPI200 Options Market

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ABSTRACT

We examine the trading activity of high frequency traders (HFTs) and the impact of HFTs on market quality in an options market. We use unique recent dataset of the KOSPI200 options market from January 2, 2012 to June 30, 2014, which not only contains detailed information about every trade and quote, but also enables us to directly identify HFTs' accounts. On average, there are 39 HFTs each trading day, and HFTs account for 37% of the transactions on the options market. We find that high frequency trading is profitable in the KOSPI200 options market, and especially HFTs who aggressively use marketable orders earn much more profits than the others. HFTs trade on information and execute their trades at better prices when they take liquidity. The price impact is higher in their liquidity taking transactions, which is 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 they do not significantly affect short-term volatility while non-HFTs increase it. Overall 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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1. **Introduction**

Recent advances in technology and electronic trading employed in financial markets allow traders to rapidly process information and submit orders. These developments in financial market have led to the rise of a new type of traders, referred to as high frequency traders (HFTs). The Securities and Exchange Commission (SEC) defines those 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 become to play a significant role in financial markets. For example, Zhang (2010) reports that HFTs account for over 70% of dollar trading volume in the U.S. capital market. However, concerns on the impact on market quality of high frequency trading have been rising. Especially since the 2010 Flash Crash, the beliefs that HFTs exploit other investors and destabilize markets have been spread among the public. On the other hand, there is an opinion that high frequency trading is nothing more than a tool that results in improved liquidity. It is still controversial whether HFTs enhance market quality or reduce it and whether high frequency trading should be regulated.

This paper provides empirical evidence on these issues by examining high frequency trading and its impact on market quality from an options market. We use the unique recent dataset for KOSPI200 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.

Several existing studies examine high frequency trading and its impact on U.S equity market. However, high frequency trading is not confined to the U.S. equity market but pervasive over the world financial markets. For instance, Zook and Grote (2014) document that HFTs account for about half of trades at stock exchanges worldwide. To our best knowledge, our paper is the first to study HFTs on an options market. Our research contributes to the literature by examining a market with different structure. A crucial advantage of the KOSPI 200 options market to carry out high frequency trading is that there are negligible transaction costs and no taxes in this market. By contrast, taxes are imposed on sellers in the Korean equity markets. In addition, highly leveraged trading and easy short selling are also advantageous for HTFs in the options market. Thus, it is natural that HFTs who are interested in Korean markets focus more on the options market rather than the stock markets. In fact, we find 39 HFT accounts each trading day on average. For these reasons, examining high frequency trading on the KOSPI200 options market will enhance the understanding of HFTs.

There has been a growing body of theoretical and empirical literature on high frequency trading. Several recent theoretical papers provide models and try to figure out the impact of high frequency trading on markets. Gerig and Michayluk (2013) extend Glosten and Milgrom (1985) model including multiple securities and an automated market maker. They argue that the automated market maker makes markets more efficient and lowers transaction costs. Rosu (2014) extends Kyle (1985)'s model with multiple informed traders who may have different speed and with changing fundamental value, suggesting that competition among the fast informed traders improve 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 where low-frequency traders may suffer from HFTs, claiming that some restrictions on HFTs may be needed. There are also models where the impact of HFTs depends on the market environment. Jovanovic and Menkveld (2012) provide a model where HFTs can mitigate or exacerbate adverse selection problem depending on the market condition. Their calibration implies that HFTs may raise welfare. Hoffmann (2014) develops a model based on the Foucault (1999) dynamic limit order market. In the model, fast traders can reduce inefficiency with their speed, but it is possible that they decrease the welfare of slow traders and the arms race for speed is triggered. Biais, Foucault and Moinas (2014) 's work, in line with Grossman and Stiglitz (1980), consider a fraction of fast institutions and costs to become faster as important elements. Fast trading is beneficial in dealing with market fragmentation, but results in adverse selection and overinvestment in speedas well. These works provide useful implications but do not cover the overall effects of diverse and complicated strategies of HFTs.

Being different from theoretical works, empirical works mainly show the positive effects of HFTs. Several empirical studies on NASDAQ examine whether HFTs generally play a positive role. Brogaard (2010) reports that HTFs contribute to 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 London Stock Exchange also suggests that HFTs tend to enhance market liquidity (Jarnecic and Snape, 2014). Malinova, Park and Riordan (2013) show that introducing the per-message fee in Canada, which constricts HFTs' trading activity, is not helpful to retail traders. However, there exist papers that have negative views on HFTs. Kirilenko, Kyle, Samadi and Tuzun (2014) claim that HFTs do not cause the 2010 flash crash but exacerbate the crash 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 price discovery process and do not improve market quality in the

KOSPI 200 futures market, which directly contrasts the studies on NASDAQ.

Our main findings are consistent with the positive views on HFTs. We first study HFTs' profits and then analyze HFTs' relationship with trading costs and impact on market quality. HFTs gain profits in general, but the distribution of the profits is wide. Aggressive HFTs seem to trade on information and earn much more profits than passive HFTs. HFTs tend to demand liquidity when it is relatively plentiful and they accompany lower trading costs. Our estimation through a VAR model also shows that HFTs significantly reduce effective spreads while non-HFTs' effect is small. Furthermore, it is surprising that HFTs do not affect or may reduce short-term volatility while non-HFTs significantly increase it. Our results are opposite to Lee (2013)'s. Our analysis has two main differences from Lee's. First, we examine the KOSPI 200 options market, while Lee examines the KOSPI 200 index futures market. Second, more importantly, we control non-HFT components in our analysis. In fact, our results become similar to Lee's when we do not control non-HFT components in the VAR analysis. The results of Lee (2013) may be due to misspecification

The remainder of the paper is organized as follows. Section 2 describes the structure of KOSPI200 options market and data. Section 3 reports the trading activity of high frequency traders. Section 4 examines the profitability of high frequency traders. Section 5 investigates the trading execution costs when HFTs are liquidity providers and when HFTs are liquidity takers. Section 6 presents the evidence regarding HFTs' impact on market quality. Finally, Section 7 summarizes and concludes.

2. **Description of the Market and Data**

We use intraday trade and quote data for KOSPI200 options on the KRX from January 2, 2012 to June 30, 2014. Our data set comprises detailed information of all trades and quotes in the KOSPI200 options market. The data includes a millisecond timestamp at which trades occurs and quotes arrive at the exchange.

The KOSPI200 options market has been launched on the KRX since July 1997. Despite its short history, the KOSPI200 options market is one of the most active derivatives markets in the world. According to the FIA (Futures Industry Association) report, the KOSPI200 options market was the most active derivatives market until 2012, in terms of trading volumes. After the option multiplier change, which raised the multiplier for KOSPI 200 Options from KRW 100,000 to KRW 500,000 since March 9, 2012, there were substantial drops in trading volumes. However, the KOSPI200 options market still remains at the top 3 active derivatives markets in the world.[1]

Here, we briefly describe the KOSPI200 options market. KOSPI200 options are European options, exercisable only at the expiration, where the contract months are the three consecutive months plus one nearest month from the quarterly cycle (March, June, September, and December). The last trading day is the second Thursday of the contract month. Each options 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 completely an electronic order-driven market. The KOSPI200 options market opens at 9:00 a.m. and closes at 15:15 p.m.[2] Trading is continuous from 9:00 a.m. to 3:05 p.m. with the opening price determined by a batch auction for a one hour pre-opening session. For the last ten 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 3 points, the tick size is 0.01 point and when option premiums are above or equal to 3 points, the tick size is 0.05 point.

A crucial advantage of the KOSPI 200 options market to carry out high frequency trading is that this market requires negligible transaction costs and no tax. For equity trading in the Korea Exchange (KRX), investors should pay 0.3% taxes on selling amount. By contrast, for option trading in the KRX, investors do not pay any tax and often commissions as well. In addition, options are highly leveraged instruments and it is easy to carry out short selling in options market. Thus, it is natural that HFTs who are interested in the Korean markets focus on options markets rather than stock markets. Moreover, our data for KOSPI200 options market is appropriate for investigating the high frequency trading. Our intraday dataset contains not only high-quality information about every order and transaction but also encoded accounts of each trader. The encoded accounts information enables us to directly identify high frequency traders. In addition, since there are buy-sell indicators and detailed millisecond time-stamps, we can exactly determine whether each trade is buyer- or seller-initiated at 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 a high frequency trader. According to the SEC (2010), HFTs submit numerous orders with extraordinarily high-speed,

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[1] According to the FIA Annual Volume Survey, the KOSPI200 options market is the highest ranked among all derivative markets in terms of trading volume until 2012. The cumulative trading volume was 1,575,394,249 contracts during 2012. However, the trading volume drops to 580,460,364 contracts during 2013, but the KOSPI200 options market ranked the 3rd derivatives market in 2013. Source: Futures Industry Association (http://www.futuresindustry.org).

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

cancel orders shortly after the original submission, and end the trading day at or near a neutral inventory position as possible. Specifically, traders who satisfy the following four conditions are selected as HFTs: (1) Submit more than 1,000 limit orders in the day; (2) have a median order duration of less than 1 second; (3) have a median cancellation duration of less than 2 seconds; (4) have an end-of-day inventory position of no more than 1% of the total volume traded on that day. We also decompose two different subcategories of HFTs based on how frequently the HFTs initiate a transaction. To be considered as a liquidity taking (aggressive, marketable) HFT, a trader must initiate more than half of the trader's total transaction; To be considered as a liquidity providing (passive, non-marketable) HFT, a trader must initiate fewer than half of the trader's total transaction.

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

3. Trading activity of high frequency traders

From the above categorization of HFTs, on average, we identify 39 accounts as high-frequency traders on a trading day on average. There are also 157 algorithmic traders and 15,317 normal traders on a trading day on average. HFTs are 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 on a day), 37% of transactions (on average, 320,431 transactions out of 875,306 transactions per day), and 31% of total trading volume (on average, 2,134,967 contracts out of 6,904,488 contracts on a day) of the overall options market. In addition, ATs are also responsible for a large portion in the option market. Although 1.01% of traders are ATs, they account for 44%, 25% and 28% of order submissions, of transactions, and of trading volumes, respectively. In other words, the participation of HFTs and ATs take a quite large portion in the KOSPI200 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 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 the event, only 4.4 domestic individual HFTs participate in the market. For the domestic institutional HFTs, the number of accounts declines from 9.2 to 5.9 after the option multiplier change. On the other hand, the number of foreign HFT accounts slightly increases from 22.8 to 26.6 after the change. Thus, the downward trend of the entire HFT is completely caused by the decrease of the domestic HFTs.

< Insert Table 1 >

Table 1 presents a summary of average daily trading behavior of our three trader categories for the sample period from January, 2, 2012 to June, 30, 2014. Panel A in Table 1 summarizes daily trading activity by the three trader groups. The table describes the daily mean of order and cancellation activity such as *Number of Order Submitted, Order Duration, Cancellation Rate,* and *Cancellation Duration*. It also provides the mean of transaction activity such as *Number of Transactions, Volume, Order to Trade Ratio,* and *|Net Position| to Volume*. All variables in Panel A show that there are 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 high frequency trader submits 62,827 orders including order submissions, revisions, and cancellations per day. They submit one order per every 0.21 seconds. ATs submit 15,854 orders and NTs submit 45 orders per person. Their order duration is relatively longer than that of HFTs. ATs submit one order per every 4.31 seconds and NTs have order duration of 994 seconds. We can also find a similar difference in cancellation orders. HFTs cancel about two-thirds of their limit orders in just a few seconds. The *Cancellation Rate*, defined as the ratio of the number of limit order cancellations to the number of limit order submissions (including the revisions), is 63.7 percent and the *Cancellation Duration*, defined as the median value of the time to cancellations for cancelled limit orders, is only 0.36 seconds. ATs also cancel pretty large amounts of their orders (49.1 percent),

[3] The multiplier for KOSPI200 Options was increased to KRW 500,000 equal to five times prior multiplier since March 9, 2012, with a step-by-step application across contract months. Both the multipliers of 100,000 and 500,000 are used for about three months after the effective date of March 9, 2012, but the use of multiplier of 100,000 disappear gradually and only the multiplier of 500,000 is used after June 15, 2012.

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 high frequency traders' in determining cancellations. On the other hand, it is unusual to cancel limit orders for NTs. Their *Cancellation Rate* is just 18 percent and *Cancellation Duration* is very long (1230 seconds). Second, in terms of transaction activity, HFTs also show distinguishable features. On average, a high frequency trader involves in 8,119 transactions per day. This is about 5.7 times greater than an algorithmic trader's number of transactions, and the dollar amount of transactions is even 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 rate. The trading volume exhibits a similar pattern to the number of transactions, but the volume per transaction of HFTs is 6.66 contracts while ATs and NTs trade 8.6 contracts in one transaction. It seems that HFTs use many small-size trades compared to other traders. Finally, although HFTs involve 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 zero inventory positions. In fact, HFTs' ratio of absolute value of net positions to trading volume is 0.08%. Moreover, 76% of HFTs end a day at the exactly zero inventory position.

Next, we examine the trading activity of HFTs regarding the level of liquidity provision. We classify HFTs into two groups based on how frequently they initiate trades. Aggressive (Passive) HFTs are traders who initiate trades more (fewer) than half of their trades in a 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 in a day. We can find some differences between the two groups. Passive HFTs place more active orders and engage more active transaction activity. They have the greatest number of orders and transactions, and they are the fastest traders in terms of order duration. Although aggressive HFTs cancel orders more quickly and frequently, the trading volume is large for them. As a result, aggressive HFTs' volume per transaction is 8.98, similar to ATs' and NTs'. However, volume per transaction of passive HFTs is only 4.45. It seems that small-size trades are usually executed by passive HFTs rather than by aggressive HFTs.

4. The profitability of high frequency traders

In this section, we examine the profitability of HFTs. Given their huge size of 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 zero inventory position to compute daily profits for each HFT. With this assumption, we calculate daily profits for each HFT, *i*, for each trading day *t* according to the marked-to market accounting. Since about three-fourths of HFTs end a 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 relatively small to profits. We calculate 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* in a trading day *t*, 1_{sell} is an indicator that have a value of one if 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-day, $y_{c,k}$ is the number of outstanding positions, and $p_{c,k}$ is the closing price of the 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-day.

<Insert Table 2>

The results of HFTs' profitability are presented in Table2. Panel A in Table 2 reports the summary statistics such as mean, median, standard deviation, skewness, and kurtosis for daily profits per account. We use 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 aggressively trade earn much more profits. Aggressive HFTs earn a mean of \$19,394 while passive HFTs earn only \$4,255 per day.[4] *Total Cumulative Profits* shows the overall profits during our sample periods. The HFTs earn an aggregate of \$311.1 million, and aggressive HFTs account for 85.8% of them. Since HFTs' trading amount is massive, we need to consider trading fees.

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

Unfortunately, trading fees differ across traders and we cannot gain exact fees for them. Because fees paid to exchange is 1.09bp of trading amounts and additional trading fees for HFTs are not big, we assume that the trading fee is 2bp.[5] After taking the fees into account, HFTs still earn money, on average. 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 entire HFTs. However, for passive HFTs, the same cannot be said. After taking into trading cost, profits of passive HFTs are quite small and actually the mean of time series net profits of them is not statistically significantly different from zero. To investigate the relationship between the profitability and the level of 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 that an HFT initiates to the number of trades that the HFT participates in for a day. Top 30% of HFTs, who have the largest liquidity taking ratio, are classified into *High* HFT, bottom 30% of HFTs enters into *Low* HFT, and those HFTs that meet neither high nor low are *Mid* HFT. Next we calculate the 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 *High* HFT group and monotonically drop to -$4,213 for *Low* HFT group. *High* HFT has huge positive profits which are statistically significant irrespective of the transaction fees, while *Mid* HFT has only tiny profits which disappear after considering trading fees. *Mid* HFT's profits are statistically not different from zero. Interestingly, *Low* HFT who trades passively loses money. Traders in *Low* HFT on average lose $7,852 per day net of expenses and this loss is statistically significant. The overall results support that HFTs who aggressively trade earn much more profits and the entire HFTs' profitability is derived by aggressive HFTs' superior performance. The results are consistent with Baron, Brogaard and Kirilenko (2012) who also show that aggressive HFTs earn more profits in the E-mini S&P 500 futures contract which has no liquidity rebates. Our results suggest a possibility that liquidity taking activity is related to a strong trade motivation or a superior trading skill rather than liquidity providing behavior. We examine the source of profitability by investigating trading costs in the next section.

While there exist positive profits on average, the distribution of profitability is very wide. Moreover, profits

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

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

of aggressive HFTs exhibit higher variation than those of passive. The skewness and kurtotis in Panel A show that the distribution deviates much from the normal distribution especially in the sense that tails have heavy excess weight. This means that there are very large gains for some HFTs, but some HFTs suffer incredibly huge losses, too. Panel A in Figure 2 shows more detailed results about the variation of profitability across HFT accounts. The figure 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 have a loss more than \$25,000 and the mean loss of them is \$118,446 in a day. The result implies that even though average HFTs earn positive profits, there is a large variation of profitability 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 vary across time substantially, too. HFTs as a whole earn \$505,103 in a day, with a high of \$23.9 million in August 9, 2012 and low of \$ -13.4 million in March 12, 2014. Loss of entire HFTs has also occurred occasionally, but they gain positive profits more than 69.0% of days over the 616 trading days. In sum, there is evidence showing that HFTs make profits on average, but there is also a 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 for market liquidity. To search for the source of HFTs' profits and the relationship between HFTs and liquidity, we analyze trading costs of transactions with liquidity providing HFTs and those with liquidity taking HFTs. In this paper, we use three simple and commonly used measures of trading costs: Effective spreads, price impacts, and realized spreads. These measures have been widely used in several studies including Lee, Mucklow and Ready (1993), Huang and Stoll (1997), Bessembinder and Kaufman (1997), and Madhavan and Cheng (1997). Effective spreads are estimated as the deviation between transaction price and an estimate of the true value of securities. We compute the effective spread as follows:

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

where D is a trade indicator variable that has a value one for buyer-initiated trades and negative one 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 the 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 security, while the non-informational component, the realized spread, can be measured by the reversal from transaction price to post-trade value. We estimate the price impact and the realized spread using the below equations:

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

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

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

where V_T is the true value of security 'T' periods after the transaction. Here, we use the first transaction price 5 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 should observe high price impacts on their liquidity taking transactions if they are trading on information. On the other side, we expect that realized spreads on HFTs' liquidity supplying trades are higher than those on non-HFTs' if HFTs have a timing skill to decide when to supply liquidity. Traditionally, the realized spreads stand for the compensation to liquidity suppliers from adverse selection. For analysis in this section, we use all transactions for which both pre- and post-trade benchmark prices are available. As a result, our sample consists of transactions executed on trading time from 9:00 a.m. to 3:00 p.m., including 442,787,602 transactions.

Table 3 summarizes the means of the spreads and price impacts. In Panel A, we report the means of each trading execution cost measure for all sample and for groups that are classified by the trading counterparty type,

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

i.e., HFTs and non-HFTs. In Panel B, we divide non-HFTs trade side by ATs and NTs.

< Insert Table 3 >

We can capture some 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 (row3, HFT-nHFT), the mean price impact is 1.156%, which is the largest among the four transaction categories in Panel A. If we fix the liquidity providers of trades as HFTs, the price impact is 0.534% for transactions with HFTs taking liquidity (row2, HFT-HFT) but only 0.384% for transactions with non-HFTs taking liquidity (row4, nHFT-HFT). Similarly, if we fix the liquidity providing side of transactions as non-HFTs, we observe the 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. Therefore, it can be inferred that HFTs have a superior skill in using private information and they 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 26.8bp when HFT provide liquidity to non-HFTs (row4, nHFT-HFT), and it is smaller than the mean realized spread on all transactions, 42.7bp (row1, ALL). If we fix the liquidity takers of trades as non-HFTs, the realized spread is 26.8bp for transactions with HFTs providing liquidity (row4, nHFT-HFT), but the value is 98.0bp for transactions with non-HFTs providing liquidity (row5, nHFT-nHFT). Similarly, if we fix the liquidity taking side of transactions as HFTs, we observe the smaller value of the mean realized spread on trades where an HFT provide liquidity. Moreover, if a HFT provide liquidity to a HFT, we observe negative the realized spread, -2.6bp. Overall, it is hard to find the evidence that HFTs are good at providing liquidity from 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 it is just 0.51% on trades between HFTs.

There is another interesting finding. If you look at Panel B, there are some differences in price impacts (realized spreads) depending on the counterparty who provides liquidity to (takes liquidity from) HFTs. When HFTs take liquidity, the price impact is larger in the order of NTs, ATs, and HFTs as liquidity providers. When HFTs take liquidity from NTs, the mean of price impacts is 1.2% (row2 in Panel B, HFT-NT), which is the largest case. When HFTs take liquidity from HFTs, the mean of price impacts is 0.53% (row2 in Panel A, HFT-HFT) which is the smallest case. Similarly, when HFTs provide liquidity, the realized spread is larger in the order of NTs, ATs, and HFTs as liquidity takers. Thus, when trading with HFTs, HFTs are the best traders and

NTs are the worst traders in terms of trading execution costs.

However, the inferences about skills from Table 3 require further tests since we do not adjust any other characteristics which 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 or not. 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 an effective spread, price impact, or realized spread as *Spread*. *HFT* is a dummy variable that has a value of 1 if an HFT participates in the trade and 0 otherwise. We separately analyze HFT participation by liquidity taking side and liquidity providing side. *Medium* and *Large* are indicator variables that control transaction size. *Medium* indicates transaction size between 10 contracts and 100 contracts, and *Large* indicates transaction size greater than 100 contracts. *Buy* is a dummy variable that takes a value of 1 if the trade is initiated by a buyer and 0 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 the standard errors within half-hour intervals following Petersen (2009). Then, at the second stage, we calculate the time-series means of estimates, Newey and West (1994) t-statistics for the time-series means, and the percent of days with a statistically significant coefficient.

The coefficient on *HFT* is of primary interest and means the difference in the spreads or price impact between trades with HFT participation and those without it after controlling for the other relevant variables. In specifications including all interaction terms, the coefficient on *HFT* indicates the trading cost differences for trade of less the 10 contracts and sell trades, and the coefficients on the interaction term are additional difference on HFT participations for 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. The 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 model 3-4 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 4.4bp tighter on 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 10.4bp 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 they do not harm market liquidity compared to non-HFTs.

Panel B and Panel C report the results for the price impact and the realized spread, which are strongly statistically significant. There is evidence suggesting that HFTs trade on information when they take liquidity, consistent with our preliminary results in Table 3. The price impact is more than 30bp greater and the realized spread is more than 35bp tighter on trades where HFTs take liquidity than trades of non-HFTs taking liquidity. In seller-initiated trades, HFTs' price impact is 24.6bp higher and in buyer-initiated trades, HFTs' price impact is 40.7bp higher due to the buy interaction term. This implies that there exists HFTs' informational advantage in both trading sides when taking liquidity, and the adverse selection costs of liquidity providers are larger on 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' trading on information is likely to be realized in small-size 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 is 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 4.6bp tighter on trades where HFTs provide liquidity. Combined with the result in Table 4, these results suggest that HFTs trade when liquidity is plentiful regardless of the direction of liquidity provisions. Overall, trading costs are low when HFTs participate in transactions.

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

Overall, the results from the regressions confirm our testable implications. Trading cost measures exhibit statistically significant differences depending on HFTs participation. HFTs have 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 have better ability to avoid adverse selection costs than do non-HFTs. Nevertheless, the ability may not be good enough to compensate the adverse selection from liquidity taking trades of HFTs. The poor performance of passive HFTs may be due to trading against aggressive HFTs. In addition, HFTs accompany low trading costs and they 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**

From 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 relationship between HFTs' trading and market quality. However, we apply a multivariate VAR model rather than use a bivariate VAR model. 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 in these trading volumes, then non-HFTs' trading volumes will predict HFTs' trading volumes because they are a noisy proxy for lagged HFTs' trading volumes.

Thus, if HFTs' trading volumes are non-HFTs' trading volumes plus noise, then the relationship between HFTs' trading volumes and market quality may be attributed to non-HFTs' trading volumes. The relationship between the two variables may change after controlling for lagged non-HFTs trading volumes. From this reason, we modify the bivariate VAR model in Lee (2013). We control non-HFTs' trading volumes using ATs' and NTs' trading volumes. Thus, our VAR is a system of four equations in which lags of HFTs' trading volumes, ATs' trading volumes, NTs' trading volumes, and market quality variables are used to explain each other. Specifically, we use the following vector autoregression (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 volumes of HFTs during the period, AT is the total trading volumes of ATs during the period, NT is the total trading volumes of NTs during the period, MQ is the market quality variable and *TimeDummy* is a dummy variable that takes a value of 1 or 0 for each respective hour time periods. *TimeDummy* is used to control 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. *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 price during the interval. *HL* is a proxy for short-term volatility. Each day, we partition the normal trading time into 2,160 ten-second intervals and conduct the above VAR analysis for each option-day.

To conduct the VAR analysis, we need a sufficient variation in the variables. Unless each variable has a 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 ten-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 total trading volume of the entire options market, the results of the analysis are not caused by some specific parts of the options market.

< Insert Table 6 >

Panel A in Table 7 reports the means of coefficients across all option-day estimations and also shows the percentage of significantly positive (negative) coefficients. This is a common method to summarize the VAR results. We also calculate the average of coefficients each day and report the t-statistics on 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 on market quality of HFTs, 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 the evidence that HFTs improve liquidity. Panel B in Table 7 supports this argument, showing that 1,000 contracts increase in the trading volume of HFTs results in 0.23% decrease in the effective spread after 10 seconds at the 1% significant level. Since the mean effective spread is 1.72% for our VAR sample and 0.23% is quite a large portion of the mean value, 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 1,000 contracts increase in the trading volume of HFTs results in 326 contract decrease in depth after 10 seconds, which is statistically insignificant. The mean coefficients of the first lagged trading volume of ATs and NTs are small compared to HFTs but statistically significant. Thus, it is difficult to tell the impact of traders on depth. Furthermore, 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 1,000 contracts increase in the trading volume of HFTs will result in 0.22% decrease in the short-term volatility after 10 seconds. Although this is statistically insignificant, all coefficients for HFTs are negative. On the contrary, 1,000 contracts increase in ATs' (NTs') trading volume results in 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]

[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 the results in table 7. The results of this analysis are not presented for brevity.

< Insert Table 7 >

Overall, HFTs enhance market quality compared to non-HFTs, consistent with Brogaard (2010). These results counter the findings from the KOSPI200 futures market (Lee, 2013). Lee (2013) reports that HFTs increase intraday volatility in the KOSPI 200 futures market. However, Lee (2013) does not consider contemporaneous correlation between HFTs' and non-HFTs' trading volume in her VAR model whereas Hirschey (2013) includes both HFT and non-HFT components in his VAR models. We run the bivariate VAR of HFTs' trading volumes and the market quality variables following Lee (2013) and obtain similar results to Lee (2013). In this estimation, 1,000 contracts increase in the trading volume of HFTs will result in 0.94% increase in the short-term volatility after 10 seconds, at the 1% significant level. Higher levels of HFTs' activity correspond to higher levels of short-term volatility, but this is not true after controlling non-HFTs' trading volumes. Nevertheless, because of different sample periods and different markets from Lee (2013), it is not certain whether the results of Lee (2013) are attributable to misspecification. Future research needs to integrate the analysis of options and futures markets.

7. **Conclusion**

High frequency trading has been 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 of 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. HFTs overall earn profits and the profits are closely related to the aggressiveness of HFTs. Aggressive HFTs earn much more profits than passive HFTs earn. Analysis on 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 they accompany 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 they do not significantly affect short-term volatility while non-HFTs increase it. Our research contributes to the understandings of HFTs with complete 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 a better insight on HFTs. In addition, it is necessary to investigate more thoroughly on the role of passive HFTs whose performance is worse than aggressive HFTs'.

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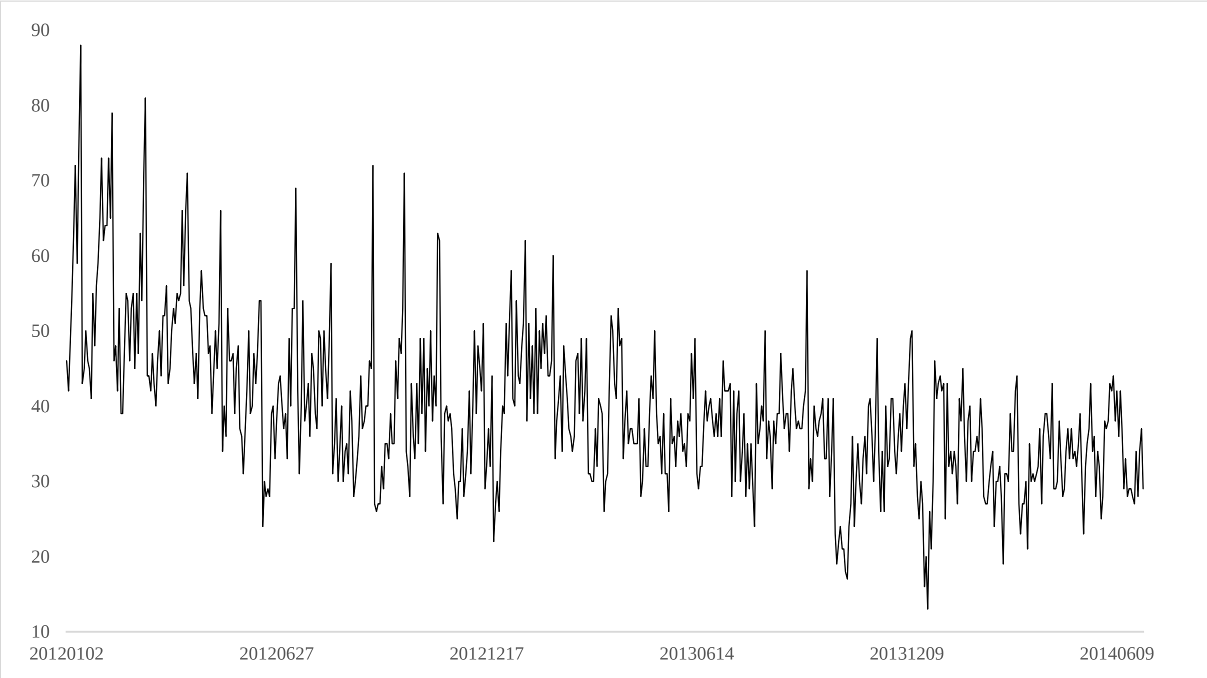
Figure 1. Number of HFT

This Figure shows the time series of daily number of HFT accounts. Each day, there are four conditions a trader must satisfy to be considered as a high frequency trader: (1) Submit more than 1,000 limit orders in the day; (2) have a median order duration of less than 1 second; (3) have a median cancellation duration of less than 2 seconds; (4) have an end-of-day inventory position, scaled by total volumes the traders 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

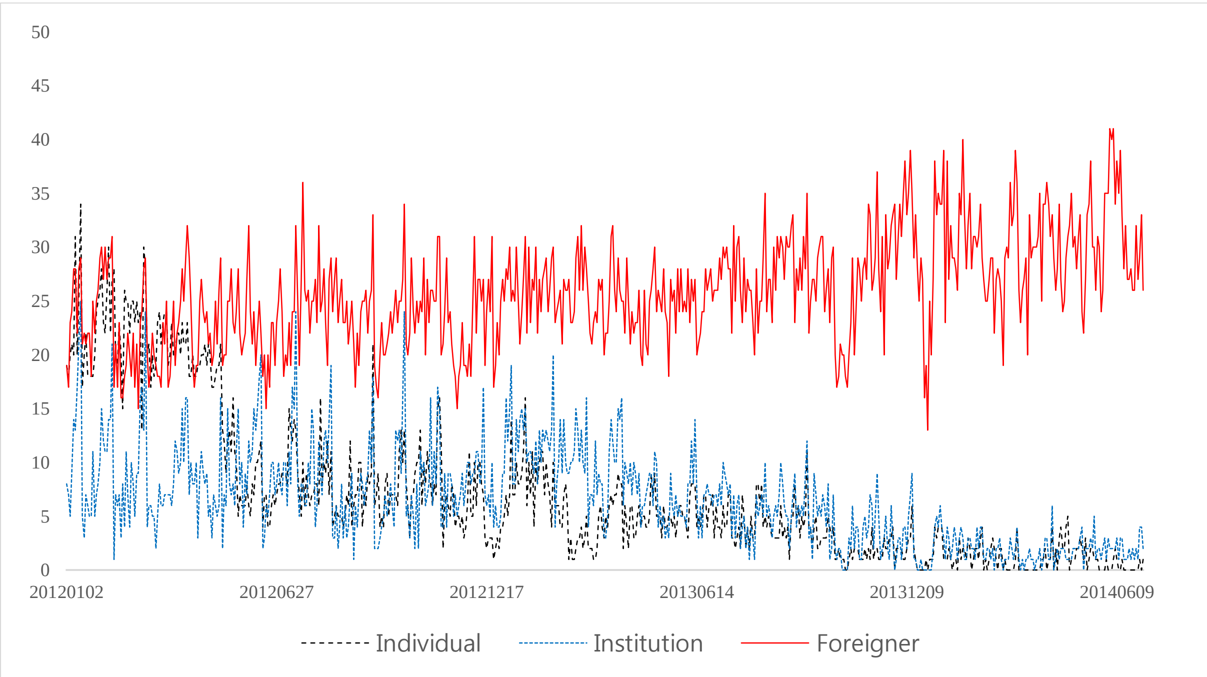
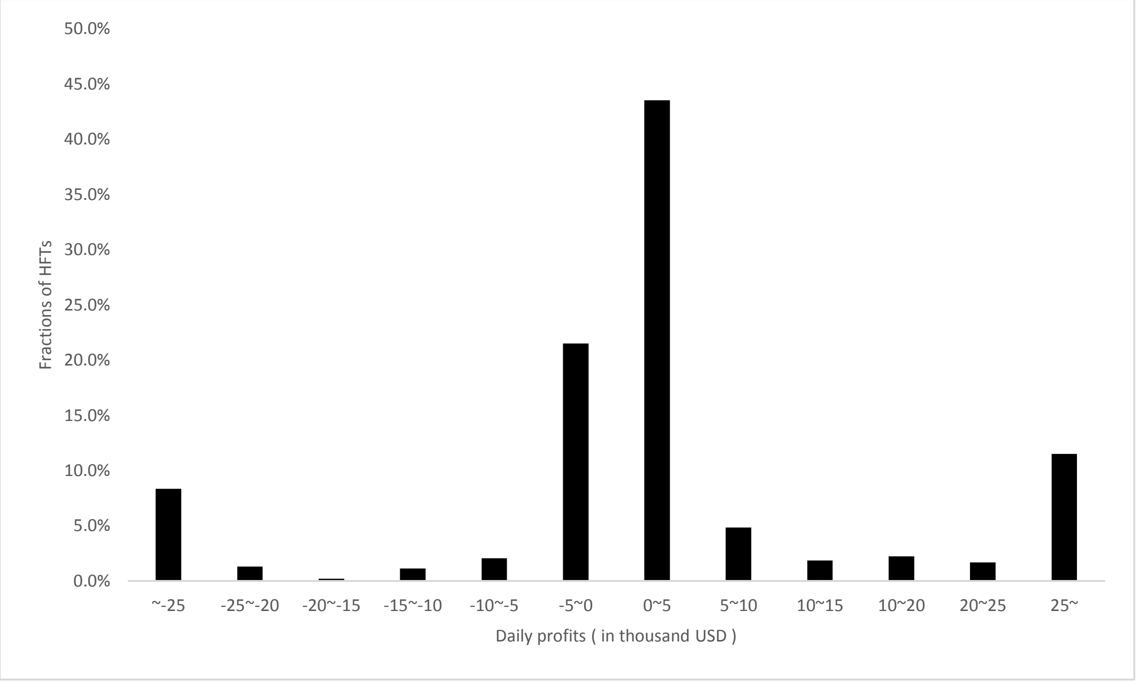


Figure 2. Distribution of HFT profits

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 profit. In panel B, each day, we combine all HFT accounts' profits and plot the time series of aggregate HFTs' profits.

Panel A: Distribution of each HFT Accounts' daily profits



Panel B. Daily Time series of aggregate HFTs profit

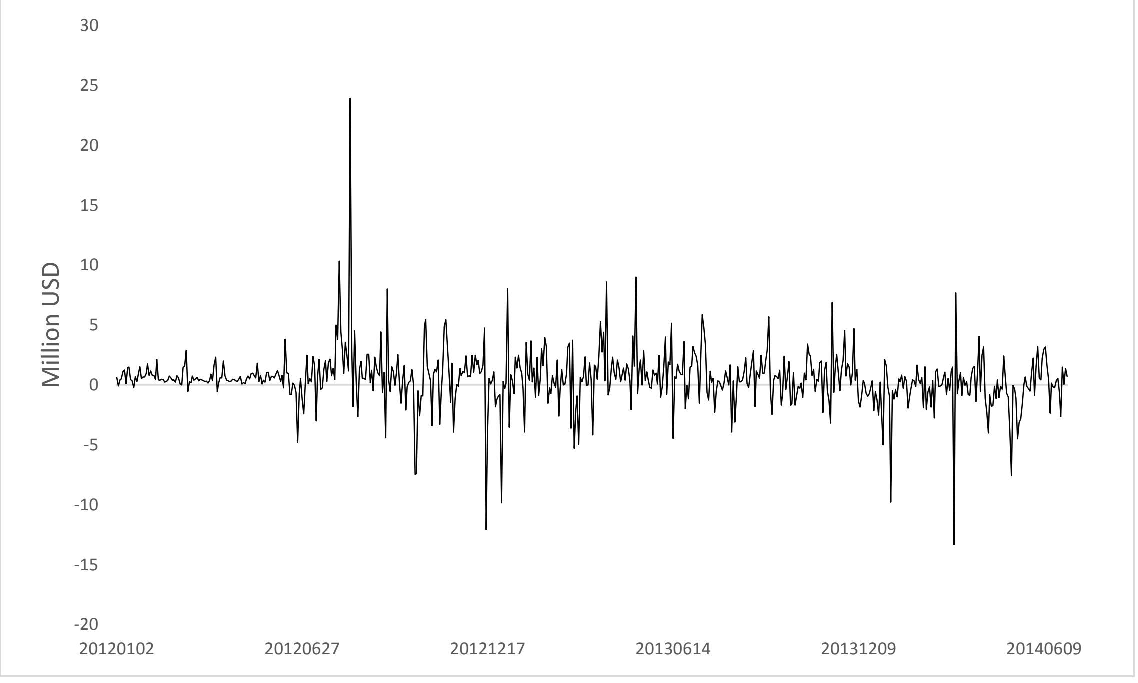


Table 1. Summary statistics of trading activity

This table shows summary statistics of trading and quoting activity of HFTs and non-HFTs in the KOSPI200 options from January 2, 2012 to June 30, 2014. There are total 616 trading days in our sample. Panel A presents summary statistics for three trader groups: high frequency traders, algorithmic traders, and normal traders. Panel B reports summary statistics for HFTs by aggressiveness subcategories: Aggressive HFTs and Passive HFTs. Panel C reports the distribution of HFTs' end-of-day net position. In the table, all statistics are calculated per trader on a daily basis. *Number of Traders* is the daily time-series average of the number of accounts which is 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 of 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, in 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 end-of-day position, scaled by the total trading volume. *Liquidity taking ratio* is the fraction of transactions that were initiated.

Panel A: Trader Groups

	High Frequency Traders	Algorithmic Traders	Normal Traders
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 Group

	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: HFT's net position

	~ -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 one USD, 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. *Total Cumulative Profits* is the overall profits during our sample periods for the HFTs. There are three rows, *All, Aggressive, and Passive* which investigate all HFTs, Aggressive HFTs, and Passive HFTs, respectively. Each day, if an HFT initiates more (-less) than half of his transactions, we consider him as Aggressive HFTs (-Passive HFTs). Panel B reports the mean daily profits by three groups based on liquidity provision. Each day, we sort HFTs by the ratio of liquidity taking transactions. Top 30% of HFTs are classified into *High,* bottom 30% of HFTs enters into *Low,* and those HFTs that meet neither *high* nor *low* are *Mid*. For each day and each group, we calculate mean profits across traders and calculate times-series mean. Newey and West (1994) *t*-statistics are reported in parentheses.

Panel A: Summary of daily profits (unit: 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 (unit: 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 of the spread and price impacts. The following formulas are used on 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 negative one for seller-initiated orders, P is the transaction price, V is the quote midpoint at the time of the trading, and V_T is the first trade price 5 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 by HTFs and non-HFTs. The first word in each trade category indicates the liquidity taker and the second word refers to the liquidity provider. HFT denotes high frequency traders; nHFT denotes non-high frequency traders. In Panel B, we divide non-HFTs' trade category by algorithmic traders and normal traders. AT signifies algorithmic traders; NT signifies normal traders.

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 observation, 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 1 if an HFT participated in the trade as a liquidity taker and 0 otherwise. *Medium* and *Large* are indicator variables that control a transaction size. *Medium* indicates a transaction size between 10 contracts and 100 contracts, and *Large* indicate a transaction size greater than 100 contracts. *Buy* is a dummy variable that takes a value of 1 if the trade is initiated by a buyer. The average of coefficients is reported in the column *estimate*. Percentage of positive (negative) coefficients that are significantly different from zero at the five percent confidence level are reported in the column *%+* (*%-*). Parentheses indicate Newey and 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 observation, 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 1 if HFT participated in the trade as liquidity provider and 0 otherwise. *Medium* and *Large* are indicator variables that control transaction size. *Medium* indicates a transaction size between 10 contracts and 100 contracts, and *Large* indicates a transaction size greater than 100 contracts. *Buy* is a dummy variable that takes a value of 1 if the trade is initiated by a buyer. The average of coefficients is reported in the column *estimate*. Percent of positive (negative) coefficients that are significantly different from zero at the five percent confidence level are reported in the column *%+* (*%-*). Parentheses indicate Newey and 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 trading volume 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 ten-second intervals for each option-day, which reduces the sample to 10,190 option-day observations. *%HFT*, *%AT*, and *%NT* are the mean of the percentage of each trader group's trading volume to total trading volume, respectively. *%HFT DEMAND*, *%AT DEMAND*, and *%NT DEMAND* are the mean of the percentage 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 <=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 <=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 <=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's trading volume and Market quality

This table presents intra-day vector autoregression (VAR) results. For each option-day observation, the following vector autoregression (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 high frequency traders during the ten-second period (in thousand contracts), *AT* is the total trading volume of algorithmic traders during the ten-second period (in thousand contracts), *NT* is the total trading volume of normal traders during the ten-second period (in thousand contracts), and *MQ* is 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 price in the interval. *TimeDummy* is a dummy variable that takes a value of 1 or 0 for each respective hour time period. For example, $TimeDummy_1$ has a value of 1 from AM 9:00 to AM 10:00 and 0 in otherwise. We require at least 1,000 non-zero trading volume intervals among 2,160 ten-second intervals for each option-day, which reduces the sample to 10,190 option-day observations. In the table, we only report estimation results for equation (4). Panel A and B report the estimation result when we using *Effective spread* as *MQ*. Panel C and D present the estimation results when we using *DEPTH* as *MQ*. Panel E and F show the estimation result when we using *HL* as *MQ*. Panel A, Panel C, and Panel E report the average coefficients in column *estimate*. Percentages of option-days with positive (negative) coefficients that are significantly different from zero at the five percent confidence level are reported in the column *%+* (*%-*). In Panel B, Panel D, and Panel F, coefficients are averaged across all options for each day, and the mean of the daily time series is reported in column *estimate.* Parentheses indicate Newey and West (1994) t-statistics for the time-series means.

Panel A: MQ=Effective spread, summary of options-day observation

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											
R2	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 options-day observation

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											
R2	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 options-day observation.

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											
R2	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)