High Frequency Trading in the Korean Index Futures Market

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Abstract

We investigate the trading behavior of high frequency trading (HFT), the impact of HFT on market quality, the role of HFT in the price discovery process, and the profitability of HFT, using a very detailed data set of the KOSPI 200 index futures market. We find that high frequency traders (HFTs) do not provide liquidity in the futures market, nor does HFT have any role in enhancing market quality. Indeed, HFT is detrimental to the price discovery process. This is contrary to the findings in the existing literature on HFT in equity markets. We further find that profitable opportunities of HFTs rarely exist after considering transaction costs, with the notable exception being that foreign HFTs do earn a profit in the index futures market.

Keywords: *High Frequency Trading; Market Quality; Liquidity Provision; Profitability*

JEL classification: F30; G11; G15

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I. Introduction

One of the striking changes in financial markets is the growth of high frequency trading brought about by advances in technology and the spread of electronic trading. Algorithmic trading (AT) and high frequency trading (HFT) methodologies have become significant components of the order stream in financial markets. In recent years, HFT has been a focus of considerable academic as well as regulatory attention. Many studies have surfaced regarding the role of HFT on market quality or price discovery. However, with the exception of a few articles (Kirilenko, Kyle, Samadi, and Tuzun, 2011), much of the empirical work on HFT has focused on equity markets. Because of inherent leverage, low transaction costs, and lack of short sale restrictions, the nature of price discovery in the futures market is different from that of equity markets. In this paper, we comprehensively investigate the trading behavior of HFT, the impact of HFT on market quality, such as bid-ask spreads, volatility, and market depth, the role of HFT in the price discovery process, and the profitability of HFT, using a very detailed data set with the complete trading records of index futures in Korea.

The classic market-making literature views that many financial markets rely on market makers who are charged with maintaining a market and the provision of liquidity. The trading behavior of market makers continually affects the dynamics of stock prices. However, over the past decade, the task of market making has shifted from designated market makers to proprietary automated systems that trade frequently (Gerig and Michayluk, 2010). We examine whether HFTs act as market makers even though they do not have responsibility for maintaining a market presence or providing liquidity.

Recently, there has been a rapid growth in literature investigating the roles of HFT in price discovery and market quality. Existing studies on HFT suggest that HFTs help to narrow bid-ask spreads and decrease intraday volatility.[1] Furthermore, empirical studies also support this idea of a positive role of HFT in price discovery, using equity trading data (Hendershott and Riordan, 2011; Hendershott and Riordan, 2012; Brogaard, 2010; Hendersott, Jones, and Menkveld, 2011). A small body of literature suggests that HFT may play a dysfunctional role in financial markets (Zhang, 2010; Jarrow and Protter, 2011; Kirilenko, Kyle, Samadi, and Tuzun, 2011).[2] However, existing research on HFT generally focuses on the equity markets. Here, we examine the KOSPI 200 index futures market to investigate the trading behavior and the role of HFT.

With regard to futures markets, a vast body of literature indicates that traders in these markets are better informed about market-wide information than those in stock markets. Several studies suggest that index futures markets play a critical role in price discovery (Chatrath el al., 1999; Lien and Tse, 2000; Yang et al., 2001, Hasbrouck, 2003; So and Tse, 2004, Hasbrouck, 2003; So and Tse, 2004; Kang et al., 2006). The futures markets generally have higher leverage, fewer constraints, a high level of liquidity, lower information asymmetry, lower transaction costs, and instruments that make it easy to speculate and hedge market-wide trends (Black, 1975; Chan, 1992; Gammill and Perold, 1989; Subrahmanyam, 1991; Lee, 2005; Ko, 2012; Kurov, 2008).

The securities that would seem to be attractive to HFTs are those with a large number of participants, high volatility, and a high level of liquidity. Such conditions

[1] Brogaard (2010, 2011) uses NASDAQ transaction level data with an HFT flag. Hasbrouck and Saar (2010) use NASDAQ public order level data without account identifiers. Hendershott, Jones, and Menkveld (2011) use electronic message traffic in a NYSE data set and find that ATs improve liquidity and enhance the informativeness of quotes.

[2] They argue that HFT increases stock price volatility after controlling for the volatility of a firm's fundamentals and other exogenous volatility drivers.

are satisfied in the KOSPI 200 index futures contracts. In particular, since no taxes are imposed on transactions in the index futures market, unlike in the stock market in Korea, HFTs are likely to prefer the KOSPI 200 index futures. Also, the KOSPI 200 index futures market, with its higher liquidity, enables HFTs to get in and out of positions frequently and achieve a flat end-of-day position. The effect of HFT on price discovery or market quality, therefore, can be investigated most effectively in an organized and transparent index futures market.

This study explores the extent to which HFT plays a role in improving market quality and price discovery in an index futures market. Also, we focus on the dollar profits for different types of HFTs for each day. We categorize HFTs into domestic individuals, domestic institutions, and foreign investors. By analyzing trading patterns by different trader types, we can address the relative role of liquidity provision and price discovery. We also examine which types of traders are better at taking profits through HFT.

Our contribution to the existing literature on the role of HFT will be three-fold. To the best of our knowledge, this is the first attempt to use a very detailed data set with complete trading records of index futures to investigate the effect of HFT on market quality, the role of HFT in the price discovery process, and the profitability of HFT. Existing literature on HFT has generally focused on equity markets. There is a lack of empirical study on the contribution of HFT to price discovery in futures markets, which have some important institutional differences from equity markets. Here, we examine the KOSPI 200 index futures market to enhance the understanding of HFT. We also maintain that our results can be particularly helpful to regulators in finding answers to their question: whether they should encourage or discourage more HFT.

Secondly, our unique intraday data allow us to directly examine the trading behavior and the profitability of each high frequency trader. This proprietary data set allows us to distinguish the type of HFTs: domestic individual traders, domestic institutional traders, and foreign traders. So far as we know, no study has yet utilized complete transaction records to investigate which category of HFTs, if any, has a positive role in improving market quality. Our intraday data also allow us to directly calculate the daily profits of each high frequency trader in the market.

Thirdly, our paper contributes to the home bias literature that domestic investors have better information than foreign investors. Some studies show that domestic investors have an advantage because information does not have to travel over physical, linguistic, or cultural distances (Choe, Kho, and Stulz, 2001; Hau, 2001, Dvorak, 2005). Conversely, other people argue that foreign investors have a comparative advantage in terms of information access and technology (Seasholes, 2004; Grinblatt and Keloharju, 2000; Ahn, Kang, and Ryu, 2008; Chou and Wang, 2009). In particular, foreign HFTs from developed markets[3] have better investment expertise, and those advantages would be more pronounced when trading in emerging markets. This paper contributes to existing literature by tracing whether foreign investors are obtaining profits through HFT in the KOSPI 200 index futures market.

Our analysis yields a number of results. We discover that overall HFTs do not provide liquidity to market participants who demand it. These results suggest that the behavior of HFTs is not consistent with the traditional definition of market makers in the KOSPI 200 index future market.

[3] According to the IOSCO (2011) consultation report citing the estimates from the Tabb Group, HFT accounts for 56% of US equity market, 38% of European markets, and the range of 10~30% of Asia-Pacific markets in 2010.

Our second question of interest is whether HFT affects the quality of trading in an index futures market. We use four measures to capture different aspects of market quality: two measures of liquidity and two measures of short-term volatility. By employing a vector auto-regression model, we do not find that HFT activity improves market quality. Though existing literature argues that HFT tends to improve equity market quality (Brogaard, 2010; Hasbrouck and Saar, 2010; Hendershott, Jones, and Menkveld, 2011), this result is quite different in the KOSPI 200 index futures market. These findings suggest that HFTs may not play an additional role in market quality where a market, e.g., the KOSPI 200 index futures market, is already liquid with low latency and has lower volatility.

As another interesting research question, we examine the role of HFT in price discovery in the KOSPI 200 index futures market. We make use of the state space model from Hendershott and Riordan (2011) to determine whether HFT contributes to the price formation process.[4] When we decompose futures price into a permanent and a transitory component (Menkveld, Koopman, and Lucas, 2007), we find no evidence that overall HFT increases price discovery and efficiency, inconsistent with the findings from prior research on price discovery of HFTs in stock markets (Hendershott and Riordan, 2011; Hendershott and Riordan, 2012; Brogaard, 2010; Hendersott, Jones, and Menkveld, 2011; Martinez and Rosu, 2011). Indeed, we find that HFT is detrimental to the price discovery process in index futures markets, suggesting that the activities of HFT play a negative role in the efficiency of index futures markets. To gain more insight into the trading behavior of HFTs, we follow Hendershott and Riordan (2011) to

[4] Hendershott and Riordan (2011) argue that a state space model has the following advantages. First, we can distinguish short-term and long term effects. Second, maximum likelihood estimation is unbiased and efficient. Third, the structural model can help us identify effects hard to be found in other analysis.

decompose HFT into passive non-marketable trading (passive HFT) and initiated marketable trading (initiated HFT). We find that passive HFT is detrimental to the price discovery process, although initiated HFT decreases pricing errors.

Finally, we calculate a time series of daily trading profits earned by each high frequency trader. We find that though HFTs generally earn positive profits by trading in the index futures market, profitable opportunities rarely exist after taking transaction costs into consideration. Among the different types of HFTs, we observe that the profits of foreign HFTs are positive even after considering transaction costs, although this is not found to be the case for either domestic institutional HFTs or individual HFTs. Overall, HFT does not seem to be a good trading strategy for domestic institutions and domestic individuals in the index futures market.

This paper is organized as follows. The next section gives an overview of the KOSPI 200 futures market. Section 3 describes the data and sample period. Section 4 presents the methodologies employed in the study. Section 5 provides the empirical results of the relation between HFT activity and traditional market quality indicators, the role of HFT in price discovery, and its profitability. Finally, Section 6 discusses our results, and Section 7 is a short conclusion.

II. Index futures market in Korea

The KOSPI 200 index futures based on the KOSPI 200[5] were introduced to the Korea Exchange (KRX) on May 3, 1996. The Korean derivatives market is the world's most actively traded. In the KOSPI 200 futures market, domestic institutional

[5] The KOSPI 200 is a value-weighted index comprising 200 leading stocks which represent over 70% of the total market capitalization of the KRX. The multiplier for the KOSPI 200 Futures is 500,000 Korean Won. There are three major players in the derivatives market in Korea: domestic institutional investors, domestic individual investors, foreign investors.

investors account for 43.7% of the total trading volume, foreign investors 29%, and domestic individual investors 27.4% in 2010 (KRX Fact Book 2010).

The Korean futures market is open from 9:00AM (the same as the stock market), and closes at 3:15PM (15 minutes later than the stock market). For the one-hour pre-opening session, orders are piled up and executed at a batch auction when the market opens. After the opening batch auction, the market clears in a continuous double auction system until 3:05PM. For the next 10 minutes until the market closes, orders are submitted to batch, and then executed in the closing batch auction.[6] Like the Korean stock market, the Korean futures market is also an electronic order-driven market. As to the trading prices, market order is executed first, and then the price priority principle must be satisfied, followed by the time priority principle.

III. Data description

Our study relies on unique complete intraday order and transaction data for index futures on the KRX for the period covering April 2009 through March 2010. The data set used in this study includes entire trading and order records for all investors who traded on the KRX during the sample period. We can clearly identify each transaction by whether it was initiated by a high frequency trader or not, which transaction belongs to a specific account, which type of investor holds the account, and whether traders are the buyer or the seller of the index futures. A distinguishing feature of the data is that it allows us to trace an investor's trading activity and construct with precision, individual traders' profitability for each day. In addition, the data allows us to

[6] On the expiration day, the futures market closes earlier at 2:50PM. Expiration day is the second Thursday of the contract months, which are March, June, September, and December. Also, there are other days with irregular trading times; the first trading day of a year and the national collegiate entrance examination day. On both days, the market opens one hour late.

decompose HFTs into passive non-marketable traders (passive HFT) and initiated marketable traders (initiated HFT). For each high frequency trader per day, we define a high frequency trader as one with mostly initiated HFT if more than 50% of total trading volume is initiated. We also define a high frequency trader as one with mostly passive HFT if more than 50% of total trading volume is passive. The data set identifies the following:

- The orders (bid and ask prices and quantities) posted by each trader, HFTs and Non-HFTs.
- The order arrival time to 1/100th of a second.
- The identities of the buyer and seller participating in the transaction.
- The transaction price and quantity of the trade.
- The cancellation, amendment, or withdrawal of the order and their times.
- The date and time at which the transaction was actually executed.

Because every transaction appears in the KRX database, we can examine the actual trading behavior of each high frequency trader in a given index future and calculate the profitability of each high frequency trader. We categorize futures traders as HFTs by using the frequency of quotes and median inter-order duration. We define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times[7] in a day, with a median inter-order duration of less than 1 second.[8]

[7] According to the Kearns, Kulesza, and Nevmyvaka (2010), HFTs hold positions between 10 milliseconds and 10 seconds.

[8] We find qualitatively similar results when we define HFTs as traders who submit orders a total of more than 4,000 times in a day, with a median inter-order duration of less than 1 second. We also find similar results when we define HFTs as traders who trade a total of more than 2,190 times in a day, with the minimum time between trades being 10-seconds. As a robustness check, we also define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times in a day, with the smallest quartile median inter-order duration. The results are economically similar. Finally, we use the definition of HFT employed by Baron, Brogaard, and Kirilenko (2012). Following Baron, Brogaard, and Kirilenko (2012), we define HFTs as traders who (i) trade more than a median of 500 contracts in all the days that this trader is active; (ii) have a median (across days) end-of-day inventory position, scaled by total contracts the trader traded that day, of no more than 5 %; (iii) have a median (across days)

Since longer-term maturity futures contracts are not commonly traded, in this study we restrict our sample to include only the nearest-to-maturity futures contracts. We focus on continuous normal trading hours from 9:00AM to 3:05PM.

Table 1 shows that HFTs account for almost 24% of the total number of contracts traded and for almost 32% of the total number of contracts quoted. It implies that HFT is a widespread, ongoing phenomenon in the index futures market.

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Table 2 reports the descriptive statistics of the daily HFT and total daily trading volume by the different types of investors. In Panel A of Table 2, taking total trading volume as an example, we find that the largest proportion of HFT is attributable to domestic institutional investors. Foreign HFTs rank second in terms of trading volume (35.11%). Panel B shows the distribution of the number of orders by HFTs per day. The median number of orders from HFTs is 5,799 and the highest number of orders from any single trader is 66,116. Panel C reports the HFTs' time interval between order submissions, including cancellations and modifications. Median inter-order duration of HFTs is 0.35 seconds and mean inter-order duration is 0.402 seconds.

Panel D of Table 2 shows the distribution of HFTs' daily inventory. Forty two percent of HFTs end the day with zero net inventories. Approximately fifty sixth percent of HFTs end the trading day with slightly negative or slightly positive net positions. These results show that HFTs usually do not carry over significant positions

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maximum variation in inventory that day (maximum position minus minimum position that day), scaled by total contracts the trader traded that day, of less than 10%. We use 500 contracts instead of the 5,000 contracts used by Baron, Brogaard, and Kirilenko (2012), since the index multiplier in the KOSPI 200 index futures is 10 times higher than E-mini S&P 500 index futures. The results from their definition are economically similar. All results with different definitions of HFT can be provided upon request.

to the next business day. Panel E reports the daily number of contracts quoted, canceled, and revised by HFTs. Taking the number of contracts quoted as an example, almost thirty three percent of orders are canceled. Panel F shows the diurnal pattern of HFTs' cancellations in our sample across various trading hours. We find a slightly U-shaped pattern. The results show that the peak of HFTs' cancellation activity usually occurs in the early morning session from 9:00AM to 10:00AM (22.68%). Panel G shows the proportion of total orders by their order prices in terms of ticks. The proportion of HFTs' orders priced at 0 tick is 42.3%, implying that most orders by HFTs are generally submitted nearer the current prices.

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IV. Methodology

We apply empirical methods from Chae, Khil, and Lee (2012) to determine whether the HFTs provide liquidity. Chae, Khil, and Lee (2012) use the standard models of market making trading from Grossman and Miller (1988) and Kyle (1985), showing that liquidity provision (extraction) implies a negative (positive) contemporaneous correlation between trades and security returns.

We use the following empirical model for the regression analysis:

$$r_{i,t} = \alpha_r + \sum_{j=1}^{6} A_j r_{i,t-j} + \sum_{j=0}^{6} B_j n_{i,t-j} + \gamma TO_t + \varepsilon_{i,t}$$

where $r_{i,t-j}$ is i^{th} futures *j*-lagged return, $n_{i,t-j}$ is i^{th} futures *j*-lagged HFTs net-buy volume (=the total number of contracts of futures bought by HFTs minus the total number of contracts of futures sold by HFTs during the period), and TO_t is overall market volume at time *t*. Positive (negative) HFTs net-buy volume means that HFTs are net buyers (sellers) during a particular period. Each daily trading session is partitioned into 2,190 intraday intervals of 10-second lengths. We use six lags of HFTs net-buy volume ($n_{i,t-1}$ to $n_{i,t-6}$), six lags of futures returns ($r_{i,t-1}$ to $r_{i,t-6}$), and overall market volume (TO_t) as control variables. We employ pooled regressions with Newey and West (1987) standard errors to control heteroskedasticity and autocorrelation of error terms. Following Chae, Khil, and Lee (2012), if we find a negative correlation between contemporaneous futures returns and net-buy volume by HFTs, it implies that HFTs serve to enhance liquidity. Conversely, if a positive relation exists, it implies that HFTs take the liquidity provided by other traders. Furthermore, the availability of investor types in our data set enables us to examine whether different types of investors behave differently from the perspective of liquidity provision.

To further investigate the relation between HFT activity and traditional indicators of market quality in the index futures market, we use vector autoregression (VAR) analysis. We use the HFTs' trading volume variable and the market quality variables as dependent variables and include six lags of the two dependent variables as explanatory variables to investigate the potential relation between HFT and market quality. We use four measures to capture different aspects of market quality: two measures of liquidity and two measures of short-term volatility. The first measure (*HL*) is defined as the highest price minus lowest price divided by the midpoint of the highest price and lowest price in an interval. The second measure (*Spread*) is the effective spread ((best ask price - best bid price) /(bestask+bestbid)/2) in an interval. The third measure (*HighLow*) is defined as the highest mid-quote in an interval minus the lowest mid-quote in the same interval. The fourth measure (*Depth*) is time-weighted average of the number of contracts in the book at the best posted prices in the interval. The VAR model is set up for each future and each day in the sample. We use the following bivariate VAR model of HFT and market quality for each day:

$$HFT_{i,\tau} = a_i + \sum_{k=1}^{6} b_i MQ_{i,t-k} + \sum_{k=1}^{6} c_k HFT_{i,t-k} + \varepsilon_{i,t}$$
$$MQ_{i,t} = \alpha_i + \sum_{k=1}^{6} \beta_i MQ_{i,t-k} + \sum_{k=1}^{6} \gamma_k HFT_{i,t-k} + \varepsilon_{i,t}$$

where $HFT_{i,\tau}$ is total number of contracts traded from HFTs during the period, $MQ_{i,\tau}$ is market quality variable. We use four measures, *HL*, *Spread*, *HighLow*, and *Depth*, as the proxy of market quality. Each daily trading session is partitioned into 2,190 intraday intervals of 10-second lengths.

Subsequently, we examine whether HFT is beneficial or detrimental to the price discovery process in the KOSPI 200 index futures market. One of the methodologies to establish how much HFT contributes to price discovery is a state space model, according to Hendershott and Riordan (2011). Applying a state space model, we decompose index futures price into a permanent component and a transitory component (Menkveld, Koopman, and Lucas, 2007; Hendershott and Riordan, 2011).

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

where $p_{i,t}$ is the (log) mid-quote at time interval *t* for each day, $m_{i,t}$ is a permanent component, and $s_{i,t}$ is a transitory component. The permanent component is modeled in the state transition equation as a martingale:

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

Following Hendershott and Riordan (2011), we argue that the permanent process implies information arrivals where $w_{i,t}$ represents permanent price changes. According to Hendershott and Menkveld (2010) and Menkveld (2011), we specify for the aggregate model as:

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

where $\widetilde{HFT}_{i,t}^{All}$ is the unexpected innovation in $HFT_{i,t}^{All}$, defined as the residual of an autoregressive model to remove autocorrelation. $HFT_{i,t}^{All}$ is total HFT order flow (buying volume minus selling volume). The residual, $\mu_{i,t}$, captures the changes in $w_{i,t}$ unrelated to trading. For the second model with initiated and passive HFT, $w_{i,t}$ is formulated as:

$$w_{i,t} = k_i^{Init}\, \widetilde{HFT}_{i,t}^{Init} + k_i^{Pass}\, \widetilde{HFT}_{i,t}^{Pass} + \mu_{i,t}$$

where $\widetilde{HFT}_{i,t}^{Init}$ and $\widetilde{HFT}_{i,t}^{Pass}$ are the unexpected innovations in $HFT_{i,t}^{Init}$ and $HFT_{i,t}^{Pass}$, calculated similarly to the first aggregate model. $HFT_{i,t}^{Init}$ and $HFT_{i,t}^{Pass}$ are the HFT initiated order flow and the HFT passive order flow, respectively. These HFT variables impact the permanent component of prices. Next, we examine how different types of investors play a different role in the price formation process and what their relative contribution are to price discovery. We apply the above analysis to each trader type: domestic individuals, domestic institutions, and foreigners.

Following Hendershott and Riordan (2011), we formulate the transitory component of prices to include an autoregressive component and trading variables. The transitory component of prices ($s_{i,t}$) is modeled as follows:

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

Similarly, the model for initiated and passive HFTs is set up as follows:

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

We can distinguish the different roles of overall HFT and initiated/passive HFT by separately analyzing the permanent and transitory component of prices with $HFT_{i,t}^{Init}$,

$HFT_{i,t}^{Pass}$, and $HFT_{i,t}^{All}$. Like the analysis of permanent price change, the analysis of transitory component of prices ($s_{i,t}$) includes investor type variables.

Finally, we examine the profitability of HFT. This is a central question to understand the behavior of HFTs. Unfortunately, there has been little comprehensive empirical evidence produced to answer this question; in particular, no research in the futures market. In this paper, we estimate the daily trading profits earned by each high frequency trader. These gains and losses are calculated after taking into account transaction costs. One of the important features for futures contracts is marking to market. Intermediate gains or losses are posted each day during the life of the futures contract. This enables us to calculate the exact profits earned by each trader. Since our data can distinguish the account for each trade, we are able to calculate profits for each specific trader. This is an advantage over extant studies, such as Brogaard (2010) where he cannot calculate the profitability between HFT firms with his aggregate data.[9] The dollar-based profits[10] for each trader i (π_i) are calculated by the following equation:

$$\pi_i = -I_0 P_0 + \sum (P_S V_S - P_B V_B) + I_T P_T - TC_i * \sum (P_S V_S + P_B V_B)$$

P_S (P_B) represents the price of a sell (buy) trade, and $V_S\,(V_B)$ the size of a sell (buy) trade. $I_0\,(I_T)$ denotes inventory of futures when market opens (closes), and $P_0\,(P_T)$ is opening (settlement) price. TC_i indicates transaction cost for trader type *i*.

[9] Brogaard (2010) mentions the limitations in estimating the profitability for HFT as follows. "First, the HFT dataset contains only 120 stocks out of the several thousand listed on NYSE and Nasdaq. Second, I can only observe trades occurring on Nasdaq. This impacts my ability to determine precisely the level of HFT activity and also the inventory held by HFTs. Finally, I can only observe HFT firms' activities in the aggregate and so cannot calculate the profitability between the firms."

[10] Dollar-based figures are calculated at the exchange rate of 1,133 Korean Won to one US Dollar, in effect on March 11, 2010, the closing date of the sample period.

The transaction cost for domestic individual traders is 0.01% of the total trading; for domestic institutions, 0.00084%; for foreigners, 0.001%.

V. Empirical results

A. Liquidity provision of HFT

We study the extent to which HFTs provide liquidity. We follow empirical methods from Chae, Khil, and Lee (2012). They argue that the trade of the liquidity provider and the price change has a negative relation, while the trade of the liquidity taker and the price change has a positive correlation. Table 3 reports the results of HFTs net-buy volume regressions, using the futures returns as our dependent variable. The coefficient for contemporaneous HFTs net-buy volume using all futures is significantly positive, suggesting that overall HFTs do not trade primarily for liquidity provision. Next, we sort futures by size quartiles at the average trading volume. We then estimate the regression model for each group. The coefficient estimates on the HFTs net-buy volume are significantly positive for all groups. These results confirm that HFTs do not provide liquidity in the futures market. Existing literature suggests that, in the stock market, HFT is associated with greater liquidity. However, based upon our results, this is not true in an index futures market with low latency, more liquidity, and lower transaction costs.

Next, we examine whether different types of HFTs play distinctly different roles in liquidity provision. We employ the HFTs net-buy volume regression for each trader type, which are reported in Panel B of Table 3. The significant and negative coefficient of net-buy volume from domestic individual HFTs shows that domestic individual HFTs do provide liquidity. The primary sources of profits for domestic individual HFTs are from their role as voluntary market makers by buying at the bid and selling at the offer. This result is consistent with Chae, Khil, and Lee (2012) who find that individual algorithm traders provide liquidity in the derivative warrants market using scalping, one of the more common investment strategies. The coefficient estimates on net-buy volume from domestic institutional HFTs and foreign HFTs are positive and significant. Overall, domestic institutional HFTs and foreign HFTs do not trade primarily for liquidity provision, while domestic individual HFTs provide liquidity to market participants who demand it.[11]

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B. The relation between HFT and market quality

Another area of interest is whether there is relation between HFT activity and traditional market quality indicators. Nearly all of the existing literature on this subject speaks of the positive impact of HFT on market quality. However, a deeper concern exists that HFT could be harming the quality of markets by reducing the liquidity available. This is because HFTs, while still trading actively like market makers, have no affirmative market making obligation, unlike designated market makers. Therefore, it is not surprising that a skeptical media has questioned the integrity of their trading strategies and have called for government oversight of their activity.[12] In particular, since the KOSPI 200 index futures market is more competitive and much more liquid than stock markets, the effect of HFT on the quality

[11] We also examined correlations between the price changes and net buy volume at various sampling frequencies including 1 second, 5 seconds, 1 minute, 10 minutes, and 30 minutes in order to better understand the results. We found that the coefficients for contemporaneous HFTs net-buy volume using all futures are significantly positive across different time horizons. We do not tabulate the results for brevity, but the results are available from the authors upon request.

[12] "High frequency trading: Why the robots must die," May 7, 2010 (http://wallstreet,blogs,fortune,cnn.com)

of futures markets almost certainly differs from stocks.

We use a vector auto-regression (VAR) model to investigate the relation between HFT activity and market quality. Each daily trading session is divided into 2,190 intraday intervals of 10-seconds. We use four measures to capture different aspects of market quality: two measures of liquidity (*Spread* and *Depth*) and two measures of short-term volatility (*HL* and *HighLow*). The results are reported in Table 4. In the equations explaining *HFT* and *HL*, HFT is significantly affected by intraday volatility, and also that such volatility is increased by HFT. Next, we examine the effect of HFT on *spread*. The results show that the coefficients for the first lagged *HFT* is insignificant. We do not find that HFT significantly narrows the effective spread in the index futures market. We then explore the effect of HFT on *HighLow*. As with *HL*, we find that market volatility (*HighLow*) does affect HFT and HFT also does increase intraday volatility (*HighLow*). Finally, we investigate the relation between HFT and *Depth*. We find that higher levels of HFT activity correspond to worse levels of market depth.

Overall, we find no evidence supporting the role of HFT in enhancing market quality in the index futures market. These results counter the findings from the equity market (Brogaard, 2010; Hasbrouck and Saar, 2010; Hendershott, Jones, and Menkveld, 2011). Existing literature argues that HFT tends to improve market quality, such as bid-ask spread and intraday volatility. However, these results are quite different in an index futures market. This suggests that the introduction of HFT might have little or no effect on futures market quality, since the index futures market is more competitive and much more liquid than stock markets.

We carry out the same analysis using other time intervals including 1 second, 5 seconds, 1 minute, and 5 minutes.[13] We find that the higher levels of HFT activity correspond to worse levels of traditional market quality indicators for time intervals less than 10 seconds. The relation between HFT activity and market quality is weaker for time intervals greater than 1 minute. These results suggest that HFT activity has a negative relation to market quality indicators at very short intervals, but that this is limited to the extreme short intervals in which latency issues matter for HFTs.

C. The relation between HFT and market quality by the three types of traders

We investigate the effects of different types of traders on market quality. Firstly, in the equation explaining domestic individual HFTs and market quality indicators, domestic individual HFT is affected by market quality indicators, but those domestic individual HFTs does not affect market quality indicators. In the case of domestic institutional investors' HFT, domestic institutional HFT increases intraday volatility and decreases market depth. Finally, we find that foreign HFT only decreases market depth, and market volatility and market depth affect foreign HFT.[14] These results show that HFT activity has a negative relation to traditional market quality indicators, and this negative effect of HFT on market quality is attributed to domestic institutional HFT.

We also examine whether HFTs' orders are affecting market quality in the index futures market using VAR analysis. We use the HFTs' order volume and the market quality variable as dependent variables and include six lags of the two dependent variables as explanatory variables. The results are similar to those in Table 4, which

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[13] The results of this analysis are not presented for brevity but are available from the authors upon request.

[14] We do not report the results, but the VAR analysis with initiated HFT instead of HFT presents qualitatively similar results.

investigate the potential relation between HFTs' trading and the market quality.[15]

INSERT TABLE 4

D. Effect of HFT on price discovery

We examine whether HFT is beneficial or detrimental to the price discovery process in the KOSPI 200 index futures market. Studying the effect of HFT on price discovery illuminates the whole understanding of the impact of technological advances on futures markets as well as on stock markets. From Hendershott and Riordan (2011), we employ the state space model to examine whether HFT contributes to the price formation process. They argue that the state space model can explain the overall roles of HFT and the differential roles of active and passive HFT in prices. Applying this model, we can also distinguish the differential contribution of each type of high frequency trader.

Table 5 presents the results of the state space model estimation for overall HFT and for each type of high frequency trader.[16] We do not find that overall HFT is positively correlated with efficient price changes. In the transitory equation, overall HFT is positively associated with transitory pricing errors, which implies that overall HFT increases the noise in prices. This is contrary to the findings from prior research on price discovery of HFT in stock markets (Hendershott and Riordan, 2011; Hendershott and Riordan, 2012; Brogaard, 2010; Hendersott, Jones, and Menkveld, 2011). We find no evidence that overall HFT increases price discovery and efficiency. Instead, we find that most HFTs trade in the same direction of transitory pricing errors.

[15] For brevity, we do not tabulate the results, but the results are available from the authors upon request.
[16] Statistical inference is conducted by averaging daily estimates. To account for outliers, we winsorize estimates at the 1% level.

In short, the activities of HFT play a negative role in the efficiency of index futures markets.

In our study, the different types of investor are assumed to have different impacts on the transitory and permanent components of prices. We categorize overall HFT into domestic individual, domestic institutional, and foreign HFTs. We then examine the roles of different types of investors in the price formation process and assess their relative contributions to price discovery. The results of the disaggregated model of HFT show that every type of high frequency trader is positively correlated with futures price changes, but the value is not significant. This suggests that no type of HFTs contributes to price discovery in the KOSPI 200 index futures market.

To gain more insight into the trading behavior of HFTs, we follow Hendershott and Riordan (2011) to decompose HFT into passive HFT and initiated HFT. In Table 5, we report the results of the disaggregated model of HFT. From the permanent price changes equation, we do not find that initiated HFT and passive HFT are positively associated with changes in the unobserved permanent price component. These results suggest that HFTs are not generally trading with the benefit of private information. In the transitory equation, initiated HFT is negatively and significantly related to transitory pricing errors, implying that it reduces transitory volatility. We can interpret that as meaning that when prices move away from their fundamental value, initiated HFT activity serves to move prices back to their efficient levels. The results also indicate that passive HFT is positively correlated to transitory pricing errors. This is consistent with the results of Hendershott and Riordan (2011). They argue that the positive coefficient of passive HFT means that HFTs are intrinsically uninformed about the transitory component price and therefore adversely selected.

Again, we categorize HFT into passive and initiated HFT by type of investor, and investigate the price contribution of each investor type. The analysis reports the initiated HFT by all types of investors decreases pricing errors, while the passive HFT by all types of investors increases them. The results of the state space model show that passive HFT is generally detrimental to the price discovery process, although we do not see this effect with initiated HFT.

INSERT TABLE 5

E. Trading profits of HFT

Here, we analyze whether HFTs can earn positive profits or not. We also go one step further to analyze which type of investor is better at sustaining profits through HFT. Examining trading profits of HFT can provide insight into the application of HFT to particular investment and trading strategies. We calculate a time series of daily trading profits earned by each high frequency trader, taking into account transaction costs.[17]

Table 6 shows the distribution of HFTs across the range of profits earned. The results show that 29.88% of HFTs make at least a $10,000 loss and 12.45% make a loss of more than $100,000. Of all HFTs, 52.47% have a net profit greater than zero after commission, while 47.53% have a net profit less than zero. To gain further insight into the distinctions among different type of HFTs, we disaggregate HFT into three types of investors. We find that 65.69% of domestic individual HFTs have a net profit less than zero. The distribution of domestic individual HFTs' profits appears skewed

[17] One limitation of the paper is that we do not combine the data of the stock market and those of the futures market. We only observe a market participant's activities in the KOSPI 200 index futures market. A loss from the index futures market does not imply that the trader loses money overall. For example, some traders may be using the index futures as a hedge and some opportunistic traders may be doing cross market arbitrage strategies. Thus, the profits or losses in the index futures market does not mean that HFTs earn or lose money overall.

to the left. We also find that 46.15% of domestic institutional HFTs lose money, while 43.06% of foreign HFTs also have a net profit less than zero.

INSERT TABLE 6

In Table 7, we present our main findings on the dollar profits and losses from HFT for all traders and each investor group. The average daily gross profit for all HFTs in the data set is significantly positive. However, the average profit after taking into account transaction costs is not statistically significantly different from zero. What we see here is that transaction costs seem to reduce any real opportunity of earning excess profits from trading at high frequency even though the cost of transactions in futures markets is significantly lower than that in the stock market. This suggests that though HFTs generally earn positive profits by trading in the index futures market, profitable opportunities rarely exist after taking transaction costs into consideration. This result is inconsistent with Brogaard (2010) who argues that HFTs earn profits of $2.8 billion annually from their U.S. equities trading activity. We can interpret this to mean that the large proportion of HFT is attributable to domestic institutions and domestic individual investors, and that they do not have appropriate knowledge about HFT and sophisticated algorithms that can exploit opportunities that may only be open for a few seconds, especially compared to foreign investors. As a result, there exists the real possibility that neither domestic institutional HFTs nor domestic individual HFTs make money.

To confirm our arguments, we decompose HFTs into domestic individual HFTs, domestic institutional HFTs, and foreign HFTs, and then analyze the trading profits earned by each trader. The results are reported in Panel B of Table 7. The average daily gross profit for domestic individual HFTs is significantly negative. After taking into account transaction costs for domestic individual HFTs, they lose money more serious. Next, exploring the dollar profits from domestic institutional HFTs, we find that while they earn gross profits, their gross profits are not sufficient to cover transaction costs. In contrast, the pattern of profits for foreign HFTs is quite different. We find that the profit of foreign HFTs is positive after taking into consideration transaction costs, a reversal of our findings for domestic institutional HFTs, domestic individual HFTs, and the market as a whole. Overall, trading strategies of foreign HFTs are much more profitable after transaction costs than domestic institutional or individual HFTs. Since most skills related to HFT are developed in more mature markets, foreign investors from these developed markets have better investment experience and expertise and, in turn, can earn profits through HFT in emerging markets.

Panel C and Panel D of Table 7 present the average daily profits of initiated HFT and passive HFT. We find that domestic individual investors have negative profits through both initiated HFT and passive HFT. Domestic institutional investors have negative profits through initiated HFT and they have positive net profits through passive HFT with little significance. Finally, foreign investors can earn profits regardless of transaction costs from both initiated and passive HFT.

INSERT TABLE 7

VI. Discussions

We have presented a number of results on liquidity provision of HFT. We demonstrate that overall HFTs do not serve to enhance liquidity. We need to discuss why overall HFTs do not provide liquidity. HFTs employ a number of strategies for

HFT. The SEC (2010) reports that the types of strategies HFTs employ vary considerably and then the SEC (2010) categorizes the strategies of HFT into passive market making, arbitrage, structural, and directional. HFTs that employ passive market making strategies may perform the liquidity providing function. However, the behavior of HFTs that employ arbitrage and directional strategies could be different. Arbitrage strategies usually focus on capturing pricing differences among the different markets, while directional strategies are based on an anticipation of an intraday price movement. Thus, it is quite possible for many HFTs using these strategies to take liquidity, in contrast to the passive market making strategy that involves providing liquidity (Hendershott, 2011).

Furthermore, our results show that the relation between foreign HFTs net-buy volume and price changes is significantly positive, suggesting that foreign HFTs do not trade primarily for liquidity provision. According to Schwarz (2012), we can also interpret a positive contemporaneous relation between foreign HFTs net-buy volume and futures return as evidence that foreign HFTs have private information. Evans and Lyons (2002) argue that there is a positive contemporaneous correlation between order flow and exchange rate movements, taking this to mean that the party placing the order has an information advantage. Following these arguments, foreign HFTs have a very short lived information advantage in the index futures market due to their latency advantage.

One of the interesting results is that domestic individual HFTs lose money, while foreign investors are better at taking profits through HFT regardless of strategies. Our results support the evidence that a foreign investor trades on market-wide information, has superior information-processing skills, or has faster access to the market (Chou and

Wang, 2009; Ahn, Kang, and Ryu, 2008). However, we need to be cautious when interpreting this result. A positive profit of foreign HFTs is not necessarily equivalent to an information advantage. Even if foreign HFTs do not have material information, they can infer it from the order flows and price moves of the futures using algorithms and earn profits (Hendershott and Riordan, 2012). Foreign HFTs would appear to have high-speed and sophisticated quantitative and algorithmic computer programs to actively monitor markets, trade, and manage risk.[18] In addition, they have more extensive experience in HFT and greater investment expertise. In this way, foreign HFTs are better able to earn money.

One possible explanation for negative profits for domestic HFTs is that they have less of a latency advantage and less sophisticated trading techniques and hardware infrastructure. To maximize profits, HFTs usually need specialized computer programs and hardware with which they detect and act on profitable trading opportunities in a very short time period. However, given that HFT is still in its infancy in Korea, domestic HFTs are typically not as sophisticated as foreign HFTs. Another possible explanation is that domestic institutional HFTs use an arbitrage strategy, which seeks to capture pricing inefficiencies between related products and markets. Since we do not combine the data of the stock market and those of the futures market, the profit calculation in one market would not reflect the total profitability for domestic institutional HFTs.

VII. Conclusion

This paper comprehensively investigates the trading behavior and its relation to

[18] *Yonhap News*, a Korean newspaper, reported on December 5, 2011 that foreign investors are the leading high frequency traders in Korea's financial derivatives markets.

market quality, the role of HFT in the price discovery process, and the profitability of HFT overall, using a very detailed data set with complete trading records of the KOSPI 200 index futures market. We find that there is a positive contemporaneous correlation between net trade and returns, suggesting that overall HFTs do not provide liquidity in the futures market. Moreover, we do not find that HFT improves market quality. Our results suggest that the activities of HFT play a negative role in the efficiency of index futures markets. In particular, passive HFT is detrimental to the price discovery process. Finally, we observe that the profits of foreign HFTs is positive after considering transaction costs, although this is not found to be the case for either domestic institutional HFTs or domestic individual HFTs.

In this paper, we investigate the index futures market to better understand the behaviors and effects of HFT. From a practical standpoint, we believe our results can be of great value to the current policy debate about whether we should encourage HFT in financial markets or not.

References

Ahn, H., Kang, J., and Ryu, D., 2008. Informed trading in the index option market: The case of KOSPI 200 options. Journal of Futures Markets 28, 1118-1146.

Baron, M., Broggard, J., and Kirilenko, A., 2012. Trading profits of high frequency traders. Working Paper.

Black, F., 1975. Fact and fantasy in the use of options. Financial Analysts Journal 31, 36–41.

Brogaard J., 2010. High frequency trading and market quality. Working Paper.

Brogaard J., 2011. High frequency trading and volatility. Working Paper.

Chae, J., Khil, J., and Lee, E.J., 2012. Who makes markets? Liquidity providers versus algorithmic traders. Journal of Futures Markets, forthcoming.

Chan, K., 1992. A further analysis of the lead-lag relationship between the cash market and stock index futures market. Review of Financial Studies 5, 123-152.

Chatrath, A., Chaudhry, M., Christie-David, R., 1999. Price discovery in strategically linked markets: The TED spread and its constituents. Journal of Derivatives 6, 77-87

Choe, H., Kho, B., and Stulz, R., 2005. Do domestic investors have an edge? The trading experience of foreign investors in Korea. Review of Financial Studies 18, 795-829.

Chou, R. K. and Wang, Y., 2009. Strategic order splitting, order choice, and aggressiveness: Evidence from the Taiwan futures exchange. Journal of Futures Markets 29, 1102-1129.

Dvorak, T., 2005. Do domestic investors have an information advantage? Evidence from Indonesia. Journal of Finance 60, 817–839.

Gammill, J. F. and Perold, A. F., 1989. The changing character of stock market liquidity. Journal of Portfolio Management, Spring, 13-18.

Gerig, A. and Michayluk, D., 2010, Automated liquidity provision and the demise of traditional market making, Working Paper

Grinblatt, M. and Keloharju, M., 2000. The investment behavior and performance of various investor types: A study of Finland's unique data set. Journal of Financial Economics 55, 43-67.

Grossman, S. J., and Miller, M. H., 1988. Liquidity and market structure. Journal of Finance 17, 617–633.

Hasbrouck, J., 1993. Assessing the quality of a security market: a new approach to transaction-cost measurement. Review of Financial Studies 6, 191−212.

Hasubrouck J. and Saar, G., 2010. Low-latency trading. Working Paper

Hau, H., 2001. Location matters: an examination of trading profits. Journal of Finance 56, 1959–1983.

Hendershott, T., and Menkveld, A.J., 2010. Price Pressures. Working Paper.

Hendershott, T., Jones, C. M. and Menkveld, A.J., 2011. Does algorithmic trading improve liquidity? Journal of Finance 66, 1-33.

Hendershott, T. and Riordan R., 2011. High frequency trading and price discovery. Working Paper

Hendershott, T., 2011. High frequency trading and price efficiency. Government Office for Science.

Hendershott, T. and Riordan R., 2012. Algorithmic trading and the market for liquidity. Journal of Financial and Quantitative Analysis, forthcoming.

Huang, R. D. and Shiu, G.Y., 2009. Local effects of foreign ownership in an emerging financial market: Evidence from qualified foreign institutional investor in Taiwan. Financial Management 38, 567-602.

International Organization of Securities Commissions, 2011. Regulatory issues raised by the impact of technological changes on market integrity and efficiency. Consultation report by the Technical Committee of the IOSCO, July.

Jarrow, R. and Protter, P., 2011. A dysfunctional role of high frequency trading in electronic markets. Working Paper. Cornell University.

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

Kang, J., Lee, C.J., and Lee, S., 2006. An empirical investigation of the lead-lag relations of returns and volatilities among the KOSPI 200 spot, futures and options markets and their explanation. Journal of Emerging Market Finance 5, 235-261.

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

Ko, K., 2012. Who wins in the money game? The case of KOSPI 200 futures, Pacific-Basin Finance Journal 20, 843-856.

KRX, 2010, KRX Fact Book, www.krx.co.kr.

Kurov, A., 2008. Tick size reduction, execution costs, and informational efficiency in the regular and E-mina NASDAQ-100 Index Futures Markets. Journal of Futures markets 28, 871-888.

Kyle, A., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1336.

Lee, J., 2005. Index arbitrage with the KOSPI 200 futures. Working paper from http://www.frontfund.com/Upload/jaehalee-FMA-2005.pdf

Lien, D., Tse, Y.K., 2000. Some recent developments in futures hedging. Working Paper, University of Texas at San Antonio.

Martinez, V. H. and Rosu, I., 2011. High frequency traders, news and volatility. Working Paper.

Menkveld, A. J., 2012. High Frequency Trading and the New-Market Makers. Working Paper. New York University.

Menkveld, A. J., S. J. Koopman, and Lucas, A., 2007. Modeling around-the-clock price discovery for cross-listed stocks using state space models. Journal of Business & Economic Statistic 25, 213-225.

Seasholes, M., S., 2004. Smart Foreign Traders in Emerging Markets. Working Paper, Harvard University, Cambridge, MA.

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

So, R.W. and Tse Y., 2004. Price discovery in the Hang Seng Index Markets: Index, futures and the tracker fund. Journal of Futures Markets 24, 887-907.

Subrahmanyam, A., 1991. A theory of trading in stock index futures. Review of Financial Studies 4, 17-51.

Yang, J., Bessler, D.A., Leatham, D.J., 2001. Asset storability and price discovery in commodity futures markets: A new look. Journal of Futures Markets 21, 279-300.

Zhang, X. F., 2010. High frequency trading, stock volatility and price discovery. Working Paper, Yale University.

Table 1

Descriptive statistics of daily trades and quotes distribution

This table presents the mean daily number of contracts traded, number of contracts quoted, and number of transactions of the KOSPI 200 index futures from April 1, 2009 to March 11, 2010. The mean daily number of contracts traded is calculated as the total number of contracts traded, divided by the number of trading days. The mean daily number of contracts quoted is calculated as the total number of contracts quoted, divided by the number of trading days. We categorize all investors as HFTs or not by using the frequency of their orders. We define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times in a day, with a median inter-order duration of less than 1 second. Daily summary statistics for HFTs are provided in Panel B and those for non-HFTs are also provided in Panel C. Proportion of HFT is daily number of high frequency trades divided by daily total number of trades.

	Overall			*HFT*			*Non-HFT*		
	Number of contracts traded	*Number of contracts quoted*	*Number of Transactions*	*Number of contracts traded*	*Number of contracts quoted*	*Number of Transactions*	*Number of contracts traded*	*Number of contracts quoted*	*Number of Transactions*
Mean	639,532	1,639,409	281,388	150,742	522,190	60,648	488,791	1,117,219	220,740
Standard deviation	125,642	324,160	56,052	65,192	250,718	23,891	77,638	146,506	38,570
Minimum	249,655	701,610	122,923	28,252	93,175	12,176	221,403	608,435	110,747
Maximum	1,026,100	2,697,607	442,430	379,326	1,497,103	131,436	808,954	1,621,007	355,120
Proportion of HFT (%)	23.57	31.85	21.55						

Table 2

HFT Descriptive Statistics

This table presents the mean daily number of trades of the KOSPI 200 index futures by investor type from April 1, 2009 to March 11, 2010. Panel A shows HFT summary statistics by investor type. We define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times in a day, with a median inter-order duration of less than 1 second. The daily HFT is calculated as the total number of high frequency orders or trades divided by the number of trading days. The daily total order (trade) is calculated as the total number of contracted quoted (traded) divided by the number of trading days. Panel B presents the distribution of the number of orders per high frequency trader. If a high frequency trader executes an HFT strategy for two different days, this is counted as two high frequency traders. Panel C shows HFTs' time interval between order submissions including cancellations and modifications. Panel D reports the distribution of HFTs' daily net position. Panel E shows the daily number of contracts quoted, canceled, and revised by HFTs. Panel F reports the diurnal pattern of HFTs' cancellations across various trading hours and Panel G shows the proportion of total orders by their order prices in terms of ticks.

Panel A: Proportion of HFT by investor type

	Order			*Trade*			
Investor type	*Daily HFT (contracts, A)*	*Daily total orders (contracts, B)*	*A/B (%)*	*Daily HFT (contracts, C)*	*Daily total trades (contracts, D)*	*C/D (%)*	*Number of Accounts*
Individual investors	69,691(13.35%)	495,619(30.23%)	14.06	10,501(6.97%)	204,447(31.97%)	5.14	10
Institutional investors	266,590(51.05%)	739,410(45.10%)	36.05	87,313(57.92%)	276,122(43.18%)	31.62	31
Foreign investors	185,910(35.60%)	404,380(24.66%)	45.97	52,928(35.11%)	158,964(24.86%)	33.30	55
Total	522,190(100%)	1,639,409(100%)		150,742(100%)	639,532(100%)		96

Panel B: Distribution of the number of orders per high frequency trader

	Min	25%	50%	Mean	75%	Max
# of orders	2,195	3,396	5,799	7,393	9,451	66,116

Panel C: HFTs' time interval between order submissions

	Min	25%	50%	Mean	75%	Max
Median Duration (Sec.)	0.000	0.200	0.350	0.402	0.595	0.990

Panel D: HFTs' net position

	~ -1,000	-1,000 ~0	0	0 ~1,000
Mean	-2,179	-55	0	47
%	2.08	28.13	41.67	28.13

Panel E: Daily number of contracts quoted, canceled, and revised

	Number of contracts quoted (%)	*Number of quotes (%)*	*Number of contracts quoted* (%)		
			Individual investors	Institutional investors	Foreign investors
Regular order	317,180 (60.74)	63,211 (53.39)	38,894 (55.81)	170,282 (63.87)	108,003 (58.09)
Revision order	32,614 (6.25)	19,362 (16.36)	2,185 (3.14)	13,818 (5.18)	16,611 (8.94)
Cancelation order	172,396 (33.01)	35,813 (30.25)	28,612 (40.05)	82,489 (30.95)	61,295 (32.97)

Panel F: The diurnal pattern of HFTs' cancellations (Percent of HFTs' cancellations placed each hour)

09:00~10:00	10:00~11:00	11:00~12:00	12:00~13:00	13:00~14:00	14:00~15:05
22.68	16.15	12.47	12.61	16.06	20.44

Panel G: Price of order (%)

	HFT	*Non-HFT*
0 tick	42.30	44.09
1 tick	33.97	28.35
2 tick	10.84	8.63
3 tick	2.46	4.75
4 tick	1.73	3.11
Over 5 tick	8.70	11.07
Total	100	100

Table 3

Contemporaneous correlation of returns and HFTs net-buy volume

This table reports pooled regression results using Newey and West (1987) standard errors for the following regression specification:

$$r_{i,t} = \alpha_r + \sum_{j=1}^{6} A_j r_{i,t-j} + \sum_{j=0}^{6} B_j n_{i,t-j} + \gamma TO_t + \varepsilon_{i,t}$$

$r_{i,t-j}$ is i^{th} futures j-lagged return, $n_{i,t-j}$ is i^{th} futures j-lagged HFTs net-buy volume (=the total number of contracts of futures bought by HFTs minus the total number of contracts of futures sold by HFTs during the period), and TO_t is overall market volume at time t. Sample includes complete intraday order and transaction data for the index futures on the KRX for the period covering April 2009 through March 2010. We define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times in a day, with a median inter-order duration of less than 1 second. In Panel A, futures are sorted into quartiles by average trading volume (4=largest). In Panel B, we categorize HFTs into domestic individual, domestic institutional, and foreign HFTs. Numbers in ( ) denote *t*-values. We implement the Wald test to show whether the difference of two statistics is statistically significant.

	n_0	n_1	n_2	n_3	n_4	n_5	n_6	r_1	r_2	r_3	r_4	r_5	r_6	TO	*Time Dummy*
Panel A: Liquidity provision by total trading volume															
all	**0.0008**	**0.0001**	0.0000	0.0000	**0.0000**	0.0000	**0.0000**	**-0.1003**	**-0.0361**	**-0.0249**	**-0.0112**	**0.0056**	**0.0207**	**0.0000**	Included
	(34.60)	**(9.63)**	(-0.38)	(0.65)	**(2.89)**	(0.92)	**(-1.85)**	**(-11.21)**	**(-5.97)**	**(-6.88)**	**(-5.14)**	**(2.38)**	**(9.46)**	**(-2.67)**	
Quartile 1	**0.0008**	**0.0002**	**0.0000**	0.0000	0.0000	**0.0001**	0.0000	**-0.1690**	**-0.0602**	**-0.0373**	**-0.0235**	**-0.0092**	0.0042	0.0000	Included
	(23.51)	**(8.53)**	**(1.74)**	(0.15)	(1.26)	**(2.93)**	(0.63)	**(-37.83)**	**(-15.00)**	**(-9.89)**	**(-6.73)**	**(-2.70)**	(1.30)	(-0.01)	
Quartile 2	**0.0009**	**0.0001**	**0.0000**	**0.0000**	**0.0000**	0.0000	**0.0000**	**-0.1257**	**-0.0529**	**-0.0370**	**-0.0229**	0.0029	**0.0175**	0.0000	Included
	(21.29)	**(5.32)**	**(2.05)**	**(2.15)**	**(2.36)**	(-1.09)	**(1.93)**	**(-27.89)**	**(-13.97)**	**(-10.43)**	**(-6.55)**	(0.82)	**(4.92)**	(-0.55)	
Quartile 3	**0.0009**	**0.0001**	0.0000	0.0000	**0.0000**	0.0000	**0.0000**	**-0.1017**	**-0.0439**	**-0.0298**	-0.0058	**0.0064**	**0.0277**	0.0000	Included
	(17.44)	**(4.18)**	(-0.96)	(0.14)	**(2.06)**	(-0.70)	**(-2.06)**	**(-22.54)**	**(-10.83)**	**(-7.75)**	(-1.61)	**(1.75)**	**(7.54)**	(-0.84)	
Quartile 4	**0.0007**	**0.0001**	0.0000	0.0000	0.0000	0.0000	**-0.0001**	**-0.0451**	-0.0108	-0.0106	-0.0052	**0.0116**	**0.0234**	**0.0000**	Included
	(18.95)	**(4.10)**	(-1.61)	(-0.20)	(0.91)	(1.32)	**(-2.61)**	**(-2.01)**	(-0.78)	(-1.46)	(-0.92)	**(1.73)**	**(4.05)**	**(-3.17)**	
Panel B: Liquidity provision by the types of HFTs															
Individuals (Ind)	**-0.0054**	0.0000	**0.0002**	**0.0001**	**0.0002**	0.0001	**0.0001**	**-0.0956**	**-0.0320**	**-0.0229**	**-0.0091**	**0.0051**	**0.0191**	**0.0000**	Included
	(-24.13)	(0.37)	**(3.29)**	**(2.30)**	**(2.75)**	(1.15)	**(2.53)**	**(-10.28)**	**(-5.18)**	**(-6.44)**	**(-4.06)**	**(2.10)**	**(8.59)**	**(-3.11)**	
Institutions (Inst)	**0.0001**	**-0.0001**	**-0.0002**	**-0.0001**	**-0.0001**	**-0.0001**	**-0.0001**	**-0.0967**	**-0.0371**	**-0.0260**	**-0.0110**	**0.0055**	**0.0199**	**0.0000**	Included
	(3.62)	**(-6.92)**	**(-11.71)**	**(-9.25)**	**(-6.88)**	**(-5.32)**	**(-5.13)**	**(-10.77)**	**(-6.09)**	**(-7.18)**	**(-5.02)**	**(2.41)**	**(9.14)**	**(-3.33)**	
Foreigners (For)	**0.0018**	**0.0003**	**0.0001**	**0.0001**	**0.0001**	**0.0000**	0.0000	**-0.1023**	**-0.0345**	**-0.0238**	**-0.0116**	**0.0053**	**0.0209**	**0.0000**	Included
	(45.14)	**(15.89)**	**(6.61)**	**(5.23)**	**(7.75)**	**(3.67)**	(1.15)	**(-11.46)**	**(-5.79)**	**(-6.61)**	**(-5.22)**	**(2.23)**	**(9.44)**	**(-2.23)**	
Wald test (*p*-value)															
Ind vs. Inst	0.0001														
Ind vs. For	0.0001														
Inst vs. For	0.0001														

Table 4

HFTs' trading volume and market quality

This table reports vector autoregression (VAR) analysis results for the following bivariate VAR model specification:

$$HFT_{i,t} = a_i + \sum_{k=1}^{6} b_i MQ_{i,t-k} + \sum_{k=1}^{6} c_k HFT_{i,t-k} + \varepsilon_{i,t}$$

$$MQ_{i,t} = \alpha_i + \sum_{k=1}^{6} \beta_i MQ_{i,t-k} + \sum_{k=1}^{6} \gamma_k HFT_{i,t-k} + \varepsilon_{i,t}$$

HFT is total number of contracts traded from HFTs during the period, *MQ* is a market quality variable. We use four measures to capture different aspects of market quality: two measures of short-term volatility (*HL* and *HighLow*) and two measures of liquidity (*Spread* and *Depth*). *HL* is defined as the highest price minus lowest price divided by the midpoint of the highest price and lowest price in an interval. *HighLow* is defined as the highest mid-quote in the interval minus the lowest mid-quote in the same interval. *Spread* is the effective spread ((best ask price - best bid price) / (bestask+bestbid)/2) in the interval. *Depth* is time-weighted average of the number of contracts in the book at the best posted prices in the interval. Sample includes complete intraday order and transaction data for the index futures on the KRX for the period covering April 2009 through March 2010. We define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times in a day, with a median inter-order duration of less than 1 second. We divide a trading day into 2,190 ten-second intervals. We employ VAR analysis for each day in the sample and report the averages of daily estimates. Overall results are reported in Panel A. In Panel B, we categorize HFTs into domestic individual, domestic institutional, and foreign HFTs. Numbers in ( ) denote *t*-values; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

	HFT	*HL*	*HFT*	*Spread*	*HFT*	*HighLow*	*HFT*	*Depth*
Panel A: Overall								
HFT_{t-1}	**0.2076*****	**0.0024*****	**0.2777*****	0.0003	**0.2132*****	**0.3979*****	**0.2594*****	**-0.0573*****
	(8.07)	**(3.52)**	**(12.88)**	(0.45)	**(7.52)**	**(2.88)**	**(11.96)**	**(-3.76)**
MQ_{t-1}	**0.5082*****	**0.1665*****	0.0331	-0.0009	**0.0217*****	**0.1303*****	**0.2058*****	**0.4992*****
	(4.49)	**(6.47)**	(0.03)	(-0.04)	**(3.33)**	**(4.59)**	**(5.54)**	**(22.98)**
Time Dummy	Included	Included	Included	Included	Included	Included	Included	Included
Adj Rsq	0.1886	0.2013	0.1784	0.0153	0.1840	0.1426	0.1934	0.4467
Panel B: By the types of HFTs								
Individual HFTs								
HFT_{t-1}	**0.0774*****	0.0000	**0.0967*****	0.0000	**0.0735*****	0.0039	**0.0892*****	-0.0007
	(3.13)	(1.25)	**(4.09)**	(0.19)	**(2.94)**	(0.73)	**(3.77)**	(-1.04)
MQ_{t-1}	**9.7528*****	**0.2048*****	-2.6517	-0.0019	0.5424	**0.1679*****	**3.5779*****	**0.4529*****
	(2.98)	**(8.71)**	(0.16)	(-0.07)	(3.31)	**(7.16)**	**(2.62)**	**(29.68)**
Time Dummy	Included	Included	Included	Included	Included	Included	Included	Included
Adj Rsq	0.0532	0.1821	0.0449	0.0159	0.0533	0.1271	0.0529	0.4030
Institutional HFTs								
HFT_{t-1}	**0.2120*****	**0.0000*****	**0.2737*****	0.0000	**0.2161*****	**0.0041****	**0.2531*****	**-0.0006*****
	(8.17)	**(2.65)**	**(11.99)**	(0.20)	**(7.96)**	**(2.07)**	**(11.00)**	**(-2.72)**
MQ_{t-1}	**37.4298*****	**0.1763*****	-3.5070	0.0092	**1.6716*****	**0.1342*****	**15.1864*****	**0.4663*****
	(4.52)	**(6.79)**	(-0.04)	(0.39)	**(3.73)**	**(4.96)**	**(5.32)**	**(20.15)**
Time Dummy	Included	Included	Included	Included	Included	Included	Included	Included
Adj Rsq	0.1688	0.1790	0.1579	0.0171	0.1658	0.1214	0.1738	0.4103
Foreign HFTs								
HFT_{t-1}	**0.0902*****	0.0000	**0.1341*****	0.0000	**0.0894*****	0.0034	**0.1277*****	**-0.0009****
	(3.52)	(1.20)	**(5.79)**	(0.42)	**(3.30)**	(1.00)	**(5.51)**	**(-2.47)**
MQ_{t-1}	**17.0051*****	**0.1922*****	3.1461	-0.0022	**0.7934*****	**0.1391*****	**5.0222*****	**0.4431*****
	(3.60)	**(7.48)**	(0.13)	(-0.09)	**(3.08)**	**(5.14)**	**(2.94)**	**(18.82)**
Time Dummy	Included	Included	Included	Included	Included	Included	Included	Included
Adj Rsq	0.0927	0.1726	0.0835	0.0158	0.0908	0.1118	0.0902	0.3922

Table 5

HFT and price discovery

This table reports the results of the state space model from Hendershott and Riordan (2011). We decompose index futures price into a permanent component and a transitory component using the state space model as follows:

$$p_{i,t} = m_{i,t} + s_{i,t}, \quad m_{i,t} = m_{i,t-1} + w_{i,t}$$

$$w_{i,t} = k_i^{All}\, H\tilde{FT}_{i,t}^{All} + \mu_{i,t}$$

$$w_{i,t} = k_i^{IND\,ALL}\, H\tilde{FT}_{i,t}^{IND\,All} + k_i^{INST\,ALL}\, H\tilde{FT}_{i,t}^{INST\,All} + k_i^{FOR\,ALL}\, H\tilde{FT}_{i,t}^{FOR\,All} + \mu_{i,t}$$

$$w_{i,t} = k_i^{Init}\, H\tilde{FT}_{i,t}^{Init} + k_i^{Pass}\, H\tilde{FT}_{i,t}^{Pass} + \mu_{i,t}$$

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

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

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

$p_{i,t}$ is the (log) mid-quote at time interval *t* for each day, $m_{i,t}$ is a permanent component, $s_{i,t}$ is a transitory component, $w_{i,t}$ represents the permanent price changes. $H\tilde{FT}_{i,t}^{All}$ is the unexpected innovation in $HFT_{i,t}^{All}$, defined as the residual of an autoregressive model to remove autocorrelation. $HFT_{i,t}^{All}$ is total HFT order flow (buying volume minus selling volume). We categorize HFT into passive HFT and initiated HFT. $H\tilde{FT}_{i,t}^{Init}$ and $H\tilde{FT}_{i,t}^{Pass}$ are the unexpected innovations in $HFT_{i,t}^{Init}$ and $HFT_{i,t}^{Pass}$, calculated similarly to the first aggregate model. $HFT_{i,t}^{Init}$ and $HFT_{i,t}^{Pass}$ are the HFT initiated order flow and the HFT passive order flow, respectively. We also categorize HFT into domestic individual, domestic institutional, and foreign HFTs. Sample includes complete intraday order and transaction data for the index futures on the KRX for the period covering April 2009 through March 2010. We define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times in a day, with a median inter-order duration of less than 1 second. We employ a pooled regression using Newey and West (1987) standard errors. Numbers in ( ) denote *t*-values; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Dep. Var.	$w_{i,t}$				$s_{i,t}$			
$HFT_{i,t}^{All}$	-0.1817				**3.8733*****			
	(-0.27)				**(2.21)**			
$HFT_{i,t}^{Ind}$		2.8136				**-137.66*****		
		(0.55)				**(-9.62)**		
$HFT_{i,t}^{Inst}$		1.1279				**-3.7823**		
		(0.95)				**(-1.28)**		
$HFT_{i,t}^{For}$		0.6314				**11.1382*****		
		(0.79)				**(4.19)**		
$HFT_{i,t}^{Init}$			0.0282				**-37.5587*****	
			(0.03)				**(-11.42)**	
$HFT_{i,t}^{Pass}$			0.3125				**22.2142*****	
			(0.41)				**(10.38)**	
$HFT_{i,t}^{IndInit}$				0.0076				**-0.0293***
				(1.09)				**(-1.68)**
$HFT_{i,t}^{IndPass}$				-0.0008				**0.0378*****
				(-0.30)				**(6.43)**
$HFT_{i,t}^{InstInit}$				-0.0001				**-0.0036*****
				(-0.22)				**(-5.59)**
$HFT_{i,t}^{InstPass}$				0.0001				**0.0030*****
				(0.52)				**(6.73)**
$HFT_{i,t}^{ForInit}$				-0.0006				**-0.0040****
				(-0.94)				**(-2.21)**
$HFT_{i,t}^{For\,Pass}$				0.0002				**0.0029*****
				(1.50)				**(6.92)**

Table 6

Distribution of HFTs net profits

This table reports the distribution of the proportion of HFTs in a range of profits. Net profits for each trader per day are calculated by the following equation:

$$\pi_i = -I_0 P_0 + \sum (P_S V_S - P_B V_B) + I_T P_T - TC_i * \sum (P_S V_S + P_B V_B)$$

P_S is the price of a sell trade, P_B represents the price of a buy trade. V_S is the size of a sell trade and V_B is the size of a buy trade. I_0 denotes inventory of futures when market opens and I_T is the inventory of futures when market closes. P_0 is the opening price and P_T is the settlement price. TC_i indicates transaction cost for each trader *i*. The transaction cost for individual traders is 0.01% of the total trading; for domestic institutions, 0.00084%; for foreigners, 0.001%. Sample includes complete intraday order and transaction data for the index futures on the KRX for the period covering April 2009 through March 2010. We define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times in a day, with a median inter-order duration of less than 1 second. Dollar-based figures are calculated at the exchange rate of 1,133 Korean Won to one US Dollar, in effect on March 11, 2010, the closing date of the sample period.

Net profit ($ thousands)	*Proportion*	*Cumulative proportion*	*Proportion*	*Cumulative proportion*	*Proportion*	*Cumulative proportion*	*Proportion*	*Cumulative proportion*
	Overall		*Individual HFTs*		*Institutional HFTs*		*Foreign HFTs*	
<-3,000	0.054	0.054	0.000	0.000	0.000	0.000	0.101	0.101
-2,000 to -3,000	0.134	0.188	0.173	0.173	0.085	0.085	0.151	0.252
-1,000 to -2,000	0.402	0.590	0.693	0.867	0.342	0.427	0.353	0.606
-500 to -1,000	1.341	1.931	1.733	2.600	1.026	1.453	1.413	2.019
-100 to -500	10.515	12.446	27.210	29.809	7.265	8.718	7.572	9.591
-50 to -100	6.518	18.965	15.598	45.407	6.581	15.299	3.836	13.428
-10 to -50	10.917	29.882	11.785	57.192	11.453	26.752	10.348	23.776
-5 to -10	4.721	34.603	2.946	60.139	4.274	31.026	5.502	29.278
0 to -5	12.929	47.532	5.546	65.685	15.128	46.154	13.781	43.059
0 to 5	14.083	61.615	5.546	71.231	15.299	61.453	15.851	58.910
5 to 10	5.526	67.141	3.986	75.217	4.103	65.556	6.815	65.724
10 to 50	13.305	80.445	10.399	85.615	17.778	83.333	11.509	77.234
50 to 100	7.028	87.473	5.719	91.334	7.265	90.598	7.269	84.503
100 to 500	10.730	98.203	7.799	99.133	8.462	99.060	12.923	97.426
500 to 1,000	1.261	99.464	0.867	100.000	0.855	99.915	1.615	99.041
1,000 to 2,000	0.322	99.785	0.000	100.000	0.085	100.000	0.555	99.596
2,000 to 3,000	0.054	99.839	0.000	100.000	0.000	100.000	0.101	99.697
> 3,000	0.161	100.000	0.000	100.000	0.000	100.000	0.303	100.000

Table 7

HFTs net profits

This table reports the results on the dollar-based profits from HFT for all HFTs and each investor group. Net profits for each trader per day are calculated by the following equation:

$$\pi_i = -I_0 P_0 + \sum (P_S V_S - P_B V_B) + I_T P_T - TC_i * \sum (P_S V_S + P_B V_B)$$

P_S is the price of a sell trade, P_B represents the price of a buy trade. V_S is the size of a sell trade and V_B is the size of a buy trade. I_0 denotes inventory of futures when market opens and I_T is the inventory of futures when market closes. P_0 is the opening price and P_T is the settlement price. TC_i indicates transaction cost for each trader *i*. The transaction cost for individual traders is 0.01% of the total trading; for domestic institutions, 0.00084%; for foreigners, 0.001%. Sample includes complete intraday order and transaction data for the index futures on the KRX for the period covering April 2009 through March 2010. We define HFTs as traders who submit orders (including cancellations or modifications) a total of more than 2,190 times in a day, with a median inter-order duration of less than 1 second. We calculate cross-sectional trading profits across traders for each day. Then we report the time series means for cross-sectional trading profits. Dollar-based figures are calculated at the exchange rate of 1,133 Korean Won to one US Dollar, in effect on March 11, 2010, the closing date of the sample period. Panel A shows the average of net profits from all HFTs. In Panel B, we decompose HFTs into domestic individual HFTs, domestic institutional HFTs, and foreign HFTs and calculate the net profits earned by different trader types. Panel C and Panel D report the results on the dollar-based profits for initiated HFT and passive HFT. In Panel C, we report the average daily gross profits and net profits for mostly initiated HFT. Panel D shows the average daily gross profits and net profits for mostly passive HFT. For each high frequency trader per day, we define a high frequency trader as one with mostly initiated (passive) HFT if more than 50% of total trading volume is initiated (passive).

		Mean	*Median*	*Min*	*Max*	*Std*	*t*
Panel A: Overall							
Gross profits		12,818	3,545	-3,945,014	4,602,904	288,156	2.72
Net profits		-179	625	-3,963,001	4,597,840	290,577	-0.04
Panel B: By types of traders							
Individuals	Gross profits	-23,686	-7,894	-2,296,839	1,226,809	229,407	-2.48
	Net profits	-61,952	-27,837	-2,510,052	983,972	246,013	-6.05
Institutions	Gross profits	8,776	6,068	-2,892,435	1,230,011	182,073	1.65
	Net profits	-4,460	782	-2,916,271	1,209,939	181,761	-0.84
Foreigners	Gross profits	25,837	2,605	-3,945,014	4,602,904	347,631	3.31
	Net profits	20,341	1,804	-3,963,001	4,597,840	346,811	2.61
Panel C: Mostly initiated HFT							
Individuals	Gross profits	-16,722	-5,313	-1,900,199	1,226,809	209,721	-1.80
	Net profits	-49,180	-12,496	-1,992,594	983,972	222,306	-5.01
Institutions	Gross profits	4,621	5,141	-2,892,435	1,230,011	198,482	0.72
	Net profits	-6,954	394	-2,916,271	1,209,939	198,527	-1.08
Foreigners	Gross profits	20,792	831	-808,742	3,507,991	241,474	2.58
	Net profits	19,213	490	-812,085	3,504,834	240,700	2.39
Panel D: Mostly passive HFT							
Individuals	Gross profits	-78,546	-38,386	-2,296,839	593,977	345,000	-1.84
	Net profits	-162,559	-108,598	-2,510,052	444,685	372,192	-3.52
Institutions	Gross profits	26,226	25,463	-642,161	261,033	81,260	4.84
	Net profits	6,016	9,171	-649,726	237,924	78,605	1.15
Foreigners	Gross profits	30,029	15,714	-3,945,014	4,602,904	415,778	2.38
	Net profits	21,278	10,466	-3,963,001	4,597,840	414,940	1.69