Speed of Trade and Liquidity

May 2011

Jun Uno, Waseda University*
Mai Shibata, Rikkyo University

* Corresponding author: Jun Uno, Waseda University, Graduate School of Finance, Accounting and Law. 1-4-1 Nihombashi, Chuo-ku, Tokyo 103-0027, Japan; Tel. 81-3-3272-6798; Fax 81-3-3272-6783; e-mail juno@waseda.jp.

Speed of Trade and Liquidity

Abstract

We investigate whether increasing the speed of order execution affects investor trading strategy and market liquidity. With the new trading platform Arrowhead, the Tokyo Stock Exchange has eliminated the three-second matching cycle, executes orders immediately, and instantaneously updates the limit order book, rendering computerized trading strategies more powerful. Since Arrowhead's introduction, there have been an increase in execution frequency and a reduction in trade size, leading to declines in effective spread and increases in adverse selection costs. Both of these trends are more pronounced for large-cap stocks characterized by high-frequency trading. These changes are consistent with previous research on US markets; however, unlike in US markets, high-frequency trading has remained unchanged for small-cap stocks.

JEL Classification: G10,G12,G14

Keywords: Liquidity Provision, High Frequency Trading, Matching Interval, Bid Ask Spread

1. Introduction

This paper investigates whether increasing the speed of order execution affects trading strategy and liquidity. Recently, global stock exchanges have been competing in how quickly information on quotes and trades can be transmitted. This competition is now in the millisecond to microsecond range as a result of strong demand from investors who take advantage of technological innovations such as algorithmic trading.

In January 2010, the Tokyo Stock Exchange (TSE) upgraded its trading platform by introducing the Arrowhead system. Many changes were brought about by the new system, a particularly important one involving the matching cycle[1]. The matching interval had been three seconds before the introduction of the new system; now, when a market and/or limit order is entered, it is processed immediately. The order is then executed immediately and the limit order book updated instantaneously. This change has made computerized trading strategies more powerful, because computers can place and cancel orders faster than human traders. Although high-frequency trading (HFT) was used in the TSE before 2010, the three-second interval in the matching process prevented quick HFT movements. Trading volume is expected to increase due to the introduction and expanded use of HFT.

Algorithms typically determine the timing, price, and quantity of trades by dynamically monitoring market conditions across different securities, reducing market impact by optimally and sometimes randomly breaking large orders into smaller pieces, and closely

[1] TSE has revised the rules for maximum price change between trades and conditions for opening and closing auction. See TSE(2010) for further details.

tracking benchmarks such as the volume-weighted average price(VWAP)[2] over the execution interval.

Faster execution allows liquidity demanders to monitor the market more closely for temporary mispricings or stale quotes, which can raise adverse selection costs (Foucault et al. 2003). Faster execution attracts more informed trading (Barclay et al. 2003). The resulting higher adverse selection can raise the cost of immediacy for liquidity demanders. If investors rely on the same or similar algorithms for their trading decisions, however, this can increase herding behavior among sophisticated investors (positive feedback effects). The order flow imbalance thus results in a higher transaction cost for liquidity demanders.

The introduction of Arrowhead in the TSE can provide insights into the tradeoff between the concentration of orders from liquidity demanders and competition in liquidity supply. Since the change at the TSE, we have observed the following: There have been an increase in execution frequency and a reduction in trade size, but no significant volume increase. The shift to HFT has been pronounced for larger stocks. We estimate a model that captures the relation between quote revisions and trading measures, which we quantify as HFT effects on MT from the new system for individual stocks. Immediate matching promotes competition among liquidity providers, and HFT reduces compensation for liquidity provision while it increases adverse selection costs. Both trends are more pronounced for stocks characterized by heavy HFT, where quote revisions have increased substantially relative to the number of trades since January 2010.

---

[2] VWAP is used frequently by institutional investors to execute large orders. VWAP target order is referring to the order submission strategy in which a brokers slices large institutional orders into small pieces and execute them throughout a day.

The remainder of this paper is organized as follows. Chapter 2 explains the TSE's new trading system and briefly surveys related research. Chapter 3 describes our hypotheses and the design of this empirical study. Chapter 4 presents our results and determinants of the spread changes brought about by Arrowhead. Chapter 5 gives our conclusions.

2. The new trading platform

On January 4, 2010, the TSE launched the new trading system Arrowhead. The main features of this system are accelerated computer processing speeds, a colocation service that reduces the physical distance between market participants (investors as well as brokerage firms) and the exchange, and a revision of the tick size. Prior to 2010, a series of computerizations in the trading process implemented by TSE to replace human-based order handling. However, Arrowhead has the potential to incur a major paradigm shift in trading by changing the balance among market participants.

Prior research related to the speed of trade is limited. Hendershott and Moulton (2009) study the 2007 introduction of Hybrid Market on the New York Stock Exchange (NYSE). The system expands the use of automated electronic execution and decreases execution times for market orders from over 10 seconds to less than one second. From the month prior to each stock's Hybrid Market activation date to the month after, NYSE's effective spreads increased from 5.6 to 5.9 basis points due to an increase in adverse selection. It has been found that decreasing execution speed leads to more information being incorporated into prices, rendering pricing more efficient.

Chordia et al. (2011) note that rapid increases in turnover ratio, a striking increase in the number of trades, and consistent reductions in trade size are characteristic of US stock markets. These findings reflect the increasing influence of HFT (or algorithmic trading). Only a few papers address algorithmic trading directly. For example, Hendershott et al. (2010) cite NYSE's 2003 switch to automated quote dissemination to show that algorithmic trading improves liquidity and, equivalently, decreases the speed of price discovery associated with trades.

With the TSE's introduction of Arrowhead, the liquidity and price formation of listed stocks may be influenced by two major changes: the matching process cycle and tick size reduction. The former impacts all stocks, while the latter affects only stocks traded within a specific price range, such as ¥2,000–5,000. Since our empirical study focuses on the effect of trading speed, we separate the stocks according to whether or not they are affected by the tick size change.

3. Empirical study design

3.1. Hypotheses

Faster execution allows all market participants to monitor the market conditions more closely and submit orders more quickly. Thus faster execution attracts more informed trading. The resulting higher adverse selection can raise the cost of immediacy for liquidity demanders.

> Hypothesis 1: HFT increases adverse selection costs due to more informed trading and faster price discovery.

As trading became more computerised, it became easier and cheaper to replace the floor traders who played the role of liquidity provider with a computer program. Algorithmic liquidity suppliers who monitor market conditions across different securities can quickly notice an abnormally wide bid–ask spread and provide liquidity accordingly via a limit order.

> Hypothesis 2: Due to increased competition between liquidity providers, HFT reduces costs of immediacy.

The TSE's introduction of Arrowhead can provide insights into the tradeoff between liquidity demanders increasing adverse selection and increasing competition among liquidity suppliers.

3.2. Samples

Boosting the speed of trade through Arrowhead is an exogenous change that affects all the stocks listed on the TSE. We collect stocks from the first section of the TSE[3] and separate them into two groups, one (Group1) unaffected by tick size changes and the other (Group2) affected by tick size changes. The sample period is from one month before the introduction of Arrowhead to one month after. We exclude the last week of December 2009 and the first week of January 2010 based upon our conversations with institutional investors who voiced their reluctance to trade in the brand new system. We exclude stocks that move into and out of different tick size and traded for fewer than five days in any month or below ¥100. Table 1 shows a number of stocks in each group and price ranges. Figure 1 shows daily movement of effective spread and figure 2 shows that the changes in depth for stocks in different price range.

---

[3] Tokyo Stock Exchange has two sections. Listing requirements for the first section stocks such as number of shares outstanding and shareholders are higher than those for the second section..

(insert Table 1, Figure 1&2 here)

4. Arrowhead's impact

4.1. Trading activities

Table 2 summarizes the trading activities for the two groups of stocks, affected by tick size change and not. After Arrowhead's introduction in the TSE, a shift toward high-frequency, small orders was observed in investors' order execution patterns. Of the four trading-related measures selected here, the number of quote revisions shows the largest percentage of change from December 2009 to January 2010. The average number of quote revisions in a five-minute period for Group1 (Group2) increased from 18.2 (25.6) to 37.1 (73.4). The average number of trades in the five-minute period increased from 5.7 (7.7) to 7.9 (16.6). The average size of trades in the five-minute period decreased from 6.9 (8.8) units to 5.7 (6.6) units. The changes for both groups are statistically significant at the 1% confidence level. The total volume in the five-minute period did not increase for either group.

It should be noted that the transition to HFT is more pronounced for large-cap stocks, and changes in quote revisions, the number of trades, as well as the size of trades are larger. For large-cap stocks, quote revisions in a five-minute period almost triple, from 45.5 (40.3) to 110.8 (125.1) for Group1 (Group2) stocks. The average number of trades in the five-minute period increases from 15.0 (12.1) to 23.9 (28.9), and the average size of trades decreases from 22.8 (15.4) units to 16.4 (11.5) units.

An examination of trading-related measures reveals that the changes following Arrowhead's introduction do not occur across the stocks listed in the TSE. Significant changes appear to be concentrated around large-cap stocks. The next section investigates this issue.

(insert Table 2 here)

4.2. Impact of HFT

Arrowhead's introduction has been characterized by a high frequency of trades and quote revisions. In particular, of the four measures in Table 2, the frequency of quote revisions increases the most. In the case of the TSE, elimination of the three-second matching cycle changes trades and quotes message traffic (MT), and the state of the limit order book between the exchange and investors. Under the three-second matching cycle, market and limit orders that came to market in between were batched and reported cumulatively. Under the Arrowhead system, these orders are executed and reported individually. As a result, the numbers of orders and quotes have increased for high-volume stocks. In addition, investors can enter, change, and cancel orders faster than before the introduction of the new system, thereby affecting their order submission behavior.

We quantify these changes by modeling the quote frequency with trade-related variables. An important issue is the normalization of the quote frequency numbers. Hendershott and Moulton (2009) use the number of electronic messages per US$100 of trading volume as a proxy for algorithmic trading instead of raw MT numbers. We model MT numbers that are influenced by not only the number of trades but also the depth and width of the spread. To estimate the relation for all stocks listed in the TSE, we use four explanatory variables: the *number of trades, depth, tick spread,* and the *log of the market cap*. The dependent variable is the number of quote revisions, which is equivalent to MT in Hendershott and Moulton (2009).

First, we estimate the following regression model using daily data from December 2009:

$$MT_{jt} = a + b\#ofTrade_{jt-1} + cDepth_{jt-1} + dTick\_spread_{jt-1} + e\log(CapSize_{j0}) + f_{jt} \qquad (1)$$

The result in Table3 shows that all variables in the equation (3) except tick spread are highly significant and the adjusted R-squire is 0.88. Using the estimated parameters, we compute the predicted MT for January 2010 and the difference between the predicted and the actual MT (i.e., the prediction error). We assume that the difference indicates the degree of change brought about by the HFT, which we call the “HFT effect” hereafter. We use the model prediction error as a proxy for the HFT effect, which reflects sliced order submissions, changing limit prices as well as quantities, and cancellations. The speedup of a few seconds provides critical new information to high-frequency traders but is unlikely to affect the trading behavior of humans. Elimination of the three-second matching interval allows algorithmic liquidity suppliers to quickly notice abnormally wide inside quotes and provide liquidity accordingly via limit orders. Algorithmic liquidity demanders can quickly access these orders via conventional market or marketable limit orders.

(insert Table 3 & 4 around here)

We form portfolios and sort them into five groups according to HFT effects. In Table 4, the heavy HFT quintile with no tick change (with tick change) stocks shows that the average deviation of the number of quote revisions during five minutes is 56.4 (83.6) from that of the previous month. The smallest HFT quintile shows that the average deviation of the number of quote revisions is slightly negative, -1.2 (-1.4), which is statistically significantly different from zero. It seems that MT patterns for stocks in lower HFT quintiles do not deviate from those in December 2009. As in Hendershott and Moulton (2009), the results are consistent with the conventional wisdom that algorithmic trading was more prevalent at the time for active, liquid stocks.

4.3. Cost of immediacy

We now examine the effects of Arrowhead's introduction on liquidity. This section focuses on spread measures such as effective spread, realized spread, and adverse selection (market impact) costs. The effective spread is the cost of immediate execution paid to the market by liquidity demanders. The wider the effective spread, the less liquid the stock. For our sample TSE stocks, effective spreads are almost always identical to quoted spreads because the TSE uses a pure order-driven mechanism.

For the *t*th trade in stock *j*, the proportional effective half-spread, *ESPRD*, is defined as

$$\text{EffectiveSpread}(ESPRD)_{jt} = q_{jt}\,(p_{jt} - m_{jt})/m_{jt}, \quad (2)$$

where q_{jt} is an indicator variable that equals +1 for buyer-initiated trades and −1 for seller-initiated trades, p_{jt} is the trade price, and m_{jt} is the quote midpoint prevailing at the time of the trade. For stock *j,* each month we calculate the simple average across days and then average it across the month.

Narrower effective spreads imply less revenue per trade for liquidity providers. We decompose effective spreads into a realized spread component(*RSPRD*) and an adverse selection or price impact component(MI), to understand the source of the improvement in liquidity under Arrowhead's implementation:

$$ESPRD_{jt} = RSPRD_{jt} + MI_{jt}$$

$$= (q_{jt}\,(p_{jt} - m_{j,t+5min})/m_{jt}) + (q_{jt}\,(m_{j,t+5min} - m_{jt})/m_{jt}), \quad (3)$$

where p_{jt} is the trade price, q_{jt} is the buy–sell indicator (+1 for buys, −1 for sells), m_{jt} is the midpoint prevailing at the time of the tth trade, and $m_{j,t+5min}$ is the quote midpoint five minutes after the tth trade. We estimate the revenue to liquidity providers using the five-minute realized spread, which assumes the liquidity provider is able to close his or her position at the quote midpoint five minutes after the trade. We measure gross losses to liquidity demanders due to adverse selection using the five-minute market impact of a trade.

Table 5 compares these measures between December 2009 and January 2010. Overall changes in effective spreads are negative for all quintiles. Stocks in the largest HFT quintile show the smallest decline (-0.006%), and those in the two lighter quintiles show a larger decline (-0.031%, -0.039%). The heavier the HFT effect, the smaller the reduction of the cost of immediacy. It seems that high-speed transactions somewhat prevent the reduction of the cost of immediacy.

Decomposing the effective spread into liquidity provider revenues—the realized spread—and adverse selection—permanent market impact—we find effects in two opposite directions. For stocks in a heavy HFT quintile, the realized spread shows a statistically significant decline (-0.014%) and market impact shows a statistically significant increase (0.008%), but for stocks in a light HFT quintile, the realized spread significantly increases (0.017%) and market impact significantly declines (-0.048%). From the results above, compensation for liquidity providers is reduced in the five-minute period due to positive market impact. This finding contradicts the results of Hendershott et al. (2010) in the US market, where both the effective spread and market impact declined. For stocks in smaller HFT quintiles, however, the source is the reduction of permanent market impact costs, similar to US stocks.

(insert Table 5 and Figure 3 around here)

4.4. Determinants of execution costs

We have observed a reduction in the cost of immediacy and compensation for liquidity provision. We now investigate the determinants of these changes. Candidate variables are the HFT effect, the cumulative yen volume, the number of trades, and the size of trades. The natural way to test these variables is by regressing the various liquidity measures, Li, on *HFT*, *Vol*, *#Trade*, and *TradeSize* and controlling variables Xi:

$$\Delta L_i = \alpha + \beta_1 HFT_i + \beta_2 \frac{Vol_{i,Jan}}{Vol_{i,Dec}} + \beta_3 \frac{\#Trade_{i,Jan}}{\#Trade_{i,Dec}} + \beta_4 \frac{TradeSize_{i,Jan}}{TradeSize_{i,Dec}} + \gamma \Delta X_j + \varepsilon_i , \quad (4)$$

where △Li is $\Delta ESPRD_i = ESPRD_{i,Jan} - ESPRD_{i,Dec}$, differences in the effective spread between December 2009 and January 2010; similarly, △*RSPRD*i is the realized spread and △*MI*i the market impact; *HFT*i is a prediction error of equation (1); $\frac{Vol_{i,Jan}}{Vol_{i,Dec}}$ is the ratio of the yen volume on January 2010 to that on December 2009; similarly, $\frac{\#Trade_{i,Jan}}{\#Trade_{i,Dec}}$ is the ratio of the numbers of trades, $\frac{\#TradeSize_{i,Jan}}{\#TradeSIze_{i,Dec}}$ is the ratio of trade sizes, and the Xi are stock-level control variables, including △*tickspread*, the difference in tick spread, and △*tickspread* x *tick size change dummy,* which is the difference in tick spread for stocks affected by tick size change, and zero otherwise.

Table 6 presents the coefficients for variants of equation (4). When the dependent variable Li is ⊿*ESPRD* for stock i, the coefficients of HFTi are positive and marginally significant at the 10% level. This means that the larger the HFT effect, the larger the increase in effective spread. The variables of the ratios of *#Trad*e and *TradeSize* show significant negative relations with effective spread change. This means that the larger the increase in the number of trades or in the size of the trades, the larger the reduction in effective spread. It is interesting that the ratio of *Vol* has a significant, positive coefficient with effective spread change. Here *Vol* is a product of the number of trades and their size, so increasing volume widens the effective spread due to adverse selection risk. The results indicate that the changes in effective spread is more strongly related with the number of trade and trade size than the HFT effects.

When the dependent variable Li is ⊿*RSPRD*i for stock i, the coefficients of *HFT* are negative and significant at the 1% level. The variables ⊿*#Trade* and ⊿*SizeTrade* do not have significant coefficients. This means that the larger the HFT effect, the greater the reduction of the compensation for liquidity providers.

When the dependent variable Li is ⊿*MI*i for stock i, the coefficient of *HFT* is positive and significant at the 1% level. Frequent quote revisions are related to a permanent price impact after the trade. Here ⊿*#Trade* and ⊿*SizeTrade* have a significant negative relation, which means that the larger the HFT effect, the greater the market impact. The negative relations of ⊿*#Trade* and ⊿*SizeTrade* imply that the frequency and size of trades indicate high liquidity.

From the results in Table 6, we conclude that the overall reduction in effective spread is due to the increased number of trades as well as the size of trades. Increased MT intensifies adverse selection risks and creates a permanent market impact after the trade.

(insert Table 6 around here)

5. Concluding remarks

Since Arrowhead's introduction at the TSE, higher-frequency and smaller trades have been observed without a volume increase. Of the transaction-related measures, MT (the number of quote revisions) increases the most. We estimate a model that captures the relations between MT and transactions and quantify an HFT effect for individual stocks in the new trading platform.

The US Securities and Exchange Commission expressed concern over the HFT effect and whether it improves liquidity or diminishes price efficiency by abrupt up and down price movements.[4]

After the launch of Arrowhead, the effective spread declined, and the compensation for liquidity provision decreased due to increased adverse selection costs. Both of these trends are more pronounced for large-cap stocks characterized by HFT stocks.

The TSE's new trading platform significantly enhanced order execution turnaround. The three-second matching cycle was eliminated, and the dissemination of trades and quotes is

[4] US SEC(2010)

now carried out instantaneously and individually. We compare liquidity between December 2009 and January 2010 and determine the new trading platform's impact on liquidity. The increased number of trades may be the natural result of more frequent matching. Reporting trades and quote revisions individually should have a real impact on investor behavior. Market participants at the TSE say that quote changes have become too fast to be perceived by humans. This has had a negative impact on the realized spread and a positive impact on adverse selection costs. This implies that increasing MT amplifies order imbalance, thus having a permanent market impact after the trade. The larger the HFT effect, the greater these changes. This can affect investors who slice large orders into smaller pieces, as in VWAP trades. The remaining permanent market impact after other traders' trades can increase transaction costs.

The role of liquidity provider may be replaced by high-frequency traders who can accumulate sliced compensation to maintain sufficient profitability as a liquidity provider. Brokerages engaging in short-term trading for their own accounts will have difficulty avoiding reduced profitability due to increasingly intense competition with HFT, making it a challenge to remain viable without some form of HFT capability. The use of HFT remains unchanged, however, for small-cap stocks, a segment of the market where algorithmic trades cannot be said to have increased the supply of liquidity.

Several important questions remain unanswered in this study, due largely to a lack of detailed data. Beyond the observed changes, which investors change their investment behavior and in what manner are interesting questions. If we examine a later period of months, our findings may be smaller or even disappear, which indicates fine tuning by market participants. We will continue these kinds of investigation in future projects.

References

Barclay, Michael J., and Terrence Hendershott, 2003, Price discovery and after trading hours, Review of Financial Studies 16, 1041–1073.

Chordia, Tarun, Richard Roll and Avanidhar Subrahmanyam, 2011, Recent Trends in Trading Activity, forthcoming Journal of Financial Economics.

Foucault, Thierry, Ailsa R©ell, and Patrik Sandas, 2003, Market making with costly monitoring: an analysis of the SOES controversy, Review of Financial Studies 16, 345–384.

Glosten, Lawrence R., 1987, Components of the bid ask spread and the statistical properties of transaction prices, Journal of Finance 42, 1293–1307.

Goldstein, Michael A., and Kenneth A. Kavajecz, 2004, Trading strategies during circuit breakers and extreme market movements, Journal of Financial Markets 7, 301–333.

Goldstein, Michael A., and Kenneth A. Kavajecz, 2000 Eighths, sixteenths, and market depth: changes in tick size and liquidity provision on the NYSE, Journal of Financial Economics.

Harris, Lawrence, 1998, Optimal dynamic order submission strategies in some stylized trading problems, Financial Markets, Institutions, and Instruments 7, 1–76.

Hasbrouck, Joel, 1991a, Measuring the information content of stock trades, Journal of Finance 46, 179–207.

Hasbrouck, Joel, and Gideon Saar, 2009, Technology and liquidity provision: the blurring of traditional definitions, Journal of Financial Markets 12, 143–172.

Hendershott, T., C. Jones, and A. Menkveld, 2010, Does algorithmic trading improve liquidity? Forthcoming Journal of Finance.

Hendershott, T., Pamela C. Moulton, 2008, Speed and stock market quality: the NYSE's Hybrid, SRRN working paper.

Jones, Charles M., Gautam Kaul, and Marc L. Lipson, 1994, Information, trading, and volatility, Journal of Financial Economics 36, 127–154.

Tokyo Stock Exchange, 2010, Guide to TSE Trading Methodology

US Securities and Exchange Commission, 2010, Concept Release on Equity Market Structure

Table 1. Sample stocks and tick size.

We collect stocks from the TSE one month before and one month after the introduction of the Arrowhead system on January 4, 2010. We exclude the last week of December and the first week of January. As of January 4, 2010, the TSE revised the tick size table, so our sample stocks must remain within the same price range listed below during the entire sample period. We exclude stocks that traded for fewer than five days in any month and below ¥100.

Price range	Number of stocks	old tick	new tick
Below 2000	1232	¥1	same
2000～3000	46	¥5	¥1
3000～5000	35	¥10	¥5
5,000～30,000	53	¥10	same
30,000～50,000	10	¥50	same
50,000～300,000	61	¥100	same
300,000～500,000	12	¥1,000	¥500
500,000～1,000,000	8	¥1,000	same
Total	1457		

Table 2. Trading measures on December 2009 and January 2010.

This table examines the number of trades, their size, cumulative volume, number of quote revisions, and number of observations. All measures are averaged over five-minute intervals each day, over the month, and then over the stocks. Stocks are categorized into two groups, one with no changes in tick size and the other with changes in tick size. Within each group, stocks are sorted by market cap to form quintiles. Test statistics are computed as $t = \frac{\bar{x}_j - \bar{x}_d}{\sqrt{\frac{s_j^2}{n_j} + \frac{s_d^2}{n_d}}}$, where the means of each measure for December and January are $\bar{x}_d$ and $\bar{x}_j$, respectively; the standard deviations are s_d and s_j, respectively; and the numbers of observations are n_d and n_j, respectively.

Tick size	Large	2	Mid	4	small	all	Large	2	Mid	4	small	all	Large	2	Mid	4	small	all
			Dec-09						Jan-10						test stats			
Number of Trades																		
no change	15.0	7.2	4.0	2.3	1.4	5.7	23.9	9.0	4.5	2.6	1.9	7.9	8.6	3.5	2.8	2.0	2.6	9.4
changed	12.1	4.9	2.1	1.9	2.3	7.7	28.9	7.2	2.6	2.0	4.7	16.6	5.5	3.4	2.2	0.6	–	5.3
all	14.6	6.9	4.0	2.3	1.4	5.8	24.6	8.8	4.4	2.6	1.9	8.5	10.1	4.0	2.9	2.0	2.6	10.6
Size of Trade																		
no change	22.8	4.6	3.0	2.6	3.5	6.9	16.4	4.0	3.1	2.5	3.8	5.7	−2.0	−2.7	0.2	−1.2	0.8	−2.1
changed	15.4	3.1	1.7	2.8	9.5	8.8	11.5	2.2	1.5	2.6	9.4	6.6	−7.0	−3.2	−1.5	−1.4	–	−6.7
all	21.7	4.5	3.0	2.6	3.6	7.1	15.6	3.9	3.0	2.5	3.8	5.8	−2.2	−3.2	0.2	−1.3	0.8	−2.3
Cumulative Volume in five minute																		
no change	444.5	63.4	21.3	14.3	10.1	102.3	452.7	72.8	26.5	15.8	14.7	107.9	0.3	1.1	1.2	0.7	1.7	1.0
changed	187.2	23.6	5.4	10.7	30.0	98.2	237.4	21.6	5.4	9.2	48.9	121.3	1.7	−1.2	0.1	−0.9	–	1.6
all	405.6	59.1	20.8	14.2	10.2	102.0	420.1	67.4	25.7	15.7	14.8	108.7	0.6	1.1	1.2	0.7	1.7	1.2
Quote Revisons																		
no change	45.5	23.5	13.6	7.9	5.0	18.2	110.8	42.6	21.2	12.5	8.7	37.1	14.1	10.3	9.3	6.4	7.1	16.7
changed	40.1	15.8	7.1	6.4	6.0	25.6	125.1	35.0	14.1	11.7	15.3	73.4	7.5	4.9	3.5	2.2	–	7.2
all	44.7	22.7	13.4	7.9	5.0	18.7	113.0	41.7	20.9	12.5	8.7	39.4	15.9	11.2	9.6	6.6	7.2	18.0
Number of observations																		
none	247	260	281	284	290	1,362	247	260	281	284	290	1,362	–	–	–	–	–	–
changes	44	31	10	7	1	93	44	31	10	7	1	93	–	–	–	–	–	–
all	291	291	291	291	291	1,455	291	291	291	291	291	1,455	–	–	–	–	–	–

Table 3. MT model estimation.

Using daily data for December 2009, we estimate the regression model for MT:

$$MT_t = a + b\#ofTrade_{t-1} + cDepth_{t-1} + dTick\_spread_{t-1} + e\log(CapSize_0) + f_t$$

The explanatory variables are *number of trades, depth, tick_spread,* and *log_marketcap*. The dependent variable is the frequency of quote revisions (MT). To avoid the problem of endogeneity, we use the lagged values of the first three explanatory variables and set *log_marketcap* as of the end of November.

Variables	Coefficient	Standard Error	t-value
Intercept	-38.208	0.669	-57.12
Depth(-1)	-6.773×10^{-7}	1.889×10^{-7}	-3.59
#Trade(-1)	2.115	0.008	265.73
Tspread(-1)	0.013	0.014	0.91
LogCap	2.522	0.034	63.91
Adj.R-sqr	0.881		
observations	23,470		

Table 4. Forecasting error of the Message Traffic (MT) model

Using the estimated parameters in Table 3, we compute the predicted MT for January 2010 and the difference between the predicted and the actual MT (i.e., the prediction error). We assume that the difference indicates the degree of change brought about by the HFT, which we call the "HFT effect".

				HFT effect			
		Light	2	Mid	4	Heavy	All
no tick change	Mean	−1.19	1.40	5.21	14.31	56.43	15.26
	St. Dev	1.31	0.67	1.68	4.43	38.03	27.32
	Obs.	272	272	272	273	273	1,362
	t−value	−15.0	34.7	51.0	53.4	24.5	20.6
tick change	Mean	−1.37	6.47	17.67	38.13	83.56	30.66
	St. Dev	2.16	3.78	3.98	8.80	39.56	36.86
	Obs.	18	18	18	18	21	93
	t−value	−2.7	7.3	18.8	18.4	9.7	8.0

Table 5. Spread measures.

The effective spread is the cost of immediate execution paid to the market by liquidity demanders We decompose effective spreads into a realized spread component and an adverse selection or price impact component, See equation (3) in the text.

Panel A: Stocks not affected by tick size change

	HFT Effect	Average	Difference	St.Dev	Sample	t-value
EffectiveSpread	Light	0.267	−0.031	0.129	272	−3.9
	2	0.257	−0.039	0.151	272	−4.3
	3	0.204	−0.018	0.072	272	−4.2
	4	0.140	−0.006	0.050	273	−2.1
	Heavy	0.099	−0.006	0.016	273	−6.1
Realized Spread	Light	0.079	0.017	0.144	272	2.0
	2	0.054	0.015	0.143	272	1.7
	3	0.032	0.010	0.087	272	1.8
	4	0.035	−0.001	0.080	273	−0.2
	Heavy	0.031	−0.014	0.023	273	−10.4
Adverse Selection	Light	0.187	−0.048	0.111	272	−7.1
	2	0.203	−0.054	0.141	272	−6.3
	3	0.172	−0.028	0.088	272	−5.2
	4	0.105	−0.005	0.073	273	−1.2
	Heavy	0.068	0.008	0.020	273	7.0

Note: Difference=Lj−Ld

Panel B: Stocks affected by tick size change

	HFT Effect	Average	Difference	St.Dev	Sample	t-value
EffectiveSpread	Light	0.181	−0.052	0.091	18	−2.4
	2	0.091	−0.057	0.023	18	−10.7
	3	0.080	−0.055	0.016	18	−14.6
	4	0.066	−0.062	0.011	18	−23.6
	Heavy	0.045	−0.072	0.010	21	−31.3
Realized Spread	Light	0.036	−0.001	0.098	18	−0.1
	2	0.007	−0.031	0.016	18	−8.0
	3	0.003	−0.033	0.021	18	−6.7
	4	0.007	−0.045	0.037	18	−5.2
	Heavy	0.013	−0.067	0.016	21	−19.2
Adverse Selection	Light	0.146	−0.051	0.060	18	−3.6
	2	0.083	−0.026	0.032	18	−3.5
	3	0.077	−0.022	0.026	18	−3.7
	4	0.059	−0.017	0.030	18	−2.4
	Heavy	0.033	−0.005	0.011	21	−2.1

Table 6. Determinants of spread change.

We have

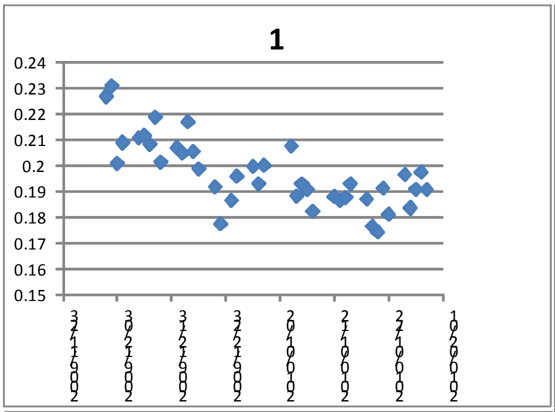
$$\Delta L_i = \alpha + \beta_1 HFT_i + \beta_2 \frac{YenVol_{i,Jan}}{YenVol_{i,Dec}} + \beta_3 \frac{\#Trade_{i,Jan}}{\#Trade_{i,Dec}} + \beta_4 \frac{TradeSize_{i,Jan}}{TradeSize_{i,Dec}} + \gamma \Delta X_j + \varepsilon_i \text{ , (6)}$$

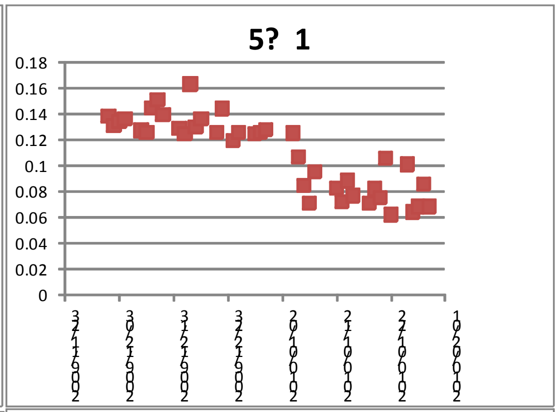
where ⊿Li is $\Delta ESPRD_i = ESPRD_{i,Jan} - ESPRD_{i,Dec}$, the difference in the effective spread between December 2009 and January 2010; *⊿RSPRD*i (realized spread) and *⊿MI*i (market impact) are similarly defined; *HFT*i is a prediction error of the equation in Table 3; $\frac{YenVol_{i,Jan}}{YenVol_{i,Dec}}$ is the ratio of the yen volume on January 2010 to that on December 2009; similarly, $\frac{\#Trade_{i,Jan}}{\#Trade_{i,Dec}}$ is the ratio of the numbers of trades; $\frac{\#TradeSize_{i,Jan}}{\#TradeSIze_{i,Dec}}$ is the ratio of trade sizes, and the Xi are stock-level control variables, including *⊿tickspread*, the difference in tick spread, and *⊿tickspread* x *tick size change dummy,* the difference in tick spread for stocks affected by tick size change, and zero otherwise.

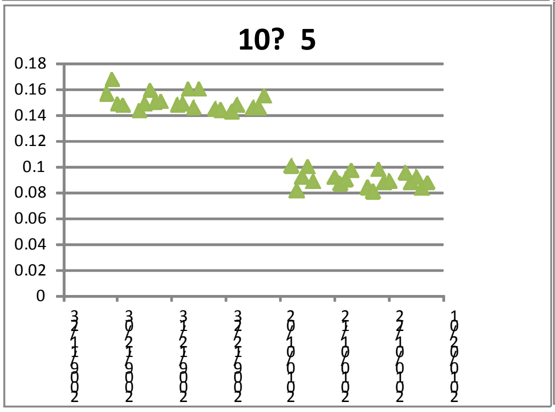
	⊿ESPRD		*⊿RSPRD*		*⊿MI*	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
ArrowheadEffect/100	0.0125	1.82	−0.0407	−3.98	0.0532	5.49
⊿Vol	0.0054	2.42	−0.0027	−0.81	0.0081	2.58
⊿TradeSize	−0.0272	−2.86	0.0157	1.11	−0.0429	−3.21
⊿NumberofTrade	−0.0157	−3.96	−0.0038	−0.65	−0.0119	−2.13
⊿TickSpread	0.0535	41.33	0.0316	16.39	0.0220	12.04
TicChangeDummyX⊿TickSpread	−0.0318	−8.94	−0.0165	−3.12	−0.0153	−3.05
⊿Depth	0.0010	0.55	0.0029	1.08	−0.0019	−0.76
Intercept	0.0228	2.53	0.0046	0.35	0.0182	1.43
Adjusted R−squared	0.561		0.173		0.129	
Observation	1,455		1,455		1,455	

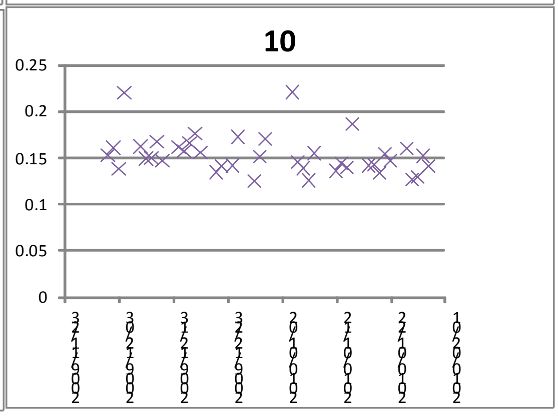
Figure 1. Effective spread (daily, tick range).

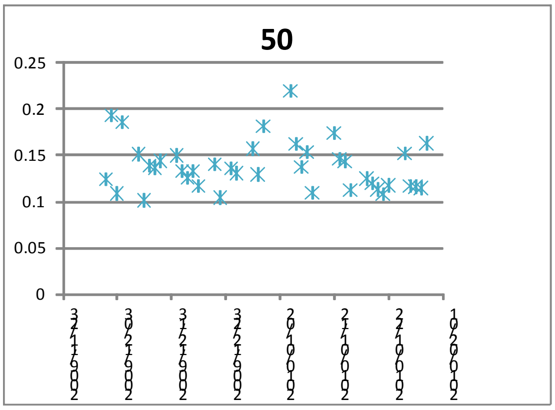
Daily movement of effective spread is computed as an average of effective spread for stocks belong to each price range defined in Table 1. Stocks moves in and out of the price ranges are excluded. The title of the chart indicates size of tick (before and after the Arrowhead).

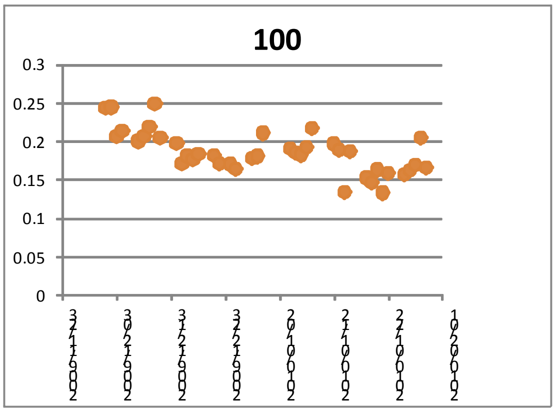

1
0.24
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0.15

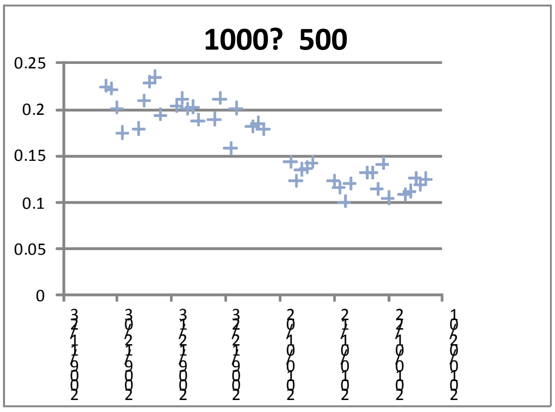

5? 1
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0


10? 5
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0


10
0.25
0.2
0.15
0.1
0.05
0


50
0.25
0.2
0.15
0.1
0.05
0


100
0.3
0.25
0.2
0.15
0.1
0.05
0


1000? 500
0.25
0.2
0.15
0.1
0.05
0

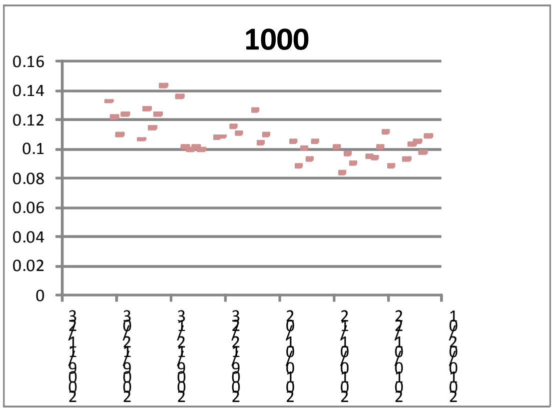

1000
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0

Figure 2. Percentage changes in depth

Depth is computed as an average of best ask-book and bid-book for individual stocks. Then we compare them between December 2009 and January 2010.

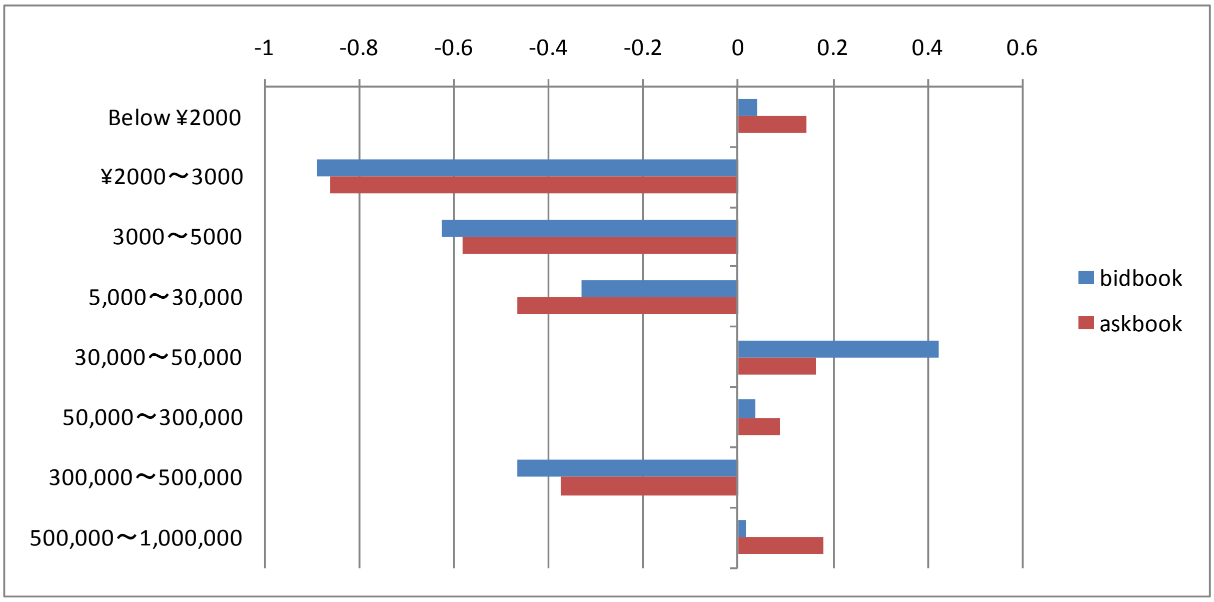
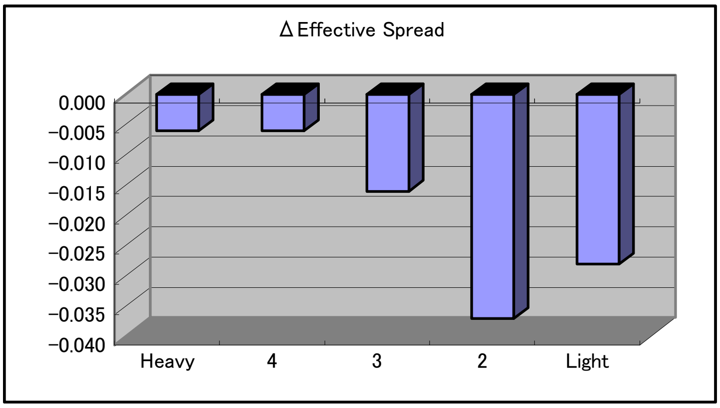
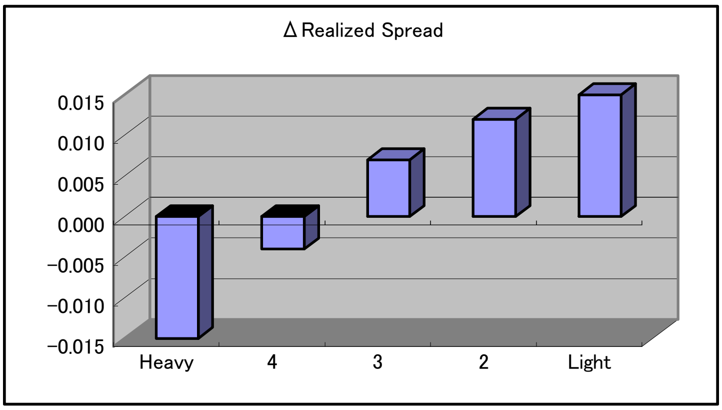


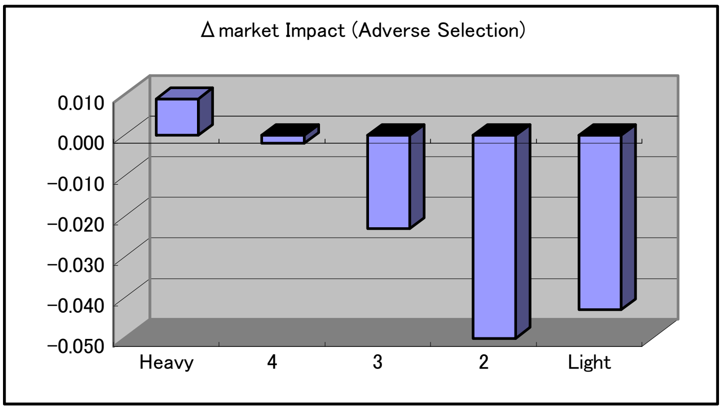
Figure 3. Spread changes by HFT effect quintiles.

Panel A: Stocks not affected by tick size change

Bar charts indicate difference in effective spread, realized spread and market impact in the Panel A of Table 5.







Panel B: Stocks affected by tick size change

Bar charts indicate difference in effective spread, realized spread and market impact in the Panel B of Table 5.