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Analysis of High-frequency Trading at Tokyo Stock Exchange

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Abstract

The main purpose of this paper is to analyze the impact of high-frequency trading (HFT) on price formation and liquidity in the Tokyo Stock Exchange (TSE) market. Analysis revealed that HFT firms tended to place more orders than non-HFT firms during auction trading sessions, most HFT orders could be classified as "make" orders, the ratio of HFT orders which restrain price movements is higher than that of conventional orders, and the execution of HFT orders tended to restrain directional price movements. These observations suggest that HFT firms at TSE adopt a market making strategy known as electronic liquidity provision.

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1. Introduction

Financial markets have recently seen an increase in millisecond trading strategies aimed at garnering profit from repeatedly trading at high speeds to accumulate small margins. This form of trading is commonly known as high-frequency trading (HFT) and, according to TABB Group (2013a, 2013b), HFT respectively accounted for 52% and 35% of all equity trading in the US and Europe in 2012. HFT is reportedly increasing in Japan after the Tokyo Stock Exchange (TSE) replaced its equity trading system in January 2010, and executions are becoming increasingly frequent and in smaller lots.[1] As a new trading technique whose presence is gradually increasing in the securities market, many aspects of HFT continue to remain unclear, and this has given rise to criticism that HFT is responsible for sudden volatility in the market. This paper

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seeks to analyze the effect of HFT on price formation and liquidity in the TSE market based on actual data.

2. Earlier Studies

(1) Definitions of HFT and Features of Earlier Studies

The financial industry does not offer a clear definition of HFT, and the authorities in various jurisdictions are also currently attempting to define it. In Ferber, M. (2012a), which was submitted to the European Parliament Committee on Economic and Monetary Affairs, an HFT firm is defined as one that satisfies at least four of the six conditions below:[2]

(1) Uses co-location service

(2) Daily trading value is at least 50% of the portfolio

(3) Order execution rate is less than 25%

(4) Order cancellation rate is more than 20%

(5) More than half of positions are offset by intraday positions

(6) Receives rebates on more than 50% of transactions or orders

(2) Earlier Studies on HFT Trading Strategies

The strategies employed by HFT firms are based on a diverse range of algorithms, making it difficult to classify them all under a certain trading pattern. ASIC (2010) categorizes HFT activity strategies into three elements – (1) electronic liquidity provision, (2) statistical arbitrage, and (3) liquidity detection. Electronic liquidity provision involves displaying both bid and ask quotes in a role similar to that of a market maker. Gomber et. al. (2011) further defines this category into (a) spread capturing and (b) rebate-driven strategies. Strategies that accumulate gains from the spread of executed quotes would fall under (a), while (b) would be those that center on garnering profit from rebates on executed trades.[3]

(3) Empirical Analysis of Impact of HFT on Stock Markets (US/Europe)

Empirical analysis of the impact of HFT on the stock market is increasing in the US and Europe, with many studies indicating that HFT supplies liquidity. Brogaard et. al. (2013) points out that HFT has contributed to improved price discovery and market efficiency by, for instance, providing liquidity in the form of orders that sought to address temporary mispricing in times of high volatility.

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[2] The definition in Ferber, M. [2012a] was a draft that was later finalized in Ferber, M. [2012b], where an HFT firm is defined as one that satisfies the third condition of an order execution rate less than 25%, and at least two of the other five conditions listed in Ferber, M. [2012a].

[3] Some exchange markets in the US and Europe adopt a maker-taker system where the exchange trading fee is the difference between the rebate given to the party that provides liquidity by placing a limit order (maker) in the order book and the fee charged to the party that takes liquidity by matching the order (taker).

Hasbrouck et. al. (2012) also suggests that HFT contributed to narrower spreads and increased depth, and could alleviate short-term volatility.

Studies on the Japanese market compare market conditions before and after the launch of the “arrowhead” trading platform (Uno and Shibata, 2012; Ohta, 2013; and Arai, 2012) and focus on how the speed of trading has increased after “arrowhead” launch (Uno, 2012). While studies on high speed trading and HFT may be considered to overlap, there are no past studies of the impact of HFT on the TSE market that differentiates between HFT and non-HFT, or conventional, orders. This paper is the first attempt at an empirical analysis of the impact on price formation and liquidity on the TSE market using TSE intraday data.

3. Data Sources and Estimates

(1) Data Used in Analysis

This paper analyzed TSE intraday data for order book reproduction with permission from TSE. Data for order book reproduction refers to a database that enables all transactions of all stocks on the TSE market to be reproduced.[4] The data is more detailed than that provided by TSE's FLEX Full market data feed and includes details on individual orders (order timestamp, order price, quantity, execution conditions, category flags, etc.) and executions (timestamp, execution price, quantity, etc.).

To cover different market conditions, the following data periods were selected for analysis:

- Light trading in a relatively flat market: 1-30 September 2012
- Rising market: 4-31 January 2013
- Falling market: 23-24 May 2013

(2) Estimates of HFT Orders

Since TSE does not identify the originating investor for each order, the data used in analysis does not contain information on investor attributes. This posed an issue in identifying whether the originating investor placed an HFT order. As such, for the purpose of identifying HFT orders, this paper applied the definition suggested in Ferber, M. (2012a) — orders that were placed by virtual servers and had execution rates of less than 25%[5], and cancellation rates of more than 20%[6] (see Fig. 1). Virtual servers refer to logical devices set up in trading participant systems to send and receive data/messages to and from the TSE matching engine. Since each virtual server is subject to an upper limit on the number of orders it can place per second, trading participants normally set up

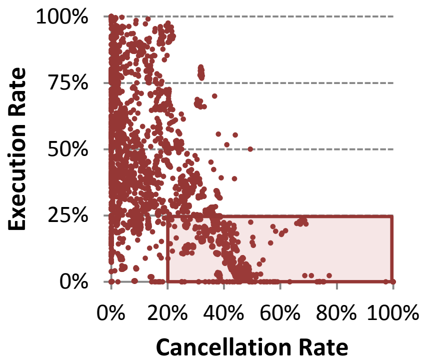
[4] Data for order book reproduction includes information on the trading participant that placed the order. However, analysis in this paper was conducted using data in a manner that does not identify the originating trading participant.

[5] No. of executions/No. of orders placed

[6] No. of cancellations/No. of orders placed

multiple virtual servers for trading. In addition, while the corresponding relationships and interactions between end-investors and trading participant virtual servers are dependent on the trading participant's system configuration and cannot be fully understood from exchange data, trading participants are able to apply to set up or remove virtual servers at any time based on their needs. Since trading participants are expected to accommodate the needs of new investors, particularly those engaged in HFT, by setting up dedicated virtual servers, this paper assumes a corresponding relationship between applications by trading participants to set up virtual servers with HFT end-investors.

Fig. 1 Distribution of Virtual Servers (Sep 2012)[7]



(Source: TSE)

(3) Stocks Selected for Analysis

Stocks for analysis were limited to domestic stocks listed on the TSE 1st Section. For the purpose of analyzing the impact of HFT on price formation and liquidity, stocks that met any of the following conditions were excluded from analysis to avoid light HFT activity and impact of corporate actions on trading activity.

- Stocks that were newly listed, delisted, or transferred to other market sections between 1 September 2012 and 24 May 2013.
- Stocks that recorded HFT trading value of JPY 50 mil. or less on any single day during the periods for analysis.
- Stocks for which the QUICK principal market is not TSE (OSE-listed stocks, etc.)

373 stocks were selected, covering about 80% of the trading value and market capitalization of the TSE 1st Section.

[7] Each data point in the scatter diagram represents a virtual server. The shaded portion indicates virtual servers considered to have engaged in HFT. The execution rate is derived using the number of execution notices as the dividend (numerator). If a single order were to be filled by more than one execution, this would result in more than one execution notice per order. As such, there may be cases where the execution rate may exceed 100%. It also follows that the sum of the execution rates and cancellation rates may exceed 100%.

(4) Share of HFT Orders/Trading

The share of HFT order and trading value was derived after differentiating between HFT and conventional orders. The results are as shown in Table 1. The HFT share rose from 27.3% to 51.6% in terms of order value and from 17.1% to 25.9% in terms of trading value between September 2012 and May 2013.

Table 1 HFT Share of Orders and Trading

	Sep 2012	Jan 2013	May 2013
Order value	27.3%	44.3%	51.6%
Trading value	17.1%	24.8%	25.9%

4. Empirical Analysis

This paper will analyze HFT order patterns and trading tendencies, and impact on liquidity and price discovery based on empirical data. Analysis will be conducted to test hypotheses regarding liquidity and stock price movement. Since price discovery and liquidity are considered to be based on the given conditions (ie, size of the bid/ask spread and amount of orders quoted in the order book) and ultimately determined by the flow of order matching, matched orders will also be analyzed.

(1) Hypotheses Regarding HFT Activity

Based on the results of earlier studies, the following two hypotheses are set regarding the impact of HFT on the market.

Hypothesis 1: HFT supplies liquidity to the market.

Hypothesis 2: HFT contributes to smoother stock price movement.

Hypothesis 1 is based on the idea that liquidity allows investors to easily buy or sell stocks when they want to. As such, as a precondition for creating a situation where trading can occur smoothly, the hypothesis asks that HFT improves liquidity by supplying quotes that do not execute immediately ("make" orders). Hypothesis 2 was set to validate claims made in earlier studies that HFT reduces volatility and pricing error. Since volatility was understood to be dependent on market conditions rather than HFT activity, analysis was conducted from the perspective of whether HFT exacerbated price moves or involved orders that allowed prices to move in smaller increments and curbed large jumps in stock prices.

(2) HFT Order Tendencies

Order tendencies between HFT and conventional orders were analyzed by comparing the time of a new order and its relationship with the best bid/offer (BBO) price to identify the price bands at which HFT orders are placed. First, orders were classified into auction and off-auction based on their timestamps. Orders placed during auction sessions were further classified based on their relationship with the price of the best bid (in the case of a buy order, or the best offer in the case of a sell order) to create seven categories ((a)-(g)) as shown in Fig. 2 below.

Fig. 2 Categorization by Order Price

(a) Off-auction orders

	Sell vol.	Price	Buy vol.		
(g)->		Market		<-(b) Market order	"Take" order
(f)->	1,000	502		<-(c)	
(e)->	900	501		<-(c) Limit orders that are executed immediately	
(d)->		500		<-(d) Limit orders that narrow the BBO spread	"Make" order
(c)->		499	200	<-(e) Limit orders at the best bid/offer	
(c)->		498	500	<-(f) Limit orders outside the BBO spread	

(g) At-the-close orders

*Prices and sell/buy volumes are indicated as examples.

The distribution of the quoted value of the various order categories across the three analysis periods is shown in Table 2. The ratios in Table 2 are indicated by investor type, HFT or non-HFT, for each order category by quoted value of all orders placed. As a result of the chi-square test of independence of the ratios of HFT and conventional orders, the null hypothesis that the ratios over the analysis periods were the same was rejected at the 0.1% significance level. As such, we can conclude that HFT and conventional orders exhibit different tendencies.

A comparison of the distribution of HFT and conventional orders over the analysis periods revealed several common characteristics. First, in terms of order time periods, off-auction HFT orders only reached 3.7%, less than conventional orders (approx. 10%). In other words, orders placed in the auction sessions made up an overwhelming majority of both HFT and conventional orders. Furthermore, for orders placed in auction sessions, low ratios of (g) at-the-close orders, which are not shown in the order book immediately, for both HFT and conventional ones were observed at 2-5% and 15-17% respectively. This trend in HFT orders can be attributed to algorithms favoring order placement that respond to real-time conditions instead of off-auction or at-the-close orders, which involve uncertainties in price movement until execution.

The ratio of auction orders that took liquidity with immediate execution ((b) market orders and (c) limit orders that are executed immediately) was low at about 5% and 13-20% for HFT and conventional orders respectively over the analysis periods. In particular, market orders accounted for only 0.2-0.3%. Strong HFT aversion to market orders can be attributed to algorithms favoring limit orders to avoid pricing risk that accompanies market orders between order placement and execution due to their nature to execute at the best price in the market. Among HFT orders, there was also a higher ratio of "make" orders ((d) to (f)), which remained in the order book, than "take" orders, which executed immediately. This finding in the TSE market concurs with suggestions by Brogaard et. al. (2013) and ASIC (2010) that HFT firms in effect conduct market making.

The above findings indicate that HFT firms tend to place orders in the auction market that increase the depth of the order book and that HFT order patterns exhibit features that can be strongly identified with liquidity provision. As such, the findings support Hypothesis 1. Returning to the trading techniques defined by earlier studies above in 2.(2), a large portion of HFT in the TSE market can be considered to fall under (1) electronic liquidity provision.

Table 2 Order Categories and Distribution in Quoted Value

Order category		Sep 2012		Jan 2013		May 2013	
		HFT	Conventional	HFT	Conventional	HFT	Conventional
a	Off-auction orders	2.6%	10.1%	3.7%	11.4%	0.7%	9.5%
b	Market orders	0.2%	1.0%	0.2%	1.9%	0.3%	3.6%
c	Limit orders that are executed immediately	6.0%	12.6%	5.3%	18.5%	5.0%	19.8%
d	Limit orders that narrow BBO spread	1.6%	2.1%	2.3%	2.3%	3.8%	3.4%
e	Limit orders at the best bid/offer	18.8%	18.6%	20.5%	18.2%	17.0%	17.2%
f	Limit orders outside BBO spread	65.8%	41.2%	64.8%	30.2%	71.1%	29.6%
g	At-the-close orders	5.1%	14.4%	3.1%	17.5%	2.0%	16.9%
Results of chi-square test of independence		6,750		18,576		10,207	

(3) Resting Time of Orders Near the BBO

Based on the order categories defined in Fig. 2, the two types of orders that improved liquidity, that is increased depth or narrowed spreads, were (d) limit orders that narrow the BBO spread and (e) limit orders at the best bid/order (collectively referred to as "orders near the BBO").

Analysis in 4. (2) above revealed that the volume of such orders was almost the same for both HFT and conventional orders. This section analyzes the behavior of orders near the BBO that were cancelled with a focus on their resting times, which was defined as the time from order placement to the time of order cancellation. The quartiles and averages of the resting times of HFT orders and conventional orders in each price range were calculated. Analysis results are shown in Table 3. Note that orders spanning both the morning and afternoon sessions (ie, remaining in the order book after the noon recess) were excluded from this analysis.

For (d) limit orders that narrow the BBO spread, while maximum and minimum order resting times for both HFT and conventional orders were almost the same, 1st quartile values were lower for HFT orders. The median values for both HFT and conventional orders, with the exception of September 2012, were around one second. As such, the resting times of HFT orders were not exceptionally short. Meanwhile, 3rd quartile values for both HFT and conventional orders also fell within a similar range. The resting times of (e) limit orders at the best bid/offer were also similarly calculated for comparison. The results revealed a similar distribution pattern among (e) limit orders at the best bid/offer but longer resting times than (d) limit orders that narrow the BBO spread.

Based on these findings, we can conclude that while the resting times of HFT orders near the BBO exhibited a trend of being cancelled within a short period of time, this trend was not unique to HFT orders since it was also observed in conventional orders.

Table 3 Resting Times of Orders Near BBO (to cancellation)

	HFT			Conventional		
	Sep 2012	Jan 2013	May 2013	Sep 2012	Jan 2013	May 2013
Min. value	0	0	0	0	0	1
1st quartile	43	95	65	193	206	234
Median	1,020	1,820	1,190	3,924	1,406	1,366
3rd quartile	10,261	8,090	5,980	11,586	13,044	7,398
Max. value	8,997,393	8,998,875	8,998,767	8,998,834	8,996,836	8,865,354
Average	57,978	30,701	18,220	74,190	74,828	27,412

Units: milliseconds

(4) Trading Value by Order Type

After analyzing whether HFT and conventional orders contributed to market liquidity in 4.(2) and 4.(3), this section will analyze matched orders to determine whether HFT provided or took liquidity. First, the trading value of all auction orders falling under (b) market orders and (c) limit orders that are executed immediately was considered “take” trading value, and the trading value of orders that were matched by such orders was considered “make” trading value.[8] The ratio of “make” trading value for HFT trading was obtained by dividing HFT “make” trading value by overall HFT trading value, likewise for conventional trading. The ratios are shown in Table 4.

First, figures for HFT “make” trading value were around 60%, and “make” orders accounted for the majority of overall trading. The “take” and “make” trading values for both categories were then calculated and a test for difference was conducted on the ratios for HFT and conventional trading. The test results found that HFT “make” ratios were higher at the 5% significance level. Further examination of the higher HFT “make” ratios revealed similar trends in values on both buy and sell sides. In a test for difference in the ratios for sell trading value by “make” orders, other than the figures for “make” trading value for September 2012, the null hypothesis that “make” sell values for both HFT and conventional trading were the same was rejected, and, as such, the conclusion was made that they were different.

Therefore, based on the observation that not only were there many HFT orders that provided liquidity, but also that, in terms of actual trading value, there were more “make” orders, we can conclude that HFT contributed to improving market liquidity. This conclusion can be considered to support Hypothesis 1.

Table 4 Ratio of “Make” Orders in HFT and Conventional Trading

	Sep 2012		Jan 2013		May 2013	
	HFT	Conventional	HFT	Conventional	HFT	Conventional
“Take” trading value	42.1%	51.2%	34.9%	54.2%	36.4%	53.8%
“Make” trading value	57.9%	48.8%	65.1%	45.8%	63.6%	46.2%
z-score	2.240		4.300		3.865	

* Table 4 shows the ratios of the value of “make” or “take” HFT/conventional orders to all HFT/conventional trading. Figures were obtained after differentiating HFT and conventional trading, and figures for “make” and “take” add up to 100%.

[8] “Make” trading value includes value due to auction orders that provided liquidity, meaning those that fell under (d) limit orders that narrow the BBO spread, (e) limit orders at the best bid/offer, and (f) limit orders outside the BBO spread, and value due to off-auction orders that were not matched in the opening auction.

(5) Price Movement and Distribution of "Take" Orders

While 4.(4) established the conclusion that HFT orders provide liquidity to the market based on the high HFT "make" trading value, price discovery is influenced by matching due to "take" orders (meaning (b) market orders and (c) limit orders that are executed immediately). This section will seek to validate Hypothesis 2 by analyzing "take" orders and the directionality of price movement to identify whether "take" orders in HFT and conventional trading exacerbated price moves or sought to counter them.

First, in order to analyze order directionality, we identify the direction of the price move (ie, market direction) before the execution of the order. Next, we classify the directionality of the matched "take" order into the following four categories:

(a) Buy "take" order in a rising market

(b) Sell "take" order in a rising market

(c) Buy "take" order in a falling market

(d) Sell "take" order in a falling market

Of the above, (a) and (d) follow the price trend (directional orders), while (b) and (c) oppose it (counter-directional orders). (Fig. 3)

Based on the ratio of directional and counter-directional orders among HFT and conventional orders shown in Table 5, we observe a higher ratio of counter-directional orders in HFT. A test for difference was conducted on the price directionality ratios (composition of directional and counter-directional orders) for HFT and conventional trading. The test results rejected the null hypothesis that the ratios of directional and counter-directional orders in HFT and conventional trading were the same at the 0.1% significance level over the analysis periods. As such, we can conclude that the ratio of HFT counter-directional orders was higher than conventional orders.

Based on the above results, even though the majority of HFT and conventional orders involved directional trading, an investment pattern that follows price trends, since the ratio of counter-directional "take" orders in HFT was higher than in conventional trading, we can consider HFT to exhibit a higher tendency toward opposing price trends. Such HFT activity contributes to smoother stock price movement and supports Hypothesis 2. Furthermore, since similar tendencies were found in HFT "take" order ratios under different market conditions, we can conclude that HFT is not easily influenced by market conditions.

Fig. 3 Categories of Order Directionality

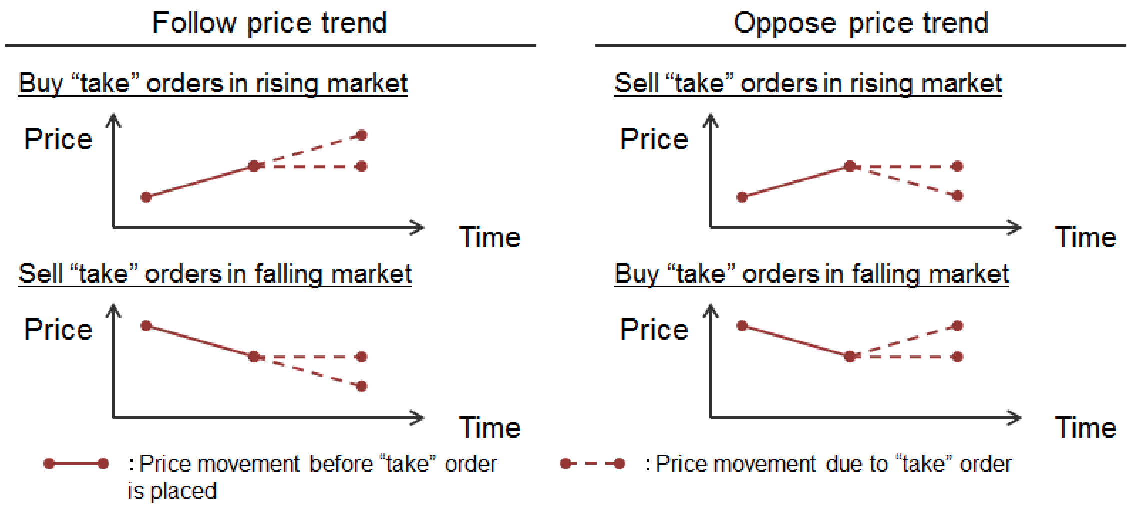


Table 5 Distribution of Directional and Counter-directional Orders by Trading Value

	Sep 2012		Jan 2013		May 2013	
	HFT	Conventional	HFT	Conventional	HFT	Conventional
Directional orders	59.2%	64.9%	59.6%	64.5%	60.2%	62.3%
Counter-directional orders	40.8%	35.1%	40.4%	35.5%	39.8%	37.7%
z-score	2,414,156		3,070,092		1,526,157	

5. Conclusion

This paper used TSE intraday data to analyze the impact of HFT on price discovery and liquidity in the TSE market based on orders that were thought to be due to HFT. The analysis set out to validate the following two hypotheses:

Hypothesis 1: HFT supplies liquidity to the market.

Hypothesis 2: HFT contributes to smoother stock price movement.

First, with regard to Hypothesis 1, analysis of HFT order tendencies revealed that auction sessions saw a greater number of HFT orders than conventional orders, and also involved a greater number of HFT "make" orders, which remained in the order book. The resting times of orders near the BBO before they were cancelled were similar for both HFT and conventional trading. Meanwhile, in terms of contribution to price discovery, a higher proportion of HFT "make" orders were matched than conventional trading. These findings support the hypothesis and establish the conclusion that

HFT firms provide liquidity to the market. It also suggests that HFT firms generally adopt a trading strategy similar to market making, thereby falling under the category of electronic liquidity provision.

As for Hypothesis 2, analysis revealed that HFT orders had a greater tendency toward being counter-directional (ie, opposing price trends) and contributed to smoother price moves. This behavior was seen across all three sets of data from periods that were subject to different market conditions, and suggests that HFT activity is not easily influenced by market conditions.

This paper analyzed the general tendency of HFT orders but did not examine the differences between order tendencies for each issue or execution costs, which directly impact user convenience. This paper only begins to study the impact of HFT on price discovery and liquidity, and recognizes that the above areas remain to be addressed in future research. Furthermore, since algorithms can be expected to be modified constantly, their behavior will need to be continually analyzed.

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References

Arai, R. (2012) "Changes in stock market liquidity and trading costs due to introduction of arrowhead – Analysis from perspective of institutional investors", Securities Analysts Journal 50.(9), pp17-24 (In Japanese)

ASIC (2010) "Australian equity market structure", Australian Securities and Investments Commission Report 215

Brogaard, J. A., T. Hendershott, and R. Riordan (2013) "High Frequency Trading and Price Discovery", ECB Working Paper Series, No. 1602

Ferber, M. (2012a) "DRAFT REPORT on the proposal for a directive of the European Parliament and of the Council on markets in financial instruments repealing Directive 2004/39/EC of the European Parliament and of the Council (recast)", EUROPEAN PARLIAMENT, pp35-36

Ferber, M. (2012b) "REPORT on the proposal for a directive of the European Parliament and of the Council on markets in financial instruments repealing Directive 2004/39/EC of the European Parliament and of the Council (recast)", EUROPEAN PARLIAMENT, pp43-44

Gomber, P., B. Arndt, M. Lutat, and T. Uhle (2011) “High-Frequency Trading”, Working Paper https://deutsche-boerse.com/dbg/dispatch/en/binary/gdb_content_pool/imported_files/public_files/10_downloads/11_about_us/Public_Affairs/High_Frequency_Trading.pdf

Hasbrouck, J. (2012) "Low-Latency Trading”, New York University Stern School Working Paper

Ota, W. (2013) "Long-term effect of increased speed of trading systems on liquidity”, Proceedings of the 21st Annual Meeting of Nippon Finance Association (In Japanese)

Tabb Group (2013a) “US Equities Market 2013 State of the Industry”, Tabb Group Report

Tabb Group (2013b) “European Equities Market 2013 State of the Industry”, Tabb Group Report

Uno, J. and M. Shibata (2012) "Trading speed and liquidity: the case of arrowhead”, Gendai Finance 31, pp87-107 (In Japanese)