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Introduction

As financial institutions' business environments and profit structures change, it is important to understand economic and market trends based on data, and to accurately grasp the business conditions of individual financial institutions and also the resilience and vulnerabilities of the financial system as a whole. From this perspective, the Financial Services Agency (FSA) has been focusing on the utilization of granular data, such as transaction-level bank loan data and financial data on individual corporations. Some case examples of data analyses using such granular data are published as a series of reports titled "FSA Analytical Notes."

This issue contains "Analysis of Impact of High-speed Trading Activity on Market Liquidity and Magnitude of Market Fluctuations." The FSA has been investigating the behavior of high-speed trading (HFT) since the introduction of a registration system for high-speed traders in April 2018. This analysis intends to conduct a more detailed analysis on HFT by focusing on its impact on market liquidity and market fluctuations. Some part of the analysis utilize neural network, a type of machine learning.

While data analysis can provide quantitative and clear results, such results are subject to models and assumptions of the analyses. The data analyses presented here are at the early stage of testing various methods by utilizing currently available granular data while the FSA is still in the process of collecting and accumulating granular data. Therefore, it should be noted that it is necessary to understand the data and model limitations as well as the underlying assumptions and premises and not to draw conclusive conclusions at an early stage when interpreting the results of these analyses.

Enhancing the use of data in financial supervision and policy-making is a medium- to long-term agenda. The FSA will continue to build its data analysis capabilities and data infrastructure.

* Unless otherwise noted, the figures and tables in this report were prepared by the FSA.

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Analysis of Impact of High-speed Trading Activity on Market Liquidity and Magnitude of Market Fluctuations

（Summary）

This paper attempts a detailed analysis of the impact of high-speed trading (HFT) on market liquidity and market fluctuations using order details data for stock index futures contracts during December 2023. Although there were some changes in the trading behavior of HFT depending on the time and the changes in the best quote, in general, a certain level of liquidity supply by HFT was observed during the period. The analysis of the impact of HFT on market fluctuations suggests that, depending on the trading strategy, HFT may contribute to suppressing market volatility in some cases, while in other cases it may contribute to increasing it. The FSA will continue to improve its analytical methods and expand the scope of analysis to better understand the trading behavior of HFT.

I. Introduction

In Osaka Exchange, where financial derivatives are traded, high-speed trading (“HFT”)[1] accounts for 35-55% of the market in terms of trading value, and 93-97% in terms of the number of orders, including new, modified, and cancelled orders.[2] In order to understand the market mechanism, it is important to analyze the impact of the behavior of HFT.

The Financial Services Agency (FSA) has been trying to understand the behavior of HFT by analyzing detailed order data. Meanwhile, as clarifying the whole picture of HFT traders' activities is not straightforward, market participants have made a variety of evaluations on the impact of the behavior of HFT on the market. Some evaluate HFT positively[3] as providing liquidity to the market by placing limit orders and contributing to tighter spreads.[4] On the other hand, some raise concerns that HFT does not contribute to the improvement of market liquidity due to its frequent use of cancel orders,

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[1] The Financial Instruments and Exchange Act was amended in May 2017 (enforced in April 2018) to require financial instruments business operators who engage in High-Speed Trading to register as registered high-speed traders. There are currently around 50 registered High-Speed Traders. In this report, such persons are referred to as “HFT traders.“

[2] FSA “Trends in High-Speed Trading”
https://www.fsa.go.jp/en/regulated/trends_hst/index.html

[3] FSA Financial Research Center "Characterization of High-Speed Trading"
https://www.fsa.go.jp/frtc/english/seika/srhonbun/20210707_Characterization_of_high_speed_tradingEN.pdf

[4] The price difference between the lowest sell order price (best ask quote) and the highest buy order price (best bid quote).

and that the high speed of HFT increases the magnitude of market fluctuations and leads to market turbulence[5].

For these reasons, this paper attempts a detailed analysis focusing on the impact of HFT on market liquidity and the impact of HFT order behavior on the magnitude of market fluctuations.

The analysis in this paper was conducted using order details data for the central contract month[6] of December 2023 for “Nikkei 225 Futures” and “Nikkei 225 mini,”[7] which are stock index futures that represent the Japanese stock market.

II. Impact of HFTs on Market Liquidity

For the purposes of this chapter, an order is defined as “providing liquidity” when it is placed by a participant within 5 ticks[8] of the best bid/ask quote[9] on the order book.[10] However, since many HFT traders place many cancellation orders, it is questionable whether an order placed just before cancellation can also be considered as having provided liquidity if the order was cancelled immediately after the order was placed. Therefore, in order to more appropriately capture the trend of liquidity provision by HFT, an indicator of market liquidity is defined by taking into account cancelled orders and the duration of liquidity supply in this analysis.

1. Definitions

The “time-weighted average of the order volume within 5 ticks of the best quote” is used as an indicator of market liquidity. The liquidity provision ratio by HFT,, $R_{j,[t_s,t_e)}$, is defined as follows, where t_s and t_e denotes the time interval subject to the measurement and j is buy or sell side of the order book.

$$R_{j,[t_s,t_e)} \coloneqq \frac{the\ avarage\ of\ \boldsymbol{HFT}\ order\ volume\ per\ time\ within\ 5\ ticks\ from\ best\ quote}{the\ avarage\ of\ \boldsymbol{ALL}\ order\ volume\ per\ time\ within\ 5\ ticks\ from\ best\ quote}$$

[5] FSA, “Publication of the Report by the Working Group on Financial Markets under the Financial System Council” https://www.fsa.go.jp/en/refer/councils/singie_kinyu/20170509.html

[6] In futures and options trading, products are divided by expiration dates, and the expiration month is called the “contract month.” The central contract month refers to the contract month with the highest volume among them. The last trading day of “Nikkei 225 Futures” and “Nikkei 225 mini” for the December 2023 contract is December 7, so the data for the March 2024 contract, which is the next central contract month, was used for the period after 7 December.

[7] In addition to the record categories of new order, change order, canceled order, and executed order, the order details data includes the trading category, price, number of orders, order quantity, order conditions, ordering party (including strategy in the case of HFT traders), and time stamps.

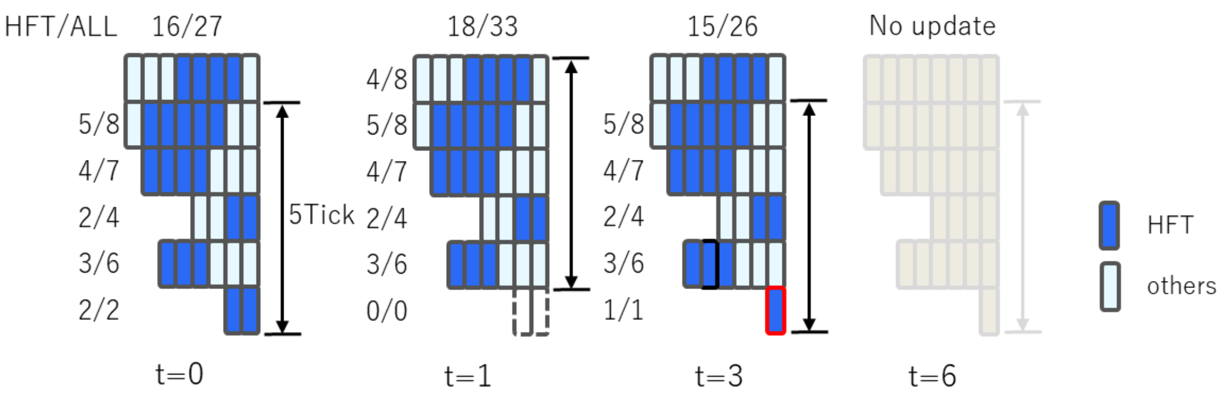
[8] The unit of price tick is called a tick.

[9] The lowest sell order price is called the “best ask quote” and the highest buy order price is called “the best bid quote.”

[10] The counterfoil of an order by issue, which records buy and sell orders from trading participants, is called the “order book.”

As shown in the definition formula, $R_{j,[t_s,t_e)}$ takes a value ranging between 0 and 1, and the larger $R_{j,[t_s,t_e)}$ indicates higher liquidity provision by HFT. Figure 1 shows an example of the calculation of $R_{j,[t_s,t_e)}$. In this case, the liquidity provision ratio by HFT in the time interval t=0 to t=6 for the sell side of the order book, $R_{sell,[0,6)}$, becomes 0.57.

Figure 1: Example of liquidity supply ratio $R_{j,[t_s,t_e)}$ calculation



$$\boldsymbol{R}_{\boldsymbol{sell},[0,6)} = \frac{the\ avarage\ of\ \boldsymbol{HFT}\ order\ volume\ per\ time\ within\ 5\ ticks\ from\ best\ quote}{the\ avarage\ of\ \boldsymbol{ALL}\ order\ volume\ per\ time\ within\ 5\ ticks\ from\ best\ quote}$$

$$= \frac{\frac{16 \times 1 + 18 \times 2 + 15 \times 3}{1+2+3}}{\frac{27 \times 1 + 33 \times 2 + 26 \times 3}{1+2+3}}$$

$$= 0.57$$

Calculation R in t∈ [0,6) when the sell board is updated at t=0,1,3

2. Liquidity Provision Ratio by HFT

In this section, the liquidity provision ratio by HFT $R_{j,[t_s,t_e)}$[11] is calculated hourly for the period December 2023.

Figure 2 shows the liquidity provision ratio by HFT for the Nikkei 225 Futures (left panel) and the Nikkei 225 mini (right panel). The ratio for the Nikkei 225 Futures and Nikkei 225 mini are 0.6-0.9 and 0.6-0.8, respectively, which can be interpreted as meaning that HFT is providing a certain amount of liquidity in both cases.[12]

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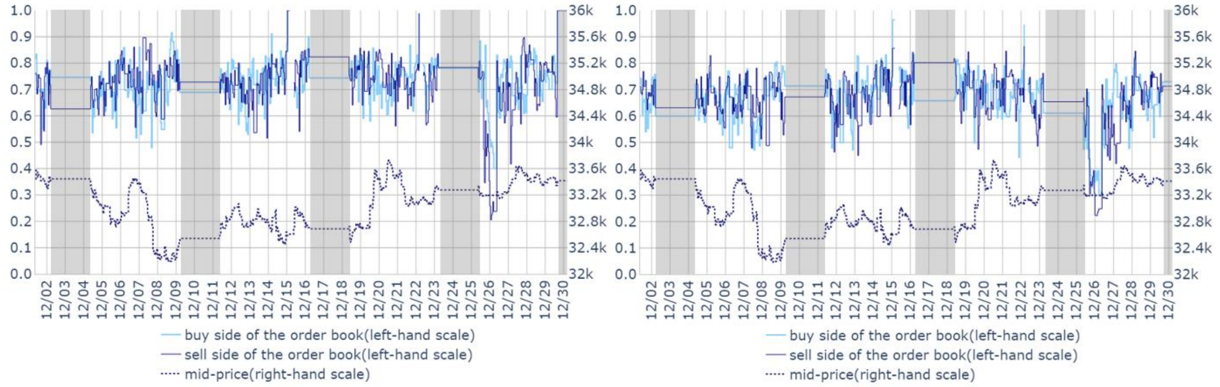
[11] The time interval $[t_s, t_e) \in \{ [t_i,\ t_i + 1hour) \mid\ where\ t_i$ *is one hour increments from 8:00 to 5:00 the next day* $\}$.

[12] The liquidity provision ratio for both the Nikkei 225 Futures and the Nikkei 225 mini declined from the 25th to the early morning of the 26th, but this can be attributed to the fact that trading participants were limited and thus the trading volume was low during this period due

Figure 2: Liquidity Provision Ratio by HFT (December 2023)

(Left: Nikkei 225 Futures, Right: Nikkei 225 mini)



3. HFT's Reaction to Changes in the Best Quote

In this section, in order to analyze HFT's response to changes in the best quote, the relationship between the direction of change in the best quote and the direction of change in liquidity provision ratio by HFT was confirmed.

Specifically, when the best quote P_j changes by $\Delta P_{j,t}$ at a certain time t as shown in Figure 3, first, the difference of the liquidity provision ratio by HFT between the 200 microsecond period starting from the reference point T_i (the closest reference time to t) and the next 200 microsecond period, $\Delta R_{j,T_i}$, is calculated. Next, based on the calculated data, "the conditional probability of the sign of $\Delta R_{j,T_i}$ relative to the sign of $\Delta P_{j,T_i}$[13]" is calculated for each day.

As shown in Figure 4, it is assumed that HFT suppresses the liquidity provision when the spread moves in a widening direction.[14] In other words, the liquidity provision ratio by HFT in the sell/buy side of the order book is assumed to decrease/increase when the best ask/bid quote rises and increase/decrease when the best ask/bid quote falls. To test this hypothesis, the trend of the liquidity

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to the holiday in the U.S. and the European markets.

[13] The conditional probability was calculated by counting the number of cases in which the liquidity provision ratio by HFT increased (decreased) when the best quote rose and also the number of cases in which the liquidity provision ratio by HFT increased (decreased) when the best quote fell. Note that only cases where the best quote of buy/sell and the buy/sell order book of the liquidity provision ratio were the same (i.e. the same j (buy/sell) for both) were included.

[14] The model presented by Avellaneda and Stoikov [2008] argues that when HFT traders hold inventory, they control the execution probability by shifting the limit position in the liquidity provision in order to reduce the inventory risk. For example, they assume that when inventories of buy positions are accumulated, the HFT traders try to prevent the inventories from further increasing by lowering the limit price on buy side of the order book to reduce the probability of execution of buy limit orders, and try to dispose of the inventories by increasing the probability of execution of sell limit orders by lowering the limit price on the sell side of the order book.

provision ratio by HFT (whether it is likely to decrease or increase) on the sell/buy side of the order book when the best ask/bid quote rises or falls.

Figure 3: Calculation of $\Delta R_{j,T_i}$ in this section

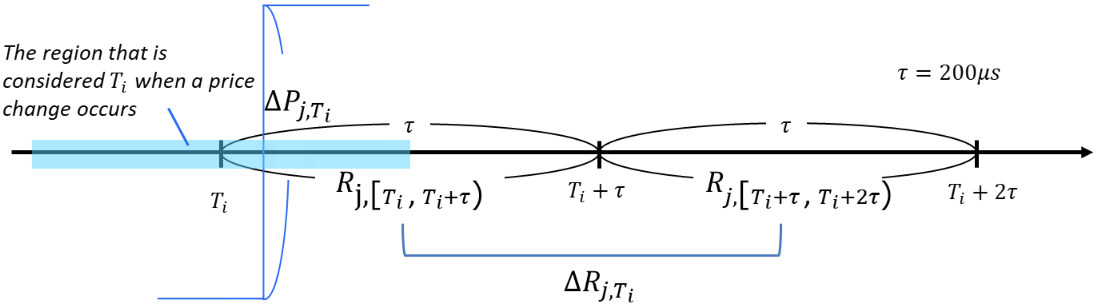


Figure 4: Example of Change in Liquidity Provision in Response to Price Change

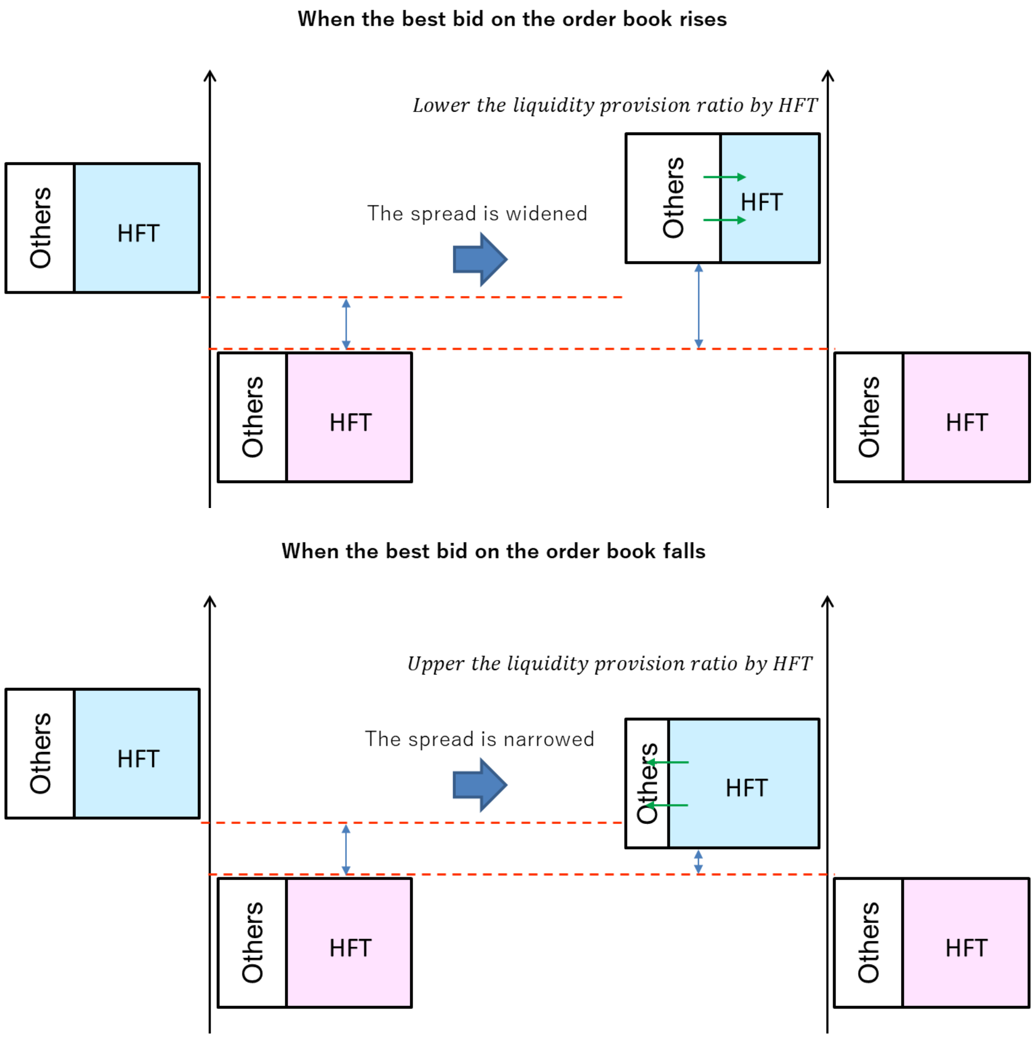


Figure 5 summarizes the results, Figure 6 shows the results for Nikkei 225 Futures, and Figure 7 shows the results for Nikkei 225 mini.[15]

For both Nikkei 225 Futures and Nikkei 225 mini, there was a high probability that the percentage of liquidity provision by HFT decreases when the best quote rises for the selling orders and when the best quote falls for the buying orders (blue area in Figure 5). This result is generally consistent with the aforementioned assumption.

On the other hand, for the Nikkei 225 Futures, there was no significant trend in the increase or decrease in the liquidity provision ratio by HFT except for two business days immediately after the closing day of the December contract month, while for the Nikkei 225 mini, there was a high probability that the liquidity provision ratio by HFT would increase after the day following the closing day of the December contract month (white areas in Figure 5). This result, with some exceptions, was different from the aforementioned assumption. This may be due to the fact that the tick size[16] of the Nikkei 225 Futures, 10 yen, is larger than that of the Nikkei 225 mini, 5 yen, and that, in general, the Nikkei 225 Futures has a larger proportion of institutional investors and a smaller proportion of retail investors than the Nikkei 225 mini.

In addition to the results below, calculations performed while changing τ in Figure 3 from 50 microseconds to 400 microseconds in order to examine the reaction speed of HFT (see Box 1 for the setting of τ), found some interesting indications. For example, the HFT reacted immediately to tightening spreads, as in the case when the best quote declines for selling orders of the Nikkei 225 mini, and HFT moved to increase the liquidity provision ratio. On the other hand, when the spread widened, as in the case when the best quote declines for buying orders of the Nikkei 225 mini, HFT did not react as quickly as the tightening spread, and the liquidity provision ratio by HFT decreased over a relatively long period of time. One possible explanation for this is that HFT has an algorithm that takes a relatively long time before deciding the next order action when the spread widens, or that non-HFT orders may intervene and delay the action by HFTs.

[15] Note that the case where the ratio of liquidity provision by HFT did not change is not plotted.
[16] The incremental range of prices at which it is possible to buy or sell.

Figure 5: Summary of Results

	Nikkei 225 Futures		**Nikkei 225 mini**	
	Sell side	Buy side	Sell side	Buy side
Rise in best quote	Liquidity provision ratio by HFT is likely to decrease.	Liquidity provision ratio by HFT remains almost unchanged, while the two days following the trading end of December contract month is an exception (liquidity provision ratio by HFT is likely to increase for the two days).	Liquidity provision ratio by HFT is likely to decrease.	Liquidity provision ratio by HFT is likely to increase after the day following the trading end of December contract month.
Decline in best quote	Liquidity provision ratio by HFT remains almost unchanged, while the two days immediately after the trading end of December contract month is an exception (liquidity provision ratio by HFT is likely to increase for the two days).	Liquidity provision ratio by HFT is likely to decrease.	Liquidity provision ratio by HFT is likely to increase after the day following the trading end of December contract month.	Liquidity provision ratio by HFT is likely to decrease.

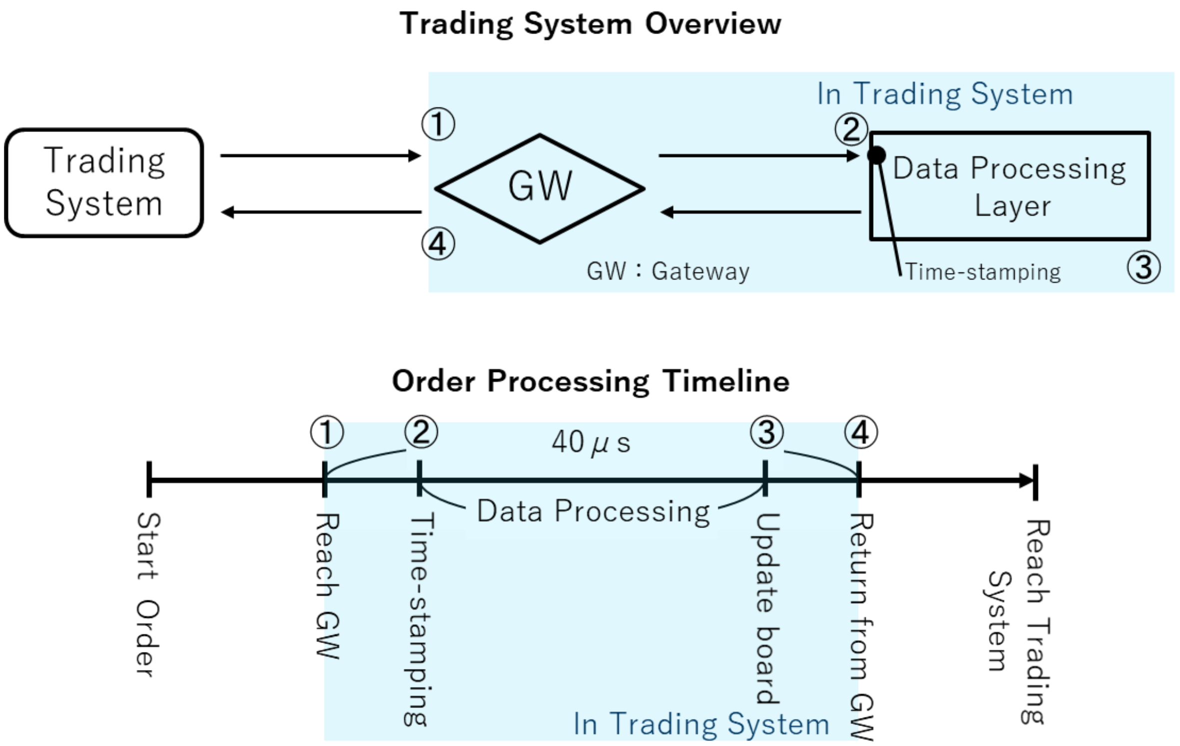
Figure 6: Probability of increase/decrease in the liquidity provision ratio (Nikkei 225 Futures)

Figure 7: Probability of increase/decrease in the liquidity provision ratio (Nikkei 225 mini)

BOX 1: Order processing latency[17] for detailed order data

It should be noted that the time stamp of the detailed order data is recorded at the time of arrival at the data processing layer, and not at the time of placement of the order by the market participant or at the time of arrival at the gateway, which is the entrance to the Osaka Exchange's trading system. This means that if multiple orders arrive at the gateway at approximately the same time, the order of arrival is guaranteed, but not the interval between the arrivals of the orders, since they are processed at the gateway. The order processing latency (50 percentile)[18] of the Osaka Exchange's trading system is 40 microseconds. This means that at least 40 microseconds elapses between the confirmations of the result of one order processing (update of order book information) and the time stamping of the next order placed by the HFT reflecting the result. This implies that τ in Section 3 needs to be at least 40 microseconds in order to confirm the result of the order that changed the best price and to observe the order that reflected it.

Figure 8: Order Processing Overview and Order Processing Latency



[17] The internal processing time measured from the receipt of an order transaction to the completion of order book registration and its response.

[18] https://www.jpx.co.jp/systems/derivatives-trading/01.html

III. Analysis of the impact of HFT on the magnitude of market fluctuations

As described in Chapter I, concerns have been raised that the high frequency of HFT may increase market volatility and cause market disturbances. This chapter will focus on the relationship between the order behavior of HFT and the magnitude of market fluctuations.

1. Outline of Analysis

One of the characteristics of HFT' order behaviors is that in addition to new orders, amend and cancel orders are also ordered in large quantity at high frequency. Therefore, in order to evaluate the impact of HFT's order behavior on the market, it is necessary to evaluate not only the executed order, but also the impact of each order action (new, amended, and cancelled) on the market.

Therefore, in this analysis, a model based on the assumption that the market is fluctuated by the arrival of a series of new, modified, and cancelled orders is constructed, and the execution status is forecast using this model.

Since the impact of each order on the market varies depending on market conditions and is considered to have a very complex relationships, neural network,[19] a model that can represent complex relationships among variables, was used in the analysis.

A neural network is used to model the relationship between the order relationship of order actions and the magnitude of market fluctuation during the Zaraba[20] period for the Nikkei 225 mini (core contract month) order data (intraday auction) for December 2023. Then, the impact of HFT on the magnitude of market fluctuations is evaluated by comparing how the distribution of predicted values of the magnitude of market fluctuations changes between when all order data is input in the model and when order data without HFT is input.

2. Analysis Method

First, "the probability of occurrence of the next order type ($NextOrder_{j,k,l}$) conditioned on the order

[19] A neural network is a type of machine learning model that structure mimics neurons, the nerve cells in the human brain. It can learn complex nonlinear relationships between variables.

[20] The trading time between the regular sessions. In this chapter, *itayose* time is excluded from the analysis.

type that arrived in the market immediately before ($CurrentOrder_{j,k,l}$),[21,22] is defined as follows.

$$\left\{P\left(NextOrder_{j,k,l} \middle| CurrentOrder_{j,k,l}\right)_{[t_s,t_{s+1})} \middle| j \in \{buy, sell\}, k \in \{Enter, Amend, Delete\}, l \in \{take, make\}\right\}$$

For each interval $[t_s, t_{s+1})$ set at 1-minute intervals, a matrix[23] is calculated for all order combinations for subscripts j, k and l.

Next, the neural network is trained with the matrix as the feature variables and the entropy of the contract price in the one-minute period as the dependent variable.[24] The entropy of the contract price is defined as an index[25] that expresses the magnitude of market fluctuation as follows. $P(ContractPrice_i)_{[t_s,t_{s+1})}$ is the probability of execution at the price $ContractPrice_i$ in the interval $[t_s, t_{s+1})$ (here 1 minute), and the character $D_{[t_s,t_{s+1})}$ is the set of index i that identifies the price $ContractPrice_i$ at which the contract was executed during the interval $[t_s, t_{s+1})$.

$$ContractPriceEntropy_{[t_s,t_{s+1})}:$$

$$= -\sum_{i \in D_{[t_s,t_{s+1})}} P(ContractPrice_i)_{[t_s,t_{s+1})} \times log_2 P(ContractPrice_i)_{[t_s,t_{s+1})}$$

The entropy of contract price is an index that evaluates the dispersion of contract prices during the aggregation period. When contracts are executed at various prices (i.e., when there is movement in the market), the entropy of the contract price will be high, and when contracts are executed only at the same amount (i.e., when there is little market movement), the entropy of the contract price will be low. The lower bound is 0, with a mean of 1.34 and variance of 0.51 during the period of tabulation.

Using a neural network model trained in this way, it is possible to predict the values of entropy of

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21 The probability of each type of order coming next when an order of a certain type came immediately before it, in a given minute. For example, if the previous order is a new buy make order, the probability that the next order is a new sell make order is x%, and so on, calculated for each combination and for all one-minute periods.

22 However, the effect of the expired FAK orders (orders with a condition that, if there remains an unexecuted quantity after a partial execution, such remaining quantity will be expired) and FOK orders (orders with a condition that, if the whole quantity is not immediately contracted, the whole quantity will be terminated) was deemed to be negligible, as they do not affect the order book or execution records, and cannot be observed by other market participants. FAK and FOK orders were aggregated only for those that were executed.

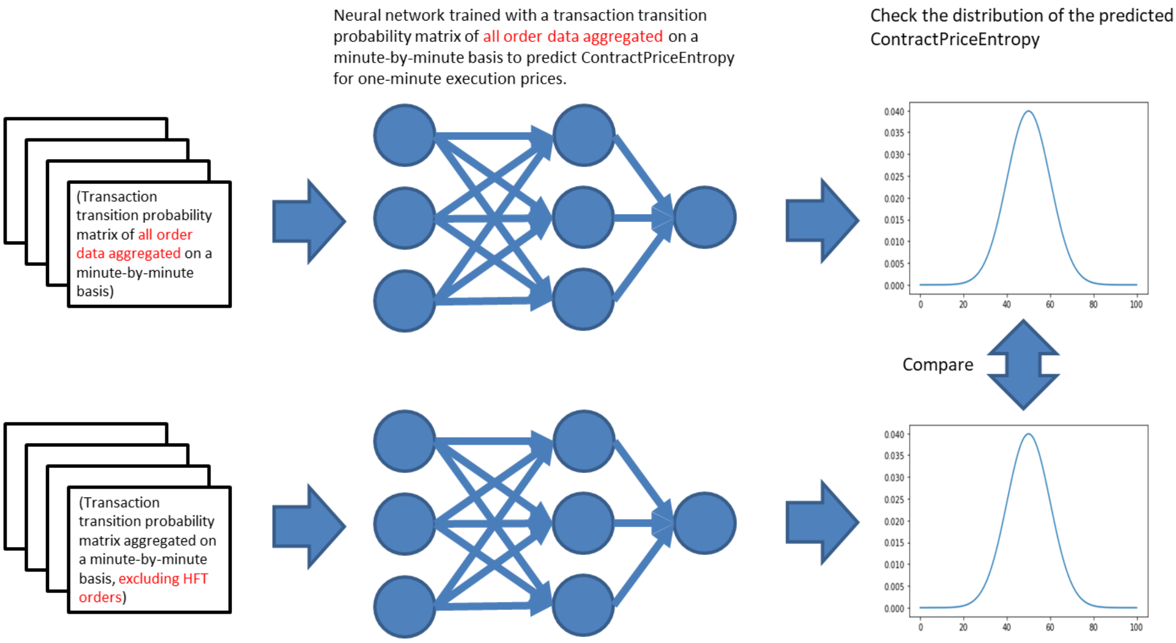
23 When all order data were arranged in time series order, there would be a sequence of order actions, for example, make orders to buy on new, make orders to sell on new, cancel orders to buy, etc. There are a total of 10 types of orders (2 x 2 x 2 + 2 x 1 x 1): sell or buy, new, change, or cancel, and take or make for new or change. This analysis focuses on which type of order comes after a particular order when the orders are arranged in time series order in this way, and the 10 types of $NextOrder_{j,k,l}$ conditioned by the 10 types of $CurrentOrder_{j,k,l}$ that arrived in the market immediately before. With this procedure, a 10×10 matrix is calculated and used as the feature.

24 80% was used as training data and 20% as validation data. A 3-layer neural network was set up, the number of nodes in the middle layer was 252, optimizer was Adam, learning rate was 0.0001, number of epochs was 50, batch size was 50, and the loss function was MeanSquaredError.

25 When estimating volatility in high-frequency financial data, it is known that valid estimates of volatility cannot be successfully obtained by standard methods because the timestamps of order data are arranged at irregular intervals and the spread between the best offer and best bid quotes becomes noise due to execution on both sides. Therefore, in this chapter, as an alternative indicator of volatility, "contract-price entropy," was defined, which is an indicator of the dispersion of contract prices by applying the concept of entropy. It is defined as a quantity that expresses uncertainty (disorder) in information theory, etc. For an application of entropy to financial market modeling, see Marcos López de Prado. "Advances in Financial Machine Learning," John Wiley & Sons, Inc. (2018) (See Marcos López de Prado) or its translation, Daiwa Asset Management (Shintaro Nagao and Torunori Kashiki (translation supervisors)), "Financial Machine Learning," Kinzai Institute for Financial Affairs,2019).

execution price for a specific order probability matrix. Then, the impact of HFT on the magnitude of market fluctuations is analyzed by comparing the two distributions, i.e., the distribution of predicted values of execution prices entropy estimated by using the order probability matrix calculated from all order data and the distribution of which estimated by using the order probability matrix recalculated from data without HFTs' orders.[26] (Figure 9)

Figure 9: Conceptual Diagram of Analysis Method



3. Estimation Results

Figure 10 plots the predicted values of the contract-price entropy against the validation data of the model set up above and the original data. There is a certain proportionality between the predicted values and the original data (correlation coefficient of 0.77 for the validation data[27]), and thus it indicates that the learned neural network model can be evaluated to have a certain forecasting ability for the task.

Figure 11 shows the distribution of the original data against the predicted value of contract-price entropy when all data is input to the model. Although there are some characteristics of the distribution

[26] The probability of occurrence of the next order type $NextOrder_{j,k,l}$, conditioned on the order type $CurrentOrder_{j,k,l}$ is recalculated in the same way as defined in this chapter by removing all order data by HFT and using only order data by non-HFT.
[27] The mean squared error (MSE) is 0.225.

that differ slightly from the original data, such as a multi-peaked distribution[28] due to the characteristics of the data, it can be evaluated that predicted values of contract-price entropy captured the characteristics of the distribution sufficiently, given that the purpose of this study was to evaluate changes in the distribution of the model's predictions when the input data is changed.

Figure 10: Predicted contract-price entropy for validation data vs. original data

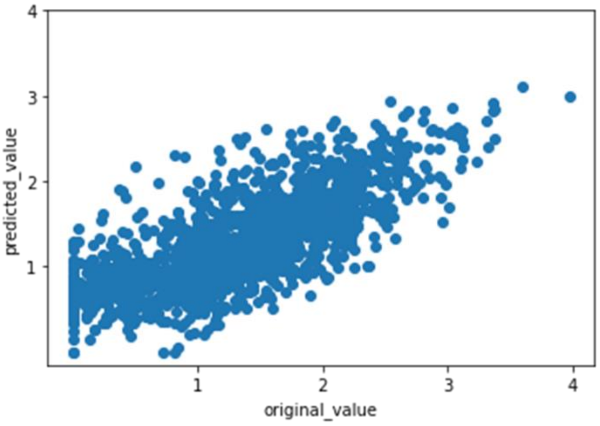


Figure 11: Comparison of predicted contract-price entropy with the distribution of the original data for all data

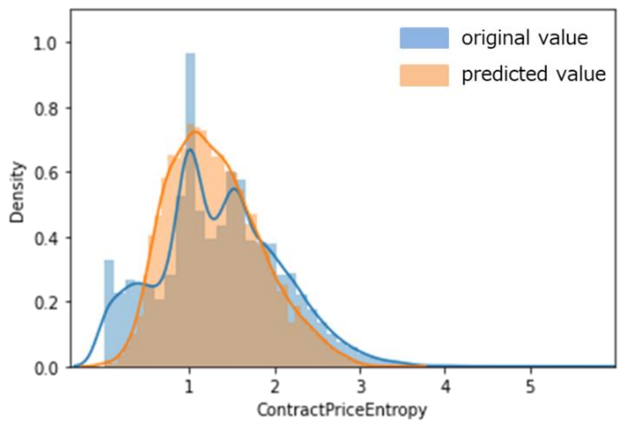


Figure 12 plots the distribution of the predicted contract-price entropy obtained from the data of all orders and the predicted contract-price entropy obtained from data without HFT orders. Comparing the two distributions, the distribution obtained from the data without HFT's orders transitions upward (i.e., greater market fluctuations). This suggests that the HFT is suppressing abrupt market volatility by providing liquidity to the market as a whole.

Figure 13 shows the distribution of predicted contact-price entropy when HFT's order data are removed for each strategy[29] using the same technique. It can be seen that the distribution of predicted values of contract-price entropy transitions upward when the market making strategy is removed from the input data, while the distribution of predicted values of contract-price entropy transitions lower when the other strategies are removed. In other words, this suggests that market-making strategies tend to contribute to reducing market fluctuations, while other strategies tend to contribute to increasing market fluctuations.

However, it should be noted that this analysis is based on two assumptions and thus should be carefully interpreted: (1) other investors behave the same way in the absence of HFT orders as in the

[28] Due to the nature of the data in which execution prices are distributed along the interval of ticks, the entropy of the contract price calculated from such data has the property that the distribution tends to be skewed around a particular value.
[29] Market-making strategies, arbitrage strategies, directional strategies, and other strategies as described in the Supervisory Guidelines for High-Speed Trading Actors III-3-1-1(2)(i).

presence of HFT orders, and (2) the neural network model trained on all data provides valid estimation even when the HFT order data is removed from the input data.

Figure 12: Comparison of the distribution of the predicted contract price entropy when all data is input and when HFTs' order data is removed

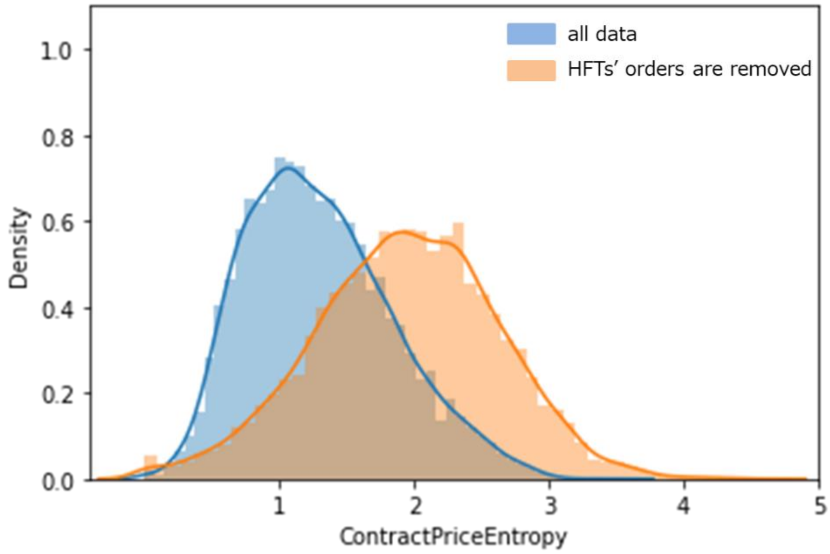
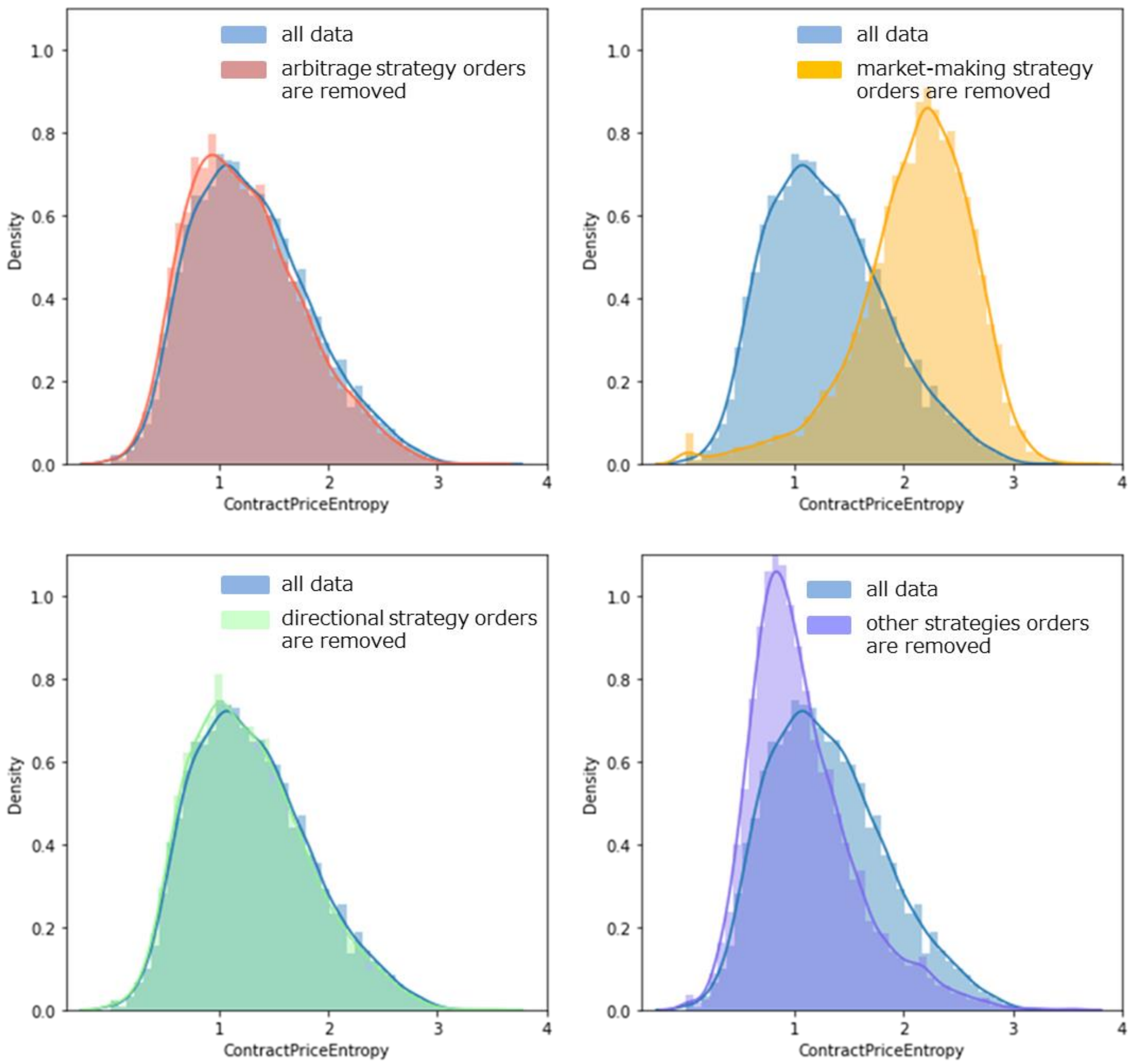


Figure 13: Comparison of the distribution of the predicted contract-price entropy when all data is input and when HFTs' order for each strategy data is removed



BOX 2: Analysis using data from the most recent contract month in December 2023

This chapter analyzed the Nikkei 225 mini for December 2023 using data for the central contract month. This box shows the results using data for the nearest contract month while applying the same analysis method as in this chapter (Figures 14 and 15 below).

It differs in that the analysis in this box uses the data of the nearest contract month, January 2024, after December 8 while the analysis in the main chapter uses the data of the central contract month, March 2024. In general, the central contract month tends to be more actively traded than the nearest contract month, and the January 2024 contract has lower trading volume than the March 2024 contract.

In Figure 14, the distribution of the predicted contact-price entropy calculated from the data without HFT's order shows that the peak of the distribution is collapsed and the left and right hem areas are thicker than the distribution calculated from all data. This result suggests that HFT may contribute to reducing the variance of the magnitude of market fluctuations in markets with low trading volume. The trend in the distribution of predicted values when order data from HFT is removed for each strategy (Figure 15) is the same as when the data for the central contract month is analyzed in the main body of the chapter.

Figure 14: Comparison of the distribution of the predicted contract-price entropy when all data is input and when HFTs' order data is removed

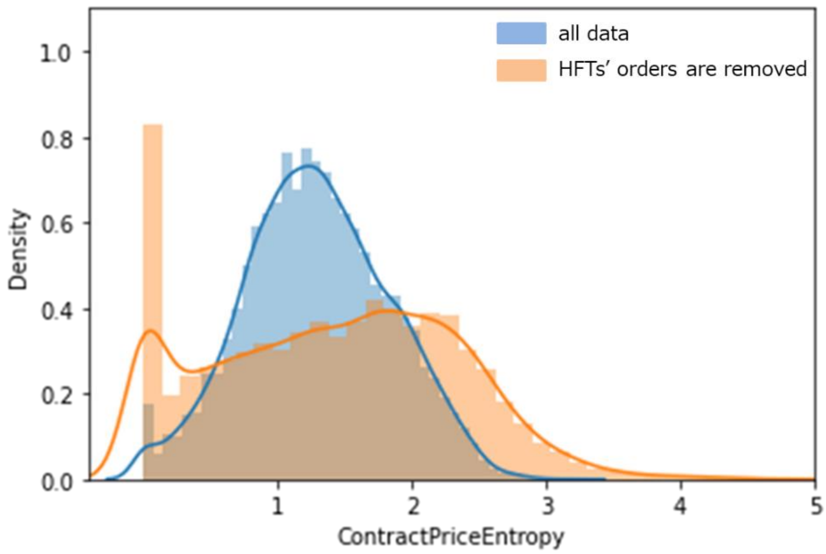
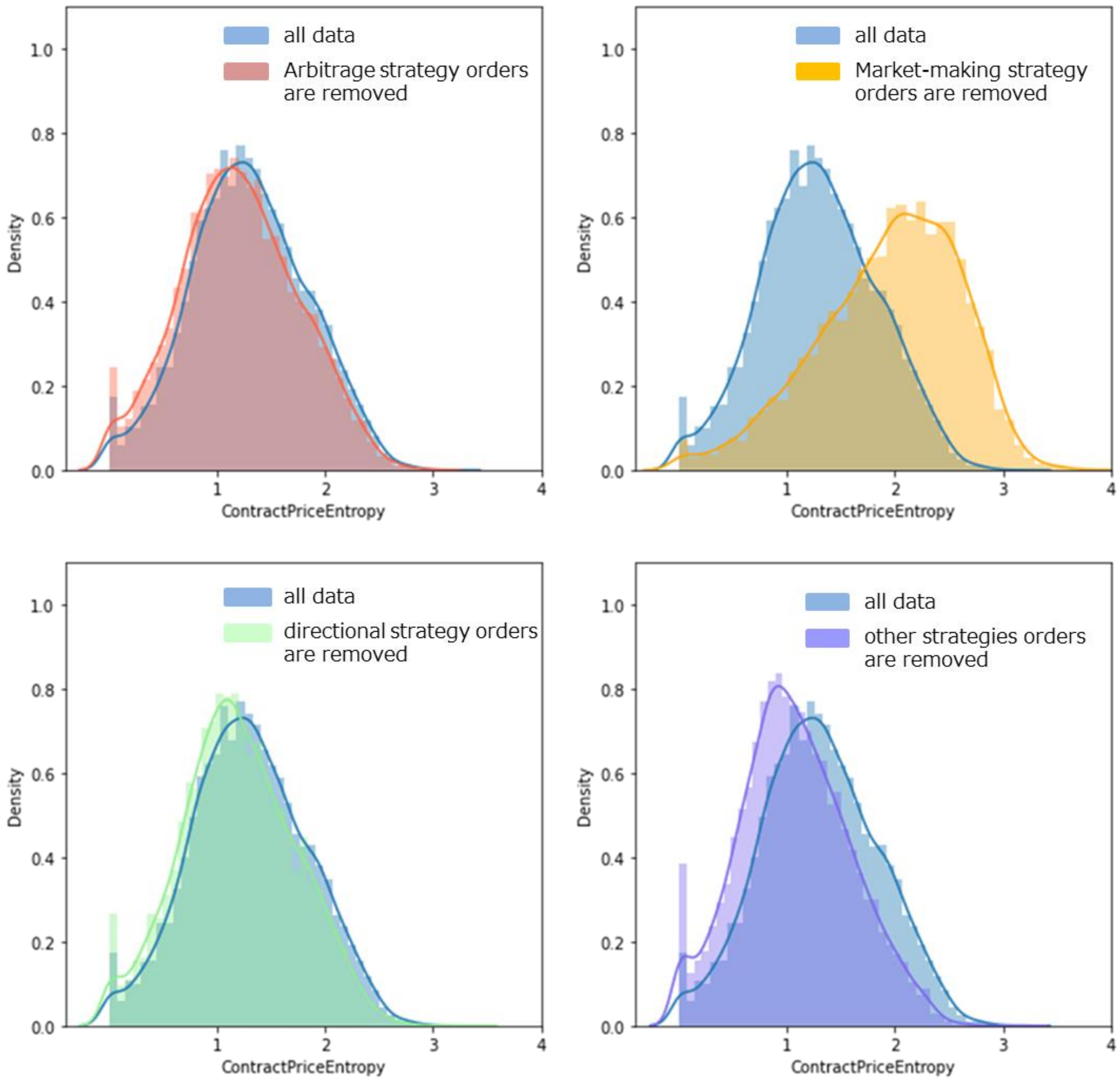


Figure 15: Comparison of the distribution of the predicted contract-price entropy when all data is input and when HFTs' order for each strategy data is removed



IV. Conclusion

This paper attempts to provide a detailed analysis of the impact of HFT on market liquidity and the magnitude of market fluctuations using stock price index futures order data for the month of December 2023 provided by the Osaka Exchange.

The analysis of the impact of HFT on market liquidity indicated that, although there exist variations in the ordering behavior of HFT depending on the time and changes in best quotes, HFT generally provides a certain amount of liquidity even when taking canceled orders into account.

The analysis of the impact of HFT on the magnitude of market fluctuations suggests that, although HFT may contribute to increasing market volatility in some cases due to differences in trading strategies, overall, HFT may tend to trade in a direction that contributes to reducing market volatility.

On the other hand, it should be noted that this analysis is based on the trend during the specific period of December 2023; and that the impact of HFT on the market may vary depending on the market conditions and should continue to be examined from various perspectives. For example, the trading behavior of HFT during volatile markets or when specific events occur may differ from the normal trading behavior of HF. In addition, as HFT traders are thought to be constantly improving and changing their trading algorithms, it would be useful to analyze different periods[30] and products.

The FSA will continue to improve our analytical methods and expand the scope of analysis to better understand the actual impact of HFT trading behavior on the market.

[30] For example, many market participants apparently go on vacation through the second half of December, and such seasonal factors may have influenced the results of this analysis.