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Analysis of Differences in Trading Behavior at Day and Night Sessions for Nikkei 225 Futures

Yasuaki Miyazaki

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Summary

This paper analyzes the impact of differences in investors' trading behavior at trading sessions on the Osaka Exchange, using the exchange's historical order data for Nikkei 225 Futures. Our hypothesis is that because night session trading is skewed toward different types of investors compared with day session trading, night trading is affected by market liquidity metrics that cannot be observed. We classify investor behavior in the form of orders entered in the order book according to an index called "order aggressiveness" and analyze its relation with the factors of trading behavior, using an ordered probit model. There may be some skewing of investor types overall; according to the published data on trading volume by main trading participants, the share of trading by some trading participants is larger in the night session than in the day session. In addition, the shared attributes of order aggressiveness in the day and night sessions indicate that orders tend to be more "aggressive" a) as the depth of the best bid-offer (BBO) on the same side of the order book becomes larger, b) as the depth of the BBO price on the opposite side of the order book becomes smaller, and c) as the latest executed volume becomes larger. Meanwhile, the night session differs in that as price discovery of these orders improves and the established factors of trading behavior and relevance of order aggressiveness grow, the tendency to emphasize depth of the BBO on the same side of the order book becomes stronger and asymmetry between sell and buy orders declines. These results indicate that during night sessions, the ratio of careful-to-trade investors to the overall market increases.

1. Introduction

The Osaka Exchange (OSE), a subsidiary of JPX group, is involved in opening financial products markets that are essential to market derivatives trading. At present (as of June 2016), it handles 23 futures and options products, including futures and options trading on domestic equity indices and long-term interest rates, as well as products based on overseas stock indices and volatility indices.

According to the global derivatives exchange rankings of the U.S. Futures Industry Association, JPX group has not ranked in the top 10 for at least the past several years. These rankings are assessed by the trading volume, which differs from the trading value. Although the results differ by the method of ranking used, the fact is that a large gap exists between the OSE and top-ranked exchanges such as the New York Stock Exchange, which comes under the umbrella of the Intercontinental Exchange (ICE), and the Chicago Mercantile Exchange, part of the CME Group. If one compares globally, one sees that the OSE has both room and the need to grow and is taking various initiatives to accomplish this.

Given that an important role of exchanges is to respond to investors' diverse needs by bringing new products to market, exchanges also need to improve their convenience and security. For instance, from the perspective of the exchange system, circuit breaker rules give investors the chance to make calm decisions while trading is suspended when the market overheats. In addition, OSE has market maker programs for certain products to ensure uninterrupted trading opportunities. Such rules are already common in derivatives exchanges in Japan and elsewhere. With the replacement of the J-GATE derivatives trading system in July 2016, several changes are planned in the trading system. These may include, for example, prohibitions on revising or canceling orders for some products in the one-minute period preceding a single price auction (*itayose*) at the opening or closing and offering features such as ensuring that the OSE systems do not accept orders from trading participants above a certain predetermined amount or volume. Such a setup would improve OSE's credibility in terms of strengthening the order management regime and eliminating uncertainty with regard to price discovery immediately before a single price auction. OSE also plans to expand its trading hours to provide more opportunity to trade. This paper analyzes night session trading.

OSE offers both trading futures and options in the auction market (auction trading) and in other markets outside the auction market (J-NET trading). J-NET trades are equivalent to ToSTNeT trades on the Tokyo Stock Exchange (TSE). This paper analyzes auction trading, not J-NET trading. OSE has auction trading both in the daytime (the day session) and at night (the night session). Although some products are not traded during the night session, most of the futures and options listed on OSE can be traded at night.[1] Note that some exchanges do not differentiate between day and night sessions.

One recent institutional reform at OSE has been the expansion of night session hours. As trading hours

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[1] As of June 2016, the Nikkei 225 VI futures and securities options are not traded on the night session.

have become longer over the past decade or so, the night session's share of trading volume has been rising. In particular, the depth (typically used as an indicator of market liquidity) and BBO spread of the Nikkei 225 Futures, which is OSE's main product, are robust at the night sessions. However, it is generally believed that fewer investors are participating in night session trading, and this could prevent the observation of indicators of market liquidity. The analysis in the paper is driven by the realization that there needs to be a deeper understanding of night session trading as it develops, given the undeniable fact that night session offers trading opportunities, strengthens the price discovery mechanism, and invigorates the market.

Yet, most existing research on the market focuses on equity markets. Since most equity markets do not have trading at night, research on these markets does not address night sessions. Even research on derivatives markets usually omits night sessions, and analyses focusing on night trading are rare. This is probably because these studies do not need to consider the differences between the daytime (morning and afternoon) trading session and night session when analyzing basic trading statistics, and their intent is to facilitate the assessment of analysis results to find correlations with equity markets by aligning trading hours. Another probable reason is that market liquidity is usually lower during the night session than during the day session.

This paper uses the metric known as order aggressiveness to compare the effects of differences in trading session on determinants of trading behavior. This entails analyzing the trading conditions for each order in the market's order flow, using historical order data available from OSE's systems. This paper is organized as follows. Section 2 describes the OSE's night sessions and shows that Nikkei 225 Futures have become the norm in night session trading. Section 3 summarizes previous research on order aggressiveness and other metrics generally used to assess market liquidity. Section 4 explains the data and analytical methodology used in the analysis herein. Section 5 gives our results and a discussion thereof. Section 6 presents conclusions and outlook for the future.

2. Expanding the night session

Here, we present an overview of Nikkei 225 Futures and the evolution of its trading hours on OSE. Nikkei 225 Futures are equity index futures contracts against Nikkei Stock Average, as calculated and published by Nikkei Inc. OSE lists both large contracts with a notional amount per contract of 1,000 times Nikkei Stock Average and mini contracts (Nikkei 225 mini) with a notional amount per contract of 100 times the Nikkei Stock Average. The name Nikkei 225 Futures usually refers to large contracts and this paper analyzes only such large contracts. Equity index futures contracts against the Nikkei Stock Average are listed on CME and Singapore Exchange in addition to OSE.

Nikkei 225 Futures contracts were listed on OSE on September 3, 1988, and night session trading

commenced on September 18, 2007. At first, the night session started at 4:30 and ended at 7:00 p.m. currently, after several changes to trading hours, night session trading ends at 3:00 a.m. the next day. Table 1 presents the changes in Nikkei 225 Futures trading hours since 2006.

Table 1. Nikkei 225 Futures trading hours since 2006

Time period	Day session hrs	Night session hrs	Total trading hrs
–2007/9/14	9:00–11:00, 12:30–15:10	-	4 hrs, 40 min
2007/9/18–2008/10/10	9:00–11:00, 12:30–15:10	16:30–19:00	7 hrs, 10 min
2008/10/14–2010/7/16	9:00–11:00, 12:30–15:10	16:30–20:00	8 hrs, 10 min
2010/7/20–2011/2/11	9:00–11:00, 12:30–15:10	16:30–23:30	11 hrs, 40 min
2011/2/14–2011/7/15	9:00–15:15	16:30–23:30	13 hrs, 15 min
2011/7/19–2016/7/15	9:00–15:15	16:30–3:00 next day	16 hrs, 45 min
2016/7/19–	8:45–15:15	16:30–5:30 next day	19 hrs, 30 min

Expansion of trading hours is significant in two primary respects. First, it offers more trading opportunities and strengthens the price discovery mechanism. With respect to offering trading opportunities, longer trading hours are not only more convenient for existing investors but also attract new investors. In addition, as stated above, Nikkei 225 Futures contracts are listed on three domestic and overseas exchanges, meaning that longer trading hours also facilitate arbitrage opportunities between markets. Interest rates and equity indices and products, which are usually handled by derivatives markets, tend to be sensitive to macroeconomic factors such as major countries' economic indicators; thus, investors have a potential need to hedge against market movements that occur at night.

Improvement of the price discovery mechanism is related to the differences between equity and derivatives markets. Above, we described how night sessions have become the norm for derivatives markets, but the situation differs for equity markets. Although some exchanges have expanded their trading hours, most have not done so. In 2014, TSE considered expanding its trading hours by adding a night session, but this is currently on hold. Meanwhile, expanded trading hours have become the norm in derivatives markets. Currently, Tokyo Commodity Exchange, which is the Japanese exchange for industrial product and grain futures, usually deals in global products such as gold and crude oil; except for a few products, its night session ends at 4:00 a.m. the following day as of June 2016. At the aforementioned CME Group and ICE, many products can be traded at night. Usually, calculation of equity indices comprising individual stocks listed on a market ends when that trading on that equity market closes. Therefore, trading during night sessions tends to be in futures on equity indices, instead of in the equity index itself, which is not updated during the night. Futures, thus, tend to serve as a substitute. As long as the futures are highly liquid, they can usually be considered to be reflective of market conditions; the longer the derivatives market is open and the better the market liquidity, the better the functioning of the price discovery mechanism.

In fact, longer trading hours are believed to have improved market liquidity for the Nikkei 225 Futures at the night sessions. While we will define market liquidity in Section 3, here we will take trading volume as a

criterion. As trading hours have become longer, night session trading volume to total day trading volume (the night session ratio) in Nikkei 225 Futures now exceeds 30% on many days. For reference, Figure 1 illustrates the day and night session monthly trading volumes and the night session ratio from April 2006 through March 2016.

The night session ratio has been continually increasing; since the change to the current trading hours in July 2011, the monthly night session ratio now exceeds 20%. Variations in trading volume due to seasonality and economic trends make generalization impossible, but the graph suggests that Nikkei 225 Futures' trading opportunities and the price discovery mechanism during the night session are improving substantially. Trading hours are now longer during the night session, driving the night session ratio to over 50% on some trading days.
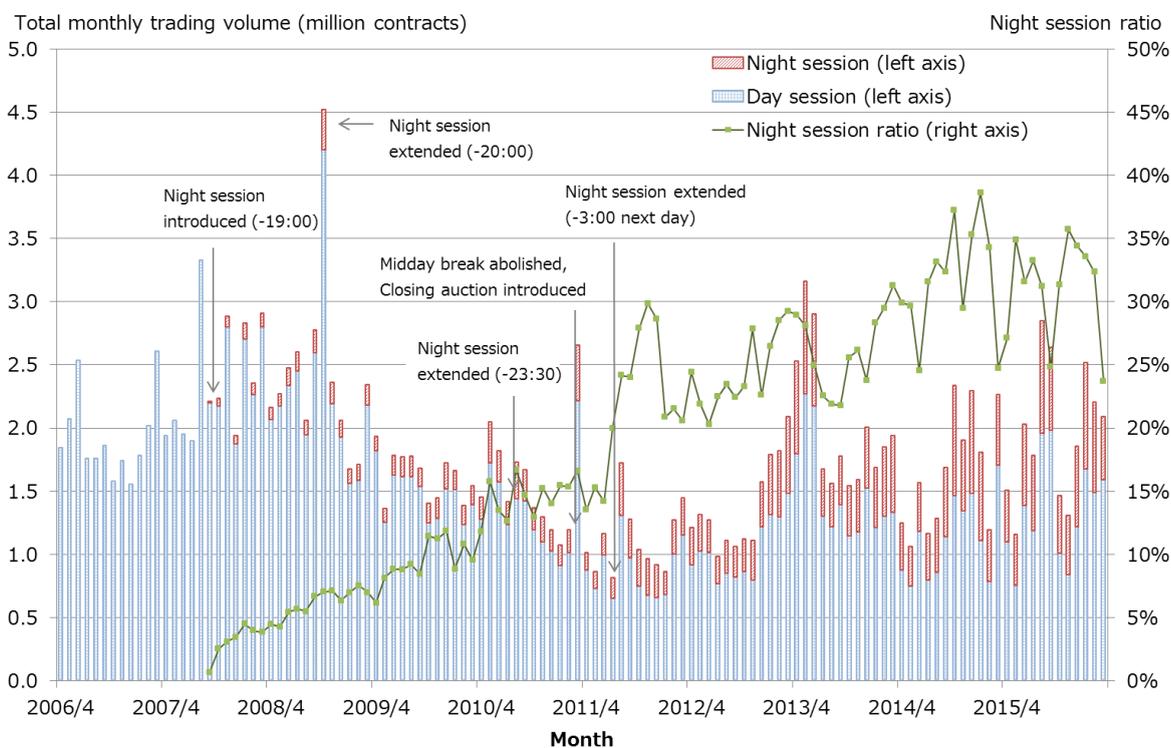

Figure 1. Auction market trading volume in the Nikkei 225 Futures over the past 10 years

3. Previous research

3.1. Market liquidity

We now describe market liquidity, a fundamental metric for analyzing trading in Nikkei 225 Futures. The degree of market liquidity is a major determinant of investors' trading behavior when looking at the market microstructure and at how news affects the market, which in turn influences investor behavior. Market liquidity can be defined in many ways, but it is usually defined, as in the study by Kyle (1985), in terms of tightness, market depth, and market resiliency. Various ways to quantify these concepts have been discussed; however, tightness can be estimated with the BBO spread, and market depth is estimated using order book data to find the depth of the BBO. This paper uses these as metrics of market liquidity. Resiliency, on the other hand, refers to how easily the market returns to its previous state after a fluctuation, which is somewhat difficult to assess or detect. BBO denotes the sell order with the cheapest price quote and the buy order with the highest price quote. The BBO spread is the difference between these two. The larger the BBO spread, the larger the deviation between transaction prices and actual prices. This also means that the greater the BBO depth, the easier it is to execute trades without changing price levels. Even if the BBO spread remains constant, actual costs will change if the price level changes. Although the BBO spread rate, which can assess cost differences as expressed by the ratio of the BBO spread divided by the average BBO (BBO average), can be a useful indicator, it is not used in this paper due to considerations of metric simplicity.

The BBO spread and BBO depth provide useful information in that they can be measured from order book data in real time. Figure 2 presents an example of how they are represented in the order book. In this example, the BBO for a sale is an order for 100 lots quoted at ¥17,010, the BBO for a buy is an order for 200 lots quoted at ¥16,990, and the BBO spread is ¥20 (¥17,010 - ¥16,990) or two ticks.
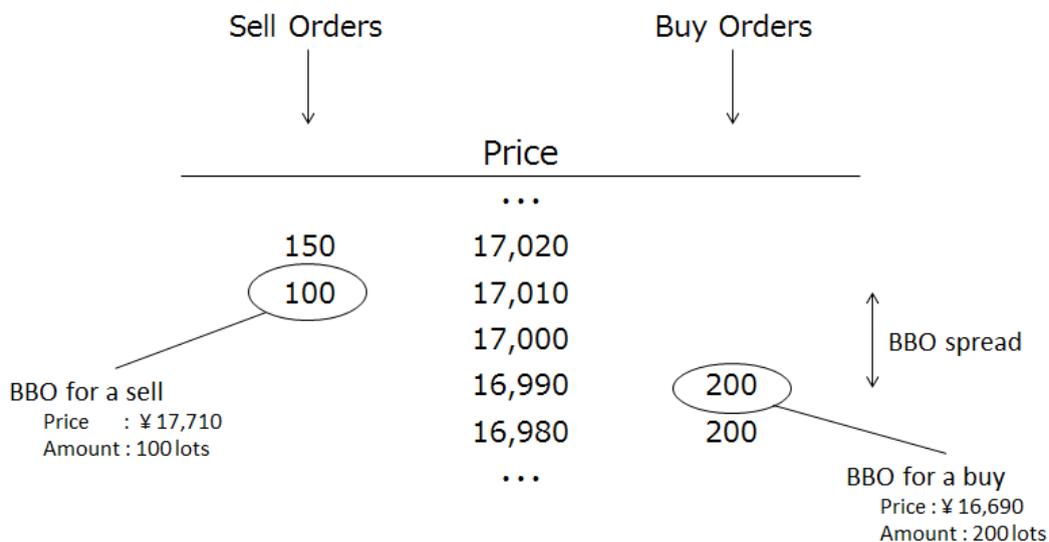

Figure 2. Overview of depth and BBO spreads

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Although some studies on night trading on derivatives markets have analyzed the effect of longer trading hours, no study has focused on the characteristics of the night session. A related study is the one by Aidov (2015), who compared the depth of derivatives trades with that of equities and analyzed depth and other attributes of day and night sessions. However, because this study did not focus on night sessions, it did not explicitly address the features of night sessions. Meanwhile, Michael and Terrence (2003) analyzed price discovery by time period for stocks listed on the U.S. NASDAQ market. Here, we would like to mention that what they called price discovery was a different concept from the price discovery mechanism in which market prices determined by several investors' trades converge to what should be the right price. They used a metric known as weighted price contribution in their analysis of price discovery. They looked at daytime trading in major markets and at electronic communication networks trades that occurred at night after the major markets closed. Furthermore, they measured how the time of day affected the standard return based on the closing prices of the stocks in the sample. They analyzed price contribution by fixed periods of time and found that it was highest during the daytime. However, when they normalized this metric by the number of trades in each time period, they found that the price contribution was highest during the night. From their results, they contended that even in times of low market liquidity, trades are done for a specific reason, so there is more information in each order at night than during the day. Although a simple comparison between the equity and derivatives markets is not possible because of different trading hours, trading systems, investors, and trading objectives, if day and night session orders move differently, the night session may have specific information.

While Michael and Terrence (2003) analyzed trends using a cross-section study, our paper restricts itself to analyzing one futures contract. Therefore, we use order aggressiveness, which we will explain in the following section, to analyze orders placed during the night session.

3.2. Order aggressiveness

A market liquidity metric expresses the characteristics of a market formed by the behavior of many unspecified investors. Many studies have analyzed how price discovery occurs through markets. Among them, Biais, Hillion, and Spatt (1995) proposed order aggressiveness as a metric for measuring the proactiveness of investors' order execution. This study classified orders into the following seven categories.

A. Buy (sell) orders in which the order price, when the order is placed, is higher (lower) than the BBO for a sell (buy)

B. Buy (sell) orders in which the order price, when the order is placed, is equal to the BBO for a sell (buy) and the order size is greater than the depth of the BBO for a sell (buy)

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C.   Buy (sell) orders in which the order price, when the order is placed, is equal to the BBO for a sell (buy) and the order size is not more than the depth of the BBO for a buy (sell)

D.   Buy (sell) orders in which the order price, when the order is placed, is less than (more than) the BBO for a sell (buy) and more than (less than) the BBO for a buy (sell)

E.   Buy (sell) orders in which the order price, when the order is placed, is equal to the BBO for a buy (sell)

F.   Buy (sell) orders in which the order price, when the order is placed, is less than (more than) the BBO for a buy (sell)

G.   Canceled orders

They also defined buy (sell) orders registered at prices higher than (lower than) the BBO for a buy (sell) as a category. These orders have not been entered in the order book at that point in time, so they cannot be compared with the other seven categories in terms of order aggressiveness. The aggressiveness of these seven types of orders is given in descending order. In particular, orders in categories A, B, and C are usually executed as soon as they are placed. Figure 3 indicates the relation between order price and order aggressiveness for buy orders based on the definition of Biais, Hillion, and Spatt (1995). In this example, buy orders at ¥17,020 or higher are A, and buy orders at ¥17,010 are B and C. B and C differ in terms of the order size. In the example, orders larger than 100 lots are B, and orders of 100 lots or less are C. Similarly, orders at ¥17,000 are D, orders at ¥16,990 are E, and orders at ¥16,980 or lower are F. Orders canceled after being placed are G, regardless of the order price.

Biais, Hillion, and Spatt (1995) defined order aggressiveness as categories A through G for discretionary orders entered in the order book, with market orders corresponding to B or C and orders for which the prices were changed after being placed having been classified as canceled orders. Classifying orders in this manner has the advantage of facilitating analysis by the order size. In addition, they asserted that though their analysis indicates that the degree of order aggressiveness changes with market conditions, this does not mean that order aggressiveness completely explains market conditions. According to Muronaga and Shimizu (1999), market liquidity metrics that do not incorporate dynamic trading processes do not reflect potential transaction demand. This implies the existence of information that cannot be obtained from the order book. For example, trading can be restricted by factors other than the desire to trade, such as short selling restriction in equity markets and margin amount requirements in derivatives markets. This problem remains unresolved in our analysis of order aggressiveness.

Sell orders   Buy orders

Order Aggressiveness category as per Biais' definition (for buy orders)

Sell orders	Price	Buy orders	Category
	...		
200	17,060		
200	17,050		
200	17,040		A
200	17,030		
150	17,020		
100	17,010		B, C
	17,000		D
	16,990	200	E
	16,980	200	
	16,970	200	
	16,960	200	F
	16,950	200	
	16,940	200	
	...		

*Canceled orders are classified as G

Figure 3. Example of order price vs. order aggressiveness

Biais, Hillion, and Spatt (1995) investigated order frequency and order volume by category of order aggressiveness. Some later studies, however, used the concept of order aggressiveness to analyze components of trading behavior other than BBO depth and spread. Ranaldo (2004) analyzed the effect of volatility on trading behavior. This study defined volatility as the standard deviation of the change in the BBO mean over a fixed time period immediately before placing of an order. It concluded that as volatility increases, investors stop placing orders. In other words, investors become less aggressive. In addition, Griffiths, Smith, Turnbull, and White (2000) investigated the autocorrelation of orders using recent order aggressiveness. This analysis used order placement as the independent variable and employed a dummy variable that identifies whether order aggressiveness changes immediately before placing an order. Classifying investors by their ordering tendencies, the study also confirmed that asymmetry exists between ordering behavior for buy and sell trades and that, with respect to buy orders, aggressive investors tends to be induced by other investors to place orders. Furthermore, Xu Y. (2009) and Lo, I. and S. G. Sapp (2010) examined the relation between order aggressiveness and order volume and showed that they were negatively correlated. This is consistent with the diversification strategies that have become widespread in recent years. Conversely, Foucault, Kadan, and Kandel (2005) built a market model using the ordered probit method to analyze investors' behavior when the market is in a state of equilibrium. Their study indicates that in equilibrium, market resiliency declines as the ratio of aggressive investors and average order frequency increases.

All the aforementioned studies focused on the equity market. A similar analysis of trading in derivatives market was attempted by Sasaki (2004). The sample trades were Nikkei 225 Futures, as in our paper, and

the analysis focused on the autocorrelation between placing an order and the period until the contract's final settlement day (remaining time to maturity). Unlike equities, futures have a last trading day. For index futures such as Nikkei 225 Futures, orders that have not settled after the last trading day are settled on the final settlement day at the final settlement price. The analysis showed that for buy orders, the shorter the remaining time to maturity, the more aggressive investors became. Further, it suggested that the trading objectives of sellers and buyers could differ.

As discussed above, previous studies have used the metric of order aggressiveness to analyze differences in trading behavior by type of investor and specific factors involved in trading behavior as well as the correlation with execution strategy. However, these studies focused on the equity markets; as far as we know, no research has addressed night sessions. Section 4 gives an overview of trading conditions for Nikkei 225 Futures, the target of this paper's analysis, and identifies the factors in trading behavior in view of these characteristics.

4. Details of analysis

4.1. Data sample

This analysis uses historical order data from OSE. This data encompasses order times, order books, order prices, order volumes, and order types for all orders. The advantage of using historical order data is that it is not necessary to construct order flows to confirm the order placement timeline. Although information vendors and the like can provide tick data for order books with regard to BBO prices and depth for each contract, it is impossible to know the conditions under which each order was placed. Datawise, execution prices may have been set outside the BBO spread immediately beforehand; Lee and Ready (1991) proposed a way to replicate order flows under these circumstances. In our paper, replicating order flows was unnecessary, allowing us to increase analytical accuracy. Note that OSE provides Futures & Options Full Order Information as a real-time data service transmitting data on all orders. Although our paper does not use such data, we were able to conduct a similar analysis using data collected for the periods.

The sample period was the 43 trading days from July 1 through August 29, 2014 (from the opening of the night session on June 30 until the closing of the day session on August 29, 2014). The issue used in the analysis was Nikkei 225 Futures September 2014 contract, the front-month contract for the sample period. In addition, because our analysis focuses on differences between trading sessions, orders during the sample period are limited to those that meet the following conditions:

Condition 1. Orders must be placed in the auction market

Condition 2. Orders must be placed during continuous trading (*zaraba*) (excluding those placed while

dynamic circuit breakers (DCB) under the immediately executable price range rule or static circuit breakers (SCB) under the circuit breaker rule are in effect)

Condition 3. Orders must be entered in the order book

Condition 4. Order must not be placed through calendar spread trading

Condition 1 is a restriction that serves as an assumption of this analysis, but the restrictions in Conditions 2 and thereafter are necessary for the following reasons:

With respect to Condition 2, when DCB and SCB are in effect, trading is halted for a certain period and then resumed in the form of a single price auction (*itayose*). It is thus difficult to evaluate order aggressiveness for orders placed while these systems are in effect. In addition, the same reasons for exclusion apply to the opening auction and closing auction, which are order acceptance periods before and after *zaraba*. However, during the sample period, the sample contract was not subject to either a DCB or an SCB. We omitted the five-minute period after trading opened and before trading closed in both the day and night sessions so that trades during the *itayose* period, which were easy to aggregate, would not significantly influence our analysis. The ratio of the omitted zaraba trades to total zaraba trades was approximately 8.5% for the day session and approximately 2.1% for the night session.

With respect to Condition 3, orders not entered in the order book represent orders that cannot be accepted because of errors when they were placed (unaccepted orders). Reasons for the occurrence of unaccepted orders include the following: (a) the order being immediately invalidated instead of being executed when placed because the conditions for their validity period were fill and kill (FAK),[2] fill or kill (FOK),[3] or the like; (b) the order placed outside the order acceptance period; (c) the establishment of combinations that J-GATE does not handle; (d) the order outside the permissible order volume or order price ranges; and (e) the occurrence of some kind of system malfunction. Unaccepted orders can reflect market conditions, but we omitted them from our sample because it is difficult to evaluate the impact of orders not reflected in the order book.

Let us now discuss the treatment of orders with stop conditions (stop orders). Stop orders refer to orders that when filled "under conditions specified at the time of placement" after J-GATE receives the order, are entered in the order book as having conditions specified at the time of placement. Since stop orders can be placed ahead of time, despite disagreement about how to evaluate their order aggressiveness, we have included them in our sample for the following two reasons. First, even though stop orders specify order conditions ahead of time, they can be regarded as orders that assess market conditions as per the specified conditions, rather than reflecting market conditions at the time of their placement. The second is concerned with our judgment regarding the replicability of our analysis. We previously mentioned that this paper was

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[2] The condition whereby if any unexecuted amount remains after a partial execution of the order, the remaining amount is canceled.
[3] The condition whereby if the entire order is not executed immediately, it is canceled in its entirety.

able to replicate Futures & Options Full Order Information data, which do not differentiate between regular and stop orders filled under conditions specified ahead of time. Therefore, we chose to assess the order aggressiveness of stop orders from order book conditions at the time the orders were entered.

With respect to Condition 4, calendar spread trades are simultaneous trades in the same product for the nearest contract month and a further-out contract month. Calendar spread trading is independent of contracts that constitute it, and the respective order books do not influence each other. Therefore, we have not analyzed orders for calendar spread trades. In addition, OSE does not offer any strategy trades other than calendar spread trades in its futures trading. Note that this did not impact our analysis much because we avoided time periods before and after the change of the central contract month.

4.2. Trading conditions by session

In establishing the sample period, we considered the relatively low influence of market movements after March 24, 2014, when TSE and OSE derivatives markets were merged, and the low impact of reduced liquidity of the front-month contract from the change of the central contract month. Figure 4 illustrates the trend in open-high-low-closing (OHLC) prices for the sample contract during the sample period. Some price fluctuation can be seen on August 8, 2014, and the following trading day. This market fluctuation is probably attributable to U.S. President Barack Obama's approval of Iraq air strikes, which was reported during the daytime on August 8, 2014, Japan time. This seems to have been the most important economic event during the sample period. Figure 5 illustrates the trend in trading volume for Nikkei 225 Futures September 2014 contract during the sample period. For many days, the night session ratio is high at approximately 30%, and the average over the two-month period is approximately 32.4%, approximately the same as the average of approximately 31.4% for all of 2014.
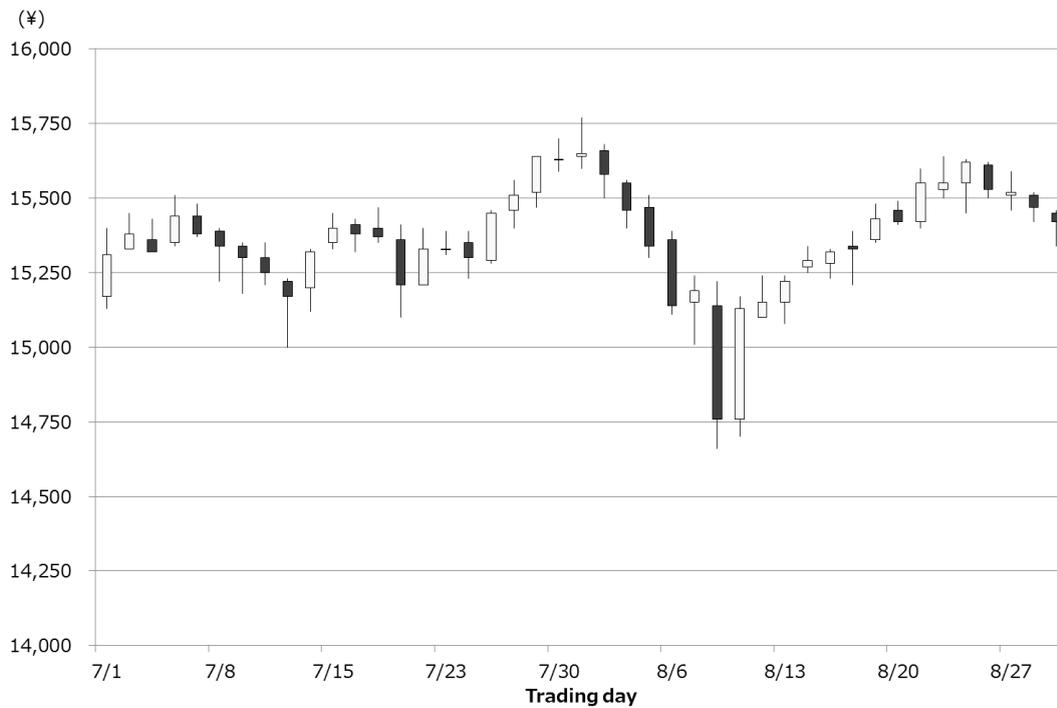
Figure 4. Open-high-low-close (OHLC) prices for Nikkei 225 Futures September 2014 contract
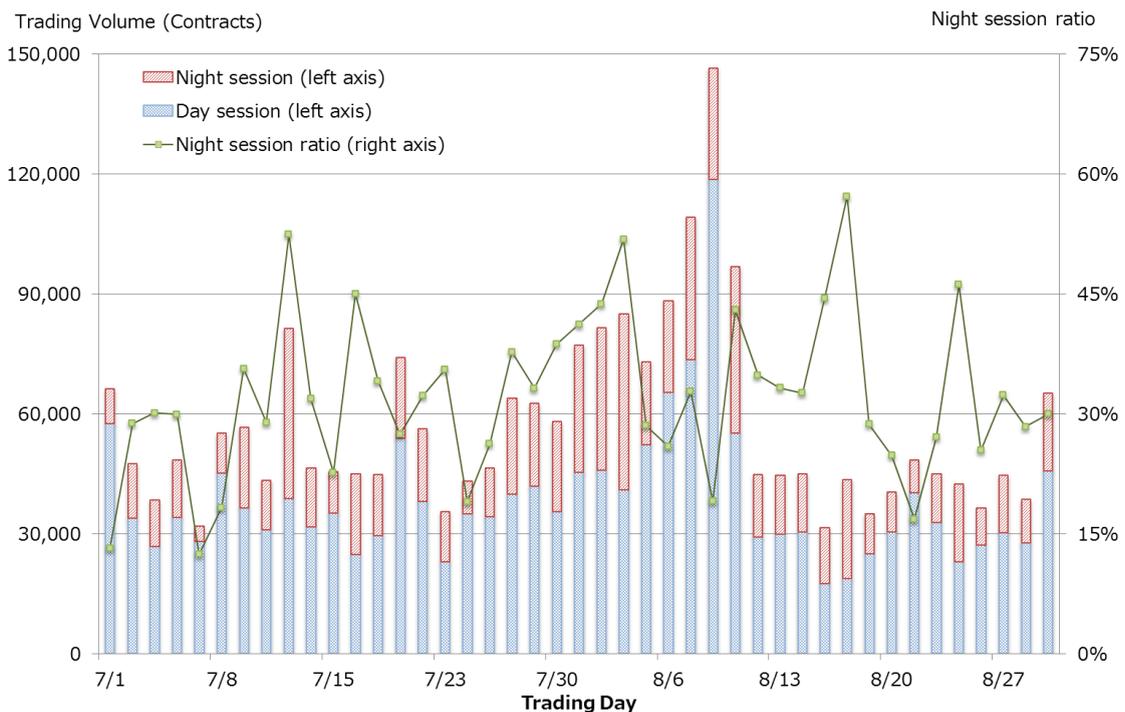
Figure 5. Trading volume for Nikkei 225 Futures September 2014 contract by trading session

In addition, in Section 1, we mentioned the possibility of differences in investors participating in day and night session trading. We can validate this by looking at the list of trading volume by main trading participants published by OSE. Tables 2 and 3 present the top five companies in terms of combined trading volume for sales and purchases of the contract in our sample. Since OSE's list of trading volume by main trading participants gives the top 15 companies for daily buy and sell volumes, we must indicate that the

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aggregate value may differ from actual sell and buy volumes over the same period. Although the top five companies in both the day and night sessions constitute more than 50% of total sell or buy volume, the night session constitutes approximately 70% of this amount. Since this publication gives sell and buy volumes for each trading participant, while we cannot identify the trading situation by an ultimate investor, we can rightly assume that the number of investors participating in these trades is declining overall.

Table 2. Top five companies by sell or buy volume in the day session

Rank	Trading participant	Sell or buy volume (contracts)	Share
1	ABN AMRO Clearing Tokyo	1,072,652	33.2%
2	Merrill Lynch Japan Securities	247,894	7.7%
3	Morgan Stanley MUFG Securities	186,023	5.8%
4	Nomura Securities	179,060	5.5%
5	SBI Securities	141,309	4.4%
	Five company total	1,826,938	56.5%
	Industry total	3,230,686	100%

Table 3. Top five companies by sell or buy volume in the night session

Rank	Trading participant	Sell or buy volume (contracts)	Share
1	ABN AMRO Clearing Tokyo	744,519	47.9%
2	SBI Securities	111,717	7.2%
3	Societe Generale Securities Japan (formerly, Newedge Japan)	95,931	6.2%
4	Merrill Lynch Japan Securities	89,804	5.8%
5	Rakuten Securities	61,313	3.9%
	Five company total	1,103,284	70.9%
	Industry total	1,555,562	100%

Let us measure the depth and BBO spread described in Section 3. The mean depth and mean BBO spread per trading day are time-weighted averages of the BBO depth for sells and buys and the BBO spread. In this case, we can find the BBO spread by dividing the difference between the BBOs for buys and sells by ¥10, which is the increment for a quotation, and then converting the result into a tick number. Table 4 shows the result of calculating the mean depth and mean BBO spread by doing this calculation throughout the sample period and then taking the average for all trading days in the sample period. We have rounded mean depth down to the nearest lot and rounded mean BBO spread to the fourth decimal place.

Table 4. Mean depth and mean BBOspread

Trading session	Mean depth (sells)	Mean depth (buys)	Mean BBO spread
Day session	231 lots	232 lots	1.000 ticks
Night session	156 lots	146 lots	1.003 ticks

As shown in Table 4, the mean BBO spread is about one tick for both the day and night sessions. Meanwhile, depth is less at the night session than the day session, but we looked at whether its level was satisfactory by evaluating the ratio of "taker" orders ("take" orders) in the order book, which were not filled at the time of placement. Here, we define the ratio of unfilled orders as the number of "take" orders that were not filled at the time of placement (number of unfilled orders) divided by the number of trades. Some points should be noted regarding the method of calculating the ratio of unfilled orders. In terms of calculations, when orders are not filled, some "take" orders probably stay unfilled in the order book. When the unfilled portion of an FAK order is canceled, we have not included it in the number of unfilled orders. This is because some FAK orders are well in excess of the BBO depth and the orders would be placed to fill orders at the BBO price, regardless of the size. In this case, the actual size is not meaningful. We decided not to include them in the number of unfilled orders. As such, we did not include orders that were canceld or not executed at all.

Our calculations of the ratio of unfilled orders as per the above conditions yielded a mean ratio of unfilled orders of approximately 4.7% for the day session and approximately 6.1% for the night session. From the perspective of depth, liquidity at the night session would not be better than that of the day session. Yet, it does not mean that market liquidity of Nikkei 225 Futures become significantly lower at the night session because the BBO depth itself is lower. Note that the ratio of unfilled orders, including FAK orders is approximately 8.7% for the day session and 12.0% for the night session. These ratios approximately double those not including the FAK orders, but the trend is the same. A ratio of unfilled orders that better reflects actual circumstances probably lies somewhere between these two levels.

Figure 6 illustrates the results of analyzing the price range distribution from market data. Here, a price range is defined as the absolute value of the difference between the highest price and lowest price during each trading session. The graph's horizontal axis denotes the price range, while its vertical axis denotes the number of days in which the market moved in each price range. During the day session, the most frequent price range was above ¥100 but not more than ¥150; for more than 90% of the sample period, the price range was above ¥50 but not more than ¥200. The widest price range during the sample period was ¥410. At the night session, the price range was above ¥50 but not more than ¥100 about half of the time, and it was ¥50 or less on some days. The widest price range for the night session was ¥270. Thus, although the maximum deviation was higher for the day session, the distribution of price ranges for the two sessions was not different.
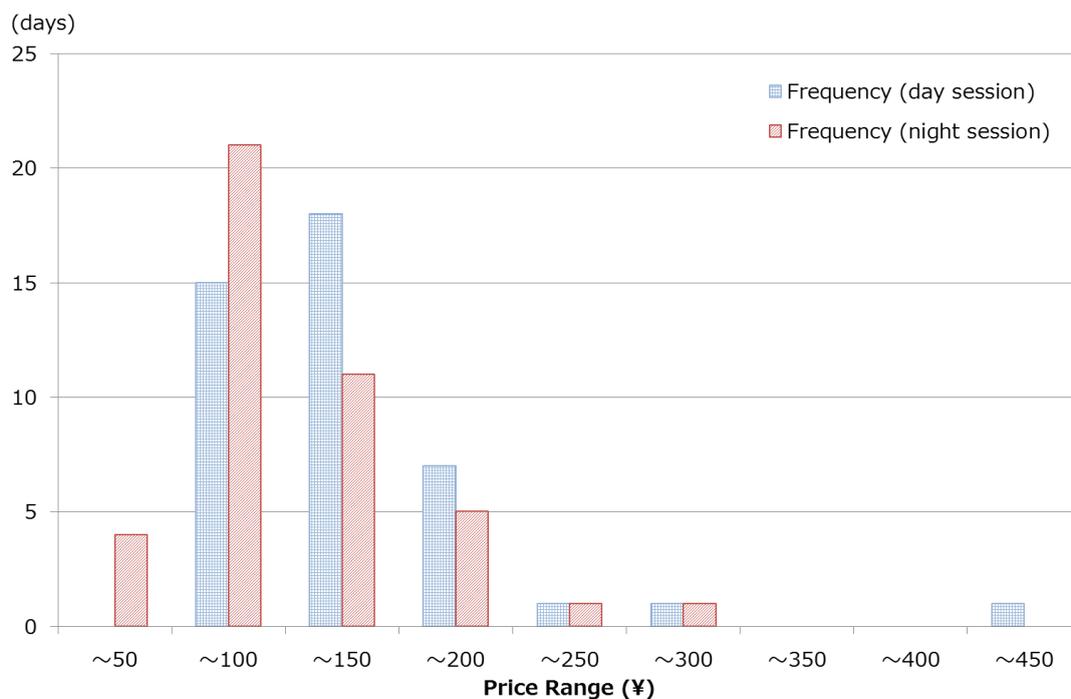
Figure 6. Histogram of price ranges by trading session

Table 5 presents the calculation of order frequency by order price range. Here, better than the BBO price means the quotation for a sell order that is cheaper than the BBO sell price or the quotation for a buy order that is higher than the BBO buy price. Worse than the BBO price means a quotation for a sell order that is higher than the BBO sell price or for a buy order that is lower than the BBO buy price. Same as the BBO price means a quotation for either a sell order or for a buy order that is equal to the BBO sell or buy price respectively. Looking at the results, regardless of the trading session, the majority orders are found to be equal to the BBO price. This is probably because the BBO for Nikkei 225 Futures is deep. In addition, although there is almost no difference between buys and sells in terms of order prices, the ratio of orders at the BBO price is higher during the night session than during the day session, while the ratio of orders that are four or more ticks worse than the BBO price is lower. When we investigated the reason for this, we found that it was because some investors at the day session placed orders at prices that were significantly different from the price at which they were executed. Investors place orders to avoid losing more than a certain amount, and they do not prefer short-term trading in a volatile market. Such orders are not as common in the night session as in the day session because these investors would not trade during the night session. However, this is purely in the realm of speculation, and the precise reasons remain unknown.

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Table 5. Order frequency by order price

Order price	Day session		Night session	
	Sell	Buy	Sell	Buy
Market orders or better of BBO price	3.0%	3.1%	2.0%	2.1%
Same as BBO price	52.9%	53.1%	58.2%	58.1%
1 tick worse than BBO price	26.5%	26.1%	29.2%	29.6%
2 ticks worse than BBO price	3.1%	3.1%	2.7%	2.8%
3 ticks worse than BBO price	1.6%	1.7%	2.9%	2.7%
4 or more ticks worse than BBO price	12.9%	12.9%	5.0%	4.8%

Finally, we summarize market liquidity and investor types during the night session insofar as we can judge from the analysis above. First, the BBO spread narrows for both trading sessions and we do not observe any malfunctioning of the price discovery mechanism. At the same time, BBO depth deteriorates in the night session. This could be because of skewness in the types of investors participating in these trades or because the proportion of orders placed at prices other than the BBO price is increasing. Earlier, we stated that tables 2 and 3 show the possibility of a skewed investor group. Meanwhile, the proportion of orders placed at the BBO price or a price that is one tick worse, as shown in Table 5, is higher in the night session than in the day session, so it is difficult to imagine just that fewer orders are being placed around the BBO price. This can be attributed to the fact that some investors trade only during the night session. As a whole, however, overall the range of investors at the day session is broader.

4.3. Test details

Using the data described in the previous section, we propose a hypothesis about the factors determining order aggressiveness. This paper sets three constraints on the factors that determine trading behavior to focus on the differences in day and night session activity. The first constraint is that these factors should be easily obtainable from the order book. Specifically, we do not treat such one-time occurrences as announcements of economic policies or economic data as factors in trading behavior. Although such elements affect trading behavior, it is difficult to evaluate any differences between the trading sessions. The second constraint is that these factors should be detected in fluctuations during trading hours. The BBO spread is excluded by the constraint. The level of the BBO spread is generally used, along with BBO depth, as an indicator of market liquidity; many previous studies have also treated it as a factor. However, in the case of Nikkei 225 Futures, as discussed in the previous section, the BBO spread is about one tick, regardless of the trading session. Since the correlation between the BBO spread and order aggressiveness cannot be expressed by the estimation model detailed in the following section, we do not use it as a factor in trading behavior. The third constraint is that no factor other than the sample contract will be used. Actual trading includes some arbitrage transactions, so the trading movements of other contracts that have the same underlying asset, such as Nikkei 225 Futures listed on overseas exchanges, Nikkei 225 mini, and other contract months for Nikkei 225 Futures are also affected. However, considering the impact of other contracts necessitates evaluating not only differences between trading sessions but also the correlations

among these other contracts, which makes it extremely difficult to analyze the results. To facilitate our evaluation, we include only factors from the sample contract.

This paper looks at the factors in trading behavior that meet the above constraints, such as BBO depth and contract volume within a fixed time period immediately before an order is placed (latest executed volume). Many previous studies have also treated BBO depth as an independent variable. These studies have concluded that aggressive orders are those with more BBO depth on the same side of the order book or with less BBO depth on the opposite side of the order book. We predict that the same will be true in our analysis as well. On the other hand, since there seem to be no studies that used the metric of latest executed volume as an independent variable, we will consider this metric's implications. Given that volatility and order autocorrelation are two factors thought to be related to execution volume, we verify whether latest executed volume is similar to order autocorrelation.

When price changes are used to measure volatility, volatility increases due to the two factors of change in the BBO price and order execution. As mentioned earlier, for Nikkei 225 Futures, the majority of price changes happen with order execution. This is very likely to be inconsistent with the results of previous research; orders become more aggressive as volatility increases. We will explain this by using the arguments regarding order autocorrelation proposed by Griffiths, Smith, Turnbull, and White (2000). They held that aggressive orders induced other aggressive orders, which agrees with the behavior of risk seekers and investors engaging in arbitrage. Considering the nature of Nikkei 225 Futures, which have multiple liquid contracts that can be used in arbitrage, it seems that latest executed volume has an impact on order aggressiveness that is akin to the impact of order autocorrelation.

We will now explain why we have not directly used volatility and order autocorrelation as independent variables. We do not use volatility directly as a factor because it is difficult to correctly set the number of orders used to calculate volatility. Since Nikkei 225 Futures front-month contract has high liquidity, it is common for 100 orders or more to be concentrated within one second. On the other hand, in quiet conditions, as in night trading, the sample period includes times when no orders were executed for more than 30 minutes. We, therefore, decided that it is difficult to set a certain necessary order sample when calculating these metrics for the number of orders placed and the time when they are placed. The same is true for order autocorrelation. Although our analysis would have been possible even if we used a methodology similar to that used in previous studies, which compared order aggressiveness immediately beforehand, we believe we would not necessarily be able to obtain accurate results if the number of orders placed had a skewed distribution.

In light of this, we used latest executed volume as the independent variable for the trading behavior factor, but for this metric, we measured execution volume for the most recent one minute. Having chosen to use one, we investigated the correlation between per-second execution volumes for the sample contract and the execution volume for the latest fixed time period. Table 6 presents the candidate times and the correlations.

Table 6. Correlation coefficients for per-second execution volume and latest executed volume

Latest executed volume	1 sec	5 sec	10 sec	15 sec	20 sec	30 sec	1 min	3 min	5 min
Correlation coefficient	0.085	0.091	0.092	0.096	0.098	0.098	0.101	0.099	0.097

Although the correlation coefficient is clearly low, we use execution volume for the latest one minute as the independent variable for order aggressiveness in the following model because this execution volume has the highest correlation. Some may disagree on comparing correlation coefficients for per-second

execution volumes, instead of placement volume of individual orders. However, we argue that order aggressiveness is correlated with execution volume because large-lot orders executed immediately would probably be the most aggressive. Even though different investors may use shorter or longer time periods to evaluate execution volumes, we do not think this deviates significantly from the overall conduct of the market.

We now summarize the supposition about the relation between order aggressiveness and factors of trading behavior. First, with respect to the impact of the BBO depth, the greater the BBO depth on the same side of the order book, or the lower the BBO depth on the opposite side of the order book, the more aggressive the orders would be. With respect to correlation with the latest executed volume, previous research has shown that the larger the latest executed volume, the more aggressive the orders. Under these assumptions, we assess the output of our model described in the next section.

4.4   Analytic approach

Based on the hypotheses in the previous section and considering the characteristics of the data used here, we classify order aggressiveness into four categories.

Aggressiveness 1. Limit orders and market orders for buys (sells) at greater than (less than) the BBO price for a sell (buy) and for the same or greater volume than BBO depth for a sell (buy)

Aggressiveness 2. Limit orders and market orders for buys (sells) at greater than (less than) the BBO price for a buy (sell) and for less volume than BBO depth for a sell (buy)

Aggressiveness 3. Buy (sell) orders not immediately executable that are above (below) the BBO price for a buy (sell)

Aggressiveness 4. Orders at the BBO price for a buy (sell) that were canceled or that were revised to a worse price from the BBO price for a buy (sell)

The numbers assigned to each category were used as dependent variables in the model estimated below. Although Ranaldo (2004) assigned higher values as order aggressiveness increased, our paper follows Sasaki (2004) in applying smaller numbers to more aggressive orders. Orders classified as Aggressiveness 1 and Aggressiveness 2 are so-called market orders. However, we also added immediately executable limit orders to these categories because their effect on the order book cannot be differentiated from that of market orders. Orders classified as Aggressiveness 1 are those for which BBO depth on the opposite side of the order book is less than the size of the order and for which the BBO price is updated. Orders classified as Aggressiveness 2 are those for which BBO depth on the opposite side of the order book is greater than the size of the order and for which the BBO price is not updated. Orders classified as Aggressiveness 3 are those that are not immediately executed even though the BBO price is updated. For contracts such as Nikkei 225 Futures, which have high market liquidity and a BBO spread that is usually one tick, this usually corresponds to orders placed after the BBO spread has widened because of either a cancellation or the complete filling of an order that was at the immediately preceding BBO price. Orders classified as Aggressiveness 4 correspond to those at the BBO price at the time of cancellation or revised to a worse price. These categories of orders are similar to B, C, D, and G proposed by Biais, Hillion, and Spatt (1995), which we mentioned in the previous section. However, the boundary between Aggressiveness 1 and Aggressiveness 2 (that is, the category of orders for amounts revised to exactly the BBO price) is different. This is because we believe that revising the BBO price would significantly impact Nikkei 225 Futures, which have a narrow BBO spread. In addition, Aggressiveness 4 has the stricter

condition of being at the BBO price when canceled. Note that changing the groupings of categories in this way was also done in previous research that used models to estimate order aggressiveness.

Table 7 presents the frequency of orders by order book, which is our measure of order aggressiveness, during the sample period. We see that during the day session, the proportion of market orders and corresponding limit orders is relatively high and the proportion of order cancellations at the BBO price is low. Quantitatively, the day session has higher trading volume, and qualitatively, the day session, when the equity market is open, offers more arbitrage opportunities and has a broader range of investors participating in trading, which is in line with our intuition that aggressive trading is more prevalent in the day session than in the night session.

Table 7. Order frequency by degree of order aggressiveness

Order aggressiveness	Day session		Night session	
	Sell	Buy	Sell	Buy
1	13,707 (1.28%)	13,367 (1.25%)	14,891 (1.12%)	14,617 (1.08%)
2	91,578 (8.58%)	91,959 (8.60%)	61,487 (4.65%)	60,271 (4.46%)
3	1,683 (0.16%)	1,611 (0.15%)	12,048 (0.91%)	12,783 (0.96%)
4	960,479 (89.98%)	962,162 (90.00%)	1,235,243 (93.32%)	1,262,984 (93.51%)
Total	1,067,447 (100.0%)	1,069,099 (100.0%)	1,323,669 (100.0%)	1,350,655 (100.0%)

* Figures in parentheses denote the percentage of orders in each category in the order book for the respective trading session.

Based on the above categories, we define the independent variables treated as determinants of order aggressiveness as shown in Table 8. We also determine the variables used in the model and the independent variables as follows. At time t, y_t^* is true order aggressiveness that is not observed, y_t is order aggressiveness classified into observable categories, and β_1 to β_3 are coefficients of the independent variables, ε_t is an error term, and γ_1 to γ_3 are thresholds for estimating y_t to y_t^*, with the constraint that $\gamma_1 < \gamma_2 < \gamma_3$. With a threshold of y_t, this gives us the correlation with y_t^* as shown in equation (1). Here time t updates whenever an order is placed. As exemplified by Ranaldo (2004), most previous studies constructed ordered probit models premised on a standard normal distribution for the error term ε_t, as we do in this paper. We also posit the ordered probit model shown in equation (2), which references Ranaldo (2004). In this model, the determination of y_t affects both the threshold and error term ε_t. The correlation between the error term ε_t and its probability density function $f(\varepsilon_t|Z_t)$ is shown in Figure 7.

Table 8. Definition of independent variables

Variable	Description
Vol_t^{Ask}	BBO depth for a sell at time t / 100
Vol_t^{Bid}	BBO depth for a buy at time t / 100
$Vol_t^{Execution}$	Execution volume from 1 min before time t until time t - 1

$$y_t = \begin{cases} 1 \ (\text{if} - \infty < y_t^* \leq \gamma_1) \\ m \ (\text{if} \ \gamma_{m-1} < y_t^* \leq \gamma_m) \quad (\text{for} \quad m=2,3) \\ 4 \ (\text{if} \ \gamma_3 < y_t^* < \infty) \end{cases} \quad \cdots(1)$$

$$y_t^* = \beta_1 Vol_{t-1}^{Ask} + \beta_2 Vol_{t-1}^{Bid} + \beta_3 Vol_t^{Execution} + \varepsilon_t \equiv Z_t + \varepsilon_t \quad \cdots(2)$$
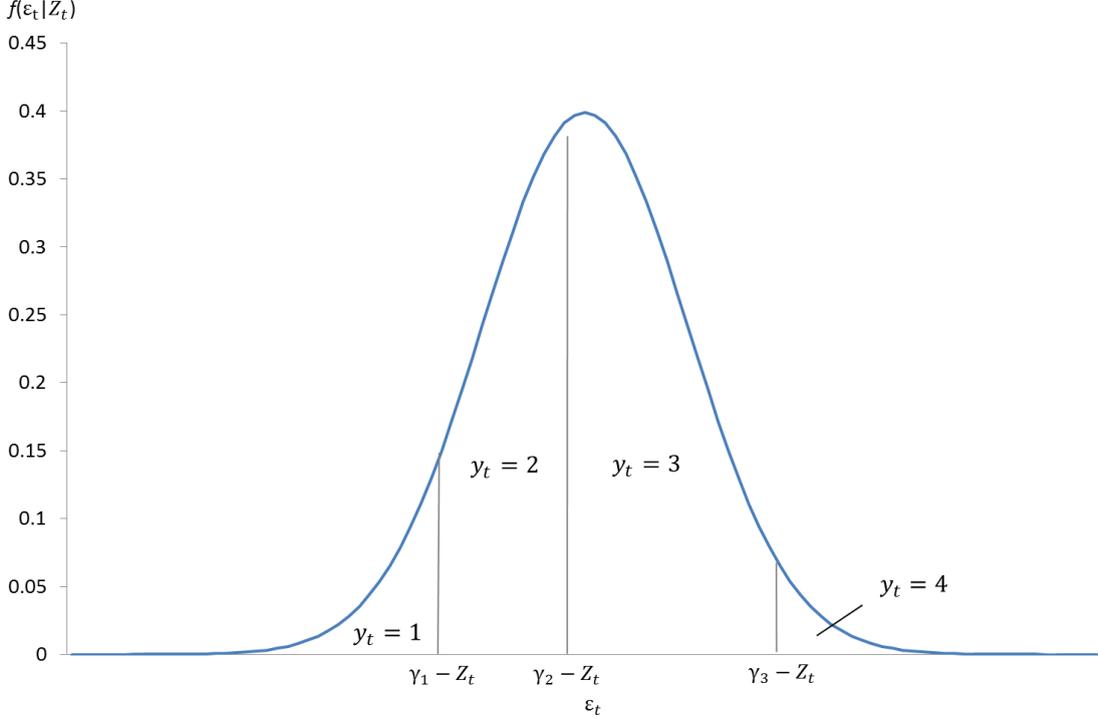

Figure 7. Correlation between the threshold and order aggressiveness

We calculate equation (2) for four combinations of sell and buy orders for the day and night sessions and compare the results. In the ordered probit model, for orders belonging to any of the above four categories of aggressiveness, the probability $P(y_t|Z_t)$ that an order placed at time t will belong to any of these categories can be expressed as follows:

$$\begin{aligned} P(y_t = 1|Z_t) &= \Phi(\gamma_1 - Z_t) \\ P(y_t = m|Z_t) &= \Phi(\gamma_m - Z_t) - \Phi(\gamma_{m-1} - Z_t) \quad (\text{for} \quad m = 2, 3) \\ P(y_t = 4|Z_t) &= 1 - \Phi(\gamma_3 - Z_t) \end{aligned} \quad \cdots(3)$$

Here, for variable x, $\Phi(x)$ denotes the cumulative distribution function of the standard normal distribution and is expressed as $\Phi(x) = \int_{-\infty}^{x} \frac{1}{2\pi} e^{-\frac{z^2}{2}} dz$. The basic statistics for these independent variables are given in Table 9. In the day session, BBO depth is highly symmetrical, and almost all items match, with the exception of kurtosis and the highest value. On the other hand, the night session has less symmetry of depth than the day session, and skewness and kurtosis are different in particular. We will address the symmetry between sell and buy orders in the estimates from our model in Section 5.

Table 9. Fundamental statistics for independent variables

Trading session	variable	Mean	Dispersion	Skewness	Kurtosis
Day session	Vol_t^{Ask}	2.344	1.446	0.561	0.176
	Vol_t^{Bid}	2.353	1.443	0.578	0.255
	$Vol_t^{Execution}$	2.223	3.283	3.237	15.667
Night session	Vol_t^{Ask}	1.521	0.865	0.581	0.626
	Vol_t^{Bid}	1.454	0.927	0.406	0.163
	$Vol_t^{Execution}$	0.659	1.054	3.479	21.417

Trading session	variable	Lowest	25% quartile	Median	75% quartile	Highest
Day session	Vol_t^{Ask}	0.01	1.23	2.26	3.25	9.77
	Vol_t^{Bid}	0.01	1.26	2.26	3.24	12.55
	$Vol_t^{Execution}$	0.00	0.09	1.12	2.96	34.34
Night session	Vol_t^{Ask}	0.01	0.81	1.51	2.08	6.56
	Vol_t^{Bid}	0.01	0.78	1.47	2.00	6.39
	$Vol_t^{Execution}$	0.00	0.01	0.22	0.92	15.71

5. Findings from analysis

5.1. Differences between day and night sessions

Tables 10–13 present the estimates from applying the trading data to the model described in the previous section using the maximum likelihood method. Tables 10 and 11 show the day session, and Tables 12 and 13 show the night session.

Table 10. Estimates of sell orders (day)

	Coefficient	Std. error	P value
β_1	-0.1736	0.0014	< 0.0001***
β_2	0.3700	0.0016	< 0.0001***
β_3	-0.0430	0.0005	< 0.0001***
γ_1	-2.4013	0.0067	< 0.0001***
γ_2	-1.2455	0.0059	< 0.0001***
γ_3	-1.2346	0.0059	< 0.0001***

Table 11. Estimates of buy orders (day)

	Coefficient	Std. error	P value
β_1	0.3671	0.0016	< 0.0001***
β_2	-0.1700	0.0014	< 0.0001***
β_3	-0.0412	0.0005	< 0.0001***
γ_1	-2.3914	0.0067	< 0.0001***
γ_2	-1.2383	0.0058	< 0.0001***
γ_3	-1.2279	0.0058	< 0.0001***

Table 12. Estimates of sell orders (night)

	Coefficient	Std. error	P value
β_1	-0.3103	0.0022	< 0.0001***
β_2	0.4202	0.0025	< 0.0001***
β_3	-0.1934	0.0013	< 0.0001***
γ_1	-2.7239	0.0069	< 0.0001***
γ_2	-1.8613	0.0063	< 0.0001***
γ_3	-1.7728	0.0063	< 0.0001***

Table 13. Estimates of buy orders (night)

	Coefficient	Std. error	P value
β_1	0.3668	0.0024	< 0.0001***
β_2	-0.4108	0.0024	< 0.0001***
β_3	-0.1759	0.0013	< 0.0001***
γ_1	-2.9289	0.0071	< 0.0001***
γ_2	-2.0664	0.0065	< 0.0001***
γ_3	-1.9712	0.0064	< 0.0001***

* The P value is the result of the Wald test of the null hypothesis, wherein the coefficient of the independent variable is 0. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively

First, let us compare these results with those of prior research. Our results for depth are comparable with those of prior research. In other words, the greater the BBO depth on the same side of the order book and the less the BBO depth on the opposite side of the order book, the more aggressive the order. Moreover, for both buy and sell orders in the day session, the absolute value of the coefficient of the depth of the BBO on the opposite side of the order book is approximately double that of the BBO depth on the same side of the order book. This indicates that investors place more importance on the BBO on the opposite side of the order book when placing orders. This is consistent with the analysis by Sasaki (2004). With respect to another analytical factor, latest executed volume, as hypothesized in Section 4, the larger the execution volume, the more aggressive the order. Although this seems to contradict the results of many previous studies, in which increasing volatility led to less aggressive orders, in our opinion it is reasonable in light of the fact that futures are often traded for hedging and arbitrage purposes and that Nikkei 225 Futures are highly liquid, even during the night session.

We will now discuss the differences in the outcomes for the day and night sessions. First, the influence of all independent variables on order aggressiveness is the same for both trading sessions. That is, our results reveal that orders become more aggressive with more BBO depth for the same side of the order book, with less BBO depth for the opposite side of the order book, and with greater latest executed volume. On the other hand, the outcomes for the night sessions differ from those for the day sessions in four respects. First, for the day sessions, the discrepancy between thresholds γ_2 and γ_3 for both buy and sell orders is approximately 0.01, but it increases to approximately 0.09 for night sessions. This indicates that the error term has a relatively small effect for orders falling into aggressiveness categories 2–4. In other words, there is more information in the order. Second, the absolute value of the coefficient of each independent variable is larger for the night session than for the day session. This indicates higher relevance of the posited factors for trading behavior in determining order aggressiveness. The third difference is that when comparing BBO depth on the same side of the order book with BBO depth on the opposite side of the order book, the difference in terms of absolute value is lower during night sessions than during day sessions. This means that relevance with BBO depth on the same side of the order book is about the same as it is with BBO depth on the opposite side of the order book. Finally, for buy orders at the night session, the absolute value of the coefficient for BBO depth β_2 is larger than that of the coefficient for BBO depth β_1. These results differ from those of other studies in that the impact of BBO depth on the same side of the order book is larger and there is less symmetry between buy and sell orders.

5.2. Night session characteristics

We now consider the implications of the four differences in the night session, as discussed in the previous section. The first difference that there is a greater magnitude of information in orders is consistent with the argument by Michael and Terrence (2003). They suggested that orders placed during the night session have a greater per-order contribution to price discovery. Derivatives markets differ from equity markets in that night session trading is possible; however, night trading, which occurs when the underlying index is not being updated, may include information that was not available during the day session. In our opinion, this is a value provided by futures markets in the form of price indexability.

Let us look at the second difference, the larger absolute value of the coefficients of the independent variables for order aggressiveness. Compared with the day session, the night session has fewer economic events with a potential impact on the Japanese economy; at night, no arbitrage opportunities exist with

the equity market that underlie the Nikkei 225 Futures. Therefore, barring any international economic trends, price movements in futures are prone to become news on which to trade in and of themselves. It shows that trading would focus more on aspects such as latest executed volume and BBO depth. Indeed, the explanation for such trading behavior is premised on Nikkei 225 Futures' high liquidity. When liquidity is good, both short-term and long-term trading strategies are valid; however, when liquidity is not good, investors expect the BBO spread to widen, and their strategies tend to consider long-term price movements.

The third difference—the relevance of BBO depth on the same side of the order book is the same as BBO depth on the opposite side of the order book—is probably because BBO depth is less at night than during the day. As shown in Table 9, depth during night sessions averages approximately 60% of depth during day sessions, so investors may consider depth during both sessions. When we tested whether BBO depth was adequate in Section 4 and defined the unexecuted order ratio, we predicted that market liquidity would not shrink much from the standpoint of depth. However, our tests of order aggressiveness show that depth may not always be adequate during night sessions. Since this and the previously mentioned lack of economic events may be factors that alter trading trends, we can view it as the outcome of investors trading more prudently during the night session.

The fourth difference—less symmetry between buy and sell orders—is probably owing to differences in the number of orders in the samples. As can be judged from Table 7, a large discrepancy exists in the number of canceled orders during the night session, particularly those at the BBO. Here, canceled buy orders outnumber canceled sell orders by approximately 27,000. This is a larger number than the discrepancy between buy and sell orders during the day session, so we believe that there is more relevance to BBO depth, even for buy orders, in the night session. Although this suggests differences in trading behavior vis-à-vis buy and sell orders in the night session, it calls for an examination of whether this can happen regardless of market trends. If a bias exists toward sell orders or buy orders when there is economic news or only on one particular day, lengthening the sample period could lead to different findings. We incorporate the impact of economic events by analyzing the relation between the number of trades from buy orders and number of trades from sell orders.

We performed the above test using data from August 8, 2014, the day that witnessed what is considered the most significant economic event during the sample period. This day saw the heaviest trading volume during the sample period. The absolute value of the difference between the closing price and opening price the day was ¥270, and the price range between the high and low for the day was ¥410. Both of these were the highest during the sample period. To evaluate the effect, we calculated the number of uptick trades and downtick trades for each trading session. The number of uptick trades refers to the number of trades from buy "take" orders, and the number of downtick trades refers to the number of trades from sell "take" orders. The ratio of uptick trades is the proportion of the number of uptick trades to total trades. In other words, when the number of uptick trades equals the number of downtick trades, the ratio of uptick trades is 50%. On August 8, 2014, the ratio of uptick trades during the day session was 47.5%, and the difference between the number of uptick trades and downtick trades was -1,638, indicating a slight preponderance of sells.

Upon investigating whether this day was an outlier compared with other days, we found that even though the market did not move as much on July 29, 2014, the ratio of uptick trades on that day was 55.9% and the difference between the number of uptick trades and downtick trades was 1,268, meaning that buys predominated. Meanwhile, both the difference between the closing price and opening price and the price range between the day's high and low were only ¥80, and the trading volume was about the same level as day session trading volume during the sample period. This indicates that skewing toward

buy or sell orders can occur even on days on which no particular economic events have occurred. Although the metrics of the number of uptick trades and the number of downtick trades do not fully assess market conditions, they can be used to measure order aggressiveness. Therefore, a skew toward buy orders or sell orders does not depend on economic events, and we surmise that this would be the case even if the sample period is extended.

Although this paper does not differentiate between institutional investors and individual investors in analyzing orders, we have indicated that the investor groups participating in day and night session trading may differ. The direction of the entire market may change if the types of investors participating in the market change and if their investment strategies change. However, we were unable to identify any major bias in open-high-low-close (OHLC) prices by trading session, and no difference was observed in the direction of the impact of trading behavior factors at the day session and the night session on order aggressiveness. Our analysis failed to reveal any insights regarding the correlation between order aggressiveness and the market's price discovery mechanism. In our opinion, additional consideration must be given to changes in investors' trading patterns to further analyze the impact on the order book of higher relevance with the BBO buy depth in the night session. However, that is beyond the scope of this paper.

6. Conclusions

This paper used Nikkei 225 Futures tick data from July and August 2014 to examine differences in investors' trading behavior at OSE trading sessions by employing the metric of order aggressiveness, which shows aggressiveness in trading. We built an ordered probit model in which BBO depth and trading volume for the one minute immediately preceding each order were the factors determining order aggressiveness. We then used the maximum likelihood method to estimate the impact of each determinant on both buy and sell orders by trading session.

The findings common to both the day and night sessions were that orders became more aggressive as BBO depth on the same side of the order book increased, as BBO depth on the opposite side of the order book decreased, and as the latest executed volume increased. This is consistent with the findings of previous research. Simultaneously, we identified that night sessions differ from day sessions in the following ways: (1) the per-order contribution to price discovery is higher; (2) there is more relevance between order book data and order aggressiveness; (3) there is more of a tendency to emphasize BBO depth on the same side of the order book; and (4) buy and sell trading behavior may be different. This suggests that for the market as a whole, a greater proportion of investors are cautious in their trading for reasons such as there being fewer factors moving the market during the night session.

In future studies, the sample length should be extended. This would require determining how to treat contracts before and after the change of the central contract month. Consideration should be given to whether to include only the contract month with the highest trading volume in the sample or whether to include orders for contract month spread trades, which were not in our sample. Furthermore, analytical findings may significantly vary depending on the treatment of specific trading factors during rollovers or changes in contract months. The setting of time periods for daytime and nighttime could also be improved. Comparing trading behavior during the night session and during the midday break, when there is no spot market trading, would be an effective way to exclude the spot market's influence on the derivatives market. This issue could be handled by dividing the sample time period into shorter segments of time. In addition, with respect to orders in the sample, more analysis of canceled orders is required. A considerable volume

of the Nikkei 225 Futures orders at the BBO price is canceled. Classifying these orders by how long they were in the order book could shed more light on the subject.

Finally, we summarize our paper. The proportion of overseas investor trading on OSE is currently high. According to the data on trading by type of investors published by OSE, overseas investors constituted approximately 69% of trading in Nikkei 225 Futures in 2015. This is about the same as the 71% trading share of overseas investors during our sample period, so the situation has not changed much. Investor types include proprietary trading firms, domestic and overseas institutional investors, individual investors, and the like, and it is difficult to evaluate, and come up with evaluation criteria for, the relation between these investors' trading behavior and their impact on the market. For all investors, however, hedging mechanisms and the price discovery mechanism play a key role in derivatives trading. With respect to Nikkei 225 Futures, which are already considered to have sufficient liquidity, further improvement will require architecting an environment that allows diverse investors to trade, and this is the task that lies ahead for the OSE markets.

References

Aidov, A and Daigler, R. T., [2015], "Depth Characteristics for the Electronic Futures Limit Order Book," *Journal of Futures Markets,* 35, 6, pp. 542–560.

Biais, B., P. Hillion and C. Spatt, [1995], "An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse," *Journal of Finance,* 50, 5, pp. 1655–1689.

Foucault, T., O. Kadan and E. Kandel, [2005], "The Limit Order Book as a Market for Liquidity," *Review of Financial Studies*, 18, pp. 1171–1217.

Griffiths, M., B. Smith, D. Turnbull and R. W. White, [2000], "The costs and the determinants of order aggressiveness," *Journal of Financial Economics*, 56, pp. 65–88.

Kyle A. S., [1985], "Continuous Auctions and Insider Trading," *Econometrica*, 53, 6, pp. 1315–1335.

Lee, Charles M. C. and M. J. Ready, [1991], "Inferring Trade Direction from Intraday Data," *The Journal of Finance*, 46, 2, pp. 733–746.

Lo, I. and S. G. Sapp, [2010], "Order Aggressiveness and Quantity: How Are They Determined in a Limit Order Market?" *Journal of International Financial Markets, Institutions and Money*, 20, 3, pp. 213–237.

Michael, J. B., and Terrence, H., [2003], "Price Discovery and Trading After Hours," *The Review of Financial Studies*, 16, 4, pp. 1041–1073.

McCullagh, P., [1980], "Regression models for ordinal data," *Journal of the Royal Statistical Society. Series B (Methodological)*, 42, 2, pp. 109–142.

Muronaga, J., and T. Shimizu, [1999], "Market Microstructure and Market Liquidity," *IMES Discussion Paper*, 99-E-14, Institute for Monetary and Economic Studies, Bank of Japan.

Ranaldo, A., [2004], "Order aggressiveness in limit order book markets," *Journal of Financial Markets*, 7, pp. 53–74.

Sasaki, K.佐々木 浩二, [2004] "Nikkei heikin sakimono tikku deta wo mochiita 'order aggressiveness' no suitei 日経平均先物ティックデータを用いた order aggressiveness の推定," Osaka Stock Exchange, Futures and Options Report 大阪証券取引所 先物・オプションレポート, 16, 10, pp. 1–4.

Xu Y., [2009], "Order Aggressiveness in the ASX Market," *International Journal of Economics and Finance,* 1, 1, pp. 51–75.