Matching Frequency, Periodical Call Auctions and Order Aggressiveness

Yi-Heng Tseng[1]

Abstract

The Taiwan Stock Exchange (TWSE) implemented three reforms during 2013-2014 to expedite the matching frequency for periodic call auctions, the length of which is eventually shortened to 5 seconds on December 29th, 2014. The three reforms aim to enrich the disclosure of quality information by revealing the top five unexecuted quotes along with order depths contained in the limit order book (LOB) immediately after each of call auctions. By examining traders' choices of order submissions, we show that swifter matching frequency substantially brings in a wealth of information in the publicized content of the LOB, thereby mitigating the degree of information asymmetry among market participants. Though order arrival rate increases after each of the three reforms, individual investors decrease their order aggressiveness, revealing that the policy of high frequency auctions steps up their expectations of order executions. These expectations may further cause the 'wait-and-see' effect among participants, and discourage them from submitting aggressive orders. Moreover, institutional investors tend to submit smaller orders, implying that quicker matching frequency stimulates their behavior of order splitting. The conservatism in trading behavior as a result of the three reforms could partially defeat the TWSE trading volume.

Keywords: Taiwan Stock Exchange, Call Auction, Duration, Limit Order Book, Order Aggressiveness.

JEL Codes : D47

[1] Corresponding author: Yi-Heng Tseng, E-mail: yhtseng@saturn.yzu.edu.tw, Associate Professor of College of Management, Yuan Ze University, No. 135, Yuan-Tung Rd., Chung-Li Dist., Taoyuan City 32003, Taiwan (R.O.C.). TEL: (886) 3-4638800 ext. 2696, FAX: (886)3-4633824.

1. Introduction

1.1 Background and motivation

Continuous auctions and call auctions are both common matching mechanisms employed in contemporary security markets. Continuous auctions are used in major stock markets such as the New York Stock Exchange (NYSE), London Stock Exchange (LSE), Deutsche Stock Exchange (DSE), Euronext, Tokyo Stock Exchange (TSE), Korea Exchange (KRX), Shanghai Stock Exchange (SSE), Shenzhen Stock Exchange (SZSE), Australian Securities Exchange (ASX), Malaysia Stock Exchange (MYX), Taiwan Futures Exchange (Taifex), etc. On the other hand, call auctions are used in both pre-opening sessions and closing sessions, but are mostly used in pre-opening sessions; examples are the NYSE, TSE, SSE, and Hong Kong Stock Exchange (HKEX). In KRX, Singapore Exchange (SGX), SZSE, ASX, Euronext, LSE, DSE, etc.

In comparison with most markets, the Taiwan Stock Exchange (TWSE) takes a unique approach: transactions in pre-opening sessions (8:30 A.M.-9:00 A.M.), normal trading hours (9:00 A.M.-13:25 P.M.), and closing sessions (13:25 P.M.-13:30 P.M.) are carried out under call auctions with different trading frequencies. In order to be in line with international practices and increase trading volume, the TWSE commenced a series of modifications to trading frequency during 2013 and 2014. With the ultimate goal of adopting continuous auction, the duration of a single call auction during normal trading hours was shortened from 20 seconds, to 15 seconds, 10 seconds, and 5 seconds progressively (Tsai, 2013).

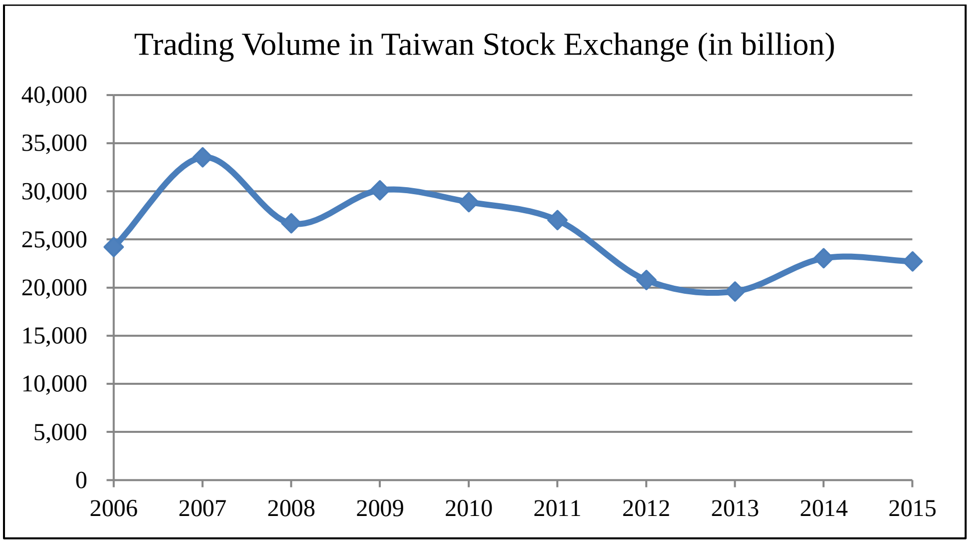
This work is inspired for the following reasons. First, how changes in trading mechanisms impact order choices, order performance, and market performance indexes such as liquidity, volatility, and efficiency has profound policy implications and has become an issue of growing concern to financial economists. Secondly, while most stock exchanges have used continuous auctions as their trading mechanisms, the matching frequency program that the TWSE introduced in 2013 was intensive, providing a unique opportunity for researchers to see how the aforementioned impacts unfold over time.

Trading frequency in TWSE has gone through a series of restructurings since 1985, when computers were utilized to assist order matching and periodic call auctions replaced the original mechanism under which orders were matched manually and intermittently. At the launch of the Fully Automated Securities Trading (FAST) system in 1993, the trading frequency of periodic call auctions in normal trading hours hastened from 2 minutes (120 seconds) per call to at most two calls every 90 seconds (Ma, 1998[2]). After that, the TWSE lessened gradually the call auction duration from 90 seconds to 20 seconds from 2002 through 2013. In this study, we focus on three policies of call matching frequency that happened during 2013 and 2014 — the call auction duration decreased from 20 seconds to 15 seconds in 2013/7/1, to 10 seconds in 2014/2/24, and further to 5 seconds in 2014/12/29.

[2] The trading frequency of periodic call auction was adjusted twice in 1993 (Lang and Lee, 1999). In 1993/9/9, it increased from 120 seconds per call to 90 seconds per call; in 1993/11/2, it changed again to 1 or 2 matches every 90 seconds — the first match would be carried out after the first 85 seconds in that call auction, and the second match would occur if a tradable order arrived in the remaining 5 seconds.

The increase of matching rate for periodic call auctions during 2013 and 2014 is an unique opportunity to provide a rare natural experiment for research community to investigate the benefits and costs of trading frequency alteration on the limit order book and market trading behavior. More specifically, our goal is to clarify the following questions. First, due to the fact that the trading volume is a key indicator of market authority's performance (Chan and Lee, 2014), it is crucial whether the plan of speedy call auctions is a remedy for the trading volume that had fallen to the bottom after the European debt crisis and the raise of capital gain tax in the Taiwan stock market in 2012 (Figure 1). As a consequence, how to revive trading activities has become the top priority for the policymakers, business leaders, and academics. Instead of exploring the trading volume at the macro level, we attempt to provide more insights from the facet of order placement and examine the ripple effect of such reform policies on order aggressiveness, order size, and order arrival time (Hasbrouck and Ho, 1987). We aim at these three factors because, in theory, a higher (lower) order aggressiveness, larger (smaller) order sizes, and a higher (lower) order arrival rate will increase (decrease) the trading volume.

Figure 1: Trading volume in Taiwan Stock Exchange from 2006 and 2015 (in billions)



Source: Authors calculations from TWES (2019)

Secondly, we are interested in whether shortening the intervals of periodic call auctions improved investors' order performance (Tseng et al., 2017). We evaluate the picking-off risk (Hollifield et al., 2006), non-execution risk (Griffiths et al., 2000), and filled rate each order faced. Our dataset contains investor identifier that enables us to distinguish individual investor from institutional investors.3 We hypothesize that the accelerations of periodic call auctions alter the costs, benefits, and risk aversion in relation to trading activities for the two types of investors in a different manner.4

[3] Institutional investors are expected to have more financial capital, more resources, more experiences, and more information than individual investors. As a result, institutional investors are usually regarded as informed traders, while individual investors are regarded as uninformed ones (Alangar et al., 1999; Ma et al., 2008; Duong et al., 2009; Lee et al., 2009; Hung et al., 2012).

[4] We can also observe whether the uninformed investor traded at more preferable prices after both types of traders changed their order aggressiveness. For example, if institutional traders' order aggressiveness increased while individual traders' order aggressiveness decreased, the uninformed would tend to be the liquidity provider and therefore gained additional premium (Tian et al., 2015).

Thirdly, given that the TWSE does not use continuous auction to match orders, nor does the TWSE unveil information continuously during normal trading hours, investors cannot instantly scrutinize the information of the LOB as soon as they intend to submit their orders. In other words, the information revelation is "paused" between two consecutive call auctions. Technically, we can construct the real-time, simulated LOB upon the actual LOB of periodic call auctions as if the trading mechanism were continuous auction. By comparing the simulated LOB to actual LOB, we can figure out how accurately market participants could learn the concurrent market situations. We postulate that speedy call auctions implicate the dissemination of quality information enclosed in the LOB. Our analysis enlightens the consequence of continuous auctions on the attributes of LOB information if the TWSE decides to switch from periodic to continuous auction platform in the future.

1.2 The innovations and significance

Three unique features motivate us to probe the 2013-2014 accelerations in periodic call auctions. First, the direction and magnitude made by the TWSE in this period denote a regular and well-planned transformation of the governing policy. To be more specific, all of the three modifications truncated the time interval of a call caution by 5 seconds in each phase: from 15 seconds to 10 seconds in 8 months, and from 10 seconds to 5 seconds in 10 months. Although the TWSE also undertook a series of intensive accelerations in 1993, they were not as systematic as the 2013-2014 reforms because the acceleration was 30 seconds on September 19, 1993 while the acceleration could be 0 or 5 seconds on November 2, 1993, depending on market situations (Sec. 1.1 and footnote 1). Notice that the adoption of acceleration program on November 2, 1993 denoted an indeterminate call auction duration. For example, in a typical settlement of a call auction, the first match would take place in the first 85 seconds, followed immediately by a second match after 5 seconds. However, if there were no tradable orders during the last 5-second period, the rest of the unexecuted orders would be merged with the orders collected from the next call auction; this situation took place randomly and therefore cumulated the duration of the two call auctions to be 90 seconds, instead of 85 seconds in a single call auction. By contrast, the 2013-2014 accelerations not only rule out the disturbing ambiguity of the call duration (85 vs. 90 seconds) mentioned above, but also deliver a well-rounded sample where we test the monotonic effects of trading frequency on order behavior and market efficiency. Understanding the monotonicity shines a light on the market dynamics brought about by periodic auction reforms during the 2013-2014 period and perhaps continuous auction deployment in the near future.

Secondly, the length in each of the three restructurings of matching frequency was intensive and longer than a half year, accumulating large database entries of LOB orders. Assuming that traders need to learn and adjust to the changes in trading frequency, we drop the order records within the 31 trading days after the implementation date of each reform and then divide the remaining data into four isochronous observation periods:

- Period I: the trading frequency is 20 seconds per call, and the data were collected from 2012/4/5 to 2012/5/14; that is, a total of 27 trading days.

- Period II: the trading frequency is 15 seconds per call, and the data were collected from 2013/8/13 (the 32nd trading day since the 1st matching frequency reform on 2013/7/1) to 2013/9/18; a total of 27 trading days.
- Period III: the trading frequency is 10 secs per call, and the data were collected from 2014/4/1 (the 32nd trading day since the 2nd matching frequency reform on 2014/2/24) to 2014/5/9; a total of 27 trading days.
- Period IV: the trading frequency is 5 secs per call, and the data were collected from 2015/2/12 (the 32nd trading day since the 2nd matching frequency reform on 2014/12/29) to 2014/3/31; a total of 27 trading days.

Finally, because the TWSE releases to the public the top five unexecuted limit orders after each call auction, we envision that shortening the duration of periodic call auctions adds to market transparency. Strictly speaking, what is disclosed by the TWSE is piecewise post-trade LOB status, rather than pre-trade or simultaneous LOB records. Take the 20-second call duration as an illustration where the TWSE announces the prevailing market price and depth for the five best quotes in the LOB at the end of the call auction, but such information will temporarily "freeze" for 20 seconds since the TWSE announcement. It is imaginable that latest orders will continuously arrive in the LOB queues before the next call, and the number of newly placed orders could be large enough to drastically alter the best bid and ask in a continuous auction market. There is no way for market participants to observe the development of limit price and depth within the 20 seconds among consecutive call durations. Put differently, the status of the LOB in the scheme of 20-second call auctions is completely "opaque", except for the moment of the TWSE's declaration on the five best quotes, from the market microstructure point of view. Conceptually, curbing the duration of periodic call auctions is equivalent to escalating the playback frequency of LOB snapshots. The shorter the time horizon between call auctions, the less likely it is for investors to wait in the dark and be ignorant of the advancements in order queues. For that reason, we interpret the 2013-2014 accelerations as a series of reforms that monotonically strengthen market transparency. Our findings expand the literature on market transparency in the framework of call auction duration.

1.3 The auxiliary tool: the continuous auction simulation and its application

As mentioned above, the reform of shortening the duration of periodic call auctions is equivalent to an increase in the update frequency of LOB status (the quotes and sizes of the best five unexecuted orders), and it can be regarded as an improvement in the transparency of the ever-changing order queues in the market. This inspires the authors to evaluate the correctness of current LOB between the last call and the next round of order matching, viz., the information disclosure quality.

To evaluate the correctness of the disclosed information, we need to first rebuild the dynamic appearances of the LOB before the next call. This can be achieved only by matching the orders one by one, that is, simulating a continuous auction by using our intraday data. It is understandable that the depth of the buying or selling queue will change as long as an order arrives the exchange during the update window, but the best available price in the LOB may not change as frequently as the depths. For this reason, we evaluate the correctness of the LOB information from the exchange on the basis of the proximity of the best prices revealed in the latest LOB observable to investors and the best prices from the continuous auction simulation (which reflects real-time changes in the LOB) when investors were making their order choices. Then, we can judge the potential benefits resulted from the reforms by examining the changes in the information disclosure qualities before and after each acceleration (e.g., Period I vs. II, Period II vs. III, or Period III vs. IV).

It is obvious that the information disclosure quality is crucial for investors to form accurate expectations about the changes in key market efficiency indexes such as the bid-ask spread, volatility, etc. in real time (Tseng and Chen, 2015). We conduct the continuous auction simulation to rebuild the dynamic LOB information during the update window, and then we estimate both types of investors' sensitivity to market efficiency indexes such as the bid-ask spread, volatility, etc. with our empirical models. By examining the changes in sensitivities before and after each trading frequency reforms, we would be able to judge whether the acceleration policy indeed improved informed and unformed traders' ability to sense real-time changes in market efficiency indexes mentioned above.

In addition, the continuous auction simulation can also be applied to the calculation of the market equilibrium price, a.k.a. the "intrinsic value", of any stock at any time point. The simulated common values enable us to estimate order performance indexes such as the picking-off risk (Hollifield et al., 2006), the non-execution risk (Griffiths et al., 2000), etc. with higher accuracy after the submission of each limit order.

To summarize, the real-time LOB status (while investors are submitting their orders) generated by the continuous auction simulation is an indispensable auxiliary tool for our appraisal of the influences of the acceleration policies on investors' order choices, order risks, and various market efficiency indexes in this study.

2. Literature Review

2.1 Trading frequency

Due to the fact that most stock markets in the world use continuous auctions as the matching mechanism during normal trading hours, there is a lack of empirical discussions in the literature about the influences resulted from changes of trading frequency in call auctions (and this is exactly what this study wants to contribute). The majority of the literature can be divided into two branches — the comparison of performances of call auctions implemented in the opening session versus the closing session, and the analysis of the impacts of a mechanism switch to call auctions in the opening session, the closing session, or for a specific stock.

In the first branch of the literature, there are a lot of studies paying attention to the benefits induced by call auctions. As an early research, Garbade and Silber (1979)'s theoretical model demonstrated that the risk of the temporary departure of transaction prices from market equilibrium values will decrease as the matching interval lengthens (mainly because there would be more investors participating in the auction). The market equilibrium value may also change between the time when an order is submitted and the actual matching time, and the magnitude of this change will increase as the matching interval increase; this constitutes another type of risk. Considering the trade-off between these two risks, there may exist an (non-zero) optimal matching interval, which minimizes the aggregate of both types of risks. This insight provides a theoretical foundation for the fact that call auctions are commonly used in the opening and closing sessions in global stock markets.

Amihud and Mendelson (1987) studied the NYSE and found that the stock returns in the opening sessions are higher than those in the closing sessions. They speculated that this results from the difference between the call auctions (such as the different matching intervals) or because there is a longer silent period before the opening session (e.g., the overnight waiting period). On the contrary, Stoll and Whaley (1990) also studied the NYSE but found that the volatility is larger in the opening session. Their conjecture is that the market has to digest more private information in the opening session, so the cause of the difference is not the call auction mechanism itself. Stoll and Whaley (1990)'s finding is also supported by empirical studies of other stock exchanges, such as Choe and Shin (1993) and Huang, Liu, and Fu (2000).

In addition to the volatility, Madhavan (1992) considered the call auctions a mechanism with a longer matching interval (relative to continuous auction). With more investors, the periodic auction offers greater price efficiency and can ameliorate the non-existence of equilibrium problem of the continuous auction when there is severe information asymmetry. Comerton-Ford et al. (2007) studied the Singapore Exchange (SGX) and and concluded that using call auctions in the opening and closing sessions helped improve market efficiency in terms of index such as liquidity. Interestingly, Ibikunle (2015) studied LSE and demonstrated that the benefits of call auctions did not apply to all sorts of stocks. For less-liquid stocks, the efficiency in the opening call auction could be worse instead. Furthermore, Ibikunle (2015) also pointed out that the overall market efficiency in the closing call auction is slightly lower than that in the continuous auction during normal trading hours.

In the second branch of research, Pagano and Schwartz (2003) found that in Euronext Paris, the volatility (including the close-to-open returns) lowers for less-liquid stocks after the introduction of the call auction. In SGX, the study has shown that the volatility indeed lowers after the introduction of call auctions in the opening and closing sessions in 2000, and this positive effect even spillovers to the normal trading session (Chang et al., 2008). Kandel et al. (2012) found that in European stock markets such as Borsa Italiana and Euronext Paris, the volatility tends to decrease after the introduction of call auctions in the closing sessions. Similarly, Pagano et al. (2013) also found a decreased volatility in NASDAQ after the introduction of the call auction in the opening session.

The other part of the literature focuses on market efficiency indexes other than the volatility. Muscarella and Piwowar (2001) found that in Euronext Paris, the liquidity of more-liquid stocks was improved after the mechanism switched from the call auction to the continuous auction (regarded as an acceleration of trading frequency). In the case of Taiwan, Taifex altered the trading mechanism from 10-sec periodic call auctions to continuous auction in 2007/7/29. During this transition which signifies an acceleration of the trading frequency, Lee et al. (2009) found a decreased liquidity; Chan and Lee (2014) also observed that the volatility was lower before this reform (i.e., in the call auctions), and this phenomenon was more pronounced when there was information asymmetry, and more evident for more-liquid stocks. With regard to TWSE, Ma (1996) studied the upgrade from computer-assisted manual matching to the FAST system (from 120 secs per call to 90 secs for at most 2 calls) in 1993 and found that the volume and liquidity increased as the trading frequency accelerated; however, the volatility also increased. Huang, Chen, and Cheng (2007) studied the introduction of the 5-minute call auction for the closing session (equivalent to a decrease in trading frequency) in 2002/7/1 and found that the liquidity was improved and the volatility also decreased.

To summarize the literature, it seems that we cannot learn definite conclusions about the relationship between trading frequency and market indexes such as liquidity and efficiency either from studies of auction mechanism reforms or comparisons of different matching mechanisms. In contrast, we can observed that volatility appears to be relatively mild when trading frequency is lower not only from global market studies (Pagano and Schwartz, 2003; Chang et al., 2008; Kandel et al., 2012) but also from studies in TWSE (Ma, 1996; Huang et al., 2007) and Taifex (Chan and Lee, 2014). This observation suggests a concern that accelerations in trading frequency may possibly push up the volatility.

2.2 Improvements in limit order book revelation and transparency

The majority of the relevant literature focuses on how an improvement of the LOB revelation influences market performance indexes such as liquidity, volatility, efficiency, etc. Their findings can be summarized into two points of view. First, the more transparent the market is, the lower the costs of collecting information and conducting transactions for the uninformed traders (Pagano and Röell, 1996). However, a higher transparency also reduces the number of noise traders and therefore decreases the liquidity in thin markets such as the Toronto Stock Exchange (TSX) and increases price volatility (Madhavan, 1996; Madhavan, Porter, and Weaver, 2005). On the other hand, (Boehmer et al., 2005) studied the NYSE and found that the uninformed traders attempted to submit more orders under higher market transparency, and it further improved the liquidity and market efficiency. The same finding was partly supported from evidence in the KRX. Eom, Ok, and Park (2007) found that an increased market transparency resulted in a deeper LOB, and this also suggested that liquidity was improved and the volatility also became smaller.

Regarding local evidence, the TWSE launched two transparency reforms during 2002 and 2003. On the basis of these reforms, Huang et al. (2007) found an improved liquidity and a smaller volatility; Lee et al. (2009) inspected listed companies with different sizes and found that a higher transparency improved the liquidity for large cap stocks, but it had no significant effects on the stocks of small cap stocks; Ma, Lin, and Chen (2008) considered the relationship between investors' order choices and market performance, and they found evidence consistent with Madhavan et al. (2005)'s proposition that a higher transparency in the LOB will bring about a higher volatility; despite so, Ma et al. (2008) found no significant changes in the liquidity and the efficiency. Regarding the pre-open disclosure reform in the TWSE in 2012/2/20, Wang, Chiao, and Tin (2014) found that the volatility became lower due to that reform, and the simulated matching information did help improve market efficiency.

In addition to market performances, part of the literature focused on how improvements in LOB transparency influences investors' order aggressiveness. Flood et al. (1999)'s experimental study suggested that a lower transparency will force the uninformed traders to increase their order aggressiveness to compete for trading opportunity. In contrast, if the market becomes more transparent, some key hidden information will be gradually revealed, and it will result in an increase of order aggressiveness from the informed traders so as to increase their competiveness. This finding was also known as the "rat race effect" in the literature (Foster and Viswanathan, 1996; Back, Cao, and Willard, 2000). Based on the two LOB transparency reforms during 2002 and 2003, Ma et al. (2008)'s study showed that institutional investors' order aggressiveness did increase over time, which is consistent with the rat race effect.

Nevertheless, the rat race effect can be observed not just from the informed traders. Bortoli et al. (2006) found that all participants submitted more market orders so as to compete for trading opportunities after the Sydney Futures Exchange (SFE) enhanced their LOB transparency. Based on the latest LOB information investors observed while they are submitting orders, Tseng (2014)'s study categorized investors' order aggressiveness into four degrees and found that individual traders were more concerned about the non-execution risk while the institutional traders were more concerned about how to hide their trading intentions in the closing sessions after the transparency reform. By using the simulated continuous auction data to evaluate traders' order aggressiveness, Tseng and Chen (2015) further found that not only the institutional traders exhibited higher order aggressiveness, the individual investors also submitted more impatient orders to some degree. Because the TWSE also allowed an extension of the closing call auction as it initiated the transparency reform in 2012/2/20, Tseng, Chang, and Wang (2017) found that investors' emotions were actually calmed down (which means a decrease in order aggressiveness and an increase in order retreats) once a delaying closing call measure was triggered; there seem to be an spillover effect in the sense that individual investors tended to had a slightly lower order aggressiveness during normal trading hours (Tseng, 2016).

In fact, not to mention the transparency reforms, the disclosed LOB contents themselves may also influence investors' order aggressiveness, especially for the choice between limit orders and market orders. Conceptually, the bid-ask spread measures the difference between the highest outstanding bid and the lowest outstanding ask. It's not hard to imagine that traders who submit market orders will suffer from a higher immediacy cost once the bid-ask spread is enlarged (Cohen et al., 1981; Copeland and Galai, 1983; Handa and Schwartz, 1996) and therefore turn to limit orders instead (Ahn et al., 2001; Pascual and Veredas, 2009; Lo and Sapp, 2010). In addition, investors are also concerned about price volatility. The larger the volatility, the more likely that market orders will end up with transaction prices far away from the true values of the stocks; as a result, investors are more likely to choose limit orders (Bae, Jang, and Park, 2003; Ranaldo, 2004). Even for limit orders, orders submitters would fact a higher picking-off risk if the volatility becomes larger, which will induce them to submit limit orders at more conservative prices as a compensation (Foucault, 1999). Interestingly enough, the depths of both sides of the LOB reflect exactly the degree of competition orders are facing from the whole market. Parlour (1998) indicated that, under continuous auctions, a longer queue of the same (opposite) side of the LOB represents a more (less) competitive environment facing the order submitters; the expected time-to-execution will be longer (shorter) and investors are more (less) likely to submit market orders. This phenomenon is known as the "crowding out effect" and is supported by empirical evidence from the TSX (Griffiths et al., 2000), the Swiss Stock Exchange (SWX) (Ranaldo, 2004), the ASX (Duong, Kalev, and Krishnamurti, 2009), the Spanish Stock Exchange (SSE) (Pascual and Veredas, 2009), the Istanbul Stock Exchange

(ISE) (Valenzuela and Zer, 2013), and even the exchange which uses call auctions, such as the TWSE (Tseng, 2016). Moreover, Goettler, Parlour, Rajan (2005) pointed out that when there are lots of outstanding orders cumulated in the same (opposite) side of the LOB, it implies that the best price in the same (opposite) side has already deviated from the market consensus value. This phenomenon is coined as the "signaling effect" in the literature. In fact, it can be easily observed in call auctions during normal trading hours as well in the TWSE (Tseng, 2016).

To summarize, there is an abundance of research regarding how disclosure of the LOB and improvements of the transparency influence investors order choices, while there is fewer empirical studies about the connection between LOB information and investors' order performance. So far as we know, Cho and Nelling (2000) studied the NYSE and found that the bid-ask spread and price volatility are closely related to the filled rate of limit orders; Valenzuela and Zer (2013) studied the Borsa Istanbul (BIST) and found that the filled rate of limit orders rose when price volatility increased; in the TWSE, Tseng et al. (2017) found that the launch of the information disclosure reform during the pre-closing session slightly raised individual investors' limit order filled rate, but there were no significant changes in the picking-off risk and unexecuted risk. The interesting part is that, with the accelerations of the trading frequency, the disclosure frequency of information about the prices and sizes of outstanding orders after each call was also increased. This can also be viewed as a transparency reform, which means that we can associate and compare our empirical findings in this study with the literature mentioned in this section.

3. The Call Auction Mechanism, Data Selection, and Statistics

3.1 Market overview and the call auction mechanism

Being the 9th stock market among the 22 Asia-Pacific stock markets in terms of the market capitalization, the TWSE is an order-driven market where investors can freely submit or amend orders during the normal trading hours (from 8:30 am to 1:30 pm). As the trading scheme of market order is absent in the TWSE, all order submissions are limit orders, specifying limit prices, the number of shares and types of leverage transactions (i.e., whether the order is placed with buying on margin, a short sale, or security lending). The limit price represents the highest (lowest) price that a buyer (seller) wants to trade. More precisely, a limit buy order is an order to obtain shares at or below a stipulated price while a limit sell order is an order to sell shares at or above a specified price. Limit order prices obey the tick size regulation.[5] The limits on daily price fluctuation was 7% higher or lower than previous closing price.[6] The upper and bottom limits of the 7% price range are called "Limit Up" and "Limit Down", respectively. In other words, the most aggressive buying (selling) order price is the Limit Up (Limit Down) in each trading day. The typical unit of an order submission is "one lot" which is equivalent to 1,000 shares whereas an "odd lot" order is less than 1,000 shares. The TWSE has used the Fully

[5] Tick size means the smallest increment in stock price and increases with stock price. According to the current TWSE rule, the tick size is NT$ (New Taiwan Dollars) 0.01 for share prices below NT$10; NT$0.05 for share prices between NT$10-50; NT$0.1 for share prices between NT$50-100; NT$0.5 for share prices between NT$100-500; NT$1 for share prices between NT$500-1,000; NT$5 for share prices over NT$1,000.

[6] Nonetheless, both up and down limit prices have been elevated to 10% from 7% since June 1st, 2015.

Automated Securities Trading (FAST) system in order submission, collection, and matching since 1993.

During normal trading hours ranging from 8:30 am to 1:30 pm, the TWSE is comprised of three forms of call auctions consecutively, so there is no break among three call auctions. The opening call auction lasts 30 minutes ranging from 8:30 am to 9:00 am, and aims at achieving the opening price. Note that all unexecuted orders from the previous trading day are canceled and thus not engaged in the LOB of the opening call session. As the TWSE did not disclose any LOB information during the opening session, the LOB transparency is fully opaque and investors need submit orders as if they were trading in the dark. The opening match takes place randomly within the first 40 seconds after 9:00 am (Tseng and Wei, 2017). The unexecuted orders after the opening match are automatically forwarded to the second trading venue of the TWSE that is so-called periodic or regular call auctions.

The session of regular call auctions occupies the majority of normal trading hours and ranges from 9:00 am to 1:25 am. During this session, the LOB is fully translucent because the TWSE will immediately disclose the best five buying and selling unexecuted orders as well as the number of lots of the remaining orders (depths of orders). Each periodic call has a fixed duration, according to the three reforms of trading frequency during 2013 and 2014. We select data periods which correspond to four different call durations (for the detailed designs, see Section 1.2) — the duration is 20 seconds in Period I (2012/4/5–2012/5/14), 15 seconds in Period II (2013/8/13–2013/9/18), 10 seconds in Period III (2014/4/1–2014/5/9), and 5 seconds in Period IV (2015/2/12–2015/3/31) — a total of 108 trading days. After each periodic call, unexecuted orders will be reserved all the way to the next call or the closing session in that day.

The closing call auction lasts 5 minutes from 1:25 pm to 1:30 pm, and the TWSE will simulate matches according to the corresponding trading frequencies during normal trading hours (for period I, II, III, and IV, the simulated matching occurs every 20, 15, 10, and 5 seconds, respectively). The simulated LOB will be revealed, including the top five "unexecuted" quotes, except for the depth information.

Investors enjoy the non-binding feature of limit orders during the opening call, periodic calls, and closing call. The non-binding feature allows investors to freely submit new orders, revise or withdraw existing ones before the auction time. When matching orders in each call, the exchange determines the transaction prices according to the "Volume Maximization Principle" where the executed price is set to maximize the trading volume. The executed prices are the opening and closing prices at the opening and closing auctions, respectively. Orders at auction time are cleared on the basis of both price and time priority. The "Price Priority Principle" refers to that a buying (selling) order will have a higher rank if it has a higher (lower) quote. The "Time Priority Principle" applies to orders with the same quotes, such that orders which arrives earlier will have a higher priority in settlement.

3.2 Selection of large/small cap stocks

We choose to study ordinary stocks in the centralized market in this research. We first exclude unsuitable stocks as follows:

(1) Stocks belonging to the financial and insurance industry category due to the high leverage (Fama and French, 1992; Ma et al., 2008; Tseng and Chen, 2015; Lin and Ma, 2011; Zhang, Wu, and Wang, 2012; Tseng, 2014);
(2) IPO stocks during the sample periods, or stocks listed before the sample periods but has at least one trading day overlapped by the 5-day window that refrains from the price-fluctuation limits;
(3) Delisted stocks;
(4) Stocks which has at least one day with no transactions during the sample periods;
(5) Stocks with special trading mechanisms or those being warned by the TWSE, such as the full-cash delivery stocks.

After excluding unsuitable stocks, we consider the weights and indicativeness of large-cap stocks and select component stocks from the FTSE/Taiwan 50 Index or the FTSE/Taiwan Mid-Cap 100 Index during our sample periods. We opted for 105 stocks most of which are leading or important companies in their industries. Market statistics (Table 1) confirms that these 105 large-cap stocks are active, value stocks and generally representative of the TWSE because they account for 66.30% and 55.69% of the market value and turnover, respectively.

As for the corresponding 105 small-cap stocks, we rule out the members of the Taiwan 50 Index or the Mid-Cap 100 Index as small-cap candidates. Following Duong et al. (2009), Tseng and Chen (2015), and Tseng and Wei (2017), our small-cap list takes into consideration the market values in addition to the investors' trading interests of the stocks under investigation. We filter out unsuitable stocks in accordance with the same screening criteria rules applied to large-cap stocks mentioned above, leading to a total of 547 small-cap stocks. We drop 100 least traded stocks from the 547 small-cap stocks on the criteria of average daily turnover so as to remove the extremely illiquid stocks. We rank the remaining 447 small-cap equities by the measure of average daily turnover and sort out 315 small-cap stocks as a result of lesser liquidity. Taking the 315 small and less liquid stocks as final candidates, we randomly pick one out of every three to compose our list of 105 small-cap stocks. As shown in Table 1, these 105 small-cap stocks constitute merely 2.38% of market capitalization and 1.34% of market turnover. Apparently, there is a sharp distinction in the market values and trading activities of these two types of securities. The average market value of large- and small-cap stocks is NT$ (New Taiwan Dollars) 151.89 and 5.4 billion, corresponding to 0.63% and 0.02% of market weight, respectively. The daily average of shares traded for each type of stock is NT$0.44 and NT$0.01 billion, equivalent to 0.53% and 0.01% of turnover ratio, respectively. The combined market weight of both the 105 large- and small-cap stocks is 68.68%, proving that our selected stocks fairly represent all of the stocks in the TWSE.

Table 1: Basic market statistics for selected stocks

Based on the statistics of both 105 large- and small-cap stocks, we tabulate the mean, median, and standard deviation (Std. Dev.) values.

Categories	**105 large cap stocks**	**105 small cap stocks**
Sources of sample	Members of the Taiwan 50 and	Other listed stocks

stocks	Mid-Cap 100 Indexes							
Items (daily average)	Median	Mean	Std. Dev.	Total	Median	Mean	Std. Dev.	Total
Market cap (NT$ billion)	60.18	151.89	322.80	15,948.84	3.90	5.40	4.29	567.09
Market weight (%)	0.25	0.63	1.33	66.30	0.02	0.02	0.02	2.38
Turnover (NT$ billion)	0.20	0.44	0.71	46.10	0.01	0.01	0.01	1.10
Turnover ratio (%)	0.25	0.53	0.84	55.69	0.01	0.01	0.01	1.34

Source: Authors Calculations from Yi-Heng Tseng (2019)

3.3 Data source, trader characterization, and order statistics

We collect four periods of sample in this study, with daily data on the record-by-record limit order book, trade blotters, and display book for 108 trading days. The data sources are Taiwan Stock Exchange Corporation (TSEC) and the databank managed by the Taiwan Economic Journal (TEJ). Every record from the limit order book contains stock code, date, time, order price, order volume, the identity of the submitter, order direction, etc.; every record from the trade blotters contains stock code, date, time, transaction price, volume, the identity of the trader, order direction, etc.; every record from the display book contains stock code, date, time, and the quotes and volume of the best five unexecuted buying and selling orders.

We analyze 84,209,978 (8,761,099) orders pertinent to the 105 large-cap (small-cap) stocks. For the large-cap (small-cap) stocks, orders from the institutional investors account for 50.37% (36.01%) of data, while those from the individual investors account for 49.63% (63.99%). We divide the sample of orders by their submitters; that is, institutional investors and individual investors, and the basic statistics of order submissions are summarized in Table 2.

With respective to the average number of orders per day, it seems that both types of investors are close to each other (about 3,700 orders for large-cap stocks), although orders of the small-cap stocks are mainly from individual investors. The retreat ratio for institutional investors is about 30 percent, while it is less than 20 percent for individual investors. Conceptually, order retreat implies that investors have sensed the changes in the intrinsic values of the stocks and therefore recognize the need to revise the terms of original orders, or even cancel original orders. The fact that institutional investors had a higher retreat ratio suggests that their operations are more flexible, expending more resources in monitoring market information, or relying more on the automated program trading (O'Hara, 2007). Turning to the scale of a single order, institutional investors' median order size is 1.59 and 0.76 times of individual investors' median order size for large-cap and small-cap stocks, respectively. As Tseng and Wei's (2017) study indicates that institutional investors' order size is 6 times (even 8 times) as large as individual investors' order size in the opening (closing) session, our observation of declined order size during periodic call auctions suggests that institutional investors may split their order more frequently during regular sessions (Ma et al., 2008; Hung et al., 2012).

Table 2: Statistics of the number of orders and aggressiveness of quotes and volume of orders during regular calls

Categories	**Large-cap stocks**	**Small-cap stocks**

Item (Averages per stock)	Institutional invests		Individual investors		Institutional invests		Individual investors	
A. Number of all orders (including new orders and retreats):								
Number of orders (per day)	3,740.14		3,685.79		278.18		494.40	
Retreat ratio (%)	35.28		14.76		42.33		13.59	
Scale of a single order (100%)	1.59		1.00		0.76		1.00	
B. Aggressiveness of the quotes and volume of orders (by trading frequency, labeled as Period I, II, III, IV)								
Trading frequency	I	II	III	IV	I	II	III	IV
Retreat ratio(%)								
Institutional investors	33.33	33.73	37.28	36.80	39.79	41.84	42.86	41.24
Individual investors	18.88	17.62	16.96	16.92	19.30	16.75	17.05	15.99
Aggressiveness in quotes of new orders (%)								
Institutional investors	34.14	32.99	26.89	27.73	20.84	17.22	15.53	16.73
Individual investors	37.94	35.57	32.04	28.84	31.68	33.12	31.99	30.92
Aggressiveness in volume of new orders (%)								
Institutional investors	41.37	40.23	46.44	42.79	43.55	22.34	22.23	34.32
Individual investors	37.37	37.87	38.26	36.76	39.31	42.82	41.79	41.94
New order arrival interval (sec)								
All investors	4.60	4.30	4.01	4.04	41.78	39.01	28.16	40.89

Source: Authors Calculations from Yi-Heng Tseng (2019)

We compare the aggressiveness between two kinds of investors different trading frequencies. The retreat ratio of institutional (individual) traders seem to increase (decrease) as trading frequency increases. It appears that institutional traders are more patient and retreat more orders than individual traders, partly because institutional traders are more effective in collecting information thanks to professional network or economies of scale in operation, or more skilled thanks to expertise or specialization in specific sectors. Greater retreat ratios suggest that trading strategies of institutional traders become more agile as the trading frequency is accelerated — it is worth noting that institutional investors’ retreat ratio reaches the maximum (37.28%) when call duration is 10 seconds (Period III), this implies that there is an upper limit of such an effect.

We explore the relationship of market transparency with order aggressiveness. A buying (selling) order is defined as aggressive if it is no lower (higher) than the best outstanding bid (ask) in the latest LOB observable to submitters. Accelerations in trading frequency may influence order aggressiveness in the following ways. First, the acceleration of disclosure frequency of the LOB improves information dissemination and thus market transparency. Following this logic, market participants who face a stiffer competition are forced to submit more impatient orders and become more aggressive (Bortoli et al., 2006; Ma et al., 2008). Secondly, assuming that the total number of orders is spread over a trading day, a shortened call duration suggests a smaller number of orders placed in a call auction, which in turn makes traders initiating more eager orders in exchange for better execution opportunities. Thirdly, the acceleration in trading frequency points to a shorter waiting period between the submission time and the matching time. Since new trading opportunities arrive sooner, investors might be more conservative; this phenomenon is called “wait-and-see effect.” From Table 2, it is obvious that both institutional and individual investors’ aggressiveness in quotes wanes with quickened trading frequencies, implying that the wait-and-see effect dominated the first two of the aforementioned effects. Similarly, we observe that institutional investors’ aggressiveness in quotes reaches the minimum (26.89%) when the call duration is 10 seconds (Period III), suggesting that the impacts of changes in trading frequency on the trading behavior of institutional investors are not monotonic.

Regarding the aggressiveness in order volume, an order is defined as aggressive if its volume (in lots) is larger than the median size of orders invested in the same stock by the same type of investors. However, we do not observe any clear relationship between changes in trading frequency and the aggressiveness in volume from Table 2. An accelerated trading frequency may expedite new order arrivals. Table 2 shows that the shorter the call duration, the shorter the order arrival intervals. The only exception is the order arrival interval in Period IV (with a 5-second trading frequency per call) when the arrival interval suddenly increased to 40.89 seconds. It is worth noting that although we can detect several relationships between changes in trading frequency and investors’ aggressiveness in quotes and volume, an adequate model is still needed to rigorously evaluate such effects by controlling other nuisance variables.

3.4 Trading frequency and the quality of disclosed LOB content

By examining the proximity of the latest disclosed LOB glimpsed by investors to the simulated LOB on the basis of the continuous auction mechanism, we can concretely measure the improvements in the quality of disclosed LOB when the trading frequency gradually increased. The continuous auction simulation reflects real-time changes in the LOB and is not disclosed by the TWSE. In each of trading days, we cumulate newly entered orders into the LOB and matches are simulated under the principle of maximizing the executable trading volume so as to replicate the best “unexecuted” bid and ask quotes. The summary of the statistics of disclosed LOB content are listed in Table 3.

The depth of the buying or selling queue changes as long as an order arrives the exchange during the update window between two consecutive matching times, but the best available price in the LOB may not change as frequently as the depths and is therefore more suitable to be used in evaluating the correctness of the disclosed LOB contents. Three kinds of scenarios are expected when we compare the best bid and ask prices in the latest disclosed LOB observable to investors to the best prices garnered from the LOB of the simulated continuous auction. The first is “both sides correct” scenario where the best prices of the latest disclosed LOB are exactly the same as the best prices of the simulated LOB; the second is “only one side correct” scenario where only one side of the latest disclosed LOB contains correct information as the simulated (real-time) best prices; the third is “both sides wrong” scenario where the best prices observed from the latest disclosed LOB are completely different from the simulated (real-time) best prices. From Table 3, the percentage of “both sides correct” scenario increases with trading frequency for both large- and small-cap stocks. It is apparent that a higher trading frequency advances the quality of disclosure on both sides of the LOB.

Table 3: Statistics of the quality of LOB in large and small cap stocks

Categories	**Large-cap stocks**				**Small-cap stocks**			
For the *i*th newly arrived order, take (A)“the latest disclosed LOB” or (B)“the simulated LOB under continuous auction” as benchmarks. Define an order as aggressive if its bid (ask) price is no smaller (larger) than the best outstanding bid (ask) in the benchmark LOBs, and denote its aggressiveness as (A)$A_i = 1$ or (B)$A_i^s = 1$, respectively if it meets the above conditions; 0 otherwise.								
Trading frequency	I	II	III	IV	I	II	III	IV
A.								
Both sides correct (%)	86.18	89.52	91.48	93.36	83.38	86.95	88.96	90.12
Only one side correct (%)	6.88	5.76	5.60	4.84	14.16	11.18	9.75	9.21
Both sides wrong (%)	6.94	4.72	2.92	1.80	2.46	1.87	1.29	0.67
Mid-quote deviation (‰)	0.36	0.26	0.16	0.13	1.10	0.63	0.73	0.66
B.								
$A_i = A_i^s$ (%)	97.11	97.95	98.80	99.15	97.98	98.46	98.86	99.03
$A_i > A_i^s$ (%)	2.03	1.39	0.79	0.52	1.62	1.25	0.92	0.85
$A_i < A_i^s$ (%)	0.86	0.66	0.41	0.33	0.40	0.29	0.22	0.13

Source: Authors Calculations from Yi-Heng Tseng (2019)

4. Model Specification and Estimation

4.1 Ordered probit (OP) model to analyze the influence of higher trading frequency on order choices

We use the ordered probit (OP) model to analyze the impact of elevated trading frequency on order choices that represent order aggressiveness, the size of the order (or order scale), and the status of order revision (or order retreat). Conceptually, OP model is a suitable tool in analyzing discrete dependent variables that have some sort of ordering, such as levels of order aggressiveness in our context. As the literature makes use of OP model to evaluate investors’ order aggressiveness (Griffiths et al., 2000; Ranaldo, 2004; Duong et al., 2009; Pascual and Veredas, 2009; Valenzuela and Zer, 2013; Tseng and Chen, 2015), we divide our data into two types of investors (individual or institutional) and conduct OP analysis to each of the 105 stocks in the large- and small-cap groups. We follow the lead of Biais et al. (1995) to categorize each order by the level of order aggressiveness, according to the position of order price relative to the prevalent best quote of the LOB. Following Biais et al. (1995) and Moshirian et al. (2012) as well as Tseng and Chen (2015)'s methodology, we classify the order aggressiveness ($\mathbf{A_i}$) of investors' ith newly arrived order as impatient ($\mathbf{A_i = 1}$) or patient ($\mathbf{A_i = 0}$) where the dichotomous variable, A_i, represents the binary level of order aggressiveness.

Let $\boldsymbol{Bp_i}$ and $\boldsymbol{Sp_i}$ be the best bid and ask prices observable to investors from the lastly disclosed LOB prior to order submission. Take $\boldsymbol{Sp_i}$ or $\boldsymbol{Bp_i}$ as the benchmark, the ith order will be regarded as an impatient order if its bid (ask) price is larger (smaller) or equal to $\boldsymbol{Sp_i}$ ($\boldsymbol{Bp_i}$), otherwise it will be regarded as a patient order. According to this definition, the so-called impatient order is aggressive and satisfies the condition that investors' orders could have been executed if those orders were sent to and queued in the LOB. Notice that the degree of order aggressiveness hinges upon the contents of the latest disclosed LOB, instead of synchronized LOB that the TWSE does not release to traders.

We follow Tseng (2014)'s methodology and specify a binary variable $\boldsymbol{Ords_i}$ to appraise the aggressiveness in order scale. m denotes the median size of the orders placed for a stock by each of two kinds of investors, an order is regarded as a large order ($\boldsymbol{Ords_i = 1}$) if its size is larger than m; it is regarded as a small order ($\boldsymbol{Ords_i = 0}$) otherwise. Whether traders revoke an order from the LOB can a proxy for aggressiveness. Investors can either cancel or revise an unexecuted order by decreasing the shares of the order while keeping the same original order price. We formally refer to the cancellation or revision of the order already forwarded to the TWSE as an order retreat (C_i=1) in our study. In contrast, a newly initiated order is designated as an original order (C_i=0).

In our OP model, let $\boldsymbol{y_i^{u*}}$ be the dependent variable representing investors' intensity of impatience. The superscript * signifies a latent variable and u takes on the value of one, two, and three to designate the aggressiveness in the limit price (A_i = 1 for impatient order and A_i = 0 for conservative order), order scale ($Ords_i$ =1 for large order and $Ords_i$ =0 for small order), and order retreat (C_i=1 for revised order and C_i=0 for newly originated order), respectively. The value of response variable $\boldsymbol{y_i^{u*}}$ is determined by the following OP equation:

$$y_i^{u*} = \sum_{k=1}^{K} \omega_k^u x_{k,i} + \epsilon_i^u, \quad (1)$$

where $\boldsymbol{\epsilon_i^u}$ is the error term, $\boldsymbol{x_{k,i}}$ is the non-interactive explanatory variable. We employ 10 indicators (K=10) computed from the disclosed information by TSEC, as delineated in **Error! Reference source not found.**.

Table 4: Explanatory variables used in the OP model (K=10)

k	$x_{k,i}$	**Explanatory variable**	**Calculations of quantitative indicator (for any new order *i*)**

Persistency			
1	$y(-1)_i^u$	Lagged Dependent Variable	The previous observation of dependent variable, calculated among new orders whose order directions are identical to order *i*.
Current States of the LOB			
2	Spr_i	Bid-Ask Spread	The relative gap (in ticks) between the prevailing best "unexecuted" bid and ask of the latest LOB before order *i* is submitted (%), which equals $(Sp_i - Bp_i)/[(Sp_i + Bp_i)/2]$.
3	Vol_i	Price Volatility	The volatility calculated based on information from the most recent two LOB disclosed before order *i* is submitted (%). Let the mid-quote of the latest LOB be $mq_i \equiv (Sp_i + Bp_i)/2$, and the mid-quote of the earlier LOB be $mq(-1)_i$. Price volatility is calculated as $\lvert ln(mq_i) - ln(mq(-1)_i) \rvert / t_i$, where t_i is the time gap between these two disclosures (in seconds).
4	Dep_i	Same-Side Order Depths	The relative proportion of the shares of the best order on the same-side to the total shares of the best orders on the both sides of the latest LOB disclosed before order *i* is submitted (%).
Space Allowance for Price Fluctuations of the Same Direction			
5	$Space_i$	Same-Direction Space	The space between the mid-quote (mq_i) of the latest LOB and the Limit Up or Limit Down before order *i* is submitted (%).
Market Activities and Special Date Effect			
6	Mkt_i	Daily Trading Activity	The relative ratio of the deviation of the turnover in the day when order *i* is submitted from the average daily turnover of the same date during the sample period (2012-2015) (%).
7	FD_i	Futures Settlement Day Dummy	If the day on which order *i* is submitted coincides with the settlement date of the Taiwan Stock Index Futures or MSCI Taiwan Index Futures, $FD_i = 1$, otherwise $FD_i = 0$.
8	MD_i	End of Month Dummy	If the day on which order *i* is submitted is the end of the month, $MD_i = 1$, otherwise $MD_i = 0$.
Margin Trading or Short Selling			
9	$marD_i$	Non Spot Trading Dummy	If order *i* is margin trading, short-selling, or involves security lending, $marD_i = 1$, otherwise $marD_i = 0$.
Implementation of the Trading Frequency Reform			
10	D_i	Trading Frequency Reform Dummy	Whether an experience of recent trading frequency reform exists. For example, if order *i* is submitted when the call duration is 15 seconds (after Period I, followed by Period II), 10 seconds (after Period II, followed by Period III), or 5 seconds (after Period III, followed by Period IV), $D_i = 1$, otherwise $D_i = 0$.

Source: Authors Calculations from Yi-Heng Tseng (2019)

4.2 Model estimation

Technically speaking, coefficients in Eq. (1) can be estimated using maximum likelihood estimation (MLE). Since there are only two levels for all observable dependent variables y_i^u ($y_i^1 = A_i$ 、$y_i^2 = Ords_i$), the signs of the marginal probability will be the same with the signs of the corresponding slope coefficients (Pascual and Veredas, 2009). For instance, if ω_k^1 is positive, the response variable y_i^u will increase with the explanatory variable $x_{k,i}$; that is, the chance of being identified as an impatient order for an newly arrival order i will increase. **Error! Reference source not found.** summarize s the coefficients of D_i (the trading frequency reform dummy variable) of our OP model estimation. The excerpt in Table 5 covers: (1) the sign of the median of the coefficients (labeled as ⊕, ⊖, respectively); (2) ratios of stocks for which the z statistic is significantly negative at 5% significance level (%z-stat < -1.96); (3) ratios of stocks for which the z statistic is significantly positive at 5% significance level (%z-stat > 1.96).

Table 5: OP Analysis of the Trading Frequency Acceleration Reform: Influences on Aspects of Order Choice

This table summarizes the estimation of the ordered probit (OP) model. The results are organized by two sizes of market capitalization, 105 large-cap stocks (left panel) and 105 small-cap stocks (right panel). Each market capitalization is categorized by two types of investors, institutional and individual investors.

Investor category	**Large-cap stocks**						**Small-cap stocks**					
	Institutional investors			**Individual investors**			**Institutional investors**			**Individual investors**		
Sample period	med	%z-stat < -1.96	%z-stat > 1.96	med	%z-stat < -1.96	%z-stat > 1.96	med	%z-stat < -1.96	%z-stat > 1.96	Med	%z-stat < -1.96	%z-stat > 1.96
Only an excerpt of the coefficients of the Trading Frequency Reform Dummy variable D_i												
Panel A. Investor decision: the quote is impatient ($A_i = 1$) or conservative ($A_i = 0$)												
I vs. II	⊖	45.10	41.18	⊖	64.42	23.08	⊖	55.91	34.41	⊖	48.54	24.27
II vs. III	⊖	81.55	15.53	⊖	71.43	13.33	⊖	41.49	38.30	⊖	60.78	17.65
III vs. IV	⊕	39.81	46.60	⊖	64.76	19.05	⊖	37.23	37.23	⊕	30.39	25.49
Panel B. Investor decision: order scale is relatively large ($Ords_i = 1$) or relatively small ($Ords_i = 0$)												
I vs. II	⊖	51.92	28.85	⊕	26.92	40.38	⊖	51.61	26.88	⊕	13.59	40.78
II vs. III	⊖	44.76	42.86	⊕	20.95	20.95	⊕	31.91	38.30	⊖	27.72	13.86
III vs. IV	⊖	47.62	34.29	⊖	34.29	15.24	⊕	23.40	46.81	⊖	14.71	22.55
Panel C. Investor decision: retreat ($C_i = 1$) or submit new orders ($C_i = 0$)												
I vs. II	⊖	54.90	18.63	⊖	37.50	17.31	⊖	32.26	34.41	⊖	33.01	4.85
II vs. III	⊕	18.10	62.86	⊕	15.24	28.57	⊖	25.00	26.04	⊕	6.86	11.76
III vs. IV	⊕	20.95	44.76	⊖	13.33	21.90	⊖	23.96	19.79	⊖	17.65	17.65

Source: Authors Calculations from Yi-Heng Tseng (2019)

Three patterns are noteworthy from Table 5 as follows. First, Panel A of Table 5 indicates the order choice; that is, impatient (A_i=1) versus conservative (Ai=0) orders. The quote aggressiveness of individual investors almost exhibits a monotonic decreasing trend throughout a series of trading frequency reforms. More precisely, 64.42%, 71.43%, and 64.76% of large-cap stocks accompany with conservative orders while only 23.08%, 13.33%, and 19.05% of large-cap stocks accompany with impatient orders during the transitions from I to II, II to III, and III to IV periods, respectively. Likewise, conservative orders dominates aggressive orders for small-cap stocks through various phases of trading frequency modification. This observation implies that the wait-and-see effect induced by trading frequency reforms largely suppress uninformed investors' desires for trading. It turns out that this wait-and-see effect outweighs the pressure caused by the improved LOB quality to compete for better execution opportunities in a high transparency market (Bortoli et al., 2006). By contrast, modest evidence sustains the systematic relationship between trading frequency reforms and institutional investors' quote aggressiveness. Our conjecture is that for institutional (informed) investors, the aggressive rat race effect (Ma et al., 2008) resulted from superior LOB transparency was somewhat neutralized by the conservative wait-and-see effect. Despite so, we detect a significant shrinkage in quote aggressiveness for large-cap stocks when the trading frequency drops from 15 seconds per call in Period II to 10 seconds per call in Period III. Corresponding to the row with the title 'Period II vs. III', 81.55% (15.33%) of the large-cap stocks are associated with statistically significant, negative (positive) coefficient of D_i; that is, institutional investors swing to conservativeness in the presence of greater trading frequency. In short, the wait-and-see effect exerts a great impact on individuals, and, to a lesser extent, on institutional investors in a transparent market as a result of the trading frequency progression.

Secondly, Panel B of Table 5 suggests a subtle decline in the order scale of institutional investors in response to higher trading frequency in that there are slightly more negative medians of coefficients of D_i than positive ones. More specifically, there are 4 negative medians of coefficients of D_i, including 3 $\ominus$ for large-cap stocks across all periods and 1 $\ominus$ for small-cap stocks between Period I and II, shown in the row entitled "I vs. II". There are only 2 positive medians of coefficients of D_i (2 $\oplus$ for small-cap stocks in both II vs. III and III vs. IV rows). The negativity of dummy variable D_i is a sign of smaller orders, and vice versa. Drawing a comparison of the ratios of stocks for which the *z* statistic is statistically significant in both "%z-stat <-1.96" and "%z-stat >1.96" columns, moderate is the difference between the stocks with negative D_i (undersized order) and the stocks with positive D_i (sizable order). Two reasons explain why institutional investors scale back their order size. One reason is that institutional investors' order sizes are 1.59 times larger than individual investors' order sizes (see **Error! Reference source not found.**) and it makes sense for institutional investors to split their orders and thus trim the magnitude of a single order. The other reason is that fewer participants and lower filled rate in each call owing to shorter call duration force institutional investors to place a smaller order. Our result is in line with Ma et al. (2008) as institutional investors camouflage their advantage of trading information by spreading the number of shares across normal trading hours.

Thirdly, institutional investors exhibit a tendency towards retreating orders in that there are more positive coefficients of D_i than negative ones for large-cap stocks shown in Panel C of Table 5, except the reform from 20 seconds to 15 seconds (Period I vs. II). The more likely it is to retreat an order, the more strategically flexible it is for institutional investors in completing order transactions. Trivial is the discrepancy between order retreat and newly arrival order in the dataset of small, illiquid stocks. The above finding is consistent with Aitken et al. (2007) and Liu (2009) that institutional investors allocate more resources to and amend orders more frequently in large, liquid stocks than small, illiquid stocks.

5. Conclusion

Although we do not control for exogenous factors in relation to a severe drop in overall trading volume in the TWSE, our results shine a light on how trading frequency reforms interact with the oscillation of TWSE trading shares through the lens of investors' order behavior. Not only do the transparency reforms increase order arrival rate, but also induce the wait-and-see effect on investors (especially individuals) who await plenty of trading opportunities between call auctions. This wait-and-see effect greatly suppress individual investors' desire to pursue immediate execution, and makes individual traders conservative in price quote along with the exacerbations of trading frequency. Due to the fact that TWSE is composed of mainly individual investors, the wait-and-see effect companying the acceleration reforms is a clear threat (or even a killer) to market volume momentum. For institutional investors whose order sizes tends to be substantial, more frequent calls make fewer participants in each call, thereby signifying a lower filled rate, on average, in each of large orders. Consistent with our hypothesis, institutional investors' aggressiveness in order scale for large-cap stocks has diminished since the reform of the 15-second call duration. The unintended consequence of transparency reforms turns out to drag TWSE market volume down, contradicting the goal of TWSE authority to heighten overall market liquidity.

Despite so, these trading frequency reforms still brought gradual improvements in the quality of disclosed LOB, and contributed to alleviate the problem of information asymmetry between informed and uninformed investors. According to our quantitative indicators, when the trading frequency is as fast as 5 seconds per call, the match ratios of the best prices glimpsed from the latest disclosed LOB and the real-time best prices are 93.36% and 90.12% for large- and small-cap stocks, respectively; the match ratio of investors' subjective aggressiveness (calculated based on the latest disclosed LOB) and objective aggressiveness (calculated based on the simulated continuous auction) for large- and small-cap stocks is as high as 99.15% and 99.03%, respectively. With regard to TSEC's future plan of replacing periodic call auction with continuous auction (Tsai, 2013), our thought is that continuous auction mechanism improves, to some degree, the quality of disclosed LOB information. Nevertheless, it is a questionable whether continuous auction system is an effective strategy to amplify trading volume. Financial professionals and regulators should be aware of the side effect of the reform from 5-second call auction to continuous auction on the TWSE trading volume in consideration of individual investors' aggressiveness of price quote and institutional investors' aggressiveness of order scale.

References

Ahn, H.-J., K.-H. Bae, & K. Chan. (2001). Limit Orders Depth & Volatility: Evidence from the Stock Exchange of Hong Kong. The Journal of Finance, 56, 767-788.

Ai, C. & E.C. Norton. (2003). Interaction Terms in Logit & Probit Models. Economics Letters, 80, 123-129.

Aitken, M., N. Almeida, F.H.deB. Harris, & T.H. McInish. (2007). Liquidity Supply in Electronic Markets. Journal of Financial Markets, 10, 144-168.

Alangar, S., C. Bathala, & R.P. Rao. (1999). The Effect of Institutional Interest on the Information Content of Dividend-change Announcement. Journal of Financial Research, 22, 429-448.

Amihud, Y. & H. Mendelson. (1987). Trading Mechanisms & Stock Returns: An Empirical Investigation. Journal of Finance, 42, 533-553.

Anagnostidis P., A. Kanas, & G. Papachristou. (2015). Information Revelation in the Greek Exchange Opening Call: Daily & Intraday Evidence. Journal of International Financial Markets, Institutions & Money, 38, 167-184.

Back, K., C. H. Cao, & G. A. Willard. (2000). Imperfect Competition among Informed Traders. The Journal of Finance, 55, 2117-2155.

Bae, K.-H., H. Jang & K. S. Park. (2003). Traders' Choice between Limit & Market Orders: Evidence from NYSE Stock. Journal of Financial Markets, 6, 517-538.

Bandi, F.M. & J.R. Russell. (2006). Separating Microstructure Noise From Volatility. Journal of Financial Economics, 79, 655-692.

Biais, B., P. Hillion, & C. Spatt. (1995). An Empirical Analysis of the Limit Order Book & the Order Flow in the Paris Bourse. The Journal of Finance, 50, 1655-1689.

Biais, B., P. Hillion, & C. Spatt. (1999). Price Discovery & Learning during the Preopening Period in the Paris Bourse. Journal of Political Economy, 107, 1218-1248.

Boehmer, E., G. Saar, & L. Yu. (2005). Lifting the Veil: an Analysis of Pre-trade Transparency at the NYSE. The Journal of Finance, 60, 783-815.

Bortoli, L., A. Frino, E. Jarnecic, & D. Johnstone. (2006). Limit Order Book Transparency. Execution Risk. & Market Liquidity: Evidence from the Sydney Futures Exchange. Journal of Futures Markets, 26, 1147-1167.

Chan, C. & J. H. Lee. (2014). Market Stability & Trading Mechanism: Evidence from Taiwan Futures Market. Taiwan Economic Review, 42, 49-101. (in Chinese)

Chang, R. P., T. Fukuda, S. G. Rhee, & M. Takano. (1993).Intraday & Interday Behavior of the TOPIX. Pacific-Basin Finance Journal, 1, 67-95.

Chang, R.P., S.T. Hsu, N.K. Huang, & S.G. Rhee. (1999). The Effects of Trading Methods on Volatility & Liquidity: Evidence From the Taiwan Stock Exchange. Journal of Business Finance & Accounting, 26, 137-170.

Chang, Rosita P., S. G. Rhee, G. R. Stone, & N. Tang. (2008).How Does the Call Market Method Affect Price Efficiency? Evidence From the Singapore Stock Market. Journal of Banking & Finance, 32, 2205-2219.

Cho, J.-W., & E. Nelling. (2000). The Probability of Limit Order Execution. Financial Analysts Journal, 56, 28-33.

Choe, H. & H. S. Shin. (1993), An Analysis of Interday & Intraday Return Volatility – Evidence From the Korea Stock Exchange. Pacific Basin Finance Journal, 1, 175-188.

Cohen, K. J., S. F. Maier, R. A. Schwartz, & D. K. Whitcomb. (1981). Transaction Costs Order Placement Strategy & the Existence of the Bid-ask Spread. Journal of Political Economy, 89, 287-305.

Comerton-Forde, C., S. T. Lau, & T. McInish. (2007). Opening & Closing Behavior Following the Introduction of Call Auctions in Singapore. Pacific-Basin Finance Journal, 15, 18-35.

Copeland, T. E., & D. Galai. (1983). Information Effects on the Bid-ask Spreads. Journal of Finance, 38, 1457-1469.

Dia, M. & S. Pouget. (2011). Sunshine Trading in An African Stock Market. Managerial Finance, 37(3), 257-274.

Duong, H. N., P. S. Kalev, C. Krishnamurti. (2009). Order Aggressiveness of Institutional & Individual Investors. Pacific-Basin Finance Journal, 17, 533-546.

Eom, K. S., J. Ok & J.-H. Park. (2007). Pre-trade Transparency & Market Quality. Journal of Financial Markets, 10, 319-341.

Eom, K.S. & J.H. Park. (2015). Price Stabilization & Discovery under A Random-end Trading Mechanism. SSRN working paper.

Fama, E.F. & K.R. French. (1992). The Cross-section of Expected Stock Returns. The Journal of Finance, 47, 427-465.

Flood, M. D., R. Huisman, K. G. Koedijk, & R. J. Mahieu. (1999). Quote Disclosure & Price Discovery in Multiple-dealer Financial Markets. Review of Financial Studies, 12, 37-59.

Foster, F. Douglas & S. Viswanathan. (1996). Strategic Trading when Agents Forecast the Forecasts of Others. The Journal of Finance, 51, 1437-1478.

Foucault, T. (1999). Order Flow Composition & Trading Costs in a Dynamic Limit Order Market. Journal of Financial Markets, 2, 99-134.

Garbade, K. D. & W. Silber. (1979). Structural Organization of Secondary Markets: Clearing Frequency. Dealer Activity & LiquidityRisk. Journal of Finance, 34, 577-593.

George, T. J. & C.-Y. Hwang. (1995). Transitory Price Changes & Price-Limit Rules: Evidence From the Tokyo Stock Exchange. Journal of Financial & Quantitative Analysis, 30, 313-327.

Goettler, R. L., C. A. Parlour, & U. Rajan. (2005). Equilibrium in a Dynamic Limit Order Market. Journal of Finance, 60, 2149-2192.

Griffiths, M.D., B. F. Smith, D.A.S. Turnbull, & R.W. White. (2000). The Costs & the Determinants of Order Aggressiveness. Journal of Financial Economics, 56, 65-88.

Handa, P. & R. A. Schwartz. (1996). Limit Order Trading. The Journal of Finance, 51, 1835-1861.

Hasbrouck, J. & T.S.Y. Ho. (1987). Order Arrival. Quote Behavior & the Return-Generating Process. The Journal of Finance, 42(4), 1035-1048.

Hollifield, B., R.A. Miller, P. Sandas, & J. Slive. (2006). Estimating the Gains from Trade in Limit-order Markets. The Journal of Finance, 61, 2753-2804.

Huang, Y.C., P.L. Chen, & Y.J. Cheng. (2007). The Impact of New Trading Rules on Market Performance: The Case of Taiwan Stock Exchange. Review of Securities & Futures Markets, 19, 135-160. (in Chinese)

Huang, Y.-S., D.-Y. Liu, & T.-W. Fu. (2000). Stock Price Behavior Over Trading & Non-Trading Periods: Evidence From the Taiwan Stock Exchange. Journal of Business Finance & Accounting, 27, 575-602.

Hung, P. H., R. S. Chen, Y.C. Huang, & H. Y. Liao. (2012). Order Imbalances. Investor Types & Stock Return. Review of Securities & Futures Markets, 24, 1-48. (in Chinese)

Ibikunle, G. (2015). Opening & Closing Price Efficiency: Do Financial Markets Need the Call Auction? Journal of International Financial Markets, Institutions & Money, 34, 208-227.

Kalay, A., W. Li, & A. Wohl. (2002). Continuous Trading or Call Auctions: Revealed Preferences of Investors at the Tel Aviv Stock Exchange. Journal of Finance, 57, 523-542.

Kandel, E., B. Rindi, & L. Bosetti. (2012). The Effect of a Closing Call Auction on Market Quality & Trading Strategies. Journal of Financial Intermediation, 21, 23-49.

Kaniel, R. & H. Liu. (2006). So What Orders Do Informed Traders Use? Journal of Business, 79, 1867-1913.

Kaniel , R., G. Saar, S. Titman. (2008). Individual Investor Trading & Stock Return. Journal of Finance, 63, 273-310.

Lang, L.H.P. & Y.T. Lee. (1999). Performance of Various Transaction Frequencies under Call Markets: The Case of Taiwan. Pacific-Basin Finance Journal, 7, 23-39.

Lee, H. C., C.-Y. Chien, Y.-F. Hsieh, & Y.-S. Huang. (2009). Auction Designs & Futures Price Behavior: Evidence From the Taiwan Futures Market. Review of Futures Markets, 17, 301-322.

Lee, Y. T., Y. J. Liu, J.Y. Wang, W. J. Chen, & W.H. Lai. (2009). Limit Order Book Transparency & Market Quality. Review of Securities & Futures Markets, 21, 51-86. (in Chinese)

Lin, Y. & T. Ma. (2011). Transparency. Information Content & Order Placement Strategy. Journal of Financial Studies, 19, 1-32. (in Chinese)

Liu, W.M. (2009). Monitoring & limit order submission risks. Journal of Financial Markets, 12, 107-141.

Lo, A. W., A. C. MacKinlay, J. Zhang. (2002). Econometric Models of Limit-order Executions. Journal of Financial Economics, 65, 31-71.

Ma, T., (1996). The Tax & Distributional Effects of ESOP - An Empirical Analysis of the Effect on Stock Prices of the Employee Stock Plans in Taiwan. Journal of Financial Studies, 3, 49-62.

Ma, T. (1998). Trading Frequencies & Stock Market Performance: The Case of Taiwan. Asia Pacific Journal of Finance, 1, 1-26.

Ma, T., Y.L. Lin, & H.K Chen. (2008). Are Investor More Aggressive in Transparent Market?. Asia-Pacific Journal of Financial Studies, 37(2), 343-380.

Madhavan, A. (1992). Trading Mechanisms in Securities Markets. Journal of Finance, 47, 607-641.

Madhavan, A. (1996). Security Prices & Market Transparency. Journal of Financial Intermediation, 5, 255-283.

Madhavan, A., D. Porter & D. Weaver. (2005). Should Securities Markets be Transparent?. Journal of Financial Markets, 8, 265-287.

Mendelson, H. (1982). Market Behavior in a Clearing House. Econometrica, 50, 1505-1524.

Moshirian, F., H.G. Nguyen, & P.K. Pham. (2012). Overnight Public Information. Order Placement. & Price Discovery during the Pre-Opening Period. Journal of Banking & Finance, 36, 2837-2851.

Muscarella, C. J. & M. S. Piwowar. (2001). Market Microstructure & Securities Values: Evidence From the Paris Bourse. Journal of Financial Markets, 4, 209-229.

Pagano, M. & A. Röell. (1996). Transparency & Liquidity: a Comparison of Auction & Dealer Markets with Informed Trading. The Journal of Finance 51, 579-611.

Pagano, M. S. & R. A. Schwartz. (2003). A Closing Call's Impact on Market Quality at Euronext Paris. Journal of Financial Economics, 68, 439-484.

Pagano,M. S., L. Peng, & R. A. Schwartz. (2013). A Call Auction's Impact on Price Formation & Order Routing: Evidence From the NASDAQ Stock Market. Journal of Financial Markets, 16, 331-361.

Pascual, Roberto & David Veredas. (2009). What Pieces of Limit Order Book Information Matter in Explaining Order Choice by Patient & Impatient Traders?. Quantitative Finance, 9, 527-545.

Parlour, C. A. (1998). “Price Dynamics in Limit Order Markets.” Review of Financial Studies. 11. 789-816.

Ranaldo, A. (2004). Order Aggressiveness in Limit Order Book Markets. Journal of Financial Market, 7, 53-74.

Rosu, Ioanid. (2009). A DynamicModel of the Limit Order Book. Review of Financial Studies, 22, 4601-4641.

Stoll, H. R. & R. E. Whaley. (1990). Stock Market Structure & Volatility. Review of Financial Studies, 3, 37-71.

Tian X., B. Do, H.N. Duong, & P.S. Kalev. (2015). Liquidity Provision & Informed Trading by Individual Investors. Pacific-Basin Finance Journal, 35(A), 143-162.

Tsai, P.W. (2010). A Planning Proposal of Disclosing the Opening & Closing Information of the Taiwan Securities Market. TWSE Monthly Review, 576, 8-20. (in Chinese)

Tsai, P.W. (2013). An Introduction of Continuous Auctions & Shortening the Lengths of Call Auctions. Securities & Futures Monthly, 31, 14-20. (in Chinese)

Tseng, Y. H. (2014). How to Determine the Order Aggressiveness in Price & Volume during the Closing Call Auction? The Influence of Information Disclosure on Individual & Institutional Investors. Taiwan Economic Review, 42, 539-599. (in Chinese)

Tseng, Y. H. (2016). Call Auctions. Limit Order Book Information & Order Aggressiveness. Review of Securities & Futures Markets, 28, 39-102. (in Chinese)

Tseng, Y.H. & S.H. Chen. (2015). Limit Order Book Transparency & Order Aggressiveness at the Closing Call: Lessons from the TWSE 2012 New Information Disclosure Mechanism. Pacific-Basin Finance Journal, 35(A), 241-272.

Tseng, Y.H & P.Y. Wei. (2017). Public Information. Price Discovery & Order Choices during the Opening Call. Academia Economic Papers, 45, 503-598. (in Chinese)

Tseng, Y.H., C.L. Chang, & K.L. Wang. (2017). Order Choices. Order Performance. & Price Discovery during Closing Call Auction - Case Study of Improved LOB Disclosure in Taiwan Stock Exchange. Journal of Financial Studies, 25(2), 105-156.

Valenzuela, M.& I. Zer. (2013). Competition. Signaling & Non-walking Through the Book: Effects on Order Choice. Journal of Banking & Finance, 37, 5421-5435.

Wang, Z.M., C.S. Chiao, & H.Y. Tin. (2014). Information Transparency on the Closing Session & Price Efficiency in the Taiwan Stock Market. Journal of Management & Business Research, 31, 107-134. (in Chinese)

Zhang, Y. R., R. C. F. Wu, & T. Wang. (2012). An Empirical Investigation on Determinants of Foreign Ownership: Evidences on Safety & Information Asymmetry. Review of Securities & Futures Markets, 24, 1-44. (in Chinese)