The Impact of Matching Mechanism Changes on Order Aggressiveness

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ABSTRACT

This study explores the impact of the shift from call auction to continuous trading in the Taiwan stock market's order matching mechanism on investor order placement behavior. The study selects intraday order and transaction data, covering 481 listed companies, and analyzes the data in 30-minute intervals. An "order activity" index, weighted by order quantity and considering price and volume, is constructed to measure order placement strategies under different matching mechanisms. Empirical results show that with shorter matching times, more immediate information disclosure, and increased market transparency, overall investors order activity significantly increases. Individual investors show the most significant increase across all time periods, while institutional investors exhibit higher activity before the market closes. Faster information transmission and improved transaction efficiency encourage investors to adopt more aggressive order placement strategies to increase trading opportunities and react to market information more promptly.

Keywords: Matching Mechanism, Continuous Trading, Order Aggressiveness

INTRODUCTION

The Taiwan Stock Exchange adjusted from call auctions to continuous auctions on March 23, 2020. The nature of the two systems is different. Continuous trading can be matched at any time without waiting, and its trading efficiency is significantly better than call auctions. The transparency of trading information is increased and the price response is more immediate. It is one of the most important changes in the Taiwan stock trading system.

Both Cheng and Kang (2007) and Kuo and Li (2011) have examined the improvements in market quality since the Taiwan Futures Exchange shifted from call auction to continuous auction in 2002. The former finds that the quality improves considerably while the latter argues that there are both advantages and disadvantages of the two trading mechanisms. While continuous auction can increase market liquidity and reduce volatility, call auction is associated with an in-depth market and a smaller price-bias. Previous studies mostly focus on market quality,

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however, we argue that the investors' behavior determines market quality. The investors may be more active in placing orders with a shorter clearing interval and a faster transaction speed.

While prior studies focus mainly on market quality, we suggest that market quality is driven by investors' behavior. A shorter clearing interval and faster execution may encourage more aggressive order placement, but the higher cost of mistaken orders may also induce more cautious strategies.

This study explores whether changes in the matching mechanism have a significant impact on the order placement activity of different types of investors. The paper is divided into five chapters. Chapter 1 explains the research motivation and objectives. Chapter 2 covers relevant literature. Chapter 3 introduces the market background, samples, and methods for measuring order placement activity. Chapter 4 presents the empirical results. Chapter 5 summarizes the entire study.

LITERATURE REVIEW

From a theoretical viewpoint of trading mechanisms, Garbade and Silber (1979) and Mendelson (1982) demonstrated that continuous auction could narrow the difference between the equilibrium value when a market participant decides to trade and the actual transaction price. Brennan and Cao (1996) suggested that continuous auction provides the opportunity for more frequent trading, causing the transaction price to move closer to the real value by responding to new information immediately, thereby increasing trading volume, reducing risks, and improving efficiency. However, Goldman and Sosin (1979) discovered that continuous trading results in substantial pricing errors in the presence of uncertainty in the dissemination of information. In addition, Pagano, Peng, and Schwartz (2013) believe that call auction could pool more orders to form a price that is closer to the equilibrium value. In contrast, continuous auction for a brief period may only reflect the beliefs of specific or a few traders and, therefore, may result in a higher level of short volatility. Empirical studies have also drawn inconsistent conclusions.

Empirical studies by Amihud, Mendelson, and Lauterbach (1997), Lauterbach (2001), and Kalay, Wei, and Wohl (2002) found that in the stock exchange markets of Israel, the shift from call auction to continuous auction improves liquidity, efficiency, and excessive gains. On the contrary, Theissen (2000) discovered that in call auction markets, the bid-ask spread is lower compared to continuous auction markets. In other words, the level of liquidity is higher in call auction markets. Chan and Lee (2014) pointed out that call auctions have lower temporary price fluctuations, and their function of stabilizing market prices is significantly better than continuous auctions when the degree of information asymmetry is high and transactions are intense. Wang and Chou (2018) explored the effects of shorter clearing time in Taiwan's stock exchange market on market quality. They find that a shorter clearing interval could reduce the bid-ask spread and increase market depth considerably, thereby improving market quality. Nevertheless, it could not reduce volatility significantly.

By reviewing the above literature in terms of their perspectives, most studies only focus on market quality (for example, liquidity, volatility, and efficiency). In this study, we believe that the behavior of investors determines market quality. Therefore, it is necessary to first observe the behavioral changes in different types of investors and then observe how these behavioral dimensions are related to market quality.

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METHODOLOGY

Sample and Data

Taiwan stocks have implemented continuous auctions since March 23, 2020. Different from call auctions, which require 5 seconds of accumulated orders before being matched, orders of continuous auctions can be matched at any time, which is better than call auctions in terms of information transparency.

The period of continuous auctions is from 9:00 am to 1:25 pm, and call auctions are still maintained during the opening and closing periods. Continuous auctions can provide a variety of order types, such as market orders, immediate or cancel (IOC), and fill or kill (FOK) orders. Investors can be more flexible in strategic choices. In order to make the length of the sample period consistent and avoid the interference of the January effect, this article selects August to December 2019 as the sub-sample period before the change of the matching mechanism, and April to August 2020 as the sub-sample period after the change of the matching mechanism.

The sample data are drawn from order, disclosure, and execution records compiled by the Taiwan Stock Exchange Corporation and the Taiwan Economic Journal database. Submitted orders are defined as "order data," among which filled orders are categorized as "execution data," while unfilled orders are classified as "disclosure data." For the purposes of this study, each trading day is divided into nine 30-minute intervals. That is, the first period runs from 9:00 to 9:30, the second from 9:30 to 10:00, and so forth.

This study defines October to December 2019 as the "pre-adjustment period" and April to June 2020 as the "post-adjustment period." In addition, the top 500 most actively traded stocks during the sample period were selected for analysis. Due to missing observations in the empirical dataset, stocks with incomplete data were excluded. As a result, the final sample consists of 481 firms.

Measuring Order Aggressiveness

To address the limitation of Ma, Lin, and Chen (2008), who considered price but neglected quantity, this section shifts the focus to both price and volume dynamics. I adapt and build upon Lee's (2005) methodology to construct the following measure for average order aggressiveness:

$$\text{Order aggressiveness to buy} = \sum_{i=1}^{n} \frac{Q_{it}^{B}}{Q_{tL}^{BT}} \times \frac{(P_{it}^{B} - P_{t-1}^{*})}{P_{t-1}^{*}} \quad (1)$$

$$\text{Order aggressiveness to sell} = \sum_{i=1}^{n} \frac{Q_{it}^{S}}{Q_{tL}^{ST}} \times \frac{(P_{t-1}^{*} - P_{it}^{S})}{P_{t-1}^{*}} \quad (2)$$

$$\text{Average order aggressiveness} = (\text{order aggressiveness to buy} + \text{order aggressiveness to sell})/2 \quad (3)$$

where P_{t-1}^{*} denotes the trading price of last transaction, P_{it}^{B} and P_{it}^{S} denote the price of the i^{th} buy and sell orders in the t_{th} transaction, respectively, Q_{it}^{B} and Q_{it}^{S} denote the volume of the i^{th} buy and sell orders in the t^{th} transaction, respectively, Q_{tL}^{BT} and Q_{tL}^{ST} denote the total volume of buy and sell orders in the t^{th} transaction, respectively, and n is the total number of orders in each transaction. Therefore, it is an indicator of order aggressiveness weighted by order volume. It is characterized by measuring the average order aggressiveness by

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considering the difference between the order price and the trading price in each transaction. When investors are more aggressive, they will submit higher prices to buy or lower prices to sell. Therefore, higher the average value calculated according to Equation (3), the more aggressive investors place orders. In contrast to Lee (2005), this study also considers price variation for different stocks. For comparison with the same indicator, the value must be normalized. Therefore, as shown in Equations (1) and (2), the denominator of the right term, or the trading price of the last transaction, is used to divide the difference between the order price and the trading price of the stock.

Empirical results

This study examines whether the adoption of the continuous trading system affects the order submission strategies of different types of investors. In addition to presenting the distribution of order aggressiveness for institutional and individual investors, it tests for differences in their order aggressiveness across various matching mechanisms.

As shown in Table 1, following the implementation of the continuous trading system, market transparency improved significantly, effectively reducing information asymmetry between institutional and individual investors and, in turn, promoting more aggressive order submission by both groups.

In particular, individual investors exhibited a significant increase in order aggressiveness at the market open (Interval 1), mid-session (Interval 4), and market close (Interval 8). This finding suggests that, with the immediate disclosure of five levels of unexecuted information and a tick-by-tick matching mechanism, individual investors have more confidence in market quotes and are more willing to adopt more aggressive order types, such as market orders and IOC orders (Immediate-or-Cancel), thus shifting their trading behavior from passive waiting to more immediate and aggressive execution.

Further, Table 2 shows that institutional investors exhibit a higher degree of order aggressiveness than individual investors, particularly toward the end of the trading session.

Table 1 The distribution of order aggressiveness and the differences between the various matching mechanisms.

The distribution of the order aggressiveness for each 30-min trading interval during the two matching mechanisms. The observations include 481 samples. This table also lists the differences between the various periods in order aggressiveness for the given trading intervals.

The differences in order aggressiveness represent the mean level of order aggressiveness within a given trading interval during the post-transparency period, minus that observed during the pre-transparency period.

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	Pre-adjustment period		Post-adjustment period	
	institutional investors	individual investor	institutional investors	individual investor
Daily	-4.46	-5.74	-1.98	-2.66
Interval 1（9:00~9:30 ）	-10.14	-11.47	-8.74	-5.83
Interval 2（9:30~10:00）	-7.84	-8.94	-3.52	-6.22
Interval 3（10:00~10:30）	-6.49	-3.96	-5.22	-0.61
Interval 4（10:30~11:00）	-5.94	-4.98	1.01	-3.05
Interval 5（11:00~11:30）	-5.41	-5.35	-2.64	-5.49
Interval 6（11:30~12:00）	-8.26	-4.91	-4.57	-3.98
Interval 7（12:00~12:30）	-3.86	-4.68	-0.46	-5.14
Interval 8（12:30~13:00）	-15.48	-4.60	16.90	-2.02
Interval 9（13:00~13:30）	1.72	-6.67	0.23	-1.32

	Difference: post-transparent period - pre-transparent period				
	institutional investors		individual investors		
	Difference	t-value	Difference	t-value	
Daily	2.48	1.83 *	3.08	2.86	***
Interval 1（9:00~9:30 ）	1.39	0.60	5.64	2.15	**
Interval 2（9:30~10:00）	4.32	1.25	2.72	0.96	
Interval 3（10:00~10:30）	1.27	1.16	3.36	0.91	
Interval 4（10:30~11:00）	6.95	1.13	1.93	2.02	**
Interval 5（11:00~11:30）	2.76	1.35	-0.14	-0.13	
Interval 6（11:30~12:00）	3.69	1.13	0.93	1.43	
Interval 7（12:00~12:30）	3.39	1.71 *	-0.46	-0.25	
Interval 8（12:30~13:00）	32.38	1.46	2.58	2.86	***
Interval 9（13:00~13:30）	-1.49	-0.67	5.35	1.12	

paired-samples t test. * indicates significant at 10%, ** indicates significant at 5%, and *** indicates significant at 1%

Table 2 The differences in the order aggressiveness between various investor types

This table lists the differences between the various investor types for the given trading intervals. The observations include 481 samples. The differences in order aggressiveness between institutional investors and individual investors represent the mean level of order aggressiveness within a given trading interval for institutional investors minus that for individual investors.

	Pre-adjustment period		Post-adjustment period	
	Difference	t-value	Difference	t-value
Daily	1.28	1.36	0.68	0.47
Interval 1（9:00~9:30 ）	1.33	0.48	-2.91	-1.84 *
Interval 2（9:30~10:00）	1.10	0.93	2.71	0.90
Interval 3（10:00~10:30）	-2.53	-1.73 *	-4.61	-1.34
Interval 4（10:30~11:00）	-0.96	-1.46	4.06	0.65
Interval 5（11:00~11:30）	-0.05	-0.06	2.85	1.33
Interval 6（11:30~12:00）	-3.35	-1.26	-0.59	-0.29
Interval 7（12:00~12:30）	0.82	0.59	4.68	1.97 **
Interval 8（12:30~13:00）	-10.88	-1.02	18.92	0.97
Interval 9（13:00~13:30）	8.39	3.13 ***	1.55	0.34

t test. * indicates significant at 10%, ** indicates significant at 5%, and *** indicates significant at 1%.

CONCLUSION

This study examines the impact of the transition from call auctions to continuous trading on investor behavior in the Taiwan Stock Exchange. I used intraday order and execution data from 481 listed companies over two periods to construct an order activity index that integrates price, quantity, and order volume.

Empirical analysis at 30-minute intervals shows that shorter matching intervals and more comprehensive information disclosure significantly improve market transparency, thereby reshaping investor order placement strategies. Notably, both institutional and individual investors exhibited higher order placement activity after adopting continuous trading, with this effect being particularly pronounced for individual investors, especially during the opening, intraday, and closing sessions; while institutional investors showed higher activity closer to the close. These findings suggest that increased transparency and execution speed encourage traders to adopt more aggressive strategies to ensure successful trades and fully utilize available information.

Based on these findings, this study offers several recommendations. First, regulators should strike a balance between transparency and liquidity when modifying matching mechanisms. While continuous trading helps improve price discovery, it also requires more robust safeguards to mitigate potential risks during periods of increased volatility. Second, market participants should readjust their risk management strategies. In particular, individual investors need to incorporate slippage considerations under immediate trading conditions, while institutional investors can further optimize their best execution strategies. Finally, future research should focus on the short-term price volatility caused by high-frequency trading and the long-term impact of algorithmic trading on the market. This will allow for a clearer understanding of how market microstructures will evolve with changes in regulations and trading methods.

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