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# Trader types and fleeting orders: Evidence from Taiwan Futures Exchange

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**Abstract**
This paper investigates the relation between trader type and fleeting order strategy based on unique data from Taiwan Futures Exchange. We find that fleeting orders are more commonly used by institutional traders than individual traders. There exists intraday seasonality of fleeting orders submitted by institutional traders. Institutional traders do not chase market prices, but respond to changes in immediate execution costs. Network orders constitute a key component of the fleeting order strategy of proprietary traders. In sum, different types of traders, including individual traders, proprietary traders, and foreign traders, exhibit significantly different behaviors when deploying the fleeting order strategy.

**KEYWORDS**
fleeting order, network trading, order cancellation, Taiwan futures markets, trader types

**JEL CLASSIFICATION**
G12, G14, G20

## 1 | INTRODUCTION

On May 6, 2010, the US financial markets, including stock indices, stock index futures, options, and exchange-traded funds, fell rapidly by more than 5 %, followed by a quick and significant rebound within only 30 min. This event is known as "flash crash." Surveys indicate that algorithmic and high frequency trading are the main contributors to flash crash events (Kirilenko, Kyle, Samadi, & Tuzun, 2016). Using algorithmic trading, high-frequency traders can engage in frequent, repeated, and ongoing interactions with the markets within milliseconds, trade aggressively with price movements, and accelerate plunges in downward-trending markets, leading to a flash crash.

With improvements in trading technology, traders have increasingly used algorithmic trading strategies in recent years (Hendershott, Jones, & Menkveld, 2010). Fleeting orders, defined by Hasbrouck and Saar (2009) as limit orders cancelled within 2 s after submission, are one of the algorithmic trading strategies commonly used in the markets. They document that as high as 93% of submitted limit orders in INET (an ECN acquired by Nasdaq in 2005) are cancelled or revised. More interestingly, about 37 % of the cancellations are fleeting orders. At present, the practice of quick order cancellation is widespread and has been of increasing concern to regulators. For example, CME Group exchanges specifically prohibit manipulative order cancellation.[1]

[1]The CME adopted new Rule 575 in September 15, 2014 to ban disruptive trading practices that were abusive to the fair execution of transactions. The new rule explicitly indicates that no person shall place quotes with the intent to cancel the orders before execution to create a misleading appearance of market depth or price movements, known as "spoofing."

  

Despite the increasing order cancellation intensity and regulatory concerns, empirical studies on fleeting orders remain limited.[2] Most of them focus on the event of order revision and cancellation, but ignore the speed of its occurrence. For example, Ellul, Holden, Jain, and Jennings (2007) show that 43% of orders submitted to the New York Stock Exchange (NYSE) are cancelled. Liu (2009) and Fong and Liu (2010) find that the most aggressive orders account for around 80% of cancellations across the entire limit order book of Australian stock markets. They also show that order cancellation is highly correlated with monitoring costs. Specifically, the frequency of order cancellation decreases when monitoring costs increase and vice versa. Raman and Yadav (2013) indicates that 24% of all incoming limit orders in Indian stock markets are cancelled. He also shows that changes in market conditions and traders' inventories of held stocks and correlated stocks influence cancellation behavior. Examining order cancellation in Taiwan Stock Exchange (TSE), Chiao, Wang, and Tong (2017) document that foreign traders cancel limit orders most actively. However, they are unable to unambiguously distinguish normal order cancellations from fleeting orders since trades in the TSE are periodically executed every 15 s for each stock.

Hasbrouck and Saar (2009) directly examine fleeting orders. They establish three hypotheses for the motives behind fleeting orders: Chasing, cost-of-immediacy, and search. In particular, the chasing hypothesis suggests that traders cancel and place a more aggressive order when the same side order price moves away from the original quoted price. The cost-of-immediacy hypothesis posits that traders cancel a limit order and switch to a market order for the reduced cost of immediacy when the opposite side best price moves toward the original best price. Finally, the search hypothesis postulates that searching for nondisplayed orders in the market is a motive of traders to submit fleeting orders. Hasbrouck and Saar find evidence supportive of both the chasing hypothesis and the search hypothesis but against the cost-of-immediacy hypothesis.

Since their data do not provide information about trader identity, Hasbrouck and Saar (2009) investigate the motives of fleeting orders by evaluating the extent to which order cancellations are dependent on subsequent changes in the best bid or ask prices without clearly identifying the sequence of orders submitted by the same trader. This lack of trader identity, however, may result in ambiguity regarding the trading strategies used by traders. In particular, because they cannot directly calculate the time interval between the submission and cancellation of a given order, Hasbrouck and Saar indirectly use the life-table method to define fleeting orders. Moreover, the sequences of order submission by a given trader cannot be identified, so the dynamic trading strategy of a trader cannot be definitively recovered from the data. Another issue is that since INET is primarily operated by market makers, the results in Hasbrouck and Saar (2009) are more closely related to the trading behavior of market makers. Therefore, the fleeting order behavior of other types of traders remains an unexplored topic.

The trader type could also be an important factor in the U-shaped pattern of order cancellation documented in Liu (2009) and Fong and Liu (2010), who show that monitoring cost is the main reason behind the pattern. If different types of trader face different levels of monitoring costs, they may have different patterns of order cancellation and fleeting orders. In addition, Raman and Yadav (2013) shows a positive relationship between order cancellations and network trading, but does not provide any evidence on such a relationship for fleeting orders. Handa and Schwarz (1996) show that traders can make profits by using a network trading strategy. By limiting risk with a predefined spread, a network trading strategy could be used by traders to generate profits. Based on these findings, we therefore conjecture that network trading strategy is probably correlated with fleeting order strategy. Such a relationship has not yet been well documented in the literature. Hence, investigating the influences of trader type and network orders on fleeting order strategy will be illuminating.

In this paper, we explore these issues based on a unique data set from Taiwan futures markets that contains all submitted orders and completed trades of each trader.[3] Based on this data set, we are able to unambiguously identify each trader and track his/her orders in this continuous auction market. We can also take snapshots of network trading to study the relationship between fleeting orders and network trading strategy. Due to the variation of update frequency of limit order book in the Taiwan Futures Exchange (hereafter TAIFEX), we define fleeting orders as the limit orders cancelled within 5 s after submission.[4] To the best of our knowledge, this is the first paper that studies fleeting orders in one of the major futures markets in Asia.

[2]See Harris (1998), Bloomfield, O'Hara and Saar (2005), Large (2004), and Rosu (2009) for the theoretical foundations of order revision and cancellation.

[3]On INET, traders are allowed to submit hidden limit orders that are not displayed for execution. However, traders in Taiwan futures markets are not allowed to submit hidden orders. We therefore do not include the empirical results of the searching hypothesis in the paper but they are available from the authors upon request.

[4]We also conduct the same empirical tests based on the fleeting orders defined by Hasbrouck and Saar (2009) as the limit orders cancelled within 2 s after submission. The results are quantitatively similar and reported later.

Our main results are as follows. First, we investigate the submission behavior of fleeting orders for individual and institutional traders separately and find that trader type does matter. Institutional traders, including proprietary traders and foreign traders, use fleeting order trading strategy more frequently than individual traders. Overall, approximately one-third of order cancellations by institutional traders take place within 2 s after submission and more than half of submitted orders are cancelled within 5 s. However, we find that only 6% of cancelled orders from individuals are fleeting orders. This result is conceivable given that, compared with individuals, institutional traders are well trained and have more resources when conducting trading. They have increasingly used algorithmic trading as technology has improved in recent years. Further, we also investigate whether there exists a significant difference in fleeting order frequency between buyer-initiated and seller-initiated orders. We find that both types of orders display similar fleeting order patterns.

Second, we discover an inverted J curve of intraday seasonality of fleeting order intensity that is different from the U-shaped curve documented in Fong and Liu (2010). We also find that proprietary traders and foreign traders behave quite similarly except during the first 15 min after the market opening. In particular, while foreigners are reluctant to aggressively submit fleeting orders in the first 15-min interval, proprietary traders actively interact with market participants through fleeting orders. To assess the statistical significance of the intraday seasonality of fleeting order intensity, we estimate linear regression models of intraday fleeting rates across 19 15-min intervals and one 10-min interval of a trading day. The coefficient in the first 15-min interval is 3.78 for foreigners and 5.05 for proprietary traders. Indeed, foreigners and proprietary traders adopt quite different fleeting order strategies in the first 15-min interval after the market opening when the trading risk is presumably high due to potential information asymmetry, as suggested by McInish and Wood (1992). Overall, the proprietary traders act like market makers who aggressively trade when market volatility is high, where as foreign traders do not aggressively interact with the markets when information asymmetry is at its greatest.

Third, based on pooled proportional hazards duration models with time-varying covariates, we find that institutional traders do not aggressively chase market prices in the limit order book. This result is inconsistent with that of Hasbrouck and Saar (2009). Nevertheless, they do actively respond to changes in immediate execution costs. Moreover, we individually estimate the same duration model for each institutional investor to see if there is significant heterogeneity of fleeting order submission behavior among institutional investors. Indeed, we discover that proprietary traders and foreign traders exhibit quite heterogeneous behavior when submitting fleeting orders. These results demonstrate the importance of trader type to the study on fleeting orders.

Finally, we investigate the interaction between fleeting order strategy and network trading strategy, finding that for proprietary traders, network trading strategy accounts for about 62% of the variation of immediate execution costs. Based on the pooled proportional hazard rate models, the original coefficient of cost-of-immediacy variable is −43.76, but it falls by 62% to −16.79 after incorporating the dummy variable of network trading orders into the models. This interesting result suggests that network orders are an important tool for proprietary traders when responding to the varying immediate execution costs. However, we do not find such relationship for foreigners. They actively response to the change of immediate execution costs simply because of their hedging purpose.

This paper contributes to the literature on fleeting orders in three aspects. First, we investigate the dynamics of order cancellation in a continuous auction market based on unique data. The data contain the information about trader identity that helps us unambiguously track the sequence of orders submitted by different types of traders and examine their fleeting order behaviors. This facilitates the study of previously unexplored motivations behind fleeting orders. Hence, our results contribute to the literature on dynamic limit order trading strategy in a market where participants interact with each other at tremendous speed.

Second, following Hasbrouck and Saar (2009), who perform survival analysis for each randomly selected stock, we estimate the pooled proportional hazards duration model for each institutional trader to show that there exists significant heterogeneity of fleeting order submission behavior among institutional traders.[5] This interesting finding enhances our understanding of the trading behaviors of market participants in financial markets.

Third, we consider the link between network trading strategy and fleeting orders, which has not been thoroughly addressed in the literature. Although Raman and Yadav (2013) shows that network trading strategy is positively associated with the intensity of order cancellations, he offers no further examination of the relationship between network trading strategy and fleeting order strategy. In addition, Handa and Schwartz (1996) suggest that network trading strategy is

[5]We sincerely thank the referee for his constructive suggestion that inspires us to investigate this issue.

**TABLE 1** Description of TXF

| | |
|---|---|
| Index futures contracts | TAIEX futures (TXF) |
| Underlying index | TAIEX |
| Ticker symbol | TX |
| Delivery months | Spot month, the next calendar month, and the next three quarterly months |
| Last trading day | The third Wednesday of the delivery month of each contract |
| Trading hours | 8:45 a.m.–1:45 p.m. Taiwan time Monday through Friday |
| Contract size | NT$200 × index point |
| Tick size | One index point |
| Daily price limit | +/−7% of previous day's settlement price |
| Daily settlement price | The daily settlement price is the volume weighted average price within the last one minute |
| Settlement | Cash settlement |

*Note*. TAIEX: Taiwan Stock Exchange Capitalization Weighted Stock Index; TXF: Taiwan Stock Exchange Capitalization Weighted Stock Index Futures. Source: Taiwan Futures Exchange.

profitable. Based on the unique data of real-time limit order book, we are able to identify network orders of institutional traders and provide evidence for a positive association between network trading strategy and fleeting orders.

The remainder of this paper is organized as follows. Section 2 describes institutional details, index futures contracts, and trader classification. Section 3 illustrates our data. Section 4 presents fill rate and cancel rate, followed by fleeting orders and network trading in Section 5. Intraday seasonality of fleeting orders is reported in Section 6. The results based on estimated proportional hazard duration model for fleeting orders are discussed in Section 7. Section 8 includes the results of robustness checks. We conclude in Section 9.

## 2 | INSTITUTIONAL DETAILS, INDEX FUTURES CONTRACTS, AND TRADER CLASSIFICATION

### 2.1 | Institutional details and index futures contracts

TAIFEX was established on July 21, 1998, and ranked nineteenth on a global scale in 2015 with a total trading volume of 265 million contracts.[6] TAIFEX is a pure order-driven market where all orders are traded through the electronic trading system (ETS). The regular trading session is from 8:45 a.m. to 13:45 p.m., Monday to Friday, excluding public holidays. Traders may submit, revise, or cancel orders through ETS during the preopening session starting at 8:30 a.m. The exchange establishes the opening price according to a single-price auction. Orders submitted after 13:40 p.m. are collected and matched to establish the closing price at 13:45 p.m. based on a single-price auction as well. During the normal continuous trading session, orders are executed immediately in accordance with price and then time priority matching rules.

Traders can submit both market orders and limit orders to ETS. Orders on TAIFEX are valid only for the current trading day. Limit orders are consolidated into the electronic limit order book. Market participants can cancel orders at any time before matching. TAIFEX disseminates order and transaction information to the public on a "real-time" basis, so that traders can observe the anonymous best five bid and ask prices with corresponding market depths on the screen when submitting their orders.

This paper uses tick-by-tick order and transaction records of TSE Capitalization Weighted Stock Index Futures (hereafter TXF). TXF was launched in 1998 with the opening of TAIFEX. It tracks the TSE Capitalization Weighted Stock Index, a stock index measuring the performance of the universe of all companies listed on TSE. TXF is based on a monthly expiration cycle, including the spot month, the next calendar month, and the next three quarterly months, making up a total of 5 contract months. The last trading day for these contracts is the third Wednesday of the delivery month. One index point increase in the transaction price yields a profit of 200 TWD for one TXF contract. The contract size of TXF is approximately

[6]According to 2016 FIA Annual Volume Survey by Futures Industry Association (FIA).

equal to an average amount of New Taiwan Dollar (NTD) 1.4 million (USD45,000) in 2008.[7] TXF is the most liquid and popular futures contract in TAIFEX with an average daily trading volume of 71,168 contracts in 2008, which was roughly 15 times the volume of the second most popular futures contract. Detailed descriptions of TXF contracts are reported in Table 1.

## 2.2 | Trader classification

Three major types of traders dominate TAIFEX: Individual traders, proprietary traders, and foreign traders.[8] They account for approximately 95% of the total trading volume of TXF in 2008, generating 63%, 22%, and 10% of the trading volume, respectively. Apparently, individual investors are the dominant market participants in Taiwan futures markets.

Previous studies show that different trader types may differ in several dimensions: Trading motives, trading strategies, possession of information, and technological and financial resources.[9] Chou and Wang (2009) and Chiu et al. (2016) find that individual traders in Taiwan futures markets adopt a more aggressive order submission strategy by placing more market orders than their institutional counterparts. In other words, while individuals place more market orders and enjoy a higher fill rate, institutional investors mostly submit limit orders with a lower fill rate. Since order cancellation involves only limit orders, it is conceivable that institutional traders have a greater propensity to cancel orders than individual traders. Indeed, this is exactly what Chou and Wang (2009), Raman and Yadav (2013), and Chiu et al. (2016) find. Because fleeting orders are those quickly cancelled after submission, they are actually a subset of cancelled limit orders. Hence, we anticipate that institutional traders, both proprietary traders and foreign traders, are more aggressive than individual traders in placing fleeting orders.

Proprietary traders and foreign traders are the two major types of institutional traders in Taiwan futures markets. They exhibit certain distinct trading characteristics. Chou, Wang, Wang, and Bjursell (2011) document that proprietary traders prefer to execute their trades in a short time horizon, and Chow, Hung, Liu, and Shiu (2013) show that they hold relatively small open positions compared with other trader types. Moreover, Chiu, Chung, and Wang (2014) show that proprietary traders often have access to order flow information since they usually hire a large number of traders to monitor order flow from the limit order book to capture instant trading opportunities. These trading characteristics of proprietary traders are quite similar with those of market makers as described in Harris (2002). He illustrates that market makers often trade frequently. They trade with small inventory positions to avoid losses when the market moves against them. Moreover, they have an advantage as order-anticipating speculators since they can see order flow more than other market participants. They usually place two-sided order flows to discover the prices. Interestingly, Raman and Yadav (2013) also indicates that market makers typically submit two-sided quotes to create their own limit order spreads.

Based on the above trading characteristics of proprietary traders, we anticipate that proprietary traders would not aggressively chase the price trend simply because they behave like market makers. Specifically, we expect to reject the chasing hypothesis for proprietary traders. By contrast, the cost of immediacy is a major concern to market makers when making the market. Hence, we postulate that proprietary traders will actively cancel limit orders in response to a drop in the cost of immediate execution.

Chien, Lee, Tai, and Liao (2013) show that foreign traders act as informed hedgers in the Taiwan futures markets. Harris (2002) characterizes hedgers as traders who use the markets to reduce their exposure to financial risks. Since their objective is to reduce risks, they prefer to trade with low transaction costs. This implies that foreign traders care about the cost of immediacy. Therefore, we expect the fleeting order submission behavior of foreign traders to be consistent with the cost-of-immediacy hypothesis, but inconsistent with the chasing hypothesis.

# 3 | DATA

## 3.1 | Description of datasets

We acquire three datasets containing order records, transaction records, and limit order book directly from TAIFEX. The tick-by-tick order data contain detailed information about the date, product identity, trader identity, trader type,

[7]In 2008, the average daily closing price of TAIEX futures for the nearest month contract was 7,106, ranging from 3,903 to 9,370.

[8]Individual traders are those who purchase securities for personal accounts rather than for an organization, as opposed to an institutional trader. Proprietary traders are local futures firms that apply for the proprietary trading license from the Securities and Futures Bureau and invest for their own interests instead of trading on behalf of their clients. A foreign institutional trader is either an institutional trader established overseas in accordance with local law, or a branch company established in Taiwan by an overseas juristic person.

[9]See Grinblatt and Keloharju (2000), Chou and Wang (2009), Huang and Shiu (2009), Hendershott et al. (2010), Kuo, Chung, and Chang (2015), and Chiu, Chung, and Wang (2016).

order number, order type, order quantity, order price, order status, and order time (to the nearest 0.001 s). The subsequent execution, revision, or cancellation can be tracked according to the order reference number, order status, and time. The transaction data contain detailed trader, order, and transaction information, including the date, product identity, trader identity, trader type, order time, order number, transaction quantity, transaction price, and transaction time (to the nearest 0.001 s). These two datasets can be unambiguously merged based on common observations, such as the trading date, the order submission time, and the trader identity.

When limit orders are submitted but not executed immediately, they will directly enter the limit order book for subsequent matching. The limit order book displays the current five best bid and ask prices with corresponding market depths. Because of limitations on computer capacity in the early days, the update frequency of the limit order book in TAIFEX was not as fast as in recent years. On March 6, 2006, the update frequency of limit order book was shortened from 5 s to 3 s. It was further reduced to 1 s on January 28, 2008, 0.25 s on August 31, 2009, and 0.125 s on December 2, 2013. During our sample period spanning from January 2005 to December 2008, the update frequency of limit order book was therefore within the range from 1 s to 5 s. Since the lowest update frequency is 5 s, this paper defines the fleeting orders as limit orders cancelled within 5 s after submission. Note that market participants in TAIFEX have complete access in real time to the limit order book when submitting their orders.

## 3.2 | Order submission by contract months

The TXF contracts for the nearest month are used in our empirical analysis because they are the most active and liquid contracts. We roll over the contracts on the last trading day in the expiration month. We analyze the trades of the nearest contract until two trading days before expiration and then switch to the trades of the next nearest contract.

Table 2 presents summary statistics of order submission for contracts in the spot month, the next calendar month, and the next three quarterly months.[10] It reports mean monthly numbers of market orders, limit orders, cancellation orders, and fleeting orders in addition to the proportion of orders submitted by different types of traders. As shown in the second column of Panel A, all market participants on average place 171,814 market orders in the spot month. The mean monthly number of market orders decreases sharply to 3,572 in the second nearest month, and reduces further to 57 orders in the first quarter month, 16 orders in the second quarter month, and four orders in the third quarter month. These results indicate that TXF contracts for the nearest month are the most active and liquid contracts. The mean monthly numbers of limit orders, cancel orders, and fleeting orders exhibit similar pattern as shown in Panels B, C, and D. We also observe a similar pattern for the number of contracts in different expiration months that is consistent with the fact that the nearest-month contracts are the most active and liquid contracts.

## 3.3 | Order submission by trader types

To determine whether there are significant differences in the order submission behavior of individual traders, proprietary traders, and foreign traders, we further break down the order submission proportion by trader type. We find that individuals place far more market orders, whereas institutional traders use more limit orders. This result is consistent with the findings of Chou and Wang (2009). Panel A of Table 2 shows that individual traders submit as much as 95% of all market orders in the spot month contract, which is much higher than institutional traders. By contrast, Panel B shows that the limit orders submitted by proprietary traders and foreigners account for 31% and 13% of all limit orders, respectively. Interestingly, the limit orders of individuals also account for 53% simply because they are dominant players in TAIFEX.

Panels C and D depict a very different picture of cancellation orders as well as fleeting orders. Although the submission percentage of cancellation orders by individuals is comparable to that of institutional investors, individuals place far fewer fleeting orders than their counterparts. In the spot month, 94% of fleeting orders are submitted by institutional traders. Among these fleeting orders, 65% and 29% are from proprietary traders and foreign traders, respectively. Institutional traders apparently have a greater propensity to cancel orders than individuals, especially in high speed.

Table 3 presents summary statistics of orders submitted by individual traders, proprietary traders, and foreign traders for the nearest-month TXF contracts. There are 157,709 individuals, 68 proprietary traders, and 255 foreigners operating trading accounts during the sample period. As shown in Panel A, individuals submit relatively more market

[10]For example, if the spot month is January 2005, the second nearest month is February 2005, the first quarter month is March 2005, and the second and third quarter months are June 2005 and September 2005, respectively.

**TABLE 2** Order submission by contract month

| | Number of orders | | | | | Number of contracts | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Spot month | Second nearest month | First quarter month | Second quarter month | Third quarter month | Spot month | Second nearest month | First quarter month | Second quarter month | Third quarter month |
| Panel A: Market order | | | | | | | | | | |
| Entire sample (100%) | 171,814 | 3,572 | 57 | 16 | 4 | 564,280 | 5,841 | 70 | 20 | 6 |
| Individuals | 0.95 | 0.89 | 0.81 | 0.63 | 0.98 | 0.93 | 0.87 | 0.84 | 0.67 | 0.95 |
| Proprietary institutions | 0.01 | 0.02 | 0.07 | 0.19 | 0.01 | 0.02 | 0.03 | 0.06 | 0.16 | 0.02 |
| Foreign institutions | 0.01 | 0.03 | 0.00 | 0.00 | 0.00 | 0.02 | 0.04 | 0.00 | 0.00 | 0.00 |
| Panel B: Limit order | | | | | | | | | | |
| Entire sample (100%) | 1,298,239 | 109,967 | 48,304 | 32,714 | 17,968 | 4,271,211 | 312,619 | 128,019 | 72,489 | 38,805 |
| Individuals | 0.53 | 0.27 | 0.11 | 0.08 | 0.10 | 0.46 | 0.15 | 0.05 | 0.04 | 0.05 |
| Proprietary institutions | 0.31 | 0.57 | 0.83 | 0.88 | 0.86 | 0.34 | 0.71 | 0.91 | 0.93 | 0.91 |
| Foreign institutions | 0.13 | 0.13 | 0.06 | 0.04 | 0.04 | 0.17 | 0.11 | 0.04 | 0.03 | 0.04 |
| Panel C: Cancel order | | | | | | | | | | |
| Entire sample (100%) | 710,635 | 86,975 | 46,677 | 31,901 | 17,515 | 2,789,125 | 264,679 | 127,707 | 71,842 | 38,173 |
| Individuals | 0.35 | 0.15 | 0.08 | 0.06 | 0.09 | 0.37 | 0.07 | 0.03 | 0.03 | 0.04 |
| Proprietary institutions | 0.43 | 0.70 | 0.86 | 0.90 | 0.88 | 0.38 | 0.82 | 0.93 | 0.94 | 0.92 |
| Foreign institutions | 0.19 | 0.14 | 0.06 | 0.04 | 0.04 | 0.23 | 0.10 | 0.04 | 0.03 | 0.04 |
| Panel D: Fleeting order | | | | | | | | | | |
| Entire sample (100%) | 255,579 | 25,812 | 8,905 | 6,977 | 3,012 | 802,579 | 65,391 | 26,132 | 17,775 | 8,598 |
| Individuals | 0.06 | 0.06 | 0.08 | 0.08 | 0.10 | 0.05 | 0.04 | 0.03 | 0.04 | 0.04 |
| Proprietary institutions | 0.65 | 0.76 | 0.80 | 0.86 | 0.88 | 0.49 | 0.85 | 0.93 | 0.93 | 0.94 |
| Foreign institutions | 0.29 | 0.18 | 0.12 | 0.06 | 0.02 | 0.46 | 0.11 | 0.04 | 0.03 | 0.02 |

*Note*. This table provides summary statistics on the orders submission of Taiwan Stock Exchange Capitalization Weighted Stock Index Futures by contract month over the period from January 2005 to December 2008. Number of orders and number of contracts in the spot month, the next calendar month, and the next three quarterly months for each futures contract are calculated. We report the mean monthly number of orders and number of contracts for market orders (Panel A) , limit orders (Panel B) , cancel orders (Panel C), and fleeting orders (Panel D) of the entire sample. We break down the submission volume and calculate the submission proportion of individuals, proprietary institutions, and foreign institutions compared with the entire markets. For example, the proportion of number of orders submitted by individuals in the spot month is the mean monthly number of orders submitted by individuals in the spot month divided by mean monthly number of orders submitted by entire markets in the spot month.

**TABLE 3** Summary statistics of orders submitted in the spot month

| | | Number of trader accounts | Number of orders: Market order | Limit order | Cancel order | Fleeting order | Number of contracts: Market order | Limit order | Cancel order | Fleeting order |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Total orders | | | | | | | | | | |
| Individuals | | 157,709 | 7,814,996 | 33,125,524 | 11,846,257 | 711,051 | 25,266,037 | 93,937,729 | 49,373,957 | 1,750,308 |
| Proprietary institutions | | 68 | 106,041 | 19,587,126 | 14,826,245 | 8,017,155 | 587,024 | 69,331,021 | 51,489,498 | 18,819,575 |
| Foreign institutions | | 255 | 78,642 | 8,356,506 | 6,414,685 | 3,539,578 | 419,838 | 35,598,843 | 30,336,968 | 17,953,756 |
| Panel B: Mean orders at trader account level | | | | | | | | | | |
| Individuals | Buy | 157,709 | 24 | 108 | 40 | 3 | 79 | 300 | 158 | 6 |
| | Sell | | 26 | 102 | 36 | 2 | 81 | 296 | 155 | 5 |
| Proprietary institutions | Buy | 68 | 770 | 145,866 | 110,256 | 58,389 | 4,182 | 485,109 | 379,372 | 138,379 |
| | Sell | | 789 | 142,180 | 107,777 | 59,515 | 4,450 | 534,464 | 377,826 | 139,851 |
| Foreign institutions | Buy | 255 | 159 | 16,894 | 13,075 | 7,114 | 857 | 71,036 | 61,626 | 35,547 |
| | Sell | | 149 | 15,877 | 12,081 | 6,868 | 790 | 68,567 | 57,342 | 34,957 |

*Note*. This table provides summary statistics on the orders of Taiwan Stock Exchange Capitalization Weighted Stock Index Futures over the period from January 2005 to December 2008. Orders submitted in the spot month are included only. Number of trader accounts, number of orders, and number of contracts submitted by individuals, proprietary institutions, and foreign institutions are presented. Orders include market orders, limit orders, cancel orders, and fleeting orders. Panel A presents the total order statistics across trader types. Panel B reports mean order statistics at trader account level across trader types.

orders, while proprietary traders and foreigners place relatively more limit orders, cancellation orders, and fleeting orders. Proprietary traders and foreign traders submitted 8,017,155 and 3,539,578 fleeting orders, respectively. Either of these numbers is significantly higher than the 711,051 fleeting orders of individual traders.

We also separate orders into two categories, buyer-initiated and seller-initiated, to examine whether there is significant asymmetry in the fleeting order pattern. Panel B shows that a proprietary trader account on average places 145,866 limit buy orders, but 110,256 of these are eventually cancelled. Among these cancelled orders, 58,389 orders are fleeting orders that are cancelled within 5 s after submission. By contrast, an individual trader account on average places 108 limit buy orders over the sample period. Among these, 40 orders are cancelled and only three of them are cancelled within 5 s after submission. Since seller-initiated limit orders exhibit a similar pattern, we conclude that the fleeting order pattern of these two categories of limit orders is symmetric. Finally, because the number of contracts also exhibits a similar pattern, we use the number of orders for our subsequent empirical analyses.

## 4 | FILL RATE AND CANCEL RATE

In this section, we present the percentage of limit orders and their fill rates, unexecuted rates, and cancellation rates by trader types. The percentage of limit orders is defined as the number of limit orders submitted by a trader type divided by the sum of the numbers of market orders and limit orders submitted by the specific trader type. Similarly, the fill rate is defined as the number of executed limit orders for a trader type divided by the number of limit orders submitted by the specific trader type. The fill rate is further categorized as partially executed and fully executed. The numerator of partial execution fill rate is the number of at least partially executed limit orders, whereas the numerator of the full execution fill rate is the number of fully executed limit orders. Finally, the cancellation (nonexecution) rate is defined as the number of cancelled (unexecuted) limit orders submitted by a trader type divided by the number of limit orders submitted by the specific trader type.

Table 4 shows that both institutional traders submit as much as 99% of limit orders. However, they only achieve 1% and 22% of partial execution and full execution fill rates, respectively. Meanwhile, about 76% of unexecuted limit orders are cancelled. Thus, less than 1% of the limit orders are left unexecuted. Individual traders achieve much better fill rates than institutional investors, with 1% of the partial execution fill rate and 59% of full execution fill rate. They also cancel

**TABLE 4** Fill rate, unexecuted rate, and cancel rate

| | Percentage of limit orders | Fill rate (partially executed) | Fill rate (fully executed) | Nonexecuted rate | Cancel rate |
|---|---|---|---|---|---|
| Individuals | 80.91% | 1.09% | 58.94% | 4.20% | 35.76% |
| Proprietary institutions | 99.46% | 1.59% | 22.51% | 0.21% | 75.69% |
| Foreign institutions | 99.07% | 0.93% | 22.03% | 0.28% | 76.76% |

*Note*. This table presents summary statistics of the percentage of limit orders of Taiwan Stock Exchange Capitalization Weighted Stock Index Futures that are submitted, partially executed, fully executed, nonexecuted, and canceled over the period from January 2005 to December 2008. Orders submitted in the spot month are included only. Percentage of limit orders is defined as the number of limit orders submitted by a trader type divided by the sum of number of market orders and limit orders submitted by the specific trader type. The fill rate is defined as the number of executed limit orders for a trader type divided by the total number of limit orders submitted by the specific trader type. The fill rate is further categorized as partially executed and fully executed. The numerator of partial execution fill rate is the number of at least partially executed limit orders, whereas the numerator of full execution fill rate is the number of fully executed limit orders. Finally, the cancellation (nonexecution) rate is defined as the number of cancelled (unexecuted) limit orders submitted by a trader type divided by the number of limit order submitted by the specific trader type. Individuals, proprietary institutions, and foreign institutions are examined.

about 36% of submitted limit orders. These results imply that when submitting limit orders, individuals are more aggressive than institutional traders.

The low fill rate for institutional traders in Taiwan futures markets is interesting. It may reflect the fact that the trading motives of traders in futures markets are different from those of traders in spot markets. Viljoen, Westerholm, Zheng, and Gerace (2015) document an average of 52% of limit order fill rate for investors in Australian stock market. Lo, Mackinlay, and Zhang (2002) show a 53% fill rate for investors in NYSE. However, institutional traders in Taiwan futures markets cancel far more limit orders than the traders studied by Fong and Liu (2010) and Raman and Yadav (2013). Fong and Liu report a cancellation rate of 4.3% for aggressive buyer-initiated orders for large stocks in Australian stock markets, whereas Raman shows a cancellation rate of 6.5% and of 22.2% for financial institutions and dealers in Indian stock markets, respectively. These results suggest that instead of being sheer speculators, institutional traders in Taiwan futures markets behave more like market makers and hedgers who adjust limit order submission strategies dynamically.

## 5 | FLEETING ORDERS AND NETWORK TRADING

### 5.1 | Fleeting orders

Given the fact that institutional traders achieve a low fill rate and cancel most of their limit orders, we now focus on the speed of order cancellation, that is, fleeting orders. We calculate the cumulative cancellation rate by trader type during a time interval from 0.3 s to 1 hr after order submission. The results are reported in Table 5. Clearly, institutional traders quickly cancel a considerable amount of orders. Panel A shows that proprietary traders cancel 33% of submitted limit orders within 2 s and 54% within 5 s. In addition, they cancel over 90% of limit orders within a time window of 1 min.

Foreign traders exhibit a similar pattern to that of proprietary traders. On average, 55% of their limit orders are cancelled within 5 s after submission. By contrast, individual traders cancel orders at a much slower speed. For instance, only 6% of order cancellation occurs within 5 s after submission. It takes 2 min for individuals to cancel 59% of their limit orders. Finally, Panels B and C show that both buyer-initiated and seller-initiated limit orders display similar patterns to those in Panel A.

In addition to the above analyses of order cancellation by trader type, we also examine it from a time series perspective. We calculate monthly cancellation (fleeting) rate as the number of cancelled (fleeting) limit orders for a trader type in a specific month divided by the total number of limit orders submitted by the specific trader type in the same month. Figure 1 demonstrates the dynamics of these rates. It shows that institutional traders consistently cancel more orders than individuals over the sample period. The cancellation rate for proprietary traders remains stable within a range of 60% to 90%, while that for foreign traders fluctuates in the first 2 years and then increases gradually in later years. In comparison with the cancellation rate, the fleeting rate exhibits an interestingly distinct pattern. Although the fleeting rate for individual traders remains low and stable over time, the fleeting rates for institutional traders show a steady upward trend from about 5% to 60% with a dramatic spike at the beginning of 2008. This phenomenon may be due to the recent significant improvement in trading technology that enables institutional traders to employ algorithmic trading strategies to interact with the market more frequently and intensively.

**TABLE 5** Cumulative proportion of order cancellation

| Time | Individuals | Proprietary institutions | Foreign institutions |
|---|---|---|---|
| Panel A: All orders | | | |
| 0.3 s | 0.00 | 0.09 | 0.00 |
| 0.5 | 0.00 | 0.13 | 0.05 |
| 1 | 0.00 | 0.22 | 0.23 |
| 2 | 0.02 | 0.33 | 0.35 |
| 5 | 0.06 | 0.54 | 0.55 |
| 10 | 0.14 | 0.71 | 0.69 |
| 1 min | 0.47 | 0.92 | 0.90 |
| 2 | 0.59 | 0.95 | 0.93 |
| 10 | 0.80 | 0.99 | 0.97 |
| 1 hr | 0.95 | 1.00 | 0.99 |
| Panel B: Buy orders | | | |
| 0.3 s | 0.00 | 0.09 | 0.00 |
| 0.5 | 0.00 | 0.13 | 0.05 |
| 1 | 0.00 | 0.21 | 0.23 |
| 2 | 0.02 | 0.32 | 0.35 |
| 5 | 0.06 | 0.53 | 0.56 |
| 10 | 0.14 | 0.71 | 0.69 |
| 1 min | 0.47 | 0.92 | 0.91 |
| 2 | 0.59 | 0.95 | 0.94 |
| 10 | 0.80 | 0.99 | 0.98 |
| 1 hr | 0.95 | 1.00 | 0.99 |
| Panel C: Sell orders | | | |
| 0.3 s | 0.00 | 0.09 | 0.00 |
| 0.5 | 0.00 | 0.14 | 0.05 |
| 1 | 0.00 | 0.22 | 0.24 |
| 2 | 0.02 | 0.34 | 0.35 |
| 5 | 0.06 | 0.55 | 0.55 |
| 10 | 0.14 | 0.71 | 0.68 |
| 1 min | 0.47 | 0.92 | 0.89 |
| 2 | 0.59 | 0.96 | 0.93 |
| 10 | 0.80 | 0.99 | 0.97 |
| 1 hr | 0.95 | 1.00 | 0.99 |

*Note*. This table provides cumulative proportion of order cancellation from 0.3 s to 1 hr after order submission on the orders of Taiwan Stock Exchange Capitalization Weighted Stock Index Futures over the period from January 2005 to December 2008. Orders submitted in the spot month are included only. Proportion of order cancellation within a time interval is number of cancel limit orders submitted by a specific trader type within a time interval divided by total number of cancel limit orders submitted by the specific trader type. Individuals, proprietary institutions, and foreign institutions are examined. Panel A reports the results of all limit orders. Panel B presents buyer-initiated orders and Panel C reports seller-initiated orders.

## 5.2 | Network trading

Hasbrouck and Saar (2009) show a great propensity of fleeting order usage based on data from INET that is primarily operated by market makers. Therefore, their results are more pertinent to the trading behavior of market makers. Raman and Yadav (2013) observes that market makers typically submit two-sided quotes to create their own limit order spread. He finds a significantly positive relationship between order cancellation and two-sided quotes. However, he does not provide any evidence on such a relationship of fleeting orders.

Handa and Schwartz (1996) define network orders as orders that contain the buy limit orders and the sell limit orders simultaneously submitted by a given trader. In this paper, we define network limit orders as at least one buy limit order and at least one sell limit order submitted by the same trader within a 1 s time interval. Summary statistics of network limit orders are reported in Table 6. The results show that proprietary traders significantly employ network trading strategies. Overall, proprietary traders place 2.5 million network orders, approximately 36,515 network orders per proprietary trader. Foreign traders, however, use network trading strategy much less frequently. During the same period, foreigners submit 510,706 network orders, approximately 2,003 network orders per foreigner account. Individual traders submit only 20,274 network limit orders. Thus, an individual trader on average places less than one network limit order. These results may again reflect different trading motives among different types of traders.

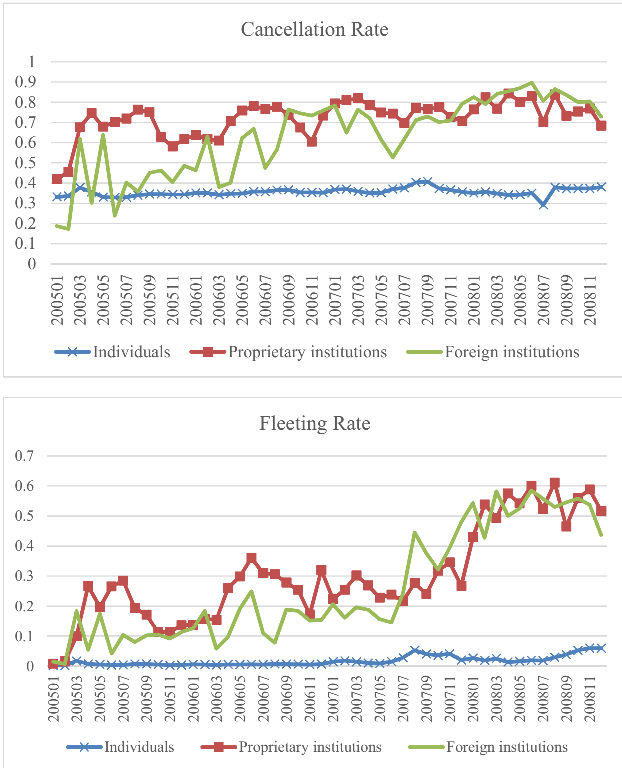


**FIGURE 1** Cancellation rate and fleeting rate over time. The figure plots the monthly cancel rate and monthly fleeting rate on the order submission of Taiwan Stock Exchange Capitalization Weighted Stock Index Futures over the period from January 2005 to December 2008. Orders submitted by individuals, proprietary institutions, and foreign institutions are included. Monthly cancellation (fleeting) rate as the number of cancelled (fleeting) limit orders for a trader type in a specific month divided by the total number of limit orders submitted by the specific trader type in the same month [Color figure can be viewed at wileyonlinelibrary.com]

We can see from Table 6 that the average spread of network orders for proprietary traders is 27 index points, which is the smallest among the three trader types. Those for foreign traders and individual traders are 30 index points and 32 index points, respectively. Moreover, proprietary traders submit network orders with lower numbers of contracts than foreign traders. In particular, the average order size is around 2.4 contracts for proprietary traders from both buy and sell sides, whereas that for foreigners is around five contracts.

Even though there are no official designated market makers in Taiwan futures markets, the above results, however, suggest that the proprietary traders in TAIFEX behave like market makers, who trade frequently through two-sided limit orders with small positions to avoid the risk of being picked off by informed traders. As suggested by Handa and Schwartz (1996), market makers commonly use a network trading strategy to predefine their profits. Harris (2002) also points out that market makers are not value traders, so they commonly keep small inventory positions to avoid large losses in case that the market moves against them.

Based on the above trading characteristics of proprietary traders, we anticipate that proprietary traders would actively manage network limit orders, so that network orders are more likely to be cancelled quickly for risk management purposes.

By contrast, foreigners submit much fewer network orders than proprietary traders, as reported in Table 6. Moreover, fewer foreign accounts actively use network orders. Among 255 foreign accounts in our sample, the one placing the most network orders accounts for 64% of total network orders. The top four foreign accounts account for approximately 97% of the total amount.[11] According to Chien et al. (2013), foreigners behave more like informed hedgers rather than market makers and their objective is to reduce the exposure to financial risk. We therefore anticipate that foreign traders would be less likely to actively cancel network orders.[12]

[11]The details are available from the authors upon request.

[12]We focus on the empirical analysis of proprietary traders and foreign traders subsequently because individual traders submit far fewer fleeting orders. Nevertheless, the empirical results for individuals are available from the authors upon request.

**TABLE 6** Summary statistics of network limit orders

| | | | Individuals | Proprietary institutions | Foreign institutions |
|---|---|---|---|---|---|
| Number of network limit orders | | | 20,274 | 2,483,042 | 510,706 |
| Spread | | Mean | 31.83 | 27.01 | 30.13 |
| | | Median | 20 | 17 | 24 |
| Volume | Buy | Mean | 1.69 | 2.48 | 5.46 |
| | | Median | 1 | 1 | 4 |
| | Sell | Mean | 1.71 | 2.40 | 5.26 |
| | | Median | 1 | 1 | 4 |

*Note*. This table reports summary statistics of network limit orders of Taiwan Stock Exchange Capitalization Weighted Stock Index Futures over the period from January 2005 to December 2008. Orders submitted in the spot month are included only. Network limit orders is defined as at least one buy limit order and at least one sell limit order submitted by the same trader within a 1-s interval. Spread is the index point difference between buy and sell orders of a network limit order. Volume is the corresponding number of contract size quoted on the buy and sell orders of a network limit order. Individuals, proprietary institutions, and foreign institutions are examined.

## 6 | INTRADAY SEASONALITY OF FLEETING ORDERS

Liu (2009) and Fong and Liu (2010) document a U-shaped pattern of intraday order cancellation and suggest that monitoring cost is the main reason behind the pattern. They, however, do not consider the potential influence of trader type on order cancellation. Specifically, we examine the intraday seasonality of fleeting orders by trader type. The daily trading hours are partitioned into 19 15-min intervals from 8:45 a.m. to 13:30 p.m., and one last 10-min interval from 13:30 p.m. to 13:40 p.m. Orders submitted before 8:45 a.m. and after 13:40 p.m. are not included because they are matched by the opening and closing call auctions. Fleeting order rates for a specific time interval for a trader type is calculated as the number of fleeting orders submitted by a specific trader type within that specific time interval divided by the total number of fleeting orders placed by that specific trader type in that trading day. In other words, the sum of fleeting order rates across the 20 time intervals equals one for each trader type.

Figure 2 depicts the intraday seasonality of fleeting order rate of institutional traders. Interestingly, the pattern is different from the U-shaped curve documented in Fong and Liu (2010). Instead, the pattern in Figure 2 is more similar to an inverted J curve, suggesting that proprietary traders and foreign traders behave quite similarly except during the first 15 min after the market opening. While foreigners are reluctant to aggressively employ fleeting order trading strategy in the first 15-min interval, proprietary traders interact with market participants actively through fleeting orders. As potential hedgers, foreign traders avoid aggressive trading during the first 15-min interval when the market is digesting overnight information and has a higher cost of immediacy. In contrast, proprietary traders behave like market makers who actively trade to create their own profitability space when the market volatility is high due to the high degree of information asymmetry during the first 15-min interval. Note that, different from Fong and Liu (2010), we do not observe a spike in the fleeting order rate when the market approaches its close. This is because the trading activity in the futures market is relatively calm after the underlying stock market closes at 13:30 p.m. Figure 2 shows that buyer-initiated as well as seller-initiated limit orders exhibit similar intraday seasonality in fleeting order rate.

We perform the following regression to examine the statistical significance of the intraday seasonality of fleeting orders:

$$\begin{aligned} FleetingOrderRate_{i,j} = {} & \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \beta_6 D_6 + \beta_7 D_7 + \beta_8 D_8 + \beta_9 D_9 + \beta_{11} D_{11} + \beta_{12} D_{12} + \beta_{13} D_{13} \\ & + \beta_{14} D_{14} + \beta_{15} D_{15} + \beta_{16} D_{16} + \beta_{17} D_{17} + \beta_{18} D_{18} + \beta_{19} D_{19} + \beta_{20} D_{20} + \varepsilon_{i,j}, \end{aligned} \tag{1}$$

where $FleetingOrderRate_{i,j}$ is the fleeting order rate for trader type j within time interval i. $D_1$, $D_2$, $D_3$,..., and $D_{20}$ are the dummy variables of 20 intraday time intervals from 8:45 a.m. to 13:40 p.m. $D_1$ represents the interval of 8:45 a.m. to 9:00 a.m., $D_2$ represents the interval of 9:00 a.m. to 9:15 a.m., and so on, that is, $D_i$ equals one if the fleeting order rate is calculated within the i time interval and zero otherwise, for i = 1, 2, ....., 20. Note that we remove the dummy variable $D_{10}$ from Equation (1) to avoid the collinearity problem.

Table 7 reports the regression results. As shown in Panel A, proprietary traders significantly employ the fleeting order trading strategy when the market has just opened, while foreigners are reluctant to aggressively use the fleeting order trading strategy so soon after the market opening. Specifically, for proprietary traders, the coefficient for this relationship

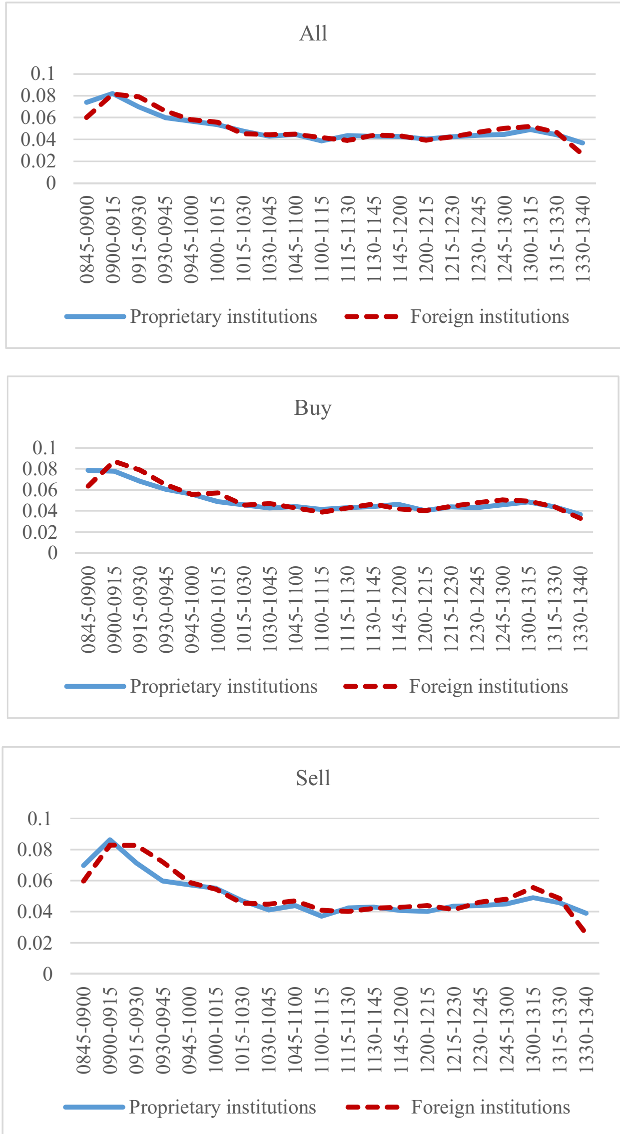


**FIGURE 2** Intraday distribution of fleeting order rate. This figure presents the intraday distribution of fleeting order rate of Taiwan Stock Exchange Capitalization Weighted Stock Index Futures over the period from January 2005 to December 2008. Orders submitted by proprietary institutions and foreign institutions are included. The daily trading hours are partitioned into 19 15-min intervals from 8:45 a.m. to 13:30 p.m., and one last 10-min interval from 13:30 p.m. to 13:40 p.m. The fleeting order rate of a specific time interval for a trader type is calculated as the number of fleeting orders submitted by a specific trader type within that specific time interval divided by the total number of fleeting orders placed by that specific trader type in that trading day. The sum of fleeting order rates across those 20 time intervals equals one for each trader type. All orders, buy-initiated orders, and sell-initiated orders are presented separately [Color figure can be viewed at wileyonlinelibrary.com]

in the first 15-min interval is among the largest of a trading day, a significant 5.05, implying that proprietary traders actively employ the fleeting order trading strategy, on average submitting 8.20% of their daily fleeting orders when asymmetric information is presumed to have its strongest effect. The coefficient estimates then decrease consistently after 10:15 a.m. in the morning. For example, the coefficient is 0.68 in the time interval of 12:00 p.m. to 12:15 p.m. and reaches its minimum, 0.62, in the time interval of 13:30 p.m. to 13:40 p.m. This pattern of estimated coefficients is consistent with our findings in Figure 2, showing that the intensity of fleeting order trading exhibits an inverted J curve.

Although foreign traders generally behave similarly to proprietary traders when submitting fleeting orders, their behaviors differ in the time interval right after the market opening. Specifically, the coefficient for foreigners in the first 15-min interval is 3.78, which is statistically significant at the 1% level, but still much lower than that for their counterparts. Further, the coefficient also reaches its minimum, 0.03, in the time interval of 13:30 p.m. to 13:40 p.m. Consistent with previous findings, foreigners are reluctant to aggressively employ a fleeting order trading strategy when the monitoring costs are relative high.

**TABLE 7** Intraday pattern of fleeting order rate

| | Intercept | 8:45–9:00 | 9:00–9:15 | 9:15–9:30 | 9:30–9:45 | 9:45–10:00 | 10:00–10:15 | 10:15–10:30 | 10:30–10:45 | 10:45–11:00 | 11:15–11:30 | 11:30–11:45 | 11:45–12:00 | 12:00–12:15 | 12:15–12:30 | 12:30–12:45 | 12:45–13:00 | 13:00–13:15 | 13:15–13:30 | 13:30–13:40 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Proprietary institutions | 3.15*** | 5.05*** | 5.54*** | 4.12*** | 2.52*** | 2.89*** | 2.74*** | 1.85*** | 0.70** | 1.20*** | 0.80** | 1.15*** | 1.07*** | 0.68** | 0.88*** | 1.30*** | 1.05*** | 1.80*** | 1.07** | 0.62 |
| Buy | 2.66*** | 6.16*** | 5.66*** | 4.57*** | 4.00*** | 2.65*** | 2.16*** | 1.72*** | 1.43*** | 1.51*** | 1.17*** | 2.21*** | 2.11*** | 0.82*** | 1.89*** | 2.15*** | 2.58*** | 1.93*** | 1.56*** | 0.53 |
| Sell | 2.55*** | 3.79*** | 6.90*** | 5.49*** | 3.41*** | 4.82*** | 3.37*** | 1.58*** | 1.60*** | 1.93*** | 1.63*** | 2.10*** | 1.01*** | 1.27*** | 2.04*** | 1.69*** | 1.39*** | 1.76*** | 2.14*** | 1.07 |
| Foreign institutions | 2.52*** | 3.78*** | 6.07*** | 5.19*** | 6.04*** | 3.28*** | 2.68*** | 1.55*** | 1.28** | 2.52*** | 1.13** | 2.07*** | 1.68** | 1.02** | 1.96*** | 2.37*** | 2.93*** | 2.43*** | 1.51*** | 0.03 |
| Buy | 2.35*** | 4.71*** | 6.15*** | 6.06*** | 5.47*** | 3.91*** | 2.85*** | 1.38*** | 2.63*** | 1.83*** | 1.75*** | 2.78*** | 1.36** | 1.55*** | 2.02*** | 2.42*** | 2.62*** | 1.68*** | 0.81*** | 0.95 |
| Sell | 2.39*** | 3.73*** | 6.22*** | 5.30*** | 6.89*** | 5.34*** | 3.34*** | 2.31*** | 2.06*** | 2.27*** | 0.99 | 1.30** | 1.09** | 1.76** | 1.02** | 1.91*** | 1.93** | 2.72*** | 1.67** | 0.27 |

*Note*. This table reports coefficients estimates for the intraday fleeting order rate through regressions on dummy variables indicating intraday time intervals. Orders of TXF submitted in the spot month over the period from January 2005 to December 2008 are included. Results of proprietary institutions and foreign institutions are reported. The daily trading hours are partitioned into 19 15-minute intervals from 8:45 a.m. to 13:30 p.m., and one last 10-minute interval from 13:30 p.m. to 13:40 p.m. Dependent variable is fleeting order rate. Fleeting order rate of a specific time interval for a trader type is calculated as the number of fleeting orders submitted by a specific trader type within that specific time interval divided by the total number of fleeting orders placed by that specific trader type in that trading day. Sum of fleeting order rates across those 20 time intervals equals one for each trader type. We perform the following regression to examine the statistical significance of the intraday seasonality of fleeting orders:

$$\begin{aligned} &\mathit{FleetingOrderRate}_{i,j} \\ &\quad = \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \beta_6 D_6 + \beta_7 D_7 + \beta_8 D_8 \\ &\quad + \beta_9 D_9 + \beta_{11} D_{11} + \beta_{12} D_{12} + \beta_{13} D_{13} + \beta_{14} D_{14} + \beta_{15} D_{15} \\ &\quad + \beta_{16} D_{16} + \beta_{17} D_{17} + \beta_{18} D_{18} + \beta_{19} D_{19} + \beta_{20} D_{20} + \varepsilon_{i,j}, \end{aligned}$$

where $\mathit{FleetingOrderRate}_{i,j}$ is the fleeting order rate for trader type j within time interval i. $D_1$, $D_2$, $D_3$, ….., and $D_{20}$ are the dummy variables of 20 intraday time intervals from 8:45 a.m. to 13:40 p.m. $D_1$ represents the interval of 8:45 a.m. to 9:00 a.m., $D_2$ represents the interval of 9:00 a.m. to 9:15 a.m., and so on, i.e., $D_i$ equals one if the fleeting order rate is calculated within i time interval and zero otherwise, for i = 1, 2, ….., 20. Note that we remove the dummy variable $D_{10}$ to avoid the collinearity problem. All coefficient estimates are scaled by $10^2$ times. In addition to all orders, buyer-initiated and seller-initiated orders are examine separately. *, **, *** indicate significantly different from zero at the 10%, 5%, and 1% levels, respectively.

## 7 | PROPORTIONAL HAZARD DURATION MODEL FOR FLEETING ORDERS

Following Hasbrouck and Saar (2009), we employ the proportional hazard duration model to investigate the underlying motivations of the fleeting order trading strategy: The chasing hypothesis and the cost-of-immediacy hypothesis.

### 7.1 | Methodology

To characterize how market conditions influence the order cancellation decisions of market participants, Hasbrouck and Saar (2009) apply Cox (1972) proportional hazard duration model with time varying covariates (Allison, 1995) to estimate the incidence of cancellation. The proportional hazard duration model is a survival analysis method, and is commonly used to consider the impact of a risk factor on the time to the occurrence of an event. In this paper, the event of interest is the limit order cancellation within 5 s after submission and the competing event is the execution of a limit order. Let $T$ denote the cancellation time of an order relative to the submission time. Fleeting orders are orders cancelled within 5 s after their submissions, namely, $T \leq 5$. For example, two limited orders are placed at the same time 10:15:20 on a trading day. Both orders are eventually cancelled. One is cancelled at time 10:15:23, whereas the other one is cancelled at time 10:15:38. In this case, the first cancelled order is then defined as a fleeting order, while the other is not. The survival function is $S(t) = \Pr(T > t)$ which describes the probability that a particular limit order is not cancelled for at least $t$ seconds. The hazard rate is the intensity of order cancellation over the next instant and modeled as $\lambda(t) = -d\log(S(t))/dt = S(t)^{-1}S'(t)$. In our case, the hazard rate measures the instantaneous risk that a fleeting order will occur at time $t$. The hazard rate for limit order $i$ submitted by trader type $j$ is modeled with the semiparametric form

$$\lambda_{i,j}(t) = \lambda_{0,j}(t)e^{X_{i,j,t}\beta_j}, \tag{2}$$

where $\lambda_{0,j}(t)$ is a nonnegative and unspecified baseline hazard rate. $X_{i,j,t}$ is a vector of exogenous factors that may affect the hazard rate. It must be observable at time t, but need not be known when the order is submitted. The vector of coefficients, $\beta_j$, is estimated in a partial-likelihood framework with a nonnegative and unspecified baseline hazard rate. Specifically, we estimate the following pooled duration model for the hazard rate of limit order $i$ submitted by trader type $j$, including proprietary traders and foreign traders.

$$\lambda_{i,j}(t) = \lambda_{0,j}(t)exp\left[\begin{array}{c} \beta_1\Delta q_{i,j,t}^{Same} + \beta_2\Delta q_{i,j,t}^{Opposite} + \beta_3(Network_{i,j}) + \beta_4(Lagged\ Fleeting\ Orders_{i,j}) \\ +\beta_5(Open\ Interest_{i,j}) + \beta_6(BBO\ Spread_{i,j}) + \beta_7|Lagged\ Return_{i,j}| + \beta_8(Lagged\ Volume_{i,j}) + \sum_{\substack{i=1 \\ i\neq 10}}^{i=20}\alpha_i D_i \end{array}\right] \tag{3}$$

Note that Equation (3) is different from the model estimated by Hasbrouck and Saar (2009) in that we include an additional variable, $Network_{i,j}$, to investigate the role of network trading on the occurrence of fleeting orders. The coefficients of key variables, $\Delta q_{i,j,t}^{Same}$, $\Delta q_{i,j,t}^{Opposite}$, and $Network_{i,j}$, are used to test the hypotheses of underlying motivations for fleeting order and the influence of network trading on traders' fleeting order strategy.

The chasing hypothesis of Hasbrouck and Saar (2009) suggests that the trader would cancel an order and resubmit a new order at a more aggressive price if someone has placed a limit order ahead of it. By doing so, he could actively influence the likelihood of order execution. Specifically, when the best bid price moves up right after a limit buy order submission, the trader will quickly cancel the order and resubmit another limit buy order at a higher price to increase the likelihood of order execution. For example, a limit buy order is submitted at 10:15:00 on a trading day. The current best bid price is 7,000 index points. Right after the order submission, the best bid price moves to 7,001 at 10:15:03. He could actively influence the likelihood of an execution by cancelling the order and resubmitting the order at a more aggressive price since someone has placed a limit order ahead of it. If the trader cancels the order at 10:15:04, such fleeting order behavior is consistent with the chasing hypothesis. To run regressions, we define the variable for testing the chasing hypothesis as $\Delta q_{i,j,t}^{Same} = (BestBid_{i,j,t} - BestBid_{i,j,t=0^+})/(BestBid_{i,j,t=0^+})$ for a limit buy order, where $t = 0^+$ represents the instant right after order submission. $BestBid_{i,j,t=0^+}$ is the best bid price in the instant right after order submission. $BestBid_{i,j,t}$ is subsequent best bid price after $t = 0^{+}$. $\Delta q_{i,j,t}^{Same}$ is the percentage change in the best bid price between the instant right after order submission and the moment of subsequent best bid price update. Since a positive $\Delta q_{i,j,t}^{Same}$ indicates an increase in the best quoted bid price right after order submission, a positive $\beta_1$ suggests that traders tend to cancel current limit buy orders and swiftly resubmit more aggressive ones to increase execution probability when the best bid price increases right after they submit limit buy orders. $\Delta q_{i,j,t}^{Same}$ is defined similarly for a limit sell order, so that a decreased ask price is associated with a positive change in the variable.

The variable for testing the cost-of-immediacy hypothesis considers the opposing-side best price change right after order submission and is defined as $\Delta q_{i,j,t}^{Opposite} = (BestAsk_{i,j,t} - BestAsk_{i,j,t1=10^{+}})/(BestAsk_{i,j,t=0^{+}})$ for a limit buy order. A negative $\Delta q_{i,j,t}^{Opposite}$ hence results from a decrease in the best quoted ask price right after the submission of a limit buy order. When the opposite side price comes down, the cost of immediate execution becomes cheaper, increasing the probability for traders to cancel submitted limit buy orders and switch to market buy orders. As a result, a negative $\beta_2$ supports the cost-of-immediacy hypothesis. Similarly, for a limit sell order, an increase in the best bid price is associated with a negative change in $\Delta q_{i,j,t}^{Opposite}$.

The final variable, $Network_{i,j}$, is defined as an indicator variable that indicates the occurrence of the event in which a certain trader consecutively submits at least one limit buy order and one limit sell order within a time interval of 1 s. Thus, the variable takes a value of one for an order that belongs to a network limit order and a value of zero otherwise. The coefficient $\beta_3$ measures the effect of network trading on fleeting orders. A positive $\beta_3$ implies that the network trading strategy is an important component of the fleeting order strategy.

To control trading pace and general market conditions, we add several control variables as suggested by Hasbrouck and Saar (2009). $Lagged\ Fleeting\ Orders_{i,j}$ is the number of fleeting orders submitted by a trader in the preceding 10 s of order submission. $BBO\ Spread_{i,j}$ is the spread of current best bid and ask prices when an order is submitted. $|Lagged\ Return_{i,j}|$ is the absolute value of the difference between the maximum log TXF index point and the minimum log TXF index point in the preceding 5 min of order submission. It measures the price volatility over the 5 min before the submission of a fleeting order. $Lagged\ Volume_{i,j}$ is the cumulative trading volume of TXF in the preceding 5 min after order submission. We also control the intraday seasonality of fleeting order by including the dummy variables as defined before. We also add $Open\ Interest_{i,j}$ to capture the effects of inventory management. Garman (1976) shows that dealers actively adjust quotes to manage inventory in response to their finite capitals. Harris (2002) documents that dealers avoid large inventory positions that expose them to losses when the market price moves against them. Finally, Rosu (2009) develops a dynamic model of waiting costs for traders with imbalanced inventory positions. Specifically, he shows that when traders have high waiting costs (costs of delayed or nonexecution of orders), they become impatient and find it optimal to place orders aggressively to rebalance their positions. For example, traders aggressively cancel or negatively modify their existing buy orders in response to an increase in their inventory.[13] We therefore decide to include the number of futures contracts held by a trader as open interest to capture the effect of inventory management on fleeting orders. Note that we use the logarithms of the above control variables as independent variables in Equation (3).

## 7.2 | Empirical results

Summary statistics of independent variables in the proportional hazard duration model are reported in Table 8. As shown in Panel A, both $\Delta q_{i,j,t}^{Same}$ and $\Delta q_{i,j,t}^{Opposite}$ have means very close to zero because of the abundant liquidity of TXF futures contracts.[14] Specifically, the means of $\Delta q_{i,j,t}^{Same}$ and $\Delta q_{i,j,t}^{Opposite}$ are $1.12 \times 10^{-5}$ and $6.24 \times 10^{-6}$, respectively. However, because of the vast number of observations, these means are statistically significant with $p < 0.01$ according to the traditional two-tailed Student $t$ tests. Furthermore, $\Delta q_{i,j,t}^{Same}$ has an underlying distribution with a positive skewness coefficient and a very high coefficient of kurtosis, while $\Delta q_{i,j,t}^{Opposite}$ have has an underlying distribution that is skewed to the left and leptokurtic. These characteristics imply that the underlying distributions for these two variables do not follow a normal distribution. The same conclusions apply to the buyer-initiated as well as seller-initiated limit orders.

Table 9 shows the results of the pooled proportional hazard duration model for proprietary traders. The first two models examine the individual effects of $\Delta q_{i,j,t}^{Same}$ and $\Delta q_{i,j,t}^{Opposite}$ on the probability of fleeting orders, whereas Models 3

[13] Ho and Macris (1984), Madhavan and Smidt (1991), Madhavan and Smidt (1993), Lyons (1995), Manaster and Mann (1996), Hasbrouck (1988), and Raman and Yadav (2013) provide empirical evidence supportive of dealers' practice of inventory management.

[14] Since TXF is a very liquid market with deep market depth, its bid-ask spread is usually 1 index point. For 2008, for example, the average closing index is 7,106, resulting in a very low mean proportional spread of $1.4 \times 10^{-4}$. In addition, the deep market depth results in infrequent changes in the best bid and ask prices.

**TABLE 8** Summary statistics of proportional hazard duration model

| | $\Delta q_{i,j,t}^{Same}$ | $\Delta q_{i,j,t}^{Opposite}$ | $p_{i,j}^{Relative}$ | $Network_{i,j}$ | *Lagged Fleeting Orders i,j* | *#Open Interest*$_{i,j}$ | *BBO Spread*$_{i,j}$ | $\lvert Lagged\ Return_{i,j}\rvert$ | *Lagged Volume*$_{i,j}$ |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: All orders (# of obs. = 61,069,156) | | | | | | | | | |
| Mean | $1.12\times10^{-5}$ | $6.24\times10^{-6}$ | $-1.00\times10^{-3}$ | 0.10 | 1.33 | 6.39 | $1.00\times10^{-3}$ | $2.70\times10^{-3}$ | 979.66 |
| Std | $3.27\times10^{-4}$ | $2.44\times10^{-4}$ | $4.00\times10^{-3}$ | 0.30 | 4.61 | 718.91 | $2.00\times10^{-3}$ | $2.40\times10^{-3}$ | 832.17 |
| Kurt | 2,221.40 | 3,132.64 | 131.57 | 5.19 | 33.06 | 59.98 | 190.11 | 13.95 | 2.89 |
| Skew | 9.93 | −2.68 | −4.00 | 2.68 | 5.01 | 1.60 | 10.74 | 2.70 | 1.39 |
| Min | −0.07 | −0.07 | −0.07 | 0.00 | 0.00 | −12,205.00 | 0.00 | 0.00 | 0.00 |
| Median | 0.00 | 0.00 | $-1.17\times10^{-4}$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 807.50 |
| Max | 0.06 | 0.08 | 0.07 | 1.00 | 114.00 | 12,858.00 | 0.11 | 0.07 | 7,548.50 |
| Panel B: Buy orders (# of obs. = 31,259,430) | | | | | | | | | |
| Mean | $1.16\times10^{-5}$ | $6.19\times10^{-6}$ | $-1.00\times10^{-3}$ | 0.10 | 1.31 | 16.57 | $1.00\times10^{-3}$ | $2.70\times10^{-3}$ | 974.49 |
| Std | $3.50\times10^{-4}$ | $2.35\times10^{-4}$ | $4.00\times10^{-3}$ | 0.30 | 4.56 | 725.59 | $2.00\times10^{-3}$ | $2.40\times10^{-3}$ | 831.80 |
| Kurt | 1,956.17 | 2,828.53 | 122.323 | 5.38 | 33.46 | 59.26 | 162.45 | 14.46 | 2.87 |
| Skew | 9.09 | −0.58 | −4.52 | 2.72 | 5.05 | 1.80 | 9.95 | 2.72 | 1.39 |
| Min | −0.07 | −0.06 | −0.07 | 0.00 | 0.00 | −12,192.00 | 0.00 | 0.00 | 0.00 |
| Median | 0.00 | 0.00 | $-1.23\times10^{-4}$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 803.00 |
| Max | 0.06 | 0.08 | 0.07 | 1.00 | 114.00 | 12,858.00 | 0.10 | 0.07 | 7,548.50 |
| Panel C: Sell orders (# of obs. = 29,809,726) | | | | | | | | | |
| Mean | $1.09\times10^{-5}$ | $6.29\times10^{-6}$ | $-1.00\times10^{-3}$ | 0.10 | 1.36 | −4.27 | $1.00\times10^{-3}$ | $2.70\times10^{-3}$ | 985.07 |
| Std | $3.02\times10^{-4}$ | $2.53\times10^{-4}$ | $4.00\times10^{-3}$ | 0.30 | 4.65 | 711.70 | $2.00\times10^{-3}$ | $2.40\times10^{-3}$ | 832.52 |
| Kurt | 2,588.31 | 3,338.01 | 142.69 | 5.01 | 32.66 | 60.77 | 208.37 | 13.43 | 2.90 |
| Skew | 11.08 | −4.43 | −3.34 | 2.65 | 4.96 | 1.37 | 11.33 | 2.69 | 1.39 |
| Min | −0.06 | −0.07 | −0.07 | 0.00 | 0.00 | −12,205.00 | 0.00 | 0.00 | 0.00 |
| Median | 0.00 | 0.00 | $-1.12\times10^{-4}$ | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 813.00 |
| Max | 0.06 | 0.06 | 0.07 | 1.00 | 114.00 | 12,226.00 | 0.11 | 0.07 | 7,548.50 |

*Note*. This table presents summary statistics of independent variables in the proportional hazard duration model. Panel A reports all limit orders. Panel B contains buyer-initiated limit orders. Panel C presents seller-initiated limit orders. For a buyer-initiated limit order, the subsequent change to the best price in the limit order book on the same side is $\Delta q_{i,j,t}^{Same} = (BestBid_{i,j,t} - BestBid_{i,j,t=0^+})/(BestBid_{i,j,t=0^+})$, where $t = 0^+$ represents the very first observable best bid price right after order submission. The opposing-side best price change right after order submission is $\Delta q_{i,j,t}^{Opposite} = (BestAsk_{i,j,t} - BestAsk_{i,j,t=0^+})/(BestAsk_{i,j,t=0^+})$. Order aggressiveness is $p_{i,j}^{Relative} = (LimitBuyOrderPrice_{i,j} - BestBid_{i,j,t=0})/(BestBid_{i,j,t=0})$, where $t = 0$ represents the time of order submission. The above three variables for a seller-initiated limit order is defined in analogous fashion with opposite signs. $Network_{i,j}$ represents network limit orders defined as at least one buy limit order and at least one sell limit order submitted by a trader within 1-s intervals. The variable takes the value of one for a buy or a sell order if the submitted order is part of network limit orders and the value of zero otherwise. *Lagged Fleeting Orders*$_{i,j}$ is the number of fleeting orders submitted by a trader in the preceding 10 s of order submission. $OpenInterest_{i,j}$ is the number of futures contracts a trader holds when order is submitted. $BBOSpread_{i,j}$ is the spread of current best bid and ask prices when order is submitted. $\lvert LaggedReturn_{i,j}\rvert$ is the absolute value of the difference between maximum log Taiwan Stock Exchange Capitalization Weighted Stock Index Futures (TXF) index point and minimum log TXF index point in the preceding 5 min after order submission. $LaggedVolume_{i,j}$ is the cumulative trading volume of TXF in the preceding 5 min after order submission. Limit orders of TXF submitted by proprietary institutions and foreign institutions in the spot month over the period from January 2005 to December 2008 are included. Mean, standard deviation, kurtosis, skewness, minimum, median, and maximum of the independent variables and number of observations are provided.

**TABLE 9** Results of proportional hazard duration model – proprietary institutions

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Panel A: All orders (# of obs. = 19,587,126) | | | | | |
| $\Delta q_{i,j,t}^{Same}$ | −29.87*** | | −35.47*** | | −35.62*** |
| $\Delta q_{i,j,t}^{Opposite}$ | | −43.76*** | | −16.79*** | −17.26*** |
| $Network_{i,j}$ | | | 0.74*** | 0.74*** | 0.74*** |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 0.06*** | 0.06*** | 0.05*** | 0.05*** | 0.05*** |
| $\#Open\ Interest_{i,j}$ $(\times 10^{-3})$ | −0.09*** | −0.09*** | −0.07*** | −0.07*** | −0.07*** |
| $BBO\ Spread_{i,j}$ | −7.49*** | −7.82*** | −15.64*** | −16.48*** | −15.49*** |
| $\lvert Lagged\ Return_{i,j}\rvert$ | 55.19*** | 55.14*** | 40.98*** | 41.04*** | 41.02*** |
| $Lagged\ Volume_{i,j}$ $(\times 10^{-3})$ | 0.01*** | 0.00*** | 0.01*** | 0.01*** | 0.01*** |
| Panel B: Buy orders (# of obs. = 9,918,888) | | | | | |
| $\Delta q_{i,j,t}^{Same}$ | −47.08*** | | −50.87*** | | −50.90*** |
| $\Delta q_{i,j,t}^{Opposite}$ | | −50.09*** | | −14.81*** | −15.44*** |
| $Network_{i,j}$ | | | 0.79*** | 0.79*** | 0.79*** |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 0.06*** | 0.06*** | 0.05*** | 0.05*** | 0.05*** |
| $\#Open\ Interest_{i,j}$ $(\times 10^{-3})$ | −0.09*** | −0.09*** | −0.05*** | −0.05*** | −0.05*** |
| $BBO\ Spread_{i,j}$ | −7.85*** | −9.03*** | −16.28*** | −18.07*** | −16.14*** |
| $\lvert Lagged\ Return_{i,j}\rvert$ | 50.03*** | 50.05*** | 31.38*** | 31.39*** | 31.42*** |
| $Lagged\ Volume_{i,j}$ $(\times 10^{-3})$ | 0.02*** | 0.02*** | 0.05*** | 0.05*** | 0.05*** |
| Panel C: Sell orders (# of obs. = 9,668,238) | | | | | |
| $\Delta q_{i,j,t}^{Same}$ | −17.50*** | | −15.72*** | | −16.00*** |
| $\Delta q_{i,j,t}^{Opposite}$ | | −39.13*** | | −17.66*** | −17.93*** |
| $Network_{i,j}$ | | | 0.69*** | 0.69*** | 0.69*** |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 0.06*** | 0.06*** | 0.05*** | 0.05*** | 0.05*** |
| $\#Open\ Interest_{i,j}$ $(\times 10^{-3})$ | −0.10*** | −0.10*** | −0.08*** | −0.08*** | −0.08*** |
| $BBO\ Spread_{i,j}$ | −6.61*** | −6.42*** | −14.39*** | −14.51*** | −14.24*** |
| $\lvert Lagged\ Return_{i,j}\rvert$ | 59.17*** | 59.11*** | 48.22*** | 48.20*** | 48.24*** |
| $Lagged\ Volume_{i,j}$ $(\times 10^{-3})$ | 0.03*** | 0.03*** | 0.01*** | 0.01*** | 0.01*** |

*Note*. This table reports the proportional hazard duration model on the fleeting hazard rate for proprietary institutions. Panel A reports all limit orders. Panel B contains buyer-initiated limit orders. Panel C presents seller-initiated limit orders. To estimate the fleeting hazard rate for limit order *i* submitted by trader type *j* at time t (relative to the time of order placement), we form the model as follows

$$\lambda_{i,j}(t) = \lambda_{0,j}(t)exp\left[\begin{array}{c}\beta_1\Delta q_{i,j,t}^{Same} + \beta_2\Delta q_{i,j,t}^{Opposite} + \beta_3(Network_{i,j}) + \beta_4(Lagged\ Fleeting\ Orders_{i,j}) \\ + \beta_5(Open\ Interest_{i,j}) + \beta_6(BBO\ Spread_{i,j}) + \beta_7|Lagged\ Return_{i,j}| + \beta_8(Lagged\ Volume_{i,j}) + \sum_{\substack{i=1 \\ i\neq 10}}^{i=20}\alpha_i D_i\end{array}\right]$$

where $\lambda_{0,j}(t)$ is a non-negative and unspecified baseline hazard rate. For a buyer-initiated limit order, the subsequent change to the best price in the limit order book on the same side is $\Delta q_{i,j,t}^{Same} = (BestBid_{i,j,t} - BestBid_{i,j,t=0^+})/(BestBid_{i,j,t=0^+})$, where $t = 0^+$ represents the very first observable best bid price right after order submission. The opposing-side best price change right after order submission is $\Delta q_{i,j,t}^{Opposite} = (BestAsk_{i,j,t} - BestAsk_{i,j,t=0^+})/(BestAsk_{i,j,t=0^+})$. The above two variables for a seller-initiated limit order is defined in analogous fashion with opposite signs. $Network_{i,j}$ represents network limit orders defined as at least one buy limit order and at least one sell limit order submitted by a trader within one-second intervals. The variable takes the value of one for a buy or a sell order if the submitted order is part of network limit orders and the value of zero otherwise. $LaggedFleetingOrders_{i,j}$ is the number of fleeting orders submitted by a trader in the preceding ten seconds of order submission. $OpenInterest_{i,j}$ is the number of futures contracts a trader holds when order is submitted. $BBOSpread_{i,j}$ is the spread of current best bid and ask prices when order is submitted. $|LaggedReturn_{i,j}|$ is the absolute value of the difference between maximum log TXF index point and minimum log TXF index point in the preceding five minutes after order submission. $LaggedVolume_{i,j}$ is the cumulative trading volume of TXF in the preceding five minutes after order submission. $D_1$, $D_2$, $D_3$, ....., and $D_{20}$ are the dummy variables of 20 intraday time intervals from 8:45 a.m. to 13:40 p.m. $D_1$ represents the interval of 8:45 a.m. to 9:00 a.m., $D_2$ represents the interval of 9:00 a.m. to 9:15 a.m., and so on, i.e., $D_i$ equals one if the fleeting order is submitted within i time interval and zero otherwise, for i = 1, 2, ....., 20. Note that we remove the dummy variable $D_{10}$ to avoid the collinearity problem. Limit orders of TXF submitted in the spot month over the period from January 2005 to December 2008 are included. *, **, *** indicate significantly different from zero at the 10%, 5%, and 1% levels, respectively.

and 4 incorporate the variable of network trading into the first two models to investigate whether the network trading strategy is an important component of proprietary traders' fleeting order strategy. The final column presents the estimated full duration model.

As shown in Panel A, the coefficient of $\Delta q_{i,j,t}^{Same}$ in Model 1 is significantly negative (−29.87), suggesting that proprietary traders do not aggressively cancel their original limit orders and resubmit more aggressive orders when the same side quoted price moves away from the original quoted price. Note that this negative $\beta_1$ is inconsistent with the chasing hypothesis. For example, proprietary trader A submits a limit buy order at a price of 6,996 index point that is not very close to the prevailing best bid price of 7,000 index point. Consider the following two scenarios. Scenario 1: The best bid price drops to 6,998 index point. Scenario 2: The best bid price goes up to 7,001 index point. The negative $\beta_1$ implies that proprietary trader A is more likely to cancel the buy limit order under Scenario 1 than Scenario 2.[15] This example manifests the adverse selection risk facing liquidity providers when submitting limit orders. In particular, instead of responding to the increasing best bid price to maintain a liquid market by cancelling the previous limit buy order and resubmitting a more aggressive one, proprietary trader A is obviously more concerned about the risk of being picked off by informed traders entailed by the decreasing best bid price.

To investigate the influence of adverse selection risk to the fleeting orders, we look further into the limit order submission behavior of proprietary traders. Interestingly, we find that proprietary traders usually submit limit orders at multiple prices on the same side of limit order book rather than at a single price. In untabulated results,[16] 65% (64) of limit buy (sell) orders with different degrees of price aggressiveness are submitted by the same proprietary trader. Furthermore, among these limit orders, most of them are submitted at either the most or the least aggressive prices. For example, 47% (30) of proprietary traders' limit buy order submission are at the most (least) aggressiveness price degree. We then examine the execution rate, cancellation rate, and fleeting rate for limit orders with different degrees of price aggressiveness. Indeed, while most aggressive orders yield the highest execution rates, the least aggressive orders have the highest cancellation and fleeting rates. In particular, as high as 85% of proprietary traders' executed limit buy orders are at the most aggressive price degree, whereas 60% of limit buy fleeting orders are at the least aggressive price degree. Note that the limit sell orders submitted by proprietary traders exhibit similar patterns. In summary, the adverse selection risk facing proprietary traders is one of the potential causes of the negative $\beta_1$.

In Model 2, the coefficient of $\Delta q_{i,j,t}^{Opposite}$ is also significantly negative (−43.76), implying that proprietary traders tend to cancel previously submitted limit orders when the opposite side quoted price moves toward the original quoted price. The negative $\beta_2$ is thus in line with the hypothesis of cost-of-immediacy that the probability of fleeting orders for proprietary traders increases when the cost of immediate execution in the market is reduced. These results indicate that proprietary traders behave like market makers who care more about the cost of market making, rather than like speculators who aggressively follow the market price trend.

To analyze how the above motivations of fleeting orders interact with network trading strategies, we incorporate a dummy variable of network trading into the models and report the estimation results in Models 3 and 4. Consistent with our conjecture, network trading strategy is positively associated with the intensity of fleeting order. In particular, the coefficients of network trading in these models are all significantly positive. Note that $\beta_2$ decreases significantly from −43.76 to −16.79 after the inclusion of the network trading variable. This suggests that proprietary traders frequently use networking orders in response to a change of immediate execution costs in the market. Finally, the full duration model is estimated and the results are shown in the last column. As we can see, all coefficients, $\beta_1$, $\beta_2$, and $\beta_3$, remain significant and have the same signs.

Control variables are consistently significant across the models. The positive coefficient for the variable, *Lagged Fleeting Orders*$_{i,j}$, suggests that proprietary traders aggressively adopt a fleeting order strategy. The higher the number of fleeting orders submitted in the 10 s before an order submission, the higher the probability of a fleeting order from a proprietary trader at the next instant. Interestingly, the significantly negative coefficient of the control variable, *Open Interest*$_{i,j}$, implies that an increase in the open interest reduces the probability of fleeting order submitted by proprietary traders. In other words, although proprietary traders act like market makers who discretely manage their inventories, they may not conduct such inventory management through fleeting orders. Moreover, the negative $\beta_6$ indicates that proprietary traders usually actively submit fleeting orders when the current best bid-ask spread is narrow. Consistent with the results of Hasbrouck and Saar (2009), both control variables, |*Lagged Return*$_{i,j}$| and *Lagged Volume*$_{i,j}$,

[15]We thank the referee for suggesting this line of insightful inquiry.

[16]The details are available from the authors upon request.

have significantly positive coefficients, demonstrating that proprietary traders aggressive deploy fleeting orders when the market is liquid and volatile.[17] Finally, we investigate whether there is a significant difference between buyer-initiated and seller-initiated fleeting orders. However, the results in Panels B and C show that both types of orders exhibit a similar pattern.

The empirical results for foreign traders are reported in Table 10. The evidence shows that similar to proprietary traders, foreign traders do not actively chase market prices, but they quickly cancel orders in response to a decrease in immediate execution costs. $\Delta q_{i,j,t}^{Same}$ and $\Delta q_{i,j,t}^{Opposite}$ are both significantly negatively associated with the intensity of fleeting orders across all models. Take Model 5 for example, the coefficients of $\Delta q_{i,j,t}^{Same}$ and $\Delta q_{i,j,t}^{Opposite}$ are $-52.01$ and $-9.50$, respectively. It is interesting to notice that although network orders constitute a significant fraction of fleeting orders of proprietary traders, this is not true for foreign traders because of the significantly negative coefficient of network trading, $-0.42$. It is in line with our conjecture that as informed hedgers, foreigners' trading objective is to reduce financial risks and would be less likely to actively cancel network orders.

Handa and Schwartz (1996) argue that for an order-driven market to operate successfully, limit order trading must be profitable for a sufficient number of market participants who are willing to provide liquidity by submitting limit orders. They indicate that trading on the short-term volatility is an important determinant of limit order placement decisions. Based on the data of the component stocks of Down Jones Industrial Average Index, they empirically examine the profitability of several limit order trading strategies, showing that a network order trading strategy by simultaneously placing buy and sell limit orders is indeed profitable. This result may explain why proprietary traders in TAIFEX use network orders.

We also investigate the relation between network order placement and market volatility. In particular, according to Handa and Schwartz (1996), there exists a positive relation between the frequency of network order submission and market volatility. Note that such a positive relation may imply that foreign traders use network orders to reduce their financial risk.

We first calculate index return for every minute and its volatility within each time interval for 19 15-min intervals from 8:45 a.m. to 1:30 p.m. and 1 10-min interval from 1:30 p.m. to 1:40 p.m. We then form four groups of network order submissions based in the market volatility within each time interval independently. Group 1 contains the bottom quartile of time intervals with the lowest volatilities, while Group 4 contains the top quartile of time intervals with the highest volatilities.

The untabulated results show that there indeed exists a positive relation between network order placement and market volatility.[18] For instance, the mean number of network order submitted by proprietary traders is 227.18 for the time intervals in Group 4, but only 93.06 for the time intervals in Group 1. The difference of the mean number of network order between Groups 4 and 1 is significantly positive. This result is supportive for the argument of Handa and Schwartz (1996) that traders in an order-driven market actively trade when the market is volatile. Specifically, traders ride on market fluctuation by actively engaging in network limit order trading strategy to gain profits.

The results also show that foreign traders submit more network orders when the market is more volatile. Although the positive relation between the network order frequency and market volatility implies that foreign trades may utilize network orders to confine their risk within certain level of price spread when the market is volatile, we are not able to completely rule out the possibility that foreign traders attempt to capture the risk premium of market volatility through network orders for pure speculation purposes.

The estimated coefficients of control variables yield conclusions similar to those for proprietary traders, except the significantly positive coefficient of the variable, $BBOSpread_{i,j}$. This implies that foreign traders intensively use fleeting orders when the current best bid-ask spread is wide. Results of buyer-initiated and seller-initiated fleeting orders in Panels B and C demonstrate a pattern similar to those in Panel A.

Overall, in contrast to the findings of Hasbrouck and Saar (2009), our results show that institutional traders in Taiwan futures markets do not aggressively chase market prices in the limit order book through fleeting orders. Nevertheless, they do actively respond to a change in immediate execution costs. We also investigate the relation between fleeting order strategy and network trading strategy, finding that proprietary traders respond to a change in immediate execution costs mainly by submitting network orders.

[17]For the sake of brevity, we do not report the coefficients of intraday seasonality dummy variables in Tables 8–10. However, most estimated coefficients are significant with a similar pattern shown in Table 7. The results are available from the authors upon request.

[18]The details are available from the authors upon request.

**TABLE 10** Results of proportional hazard duration model – foreign institutions

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Panel A: All orders (# of obs. = 8,356,506) | | | | | |
| $\Delta q_{i,j,t}^{Same}$ | −52.11*** | | −52.08*** | | −52.01*** |
| $\Delta q_{i,j,t}^{Opposite}$ | | −10.39*** | | −10.54*** | −9.50*** |
| $Network_{i,j}$ | | | −0.42*** | −0.42*** | −0.42*** |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 0.09*** | 0.09*** | 0.08*** | 0.08*** | 0.08*** |
| $\#Open\ Interest_{i,j}$ ($\times 10^{-3}$) | −0.02*** | −0.02*** | −0.03*** | −0.03*** | −0.03*** |
| $BBO\ Spread_{i,j}$ | 67.35*** | 68.97*** | 69.01*** | 70.59*** | 68.83*** |
| $\lvert Lagged\ Return_{i,j}\rvert$ | 82.82*** | 83.12*** | 83.93*** | 84.22*** | 83.95*** |
| $Lagged\ Volume_{i,j}$ ($\times 10^{-3}$) | 0.05*** | 0.05*** | 0.04*** | 0.04*** | 0.04*** |
| Panel B: Buy orders (# of obs. = 4,307,970) | | | | | |
| $\Delta q_{i,j,t}^{Same}$ | −49.93*** | | −50.09*** | | −50.05*** |
| $\Delta q_{i,j,t}^{Opposite}$ | | −11.30*** | | −11.20*** | −9.83*** |
| $Network_{i,j}$ | | | −0.44*** | −0.44*** | −0.44*** |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 0.08*** | 0.08*** | 0.08*** | 0.08*** | 0.08*** |
| $\#Open\ Interest_{i,j}$ ($\times 10^{-3}$) | −0.02*** | −0.02*** | −0.02*** | −0.02*** | −0.02*** |
| $BBO\ Spread_{i,j}$ | 64.90*** | 66.66*** | 66.43*** | 68.15*** | 66.29*** |
| $\lvert Lagged\ Return_{i,j}\rvert$ | 96.53*** | 97.17*** | 97.63*** | 98.23*** | 97.63*** |
| $Lagged\ Volume_{i,j}$ ($\times 10^{-3}$) | 0.10*** | 0.10*** | 0.09*** | 0.10*** | 0.09*** |
| Panel C: Sell orders (# of obs. = 4,048,536) | | | | | |
| $\Delta q_{i,j,t}^{Same}$ | −58.00*** | | −57.98*** | | −57.80*** |
| $\Delta q_{i,j,t}^{Opposite}$ | | −9.62*** | | −9.79*** | −8.86*** |
| $Network_{i,j}$ | | | −0.39*** | −0.39*** | −0.39*** |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 0.09*** | 0.09*** | 0.08*** | 0.08*** | 0.08*** |
| $\#Open\ Interest_{i,j}$ ($\times 10^{-3}$) | −0.03*** | −0.03*** | −0.03*** | −0.03*** | −0.03*** |
| $BBO\ Spread_{i,j}$ | 69.38*** | 70.94*** | 71.16*** | 72.70*** | 70.95*** |
| $\lvert Lagged\ Return_{i,j}\rvert$ | 66.29*** | 66.26*** | 67.43*** | 67.39*** | 67.46*** |
| $Lagged\ Volume_{i,j}$ ($\times 10^{-3}$) | 0.02*** | 0.02*** | 0.02*** | 0.02*** | 0.02*** |

*Note*. This table reports the proportional hazard duration model on the fleeting hazard rate for foreign institutions. Panel A reports all limit orders. Panel B contains buyer-initiated limit orders. Panel C presents seller-initiated limit orders. To estimate the fleeting hazard rate for limit order *i* submitted by trader type *j* at time t (relative to the time of order placement), we form the model as follows

$$\lambda_{i,j}(t) = \lambda_{0,j}(t)exp\left[\begin{array}{c}\beta_1\Delta q_{i,j,t}^{Same} + \beta_2\Delta q_{i,j,t}^{Opposite} + \beta_3(Network_{i,j}) + \beta_4(Lagged\ Fleeting\ Orders_{i,j})\\ + \beta_5(Open\ Interest_{i,j}) + \beta_6(BBO\ Spread_{i,j}) + \beta_7|Lagged\ Return_{i,j}| + \beta_8(Lagged\ Volume_{i,j}) + \sum_{\substack{i=1\\ i\neq 10}}^{i=20}\alpha_i D_i\end{array}\right]$$

where $\lambda_{0,j}(t)$ is a non-negative and unspecified baseline hazard rate. For a buyer-initiated limit order, the subsequent change to the best price in the limit order book on the same side is $\Delta q_{i,j,t}^{Same} = (BestBid_{i,j,t} - BestBid_{i,j,t=0^+})/(BestBid_{i,j,t=0^+})$, where $t = 0^+$ represents the very first observable best bid price right after order submission. The opposing-side best price change right after order submission is $\Delta q_{i,j,t}^{Opposite} = (BestAsk_{i,j,t} - BestAsk_{i,j,t=0^+})/(BestAsk_{i,j,t=0^+})$. The above two variables for a seller-initiated limit order is defined in analogous fashion with opposite signs. $Network_{i,j}$ represents network limit orders defined as at least one buy limit order and at least one sell limit order submitted by a trader within one-second intervals. The variable takes the value of one for a buy or a sell order if the submitted order is part of network limit orders and the value of zero otherwise. $LaggedFleetingOrders_{i,j}$ is the number of fleeting orders submitted by a trader in the preceding ten seconds of order submission. $OpenInterest_{i,j}$ is the number of futures contracts a trader holds when order is submitted. $BBOSpread_{i,j}$ is the spread of current best bid and ask prices when order is submitted. $|LaggedReturn_{i,j}|$ is the absolute value of the difference between maximum log TXF index point and minimum log TXF index point in the preceding five minutes after order submission. $LaggedVolume_{i,j}$ is the cumulative trading volume of TXF in the preceding five minutes after order submission. $D_1$, $D_2$, $D_3$, ....., and $D_{20}$ are the dummy variables of 20 intraday time intervals from 8:45 a.m. to 13:40 p.m. $D_1$ represents the interval of 8:45 a.m. to 9:00 a.m., $D_2$ represents the interval of 9:00 a.m. to 9:15 a.m., and so on, i.e., $D_i$ equals one if the fleeting order is submitted within i time interval and zero otherwise, for i = 1, 2, ....., 20. Note that we remove the dummy variable $D_{10}$ to avoid the collinearity problem. Limit orders of TXF submitted in the spot month over the period from January 2005 to December 2008 are included. *, **, *** indicate significantly different from zero at the 10%, 5%, and 1% levels, respectively.

**TABLE 11** Summary statistics of order submission by trader account

| | Mean | Std | Min | p25 | Median | p75 | Max | Kurt | Skew |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Proprietary institutions | | | | | | | | | |
| Market order | 1,559.18 | 6,079.12 | 1 | 5 | 51 | 1,601 | 34,850 | 20.70 | 4.32 |
| Limit order | 288,046.44 | 691,059.25 | 1 | 561 | 11,830 | 83,810 | 5,147,219 | 45.50 | 6.43 |
| Cancel order | 218,033.06 | 598,254.06 | 0 | 64 | 2,762 | 26,017 | 4,545,050 | 51.65 | 7.00 |
| Fleeting order | 117,897.33 | 483,553.52 | 0 | 0 | 106 | 1,825 | 3,746,841 | 57.52 | 7.50 |
| Panel B: Foreign institutions | | | | | | | | | |
| Market order | 308.46 | 3,225.97 | 1 | 3 | 16 | 98 | 39,906 | 148.38 | 12.06 |
| Limit order | 32,770.51 | 130,110.66 | 1 | 25 | 293 | 5,049 | 1,573,320 | 92.42 | 9.10 |
| Cancel order | 25,155.84 | 124,388.16 | 0 | 6 | 69 | 782 | 1,545,910 | 102.44 | 9.68 |
| Fleeting order | 13,879.70 | 82,515.48 | 0 | 0 | 1 | 17 | 1,090,521 | 132.32 | 11.14 |

*Note.* This table presents summary statistics of order submission by trader account. Orders of TXF submitted in the spot month over the period from January 2005 to December 2008 are included. Panel A reports the results of proprietary institutions and Panel B reports the results of foreign institutions. We calculate number of market orders, number of limit orders, number of cancel orders, and number of fleeting orders submitted by each trader account and report the mean, standard deviation, minimum, p25, median, p75, kurtosis, skewness, and maximum by trader type.

## 7.3 | Empirical results—by trader account

In previous section, we pool all fleeting orders to estimate the duration models. This assumes that fleeting orders are independent and homogeneous across different types of traders. To examine the potential heterogeneity in the fleeting order submission of traders, we follow Hasbrouck and Saar (2009) to separately estimate the proportional hazard duration model for each institutional trader account. Hasbrouck and Saar (2009) estimate the same model for 100 sample stocks individually based on a random sample of 1,500 limit orders tracked for fleeting orders. Unlike Hasbrouck and Saar (2009), we include all limit orders submitted by proprietary traders and foreign traders who place at least 25 fleeting orders over the sample period, yielding a final sample of 40 proprietary trader accounts and 61 foreigner accounts.

Summary statistics of this subsample are reported in Table 11. Apparently, a typical proprietary trader is more active in cancelling fleeting orders than a typical foreign trader. Moreover, the high standard deviations of fleeting orders for both types of traders suggest the existence of significant heterogeneity of fleeting order behavior among institutional traders.

We estimate the duration model separately for each proprietary trader account and present the results in Table 12. The estimated coefficient of each variable is reported in the following format. First, the numbers of positive and negative coefficients are reported for each estimated coefficient, followed by a bracket [$x$, $y$], where $x$ indicates the number of significant coefficient and $y$ indicates the number of nonsignificant coefficient. In Model 5, for example, among the 40 sample proprietary traders, 14 have positive estimated coefficients on $\Delta q_{i,j,t}^{Same}$ with six being significant and eight not significant, while the others have negative estimated coefficients with 18 being significant and 8 not significant.

Based on these results, we can see that even though the pooled duration models in Table 9 demonstrate that the average fleeting order behavior of proprietary traders is consistent with the hypothesis of cost-of-immediacy but inconsistent with the chasing hypotheses, there are noteworthy differences in the fleeting order strategy among proprietary traders. Taking the coefficient $\beta_2$ in Model 5 for example, 16 out of 40 estimated coefficients are positive and yet only five of them are statistically significant, whereas the other 24 estimated coefficients are negative and nine of them are statistically significant.

To look into the above results, we find that the trader accounts that place the most fleeting orders actually dominate the results in Table 9. For example, the nine significantly negative coefficients of $\beta_2$ cost-of-immediacy are for the proprietary traders who rank the 1st, 2nd, 3rd, 5th, 6th, 7th, 13th, 14th, and 18th places in term of the number of fleeting order, making up 92% of total fleeting orders submitted by proprietary traders. On the other hand, the five significantly positive coefficients are for the proprietary traders who rank the 8th, 9th, 10th, 12th, and 17th places, accounting for only 5% of total fleeting orders submitted by proprietary traders. In other words, the fleeting order behavior of dominant proprietary traders is consistent with the cost-of-immediacy hypothesis.

Similarly, the foreign traders who place the most fleeting orders dominate the results in Table 10. For example, as shown in Table 13, foreign traders who ranked the first, second, third, fourth, seventh, and ninth places in term of the number of fleeting order submission and make up 81% of total fleeting orders submitted by foreign traders, are among those 16 foreign traders with significantly negative coefficients for the cost-of-immediacy hypothesis. In other words, foreign traders behave similarly to their local counterparts when submitting fleeting orders. In sum, the results in

**TABLE 12** Results of proportional hazard duration model by trader account– proprietary institutions

| | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Positive** | **Negative** | **Positive** | **Negative** | **Positive** | **Negative** | **Positive** | **Negative** | **Positive** | **Negative** |
| $\Delta q_{i,j,t}^{Same}$ | 13 | 27 | | | 13 | 27 | | | 14 | 26 |
| | [6,7] | [17,10] | | | [6,7] | [17,10] | | | [6,8] | [18,8] |
| $\Delta q_{i,j,t}^{Opposite}$ | | | 16 | 24 | | | 15 | 25 | 16 | 24 |
| | | | [6,10] | [12,12] | | | [5,10] | [12,13] | [5,11] | [9,15] |
| *Network*$_{i,j}$ | | | | | 26 | 14 | 27 | 13 | 26 | 14 |
| | | | | | [18,8] | [12,2] | [19,8] | [12,1] | [18,8] | [12,2] |
| *Lagged Fleeting Orders*$_{i,j}$ | 24 | 16 | 24 | 16 | 25 | 15 | 25 | 15 | 25 | 15 |
| | [23,1] | [6,10] | [22,2] | [6,10] | [23,2] | [6,9] | [22,3] | [6,9] | [22,3] | [6,9] |
| *#Open Interest*$_{i,j}$ $(\times 10^{-3})$ | 17 | 23 | 17 | 23 | 16 | 24 | 16 | 24 | 16 | 24 |
| | [9,8] | [16,7] | [9,8] | [16,7] | [8,8] | [16,8] | [8,8] | [16,8] | [8,8] | [16,8] |
| *BBO Spread*$_{i,j}$ | 20 | 20 | 19 | 21 | 20 | 20 | 19 | 21 | 20 | 20 |
| | [13,7] | [10,10] | [13,6] | [10,11] | [12,8] | [10,10] | [12,7] | [10,11] | [12,8] | [10,10] |
| \|*Lagged Return*$_{i,j}$\| | 25 | 15 | 26 | 14 | 26 | 14 | 26 | 14 | 26 | 14 |
| | [19,6] | [6,9] | [19,7] | [6,8] | [19,7] | [6,8] | [19,7] | [6,8] | [19,7] | [6,8] |
| *Lagged Volume*$_{i,j}$ $(\times 10^{-3})$ | 18 | 22 | 18 | 22 | 18 | 22 | 18 | 22 | 18 | 22 |
| | [13,5] | [14,8] | [12,6] | [14,8] | [12,6] | [14,8] | [11,7] | [14,8] | [11,7] | [14,8] |

*Note.* This table reports the proportional hazard duration model on the fleeting hazard rate for proprietary institutions. Panel A reports all limit orders. Panel B contains buyer-initiated limit orders. Panel C presents seller-initiated limit orders. To estimate the fleeting hazard rate for limit order *i* submitted by trader type *j* at time t (relative to the time of order placement), we form the model as follows

$$\lambda_{i,j}(t) = \lambda_{0,j}(t)exp\begin{bmatrix} \beta_1 \Delta q_{i,j,t}^{Same} + \beta_2 \Delta q_{i,j,t}^{Opposite} + \beta_3(Network_{i,j}) + \beta_4(Lagged\ Fleeting\ Orders_{i,j}) \\ + \beta_5(Open\ Interest_{i,j}) + \beta_6(BBO\ Spread_{i,j}) + \beta_7|Lagged\ Return_{i,j}| + \beta_8(Lagged\ Volume_{i,j}) \end{bmatrix}$$

where $\lambda_{0,j}(t)$ is a non-negative and unspecified baseline hazard rate. For a buyer-initiated limit order, the subsequent change to the best price in the limit order book on the same side is $\Delta q_{i,j,t}^{Same} = (BestBid_{i,j,t} - BestBid_{i,j,t=0^+})/(BestBid_{i,j,t=0^+})$, where $t = 0^+$ represents the very first observable best bid price right after order submission. The opposing-side best price change right after order submission is $\Delta q_{i,j,t}^{Opposite} = (BestAsk_{i,j,t} - BestAsk_{i,j,t=0^+})/(BestAsk_{i,j,t=0^+})$. The above two variables for a seller-initiated limit order is defined in analogous fashion with opposite signs. $Network_{i,j}$ represents network limit orders defined as at least one buy limit order and at least one sell limit order submitted by a trader within one-second intervals. The variable takes the value of one for a buy or a sell order if the submitted order is part of network limit orders and the value of zero otherwise. $LaggedFleetingOrders_{i,j}$ is the number of fleeting orders submitted by a trader in the preceding ten seconds of order submission. $OpenInterest_{i,j}$ is the number of futures contracts a trader holds when order is submitted. $BBOSpread_{i,j}$ is the spread of current best bid and ask prices when order is submitted. $|LaggedReturn_{i,j}|$ is the absolute value of the difference between maximum log TXF index point and minimum log TXF index point in the preceding five minutes after order submission. $LaggedVolume_{i,j}$ is the cumulative trading volume of TXF in the preceding five minutes after order submission. Limit orders of TXF submitted in the spot month over the period from January 2005 to December 2008 are included. We estimate the proportional hazard duration model separately for each trader account. The number of positive (negative) coefficient is reported, followed by a bracket [x, y], where x indicates the number of significant coefficient and y indicates the number of non-significant coefficient. Significant coefficient estimate means that the coefficient estimate is significantly different from zero at the 5% level.

**TABLE 13** Results of proportional hazard duration model by trader account– foreign institutions

| | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Positive | Negative | Positive | Negative | Positive | Negative | Positive | Negative | Positive | Negative |
| $\Delta q_{i,j,t}^{Same}$ | 17 | 44 | | | 17 | 44 | | | 16 | 45 |
| | [7,10] | [28,16] | | | [7,10] | [28,16] | | | [7,9] | [27,18] |
| $\Delta q_{i,j,t}^{Opposite}$ | | | 28 | 33 | | | 28 | 33 | 25 | 36 |
| | | | [12,16] | [19,14] | | | [12,16] | [19,14] | [12,13] | [16,20] |
| $Network_{i,j}$ | | | | | 11 | 50 | 11 | 50 | 11 | 50 |
| | | | | | [4,7] | [39,11] | [4,7] | [39,11] | [4,7] | [39,11] |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 36 | 25 | 36 | 25 | 36 | 25 | 36 | 25 | 36 | 25 |
| | [34,2] | [18,7] | [34,2] | [19,6] | [34,2] | [19,6] | [34,2] | [18,7] | [34,2] | [18,7] |
| $\#Open\ Interest_{i,j}$ $(\times 10^{-3})$ | 27 | 34 | 27 | 34 | 27 | 34 | 27 | 34 | 27 | 34 |
| | [11,16] | [25,9] | [12,15] | [25,9] | [11,16] | [25,9] | [12,15] | [25,9] | [11,16] | [25,9] |
| $BBO\ Spread_{i,j}$ | 32 | 29 | 33 | 28 | 32 | 29 | 33 | 28 | 31 | 30 |
| | [17,15] | [13,16] | [17,16] | [13,15] | [16,16] | [13,16] | [17,16] | [13,15] | [18,13] | [13,17] |
| $\lvert Lagged\ Return_{i,j}\rvert$ | 33 | 28 | 34 | 27 | 34 | 27 | 34 | 27 | 33 | 28 |
| | [22,11] | [14,14] | [23,11] | [14,13] | [24,10] | [12,15] | [22,12] | [13,14] | [22,11] | [14,14] |
| $Lagged\ Volume_{i,j}$ $(\times 10^{-3})$ | 38 | 23 | 37 | 24 | 38 | 23 | 37 | 24 | 37 | 24 |
| | [24,14] | [12,11] | [25,12] | [12,12] | [24,14] | [12,11] | [25,12] | [12,12] | [24,13] | [12,12] |

*Note.* This table reports the proportional hazard duration model on the fleeting hazard rate for foreign institutions. Panel A reports all limit orders. Panel B contains buyer-initiated limit orders. Panel C presents seller-initiated limit orders. To estimate the fleeting hazard rate for limit order *i* submitted by trader type *j* at time *t* (relative to the time of order placement), we form the model as follows

$$\lambda_{i,j}(t) = \lambda_{0,j}(t) exp\begin{bmatrix} \beta_1 \Delta q_{i,j,t}^{Same} + \beta_2 \Delta q_{i,j,t}^{Opposite} + \beta_3(Network_{i,j}) + \beta_4(Lagged\ Fleeting\ Orders_{i,j}) \\ +\beta_5(Open\ Interest_{i,j}) + \beta_6(BBO\ Spread_{i,j}) + \beta_7|Lagged\ Return_{i,j}| + \beta_8(Lagged\ Volume_{i,j}) \end{bmatrix}$$

where $\lambda_{0,j}(t)$ is a nonnegative and unspecified baseline hazard rate. For a buyer-initiated limit order, the subsequent change to the best price in the limit order book on the same side is $\Delta q_{i,j,t}^{Same} = (BestBid_{i,j,t} - BestBid_{i,j,t=0^+})/(BestBid_{i,j,t=0^+})$, where $t = 0^+$ represents the very first observable best bid price right after order submission. The opposing-side best price change right after order submission is $\Delta q_{i,j,t}^{Opposite} = (BestAsk_{i,j,t} - BestAsk_{i,j,t=0^+})/(BestAsk_{i,j,t=0^+})$. The above two variables for a seller-initiated limit order is defined in analogous fashion with opposite signs. $Network_{i,j}$ represents network limit orders defined as at least one buy limit order and at least one sell limit order submitted by a trader within 1-s intervals. The variable takes the value of one for a buy or a sell order if the submitted order is part of network limit orders and the value of zero otherwise. $LaggedFleetingOrders_{i,j}$ is the number of fleeting orders submitted by a trader in the preceding 10 s of order submission. $OpenInterest_{i,j}$ is the number of futures contracts a trader holds when order is submitted. $BBOSpread_{i,j}$ is the spread of current best bid and ask prices when order is submitted. $|LaggedReturn_{i,j}|$ is the absolute value of the difference between maximum log Taiwan Stock Exchange Capitalization Weighted Stock Index Futures (TXF) index point and minimum log TXF index point in the preceding 5 min after order submission. $LaggedVolume_{i,j}$ is the cumulative trading volume of TXF in the preceding 5 min after order submission. Limit orders of TXF submitted in the spot month over the period from January 2005 to December 2008 are included. We estimate the proportional hazard duration model separately for each trader account. The number of positive (negative) coefficient is reported, followed by a bracket [*x*, *y*], where *x* indicates the number of significant coefficient and *y* indicates the number of nonsignificant coefficient. Significant coefficient estimate means that the coefficient estimate is significantly different from zero at the 5% level.

Tables 12 and 13 highlight the importance of trader heterogeneity in testing the underlying motivations of fleeting orders. The trader accounts that place the most fleeting orders dominate the results of pooled regression analysis. The fleeting order behaviors of dominant institutional traders are consistent with the cost-of-immediacy hypothesis.

## 8 | ROBUSTNESS CHECKS

Considering the change in limit order book update frequency, we define fleeting orders as limit orders cancelled within 5 s after submission. However, the update frequency was shortened from 3 s to 1 s on January 28, 2008. In addition, as shown in Figure 1, there was an apparent surge in 2008 of fleeting orders submitted by institutional investor. To

**TABLE 14** Results of proportional hazard duration model – 2 seconds

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Panel A: Proprietary institutions (# of obs. = 9,856,909) | | | | | |
| $\Delta q_{i,j,t}^{Same}$ | −25.48*** | | −24.80*** | | −23.39*** |
| $\Delta q_{i,j,t}^{Opposite}$ | | −38.06*** | | −20.25*** | −20.91*** |
| $Network_{i,j}$ | | | 0.64*** | 0.64*** | 0.64*** |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 0.05*** | 0.05*** | 0.04*** | 0.04*** | 0.04*** |
| $\#Open\ Interest_{i,j}$ ($\times 10^{-3}$) | −0.10*** | −0.10*** | −0.13*** | −0.13*** | −0.13*** |
| $BBO\ Spread_{i,j}$ | −23.12*** | −22.34*** | −22.51*** | −21.81*** | −21.93*** |
| $\left\lvert Lagged\ Return_{i,j} \right\rvert$ | 10.47*** | 10.54*** | 6.61*** | 6.69*** | 6.67*** |
| $Lagged\ Volume_{i,j}$ ($\times 10^{-3}$) | 0.02*** | 0.02*** | 0.03*** | 0.03*** | 0.03*** |
| Panel B: Foreign institutions (# of obs. = 5,220,733) | | | | | |
| $\Delta q_{i,j,t}^{Same}$ | −5.83*** | | −4.85*** | | −4.83*** |
| $\Delta q_{i,j,t}^{Opposite}$ | | −8.37*** | | −7.93*** | −7.91*** |
| $Network_{i,j}$ | | | −0.35*** | −0.35*** | −0.35*** |
| $Lagged\ Fleeting\ Orders_{i,j}$ | 0.06*** | 0.06*** | 0.06*** | 0.06*** | 0.06*** |
| $\#Open\ Interest_{i,j}$ ($\times 10^{-3}$) | −0.02*** | −0.02*** | −0.03*** | −0.03*** | −0.03*** |
| $BBO\ Spread_{i,j}$ | 33.67*** | 33.85*** | 35.61*** | 35.74*** | 35.45*** |
| $\left\lvert Lagged\ Return_{i,j} \right\rvert$ | 54.70*** | 54.70*** | 55.87*** | 55.87*** | 55.88*** |
| $Lagged\ Volume_{i,j}$ ($\times 10^{-3}$) | 0.09*** | 0.09*** | 0.09*** | 0.09*** | 0.09*** |

*Note*. This table reports the proportional hazard duration model on the fleeting hazard rate. Panel A reports results of proprietary institutions. Panel B reports results of foreign institutions. To estimate the fleeting hazard rate for limit order *i* submitted by trader type *j* at time t (relative to the time of order placement), we form the model as follows

$$\lambda_{i,j}(t) = \lambda_{0,j}(t)exp\begin{bmatrix} \beta_1 \Delta q_{i,j,t}^{Same} + \beta_2 \Delta q_{i,j,t}^{Opposite} + \beta_3(Network_{i,j}) + \beta_4(Lagged\ Fleeting\ Orders_{i,j}) \\ +\beta_5(Open\ Interest_{i,j}) + \beta_6(BBO\ Spread_{i,j}) + \beta_7|Lagged\ Return_{i,j}| + \beta_8(Lagged\ Volume_{i,j}) \end{bmatrix}$$

where $\lambda_{0,j}(t)$ is a non-negative and unspecified baseline hazard rate. For a buyer-initiated limit order, the subsequent change to the best price in the limit order book on the same side is $\Delta q_{i,j,t}^{Same} = (BestBid_{i,j,t} - BestBid_{i,j,t=0^+})/(BestBid_{i,j,t=0^+})$, where $t = 0^+$ represents the very first observable best bid price right after order submission. The opposing-side best price change right after order submission is $\Delta q_{i,j,t}^{Opposite} = (BestAsk_{i,j,t} - BestAsk_{i,j,t=0^+})/(BestAsk_{i,j,t=0^+})$. The above two variables for a seller-initiated limit order is defined in analogous fashion with opposite signs. $Network_{i,j}$ represents network limit orders defined as at least one buy limit order and at least one sell limit order submitted by a trader within one-second intervals. The variable takes the value of one for a buy or a sell order if the submitted order is part of network limit orders and the value of zero otherwise. $LaggedFleetingOrders_{i,j}$ is the number of fleeting orders submitted by a trader in the preceding ten seconds of order submission. $OpenInterest_{i,j}$ is the number of futures contracts a trader holds when order is submitted. $BBOSpread_{i,j}$ is the spread of current best bid and ask prices when order is submitted. $|LaggedReturn_{i,j}|$ is the absolute value of the difference between maximum log TXF index point and minimum log TXF index point in the preceding five minutes after order submission. $LaggedVolume_{i,j}$ is the cumulative trading volume of TXF in the preceding five minutes after order submission. Limit orders of TXF submitted in the spot month over the period from February 2008 to December 2008 are included. *, **, *** indicate significantly different from zero at the 10%, 5%, and 1% levels, respectively.

establish the robustness of our results, we decide to follow Hasbrouck and Saar (2009) to define the fleeting orders as limited order cancelled within 2 s after submission and re-estimate the pooled duration models with a subsample spanning from February 2008 to December 2008.

As shown in Table 14, the results are consistent with the previous finding that institutional traders do not aggressively chase market prices but do actively respond to changes in immediate execution costs. In addition, network orders constitute a key component of the fleeting order strategy of proprietary traders. The results indicate that our findings are robust to the definition of fleeting orders.

## 9 | CONCLUSION

Based on a comprehensive data set that contains information about trader identity, we are able to unambiguously track the sequence of orders submitted by each trader as well as the dynamic limit order trading strategy in TAIFEX, where participants interact with each other at tremendous speed. Taking advantage of this detailed data set, we investigate the previously unexplored relation between trader type and fleeting orders. Moreover, our data allow us to take snapshots of the limit order book to identify network trades. This enables us to shed light on the link between network trading strategy and fleeting orders, a link not thoroughly addressed in the literature.

The results show that trader type does matter in submitting fleeting orders. Institutional traders use more limit orders but also cancel most of them, which yields more than a half of the cancellation as fleeting orders. By contrast, we find that only 6% of cancelled orders from individuals are fleeting orders. Fleeting orders are more commonly used by institutional traders than individual traders.

Second, the intraday seasonality of fleeting order rate shows that proprietary traders and foreign traders behave differently when the degree of information asymmetry is presumably high. As potential hedgers, foreign traders avoid aggressive trading during the first 15-min interval. However, proprietary traders behave like market makers who actively trade to create their own profitability space when the market volatility is high.

Third, based on the pooled proportional hazards duration model, institutional traders actively respond to a change in immediate execution costs but do not aggressively chase market prices in the limit order book. Moreover, network orders constitute a key component of the fleeting order strategy of proprietary traders. This result implies that similar to the trading behavior of market makers, proprietary traders respond to a change in immediate execution costs by submitting networking orders. Using the same model for each institutional investor, we find that proprietary traders and foreigners exhibit heterogeneous behavior when they adopt a fleeting order strategy. These results demonstrate the importance of trader type when studying fleeting orders.

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### REFERENCES

Allison, P. D. (1995). *Survival analysis using the SAS system: A practical guide.* Cary, NC: SAS Institute.

Bloomfield, R., O'Hara, M., & Saar, G. (2005). The "make or take" decision in an electronic market: Evidence on the evolution of liquidity. *Journal of Financial Economics*, *75*, 165–199.

Chiao, C., Wang, Z. M., & Tong, S. Y. (2017). Order cancellations across investor groups: Evidence from an emerging order-driven market. *Review of Quantitative Finance and Accounting*, *49*, 1167–1193.

Chien, C. Y., Lee, H. C., Tai, S. W., & Liao, T. H. (2013). Information, hedging demand, and institutional investors: Evidence from the Taiwan futures exchange. *Journal of Finance*, *23*, 394–414.

Chiu, J., Chung, H., & Wang, G. H. K. (2014). Intraday liquidity provision by trader types in a limit order market: Evidence from Taiwan index futures. *Journal of Futures Markets*, *34*, 145–172.

Chiu, J., Chung, H. M., & Wang, G. H. K. (2016). Order aggressiveness, trading patience, and trader types in a limit order market. *Journal of Futures Markets*, *37*(11), 1094–1123.

Chou, R. K., Wang, G. H. K., Wang, Y. Y., & Bjursell, J. (2011). The impacts of large trades by trader types on intraday futures prices: Evidence from the Taiwan futures exchange. *Pacific-Basin Finance Journal*, *19*, 41–70.

Chou, R. K., & Wang, Y. Y. (2009). Strategic order splitting, order choice and aggressiveness: Evidence from the Taiwan futures exchange. *Journal of Futures Markets*, *12*, 1102–1129.

Chow, E. H. Y., Hung, C. W., Liu, C. S. H., & Shiu, C. Y. (2013). Expiration day effects and market manipulation: Evidence from Taiwan. *Review of Quantitative Finance and Accounting*, *41*, 441–462.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society, Series B (Methodological)*, *34*, 187–220.

Ellul, A., Holden, C. W., Jain, P., & Jennings, R. (2007). Order dynamics: Recent evidence from the NYSE. *Journal of Empirical Finance*, *14*, 636–661.

Fong, K. Y. L., & Liu, W. M. (2010). Limit order revisions. *Journal of Banking and Finance*, *34*, 1873–1885.

Garman, M. B. (1976). Market microstructure. *Journal of Financial Economics*, *3*, 257–275.

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: A study of Finland's unique data set. *Journal of Financial Economics*, *55*, 43–67.

Handa, P., & Schwartz, R. A. (1996). Limit order trading. *Journal of Finance*, *51*, 1835–1861.

Harris, L. (1998). Optimal dynamic order submission strategies in some stylized trading problems. *Financial Markets, Institutions and Instruments*, *7*, 1–76.

Harris, L. (2002). *Trading and exchanges: Market microstructure for practitioners*. Oxford University Press: New York, NY.

Hasbrouck, J. (1988). Trades, quotes, inventories and information. *Journal of Financial Economics*, *22*, 229–252.

Hasbrouck, J., & Saar, G. (2009). Technology and liquidity provision: The blurring of traditional definitions. *Journal of Financial Markets*, *12*, 143–172.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2010). Do algorithmic trading improve liquidity? *Journal of Finance*, *66*, 1–33.

Ho, T. S. Y., & Macris, R. G. (1984). Dealer bid-ask quotes and transaction prices: An empirical study of some AMEX options. *Journal of Finance*, *39*, 23–45.

Huang, R. D., & Shiu, C. Y. (2009). Local effects of foreign ownership in an emerging financial market: Evidence from qualified foreign institutional investors in Taiwan. *Financial Management*, *38*, 567–602.

Kirilenko, A., Kyle, A. S., Samadi, M., & Tuzun, T. (2016). The flash crash: The impact of high frequency trading on an electronic market. *Journal of Finance*, *72*, 967–998.

Kuo, W. H., Chung, S. L., & Chang, C. Y. (2015). The impacts of individual and institutional trading on futures returns and volatility: Evidence from emerging index futures markets. *Journal of Futures Markets*, *35*, 222–244.

Large, J., 2004. Cancellation and uncertainty aversion on limit order books. University of Oslo.

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

Lo, A. W., Mackinlay, A. C., & Zhang, J. (2002). Econometric models of limit order execution. *Journal of Financial Economics*, *65*, 31–71.

Lyons, R. K. (1995). Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics*, *39*, 321–351.

Madhavan, A., & Smidt, S. (1991). A Bayesian model of intraday specialist pricing. *Journal of Financial Economics*, *30*, 99–134.

Madhavan, A., & Smidt, S. (1993). An analysis of changes in specialist quotes and inventories. *Journal of Finance*, *48*, 1595–1628.

Manaster, S., & Mann, S. C. (1996). Life in the pits: Competitive market making and inventory control. *Review of Financial Studies*, *9*, 953–976.

McInish, T. H., & Wood, R. A. (1992). An analysis of intraday patterns in bid-ask spreads for NYSE stocks. *Journal of Finance*, *47*, 753–764.

Raman, V., & Yadav, P. 2013. The who, why and how well of order revisions: An analysis of limit order trading. Working paper.

Roşu, I. (2009). A dynamic model of the limit order book. *Review of Financial Studies*, *22*, 4601–4641.

Viljoen, T., Westerholm, J., Zheng, H., & Gerace, D. (2015). Fleeting orders and dynamic trading strategies: Evidence from the Australian Security Stock Exchange (ASX). *Journal of Accounting and Finance*, *15*, 108–134.

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