Strategic Spoofing Order Trading by Different Types of Investors in the Futures Markets

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ABSTRACT

We set out in this study to investigate the strategic behavior of spoofing trading orders in the index futures market in Taiwan, including their characteristics, profitability, determinants and real-time impacts. We find the existence of both spoofing-buy and spoofing-sell strategies, with such spoofing orders being discernible not only among institutional investors, but also individual traders. Spoofing trading is profitable, with traders are more likely to submit spoofing orders when both volume and volatility are high, and the price for spoofing-sell (buy) orders is high (low). Furthermore, spoofing trading induces subsequent volume, spread and volatility, and spoofing-buy (sell) orders have a positive (negative) effect on the subsequent price. Our findings provide general support for the view that spoofing trading destabilizes the market.

Keywords: Spoofing orders; Price manipulation; Market efficiency; Liquidity; Volatility; Profitability; Institutional investors; Individual traders.

JEL Classification: G10; G14.

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1. INTRODUCTION

The issue of market manipulation is clearly of significant importance both in academia and in practice. Recently, the high-frequency trader Navinder Sarao's 'Flash Crash' case highlights problem of 'spoofing' order trading.[1] U.S. Commodity Futures Trading Commission (CFTC) said Mr. Sarao entered large number of orders to sell futures contracts, and then canceled the vast majority of them, which contributed to the May 2010 meltdown that came to be called the 'Flash Crash'. In modern-day financial markets, manipulation is often undertaken in ways that cannot be easily detected or outlawed, and this is certainly the case for strategic spoofing order trading.

'Spoofing orders' are orders that are submitted into the market, with no intention of the order being executed, as a means of injecting misleading information with regard to the demand or supply of an asset, with the ultimate aim of coercing other traders to trade in a particular way. 'Spoofers', that is, those submitting spoofing trading orders, will subsequently submit their real orders, in order to take advantage of the price changes resulting from trading by other market participants in response to their earlier spoofing orders.

Strategic spoofing order trading has received growing attention over recent years, essentially because high-frequency trading has become commonplace in many

[1] Wall Street Journal, May 6, 2015. http://www.wsj.com/articles/navinder-saraos-flash-crash-case-highlights-problem-of-spoofing-in-complex-markets-1430943635.

exchanges around the world. High-frequency trading is a type of trading whereby profits are attempted to be made by rapidly submitting and/or cancelling orders, with a typical holding period, as noted in several related studies, being measured in terms of mere seconds or milliseconds.[2] Several other studies, including Biais and Woolley (2011) and Leis and Alexander (2012), have also expressed concern that high-frequency trading may well increase the prevalence of market manipulation, with particular reference to spoofing order trading.

Despite the existence of a wealth of theoretical literature relating to market manipulation,[3] there appears to have been relatively little empirical research effort focusing on a comprehensive analysis of market manipulation, particularly with regard to strategic spoofing order trading behavior. One exception, however, is the examination of spoofing order trading strategies in the Korean stock market undertaken by Lee, Eom and Park (2013); they found that investors placed strategic spoofing orders with the sole intention of manipulating subsequent prices, and also demonstrated that spoofing orders were still discernible in the Korean Exchange even after the change in the order-disclosure rule.

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[2] Examples include Carrion (2013), Hasbrouck and Saar (2013) and Chordia, Goyal, Lehmann and Saar (2013). Chordia et al. (2013) suggested a number of common characteristics of high-frequency traders, including: "(i) the use of extraordinarily high-speed and sophisticated computer programs for generating, routing and executing orders; (ii) very short time-frames for establishing and liquidating positions; (iii) the submission of numerous orders that are cancelled shortly after submission; and (iv) ending the trading day in as close to a flat position as possible".

[3] See, for example, Allen and Gale (1992), Allen and Gorton (1992), Jarrow (1992, 1994), Kumar and Seppi (1992) and Pirrong (1993).

Although Lee et al. (2013) provided an important examination of strategic spoofing behavior, there are still many important issues yet to be determined, including: (i) whether there is spoofing order trading in other exchange with differ pre-trade transparency; (ii) whether there are different types of spoofing order strategies, such as spoofing-buy and spoofing-sell strategies; (iii) whether there are discernible changes in spoofing behavior dependent upon different market conditions, specifically volume, returns, volatility and price; (iv) whether spoofing order strategies exhibit an intraday pattern in the futures markets; (v) the overall profitability of spoofing traders within the futures markets; and (vi) whether, and if so, in what ways, spoofing orders affect the markets, specifically volume, price, bid-ask spread and volatility.

We address these issues in the present study by carrying out an examination of comprehensive data on order flows and trading records obtained from the Taiwan Futures Exchange (TAIFEX), and while being closely related to several of the prior studies in this field, our study differs in a number of ways, as described below.

Firstly, the limited empirical evidence provided by most of the prior related studies is based upon prosecuted cases of market manipulation as the means of exploring overall manipulative behavior;[4] however, as pointed out by Aggarwal and

4 Example include Pirrong (2004), Aggarwal and Wu (2006), Allen, Litov and Mei (2006), and Comerton-Forde and Putnins (2011).

Wu (2006), such studies do not consider cases where manipulation may well occur, but is unobserved, and thus, not outlawed. As such, the prior results essentially apply only to ‘poor’ manipulators; that is, those who were not sufficiently skilled in the practice to avoid detection. In contrast, the unique dataset adopted for the present study enables us to trace all order submission and cancellation records for each account within the exchange; thus, we are able to provide comprehensive empirical evidence on the prevalence of such market manipulation.

Secondly, Lee et al. (2013) consider a special microstructure in Korea Exchange (KRX) in which the total quantity on each side of the order book is disclosed, but the price of each order is not disclosed.[5] The additional information of total quantity provides an opportunity for microstructure-based manipulation. However, most exchanges are not the case. For example, Chicago Mercantile Exchange (CME) discloses the 5 best buy/sell prices and quantities at those prices, Eurex Exchange (EUREX) discloses the 10 best buy/sell prices and quantities at those prices, and Singapore Exchange discloses all order information. Therefore, it is not clear whether there is spoofing order trading in other exchange with differ pre-trade transparency. By examining the comprehensive order flows and trading records of each account in TAIFEX, which discloses the 5 best buy/sell prices and quantities at those prices, our

[5] Starting in January 2002, the size of the total order book was no longer disclosed in Korea Exchange (KRX).

empirical results can extend the existing findings on spoofing order trading in exchange with differ pre-trade transparency.

Thirdly, as a result of the short-sales constraints in the Korean stock market, the analysis in Lee et al. (2013) was limited to 'spoofing-buy strategies', which describes a situation in which a limit-buy order is followed by a sell order and the subsequent cancellation of the initial limit-buy order. Given the long and short positions of futures contracts and the availability of precise information on the direction of each order (buy/sell), we are able to provide a detailed and much clearer picture of different spoofing strategies, including both spoofing-buy and spoofing-sell strategies. By comparing the differences in the proportion, the intraday pattern and profitability between spoofing-buy and spoofing-sell strategies, we contribute to the extant literature on different spoofing order strategies.

Fourthly, although Lee et al. (2013) explored spoofing orders exclusively in the stock market, we argue that the futures market provides an ideal experimental setting for an exploration of spoofing order trading. Trading in futures markets requires less capital, has lower transaction costs and involves fewer short sales constraints, which may make it more attractive for spoofing traders. By closely tracking the order flows of each account, our empirical results can extend the existing findings on spoofing order trading in the stock markets to the futures markets, which can improve our understanding of the trading behavior of futures traders, an area that has received relatively less attention in the literature.

Fifthly, we additionally study whether the spoofing order strategies of traders are subject to change, depending on prior market conditions (volume, returns, volatility and price). Since spoofing traders are very strategic in their trading behavior, we may expect to find that the timing of their spoofing order trading will also be strategic. To the best of our knowledge, few studies have been able to provide detailed analysis of the impacts of market conditions on such spoofing order trading behavior.

Sixthly, the limited empirical evidence provided in the prior related studies is based upon daily data as the means of exploring the impacts of market manipulation, despite the fact that the market impacts of spoofing order trading may well be found to persist for only a very short period of time.[6] In the present study, we examine the real-time (intraday) market impacts of spoofing order trading, which can contribute to our understanding of the overall effects of such manipulation on the markets.

Finally, we explore the spoofing order trading behavior of different types of traders, including foreign institutions, proprietary firms, domestic institutions and individual traders, since institutional traders are generally regarded as being more likely to engage in spoofing trading in the market. Hillion and Suominen (2004)

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[6] See Jiang, Mahoney and Mei (2005), Aggarwal and Wu (2006), and Comerton-Forde and Putnins (2011).

constructed an agency-based model of price manipulation in which brokers manipulated the price of a stock in order to give a better impression to customers of their execution quality. Khwaja and Mian (2005) subsequently went on to reveal unusual trading patterns and systematic profitability differences arising from trades between brokers and outside investors, arguing that the evidence was indicative of stock price manipulation by collusive brokers; however, their study provides, at best, only indirect evidence of manipulation by brokers.

Furthermore, although Lee et al. (2013) reported the proportions of spoofing orders by different types of investors, they provided no further analysis of spoofing order trading behavior by the different types of investors, such as intraday patterns, different spoofing trading strategies, profitability, determinants of spoofing trading and the overall impacts on the markets. In the present study, we provide direct empirical evidence and detailed analysis of spoofing trading by different types of traders in the futures market, a relatively sparse area of research in the prior empirical literature.

Several noteworthy results are obtained from our empirical analysis, as follows. Since traders are found to submit spoofing orders in the TAIFEX, this thereby provides empirical evidence in support of the prior theoretical literature (Kyle, 1984; Easterbrook, 1986) as well as anecdotal evidence of the existence of spoofing trading in the futures markets. Both spoofing-buy and spoofing-sell strategies are found to exist and not only among institutional traders, since individual traders are also found to submit spoofing orders. We find further evidence to indicate that spoofing trading is profitable, with traders being more likely to submit spoofing orders when both volume and volatility are high, and more specifically, to submit spoofing-sell (spoofing-buy) orders when the price is high (low). These results therefore suggest that spoofing order trading is dependent upon market conditions.

As regards the effects of spoofing order trading on the markets, we find that spoofing trading induces the subsequent volume, spread and volatility, with spoofing-buy (spoofing-sell) orders being found to have a positive (negative) effect on the subsequent price. These findings provide general support for the criticism that spoofing order trading has a destabilizing effect on the market.

The remainder of this paper is organized as follows. A review of the literature is provided in Section 2, along with the development of our hypotheses, followed in Section 3 by a description of the institutional features of the TAIFEX and the data. Section 4 begins with the presentation of evidence on spoofing order trading, along with the intraday patterns, before going on to report the daily and intraday regression analyses on the determinants of spoofing order trading and the overall impacts of spoofing order trading on the markets. Finally, the conclusions drawn from this study are presented in Section 5.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Since the purpose of spoofing order trading is to mislead other investors, information asymmetry is an important condition for the success of such a strategy; and indeed, it is noted in several prior studies that information varies over the course of the trading day, with some studies demonstrating that information asymmetry tends to be higher at the beginning and the end of the trading day (Admati and Pfleiderer, 1988; Foster and Viswanathan, 1993). From their exploration of the daily pattern of spoofing order trading in the Korean stock market, Lee et al. (2013) found that such trading was at its highest at the market opening period, reducing steadily during the trading day and then increasing again during the market closing period.

Closing price manipulation is another possible factor relating to the intraday pattern of spoofing order trading, although this is invariably explored in the underlying market as opposed to the derivative markets.[7] Kumar and Seppi (1992), for example, modeled investors taking up positions in the futures market and then manipulating the spot price to profit from their futures positions. Based on the implications of the prior studies, we develop the first of our hypotheses, as follows:

Hypothesis 1: *Spoofing order trading patterns in the futures market will be high* (*low*) *during the market opening* (*closing*) *period*.

[7] See, for example, Kumar and Seppi (1992), Felixson and Pelli (1999), Hillion and Suominen (2004) and Comerton-Forde and Putnins (2011).

Based upon their development of a model of transaction-based manipulation, Allen and Gale (1992) demonstrated that when market participants were unaware of whether or not manipulative investors were in possession of private information, even those who did not possess such private information could profit from price manipulation, with information asymmetry being a key element of their argument. Investors can never be certain whether a major investor who buys a stock does so because he knows it is undervalued or because he intends to manipulate the price, and it is this pooling that allows manipulation to be profitable.

Allen and Gorton (1992) derived an equilibrium model where the existence of noise traders made it possible to manipulate prices, while the Lee et al. (2013) study subsequently found that spoofing order traders in the Korean stock market achieved substantial profits. This leads to the formulation of our next hypothesis, as follows:

Hypothesis 2: *Spoofing order trading is profitable in the futures markets.*

Since spoofing traders are very strategic in their trading behavior, we may expect to find that the timing of their spoofing order trading will also be strategic; however, volume may have two opposing effects on spoofing order trading. On the one hand, large volume makes spoofing difficult, since the spoofing order has to be very large to alter the supply and demand balance; on the other hand, however, larger trading volume allows spoofing traders to better disguise their spoofing behavior.

When potential market manipulators set out to manipulate prices, it will generally be easier for them to make the price fall in a bear market and rise in a bull market. In a bear (bull) market, investors will be very wary (optimistic) about the future of the economy; therefore, a spoofing-sell (spoofing-buy) strategy can easily mislead traders. We therefore expect to find that spoofing order trading will be related to market returns. Furthermore, since information asymmetry is an important factor relating to the success of a spoofing strategy (Allen and Gale, 1992), spoofing orders are likely to be more effective when there is greater uncertainty with regard to the market; thus, we expect to find a greater likelihood of traders submitting spoofing orders when market volatility is high.

Market prices are also likely to influence spoofing order trading behavior. Lee et al. (2013) showed that higher market prices made spoofing strategies more costly; however, market prices can have different effects on spoofing-buy and spoofing-sell strategies, since the higher market price, representing higher costs for a spoofing-buy strategy, will in fact benefit a spoofing-sell strategy. We therefore expect to find that market prices will be inversely (positively) related to spoofing-buy (sell) orders. This leads to the formulation of our next hypothesis, as follows:

Hypothesis 3: *Spoofing order trading strategies will be found to vary with market conditions.*

Although spoofing order traders are accused of destabilizing markets, the effects and severity of spoofing order trading on the markets remain unclear. Aggarwal and Wu (2006) developed a theory on the evolution of prices, volume and volatility in cases of stock market manipulation and went on to generate testable implications. The aim of spoofing order trading is to influence prices, and in order to do so, the orders must mislead speculators and arbitrageurs and induce them to engage in trading. Thus, given that price increases caused by spoofing traders may induce buying by momentum traders, or induce selling by sophisticated investors and arbitrageurs who recognize an opportunity to profitably counteract spoofing trading, we expect to find a positive relationship between spoofing order trading and subsequent volume.

Given that the primary intention of spoofing order traders is to influence market prices, it is clearly of crucial importance to examine whether spoofing orders do indeed have direct impacts on such prices. The Aggarwal and Wu (2006) model predicts that prices will increase throughout the period of manipulation, and indeed, based upon a sample of manipulation cases, they found that manipulation was associated with higher returns, turnover and volatility. However, from an examination of the 'stock pools' of the 1920s – which stands out as a classic account of stock manipulation – Jiang et al. (2005) could find no evidence of stock pool trades driving prices to artificially high levels.

It should be noted that different spoofing strategies are likely to have diverse impacts on market prices; for example, a spoofing-buy strategy will have the effect of moving the subsequent market price upwards, whereas a spoofing-sell strategy will have the effect of moving the subsequent market price downwards. In contrast to the prior studies which provide no distinction between the different strategies, in the present study, we carry out separate examinations of spoofing-buy and spoofing-sell strategies, and expect to find that a spoofing-buy strategy will have the effect of increasing subsequent market prices, whereas a spoofing-sell strategy will have the effect of reducing subsequent market prices.

In their efforts to inflate (deflate) the price to an artificial level, spoofing order traders will tend to submit large and aggressive buy (sell) orders, and given that spoofing buy (sell) orders will consume depth on the ask (bid) side of the order book by canceling the spoofing orders, thereby increasing the ask (bid) price and widening the bid-ask spread, we expect to find that spoofing order trading will widen the subsequent market spread. Furthermore, since the market is destabilized when traders attempt to inflate or deflate market prices, market volatility will also be affected; we expect to find that spoofing order trading will increase subsequent market volatility, which therefore leads on to our final hypothesis, as follows:

Hypothesis 4: *Spoofing order trading strategies destabilize the market*.

3. DATA AND MARKET DESCRIPTION

The TAIFEX is an order-driven electronic futures market within which there are no designated market makers, and since the index discloses 5 best buy/sell prices and quantities at those prices every 250 milliseconds, traders can instantly see orders placed by other traders. The sample adopted for this study comprises of all Taiwan Capitalization Weighted Stock Index (TAIEX) futures contracts, with the sample period running from January 2003 to December 2008; TAIEX futures are the most actively traded futures contracts on the TAIFEX, and we use the nearby contracts in our analysis essentially because they are the most liquid contracts.[8]

The dataset adopted for this study, which is obtained from the TAIFEX, contains comprehensive details on all order flows and transactions undertaken within the market. The order flow data reports the date and time of the arrival of the order, its direction (buy or sell), the quantity, the price, order status (execution or cancellation), trader type identification, and most importantly, account identification. This comprehensive dataset enables us to trace the order submission records for each account, thereby also enabling us to identify spoofing orders. The identification of each trader type allows us to categorize four types of traders, foreign institutions, proprietary firms, domestic institutions and individual traders.

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[8] During the maturity month, when the trading volume of the first deferred contract is greater than the trading volume of the nearby contract, the nearby futures prices are rolled over to the first deferred contract, with these rollovers often occurring in the middle or later parts of the maturity month.

The summary statistics of the mean daily order volume on the TAIFEX are presented in Table 1, where the details are reported for different types of traders comprising of foreign institutions, proprietary firms, domestic institutions and individual traders. As shown in Panel A of Table 1, the largest proportion of the total order volume is attributable to individual traders, with their trades accounting for 69.45% of the total order volume. Proprietary firms are ranked in second place, with 21.89% of the total order volume, foreign institutions are ranked in third place, accounting for 7.19%, and domestic institutions are ranked in last place, accounting for only 1.47% of the total order volume.

<Table 1 is inserted about here>

4. EMPIRICAL RESULTS

4.1 Evidence of Spoofing Order Trading

We begin our analysis by exploring whether the orders placed by our sample of traders are indeed spoofing orders. A ‘spoofing order’ is defined as an order submitted with no intention of the order being executed, but instead, with the overall aim of encouraging other investors to trade in certain contracts by injecting misleading information regarding the demand or supply of such contracts; the spoofing trader subsequently submits a real order so as to take advantage of the price change resulting from the earlier submission of the spoofing order.

Since TAIFEX discloses the 5 best buy/sell prices and quantities at those prices every 250 milliseconds, traders can refer to those order flow information to submit spoofing orders which are little chance of being executed but will be disclosed in the order book. A spoofing-buy (sell) order is further defined in this study as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order.[9] The summary statistics of daily spoofing orders are presented in Panel B of Table 1, from which we can see that the average daily spoofing orders involve 2,016 contracts. These results provide empirical evidence in support of the theoretical literature (Kyle, 1984; Easterbrook, 1986) and anecdotal evidence to suggest that spoofing order trading does indeed take place in the futures markets.

It should be noted that our results indicate that spoofing orders are associated with all four types of traders, with the majority of spoofing orders being submitted by individual traders; more specifically, the average daily spoofing orders are found to be 1,349 contracts for individual traders, 589 contracts for proprietary firms, 70 contracts for foreign institutions and 8 contracts for domestic institutions.

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[9] In order to observe all spoofing orders and further enhance the robustness of our results, we also define spoofing orders by various order sizes (for example, where the order size is 80%, 60%, 40% of prior the best fifth quantity). The results, which remain very similar, are not reported here, but are available upon request.

Due to the short-sales constraints in the Korean stock market, the analysis in Lee et al. (2013) was limited to spoofing-buy strategies; however, given the long and short positions of futures contracts, in the present study we aim to provide a clear and comprehensive picture of different types of spoofing strategies; thus, we classify them into spoofing-buy and spoofing-sell strategies. A spoofing-buy strategy is defined as any limit-buy orders that are quickly followed by a sell order and the subsequent cancellation of the initial limit-buy order, while a spoofing-sell strategy is defined as any limit-sell orders that are quickly followed by a buy order and the subsequent cancellation of the initial limit-sell order.

Details of the daily spoofing-buy and spoofing-sell orders are presented in Panel B of Table 1, which shows that spoofing-sell orders are similar prevalent with buy orders, and this is found to be fairly consistent across the four types of investors. Taking individual traders as an example, the daily spoofing-buy (sell) orders among such traders are found to be 1,059 contracts (957 contracts). These results clearly indicate that some traders place spoofing-buy (sell) orders to inflate (deflate) the market price, with the aim of subsequently selling (buying) at a higher (lower) price.

In order to provide a good understanding of the prevalence of strategic spoofing behavior, we calculate the overall proportion of spoofing orders on the TAIFEX. As shown in Panel C of Table 1, spoofing orders account for 1.55% of all market contracts, which is higher than the finding of Lee et al. (2013) in the Korean stock market, where total spoofing orders accounted for less than 1%.[10] We further report the proportion of spoofing orders over all cancelled orders, as shown in Panel D of Table 1, from which we can see that spoofing orders accounted for 1.13% of all cancelled orders.

Since Lee et al. (2013) noted that spoofing orders could actually be a part of a day trading strategy, we also go on to calculate the proportion of spoofing orders placed by day traders. Following Chou, Wang and Wang (2014), an account is defined as a 'day trader' account if the total amount of contracts purchased and sold on a particular day are the same. As we can see from Panel E of Table 1, the number of spoofing orders placed by day traders is found to account for only 27.50% of our sample, such that 72.50% of spoofing orders are unrelated to day trading, thereby clearly indicating that a spoofing order strategy differs from a day trading strategy.

In an attempt to determine whether spoofing orders are concentrated among certain types of traders, we present the distribution of the total number of spoofing orders per spoofing trader, by the four different types of traders. The distribution of the number of spoofing trades for each spoofing trader is reported in Table 2, which shows that among all traders, 43.26% of spoofing traders submit more than one

[10] According to the results reported in Table 1 of the Lee et al. (2013) study, the proportion of spoofing orders was found to be about 0.81%.

spoofing order.

For specific types of traders, spoofing traders submitting more than one spoofing order account for 86.65% in foreign institutions, 100% in proprietary firms, 58.24% in domestic institutions and 42.75% in individual traders. It is also clear that there are ‘frequent’ spoofing traders (that is, those submitting more than 101 spoofing orders), with these being particularly discernible in proprietary firms and among individual traders.

<Table 2 is inserted about here>

The results presented above reveal an overall tendency among traders on the TAIFEX to engage in spoofing order trading, providing empirical evidence and support for the theoretical literature (Kyle, 1984; Easterbrook, 1986) and anecdotal evidence that spoofing trading does indeed exist in the futures markets. Both spoofing-buy and spoofing-sell strategies are found to be prevalent, and not only among institutional investors, but also among individual traders.

4.2 Intraday Pattern of Spoofing Order Trading

Since our analysis provides direct evidence of the existence of spoofing order trading in the Taiwan futures market, we go on to investigate the process of spoofing order trading strategies over the course of a normal trading day, which is divided into five separate one-hour intervals, from 8:45 am to 13:45 pm. The average numbers of spoofing-buy and spoofing-sell orders during the trading day, by the four different types of traders, are illustrated in Figure 1, which shows that spoofing orders tend to be at their highest during the market opening period.

<Figure 1 is inserted about here>

Our finding of higher levels of spoofing orders at the market open may be attributable to the higher level of information asymmetry at the start of the trading day;[11] given that the purpose of spoofing orders is to mislead other investors, information asymmetry is an extremely important condition for the success of such a strategy. Another possible reason is that if traders submit spoofing orders in the early session of the trading day, there will be more opportunities to subsequently submit real orders before the market closes; and indeed, we do find a decline in spoofing orders towards the end of the trading day, a finding which is similar for all four types of traders.

In contrast to the closing price manipulation found in the equity markets, which involves manipulative trading at the end of the trading day in order to push the closing price to an artificial level,[12] we can find little evidence of closing price manipulation in the futures markets. Thus, given that our findings indicate that the intraday spoofing order trading pattern in the futures market is higher (lower) at the market

[11] See Wood, Mclnish and Ord (1985), Jain and Joh (1988) and Gerety and Mulherin (1992).
[12] See Felixson and Pelli (1999), Hillion and Suominen (2004), Comerton-Forde and Putnins (2011).

open (market close), support is provided for our Hypothesis 1.

4.3 Profitability of Spoofing Order Trading

In this section, we go on to measure the profitability of spoofing order trading, since this is regarded as being of great concern, both practically and academically. The profits of spoofing-buy orders are calculated as the actual selling price, net of the market selling price at the time that a spoofing-buy order is submitted, multiplied by the number of shares sold. The profits of spoofing-sell orders are calculated as the market buying price at the time that a spoofing-sell order is submitted, net of the actual buying price, multiplied by the number of shares bought; the profits are then adjusted to take transaction costs into account.[13]

The spoofing-buy and spoofing-sell order profits are combined to calculate the proportion of spoofing orders with positive, zero or negative profits; as we can see from the results are reported in Table 3, most spoofing orders generate positive profits. For example, when examining all traders, we can see that the proportion of positive profits is 68.29%, with the results being similar for all four types of traders; as regards the different types of traders, foreign institutions are found to have positive profits of 51.80%, proprietary firms 76.55%, domestic institutions 61.74% and individual

[13] Transaction costs include commission and tax; the commission varies among different brokerage houses, with the average being about NT$ 150. During our sample period, from 1 January 2006 to 5 October 2008, the transaction tax was 1 basis point; however, on 6 October 2008, the Taiwanese government reduced the tax levied on futures transactions on the TAIFEX from 1 to 0.4 basis points.

traders 62.12%. These results clearly indicate that spoofing order trading is profitable, thereby providing support for our Hypothesis 2.

<Table 3 is inserted about here>

4.4 Determinants of Spoofing Order Trading

We go on in this sub-section to further investigate whether the spoofing order trading strategies of investors are subject to change, depending on the previous market condition variables (*Volume*, *Return*, *Volatility* and *Price*). *Volatility*, which is measured as 'realized volatility' (Andersen, Bollerslev, Diebold and Ebens, 2001), is calculated as $\sqrt{\sum_{t=1}^{n}(r_t)^2}$, where r_t are the five-minute intraday returns; and n is the number of five-minute intraday returns.

The daily regression analyses of the influences of the market condition variables on spoofing order trading behavior among the different types of traders are reported in Table 4, where the dependent variable is the spoofing orders submitted by the different types of traders, with Panel A reporting all spoofing orders, Panel B reporting spoofing-buy orders and Panel C reporting spoofing-sell orders. Model (1) reports the results for all traders, while Models (2) to (5) report the respective results for foreign institutions, proprietary firms, domestic institutions and individual traders. The independent variables include *Volume*, *Return*, *Volatility* and *Price*, each of which is lagged by one period to avoid simultaneous equation bias.[14]

<Table 4 is inserted about here>

As we can see from the table, all of the coefficients on *Volume* are found to be significantly positive at the 5% level, at the very least, with this result being found to be fairly consistent across each of the different types of traders (Models 1 to 5) as well as for different types of spoofing strategies (Panels A to C). These results indicate that traders are more likely to submit spoofing orders when volume is high, thereby providing support for the notion that larger trading volume allows spoofing traders to better disguise their spoofing orders.

Furthermore, the coefficients on *Return* are found to be significant positive in Panel B and significant negative in Panel C, which is consistent across different types of traders (Models 1 to 5). The results indicate that traders are more likely to submit spoofing-buy (sell) orders in a bull (bear) market which they can sell (buy) later at a higher (lower) price. By examining spoofing-buy and spoofing-sell orders separately, we observe the opposite effects of market return on spoofing-buy and spoofing-sell trading.

All of the coefficients on *Volatility* are found to be significantly positive, with this being consistent across both the different types of traders (Models 1 to 5) and the

[14] Refer to Wang and Yau (2000) for further discussion on this issue.

different types of spoofing strategies (Panels A to C). These results appear to provide support for our suggestion in Section 4.2 that the higher proportion of spoofing orders at the market open is associated with information asymmetry. With high market volatility, traders are more likely to submit spoofing orders, essentially because spoofing orders will be more effective when there is greater uncertainty in the market.

As regards the coefficients on *Price*, those on all spoofing orders (Panel A) are found to be significantly negative in Models (1) and (5), thereby indicating that a higher market price equates to higher costs for individual traders' spoofing strategy; however, if spoofing-buy and spoofing-sell orders (Panels B and C) are considered separately, we find that market returns have a negative correlation with spoofing-buy orders, as compared to a positive correlation with spoofing-sell orders. This may be due to the fact that if their spoofing-sell strategy is successful, traders can buy back at a lower price.

In an attempt to enhance the robustness and reliability of our results, we carry out a further intraday regression analysis of the determinants of spoofing order trading. This additional analysis is similar to that undertaken above, with the exception that we observe a one-hour time interval as opposed to one day. On the one hand, since we are interested in the influence on spoofing order trading which may be attributable to short-term variations in market conditions, the time interval examined should also be suitably brief. On the other hand, however, if the time interval selected is too short, then the total number of observations may be insufficient to obtain reliable estimates. Striking a balance between these two concerns, we ultimately selected a one-hour interval for our regression analysis.

The intraday regression results on the influences of market conditions on spoofing order trading by the different types of investors are presented in Table 5. Consistent with the daily regression results reported in Table 4, the results show that traders are more likely to submit spoofing orders when both volume and volatility are high. As regards market returns, we once again find that such returns have a positive (negative) association with spoofing-buy (sell) strategies, which suggests that high market returns tend to increase (reduce) the number of spoofing-buy (sell) orders. Market prices are inversely (positively) related to spoofing-buy (sell) orders, which once again support that higher market price made spoofing-buy (sell) strategy more (less) costly.

<Table 5 is inserted about here>

We find most of the coefficients on the time-of-day dummies in the first hour section (D_{0945}) are significantly positive for Panels A to C. This finding provides further evidence of an intraday pattern in spoofing order behavior, which is at its highest during the first hour of the day. The above results provide overall support for our Hypothesis 3 that spoofing trading strategies will tend to vary with market conditions.

4.5 Effects of Spoofing Order Trading on the Markets

The impacts of spoofing order trading on the markets are important for both regulators and the exchanges themselves; however, while spoofing order traders are accused of destabilizing the markets and impeding market efficiency, the actual effects and severity of spoofing order trading on the markets remain unclear. Thus, in this section, we attempt to determine the overall impacts of spoofing order trading, examining volume, price, bid-ask spread and volatility.[15]

The results of the daily regression analyses on the market influences of the spoofing orders undertaken by the different types of traders are reported in Table 6, with Models (1) and (2) reporting the results on *Volume*, Models (3) and (4) reporting those on *Price*, Models (5) and (6) reporting those on *Spread* and Models (7) and (8) reporting those on *Volatility*.

The independent variables are the spoofing orders submitted by the different types of traders, with Panel A reporting the results for all spoofing orders, Panel B reporting those for spoofing-buy orders and Panel C reporting those for spoofing-sell orders. In order to avoid simultaneous equation bias, the independent variables are

[15] Volatility is measured by 'realized volatility', which is defined as the sum of the squared five-minute returns. Spread is measured by 'percentage effective spread', which is defined as the ratio of effective spread to the value of the contract.

lagged by one period. The control variables comprise of lagged *Volume*, lagged *Return*, lagged *Spread* and lagged *Volatility*.

<Table 6 is inserted about here>

As shown in Models (1) and (2) of Table 6, the coefficients on spoofing orders are all found to be significantly positive, and this is found to be fairly consistent across both the different types of investors and the different types of spoofing order trading. These findings provide support for the supposition that spoofing orders induce more trading, regardless of whether the orders are submitted by institutional or individual spoofing traders. As regards the control variables in Models (1) and (2), the significantly positive coefficients on lagged *Volume* indicate the persistence of trading volume. In contrast, the coefficients on lagged *Spread* are significantly negative, essentially because spread represents a trading cost which reduces the overall amount of trading.

The results reported in Models (3) and (4) in Table 6 show that the coefficients on spoofing-buy orders (Panels B) are significantly positive, while those on spoofing-sell orders (Panel C) are significantly negative. These results are found to be consistent across the spoofing orders of all four types of traders. We provide clear evidence to show that spoofing-buy and spoofing-sell strategies have opposite effects on market price. A spoofing-buy strategy pushes the subsequent market price up, whereas a spoofing-sell strategy pushes the subsequent market price down.

The effects of spoofing orders on *Spread* are reported in Models (5) and (6) of Table 6, from which we can see that spoofing orders are found to have significantly positive effects, with the results being consistent across the different types of order spoofing strategies (Panels A to C) as well as the different types of investors. These results provide support for the argument that spoofing orders induce greater spread; indeed, the coefficients on lagged *Volatility* are found to be positively significant, a result which is expected, essentially because an increase in price volatility implies that market makers will be faced with increased inventory risk, as well as the risk of trading against informed traders, as a result of which they will tend to increase the spread.

Finally, as we can see from Models (7) and (8) of Table 6, the coefficients of spoofing orders on *Volatility* are found to be significantly positive, thereby indicating that spoofing orders increase market volatility; these results are consistent across both the different types of investors and the different types of order spoofing strategies (Panels A to C), thereby providing support for the argument that spoofing order trading generally has a destabilizing effect on the market.

In order to enhance the robustness of our results, we go on to undertake an additional intraday regression to confirm the real-time effects of spoofing orders on the markets. The regression analysis is similar to that reported in Table 6, with the exception that each day is divided into five one-hour intervals and intraday dummy variables are included to capture the intraday effects of the dependent variables.

The intraday regression results of the effects of spoofing orders on the markets are reported in Table 7, from which we can once again see that spoofing orders are associated with positive volume, spread and volatility, with spoofing-buy (sell) orders having a positive (negative) impacts on the subsequent market price.

<Table 7 is inserted about here>

Overall, our results indicate that spoofing order trading does have direct effects on the market, including volume, price, spread and volatility, with such spoofing trading inducing subsequent volume, spread and volatility, thereby providing support for our Hypothesis 4, that spoofing trading destabilizes the market.

4.6 Simultaneous Analysis

In sub-sections 4.4 and 4.5, we examine the determinants and effects of spoofing orders separately and use lagged independent variables to avoid simultaneous equation bias. To further enhance the robustness of our results, we carry out a further VARs analysis. We explore simultaneously the intraday (hourly) relationship among spoofing orders, volatility, volume, spread, return and price within VARs system, which are presented in Table 8.[16]

[16] To save space, only the results of spoofing-buy orders and spoofing-sell orders for all traders are reported. The results by types of traders are similar, which are available upon request.

<Table 8 is inserted about here>

From Table 8, it still shows that traders are more likely to submit spoofing orders when both volatility and volume are high, and the price for spoofing-sell (buy) orders is high (low). Meanwhile, spoofing trading induces subsequent volume, spread and volatility, and spoofing-buy (sell) orders have a positive (negative) effect on the subsequent price.

5. SUMMARY AND CONCLUSIONS

We set out in this study, using a unique dataset, to carry out a detailed analysis on the strategic behavior of spoofing order trading, including its characteristics, profitability, determinants and real-time impacts in the Taiwan futures market. The unique order flow dataset obtained from the TAIFEX provides detailed information on order submission records and account identification, which enables us to trace all order submissions for each account; thus, we can identify spoofing order trading behavior among different types of investors to facilitate our examination of the strategic behavior of spoofing order trading.

Our empirical results reveal a tendency among traders on the TAIFEX to submit spoofing orders, thereby providing empirical evidence in support of the theoretical literature (Kyle, 1984; Easterbrook, 1986) and anecdotal evidence to show that spoofing trading exists in the futures markets. Both spoofing-buy and spoofing-sell strategies are discernible, not only among institutional investors, but also individual traders; we also find that spoofing order trading is profitable. Furthermore, traders are found to be more likely to submit spoofing orders when both volume and volatility are high, while market prices are found to have a negative (positive) correlation with spoofing-buy (sell) strategies, thereby suggesting that high market prices reduce (increase) the prevalence of spoofing-buy (sell) orders.

More importantly, we find that spoofing orders do indeed affect the market, including volume, price, spread and volatility, with spoofing trading inducing subsequent volume, spread and volatility, and spoofing-buy (sell) orders having positive (negative) effects on the subsequent market price. These findings provide general support for the view that spoofing order trading destabilizes the market.

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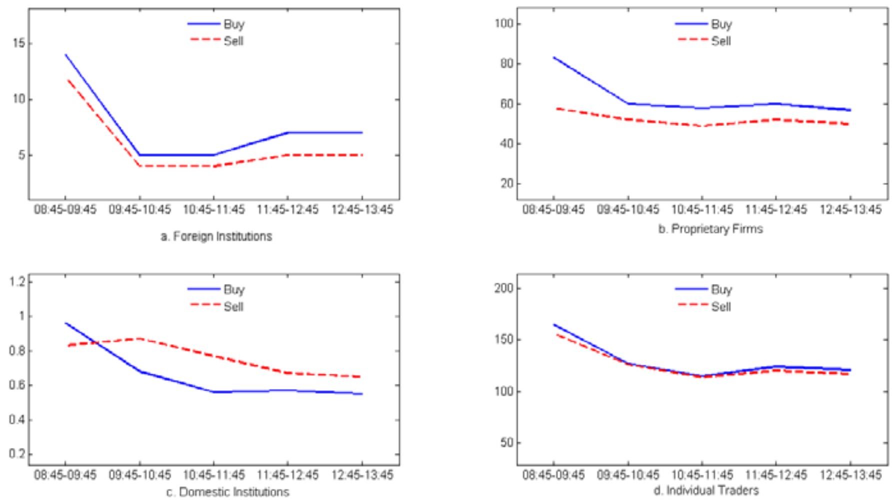

Figure 1　Intraday pattern of spoofing order trading, by trader types

Table 1 Summary statistics of daily order and daily spoofing order trading, by trader types

This table reports the summary statistics of daily order and daily spoofing order trading by the different types of traders on the TAIFEX (foreign institutions, proprietary firms, domestic institutions and individual traders). The orders are reported as the number (No.) and percentage (%) of contracts, with the sample period running from January 2003 to December 2008. A spoofing-buy (sell) order is defined as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order. The proportion of spoofing orders is calculated as the total daily spoofing orders divided by the total daily orders. An account is defined as a 'day trader' account if the total amount of contracts purchased and sold on a particular day are the same.

Trader Types	All Orders		Buy Orders		Sell Orders	
	No.	%	No.	%	No.	%
Panel A: Daily orders						
Foreign Institutions	9,349	7.19	4,528	6.95	4,821	7.44
Proprietary Firms	28,458	21.89	14,267	21.89	14,191	21.89
Domestic Institutions	1,911	1.47	970	1.49	941	1.45
Individual Traders	90,295	69.45	45,420	69.68	44,875	69.22
All Traders	130,012	100.00	65,185	100.00	64,827	100.00
Panel B: Daily spoofing orders						
Foreign Institutions	70	3.46	38	3.62	32	3.30
Proprietary Firms	589	29.24	324	30.65	265	27.68
Domestic Institutions	8	0.39	4	0.35	4	0.44
Individual Traders	1,349	66.90	692	65.39	656	68.58
All Traders	2,016	100.00	1,059	100.00	957	100.00
Panel C: Proportion of spoofing orders						
Foreign Institutions	–	0.75	–	0.85	–	0.65
Proprietary Firms	–	2.07	–	2.27	–	1.87
Domestic Institutions	–	0.42	–	0.38	–	0.45
Individual Traders	–	1.49	–	1.52	–	1.46
All Traders	–	1.55	–	1.62	–	1.48
Panel D: Proportion of spoofing orders over cancelled orders						
Foreign Institutions	–	0.051	–	0.065	–	0.036
Proprietary Firms	–	0.526	–	0.655	–	0.387
Domestic Institutions	–	0.005	–	0.005	–	0.005
Individual Traders	–	0.549	–	0.593	–	0.501
All Traders	–	1.130	–	1.318	–	0.929
Panel E: Proportion of spoofing orders placed by day traders						
Foreign Institutions	–	1.02	–	1.03	–	1.57
Proprietary Firms	–	0.21	–	0.20	–	0.31
Domestic Institutions	–	0.14	–	0.11	–	0.16
Individual Traders	–	26.14	–	24.00	–	36.61
All Traders	–	27.50	–	25.34	–	38.65

Table 2 Distribution of spoofing orders for each spoofing trader, by trader types

This table describes the distribution of the number of spoofing orders for each spoofing trader ('spoofer'), by the different types of traders (foreign institutions, proprietary firms, domestic institutions and individual traders), with the sample period running from January 2003 to December 2008. A spoofing-buy (sell) order is defined as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order.

No. of Spoofing Orders	Distribution of Spoofing Traders									
	All Traders		Foreign Institutions		Proprietary Firms		Domestic Institutions		Individual Traders	
	No.	%	No.	%	No.	%	No.	%	No.	%
2	2,710	15.78	7	9.33	2	4.17	28	16.47	2,673	15.84
3	1,285	7.48	6	8.00	1	2.08	18	10.59	1,260	7.47
4	745	4.34	2	2.67	0	0.00	13	7.65	730	4.33
5	453	2.64	6	8.00	1	2.08	7	4.12	439	2.60
6	339	1.97	0	0.00	0	0.00	5	2.94	334	1.98
7	254	1.48	1	1.33	0	0.00	4	2.35	249	1.48
8	179	1.04	2	2.67	1	2.08	0	0.00	176	1.04
9	144	0.84	1	1.33	0	0.00	0	0.00	140	0.83
10	116	0.68	1	1.33	0	0.00	6	3.53	109	0.65
11-15	352	2.05	7	9.33	0	0.00	4	2.35	341	2.02
16-20	177	1.03	3	4.00	1	2.08	2	1.18	171	1.01
21-30	184	1.07	4	5.33	3	6.25	3	1.76	174	1.03
31-40	110	0.64	4	5.33	1	2.08	5	2.94	100	0.59
41-50	66	0.38	3	4.00	2	4.17	0	0.00	60	0.36
51-100	116	0.68	5	6.67	2	4.17	2	1.18	107	0.63
>101	199	1.16	13	17.33	34	70.84	2	1.18	150	0.89
Total	7,429	43.26	65	86.65	48	100.00	99	58.24	7,213	42.75
Mean	16.70		170.55		2,779		6.88		8.25	
STD	460.21		774.27		8,125.86		19.64		84.03	
Min	1		1		2		1		1	
Max	45,566		6,557		45,566		210		4,284	

Table 3 Profitability of spoofing order trading

This table reports the proportion of spoofing orders under three categories of spoofing profits, which are positive, zero or negative. A spoofing-buy (sell) order is defined as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order. The profits of spoofing buy orders are calculated as the actual sell price net of the market sell price at the time when a spoofing buy order is submitted, multiplied by the number of shares sold; the profits of spoofing sell orders are calculated as the market buy price at the time that a spoofing sell order is submitted net of the actual buy price, multiplied by the number of shares bought. Traders comprise of foreign institutions, proprietary firms, domestic institutions and individual traders, with the sample period running from January 2003 to December 2008. All figures are expressed in percentage terms.

Profits	All Traders	Foreign Institutions	Proprietary Firms	Domestic Institutions	Individual Traders
Positive	68.29	51.80	76.55	61.74	62.12
Zero	9.55	30.32	7.67	10.04	11.06
Negative	22.16	17.88	15.77	28.22	26.82
Total	100.00	100.00	100.00	100.00	100.00

Table 4 Daily regression analysis on the determinants of spoofing orders

This table describes the effects of trading volume, returns, return volatility and price on spoofing order trading, with the sample period running from January 2003 to December 2008. A spoofing-buy (sell) order is defined as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order. The dependent variable is the proportion of spoofing orders, by different types of traders, comprising of foreign institutions, proprietary firms, domestic institutions and individual traders. Volatility, which is measured by 'realized volatility', is defined as the sum of the squared five-minute returns. Model (1) refers to All Traders; Model (2) refers to Foreign Institutions; Model (3) refers to Proprietary Firms; Model (4) refers to Domestic Institutions; and Model (5) refers to Individual Traders. *** indicates significance at the 1% level; ** indicates significance at the 5% level; and * indicates significance at the 10% level.

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel A: All spoofing orders										
Intercept	-1.370 **	-2.03	-111.728 ***	-26.77	-7.047 ***	-5.21	-56.301 ***	-8.50	0.035	0.04
$Volume_{t-1}$	0.137 ***	3.44	3.662 ***	16.68	0.267 ***	2.92	2.407 ***	7.48	0.132 ***	2.88
$Return_{t-1}$	-0.003	-0.31	-0.086	-0.94	0.017	1.17	-0.004	-0.05	-0.012	-1.02
$Volatility_{t-1}$	0.055 *	1.80	0.094 **	1.97	0.089 ***	4.90	0.309 ***	3.22	0.039 *	1.84
$Price_{t-1}$	-0.209 **	-2.24	-0.836	-1.58	0.027	0.21	0.137	1.36	-0.685 ***	-7.65
Adj. R^2 (%)	7.86		35.03		6.48		13.16		5.56	
F-statistics	12.00***		106.52***		12.06***		30.67***		12.52***	

Table 4 (*Contd.*)

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel B: Spoofing-buy orders										
Intercept	-2.253***	-2.97	-104.516***	-21.28	-9.796***	-3.90	-45.516***	-6.85	-1.675*	-1.94
$Volume_{t-1}$	0.269***	6.12	4.080***	17.88	0.781***	5.32	1.800***	5.39	0.234***	4.52
$Return_{t-1}$	0.034***	2.77	0.107*	1.89	0.070**	2.49	0.103*	1.77	0.030**	2.06
$Volatility_{t-1}$	0.051*	1.90	0.136***	2.58	0.118***	3.85	0.295***	2.78	0.055*	1.94
$Price_{t-1}$	-0.557***	-6.33	-5.489***	-9.00	-0.320*	-1.90	-1.680**	-1.99	-0.596***	-6.01
Adj. R^2 (%)	9.76		35.19		6.49		19.79		5.67	
F-statistics	22.16***		106.77***		14.59***		32.24***		12.76***	
Panel C: Spoofing-sell orders										
Intercept	-2.237**	-2.31	-100.383***	-18.84	-23.151***	-7.08	-48.168***	-7.97	-0.193	-0.17
$Volume_{t-1}$	0.318**	2.34	3.495***	14.02	0.501***	3.06	1.858***	5.60	0.158**	1.99
$Return_{t-1}$	-0.051***	-4.41	-0.092*	-1.95	-0.035*	-1.87	-0.210**	-2.36	-0.067***	-4.31
$Volatility_{t-1}$	0.048*	1.66	0.156***	2.59	0.119***	3.53	0.328***	3.11	0.041*	1.73
$Price_{t-1}$	0.248**	2.14	4.661***	8.30	1.484***	5.18	1.681**	2.09	0.514***	4.90
Adj. R^2 (%)	8.31		37.92		5.01		20.66		6.86	
F-statistics	13.63***		125.48***		11.33***		34.36***		12.86***	

Table 5 Intraday (hourly) regression analysis on the determinants of spoofing orders

This table describes the effects of trading volume, returns, return volatility and price on spoofing order trading for one-hour periods, with the sample period running from January 2003 to December 2008. A spoofing-buy (sell) order is defined as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order. The dependent variable is the proportion of spoofing orders over a one-hour period placed by different types of traders, comprising of foreign institutions, proprietary firms, domestic institutions and individual traders. *Volume* refers to the market trading volume during the one-hour period and *Volatility* is measured by the absolute value of the hourly returns, with a 'time of day' dummy being included for each one-hour period. Model (1) refers to All Traders; Model (2) refers to Foreign Institutions; Model (3) refers to Proprietary Firms; Model (4) refers to Domestic Institutions; and Model (5) refers to Individual Traders. *** indicates significance at the 1% level; ** indicates significance at the 5% level; and * indicates significance at the 10% level.

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel A: All spoofing orders										
Intercept	-2.265***	-2.72	-58.330***	-11.45	-34.562***	-8.44	-33.409***	-13.60	-0.792	-0.79
$Volume_{t-1}$	0.215**	2.31	2.517***	10.26	0.860***	3.57	0.341**	2.15	0.187**	2.22
$Return_{t-1}$	-0.036**	-2.09	-0.103***	-2.83	-0.018	-0.43	-0.048	-1.43	-0.050**	-2.48
$Volatility_{t-1}$	0.794***	9.37	0.528**	2.18	1.132***	4.37	0.720***	3.76	1.033***	12.11
$Price_{t-1}$	-0.319***	-3.17	-0.105***	-3.40	1.053	1.61	0.382	1.59	-0.332***	-2.81
D_{0945}	0.182***	3.20	0.734***	3.58	0.194*	1.88	0.169	1.40	0.104*	1.90
D_{1045}	-0.098	-1.35	-0.304*	-1.73	-0.134	-0.75	-0.180	-1.27	-0.048	-0.52
D_{1245}	-0.038	-0.50	0.116	0.69	-0.107	-0.59	0.182	1.28	-0.034	-0.35
D_{1345}	0.065	0.62	0.130	1.23	0.062	1.31	0.109	1.45	0.092	0.68
Adj. R^2 (%)	9.78		23.64		16.15		7.22		9.32	
F-statistics	48.20***		133.26***		84.89***		34.89***		45.74***	
Panel B: Spoofing-buy orders										
Intercept	-8.250***	-5.60	-46.665***	-12.70	-40.378***	-8.37	-26.421***	-12.34	-7.963***	-4.85
$Volume_{t-1}$	0.185*	1.90	2.585***	12.83	1.200***	4.14	0.263**	2.41	0.235**	2.04
$Return_{t-1}$	0.096**	2.23	0.071*	1.93	0.083**	2.07	0.035*	1.81	0.078*	1.66

Table 5 (*Contd.*)

Variables	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel B: Spoofing-buy orders (*Contd.*)										
$Volatility_{t-1}$	1.056***	11.09	0.381*	1.90	1.922***	5.92	0.736***	4.13	1.159***	9.82
$Price_{t-1}$	-0.643***	-4.36	-0.409**	-2.49	-0.725***	-3.86	-0.866***	-4.20	-0.683***	-3.91
D_{0945}	0.129*	1.84	0.967***	4.74	0.346*	1.70	0.082	1.54	0.148*	1.66
D_{1045}	-0.046	-0.41	-0.410**	-2.37	0.078	0.38	-0.051	-0.43	-0.067	-0.51
D_{1245}	0.101	0.85	-0.011	-0.06	0.306	1.49	0.270**	2.15	0.014	0.10
D_{1345}	0.032	0.93	0.077	0.84	0.049	0.78	0.033	0.91	0.043	0.79
Adj. R^2 (%)	12.91		21.37		21.15		5.13		13.01	
F-statistics	65.56***		113.10***		117.67***		24.46***		66.13***	
Panel C: Spoofing-sell orders										
Intercept	-6.238***	-3.36	-36.365***	-10.50	-58.452***	-9.39	-23.709***	-10.82	-5.526***	-2.80
$Volume_{t-1}$	0.252**	2.39	1.729***	9.75	1.381***	4.19	0.294**	2.54	0.157*	1.92
$Return_{t-1}$	-0.119***	-4.28	-0.135***	-3.41	-0.143***	-2.92	-0.086*	-1.88	-0.171***	-5.19
$Volatility_{t-1}$	1.112***	7.90	0.435**	2.43	1.100***	3.12	0.298**	2.44	1.418***	9.92
$Price_{t-1}$	0.355***	3.28	1.060**	2.16	4.945***	4.75	1.032***	3.01	0.537***	2.89
D_{0945}	0.180*	1.93	0.571***	2.88	0.430*	1.72	0.279**	1.99	0.352***	2.62
D_{1045}	0.023	0.17	-0.196	-1.16	-0.302	-1.34	-0.240**	-2.12	0.226	1.43
D_{1245}	-0.188	-1.34	0.151	0.91	-0.307	-1.40	-0.132	-1.19	-0.070	-0.41
D_{1345}	0.029	0.55	0.088	0.50	0.109	1.13	0.023	0.75	0.113	0.96
Adj. R^2 (%)	9.18		24.34		17.13		7.20		9.30	
F-statistics	46.67***		125.02***		91.00***		35.31***		45.62***	

Table 6 Daily regression analysis on the effects of spoofing order trading on the market

This table describes the effects of spoofing order trading on the market by different types of traders, comprising of trading volume, price, spread and volatility, with the sample period running from January 2003 to December 2008. A spoofing-buy (sell) order is defined as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order. Traders are classified into four types: foreign institutions (*FI*), proprietary firms (*PF*), domestic institutions (*DI*) and individual traders (*IT*), with the regression including control variables comprising of lagged volume, lagged return, lagged volatility and lagged spread. Volatility is measured by 'realized volatility', which is defined as the sum of the squared five-minute returns. Spread is measured by 'percentage effective spread', which is the ratio of the effective spread to the value of the contract. *** indicates significance at the 1% level; ** indicates significance at the 5% level; and * indicates significance at the 10% level.

Variables	*Volume*				*Price*			
	All traders		By trader types		All traders		By trader types	
	Model (1)		Model (2)		Model (3)		Model (4)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel A: All spoofing orders								
Intercept	17,862***	3.39	28,293***	5.23	6,840***	49.95	6,821***	48.60
$SO_{Total,t\text{-}1}$	204,626*	1.76	–	–	4,807***	7.25	–	–
$SO_{FI,t\text{-}1}$	–	–	65,849*	1.74	–	–	1,900**	2.27
$SO_{PF,t\text{-}1}$	–	–	91,899**	2.08	–	–	1,643**	2.01
$SO_{DI,t\text{-}1}$	–	–	16,030*	1.73	–	–	1,841**	1.99
$SO_{IT,t\text{-}1}$	–	–	75,089*	1.89	–	–	1,789***	11.00
$Volume_{t\text{-}1}(10^{-1})$	8.215***	26.04	8.181***	25.49	0.031***	3.71	0.026***	3.22
$Return_{t\text{-}1}$	-44,598	-0.42	-58,439	-0.56	3,086	0.99	3,041	1.03
$Spread_{t\text{-}1}$	-274,941**	-2.23	-267,615**	-2.19	-11,749**	-2.37	-11,883**	-2.55
$Volatility_{t\text{-}1}$	167*	1.86	229*	1.91	117***	10.80	94***	8.53
Adj. R^2 (%)	75.84		75.87		10.10		16.66	
F-statistics	570.51***		357.04***		21.38***		23.66***	
Panel B: Spoofing-buy orders								
Intercept	17,300***	3.92	26,891***	5.01	6,559***	50.32	6,784***	50.44
$SO_{Total,t\text{-}1}$	141,846**	2.28	–	–	17,794***	4.29	–	–
$SO_{FI,t\text{-}1}$	–	–	38,455**	2.01	–	–	5,643***	2.86
$SO_{PF,t\text{-}1}$	–	–	42,797*	1.86	–	–	4,355**	2.10

Table 6 (*Contd.*)

Variables	*Volume*				*Price*			
	All traders		By trader types		All traders		By trader types	
	Model (1)		Model (2)		Model (3)		Model (4)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel B: Spoofing-buy orders (*Contd.*)								
$SO_{DI,t-1}$	–	–	9,595*	1.71	–	–	2,929***	3.17
$SO_{IT,t-1}$	–	–	38,306*	1.86	–	–	6,359***	6.76
$Volume_{t-1}(10^{-1})$	8.143***	25.88	8.227***	2.59	0.034***	3.97	0.025***	2.78
$Return_{t-1}$	-35,661	-0.34	-42,345	-1.26	3,275	1.05	5,390*	1.71
$Spread_{t-1}$	-265,626***	-5.20	-272,330***	-5.34	-10,900**	-2.17	-11,144**	-2.39
$Volatility_{t-1}$	126	1.06	193	1.39	115***	10.17	100***	8.54
Adj. R^2 (%)	75.94		75.66		8.74		14.75	
F-statistics	573.68***		349.47***		18.37***		20.42***	
Panel C: Spoofing-sell orders								
Intercept	24,695***	5.23	27,031***	5.22	6,721***	48.37	6,720***	49.19
$SO_{Total,t-1}$	115,519*	1.94	–	–	-12,988***	-5.74	–	–
$SO_{FI,t-1}$	–	–	39,208*	1.74	–	–	-4,193**	-1.99
$SO_{PF,t-1}$	–	–	47,746**	2.27	–	–	-2,165***	-5.41
$SO_{DI,t-1}$	–	–	6,940*	1.79	–	–	-1,818*	-1.94
$SO_{IT,t-1}$	–	–	40,235*	1.73	–	–	-5,658***	-11.81
$Volume_{t-1}(10^{-1})$	8.214***	25.78	8.122***	24.83	0.026***	3.18	0.023***	3.05
$Return_{t-1}$	-57,067	-0.54	-61,963	-0.56	3,780	1.22	1,594	0.54
$Spread_{t-1}$	-263,879**	-2.18	-266,303**	-2.18	-12,277**	-2.45	-11,874***	-2.65
$Volatility_{t-1}$	180*	1.66	245*	1.75	113***	10.96	90***	8.96
Adj. R^2 (%)	75.80		75.49		9.44		16.40	
F-statistics	569.21***		338.35***		19.90***		22.51***	

Table 6 (*Contd.*)

Variables	*Spread*				*Volatility*			
	All traders		By trader types		All traders		By trader types	
	Model (5)		Model (6)		Model (7)		Model (8)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel D: All spoofing orders								
Intercept	-0.010	-0.57	-0.002	-0.18	0.455***	2.69	0.367***	2.64
$SO_{Total,t\text{-}1}$	0.672**	2.39	–	–	8.713**	1.98	–	–
$SO_{FI,t\text{-}1}$	–	–	0.291*	1.93	–	–	1.985*	1.74
$SO_{PF,t\text{-}1}$	–	–	0.127*	1.89	–	–	1.766*	1.83
$SO_{DI,t\text{-}1}$	–	–	0.072*	1.78	–	–	1.541*	1.76
$SO_{IT,t\text{-}1}$	–	–	0.223**	1.98	–	–	2.215**	2.45
$Volume_{t\text{-}1}(10^{-6})$	-0.077**	-2.35	-0.084***	-2.63	1.330*	1.89	1.520**	1.98
$Return_{t\text{-}1}$	0.183**	1.98	0.195**	2.09	-7.953	-1.57	-7.983	-1.61
$Spread_{t\text{-}1}$	0.152	1.27	0.163	1.30	19.953	1.09	20.056	1.10
$Volatility_{t\text{-}1}$	0.083*	1.78	0.083*	1.78	0.689***	6.15	0.681***	6.05
Adj. R^2 (%)	1.48		1.14		49.24		49.30	
F-statistics	3.72***		2.31***		174.62***		109.78***	
Panel E: Spoofing-buy orders								
Intercept	-0.032	-1.51	-0.008	-1.01	0.313**	2.15	0.394***	2.94
$SO_{Total,t\text{-}1}$	0.299**	2.25	–	–	2.862**	2.11	–	–
$SO_{FI,t\text{-}1}$	–	–	0.198**	1.99	–	–	0.812*	1.88
$SO_{PF,t\text{-}1}$	–	–	0.104*	1.92	–	–	0.513*	1.70
$SO_{DI,t\text{-}1}$	–	–	0.024*	1.68	–	–	0.538*	1.93
$SO_{IT,t\text{-}1}$	–	–	0.120*	1.88	–	–	0.738**	2.09

Table 6 (*Contd.*)

Variables	*Spread*				*Volatility*			
	All traders		By trader types		All traders		By trader types	
	Model (5)		Model (6)		Model (7)		Model (8)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel E: Spoofing-buy orders (*Contd.*)								
$Volume_{t\text{-}1}(10^{-6})$	-0.090*	-1.87	-0.083*	-1.77	1.390*	1.93	1.500*	1.85
$Return_{t\text{-}1}$	0.093	0.89	0.200**	1.97	-7.623	-1.52	-7.076	-1.40
$Spread_{t\text{-}1}$	0.187*	1.91	0.167*	1.82	20.089	1.10	19.708	1.08
$Volatility_{t\text{-}1}$	0.103**	2.17	0.103**	2.16	0.688***	6.12	0.683***	6.11
Adj. R^2 (%)	5.50		4.19		49.20		49.22	
F-statistics	11.53***		9.35***		174.38***		108.35***	
Panel F: Spoofing-sell orders								
Intercept	0.013	0.82	0.002	0.29	0.516***	2.87	0.339**	2.30
$SO_{Total,t\text{-}1}$	0.239**	2.45	–	–	5.399**	2.44	–	–
$SO_{FI,t\text{-}1}$	–	–	0.169*	1.89	–	–	1.101*	1.78
$SO_{PF,t\text{-}1}$	–	–	0.107*	1.68	–	–	1.314*	1.87
$SO_{DI,t\text{-}1}$	–	–	0.065*	1.83	–	–	1.016*	1.72
$SO_{IT,t\text{-}1}$	–	–	0.115**	2.46	–	–	1.409**	2.21
$Volume_{t\text{-}1}(10^{-6})$	-0.082*	-1.92	-0.072**	-2.09	1.500**	2.08	1.310*	1.73
$Return_{t\text{-}1}$	-0.216**	-2.17	-0.232**	-2.25	-7.907	-1.57	-8.301	-1.60
$Spread_{t\text{-}1}$	0.102	1.46	0.140	1.34	19.539	1.07	20.081	1.10
$Volatility_{t\text{-}1}$	0.195**	2.16	0.190**	2.13	0.690***	6.17	0.682***	6.07
Adj. R^2 (%)	5.17		4.10		49.30		49.24	
F-statistics	10.01***		4.21***		175.03***		105.90***	

Table 7 Intraday (hourly) regression analysis on the effects of spoofing order trading on the market

This table describes the effects of spoofing order trading on the market by different types of traders, including trading volume, price, spread and volatility, with the sample period running from January 2003 to December 2008. A spoofing-buy (sell) order is defined as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order. Traders are classified into four types: foreign institutions (*FI*), proprietary firms (*PF*), domestic institutions (*DI*), and individual traders (*IT*), with the regression including control variables of lagged volume, lagged return, lagged volatility, lagged spread, and intraday dummy variables. Volatility is measured by 'Realized Volatility', which is defined as the sum of the squared five-minute returns. Spread is measured by 'Percentage Effective Spread', which is the ratio of effective spread to the value of the contract. *** indicates significance at the 1% level; ** indicates significance at the 5% level; and * indicates significance at the 10% level.

Variables	*Volume*				*Price*			
	All traders		By trader types		All traders		By trader types	
	Model (1)		Model (2)		Model (3)		Model (4)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel A: All spoofing orders								
Intercept	2,142***	8.55	1,797***	6.71	6,423***	12.82	6,649***	13.01
$SO_{Total,t\text{-}1}$	14,245**	2.05	–	–	2,202	1.62	–	–
$SO_{FI,t\text{-}1}$	–	–	3,163**	2.55	–	–	1,671	0.89
$SO_{PF,t\text{-}1}$	–	–	2,944**	2.29	–	–	714	1.10
$SO_{DI,t\text{-}1}$	–	–	1,428**	2.08	–	–	644	0.61
$SO_{IT,t\text{-}1}$	–	–	6,558**	2.27	–	–	1,441	1.43
$Volume_{t\text{-}1}$	0.751***	49.38	0.750***	48.45	0.088***	3.16	0.082***	2.97
$Return_{t\text{-}1}$	1,040	0.85	2,183	1.10	-15,884	-0.42	-15,884	-0.41
$Spread_{t\text{-}1}$	-2,707***	-3.20	-1,129***	-2.73	-200	-0.46	-397	-0.70
$Volatility_{t\text{-}1}$	50,730**	2.53	53,504***	2.60	-154,769***	-3.25	-149,529***	-3.14
D_{0945}	9,016***	35.97	9,001***	35.69	156	0.21	186	0.24
D_{1045}	-2,800***	-12.24	-2,786***	-12.09	-321	-0.46	-328	-0.47
D_{1245}	1,410***	6.49	1,428***	6.46	135	0.38	150	0.49
D_{1345}	113	1.28	109	1.25	87	0.15	85	0.14
Adj. R^2 (%)	60.25		60.18		2.08		2.06	
F-statistics	1,115.92***		795.23***		4.89***		4.66***	

Table 7 (*Contd.*)

Variables	*Volume*				*Price*			
	All traders		By trader types		All traders		By trader types	
	Model (1)		Model (2)		Model (3)		Model (4)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel B: Spoofing-buy orders								
Intercept	1,821***	7.63	1,790***	6.96	6,199***	9.36	6,608***	14.57
$SO_{Total,t\text{-}1}$	8,328***	3.24	–	–	14,134***	2.78	–	–
$SO_{FI,t\text{-}1}$	–	–	2,925***	2.76	–	–	6,132**	2.42
$SO_{PF,t\text{-}1}$	–	–	1,330**	2.23	–	–	2,014**	2.37
$SO_{DI,t\text{-}1}$	–	–	1,051**	2.17	–	–	1,443**	2.54
$SO_{IT,t\text{-}1}$	–	–	3,868***	2.68	–	–	5,896**	2.43
$Volume_{t\text{-}1}$	0.751***	49.50	0.748***	47.88	0.087***	3.27	0.079***	3.03
$Return_{t\text{-}1}$	2,055	1.09	1,284	0.91	-15,647	-0.41	-15,232	-0.39
$Spread_{t\text{-}1}$	-2,635***	-2.67	-1,748**	-2.26	-299	-0.65	-506	-0.64
$Volatility_{t\text{-}1}$	54,789**	2.35	52,358**	2.24	-157,713***	-3.24	-148,900***	-3.17
D_{0945}	9,057***	36.24	8,998***	34.71	181	0.24	193	0.24
D_{1045}	-2,778***	-12.13	-2,811***	-11.99	-299	-0.42	-317	-0.44
D_{1245}	1,388***	6.39	1,462***	6.43	116	0.15	167	0.21
D_{1345}	102	1.05	115	1.09	98	0.12	135	0.24
Adj. R^2 (%)	60.24		59.95		4.01		3.97	
F-statistics	1,115.46***		762.99***		6.93***		6.62***	

Table 7 (*Contd.*)

Variables	*Volume*				*Price*			
	All traders		By trader types		All traders		By trader types	
	Model (1)		Model (2)		Model (3)		Model (4)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel C: Spoofing-sell orders								
Intercept	2,370***	9.87	2,251***	8.02	6,626***	17.14	7,003***	9.68
$SO_{Total,t\text{-}1}$	6,935***	5.32	–	–	-12,689**	-2.21	–	–
$SO_{FI,t\text{-}1}$	–	–	1,278***	3.49	–	–	-5,104***	-2.63
$SO_{PF,t\text{-}1}$	–	–	2,667**	2.42	–	–	-2,099*	1.72
$SO_{DI,t\text{-}1}$	–	–	970*	1.74	–	–	-1,156**	-1.98
$SO_{IT,t\text{-}1}$	–	–	2,856**	2.31	–	–	-4,144**	-2.12
$Volume_{t\text{-}1}$	0.748***	49.17	0.743***	45.73	0.086***	3.19	0.070**	2.53
$Return_{t\text{-}1}$	-1,755	-0.38	-464	-0.12	-17,822	-0.46	-19,590	-0.48
$Spread_{t\text{-}1}$	-2,563**	-2.13	-1,124*	-1.72	-278	-0.63	-407	-0.70
$Volatility_{t\text{-}1}$	48,592**	2.46	43,960**	2.26	-152,675***	-3.32	-141,403***	-2.91
D_{0945}	8,973***	35.92	8,966***	32.88	122	0.17	119	0.14
D_{1045}	-2,786***	-12.20	-2,864***	-11.52	-316	-0.45	-319	-0.40
D_{1245}	1,404***	6.46	1,495***	6.15	136	0.18	127	0.15
D_{1345}	572	0.98	586	1.13	78	0.25	96	0.38
Adj. R^2 (%)	60.34		59.22		3.88		3.81	
F-statistics	1,119.83***		687.25***		5.95***		5.46***	

Table 7 (*Contd.*)

Variables	*Spread*				*Volatility*			
	All traders		By trader types		All traders		By trader types	
	Model (5)		Model (6)		Model (7)		Model (8)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel D: All spoofing orders								
Intercept (10^{-3})	-1.210	-0.37	-1.840	-0.67	0.646***	3.52	0.499**	2.57
$SO_{Total,t\text{-}1}$	0.041***	2.74	–	–	0.137***	4.15	–	–
$SO_{FI,t\text{-}1}$	–	–	0.135***	2.58	–	–	0.063**	2.25
$SO_{PF,t\text{-}1}$	–	–	0.073**	2.36	–	–	0.043**	2.11
$SO_{DI,t\text{-}1}$	–	–	0.058*	1.83	–	–	0.016**	2.15
$SO_{IT,t\text{-}1}$	–	–	0.032*	1.93	–	–	0.050***	4.04
$Volume_{t\text{-}1}$(10^{-7})	-1.987	-1.04	-2.231	-1.23	1.254***	10.13	1.283***	10.17
$Return_{t\text{-}1}$	0.442*	1.80	0.438*	1.76	-0.031*	-1.71	-0.032*	-1.79
$Spread_{t\text{-}1}$	0.586***	4.15	0.557***	3.40	0.063	0.15	0.062	0.04
$Volatility_{t\text{-}1}$	0.073*	1.78	0.100**	2.26	0.096***	3.37	0.092***	3.23
D_{0945}	0.213	0.83	0.204	1.27	0.332***	11.36	0.302***	10.60
D_{1045}	-0.108**	-2.01	-0.103*	-1.79	-0.001***	-5.39	-0.001***	-5.34
D_{1245}	1.260	0.71	1.340	0.82	0.430***	3.23	4.335***	3.21
D_{1345}	0.016	0.68	0.018	0.77	0.025*	1.92	0.032*	1.75
Adj. R^2 (%)	33.57		27.13		14.86		15.23	
F-statistics	370.66***		195.61***		129.38***		95.35***	

Table 7 (*Contd.*)

Variables	*Spread*				*Volatility*			
	All traders		By trader types		All traders		By trader types	
	Model (5)		Model (6)		Model (7)		Model (8)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel E: Spoofing-buy orders								
Intercept	-0.004	-1.12	-0.003	-1.11	0.001 ***	3.98	0.001***	3.39
$SO_{Total,t\text{-}1}$	0.233 **	2.31	–	–	0.084 ***	4.03	–	–
$SO_{FI,t\text{-}1}$	–	–	0.101 **	2.09	–	–	0.042 ***	3.27
$SO_{PF,t\text{-}1}$	–	–	0.153 ***	2.94	–	–	0.024 **	2.53
$SO_{DI,t\text{-}1}$	–	–	0.032 **	1.99	–	–	0.013 *	1.78
$SO_{IT,t\text{-}1}$	–	–	0.041 *	1.85	–	–	0.012 ***	3.16
$Volume_{t\text{-}1}(10^{-7})$	-1.823	-0.96	-2.374	-1.27	1.236 ***	10.05	1.267 ***	10.00
$Return_{t\text{-}1}$	0.438 *	1.77	0.342	1.38	-0.032 *	-1.78	-0.037 *	-1.89
$Spread_{t\text{-}1}$	0.584 ***	4.15	0.537 ***	3.20	-0.003	-0.07	-0.002	-0.38
$Volatility_{t\text{-}1}$	0.109 *	1.77	0.206 *	1.95	0.096 ***	3.39	0.092 ***	3.17
D_{0945}	0.013	0.91	0.013	0.82	0.002 ***	11.32	0.002 ***	10.39
D_{1045}	-0.103 *	-1.84	-0.103 *	-1.78	-0.001 ***	-5.30	-0.001 ***	-5.41
$D_{1245}(10^{-4})$	9.617	0.53	9.475	0.56	4.241 ***	3.18	4.273 ***	3.08
D_{1345}	0.026	0.81	0.024	0.72	0.092*	1.95	0.088*	1.69
Adj. R^2 (%)	33.68		28.89		14.89		15.15	
F-statistics	372.40***		206.76***		129.61***		91.91***	

Table 7 (*Contd.*)

Variables	*Spread*				*Volatility*			
	All traders		By trader types		All traders		By trader types	
	Model (5)		Model (6)		Model (7)		Model (8)	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel F: Spoofing-sell orders								
Intercept (10^{-4})	1.850	0.61	1.766	0.06	8.491***	4.86	5.205**	2.54
$SO_{Total,t\text{-}1}$	0.128**	2.47	–	–	0.064**	2.29	–	–
$SO_{FI,t\text{-}1}$	–	–	0.204**	2.31	–	–	0.022**	2.04
$SO_{PF,t\text{-}1}$	–	–	0.118**	2.04	–	–	0.021**	1.96
$SO_{DI,t\text{-}1}$	–	–	0.077**	2.24	–	–	0.004*	1.80
$SO_{IT,t\text{-}1}$	–	–	0.047**	2.11	–	–	0.025***	3.52
$Volume_{t\text{-}1}$(10^{-7})	-1.742	-0.91	-2.005	-1.03	1.251***	10.10	1.347***	10.19
$Return_{t\text{-}1}$	0.419*	1.79	0.441*	1.68	-0.031*	-1.74	-0.033*	-1.73
$Spread_{t\text{-}1}$	0.585***	4.15	0.557***	3.40	0.001	0.23	0.002	0.37
$Volatility_{t\text{-}1}$	0.069*	1.68	0.067*	1.66	0.098***	3.46	0.089***	3.00
D_{0945}	0.012	0.69	0.015	1.31	0.012***	11.22	0.012***	9.82
D_{1045}	-0.003**	-2.00	-0.003*	-1.72	-0.001***	-5.48	-0.001***	-5.32
D_{1245}(10^{-3})	1.330	0.76	1.560	0.86	0.443***	3.32	0.498***	3.36
D_{1345}	0.015	0.78	0.019	0.79	0.025**	1.98	0.021*	1.84
Adj. R^2 (%)	33.61		27.09		14.72		15.64	
F-statistics	371.24***		175.69***		127.90***		88.58***	

Table 8 VARs analysis

The table reports the intraday (hourly) relationship among spoofing orders, volatility, volume, spread, return and price within VARs system, with the sample period running from January 2003 to December 2008. A spoofing-buy (sell) order is defined as an order price which is higher (lower) than prior the best fifth bid (ask) price, and with their order size is larger than prior the best fifth bid (ask) quantity, quickly followed by an order on the opposite side of the market and subsequently followed by the withdrawal of the initial order. *** indicates significance at the 1% level; ** indicates significance at the 5% level; and * indicates significance at the 10% level.

Variables	Spoofing orders$_t$		*Volatility*$_t$		*Volume*$_t$		*Spread*$_t$		*Return*$_t$		*Price*$_t$	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel A: Spoofing-buy orders												
Spoofing orders $_{t-1}$	0.232***	11.52	0.020***	2.85	17,395***	2.77	0.100**	2.11	0.014	1.05	4.849 **	2.10
Spoofing orders $_{t-2}$	0.228***	9.34	0.013**	2.09	9,369*	1.88	0.039*	1.67	0.007	0.80	31.110 **	2.53
Volatility$_{t-1}$	0.162*	1.92	0.079***	3.25	120,245***	3.18	0.424**	2.03	-0.004	-0.12	20.200	0.09
Volatility$_{t-2}$	0.123*	1.87	0.076***	4.43	97,377**	2.50	0.125*	1.91	0.045*	1.85	126.310	0.80
Volume$_{t-1}$	0.038*	1.73	0.088***	6.54	0.580***	26.67	-0.013**	-2.25	-0.003	-1.14	-0.064	-0.51
Volume$_{t-2}$	0.021	0.49	0.034***	3.01	0.236***	13.11	-0.012*	-1.77	-0.002	-1.02	-0.034	-0.40
Spread$_{t-1}$	-0.001	-0.12	0.003*	1.72	-5,491***	-2.57	0.914***	77.29	0.001	0.40	2.366	0.20
Spread$_{t-2}$	0.010	1.52	0.001	0.84	-4,655***	-2.71	0.090***	9.49	-0.003	-0.21	1.369	0.14
Return$_{t-1}$	0.052*	1.78	-0.035**	-2.00	-17,335	-0.61	-0.054	-0.34	0.032	1.30	574.091 ***	3.57
Return$_{t-2}$	0.014	0.35	-0.012	-1.08	8,320	0.48	-0.218**	-2.25	0.056***	3.69	284.150 ***	2.86
Price$_{t-1}$	-0.058*	-1.87	-0.002	-0.63	-2.966	-1.05	0.033	0.31	-0.001	-0.26	0.926 ***	57.51
Price$_{t-2}$	-0.001	-0.83	0.001	0.61	1.368	1.02	-0.003	-0.25	0.006	0.85	0.074 ***	4.58
Intercept	0.009*	1.68	0.003 **	2.15	294.157	1.14	-0.002	-1.55	0.018	0.79	2.834 *	1.94
Adj. R^2 (%)	10.81		16.30		63.66		85.48		2.29		59.98	
F-statistics	30.39***		48.21***		425.80		1428.97***		3.71**		396.00***	

Table 8 (*Contd.*)

Variables	Spoofing orders$_t$		*Volatility*$_t$		*Volume*$_t$		*Spread*$_t$		*Return*$_t$		*Price*$_t$	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel B: Spoofing-sell orders												
Spoofing orders $_{t-1}$	0.259***	12.48	0.019***	2.70	7,510*	1.94	0.035*	1.78	-0.007	-1.01	-62.892 ***	-2.78
Spoofing orders $_{t-2}$	0.213***	8.13	0.014**	2.28	2,511	1.25	0.013	1.02	-0.006	-0.72	-53.478 *	-1.93
Volatility$_{t-1}$	0.130*	1.93	0.075***	3.22	124,493***	3.29	0.423**	2.01	-0.002	-0.07	39.092	0.18
Volatility$_{t-2}$	0.180**	2.51	0.077***	4.47	92,365***	3.32	0.006	0.04	0.046*	1.89	139.528	0.88
Volume$_{t-1}$	0.034***	2.54	0.009***	6.75	0.581***	26.67	-0.004**	-2.29	-0.001	-0.27	-0.008	-0.66
Volume$_{t-2}$	0.020	0.41	0.004***	3.24	0.236***	13.02	0.002*	-1.80	-0.002	-1.12	-0.005	-0.53
Spread$_{t-1}$	-0.003	-0.53	0.009*	1.67	-5,111**	-2.40	0.915***	77.57	0.001	0.29	1.041	0.09
Spread$_{t-2}$	-0.003	-0.57	0.002	0.81	-4,574***	-2.66	0.091***	9.51	-0.003	-0.21	1.315	0.13
Return$_{t-1}$	-0.136*	-1.85	-0.030*	-1.72	17,980	0.63	-0.030	-0.19	0.029	1.17	547.631 ***	3.40
Return$_{t-2}$	-0.072	-1.58	-0.006	-0.52	10,842	0.62	0.224**	2.29	0.053***	3.44	257.170 ***	2.58
Price$_{t-1}$	0.019**	2.21	-0.002	-0.85	-3	-1.07	0.004	1.27	-0.002	-1.36	0.926 ***	57.53
Price$_{t-2}$	0.009	1.21	0.001	0.61	2	1.02	-0.003	-0.43	0.001	0.27	0.074 ***	4.61
Intercept	0.018*	1.94	0.005*	1.71	729*	1.81	-0.002	-1.25	0.003	1.32	4.534 ***	2.75
Adj. R^2 (%)	11.60		16.18		63.60		85.46		1.34		54.23	
F-statistics	32.81***		47.81***		424.68***		1426.80***		2.83*		258.19***	