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# Limit order book transparency and order aggressiveness at the closing call: Lessons from the TWSE 2012 new information disclosure mechanism

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Based on the recent TWSE limit order book (LOB) information disclosure mechanism, this paper contributes to the studies on the determinants of order aggressiveness in the closing call. First, on the less well-studied effect of market transparency, we find that, in entering new orders, both individual and institutional investors become more aggressive after the market becomes partially transparent. Second, even though order book information is not available during the opaque period, the effect of the spread on order aggressiveness is still significant, which is evidence of the existence of the expectation effect. Third, the launch of the new mechanism has further reinforced the effect of the spread for individual investors; it, therefore, may answer to the need of individual investors more than it may do for institutional investors.



## 1. Introduction

There has been a proliferation of research concerning the microstructure of financial markets in recent years. Various aspects concerning the behavior of different players in the stock market have received quite a lot of attention and the plausible determinants of their behavior have been scrutinized.

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Consider the case of an order driven market, where the order placement activities, frequently characterized by *order aggressiveness*, play a crucial role. Studies indicate that knowledge regarding the order aggressiveness of informed and uninformed traders is vital to understanding how new information is incorporated into prices (Harris, 1998; Anand et al., 2005; Bloomfield et al., 2005).[1] Both the theoretical and empirical literature often suggest that order aggressiveness is influenced by factors such as the bid–ask spread (Handa and Schwartz, 1996; Ahn et al., 2001; Lo and Sapp, 2010), volatility (Foucault, 1999; Ranaldo, 2004; Goettler et al., 2005; Aitken et al., 2007), order size (Duong et al., 2009; Moshirian et al., 2012), submission time (Harris, 1998; Anand et al., 2005; Bloomfield et al., 2005; Ellul et al., 2007; Ma et al., 2008; Duong et al., 2009), market depth (Parlour, 1998; Griffiths et al., 2000; Ranaldo, 2004; Pascual and Veredas, 2009; Valenzuela and Zer, 2013), the long-memory property of order aggressiveness (Biais et al., 1995; Griffiths et al., 2000; Ellul et al., 2007; Pascual and Veredas, 2009; Yamamoto, 2011), and the transparency of the Limit Order Book (hereafter, LOB) (Flood et al., 1999; Bortoli et al., 2006; De Winnie and Dhondt, 2007; Ma et al., 2008). However, most of these studies focus on the regular continuous-auction period. Studies concerning the forces influencing order aggressiveness outside the regular trading period, such as the pre-opening or closing periods, are rare. To what extent the results of these studies can be extended to the beginning and ending sessions remains to be addressed.

One purpose of this paper is to extend the study of order aggressiveness to the closing period, which in turn is motivated by a new information disclosure mechanism carried out by the Taiwan Stock Exchange (TWSE) on its closing call auction. The *closing call auction* is a mechanism designed to determine the *closing price* for each trading day.[2] It has been widely used to determine the closing prices in major stock exchanges since the late 1990s, partially because it can help improve the market performance indicators (Pagano and Schwartz, 2003) and reduce the degree of market manipulation (Comerton-Forde et al., 2007).[3] Following this trend, since July 2002 the TWSE has instituted a closing call auction for the last 5 min of the market, i.e., from 13:25 to 13:30. Initially, no real-time LOB information was provided during this closing call period. Investors, therefore, were not insulated from the fear of being the victims of information asymmetry due to these so-called "black-box" transactions. In response, the TWSE introduced a new disclosure mechanism for the closing call on February 20, 2012. Under this new mechanism, the best simulated quotes, namely, both the best bid and ask of the closing call session are required to be disclosed every 20 s.[4] This marked the end of a long-lasting era of the "black-box" transactions during the last 5 min of a trading day on the TWSE.[5]

The TWSE "experiment" provides a *unique* opportunity to examine the effect of information disclosure on investors' order aggressiveness during the closing call auction. The uniqueness lies in the nature of the changes concerning the transparency levels of the LOB information. Prior to this new mechanism, the transactions were completely opaque, and termed as "black-box" transactions. Some degree of transparency has ensued because of the new mechanism. This unique switch from the completely opaque period to a partially

[1] Additionally, in a continuous auction, order aggressiveness even determines the incoming trader's expected time-to-execution (Harris and Hasbrouck, 1996; Lo et al., 2002).

[2] Compared to the intraday prices, the closing price plays a unique information role for investors. For example, it is pertinent for mutual fund performance (Hillion and Suominen, 2004), the final settlement price of composite futures (Huang and Chan, 2010), arbitrage strategies of futures, technical analysis (Ko et al., 2014), candlestick charting (Lu, 2014) and the value of security collateral assessed by the financial sector. In addition, it may also affect the opening price and limit-up, limit-down prices of the next trading day, especially in many Asia-Pacific stock exchanges, which set daily price limits.

[3] Most major stock exchanges have both opening call and closing call auctions. The Hong Kong Stock Exchange (HKSE) and SHSE are among the few exceptions that have only opening call auctions. For the stock exchanges with closing call auctions, daily closing prices will be usually based on the closing auction price (Kandel et al., 2012). Nasdaq and the Tel Aviv Stock Exchange (TASE) are the only exceptions to this. The former employs the closing cross price, introduced in April 2004, and the latter takes a weighted average of the transaction prices.

[4] More precisely, it is the best simulated *unexecuted* quotes. In this paper, both the simulated best quotes released by the TWSE in a 20-second increment and our simulated best quotes using the reconstructed real-time order book all refer to the best simulated *unexecuted* quotes. With this understanding, from now on, we shall simply use "best simulated quotes" or "best simulated bid and ask" by making "unexecuted" implicit.

[5] In spite of this the extent of the LOB information disclosure in Taiwan has remained considerably insufficient compared to international standards. For example, the Singapore Exchange (SGX), London Stock Exchange (LSE), and Australian Securities Exchange (ASX) all disclose the entire quotes and volume information of the LOB. The Korea Exchange (KRX) and Tokyo Stock Exchange (TSE) disclose the top three and four quotes of the LOB. The Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE), based on the simulated matching of the LOB, disclose what is known as the indicative auction price, indicative equilibrium volume, and expected unexecuted volume.

transparent level is not easily observed or replicated in other exchanges. This is due to the fact that most of them already have some level of transparency concerning the LOB information and a further regime change can only be *incremental*. Hence, the new information disclosure mechanism of the TWSE provides us with a good opportunity to comprehend how order aggressiveness choices are affected when the *first glimpses of transparency are made available*.

Order aggressiveness is normally studied in the continuous market, and there are very few studies of order aggressiveness in the call market.[6] The concept of order aggressiveness in these two markets can be related, but not the same. This is because in the call market a submission can be canceled or revised before the auction time, and hence is less binding (Biais et al., 1999). In addition, the execution of the submission in the call market is not immediate, but there is a certainty in time to know whether a submission can be executed. These differences may in turn alter our concept of the *non-execution risk* and the *winner's curse* (to be reviewed in Section 2.1), the two fundamental factors concerning traders in the continuous market (Foucault, 1999). For example, the price under the call auction is determined by a collection of submissions, which makes the winner's curse issue milder; similarly, under the grouping match, a submission does not have to be excessively aggressive to avoid the non-execution risk. Nevertheless, as long as the call auction is governed by *the price and time priority rule*, the two fundamental concerns in the call market are only a matter of degree, and not a matter of presence or absence.

Despite this being the case, it is still not clear whether the determinants which are found to be significant in the continuous market (to be reviewed in Section 2.2) can also be extended to the call market. This is because, in the continuous market, traders can see order book information, such as the bid–ask spread, in real time, but in the call market this information is either unavailable, e.g., the opaque period (before the new TWSE mechanism), or only disclosed in discrete time, e.g., the partially transparent period (after the TWSE mechanism). Therefore, if the spread information is not constantly disclosed, can it still be a determinant of order aggressiveness?

Presumably, even though the order book information is not available in real time, as long as it is pertinent to the decision on order aggressiveness, investors may still tend to form their subjective expectations based on their own limited information, called the *expectation effect*. In a sense, they attempt to construct part of the real-time order book using their own information. The question then is how close their 'perceived order book' is to the 'actual order book', or, to a lesser extent, how close their perceived real-time spread is to the actual real-time spread. We would not intend to involve any formal rational-expectation argument, nor would we intend to incur the troubling infinite-regress problem. Instead, an intuitive argument is that if the information is revealed more frequently, say, from no disclosure (the opaque period) to every 20 s (the partially transparent period), the two 'books' (two spreads) will be closer than otherwise; furthermore, if the two 'books' are closer, then the working of each determinant in both markets will become more similar.

The above argument provides us with a 'theoretic' foundation and basic drive for empirically examining whether the order aggressiveness pattern in relation to the key chosen determinants changes after the launch of the new information disclosure mechanism. By the argument above we would expect that the partially transparent market may enable investors to have a perceived order book or perceived spread closer to the actual ones than what the opaque market may do. If so, we may expect a change in the order aggressiveness behavior in the two markets; the partially transparent one is expected to be better predicted by the determinants conventionally employed in the continuous market, but the opaque one is expected to be less predicted by them. The purpose of this empirical study is to ascertain whether this is the case.

Our research question with regard to the effect of the initial market transparency is refined by distinguishing two types of investors, namely, *individual investors* and *institutional investors*.[7] Traditionally, individual investors are regarded as uninformed traders owing to the lower private information that they possess relative to institutional investors, who are regarded as informed traders (Ma et al., 2008; Duong

[6] The only exception known to us is Moshirian et al. (2012). They examine the determinants of order aggressiveness during the pre-opening call auctions on the ASX.

[7] Though there are many studies investigating the determinants of order aggressiveness, only a few of them distinguish traders into multiple groups based on their identities (Aitken et al., 2007; Duong et al., 2009). Among these studies, Aitken et al. (2007) highlight the supply of liquidity and the price aggressiveness of several types of institutional investors, including hedge funds, mutual funds, index funds, and insurance companies. Duong et al. (2009) distinguish traders into individual and institutional investors. Their results document that both these types of investors tend to become less aggressive when the spread widens.

et al., 2009).[8] Thus, we can compare the order aggressiveness of these two types of investors through their responses to an initial improvement in the LOB transparency.

By making this comparison, we can see how *differently* individual investors and institutional investors react to 'a light after long darkness' and how the different reactions are related to their original information advantageous position. Can this 'little light' help the information disadvantaged traders to improve their quote precisions and economic well-being? By answering these questions, we can have a reference point to evaluate what may happen if more 'light' is further brought into the market, or answer the policy-oriented question: when will the 'light' be sufficient?

Our research question is further refined by also distinguishing large and small cap stocks,[9] in order to account for the fact that traders may expend varying amounts of resources on monitoring the status of the LOB information.[10]

We formulate the order aggressiveness behavior of investors using a three-stage stochastic choice model. In a similar vein to Biais et al. (1995) and many subsequent studies,[11] we classify order aggressiveness choices into four levels, via three stages. Technically, the classification is based on the position of the order prices relative to that of the best quotes of the LOB.

The above stochastic choice model can be represented by a *three-stage sequential ordered probit* (hereafter, SOP) model (Pascual and Veredas, 2009; Valenzuela and Zer, 2013). This setup with a binary choice in each stage enables us to gauge the effect of each determinant (regressor), such as the level of transparency, simply from the sign of the respective coefficient, except interactive terms.[12] The proposed probit model is then estimated using the intraday tick data corresponding to the period when the regime change occurred. We employ two sample periods. The first or the *opaque period* is from November 21, 2011 to February 17, 2012, i.e., *three months before* the introduction of the new information disclosure mechanism. The second or the *partially transparent period* is from February 20, 2012 to May 15, 2012, the *three months after* the introduction.

A quick glossary of our findings is as follows. The effects of a few major determinants on order aggressiveness, such as spread, volatility, lagged level of order aggressiveness, and size are all founded to be in line with what are known in the literature. There are, nonetheless, three departures contributing to this body of literature. First, on the less well-studied effect of market transparency, we find that, in entering new orders, both individual and institutional investors become more aggressive after the market became partially transparent. Second, order aggressiveness is found to decrease over time. This time pattern is at odds with the existing literature. Third, the month-end effect, a determinant largely ignored in the literature, has a positive effect on the order aggressiveness of institutional investors. The last two additions suggest that, although the empirical order aggressiveness models used in the continuous market may be communicated to the closing call auction, due to its unique function, the closing call deserves its own identity.

Fourth, it is interesting to see the significance of the spread on order aggressiveness, in particular, given that the spread information is not at all available during the opaque period. Hence, our finding confirms the *expectation effect*, i.e., investors based their decisions on their own 'simulated' quotes. We further find that after the launch of the new mechanism the expectation effect is more prominent for individual investors but less so for institutional investors, which indicates that the limited market transparency policy up to this point may answer to the need of individual investors more than it may do for institutional investors. This result may be anticipated due to the stereotype of individual investors being uninformed traders, but whether

[8] Some studies provide evidence for institutional investors having a better advantage regarding private information than individual investors (Szewczyk et al., 1992; Alangar et al., 1999). Additionally, Anand et al. (2005) document that the rate of return of institutional limit orders surpasses that on the retail limit orders.

[9] The shares are classified into large and small cap stocks based on their market capitalization.

[10] Several studies have made a distinction between the monitoring activities concerning large and small cap stocks. For example, active institutional investors, such as hedge funds, may expend more resources to monitor the status of the LOB information of large cap stocks compared to small caps (Aitken et al., 2007; Liu, 2009). Duong et al. (2009) argue that the institutional investors adopt fewer 'picking-off' activities in small cap stocks, since monitoring is relatively low in small cap stocks.

[11] See, for example, Griffiths et al. (2000), Ranaldo (2004), Ma et al. (2008), Duong et al. (2009), Pascual and Veredas (2009), and Valenzuela and Zer (2013).

[12] For the ordered probit model, if there are more than two choices, then the effect of the regressor on the intermediate-level choices will be harder to decide just by reading the sign of the respective coefficients. Several early models of order aggressiveness do have this form (Griffiths et al., 2000; Ranaldo, 2004; Duong et al., 2009; Pascual and Veredas, 2009; Valenzuela and Zer, 2013). For interactive term, see the discussion in Section 6.3.

this can have any implications for the economic well-being of individual investors deserves further investigation.

The remainder of this paper is structured as follows. In the next section, we briefly review the relevant literature by focusing on the determinants of the choice of order aggressiveness. Section 3 presents the institutional details of the TWSE. Section 4 gives the data description, including the basic structure of order submissions. Section 5 introduces the three-stage binary choice model as the classification scheme of order aggressiveness and presents the basic statistics of order aggressiveness during the closing call session of the TWSE. Section 6 introduces the sequential ordered probit model applied in this paper with a description of the included explanatory variables. Section 7 presents the empirical results with discussions, and is followed by the concluding remarks given in Section 8.

## 2. Literature review

In this section, we review the literature on order aggressiveness, mainly focusing on its determinants. Early studies (Cohen et al., 1981; Copeland and Galai, 1983; Handa and Schwartz, 1996) conclude that the choices regarding market and limit orders often depend on the trade-offs between different types of costs.

### *2.1. Fundamental concerns: non-execution risk and winner's curse*

While incoming traders immediately incur a higher transaction cost when delivering market orders, they face a non-execution (hereafter, NE) risk if they submit limit orders. For limit orders, an increase (decrease) in bid (ask) prices contributes to the chance of making a deal. However, it is likely to lead a trader to buy (sell) stocks at relatively high (low) prices. This, in turn, potentially aggravates the so-called winner's curse (hereafter, WC) problem.

Consequently, the degree of order aggressiveness may depend on the risk of non-execution and the potential for WC. Higher risks of NE and a fall in the potential for WC tend to stimulate the degree of order aggressiveness and vice versa. Foucault et al. (2005) and Rosu (2009) characterize the choices of order aggressiveness with a simple dichotomy. In the presence of information asymmetry, they argue that uninformed traders tend to submit limit orders to avoid the WC problems. Informed traders, on the other hand, are likely to submit market orders given their information advantage regarding the likely market transactions.

### *2.2. Specific determinants*

Many studies have attempted to explore specific determinants of order aggressiveness for incoming traders from the historical records of stock prices, the state of the LOB, and the characteristics of current order submissions. Non-execution risk and the winner's curse provide us with a basic framework to understand the role of these specific determinants.

#### *2.2.1. Volatility*

With respect to the historical records of stock prices, Foucault (1999) develops a dynamic model and argues that with an increase in volatility, uninformed traders become concerned that the market consensus value may change at anytime and that the risk of being picked off by informed traders increases. Thus, they are forced to be more prudent (or less aggressive) in placing their orders. Bae et al. (2003) and Ranaldo (2004) find that when volatility increases, market orders are less attractive and there is an increase in the proportion of limit orders in the total flow of orders. Goettler et al. (2005) and Aitken et al. (2007) further document that investors may submit less aggressive order prices when price volatility increases. However, few studies instead expect greater ‘picking-off’ activity along with a higher degree of order aggressiveness by some institutional investors when volatility increases (Aitken et al., 2007; Duong et al., 2009).

#### *2.2.2. Bid/ask spread and the order depth*

The state of the LOB has been identified as a determinant of order aggressiveness in the later studies. In general, states of the LOB are meant to be publically disclosed real time information, such as bid/ask quotes along with depths. Handa and Schwartz (1996) indicate that a wider bid–ask spread not only reflects a decrease in market liquidity, but also implies an increase in the transaction costs immediately incurred on the market orders (i.e., an aggravation of the potential WC problems) and thus induces investors toward submitting limit orders. This viewpoint has received support from different empirical studies (Ahn et al., 2001; Lo and Sapp, 2010).

Choice of order aggressiveness may also depend on the order depth. Parlour (1998) argues that an increase in the depth of the same side of the LOB may delay the expected time-to-execution, thus stimulating the investor's order aggressiveness. The reverse holds true for an increase in the depth of the opposite side of the LOB. This argument is referred to as the *crowding-out effect* in the later literature (Griffiths et al., 2000; Ranaldo, 2004). However, it is not uncommon to observe that the limit orders cluster away from the best quotes (Rosu, 2009). Pascual and Veredas (2009) and Valenzuela and Zer (2013) discuss the *signal effect*, which indicates that higher depths away from the best ask (bid) quote may signal that the quote is "too low (high)". This signal, in turn, affects the choice of order aggressiveness for the incoming traders.

#### *2.2.3. Order size and private information*

The state of the trader's own order placement decision may also influence the choice of order aggressiveness. Prior studies suggest that order size may reveal the information about the true value of an asset, since informed traders are more likely to submit large orders (Easley and O'Hara, 1987). Large orders are often driven by private information. When information regarding sizeable orders is revealed, it may attract more investors to compete. This phenomenon is known as the *front-running risk* in the literature (Danthine and Moresi, 1998). To lessen the front-running risk caused by the imitation behaviors of uninformed traders, it has been documented that larger orders tend to be more aggressive (Duong et al., 2009; Moshirian et al., 2012).

#### *2.2.4. Submission time*

Some studies investigate the relationship between the timing of order submission and order aggressiveness (Anand et al., 2005; Bloomfield et al., 2005; Ellul et al., 2007; Ma et al., 2008; Duong et al., 2009). These studies indicate that the intraday patterns of order aggressiveness are not similar across different groups of investors. Informed traders tend to place relatively aggressive orders during opening hours by virtue of their information advantage, whereas uninformed traders tend to be conservative at this stage. However, uninformed traders may increase their order aggressiveness in the later trading hours because they are able to gradually accumulate relevant information from the market over time. Harris (1998) argues that some institutional investors place their most aggressive orders at the end of the trading day, since they may be under pressure to meet their targeted transaction volume for the day.

#### *2.2.5. Persistence*

Similar to the long-memory feature of high-frequency data in the financial markets, some studies focus on the persistence of order aggressiveness. Biais et al. (1995) report the *diagonal effect*, which indicates that a positive serial correlation in order aggressiveness may be a result of the imitation of uninformed traders, the order splitting of informed traders, competition for the few transaction opportunities, and even reactions to the sudden events that recently took place in the market. Evidence of similar order-by-order serial correlation in order aggressiveness is found repeatedly in various empirical studies (Griffiths et al., 2000; Ellul et al., 2007; Pascual and Veredas, 2009).

#### *2.2.6. Degree of transparency*

Compared to other determinants, relatively few studies tend to discuss the effect of the transparency of the LOB information on the choices of order aggressiveness.[13] In theory, an improvement in the transparency of the LOB information undoubtedly alters the degree of information advantage for both informed and uninformed traders. Given the high cost of collecting relevant transaction information (Pagano and Roell, 1996), Flood et al. (1999) argue that uninformed traders may be forced to submit more aggressive orders in a less transparent market (or trading environment), in exchange for the higher probability of execution.

[13] Most in the literature concerning the improvement of the transparency of the LOB information mainly focuses on its impact on indicators of market performance, such as liquidity, volatility, and efficiency. However, the reactions of these indicators remain controversial. See the details in Madhavan (1996), Boehmer et al. (2005), Madhavan et al. (2005), and Eom et al. (2007).

Based on this argument, uninformed traders may decrease their degree of order aggressiveness when the market is more transparent. However, the improvement in market transparency may also alleviate the WC problem, meanwhile stimulating the uninformed trader's degree of order aggressiveness.

In addition, according to the argument known as the *rat race effect*, once the relevant information about the transaction is revealed, it may intensify the competition among informed traders (Foster and Viswanathan, 1996; Back et al., 2000). There has been some evidence for the rat race effect. For the Sydney Futures Exchange, Bortoli et al. (2006) conclude that the traders are forced to deliver more market orders in exchange for a higher probability of execution under the over-transparent environment of the LOB information.

Finally, if the LOB information disclosure is partial, informed traders may have an incentive to camouflage their trading information as much as possible (Barclay and Warner, 1993), for example, by hiding their order information by submitting limit orders with undisclosed quotes (De Winnie and Dhondt, 2007). TWSE has improved the transparency of the LOB information on two occasions for the regular session in the years 2002 and 2003.[14] During this process, Ma et al. (2008) observe that even though the institutional investors attempt to hide transaction information by splitting their orders, order aggressiveness still increases, just as predicted by the race rat effect.

### 2.2.7. Price discovery without trading

The non-binding feature of the call market as discussed in Section 1 motivates us to review the literature on price discovery without trading. Due to the non-binding features, some orders in call sessions can be manipulative (Biais et al., 1999) or strategic (Kuk et al., 2014), which have limited intention of trading. On the other hand, the literature also points out that some devices, such as the crossed or locked quotes used by the dealers on the NASDAQ, can also enhance the real intent of trading and make the disclosed information part of the price discovery (Cao et al., 2000). Biais et al. (1999) has added a time frame for this mixture of intents indicating the transition from the early noisy hypothesis to the later learning hypothesis. Actually, Moshirian et al. (2012) find that during the pre-opening period on the ASX, learning about the equilibrium valuation of securities prices occurs as the market approaches the opening time.

This literature can have two implications for our study of order aggressiveness. First, since we study the effect of the new information disclosure mechanism in the closing call auction, we can expect that some strategic orders can occur so as to manipulate the disclosed simulated quotes. These orders with limited intention of trading will lead to subsequent order revisions or cancelations. Hence, after the launch of the new mechanism there will be an increase in the tendency for submitted order revisions and cancelations. Moreover, apart from the strategic considerations, the information disclosure may still have a signal effect to help investors, particularly uninformed traders with true intent of trading, to revise or cancel prior improper orders. Therefore, by combining these two effects, the strategic play and the signal effect, together, we may expect that the new information disclosure mechanism can have a positive effect on order revisions and cancelations. Second, the time frame of the non-binding feature also suggests that the order revisions and cancelation may decrease as the closing time is approaching. Both of these two implications will be formulated into hypotheses and will be tested in this paper (Sections 7.1.1 and 7.2.3).

## 3. Institutional details

The TWSE has been an order driven market with a fully electronic and computerized trading platform since 1993. There were 824 stocks that were listed on the TWSE as of February 2014. Unlike most other exchanges that allow market orders, the TWSE *accepts only limit orders* and these are executed *on the basis of a strict price and time priority*. The daily price fluctuation limits for stocks are set at 7% of the closing price for the preceding trading day. Therefore, this limit-up (down) can be treated as the highest (lowest) possible order price.

The trading period during a day is divided into three sessions. The first of these is the opening call auction session that commences at 8.30 am and lasts for 30 min. Investors can begin to submit, revise, or cancel their orders during this period.[15] However, none of the LOB information was disclosed from 8:30–9:00 and it

[14] On July 1, 2002, the TWSE increased the disclosure level LOB information from the best quotes to the best quotes along with depths. On January 2, 2003, the disclosed LOB information was increased to the top five quotes, along with depths.

[15] For the TWSE, the only allowable form of order submission is the *reduction* of order size. The original bid and ask should remain intact. The time priority of the order revision remains the same as its original submission.

remains a “black box”. These orders over the pre-trading time are then matched to determine the opening price at 9:00. Between 9:00 and 13:25, the second or the regular trading session consisting of incessant 20-second call auctions takes place. In this design, there is no break time or a separation of the entire regular trading session into morning and afternoon sessions. During this period, the top five quotes along with the depths of those unexecuted orders are disclosed right after every 20-second call auction.

The third or the closing session is essentially a single 5-minute call auction that takes place during the last 5 min (from 13:25 to 13:30) of the trading day. Since there is no restriction regarding the non-cancelation period, investors are free to submit new orders, and make revisions or cancelations of their original order submissions. All orders participating in the closing call are not executed until 13:30. At 13:30, the closing prices are determined by calculating the transaction price that allows for maximizing the executable trading volume. Those unexecuted orders from the closing session are then purged from the order book overnight. During the entire closing session, no updated LOB information was disclosed prior to February 20, 2012. Thus the “black box” trading which prevails in the opening call recurs during the last 5 min of every trading day.

In a move to enhance the market transparency of the closing session, the TWSE recently introduced a new information disclosure mechanism for the closing calls, starting from February 20, 2012. According to this new mechanism, the simulated best bid/ask quotes of the LOB are disclosed every 20 s in the closing call (from 13:25 to 13:30), just with the same frequency as that employed in the regular trading session. Although orders are not actually executed until 13:30, TWSE keeps calculating the simulated transaction price every 20 s, with the objective being to maximize the executable trading volume. The best bid/ask quotes of those “unexecuted” orders are disclosed right after every 20-second simulated call auction. The investors are allowed to freely submit new orders, and also revise and cancel their original orders during the closing call, as they did before the new mechanism was introduced.

## 4. Data description

The data for this study come from the Taiwan Stock Exchange Corporation (TSEC) and Taiwan Economic Journal (TEJ) database, and cover a total of 121 large cap and 121 small cap listed stocks in the TWSE (to be detailed in Section 4.1). The time period under consideration includes 118 trading days, consisting of two separate spans lasting from November 21, 2011 to February 17, 2012, and from February 20 to May 15, 2012, respectively. These two spans, which are centered around the event date, represent distinct degrees of transparency of the LOB information during the closing call auction. In this paper, the former is referred to as the *opaque period*, covering around three months before the new closing call's information disclosure mechanism was introduced on February 20, 2012. The latter is called the *partially transparent period*, and refers to the three months after its introduction.

During the closing call auction, there is no updated LOB information disclosure in the opaque period, whereas the simulated best bid/ask quotes of the LOB are disclosed every 20 s in the partially transparent period. Unlike the regular trading session, where the top five bid/ask quotes along with depths are completely disclosed every 20 s, the degree of transparency during the closing call is still relatively limited even after the changes in the disclosure norm. Hence, we refer to this as the ‘partially’ transparent period.

### *4.1. Large and small cap stocks*

In this paper, the sample is separated into two parts, viz., the large cap and small cap stocks, in order to investigate the possible differences in the order choices. There are a total of 824 stocks listed on the TWSE during the sample period. Based on the consideration of market capitalization and trading activity (Duong et al., 2009), we select both 121 large cap stocks and 121 small cap stocks, a total of 242 stocks, by the following procedure. First, we do not consider full-cash delivery stocks, warned securities, disposition securities, attention securities, initial public offering (IPO) securities or de-listed securities. Due to various concerns, they are not applicable to the measure of order aggressiveness proposed in this paper.[16] Second, we also eliminate financial and insurance shares beforehand due to their relatively high leverage ratio

[16] For example, the new disclosure mechanism does not apply to full-cash delivery stocks, and there are no daily price fluctuation limits for IOP shares in their first five trading days.

(Fama and French, 1992). After these two screenings, there remain a total of 687 stocks. Third, among these 687 remaining stocks, those which are included in the Taiwan 50 and Taiwan Mid-Cap 100 are designated as the large cap listed stocks for the use of this study. There are a total of 121 such stocks; among them, based on the information dated 20 February 2012, 39 are from the Taiwan 50 and 82 are from the Mid-Cap 100. Fourth, after removing these 121 large cap stocks, we rank the remaining 566 stocks by their average daily trading volume, and delete the bottom one third (188 stocks); for the remaining 378 stocks, we then designate the 121 stocks with the least daily trading volumes as the small cap listed stocks for the use of this study. Through these procedures, the selected 242 stocks can account for 73.23% of market capitalization and 82.98% of it, if financial and insurance shares are not taken into account. The mean weights of market capitalization for each share in the large and small cap stocks are 0.59% and 0.02%, respectively. Table 1 provides the basic descriptive statistics for these stocks by capitalization groups.

### 4.2. Datasets

We utilize two different datasets from the TSEC and the TEJ databases for each sample stock. The first dataset is the proprietary *Order Book Dataset*, which records the details of each order, including order types (denoting the state of order submission, revision, and cancelation), date, timing of delivery (precise to the nearest hundredth of a second), order price, order volume, order direction (buy or sell order), and the identity of investors (individual or institutional investors). The second is the *Disclosure Book Dataset*, which records the contents of each entry of the publically disclosed LOB information, including disclosure date and time, and more importantly, the disclosed details about bid/ask quotes along with depths (denoted by the numbers of shares). It should be noted that for the regular trading session (from 9:00 to 13:25), the information regarding the top five bid/ask quotes, along with depths for every 20 s, are completely available in the *Disclosure Book Dataset*. By contrast, for the closing call session (from 13:25 to 13:30), none of the disclosed LOB information can be found until the introduction of the new information disclosure mechanism. Since 20 February 2012, the simulated best bid/ask quotes for every 20 s during the closing call session have been available from the *Disclosure Book Dataset*.

### 4.3. Basic structure of order submissions

Table 2 provides the basic structure of the order submissions during the closing call session for the 121 large and 121 small cap stocks under investigation. In total, we investigate 4,112,929 orders submitted by all investors, including 3,230,389 orders of large cap stocks, and 882,540 orders of small cap stocks. Table 2 shows how the order submissions, in quantity and value, are distributed between the individual investors and institutional investors for both the large and small cap stocks.

**Table 1**
Basic statistics of large and small cap stocks.

| Capitalization group | Market cap (B NTD) | Market share (%) | Trading volume (M NTD) | Number of submissions (closing call auction) |
|---|---|---|---|---|
| *Large cap* | | | | |
| Average | 119.03 | 0.59% | 503.89 | 226.25 |
| (Std. dev) | (239.67) | (1.18%) | (788.79) | (188.89) |
| *Small cap* | | | | |
| Average | 4.14 | 0.02% | 46.59 | 61.81 |
| (Std. dev) | (1.43) | (0.01%) | (40.85) | (30.55) |

What is shown in columns two to five are descriptive statistics of market capitalization (column two), market share in terms of capitalization (column three), trading volume (column four), and the number of submissions during the closing call auction (column five) of the large and small cap stocks. The descriptive statistics reported include the average (rows two and four) and the standard deviation (rows three and five) of the population of 121 stocks for each group. We first calculate the daily average of each of the four variables for each stock. The average is taken over the entire sample period, from Nov. 21, 2011 to May 15, 2012, amounting to 118 trading days. The unit for market capitalization is NTD billions (B NTD), and the unit for daily trading volume is NTD millions (M NTD). We then use 121 daily averages from each capitalization group to derive the corresponding group statistics.

**Table 2**
The structure of order submissions.

| Block 1 | % of number of submitted by | | % of number of orders belonging to | |
|---|---|---|---|---|
| | Individual investors | Institutional investors | Orders entered | Orders canceled (revised) |
| Large cap stocks | 68.15% | 31.85% | 78.71% | 20.81% (0.47%) |
| Small cap stocks | 76.28% | 23.72% | 79.78% | 19.63% (0.59%) |
| **Block 2** | **% of number of orders entered by** | | **% of number of orders revised or canceled by** | |
| | Individual investors | Institutional investors | Individual investors | Institutional investors |
| Large cap stocks | 68.12% | 31.88% | 68.21% | 31.79% |
| Small cap stocks | 74.25% | 25.75% | 84.57% | 15.43% |
| **Block 3** | **% of value of shares of orders entered by** | | **% of value of shares of orders revised or canceled by** | |
| | Individual investors | Institutional investors | Individual investors | Institutional investors |
| Large cap stocks | 23.82% | 76.18% | 47.98% | 52.02% |
| Small cap stocks | 56.90% | 43.10% | 82.85% | 17.15% |
| **Block 4** | **Value of shares per order entered by (in terms of millions of NTD)** | | **Value of shares per order revised or canceled by (in terms of millions of NTD)** | |
| | Individual investors | Institutional investors | Individual investors | Institutional investors |
| Large cap stocks | 0.25 | 2.81 | 0.33 | 1.05 |
| Small cap stocks | 0.16 | 0.43 | 0.25 | 0.25 |

This table presents the structure of orders submitted by individual and institutional investors during the closing call auction (from 1:25 pm to 1:30 pm). The value reported here is the average taken over the whole population of the 121 stocks for both large cap and small cap, respectively. For each stock, the structure of orders is derived using the data in the closing call auction for the whole sample period, from 21 November 2011 to 15 May 2012, amounting to 118 trading days. The table is organized as four blocks, each with a left and a right panel. In the left panel of the first block, we present the percentages of the number of orders submitted by individual and institutional investors. Since on the TWSE the investors are allowed to freely submit new orders, or decrease the shares of orders already submitted (order revision), or even decrease the shares of orders already submitted to zero (order cancelation) during the closing call, we also provide the percentages of the number of orders belonging to the first kind (new orders) and those belonging to the second kind (revisions and cancelations) in the right panel of the first block. In the second block, we present the percentages of the number of orders submitted by individual and institutional investors, both the first kind (on the left) and the second kind (on the right). In the third block, we present the percentages of the value of shares of orders submitted by individual and institutional investors, both the first kind (left) and the second kind (right). In the fourth block, we also report the value of shares per order submitted by individual and institutional investors, both the first kind (left) and the second kind (right). The unit is NTD millions.

From Table 2, we can see that, in terms of quantity, irrespective of market capitalization and order types (new orders, revisions, or cancelations), the closing call auction of the TWSE is dominated by individual investors. They account for 70% to 80% of all orders. In terms of market value, individual investors still dominate the small cap stocks. However, institutional investors are more engaged in trading large cap stocks and they contribute to three-fourths of the new orders in the closing call auction. For large cap stocks, their submitted value of shares per order (2.81 million NTD) is ten times higher than that for individual investors (0.25 million NTD). In addition, the value of shares per new order of small cap stocks for institutional investors is only 0.43 million NTD, indicating again that institutional investors have large cap stocks as their investment focus. Table 2 also indicates that among the two kinds of order submissions, new orders are the major kind, accounting for 80% of all orders.

## 5. Order aggressiveness

As in most empirical studies (Griffiths et al., 2000; Ranaldo, 2004; Ma et al., 2008; Duong et al., 2009; Pascual and Veredas, 2009; Valenzuela and Zer, 2013), we utilize the classification scheme consistent with that of Biais et al. (1995) to measure the level of order aggressiveness of each order submission. Specifically, in this study, it is measured by the position of the order price relative to that of the latest best quotes. We use the reconstructed real-time order book to determine the latest best bid/ask quotes (see Section 5.2).[17]

### 5.1. Classification scheme: three-stage binary choice model

Our classification of order aggressiveness can be illustrated by the proposed *three-stage binary choice model*, which can be depicted as a *binary decision tree*, as shown in Fig. 1. Basically, we treat each order submission as an outcome of a sequential decision-making process and endow this process with such a decision tree. From the leftmost part in Fig. 1, the first decision node (node I), asks whether the trader is still 'passionate' about trading. The trader who submits a cancelation order will be considered the least aggressive, indexed by $C1$.[18] If the trader submits a revised order or a newly-entered order, then node II is presented to the trader.[19]

Node II asks whether the trader would submit an *impatient order*. Specifically, it asks whether the trader would offer a price which is at least not inferior to the best unexecuted quote of the opposite side of the real-time LOB. For example, for a buy order, it means that the price offered cannot be lower than the current best ask in the LOB; similarly, for a sell order, this means that the price offered cannot be higher than the current best bid in the LOB. If the answer is no, then that decision (the patient order) is classified as the second least aggressive level, indexed by $C2$. If the answer is yes, then the trader is presented with node III.

Node III asks whether the trader would offer the *most aggressive* price. Specifically, it asks whether the trader would offer the maximum possible price (limit up) for a buy order or the minimum possible price (limit down) for a sell order.[20] If the answer is yes, that decision is classified as the most aggressive level, indexed by $C4$; otherwise, it is classified as the second most aggressive level, indexed by $C3$.

To sum up, we classify all order submissions into four levels of order aggressiveness (also shown in the gray squares in Fig. 1):

- ($C1$) The least aggressive price: order cancelation
- ($C2$) The second least aggressive price (patient order): order submission with a price inferior to the current best quote on the opposite side of the LOB
- ($C3$) The second most aggressive level (impatient order): order submission with a price not inferior to the current best quote at the opposite side of the LOB, but not high to limit up or low to limit down
- ($C4$) The most aggressive level (impatient order): order submission with limit up (for buy orders) or limit down (for sell orders).

### 5.2. Order book: discrete time vs. Real time

Most studies on the classification of order submissions deal with continuous markets, and the order book information is disclosed in continuous time, whereas our study deals with call markets and the order book information in the call market is disclosed only in discrete time. This difference introduces a fundamental question with regard to *the version of the order book* which is suitable for defining the relative position of each order submitted in real time. How accurate is the classification of order aggressiveness given that the order book information is not disclosed in real time, but only in a 20-second increment? If we use the same information disclosed at 13:30:20, should a classification of an order submitted right after this disclosure, say at 13:30:21, be more accurate than the classification of an order submitted right before the next disclosure, say 13:30:39? One may suspect that the information disclosed at 13:30:20 may be current for

[17] While in several studies the depths of the order book are also used to determine the levels of order aggressiveness (Pascual and Veredas, 2009; Valenzuela and Zer, 2013), due to the limited transparency of the LOB information for the TWSE, we do not consider depth quotes in our measure.

[18] Ranaldo (2004) also classifies order cancelation as the least aggressive level.

[19] In this paper, the way in which we deal with the revised order is to treat it as a cancelation of the original order, which is then followed by a submission of a new order. As we can see from Table 2, order submissions account for less than 0.6% of the total submissions; hence the effect of this handling is very limited.

[20] As mentioned in Section 3, on the TWSE, the daily price fluctuation limits for stocks are set at 7% of the closing price for the preceding trading day.

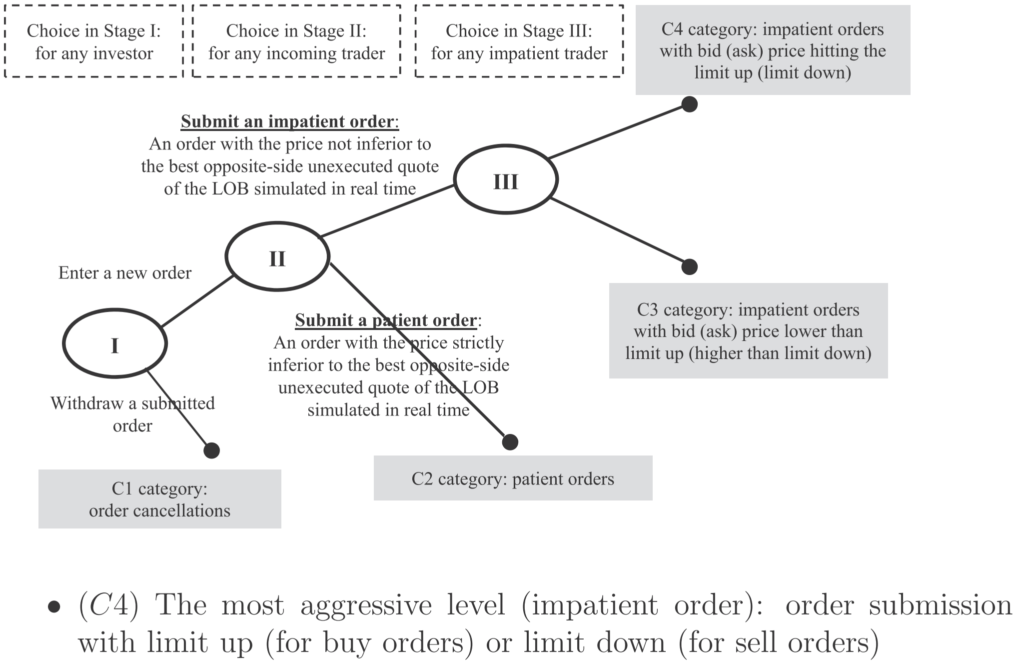



**Fig. 1.** The three-stage decision tree of order aggressiveness.

the former but stale for the latter. In this case, *can we still use the order book information disclosed in discrete time to perform the classification*?

We consider this issue to be basically an empirical one, and it can be properly addressed only through empirical evidence. In this section, in addition to the discrete-time order book, we use the data from the

**Table 3**
Consistency rate between the real-time order book and the discrete-time order book: quotes and order aggressiveness.

| Intervals | 121 large cap stocks | | | 121 small cap stocks | | |
|---|---|---|---|---|---|---|
| | $B_i^e = B_i$ | $A_i^e = A_i$ | $C_i^{dis} = C_i$ | $B_i^e = B_i$ | $A_i^e = A_i$ | $C_i^{dis} = C_i$ |
| Whole | 38.46% | 36.31% | 92.86% | 44.11% | 45.90% | 93.76% |
| 1st half | 41.14% | 38.65% | 94.04% | 48.27% | 51.25% | 94.83% |
| 2nd half | 32.83% | 31.33% | 90.28% | 36.98% | 36.61% | 91.88% |
| Whole | 82.77% | 81.92% | 98.38% | 86.10% | 86.56% | 98.54% |
| Within 10 s | 83.71% | 82.66% | 98.73% | 88.70% | 89.69% | 98.94% |
| Beyond 10 s | 82.47% | 81.68% | 98.28% | 85.49% | 85.83% | 98.45% |

The table shows the consistency rates of simulated quotes and actual quotes and the consistency rate of order aggressiveness classification made using simulated and actual quotes. $B_i^e$ and $A_i^e$ refer to the quotes available at the moment immediately prior to the submission of order $i$, denoted by $t_i$. In the case of the opaque market, $B_i^e$ and $A_i^e$ refer to the last publicly announced best bid and ask before 13:25. In the case of the partially transparent market, $B_i^e$ and $A_i^e$ are the simulated discrete-time best bid and ask announced at the time for which the subsequent 20 s contain $t_i$. $B_i$ and $A_i$ are the actual (real-time) best bid and ask at $t_i$, which are based on our reconstructed real-time order book. In addition, $C_i$ denotes the level of order aggressiveness of order $i$ evaluated using the simulated real-time quotes, whereas the $C_i^{dis}$ denotes the one evaluated using the discrete-time quotes released by the TWSE. The table presents the percentage of each of the three equalities, (1) $B_i^e = B_i$ (2) $A_i^e = A_i$ (3) $C_i^{dis} = C_i$, over all submissions. The percentage shown in each cell of the table is the average over all 121 large cap stocks or 121 small cap stocks. The upper panel shows the results of the pre-event period (2011/11/21–2012/02/17), whereas the lower panel shows the results of the post-event period (2012/02/20–2012/05/15). The 'silent moment' of each period is further divided into two halves: for the pre-event period, 13:25:00 to 13:27:30 (first half) and 13:27:30 to 13:30:00 (second half); for the post-event, the 10 s immediately after the disclosure (first half), and the 10 s immediately before the next disclosure (second half).

TWSE dataset (Section 4.2) to reconstruct a continuous-time order book, and use the best bid/ask quotes from both versions of the order book plus the same definition given in Section 5.1 to decide their levels. We then check, order by order, if under these two possibly different sets of quotes the classification result is the same. Denote the level of order aggressiveness of order $i$ evaluated using the real-time quotes by $C_i$, and denote the one evaluated using the discrete-time quotes by $C_i^{dis}$. Then, for each order $i$, either $C_i^{dis} = C_i$ or $C_i^{dis} \neq C_i$. We calculate the percentage of the former (the consistency rate) and the result is shown in Table 3.

What accompanies the consistency rate of the order aggressiveness classification is the consistency rate of quotes. The idea of this consistency rate is to show how the 'perceived' best quotes and the actual best quotes differ at the moment immediately *prior* to each submission. Let $t_i$ be the moment immediately prior to the submission of order $i$. At one extreme, we assume that the 'perceived' best quotes are the latest available order book information announced by the TWSE at $t_i$. We denote the best bid and ask available for investors at time $t_i$ by $B_i^e$ and $A_i^e$, respectively. In the case of the opaque market, $B_i^e$ and $A_i^e$ refer to the last publicly announced best bid and ask before 13:25, since after that there would be no further information available. In the case of the partially transparent market, $B_i^e$ and $A_i^e$ are the simulated discrete-time best bid and ask announced at the time at which the subsequent 20 s contain $t_i$. The *actual* best bid and ask at $t_i$ are based on our reconstructed real-time order book, denoted by $B_i$ and $A_i$, respectively. We check whether $B_i^e = B_i$ and whether $A_i^e = A_i$ over all submission time $t_i$, and the percentage of time that they are the same (the consistency rate) is also shown in Table 3.

Table 3 is composed of two panels. The upper panel shows the results of the opaque period, whereas the lower panel shows the results of the partially transparent period. For each period, we further divide the 'silent moment' into two halves. For the opaque period, the first half is from 13:25:00 to 13:27:30, and the second half is from 13:27:30 to 13:30:00. For the partially transparent period, since the simulated quote is released every 20 s, we take the 10 s immediately after the disclosure as the first half and the 10 s immediately before the next disclosure as the second half. This division into two halves can further help us to see whether the 'stale' state can matter for the consistency rate.

The results in Table 3 can be summarized in two points. First, not surprisingly, the consistency rates of quotes ($B_i^e = B_i$ and $A_i^e = A_i$) are low during the opaque period; only for 30% to 50% of the time are the two quotes equal. However, after the market becomes partially transparent, the consistency rate doubles; for more than 80% of the time the two quotes are the same. With the narrowing gap between the two quotes, investors can form their perceived spread more accurately after the launch of the new mechanism. This may help explain why the classifications of order aggressiveness made based on the simulated real-time quote and the simulated discrete-time quote, $C_i^{dis}$ and $C_i$, become so close during the partially transparent regime; in more than 98% of the time the classifications using the two quotes are consistent.

**Table 4**
The level distribution of order aggressiveness.

| Levels of order aggressiveness | Large cap stocks | | Small cap stocks | |
|---|---|---|---|---|
| | Individual investors | Institutional investors | Individual investors | Institutional investors |
| $C1$ | 21.19% | 21.02% | 22.29% | 13.59% |
| $C2$ | 28.75% | 53.92% | 30.08% | 79.31% |
| ($C2^*$) | (*0.52%*) | (*0.17%*) | (*0.58%*) | (*0.29%*) |
| $C3$ | 20.69% | 8.36% | 22.71% | 3.21% |
| $C4$ | 29.36% | 16.70% | 24.92% | 3.89% |
| Total | 100.00% | 100.00% | 100.00% | 100.00% |
| # of orders | 20,568 | 6,215 | 5,818 | 1,501 |

This table presents the level distribution of order aggressiveness during the closing call auction (from 13:25 to 13:30). The percentages shown here are the mean taken over the sample of 121 large or small cap stocks. Order aggressiveness is classified into four levels (Section 5.1). Quite symmetric to the two emanating nodes of the choice of an impatient order, it is possible that we can have two terminal nodes emanating from the choice of a patient order. In addition to $C2$, the other, denoted by $C2^*$, refers to the orders which buy (sell) with prices just equal to limit-down (limit-up). Obviously, $C2^*$ is even less aggressive than $C2$. Their percentages are also presented in the table. Since its percentages are negligible, this class (as shown in italics), therefore, is not included in our SOP model. At the bottom of the table, we show the mean number of orders, submitted by the individual (institutional) investors during the whole closing call auction across the 121 large cap stocks and the 121 small cap stocks.

Second, as far as the 'stale' state is concerned, without being updated in a timely manner the information announced in the first half becomes naturally more out-of-date in the second half. That is why we see that the consistency rates, both in quotes and in terms of the order aggressiveness classification, are lower in the second halves. During the opaque period, the already low consistency rate in quotes can further drop by 10% to 15% for the small cap stocks. Nonetheless, after the market becomes partially transparent, quotes are updated more frequently, and the consistency rate is improved substantially; even though it still drops in the second half, the magnitude is either negligible or limited.

In sum, the discrete-time quotes and the real-time quotes largely lead to the same classification results. Given their great similarities, we decide to use the real-time best bid and ask to measure order aggressiveness, because it provides us with an 'objective' measure of order aggressiveness in light of the information we have at the time when an order is submitted.

### 5.3. Basic characteristics of order aggressiveness

Table 4 shows how orders are distributed among the four levels of order aggressiveness introduced in Section 5.1. We present the distribution by capitalization and investor types. Two features stand out. First of all, individual investors are more aggressive; their impatient orders ($C3$ and $C4$) account for a large proportion of all orders, 50.05% for large cap stocks and 47.63% for small cap stocks. The same ratios for institutional investors are only 25.06% and 7.10%, respectively. On the other hand, orders submitted by institutional investors are mainly classified as patient orders ($C2$); the percentage of $C2$ is 53.92% for large cap stocks and 79.31% for small cap stocks. Second, market capitalization has little effect on the distribution of the aggressiveness level in the case of individual investors, whereas it has a discernable effect in the case of institutional investors.

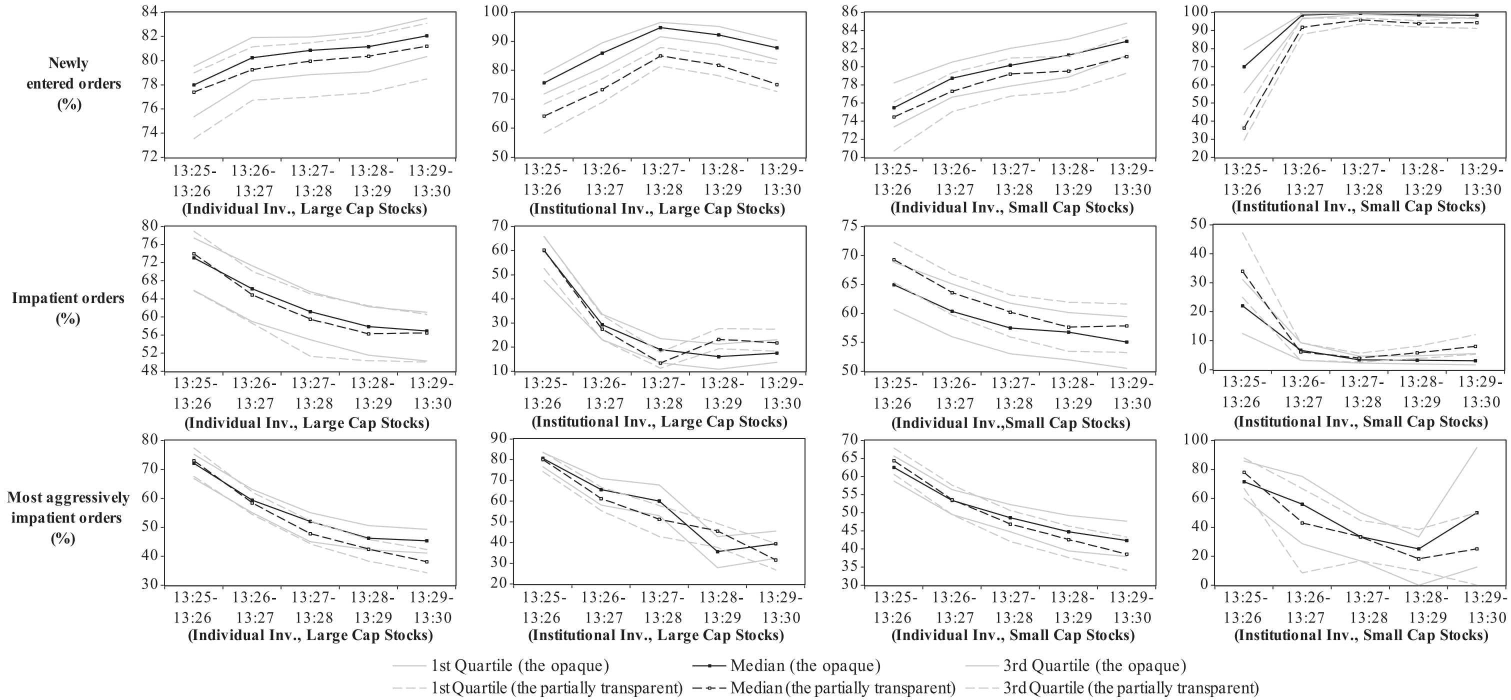
We have seen how order aggressiveness differs with respect to capitalization and the investor type. It will also be useful to have a general picture of how order aggressiveness changes over time, i.e., the time patterns of order aggressiveness. To do so, we divide the whole closing call session into five 1-minute sessions, beginning with the session from 13:25 to 13:26 and ending with the session from 13:29 to 13:30, and derive the aggressiveness statistics for each session and for each stock.[21] We then trace the time paths of the proportions of newly-entered orders (levels $C2$, $C3$, and $C4$), as well as the impatient (levels $C3$ and $C4$) and the very impatient orders (level $C4$) through these five intervals. The results of these three proportions over time are shown in Fig. 2, in the first, second, and third rows, respectively.[22] As before, the time paths are drawn separately with respect to capitalization and investor types, and are presented, from left to right, by the following sequence: large, individual (first column); large, institutional (second column); small, individual (third column); small, institutional (fourth column). Since the main purpose of this paper is to examine the effect of the new LOB disclosure mechanism on order aggressiveness, we also prepare these time paths separately based on market transparency. They are drawn in the same sub-diagram to make comparison easier. The one corresponding to the opaque period is drawn with the solid line, whereas the one corresponding to the partially transparent period is drawn with the dashed line.

Based on what we describe, there are a total of 12 sub-figures in Fig. 2. These sub-figures reveal strong time trends of order aggressiveness for all three kinds of orders. For the proportion of newly entered orders, there is a tendency for it to increase over time, except for the "large, institutional" case; for the proportion of impatient orders and very impatient orders, there is a tendency for it to decline. Hence, regardless of being individual or institutional investors, the degree of order aggressiveness tends to unanimously decrease over time during the closing call session. Clearly, the new disclosure mechanism has no effect on these time trends; these trends are quite consistent both before (the solid lines) and after the event (the dashed lines).

Nonetheless, the new mechanism may have an effect on the level, which is well demonstrated in the first row (the case of newly-entered orders). There the four time paths of the newly-entered orders that all shift

[21] It is worth noting that order submissions are not evenly distributed over the last 5 min. The number of submissions actually declines almost monotonically over time. The largest amount of submissions occurs in the first 1-minute interval (13:25–13:26), which accounts for one third of the total submissions in the closing call session for large cap stocks and more than one fourth for the small cap stocks, whereas the orders submitted in the last minute account for only around 10% of the total submissions in the closing call session.

[22] Since there are a total of 121 stocks for each capitalization and investor group, what is drawn here is mainly the median of the distribution of the corresponding 121 proportions. To have a better picture of the distribution, the median (shown in the black lines) is accompanied by the first and third quartiles in the figure (shown in the gray lines).




**Note:** This figure shows the minute-by-minute proportions of different levels of order aggressiveness during the closing call auction, with respect to individual and institutional investors. Three proportions are considered: first, the proportion of newly entered orders (the ratio of the sum of C2, C3, and C4 orders to all orders), second, the proportion of impatient orders (the ratio of the sum of C3 and C4 orders to all the newly entered orders), and, third, the proportion of the most aggressively impatient orders (the ratio of C4 orders to all the impatient orders). The black line represents the median, and the lower (upper) gray line shows the first (third) quartile, across the 121 large or small cap stocks of five one-minute intervals in the closing call, including 13:25~13:26, 13:26~13:27, 13:27~13:28, 13:28~13:29, and 13:29~13:30. Moreover, the minute-by-minute patterns of the *opaque* and the *partially transparent period* are distinguished by solid and dashed lines, respectively.

**Fig. 2.** The minute-by-minute proportions of different levels of order aggressiveness.

down in parallel when the market becomes more transparent. Therefore, market transparency has a positive effect on order cancelation ($C1$), even minute by minute. Unfortunately, a similar kind of argument cannot be found in the next two rows where we see the lines crossing each other in a patternless manner. Hence, the changes in the degree of order aggressiveness between the opaque and the partially transparent periods are hard to infer from the figure. In order to have a rigorous investigation, we need to resort to an empirical model and we take this up in Section 6.

## 6. Empirical model and explanatory variables

### 6.1. The three-stage sequential ordered probit model

In this section, we shall show that the three-stage sequential binary choice model as introduced in Section 5.1 can be represented by a three-stage sequential ordered probit (SOP) model. To do so, let us start with some notation. For an order $i$, let $L_i^l$ denote the trader's observable choice of order aggressiveness at the *applicable* node $l$ ($l = \mathrm{I, II, III}$).[23] Furthermore, let $L_i^{l\,*}$ be the unobservable degree of order aggressiveness of an order $i$ at node $l$, which is a linear function of $K$ observable explanatory variables, denoted by $x_{k,i}^l (k = 1, 2,..., K)$. The linear function can be represented as:

$$L_i^{l*} = \sum_{k=1}^{K} \beta_k^l x_{i,k}^l + \varepsilon_i^l, \quad l = \mathrm{I, II, III}, \tag{1}$$

where $\varepsilon_i^l$ is the error term and $\beta_k^l$ is the slope coefficient associated with the $k$th regressor. $L_i^{l\,*}$, also known as the latent dependent variable, is assumed to have the following mapping relation with the observable dependent variable $L_i^l$:

$$L_i^l = \begin{cases} 0, & \text{if} \quad L_i^{l*} \leq \delta^l, \\ 1, & \text{if} \quad L_i^{l*} > \delta^l, \end{cases} \tag{2}$$

where $\delta^l$ is the unknown threshold in decision node $l$, to be estimated along with the slope parameters, $\beta_k^l$ ($k = 1, 2, \ldots, K$) in Eq. (1). We shall assume that $L_i^{i\,*}$ is positively related to the tendency toward order aggressiveness. Hence, $L_i^l = 1$ indicates that the trader of the $i$th order actually submits a relatively aggressive order in the decision node $l$, such as a newly-entered order at node I, an impatient order at node II, and a very impatient order at node III (see Fig. 1). Similarly, $L_i^l = 0$ denotes a conservative choice being made in the decision node $l$. The conditional probability of observing a choice of $h(=0, 1)$ for an order $i$ at an applicable node $l$ is represented as:

$$\Pr\left(L_i^l = h \middle| x_i^l, \beta^l, \delta^l\right) = \begin{cases} F\left(\delta^l - \sum_{k=1}^{K} \beta_k^l x_{k,i}^l\right), & \text{if} \;\; h = 0, \\ 1 - F\left(\delta^l - \sum_{k=1}^{K} \beta_k^l x_{k,i}^l\right), & \text{if} \;\; h = 1, \end{cases} \tag{3}$$

where $x_i^l$ represents the vector of $K$ explanatory variables,

$$x_i^l = \left\{x_{1,i}^l, x_{2,i}^l, \ldots, x_{K,i}^l\right\},$$

and $\beta^l$ represents the unknown slope coefficients presented in Eq. (1),

$$\beta^l = \left\{\beta_1^l, \beta_2^l, \ldots, \beta_K^l\right\}.$$

$F(.)$ represents the cumulative distribution function (CDF) operator. Following some empirical studies using the ordered probit model (Griffiths et al., 2000; Ranaldo, 2004; Duong et al., 2009) and the sequential ordered probit model (Pascual and Veredas, 2009; Valenzuela and Zer, 2013) to investigate the choices of order

[23] Clearly, not all nodes are applicable for each order; for example, nodes II and III are not applicable for cancelations.

aggressiveness, we assume that the probability distributions of the error term $\varepsilon_i^l$ in all decision nodes are normal. Hence, in Eq. (3), $F(.)$ can be represented by the normal cumulative distribution function $\Phi(.)$. For any order $i$, in order to determine the direction of the change in the probability of each level of order aggressiveness with respect to the change in any $k$th regressor, say, $x_{k,i}^l$, the corresponding marginal probability can be calculated as follows:

$$\frac{\partial \Pr\left(L_i^l = h\right)}{\partial x_{k,i}^l} = \begin{cases} -\phi\left(\delta^l - \sum_{k=1}^K \beta_k^l x_{k,i}^l\right)\beta_k^l, & \text{if } h = 0, \\ \phi\left(\delta^l - \sum_{k=1}^K \beta_k^l x_{k,i}^l\right)\beta_k^l, & \text{if } h = 1, \end{cases} \tag{4}$$

where $\phi(.)$ is the normal density function and is always positive. From Eq. (4), we can infer the effect of the $k$th regressor, $x_k^l$, on the tendency for order aggressiveness unambiguously from the sign of the associated coefficient $\beta_k^l$. If the sign of the estimated $\beta_k^l$ is positive (negative), then the larger (smaller) the $x_k^l$, the more (less) aggressive the order. Hence, for our purpose, it is sufficient to know the estimated slope coefficients, and calculating marginal probabilities becomes extraneous.[24]

The above SOP model, characterized by Eqs. (1) to (3), can be estimated by the maximum likelihood method. For convenience, let $P_{i,h}^l$ denote the probability that the trader of order $i$ at decision node $l$ takes level $h$ (where $h = 0$ or $1$). By Eq. (3),

$$P_{i,0}^l = \Phi\left(\delta^l - \sum_{k=1}^K \beta_k^l x_{k,i}^l\right), P_{i,1}^l = 1 - \Phi\left(\delta^l - \sum_{k=1}^K \beta_k^l x_{k,i}^l\right).$$

In the first stage, i.e., node I, the corresponding log-likelihood for all observations (orders) is:

$$ln\ L^I = \sum_{i=1}^N \left(d_{i,0}^I ln\ P_{i,0}^I + d_{i,1}^I ln P_{i,1}^I\right), \tag{5}$$

where $N$ is the total number of orders, $d_{i,h}^I$ is the indicator function such that $d_{i,h}^I = 1$ if $L_i^I = h$ and $d_{i,h}^I = 0$ otherwise. We then maximize the log-likelihood, Eq. (5), with respect to $\{\delta^I, \beta_k^I\}$ $(k = 1, 2, \ldots, K)$ and obtain the maximum-likelihood estimates (MLE) of these parameters.

Similarly, for decision node II, the corresponding log-likelihood of the observations (orders) is:

$$ln\ L^{II} = \sum_{i=1}^N \left\{d_{i,1}^I \left[ln\ \hat{P}_{i,1}^I + d_{i,0}^{II} ln\ P_{i,0}^{II} + d_{i,1}^{II} ln\ P_{i,1}^{II}\right] + d_{i,0}^I ln\ \hat{P}_{i,0}\right\}, \tag{6}$$

where $d_{i,h}^{II}$ is the indicator function that $d_{i,h}^{II} = 1$ if $L_i^{II} = h$ and $d_{i,h}^{II} = 0$ otherwise. The term denoted as $\hat{P}_{i,1}^I$ $(\hat{P}_{i,0}^I)$ on the right-hand side of Eq. (6) is the predicted value of $P_{i,1}^I$ $(P_{i,0}^I)$, which is inherited from the MLE estimates in the first stage. By maximizing the log-likelihood function (6) with respect to $\{\delta^{II}, \beta_k^{II}\}$ $(k = 1, 2, \ldots, K)$, we can obtain the MLE estimates of these parameters. Finally, for decision node III, the corresponding log-likelihood of the observations (orders) is:

$$ln\ L^{III} = \sum_{i=1}^N \left\{d_{i,1}^I \left[d_{i,1}^{II}\left(ln\ \hat{P}_{i,1}^I + ln\ \hat{P}_{i,1}^{II} + d_{i,0}^{III} ln\ P_{i,0}^{III} + d_{i,1}^{III} ln\ P_{i,1}^{III}\right) + d_{i,0}^{II}\left(ln\ \hat{P}_{i,1}^I + ln\ \hat{P}_{i,0}^{II}\right)\right] + d_{i,0}^I ln\ \hat{P}_{i,0}^I\right\}, \tag{7}$$

[24] If there are more than two levels of choices (where $h = 0, 1, \ldots, H$, and $H > 1$) at the same node, then the marginal probability of any intermediate level $h$ (where $0 < h < H$) should be

$$\left[\phi\left(\delta_{h+1}^l - \sum_k \beta_k^l x_{k,i}^l\right) - \phi\left(\delta_h^l - \sum_k \beta_k^l x_{k,i}^l\right)\right]\beta_k^l.$$

The sign of the estimated marginal probability may depend on the actual values of the explanatory variables, and may not be unambiguously determined simply based on the sign of the respective coefficient $\beta_k^l$. This issue has been well noticed and some recent studies have tried to reduce the number of intermediate levels of order aggressiveness under the flat ordered probit model by adopting the multi-stage sequential ordered probit model, although intermediate levels still remain (Pascual and Veredas, 2009; Valenzuela and Zer, 2013).

where $d^{III}_{i,h}$ is the indicator function so that $d^{III}_{i,h} = 1$ if $L^{III}_i = h$ and $d^{III}_{i,h} = 0$ otherwise. The term denoted as $\hat{P}^{II}_{i,1}$ ($\hat{P}^{II}_{i,0}$) on the right-hand side in Eq. (7) is the predicted value of $P^{II}_{i,1}$ ($P^{II}_{i,0}$), which is inherited from the MLE estimates in the second stage. Likewise, by maximizing the log-likelihood function (7) with respect to $\{\delta^{III}, \beta^{III}_k\}$ ($k = 1, 2, \ldots, K$), we can obtain the MLE estimates of these parameters.

As in some early studies (Pascual and Veredas, 2009; Valenzuela and Zer, 2013), our proposed SOP model *is not nested* because the natural logarithm of the estimated probabilities of observing all the dual choices of order aggressiveness ($h = 1$ or 0) in the three successive stages, namely, the log-likelihood functions, can be expressed as the addictive forms of Eqs. (5)–(7). The econometric implication is that the three likelihood functions in our SOP model can be estimated individually.

## 6.2. Explanatory variables

Based on the prior theoretical and empirical works on the determinants of order aggressiveness indicated in the literature review (Section 2.2), a total of twelve explanatory variables ($K = 12$) are utilized in every decision node of the three-stage SOP model. They are summarized in Table 5.

**Table 5**
Definitions of explanatory variables and list of hypotheses.

| Variables | Definition |
|---|---|
| $C(-1)_i$ | The one lag of the level of order aggressiveness, conditional on the previous same-side order (buy or sell) submitted by a trader of the same type (individual or institution) |
| $SPR_i$ | The 'relative bid–ask spread' ratio calculated as the percentage of the bid–ask spread over the bid–ask midpoint, at the time of order submission, where the bid and ask are the best unexecuted bid and ask simulated in real time |
| $VOL_i$ | The standard deviation of the five most recent mid-quote (the bid–ask midpoint) returns, multiplied by 100, where the bid and ask are the best unexecuted bid and ask simulated in real time |
| $Size_i$ | The number of 1000 shares entered, revised, or canceled in this particular order |
| $Time_i$ | The elapsed time in seconds between 13:25 and the submission time of order *i* |
| $MonD_i$ | 1 if order *i* is submitted on one month-end day; 0, otherwise |
| $HolD_i$ | 1 if order *i* is submitted on a pre-holiday; 0, otherwise. |
| $InfD_i$ | 0 if order *i* is submitted before Feb 20, 2012; 1, otherwise. |
| $SPR_i \times InfD_i$ | The cross-product term of $SPR_i$ and $InfD_i$ |
| $VOL_i \times InfD_i$ | The cross-product term of $VOL_i$ and $InfD_i$ |
| $SPRbf_i$ | The 'relative bid–ask spread' ratio calculated as the percentage of the bid–ask spread over the bid–ask midpoint, where the bid and ask are the best unexecuted bid and ask disclosed immediately after the last actual match of orders before the closing call auction (that is, before 13:25) |
| $VOLbf_i$ | The standard deviation of the 20 last mid-quote (the bid–ask midpoint) returns before the closing call auction (that is, before 13:25), multiplied by 100, where the bid and ask are the best unexecuted bids and asks disclosed immediately after these actual matches of orders before the closing call auction |

| Hypotheses | The stage of the SOP model | Prediction | Related literature |
|---|---|---|---|
| Hypo. 1 | The 1st stage | $InfD_i$ negatively related to the probability of entering a new order, instead of canceling an order | Biais et al. (1999) presents the 'noise hypothesis' during the preopening call auction |
| Hypo. 2 | The 2nd stage | $InfD_i$ positively related to the probability of submitting an impatient order | The 'Rat race effect' presented by Foster and Viswanathan (1996) and Back et al. (2000) |
| Hypo. 3 | The 2nd stage | $SPR_i \times InfD_i$ reinforces the effect of $SPR_i$ | Expectation effect |
| Hypo. 4 | The 2nd stage | $VOL_i \times InfD_i$ reinforces the effect of $VOL_i$ | Expectation effect |
| Hypo. 5 | The 2nd stage | $C(-1)_i$ positively related to the probability of submitting an impatient order | The 'Diagonal effect' presented by Biais et al. (1995) |
| Hypo. 6 | The 2nd stage | $Size_i$ positively related to the probability of submitting an impatient order (institutional investors) | Motivated by the front-running effect (Danthine and Moresi, 1998) |
| Hypo. 7 | The 1st, 2nd and 3rd stages | $Time_i$ negatively related to the probability of submitting a cancelation (1st stage) and an impatient order (2nd and 3rd stages) | Non-binding feature<br>The price and time priority rule |

The upper panel of the table provides the definitions of the 12 explanatory variables investigated in each stage of the SOP model, Eqs. (1) to (3). The lower panel of the table provides a list of seven hypotheses to be examined in Section 7.

#### 6.2.1. One lag of the level of order aggressiveness ($C(-1)_i$)

According to the *diagonal effect* (Section 2.2.5), there may be a positive serial correlation in order aggressiveness. We, therefore, take one lag of the level of order aggressiveness as the explanatory variable. The lag is conditional on the same side of order *i* and the same type of investor who submits order *i*. We denote this variable by $C(-1)_i$.

#### 6.2.2. Bid–ask spread ($SPR_i$) and price volatility ($VOL_i$)

The bid–ask spread is defined as the percentage of the bid–ask spread over the bid–ask midpoint, at the time when order *i* is submitted. The volatility is defined as the standard deviation of the five most recent mid-quote (the bid–ask midpoint) returns, at the time when order *i* is submitted, multiplied by 100.[25] As mentioned in Section 5.2, the bid and ask used here are the best unexecuted bid and ask simulated in real time. These two variables should be included (Sections 2.2.1 and 2.2.2); however, it is not immediately clear whether these two variables can operate in the same way as they do in the continuous market (Section 1), since the LOB information is, at most, disclosed in discrete time and hence may not be current enough.

Nonetheless, as we also argue in Section 1, as long as investors still try to 'simulate' the possible spread and volatility based on the information that they have, then a higher degree of market transparency can facilitate their 'simulation' and make these variables more involved in determining order aggressiveness than otherwise. Hence, the key issue to be addressed here is to see how the new information disclosure mechanism has affected the significance of these two variables, compared to the opaque period. We shall perform this test by adding two product terms, i.e., multiplying both $SPR_i$ and $VOL_i$ by a dummy (see below), $InfD_i$, which is used to distinguish the opaque period from the partially transparent period.

#### 6.2.3. Order size ($Size_i$)

The size of order *i* ($Size_i$) is defined by the number of 1000 shares entered, revised, or canceled in order *i*. Due to the front-running risk, order aggressiveness can be affected by order size (Section 2.2.3). Nonetheless, in call markets, since orders are not matched immediately (Section 1), informed traders may have the incentive to disguise their private information by splitting larger orders into smaller ones (Barclay and Warner, 1993), implying that smaller orders are not always less aggressive. Therefore, it is interesting to see the net of these two effects (front-running vs. splitting) in the call market and examine whether the effect of order size on order aggressiveness is still positive.[26]

#### 6.2.4. Submission time ($Time_i$)

$Time_i$ is defined as the elapsed time in seconds between 13:25 and the submission time of order *i*. Order submission time is also an important variable in a continuous market (Section 2.2.4). However, all orders submitted in the closing call auction are not matched until the closing time. Before the closing time, investors can revise or cancel their original orders (Section 2.2.7). Because of this non-binding feature, under the price and time priority rule investors may want to submit more aggressively in the initial time. As the closing time is approaching, and the time to revise or cancel gets tight, order aggressiveness may decline.

#### 6.2.5. Month-end days ($MonD_i$) and pre-holiday ($HolD_i$)

There is a substantial literature documenting that for the purpose of beefing up the fund performance institutional investors may carry out some price manipulations in the month-end days (Cushing and Madhavan, 2000; Carhart et al., 2002; Huang and Chan, 2010). Since the closing call auction is the last short span before the end, i.e., the end of the end, it will be interesting to see whether various considerations related to the month-end days may affect order aggressiveness. As a result, we include a dummy variable for the month-end day (*MonD*), which is one if a month-end day applies to order *i* and 0 otherwise. Similarly, we also include a dummy for the pre-holiday (*HolD*), which is one if the day when order *i* is submitted is the last day before the stock market holiday(s) and 0 otherwise. In our sample period, there are a total of

[25] This definition is similar to Ranaldo (2004) and Duong et al. (2009), who define volatility as the standard deviation of the most recent 20 mid-quote returns at the time of order submission, multiplied by 100.

[26] Moshirian et al. (2012), whose study is one of the few studies on order aggressiveness, find that the positive relation between size and order aggressiveness also applies to the opening call session.

6 month-end days (3 in the pre-event period and 3 in the post-event period), and there are a total of 26 pre-holidays (12 in the pre-event period and 14 in the post-event period).

*6.2.6. Dummy variables for the new information disclosure mechanism ($InfD_i$, $SPR_i \times InfD_i$, $VOL_i \times InfD_i$)*

Theoretically, the improvement in market transparency lessens the information asymmetry between uninformed and informed traders, but influences on order aggressiveness remain controversial. Although the rat race effect (Section 2.2.6) suggests a positive effect, the 'camouflage effect' works in the opposite direction if the LOB information disclosure is partial. To see whether the expected rat race will 'get out of the camouflage', $InfD_i$ is zero if order $i$ is submitted during the opaque period and is one otherwise. The introduced dummy is also applied to the variable spread and volatility, namely, $SPR_i \times InfD_i$ and $VOL_i \times InfD_i$.

*6.2.7. Last available spread and volatility before the closing call session ($SPRbf_i$ and $VOLbf_i$)*

When the order book information is disclosed in discrete time, it begs the question as to how well subjects can actually perceive the possible best quotes in real time. $SPRbf_i$ is the 'relative bid–ask spread' ratio immediately after the last match before the closing call auction (before 13:25), and $VOLbf_i$ is the standard deviation of the 20 last mid-quote (the bid–ask midpoint) returns before the closing call auction, multiplied by 100. Since they are the last available disclosed spread and volatility before the closing call auction, they may be taken as a basis for 'simulating' the real-time quotes in the closing call auction[27]; hence, they are included. Notice that here the bids and asks are based on the disclosure of the TWSE in discrete time, and not on our reconstructed real-time order book (Section 5.2).

*6.3. Interactive terms in the probit model*

From the previous section, we see that, among the 12 independent variables, two are interactive terms, namely, $SPR_i \times InfD_i$ and $VOL_i \times InfD_i$. When there are interaction terms in the probit model, it is known that we cannot interpret the significance of these interaction effects directly from the estimated coefficients of the interaction terms $\beta_k^l$ with the associated $t$ test, because in this case the interaction effects depend not only on the interaction terms, but also on the values of the $x^l$, $\beta^l$, and $\delta^l$ (Ai and Norton, 2003). To properly assess the interaction terms' sign and statistical significance, Ai and Norton (2003) propose a statistical procedure which receives a great deal of attention. By this methodology, one can use the Delta method to show that the cross derivative of the conditional expectation with respect to interactive terms is asymptotically normal,

$$\frac{\Delta^2 \hat{E}\left(L^l \middle| x^l\right)}{\Delta x_u^l \Delta x_v^l} = \frac{\Delta^2 H\left(x^l, \hat{\beta}^l, \hat{\delta}^l\right)}{\Delta x_u^l \Delta x_v^l} = \hat{\gamma}_{uv} \sim N\left(\gamma_{uv}, \sigma_{uv}^2\right) \tag{8}$$

where

$$H\left(x^l, \hat{\beta}^l, \hat{\delta}^l\right) \equiv \hat{E}\left(L^l | x^l\right) = 1 - \Phi\left(\hat{\delta}^l - \Sigma_{k=1}^K \hat{\beta}_k^l x_k^l\right).$$

$\Delta$ denotes either the difference or differential operator, depending on whether the regressor is discrete or continuous. $x_u x_v$ is the interactive term; for example, $x_u$ is $InfD$ and $x_v$ is $SPR$ or $VOL$. $\hat{\beta}^l$ and $\hat{\delta}^l$ are MLE estimates of the sequential ordered probit model. $\sigma_{uv}^2$ appearing in Eq. (8) can be estimated as

$$\hat{\sigma}_{uv}^2 = \frac{\partial}{\partial \theta^{l'}} \left[\frac{\Delta^2 H\left(x^l, \hat{\theta}^l\right)}{\Delta x_u^l \Delta x_v^l}\right] \hat{\Omega}_{\theta^l} \frac{\partial}{\partial \theta^l} \left[\frac{\Delta^2 H\left(x^l, \hat{\theta}^l\right)}{\Delta x_u^l \Delta x_v^l}\right], \tag{9}$$

where $\theta^l = \{\beta^l, \delta^l\}$ and $\hat{\Omega}_{\theta^l}$ is the consistent covariance estimator of $\Omega_{\theta^l}$ based on the heteroskedastic-consistent estimates of the covariance matrix of error terms (White, 1980).

[27] Notice that this is particular so in the opaque period where no further disclosure is possible once entering into the closing call auction.

One can then calculate $\hat{\gamma}_{uv}/\hat{\sigma}_{uv}$ and apply the $t$ statistic to test the hypothesis that the interaction effect is zero for given values of independent variables, for example, using the ones corresponding to the average values in the sample (Greene, 2010; Karaca-Mandic et al., 2012). In this paper, we shall follow this methodology to present the interactive effects and $t$-values calculated using this methodology.[28]

## 7. Empirical results

The three-stage SOP model, Eqs. (1) to (3), with the 12 explanatory variables, is estimated using the maximum likelihood method. The estimation is applied to each stage (each node), each stock, and each type of investor. Therefore, there are a total of 1452 (=3 (stages) × 2 (types of investors) × 2 (types of capitalization) × 121 (stocks)) equations being estimated. Given these gigantic results, we follow what seems to be a 'standard' practical way to organize our results.[29] The results are summarized by three tables, one for each stage, as shown in Table 6 (stage I), Table 7 (stage II), and Table 8 (stage III). Each of these three tables is further organized into four panels corresponding to the groups, 'individual, large' (upper left), 'institutional, large' (upper right), 'individual, small' (lower left), and 'institutional, small' (lower right). Within each panel, we present the results of each of the twelve coefficients in the form of the median of the (121) estimates, with their percentages being significantly negative and significantly positive. Hence, we present both the magnitudes of the coefficients and their significance as a group (of 121 stocks). The only exceptions here are the coefficients of the two interactive terms, $SPR \times InfD$ and $VOL \times InfD$. Based on Section 6.3, what should be presented here is $\hat{\gamma}_{uv}$ and the $t$ test based on $\hat{\gamma}_{uv}/\hat{\sigma}_{uv}$.

Given this table's structure, our discussion of the results, specifically, the seven hypotheses proposed in Table 5, will be based on the percentages of negative signs and positive signs, i.e., the percentages shown in the column headed by '% $t$-stat $< -1.96$' and '% $t$-stat $> 1.96$'. Furthermore, to facilitate our discussion, we shall introduce the following abbreviations for the four groups of samples: 'Ind-L' for 'individual, large', 'Ins-L' for 'institutional, large', 'Ind-S' for 'individual, small', and 'Ins-S' for 'institutional, small'. We also use the minus (−) and the plus (+) signs to denote the group of significantly negative estimates and the group of significantly positive estimates.

### 7.1. Market transparency

The main purpose of this paper is to understand the effect of market transparency on order aggressiveness in the closing call auction. The key variables which may summarize these effects are the dummy variable ($InfD$) and the product variables involving the dummy variable, i.e., ($SPR \times InfD$) and ($VOL \times InfD$). In this section, we shall begin with the direct effect of the market transparency, characterized by the coefficient of $InfD$ (Section 7.1.1), and then look at the indirect effects, characterized by the coefficients of $SPR \times InfD$ (Section 7.1.2) and $VOL \times InfD$ (Section 7.1.3).

#### 7.1.1. Direct effect

There are two hypotheses related to the direct effect, namely, Hypotheses 1 and 2 (see Table 5, lower panel). Hypothesis 1 asserts that, at the first stage of the sequential decisions, the new information disclosure mechanism will increase the choice probability of order cancelation, i.e., a lower level of order aggressiveness. Hypothesis 2 asserts that at the second and third stages, the new mechanism will increase the choice probability of impatient order submission, i.e., a higher level of order aggressiveness. The first hypothesis requires the coefficient of $InfD$ to be negative, whereas the second hypothesis requires it to be positive. Hypothesis 1 is motivated by our early discussion of the non-binding feature of the call auction (Sections 1 and 2.2.7). Hypothesis 2 is motivated by the rat race effect mainly applied to informed traders (institutional investors) and the alleviation of the winner's curse for uninformed traders (individual investors) (Section 2.2.6).

These two hypotheses are basically very well supported by the data. For Hypothesis 1, after the introduction of the new mechanism, there is a significant increase in order cancelations for institutional investors; for Ins-L,

[28] In econometric practice, this procedure has been frequently followed using the *inteff* command in *Stata*. However, our ordered probit model with the use of the heteroskedastic-consistent estimates is not susceptible to this package. Therefore, we have written our own GAUSS program to implement this procedure, which is available upon request.

[29] See, for example, Duong et al. (2009), Pascual and Veredas (2009), and Valenzuela and Zer (2013).

**Table 6**
The determinants of order aggressiveness: stage I of the SOP model.

| Determinants | Individual investors | | | Institutional investors | | |
|---|---|---|---|---|---|---|
| | Est. coeff. (median) | % *t*-stat <−1.96 | % *t*-stat >1.96 | Est. coeff. (median) | % *t*-stat <−1.96 | % *t*-stat >1.96 |
| | 121 large cap stocks | | | 121 large cap stocks | | |
| *C*(−1) | 0.022 | 5.79% | 57.02% | 0.237 | 0.00% | 88.43% |
| *SPR* | 0.003 | 3.31% | 1.65% | −0.020 | 18.18% | 9.92% |
| *VOL* | 0.662 | 0.83% | 36.36% | −0.147 | 11.57% | 7.44% |
| *Size* | −0.003 | 70.25% | 1.65% | 0.006 | 0.83% | 88.43% |
| *Time* | 0.001 | 2.48% | 76.03% | 0.002 | 0.83% | 87.60% |
| *MonD* | 0.021 | 4.13% | 6.61% | 0.000 | 9.92% | 8.26% |
| *HolD* | 0.001 | 9.09% | 4.13% | −0.073 | 29.75% | 3.31% |
| *SPR* × *InfD* | 0.001 | 2.48% | 4.13% | 0.023 | 9.09% | 12.40% |
| *VOL* × *InfD* | −0.071 | 8.26% | 3.31% | −0.027 | 19.83% | 9.09% |
| *InfD* | −0.031 | 22.31% | 3.31% | −0.411 | 80.17% | 0.83% |
| *SPRbf* | −0.051 | 18.18% | 5.79% | 0.044 | 8.26% | 16.53% |
| *VOLbf* | 0.213 | 6.61% | 23.14% | 0.145 | 10.74% | 20.66% |
| # of obs | 13,851 | | | 5,342 | | |
| | 121 small cap stocks | | | 121 small cap stocks | | |
| *C*(−1) | 0.015 | 4.96% | 27.27% | 0.147 | 2.63% | 27.19% |
| *SPR* | −0.002 | 3.31% | 2.48% | 0.107 | 5.26% | 11.40% |
| *VOL* | 0.785 | 0.00% | 42.98% | −0.490 | 13.16% | 4.39% |
| *Size* | −0.005 | 69.42% | 1.65% | 0.038 | 0.88% | 71.93% |
| *Time* | 0.001 | 0.83% | 87.60% | 0.002 | 0.88% | 47.37% |
| *MonD* | 0.015 | 1.65% | 3.31% | −0.117 | 11.40% | 7.02% |
| *HolD* | −0.004 | 4.13% | 3.31% | −0.025 | 8.77% | 7.02% |
| *SPR* × *InfD* | 0.001 | 4.96% | 0.83% | 0.005 | 0.00% | 1.77% |
| *VOL* × *InfD* | −0.155 | 13.22% | 3.31% | −0.026 | 4.42% | 0.00% |
| *InfD* | −0.026 | 11.57% | 5.79% | −0.765 | 64.91% | 3.51% |
| *SPRbf* | 0.012 | 7.44% | 3.31% | 0.099 | 6.14% | 14.04% |
| *VOLbf* | 0.211 | 1.65% | 10.74% | −0.166 | 7.89% | 14.04% |
| # of obs | 4,271 | | | 1,173 | | |

The table summarizes the estimation results of the first-stage of the SOP model (Eq. (1), $l$ = I), i.e., the choice between submitting a new order or cancelation order. The results are organized by groups with respect to two sizes of market capitalization, large (upper panel) and small (lower panel), and two types of investors, individual (left panel) and institutional (right panel). There are a total of 121 stocks in each group. The descriptions of the 12 explanatory variables are given in Table 5. For each of these 12 coefficients, we report the median of the 121 estimates, followed by the percentages of them being significantly negative and positive at the 5% significance level, in the column with the titles '% *t*-stat < −1.96' and '% *t*-stat > 1.96', respectively. The coefficients of the two interactive terms are treated following Ai and Norton (2003) (Section 6.3). The *t*-stat is calculated by the heteroskedastic-consistent covariance matrix estimator (White, 1980). The median number of order submissions is also reported in the row with the title '# of obs'.

we have 80.17% (−) vs. 0.83% (+), and for Ins-S, we have 64.91% (−) vs. 3.51% (+). This tendency also exists for the individual investors, but in a much milder way (Table 6). For Hypothesis 2, from Table 7, one can see that there is a substantial proportion of significant cases for each of the four groups of samples, 54.55% (Ind-L), 48.74% (Ins-L), 38.84% (Ind-S), and 33.06% (Ins-S), respectively. Among these significant cases the sign of the coefficient is overwhelmingly positive: 39.67% (+) vs. 14.88% (−) (Ind-L), 45.38% (+) vs. 3.36% (−) (Ins-L). In the last stage, the effect on the most aggressive orders, which quote the limit-up (limit-down) price, is not evident (Table 8), except that for the Ind-L group, 30.58% (−) vs. 11.57% (+).

In light of our literature review (Section 2.2.6), the results above may resonate well with the stereotypes of institutional investors being informed traders and individual investors being uninformed traders. The new disclosure mechanism, therefore, helps to guide and encourage individuals to revise or cancel the prior stale orders (the first stage) and then alleviate their concerns with the winner's curse so that they can trade more aggressively (the second stage). Actually, our results may suggest different types of uninformed traders, some who weight more on the winner's curse and some who weight more on the non-execution cost. When the simulated best quote becomes available, it entices the former to be willing to be more aggressive (Table 6). As to the latter, in the opaque period, quoting the limit-up or limit-down price is the most assured way to do it

**Table 7**
The determinants of order aggressiveness: stage II of the SOP model.

| Determinants | Individual investors | | | Institutional investors | | |
|---|---|---|---|---|---|---|
| | Est. coeff. (median) | % *t*-stat <−1.96 | % *t*-stat >1.96 | Est. coeff. (median) | % *t*-stat <−1.96 | % *t*-stat >1.96 |
| | 121 large cap stocks | | | 121 large cap stocks | | |
| *C*(−1) | 0.079 | 0.00% | 95.87% | 0.219 | 0.84% | 88.24% |
| *SPR* | −0.233 | 61.98% | 0.00% | −0.051 | 21.01% | 6.72% |
| *VOL* | 0.460 | 0.00% | 33.06% | 5.750 | 0.00% | 98.32% |
| *Size* | 0.003 | 5.79% | 59.50% | −0.009 | 92.44% | 3.36% |
| *Time* | −0.002 | 98.35% | 0.00% | −0.004 | 98.32% | 0.00% |
| *MonD* | −0.042 | 24.79% | 14.88% | 0.343 | 0.00% | 73.11% |
| *HolD* | 0.008 | 12.40% | 21.49% | 0.022 | 8.40% | 10.08% |
| *SPR* × *InfD* | −0.087 | 47.11% | 6.61% | −0.050 | 17.65% | 9.24% |
| *VOL* × *InfD* | −0.057 | 11.57% | 2.48% | −0.107 | 23.53% | 13.45% |
| *InfD* | 0.059 | 14.88% | 39.67% | 0.173 | 3.36% | 45.38% |
| *SPRbf* | −0.288 | 53.72% | 12.40% | −0.038 | 14.29% | 10.92% |
| *VOLbf* | −0.770 | 54.55% | 0.83% | 0.460 | 7.56% | 26.89% |
| # of obs | 11,628 | | | 4,335 | | |
| | 121 small cap stocks | | | 121 small cap stocks | | |
| *C*(−1) | 0.065 | 0.00% | 80.99% | 0.044 | 4.96% | 14.05% |
| *SPR* | −0.386 | 73.55% | 0.00% | −0.412 | 20.66% | 3.31% |
| *VOL* | 0.976 | 0.83% | 55.37% | 3.472 | 0.00% | 76.03% |
| *Size* | 0.003 | 4.13% | 29.75% | −0.020 | 52.07% | 7.44% |
| *Time* | −0.001 | 95.87% | 0.00% | −0.002 | 43.80% | 1.65% |
| *MonD* | 0.002 | 4.13% | 9.09% | −0.086 | 15.70% | 6.61% |
| *HolD* | 0.019 | 6.61% | 7.44% | 0.005 | 0.83% | 4.13% |
| *SPR* × *InfD* | −0.083 | 30.58% | 2.48% | −0.011 | 1.65% | 0.00% |
| *VOL* × *InfD* | −0.091 | 17.36% | 4.13% | 0.070 | 0.83% | 4.96% |
| *InfD* | 0.097 | 1.65% | 37.19% | 0.439 | 2.48% | 30.58% |
| *SPRbf* | −0.255 | 49.59% | 1.65% | −0.074 | 12.40% | 9.09% |
| VOLbf | −0.501 | 30.58% | 2.48% | 0.423 | 9.92% | 14.88% |
| # of obs | 3,448 | | | 1,107 | | |

The table summarizes the estimation results of the second-stage of the SOP model (Eq. (1), $l$ = II), i.e., the choice between submitting a patient order or an impatient order. The results are organized by groups with respect to two sizes of market capitalization, large (upper panel) and small (lower panel), and two types of investors, individual (left panel) and institutional (right panel). There are a total of 121 stocks in each group. The descriptions of the 12 explanatory variables are given in Table 5. For each of these 12 coefficients, we report the median of the 121 estimates, followed by the percentages of them being significantly negative and positive at the 5% significance level, in the column with the titles '% *t*-stat < −1.96' and '% *t*-stat > 1.96', respectively. The coefficients of the two interactive terms are treated following Ai and Norton (2003) (Section 6.3). The *t*-stat is calculated by the heteroskedastic-consistent covariance matrix estimator (White, 1980). The median number of order submissions is also reported in the row with the title '# of obs'.

(Flood et al., 1999). However, the release of the simulated best quotes provides them with a more precise range to bid/ask spread.

However, for institutional investors, it may work in a different way. For already informed traders, the LOB disclosure may not bring them much more 'light' as it did for uninformed trades; instead, it probably may entice them to actively send manipulative orders with no real trading intent in the first stage (Biais et al., 1999; Moshirian et al., 2012; Kuk et al., 2014) and may also trigger the rat race effect (Section 2.2.6) in the second stage.

### *7.1.2. Spread and the indirect effect*

As discussed in Sections 1 and 6.2, in the pre-event period (opaque period), both spread and volatility were not available and can only be gauged ('simulated' in the dark); therefore, in the post-event period when this information becomes available, even in discrete time, there is reason to hypothesize that the effect of spread and volatility can become even more evident due to the fact that investors can 'simulate' the book 'with some light'. This interest motivates the two hypotheses, Hypotheses 3 and 4 (Table 5, lower panel).

**Table 8**
The determinants of order aggressiveness: stage III of the SOP model.

| Determinants | Individual investors | | | Institutional investors | | |
|---|---|---|---|---|---|---|
| | Est. coeff. (median) | % *t*-stat >1.96 | % *t*-stat <1.96 | Est. coeff. (median) | % *t*-stat >1.96 | % *t*-stat <1.96 |
| | 121 large cap stocks | | | 121 large cap stocks | | |
| *C*(−1) | 0.027 | 0.83% | 52.07% | 0.134 | 1.65% | 77.69% |
| *SPR* | 0.257 | 0.83% | 52.07% | 0.132 | 1.65% | 14.88% |
| *VOL* | 0.023 | 5.79% | 6.61% | 0.053 | 6.61% | 2.48% |
| *Size* | 0.002 | 9.92% | 35.54% | −0.002 | 53.72% | 4.13% |
| *Time* | −0.003 | 97.52% | 0.00% | −0.005 | 99.17% | 0.00% |
| *MonD* | −0.036 | 20.66% | 9.92% | 0.166 | 0.83% | 31.40% |
| *HolD* | 0.010 | 8.26% | 12.40% | −0.037 | 10.74% | 1.65% |
| *SPR* × *InfD* | 0.045 | 9.09% | 12.40% | 0.005 | 14.88% | 8.26% |
| *VOL* × *InfD* | 0.060 | 4.96% | 10.74% | −0.081 | 10.74% | 6.61% |
| *InfD* | −0.042 | 30.58% | 11.57% | −0.045 | 14.88% | 10.74% |
| *SPRbf* | 0.044 | 10.74% | 15.70% | 0.171 | 7.44% | 14.05% |
| *VOLbf* | −0.289 | 21.49% | 4.13% | −0.465 | 14.05% | 0.83% |
| # of obs | 6,991 | | | 1,330 | | |
| | 121 small cap stocks | | | 121 small cap stocks | | |
| *C*(−1) | 0.047 | 0.00% | 52.07% | −0.031 | 3.45% | 9.20% |
| *SPR* | 0.383 | 0.00% | 59.50% | 0.411 | 6.90% | 18.39% |
| *VOL* | −0.240 | 9.92% | 0.83% | −1.803 | 16.09% | 1.15% |
| *Size* | −0.000 | 19.01% | 9.09% | −0.014 | 36.78% | 2.30% |
| *Time* | −0.002 | 98.35% | 0.00% | −0.006 | 62.07% | 0.00% |
| *MonD* | −0.056 | 14.05% | 4.13% | −0.208 | 22.99% | 14.94% |
| *HolD* | 0.013 | 6.61% | 5.79% | −0.050 | 8.05% | 8.05% |
| *SPR* × *InfD* | 0.008 | 7.50% | 9.17% | 0.000 | 3.45% | 5.75% |
| *VOL* × *InfD* | 0.062 | 5.00% | 3.33% | 0.225 | 2.30% | 2.30% |
| *InfD* | −0.003 | 11.57% | 4.13% | −0.044 | 9.20% | 8.05% |
| *SPRbf* | 0.090 | 3.31% | 16.53% | 0.119 | 8.05% | 8.05% |
| *VOLbf* | −0.071 | 9.92% | 12.40% | 0.713 | 6.90% | 10.34% |
| # of obs | 2,090 | | | 75 | | |

The table summarizes the estimation results of the third-stage of the SOP model (Eq. (1), $l$ = III), i.e., the choice between submitting an impatient order or a very impatient order with a limit-up or limit-down price. The results are organized by groups with respect to two sizes of market capitalization, large (upper panel) and small (lower panel), and two types of investors, individual (left panel) and institutional (right panel). There are a total of 121 stocks in each group. The descriptions of the 12 explanatory variables are given in Table 5. For each of these 12 coefficients, we report the median of the 121 estimates, followed by the percentages of them being significantly negative and positive at 5% significance level, in the column with the titles '% $t$-stat < −1.96' and '% $t$-stat > 1.96', respectively. The coefficients of the two interactive terms are treated following Ai and Norton (2003) (Section 6.3). The $t$-stat is calculated by the heteroskedastic-consistent covariance matrix estimator (White, 1980). The median number of order submissions is also reported in the row with the title '# of obs'.

Hypothesis 3 asserts that after the new disclosure mechanism the effect of the spread can be more prominent. The exact formulation of 'testing' Hypothesis 3 is a little subtle. First, as a minimum, the coefficient of the variable $SPR \times InfD$ should be significant. It can be either sign, but, to be convincing, the sign of most cases in a group should be consistent, instead of being divergent. Second, it would be more convincing if the original effect of the spread (volatility) on order aggressiveness could be *reinforced* by the effect of $SPR \times InfD$ ($VOL \times InfD$), which means the coefficients of the two variables should also be consistent in terms of their sign. Hypothesis 3 is motivated by the discussion in Sections 1 and 6.2. In a nutshell, the disclosure of the simulated quotes helps investors to 'simulate' the real-time best quotes more closely and hence can better connect their decisions on order aggressiveness to the real-time spread.

First, we look at the results for $SPR \times InfD$, with a focus on the second stage.[30] For the individual investors, the two groups have substantial proportions of significance: 53.72% (Ind-L) and 33.06%, (Ind-S). Among

[30] The effect of $SPR \times InfD$ is not significant in the first and the third stages. In each of them, the percentages of significant cases are at most 25%, and there is no clear indication of the dominant sign.

the significant cases, the percentage of the negative sign far exceeds the percentage of the positive sign: 47.11%(−) vs. 6.61% (+) (Ind-L) and 30.58% (−) vs. 2.48% (+) (Ind-S). Hence, the group consistency as required by Hypothesis 3 is satisfied. For the institutional investor, this effect can also be found in the case of large cap stocks, while it is milder, 17.65%(−) vs. 9.24% (+).

Are these results consistent with those of *SPR* so that *SPR* × *InfD* can reinforce the effect of *SPR*? By also focusing on the second stage (Table 7), the answer is positive. As we can see from Table 7, *SPR*, in the individual group, has a dominant negative effect: 61.98%(−) vs. 0% (+) (Ind-L) and 73.55% (−) vs. 0% (+) (Ind-S). For individual investors, the spread obviously has a negative effect on order aggressiveness, which is consistent with the literature surveyed in Section 2.2.2. For institutional investors, the negative effect also applies, although to a lesser extent, 21.01% (−) vs. 6.72% (+) (Ins-L) and 20.66% (−) vs. 3.31% (Ins-S) (+). Since both variables have a negative effect, the reinforcement condition as required by Hypothesis 3 is also satisfied.

The consistent pattern between these two variables also demonstrates that while this limited disclosure is useful to informed traders, but it means more for uninformed traders as we can see from the above differences in percentages of the negative and positive signs. Roughly speaking, in the 'black-box' era, individual investors had rather limited perception of the real-time quotes and hence the effect of the spread, while existing, was smaller in magnitude; after quotes are disclosed, even just the 'artificial' ones, investors can use it to keep track of the possible real-time quotes. Therefore, the spread now plays a more important role with the increase in market transparency.

*7.1.3. Volatility and the indirect effect*

Another indirect effect of market transparency on order aggressiveness is through volatility, characterized by *VOL* × *InfD*. The motivation of having this variable in our model is the same as that of having *SPR* × *InfD*, and is manifested by Hypothesis 4. Hypothesis 4 asserts that after the new disclosure mechanism the effect of volatility can be more prominent, prominent in the same sense as Hypothesis 3, i.e., we need to check both the consistency condition and the reinforcement condition. However, as we shall see below, neither of these two conditions is satisfied.

First of all, the variable *VOL* × *InfD* is generally not significant. Table 7 shows that it is only significant in the Ins-L group. In this group, we have 25.53% (−) vs. 13.45% (+), meaning the dummy variable reinforces the effect of *VOL* in a negative direction. For the other three groups, although we have the same direction of reinforcement, the problem is that their percentages of significant cases are lower than 20%, and hence are less convincing.

Second, also from Table 7, we can see that this reinforcement direction does not coincide with the original effect of *VOL*. Table 7 shows that the variable VOL is positively significant in all four groups: 0% (−) vs. 33.06% (+) (Ind-L), 0% (−) vs. 98.32% (+) (Ins-L), 0.83% (−) vs. 55.37% (+) (Ind-S), 0% (−) vs. 76.03% (Ins-S). The statistics shown here are so overwhelmingly that they can hardly escape our attention. This strong effect occurred at a moment when investors were completely in the dark (the opaque period), but with this result they behaved as if they were in a continuous market. In the continuous market, the literature has both negative and positive results (Section 2.2.1). Our result seems to be in line with the latter (Aitken et al., 2007; Duong et al., 2009), which suggests that informed traders take advantage of the volatile market by engaging in some 'picking-off' strategies and trading more aggressively. As to uninformed traders, even in the dark, they can still trade with the 'market momentum' or 'street news' through herding and imitation; hence they may also trade more aggressively with the increase in market volatility (Kaniel et al., 2008).

Why does the disclosure of the simulated best quotes not reinforce the effect of volatility in the same direction, as it did for the spread? Our conjecture is as follows. The spread is basically point estimation, whereas the volatility, or the mid-quote volatility, requires observations over a period. If we assume that the volatility is calculated based on a window length of five observations, then it actually implies a window of 100 s under the current disclosure frequency (once per 20 s). Hence, unlike point estimation, the lag corresponding to the real-time estimation of volatility can come up with a delay of 100 s, instead of just 20 s, which means that the disclosed simulated best quote can hardly help investors to 'simulate' the real-time volatility in the way that it can do for them on the spread. Of course, as we have mentioned, the market has its mood and momentum, and 'on-site' investors can still sense it and react upon it; it is just the disclosed simulated quotes that are of little help on this occasion. Hence, the coefficients of *VOL* × *InfD* and *VOL* are not tied as well as those of *SPR* × *InfD* and *SPR*.

#### 7.1.4. The 'last glances'

The other two variables which may also be related to the new disclosure mechanism are *SPRbf* and *VOLbf*. The role that these two variables can play is the 'last glance' of the spread or volatility based on *actual matches* (Section 6.2). If order aggressiveness is affected by the 'real' spread in the regular session, then it may be continuously affected by the 'imaginary' one in the closing session (Section 7.1.2). *SPRbf*, apart from *SPR*, is another imaginary one after 13:25. The only difference is that it was once real and the last real one before the closing call auction.

Table 7 shows the results of *SPRbf*. Let us first look at how it works for individual traders. The proportions of significant cases are more than 50%; the percentages for the negative sign vastly surpass those for the positive sign: 53.72% (−) vs. 12.40% (+) (Ind-L) and 49.59% (−) vs. 1.65% (Ind-S). This result shows that individual traders, probably being less resourceful in terms of information, tend to value this 'last glance'. From the result, the 'last glance' almost plays the same role as another imaginary spread, namely, *SPR*. They have the same sign and same importance.

Next, for institutional investors, the result as shown in Table 7 is very consistent with the effect of *SPR*. Basically, it is much less important as compared to the case of individual investors, and there is only a minor difference in the percentages of the signs. Hence, both *SPR* and *SPRbf* have a mild effect on order aggressiveness for institutional investors. One possible explanation is that institutional investors, symbolizing informed traders, can gain access to other sources regarding information of the real spread, and hence may care less about these 'imaginary' spreads.

*VOLbf* is the other 'last glance' in the model. Would individual investors also value *VOLbf*? The answer is yes, but not in the direction that *VOL* has indicated. Earlier, we have already seen that *VOL* has a positive effect for individual investors. Here, we find that *VOLbf* generally has a negative effect for them. The percentages of the signs are 54.55% (−) vs. 0.83% (+) (Ind-L) and 30.58% (−) vs. 2.48% (+) (Ind-S). Hence, in addition to $VOL \times IndD$, *VOLbf* also does not tie well with *VOL*. All of this evidence together shows that our model, quite paradoxically, supports both sides in terms of the opinion in the literature (Section 2.2.1). Perhaps this simply indicates the complexity of volatility; there may be different versions of volatilities working differently for a group of heterogeneous individual investors. This can be one area of future work in this research.

### 7.2. Effects of other determinants

#### 7.2.1. Lag and the diagonal effect

On the lag variable of the level of order aggressiveness, $C(-1)$, we have one hypothesis, Hypothesis 5 (Table 5). Hypothesis 5 asserts that the level of order aggressiveness is positively serially correlated. The hypothesis, also known as the diagonal effect (Section 2.2.5), requires the coefficient of $C(-1)$ to be positive. From Tables 6 to 8, the diagonal effect can be well applied to our individual investors, who symbolize uninformed traders. The percentages in the three stages are 57.02% (+), 95.87% (+), 52.07% (+) for large cap stocks and 27.27% (+), 80.99% (+), and 52.07% (+) for the small cap stocks. According to Biais et al. (1995), due to the lack of information, uninformed traders may trade with the 'market mood', herding, and imitation. Hence, even in our closing call auction, in which information disclosure is very limited, the diagonal effect can still persist through what is termed the *bandwagon effect* (Kaniel et al., 2008). Hence, we provide new evidence that positive autocorrelation in order aggressiveness may be carried over beyond the regular trading session.

Biais et al. (1995) actually argue that a positively serial correlation may also arise from order splitting by informed traders. Nonetheless, this argument has not drawn much attention in existing empirical studies. From the three tables, we can see that the diagonal effect also applies to our institutional investors for large cap stocks (88.43% (+), 88.24% (+), and 77.69% (+), for the three stages, respectively), but not for small cap stocks.

#### 7.2.2. Size, front-running, and order splitting

On the variable of order size, we have one hypothesis, Hypothesis 6 in Table 5. Hypothesis 6 asserts that the probability of submitting an aggressive (impatient) order tends to increase with the size of the order, especially for institutional investors. This hypothesis requires the coefficient of Size to be positive. As we have reviewed in Section 2.2.3, this hypothesis is motivated by the front-running effect (Danthine and Moresi, 1998). However, as we also argue there the front-running effect may not apply well to the closing call session of the TWSE, because the real-time order depths of the LOB are not disclosed during the entire closing call auction, even after the introduction of the new mechanism on February 20, 2012. Therefore, one may be interested in knowing the validity of this hypothesis under this situation.

Indeed, as we can see from Tables 7 and 8, the front-running effect does not apply to our institutional investors. Taking the second stage as an example, the percentages of negative and positive signs are 92.44% (−) vs 3.36 (+) and 52.07% (−) vs. 7.44% (+). This result is more consistent with the *order splitting hypothesis* in that informed traders may have the incentive to disguise their private information by splitting larger orders into smaller ones (Barclay and Warner, 1993). If so, in comparison, institutional investors show relatively weak evidence in order splitting on small cap stocks with a dramatic drop of the percentage of the negative sign from 92.44% to 52.07%.

While the main interest of Hypothesis 6 is to examine the behavior of institutional investors with large size orders, in our case, it seems to fit that of individual investors better, at least, in the case of large cap stocks. The percentages of the positive sign are 59.50% and 35.54% for the two consecutive stages. However, as we have seen in Table 2, the average order size of the individual investor is only 10% of that of the institutional investor, hence what may concern them more is the non-execution risk rather than the information exposure.

#### 7.2.3. Time

We have one hypothesis for the time variable, namely, Hypothesis 7 (Table 5). Hypothesis 7 asserts that, with the increase in the elapsed time between the beginning time of the closing call auction (13:25) and the order submission time, the probability of submitting a cancelation will decrease. In addition, it also asserts that with the increase in the elapsed time the probability of submitting an impatient order or very impatient order will also decrease. This hypothesis requires the coefficient of time to be positive in the first stage of the SOP model and to be negative in the remaining two stages. This hypothesis is well motivated in Sections 2.2.7 and 6.2, and in brief, can be termed the *binding hypothesis* since it predicts that order aggressiveness declines when the binding effect increases over time.

Going over the three tables in succession (Tables 6 to 8), we can see that this hypothesis is overwhelmingly well accepted. Taking the individual investors over the three stages in large cap stocks as an example, the percentage of negative and positive signs is: 2.48% (−) vs. 76.03% (+), 98.35% (−) vs. 0% (+), and 97.52% (−) vs. 0% (+). The results are in accord with the minute-by-minute time-paths of various classifications as depicted in Fig. 2. This finding suggests that the incoming traders tend to be prudent when there is less time to deliver order cancelations or revisions (more binding). The finding that incoming traders would be more conservative over time during the closing call auction is interesting, compared to those studies which show that individual investors would be more aggressive over time (Anand et al., 2005; Bloomfield et al., 2005; Ellul et al., 2007; Duong et al., 2009). Of course, this is just one case demonstrating that the results of a continuous market may not be carried over the closing call auction.

#### 7.2.4. Pre-holidays and month-end days

Basically, our data do not give a clear indication as to the prominence of the pre-holiday effect. The proportion of significant cases is generally low with respect to stages, capitalizations, and investor groups. Even though, for some groups, the proportions are modest, the percentages of negative and positive signs are too close to give a clue. The only exception is the order-entering decisions of the institutional investors, particularly for large cap stocks. Table 6 shows a contrast of 29.75% (−) vs. 3.31% (+), which indicates that institutional investors tend to be less willing to submit in the last moment of pre-holidays. If we just focus on those 39 stocks listed in the Taiwan 50, then the contrast becomes even sharper, 41.03% (−) vs. 0% (+). This may indicate a degree of prudence due to possible unexpected events during holidays. As to the effect of the month-end days, from Table 7, we can see that institutional investors become more aggressive (impatient) in the last moments of the month-end days, 0% (−) vs. 73.11% (+). Again, with a further restriction to the Taiwan 50, the contrast becomes 0% (−) vs. 100%. Clearly, month-end days are important days for institutional investors.

### 7.3. Robustness check

The main purpose of the robustness check is to see whether the effects of the new disclosure mechanism on order aggressiveness obtained in the main text are sensitive to the chosen sample periods. The original sample scheme, called Scheme X, divides the whole sample period into a pre-event, covering 59 trading days from 2011/11/21 to 2112/02/17, and a post-event period, covering 59 trading days from 2012/02/20 to 2012/05/15. For the purpose of this robustness check, we consider two different sampling schemes, motivated by different reasons. The first one, called Scheme A, is motivated by the possible effect due to the *transition period*, and the second one, called Scheme B, as suggested by Ma et al. (2008), is based on the consideration of the possible *market trend* (time trend).

For Scheme A, we first divide both pre-event and post event periods into two halves, and take the first half from the pre-event period and the second half from the post-event period to form our new sample. The former half covers 29 trading days from 2011/11/21 to 2011/12/29, and the latter half covers another 29 trading days from 2012/04/03 to 2012/05/15. Obviously, by doing so, we have removed the middle half from the whole sample. By considering the middle half as a possible period for transition, including various possible behavioral adaptations to the new mechanism, we can reevaluate the results by leaving aside, probably, an unsettled period.

For Scheme B, as before, we simply divide both pre-event and post event periods into two halves, and keep all the four sub-periods. We shall first then apply our three-stage SOP model to the first two halves of the pre-event period (2011/11/21-2011/12/29 and 2012/01/02-2012/02/17), called Scheme B-1, and examine whether there is a change in order aggressiveness in time. We then do the same thing for the next two halves of the post-event period (2012/02/20-2012/03/30 and 2012/04/03 to 2012/05/15), called Scheme B-2. By comparing the two halves of both periods, we can examine whether a time trend exists, i.e., order aggressiveness actually increases with time and has nothing to do with the new mechanism.

We apply the same SOP model with the same set of 12 variables to these two (three) schemes, A and B (B-1 and B-2). Of course, the dummy variable will be adjusted based on the sample period considered, but

**Table 9**
Robustness check with different sample periods.

| | Scheme X | Scheme A | Scheme B-1 | Scheme B-2 |
|---|---|---|---|---|
| | 121 large cap stocks | | | |
| Individual investors | | | | |
| Est. coeff (med) | 0.059 | 0.095 | 0.029 | 0.060 |
| % $t$-stat < −1.96 | 14.88% | 10.00% | 16.67% | 8.26% |
| % $t$-stat > 1.96 | 39.67% | 28.33% | 16.67% | 21.49% |
| # of obs (med) | 11,628 | 4920 | 5752 | 5062 |
| Institutional investors | | | | |
| Est. coeff (med) | 0.173 | 0.022 | −0.151 | 0.080 |
| % $t$-stat < −1.96 | 3.36% | 11.76% | 30.83% | 16.67% |
| % $t$-stat > 1.96 | 45.38% | 16.97% | 5.83% | 12.50% |
| # of obs (med) | 4,335 | 2,036 | 1,982 | 2,238 |
| | 121 small cap stocks | | | |
| Individual investors | | | | |
| Est. coeff (med) | 0.097 | 0.149 | 0.116 | −0.036 |
| % $t$-stat <−1.96 | 1.65% | 4.96% | 3.42% | 13.22% |
| % $t$-stat > 1.96 | 37.19% | 28.10% | 20.51% | 6.61% |
| # of obs (med) | 3,448 | 1,195 | 1,403 | 1,820 |
| Institutional investors | | | | |
| Est. coeff (med) | 0.439 | 0.608 | 0.240 | 0.052 |
| % $t$-stat < −1.96 | 2.48% | 2.59% | 3.64% | 6.90% |
| % $t$-stat > 1.96 | 30.58% | 35.34% | 16.36% | 14.66% |
| # of obs (med) | 1,107 | 545 | 670 | 391 |

The table summarizes the estimation results of the dummy variable of the second-stage of the SOP model (Eq. (1), $l$ = II), i.e., the choice between submitting a patient order or an impatient order. The dummy variable is taken to distinguish two halves of the data under four different sample schemes, X, A, B-I, and B-II (see the text for the exact beginnings and ends). The results are organized by groups with respect to two sizes of market capitalizations, large (upper panel) and small (lower panel), and two types of investors, individual and institutional. There are a total of 121 stocks in each group. We report the median of the 121 estimates, followed by the percentages of them being significantly negative and positive at the 5% level, in the column with the titles '% $t$-stat < −1.96' and '% $t$-stat > 1.96', respectively. The $t$-stat is calculated by heteroskedastic-consistent covariance matrix estimator (White, 1980). The median number of order submissions is also reported in the row with the title '# of obs'.

again a value of 0 is assigned to the former half, and a value of 1 is assigned to the latter half. Since the main purpose of the robustness check relates to the effect of the new mechanism, so as not to make this paper oversized, we only report the results associated with the dummy variable, *InfD*, and only focus on the second stage. In this way, the original size of Tables 6 to 8 can now be economized into Table 9.

In Table 9, we present the results of the dummy variable in the same way that we did in Tables 6 to 8. To make the comparison easier, our results in the main text are copied here (the second column). The third column then presents the results without involving a 'transition period' (Scheme A). Using this 'transition-free' sample, we can see that the effect of the new mechanism remains for all four groups: 10.00% (−) vs. 28.33% (+) (Ind-L), 11.76% (−) vs. 15.97% (+) (Ins-L), 4.96% (−) vs. 28.10% (Ind-S) (+), 2.59% (−) vs. 35.34% (+) (Ins-S), even though for the Ins-L group, the contrast is less evident. One possible reason for this unique case is that for some reason the order aggressiveness for the first-half period is generally high in this period. We do not have compelling evidence at this stage. The confirmation of this conjecture requires more study, but a quick check can be done by looking at Scheme B-1.

By dividing the pre-event period into two halves, we intend to see whether there is a time momentum that has already set in. From the fourth column of Table 9, we basically do not find a convincing time trend. While, for small cap stocks, the percentage of positive signs is greater than that of negative signs, the percentages of significant cases are all less than one fourth. For large cap stocks, we even see the decline in the level of order aggressiveness (30.83% (−) vs. 5.83 (+) (Ins-L)), which actually supports our early conjecture that the level of order aggressiveness of the first half, due to some unknown reason, may have already been leveled up.

Finally, the last column shows the change in the two sub-periods after the launch of the new mechanism. The evidence of a time trend cannot be found. In the case of small cap stocks, for almost 80% of the cases the effect is insignificant. For the large cap stocks, the significance proportion is as high as 30%, but for the Ins-L group, the contrast is weak, 16.67% (−) vs. 12.50 (+). Only for the Ind-L group do we see the increase in the level of order aggressiveness, 8.26% (−) vs. 21.49% (+). Hence, the analysis based on Scheme B, as a whole, does not support the time trend pattern. However, the transition process may still play a role, which suggests that from the dark to the light one needs some time to adjust their behavior, particularly when one is situated in the dark for a long time, and that may help explain what we saw from the Ind-L group.

In sum, the robustness check does not fundamentally challenge our early results that the new disclosure mechanism has a positive effect on the level of order aggressiveness. Nonetheless, it does suggest that some follow-up studies need to be conducted so as to address the effect of adaptation or learning or the long-run effect.

## 8. Concluding remarks

In this paper, we study the order aggressiveness of individual and institutional investors in the closing call auction of the TWSE both before and after a new information disclosure mechanism. Determinants of order aggressiveness have been studied for some years, but most of them are devoted to the continuous market using the real-time order book. It seems to be more problematic how order aggressiveness can be measured and classified when the order book information does not exist or does exist but is only disclosed in discrete time. The key issue here is how we conceptualize order aggressiveness 'when there is no light'. The answer to this question is that when there is no 'light', we still have 'sounds', but, with a little light, things can be different.

We begin with the assumption that investors, informed or uninformed, do have their own 'simulated' quotes using their own information. This assumption is nothing atypical; after all, forming expectations is seen everywhere in the market, called the expectation effect in the paper. However, this 'simulation' may be enhanced if more information becomes available, in particular for individual investors, who symbolize uninformed traders. In our study, using the reconstructed real-time limit order book, we find that the significance of the spread on order aggressiveness was already there even in the opaque market. How could this happen? The answer is the expectation effect. Individual investors make efforts to use other information to simulate the real quotes. The significance of the 'last glance' (the last available best quotes before the closing call auction) provides such evidence (Section 7.1.4). For individual investors, the disclosed simulated best quotes, even in an increment of 20 s, enable them to stand in a better position to stalk the markets and to simulate the real quotes, and hence reinforce the spread effect (Section 7.1.2).

The TWSE is still under a transition toward a more transparent market. For the closing call, it has set up a schedule to gradually increase the number of best quotes from one to five and to reduce the increment of disclosure from 20 s to, eventually, 5 s. What can we expect from this policy agenda? The current disclosure of best quotes is only at an increment of 20 s, which in terms of 'simulating' real time volatility, as explained in Section 7.1.3, may help little. This is probably why we do not see the reinforcement effect attaching to volatility. However, with a 5-second disclosure increment, individual investors may have a better chance of simulating volatility and the effect of volatility on order aggressiveness can be better evaluated.[31]

None of the effects mentioned above can apply to the institutional investors to even a close degree. This contrast may imply that institutional investors rely less on the TWSE information disclosure; one possible explanation is their advantage in terms of information resources. As we have seen above, a more transparent market may help ameliorate the information asymmetry existing between the two types of investors at least, to some extent; nevertheless, can this narrowing gap be translated, in any sense, into economic well-being? For example, can the additional market transparency help individual investors to improve their quote precisions so as to improve their trading performance? A thorough treatment of this issue may be beyond the scope of this paper. Based on the results that we have so far, since both individual traders and institutional investors become more aggressive (impatient) in the partially transparent market, it will be hard to tell who will give in more. The development of some new indexes may be required before we can answer this question. This is a direction for future study.

Last, but not least, being a model of order aggressiveness, our model with its findings contributes to the existing literature on order aggressiveness, specifically, with an extension to the closing call. We show that the results from the regular continuous call session may carry over to the closing call. The determinants found significant in the former remain to be important in the latter. The feature that institutional investors expend more resources on staking large cap stocks is also supported in our study: a number of effects, such as the picking-off effect (the volatility effect), the diagonal effect, the order-splitting effect (the size effect), and the month-end effect, which are found to be significant in large cap stocks, turn out to be negligible in small cap stocks. Nonetheless, the closing call has its own uniqueness; the decaying time pattern of order aggressiveness and the positive month-end effect found in this paper can all be related to its 'deadline' function.

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[31] Compared with the spread, volatility seems to be more complex. What investors 'read' about volatility and what they actually live through on a real-time basis may be two different things. While one may still use the simulated quotes or the 'last glance' to obtain a simulated volatility, its meaning can be different from what they may perceive in real time. In this study, we find that the two versions of volatility actually depart in their effects on order aggressiveness. The real-time volatility which investors can only feel through their engagement in the market has a positive effect for both types of investors, but those 'imaginary' ones, based on the simulated quotes and the last glance, either have no effect or the opposite effect.

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