Order Aggressiveness and the Heating and Cooling-off Effects of Price Limits: Evidence from Taiwan Stock Exchange

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This study investigates the relationship between order aggressiveness and the distance between stock market prices and price limits in order to shed some light on the 'heating' and 'cooling-off' effects of these limits. Using intraday data on the Taiwan Stock Exchange (TSE), in conjunction with piecewise ordered probit regressions, we find that a significant 'inverted-N' ('N') shape pattern is discernible on the sell (buy) side of the relationship between order aggressiveness and price distance, which is consistent with the heating effect of upper (lower) price limits, as well as a cooling-off effect of lower (upper) price limits for market sellers (buyers). This study is the first to analyze changes of market participants' order aggressiveness when approaching price limits. Our findings offer clear indications to policymakers that price limits could counteract irrational stock markets.

Keywords: market microstructure, heating effect, cooling-off effect, price limits, order aggressiveness

JEL classification: D47, G13, G14

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1   Introduction

Regulatory authorities in the stock markets of many emerging economies have unilaterally applied price limits in order to suppress irrational transactions of individual traders during extreme price swings. It is argued in a number of prior studies that price limits are incapable of managing disordered market behavior; instead, they simply bring about several adverse effects of market quality, with particular emphasis on the 'heating effect' that results in a dysfunctional price limit policy. Chen (1998), Chan *et al.* (2005), Kim and Sweeney (2002), and Yang (2005) evaluate the performance of circuit breakers that look at market quality (volatility, trading activity, liquidity, order flow, and price trends) after the resumption of a continuous session. Cho *et al.* (2003) also note that price limits accompany other adverse effects about market quality such as volatility spillovers (Fama, 1989; Kim and Rhee, 1997; Yang, 2005), a delay in price discovery (Fama, 1989; Lehmann, 1989; Chen, 1993), and a reduction in liquidity (Fama, 1989; Lehmann, 1989; Chen, 1993). Thus, the question arises as to why policymakers within the stock markets of emerging economies choose to emphasize and adhere to the viability of the protection function for individual investors as a type of 'cooling-off effect'. To answer this question, our study is the first to analyze the changes of order aggressiveness of market participants when approaching price limits. We propose that price limits exist to counteract stock markets' irrational behavior.

As proponents of the cooling-off effect, Chung and Gan (2005) and Kim *et al.* (2013) document that the daily price limit acts as a stabilizing mechanism within the market. Deb *et al.* (2017) find price limit rules work quite efficiently for lower limits and successfully curbs transitory volatility on post limit-hit days. Arak and Cook (1997) suggest that day traders try to avoid the potential enlargement of losses as a result of holding contentious overnight positions. Thus, when a stock is close to its limit, such bullish (bearish) traders have less incentive to buy (sell), thereby reducing demand (supply) and slowing the price rise (decline).

Critics argue that there are three main reasons for the heating effect as the exact opposite of the cooling-off effect: 'overreaction', 'information', and 'illiquidity'. The 'overreaction' argument proceeds along the lines that if market participants

believe that the price is shifting towards its limit, then they will trade sooner rather than later so as to avoid being shut out of the trend (Cho *et al.*, 2003). The 'information' hypothesis argues that during the overnight period following limit moves, stock prices tend to continue the trend that had prevailed prior to such limit moves (Chen, 1998; Chan *et al.*, 2008). As for the third reason, 'illiquidity', if market participants fear the potential illiquidity of the target stocks, then this will provoke more active trading by such participants, thereby inducing prices to reach their limits (Lehmann, 1989; Chan *et al.*, 2005).

However, it is suggested in several theoretical studies that the examination of price limits should be capable of distinguishing between informed and uninformed traders (Subrahmanyam, 1997). Lehmann (1989) further notes that this is a deceptively simple view of the effect of price limits on price fluctuations, essentially because the observed market prices do not contain information on trading strategies to provide an appropriate answer to the simple question of whether 'overly enthusiastic' and 'rational' traders will behave the same when a stock price approaches its limits. Although prior studies have generally used the *Returns* variable to directly test the effects of price limits, based upon the observed market prices, this variable invariably provides relatively scant information content, leading to narrow conclusions. Thus, there is a requirement to identify other, more appropriate, key intraday variables to effectively examine the market behaviors of 'overly enthusiastic' and 'rational' traders associated with price limits. Thus, we adopt the order aggressiveness of market participants herein in an attempt to effectively analyze this issue.

Glosten (1994) sets the basic rational for order strategies as a trade-off between the non-execution costs and the picking-off risk carried by limit orders. Tsai *et al.* (2007) develop a dynamic model that shows several factors influencinge the uninformed trader's' order submission strategies and the limit price. Handa *et al.* (2003) further suggest that the greatest concerns, in terms of non-execution risk, are invariably   to be found amongst informed traders, whereas uninformed traders tend to be more concerned with the risk of adverse selection; hence, information on approaching price limits will hasve considerable impacts on both non-execution risk and adverse selection risk for informed and uninformed traders alike.

Abad and Pascual (2007) argue that the likelihood of a trading halt being

triggered is inversely proportional to the distance to the intraday price limit, which thereby implies that informed traders who are concerned with any likely impediment to trading may alter their trading strategies, such as advancing the submission of their orders in order to increase the probability of executing such orders. Kim and Sweeney (2002) argue that if such informed traders expect that an excessive amount of information will be leaked overnight, then they will be less likely to wait for the price limits. If short-term call auctions are efficient in revealing information, then the risk supported by informed traders would be augmented close to the price limits, encouraging such traders to trade earlier (Abad and Pascual, 2007). Thus, these studies demonstrate that the behavior of informed traders on price limits correlates more to non-execution risk.

Arak and Cook (1997) argue that if the price is close to its limit, then there will be an increase in the potential loss arising from holding overnight positions. Farag (2015) finds evidence of the overreaction anomaly within different price limit regimes, whereby larger initial price movements lead to greater subsequent reversals. Ackert et al. (2015) noted that a price limit is more likely to be triggered when investor sentiment is extreme. Thus, while some price changes reflect fundamental information, investors are prone to sentiment that moves markets based on misinformation. Chan et al. (2005) also present that since price limits may actually increase information asymmetry, there will be some recognition amongst uninformed traders that price limits increase the adverse selection risk. The behavior of uninformed traders on price limits is thus more related to adverse selection risk.

Our approach to the motivation of aggressive and non-aggressive traders is simplistic. Aggressive traders are assumed to be information-motivated and thus prefer to be concerned about non-execution risk, whereas patient traders are described as liquidity or uninformed traders and thus are more concerned about adverse selection risk. Griffiths et al. (2000), Ranaldo (2004), Chakrabarty et al. (2006), and Hasbrouck and Saar (2009) state that higher (lower) order aggressiveness provides an indication that market traders may face higher (lower) non-execution risk and lower (higher) adverse selection risk. Pascual and Veredas (2009), Yamamoto (2011), and Engelberg et al. (2012) document that the state of the limit order book influences stock investors' strategies. Investors place more aggressive orders when the same side of the order book is thicker and less

aggressive orders when it is thinner. We use order aggressiveness to represent fluctuations in non-execution risk and the adverse selection risk of informed and uninformed traders in order to gain a better understanding of whether absolute changes in such order aggressiveness may bring about a reduction (as the cooling-off effect) or an increase (as the heating effect) in market participation, thereby testing the validity of price limits.

The study period we choose is based on not having been influenced by the recent global economic crises, because government financial authorities initiated many policies to intervene in the markets during them. If the research were to span a financial crisis, then we would be unable to confirm whether the change in investors' trading behavior was due to price limits or other regulatory measures by governments. In order to avoid such research biases, we choose to avoid financial crises and economic changes, so that our research conclusions have good credibility. The dot-com bubble in 2000 and the 911 terrorist attacks in 2001 both impacted Taiwan stock market trading. Following the U.S. subprime mortgage crisis in 2007, the U.S. Federal Reserve implemented a quantitative easing (QE) monetary policy multiple times. The interference factors of the QE policy have complex systemic risks, which have different degrees of impact on financial market transactions. We thus choose March 2003 to June 2007, because there was no huge economic change during this period. When a financial market is not affected by economic changes, how does a price limit policy affect investors' trading behavior? We look to analyze the extreme impact of investors' order aggressiveness to capture how price limits influence their trading behavior.

The remainder of this paper is organized as follows. Section 2 provides aA definition of order aggressiveness is provided in Section 2, along with the 'heating' and 'cooling-off' effects hypotheses. Section 3 explains tThe methodology adopted hereinfor this study is explained in Section 3. Section 4 provides a description of the trading mechanism and the data on the Taiwan Stock Exchange for this study. Section 5 presents the analysis of the empirical results. Section 6 draws conclusions from this study.

2   Heating/Cooling-off Effects of Price Limits

2.1   Definition of Order Aggressiveness

The call auction system in an order-driven market ensures that the trading mechanism periodically ranks all buy orders by the setting price, from the highest to the lowest, and all sell orders by the setting price, from the lowest to the highest, and then matches the orders on both sides by maximizing the accumulated order volume. A variety of orders is entered into the trading system during each call auction; they are then stored until they are matched during the trading day. 'Market aggregate order aggressiveness' refers to the integration of the order aggressiveness of all "new arriving orders" during each auction; hence, market aggregate order aggressiveness can be taken as being representative of the willingness to trade amongst all market participants at each auction, including the reflection by such investors when approaching price limits.

Griffiths *et al.* (2000) define higher order aggressiveness as a situation within which the buyer (seller) sets a higher (lower) price $P^{*}_{b,t}$ ($P^{*}_{a,t}$) of the limit order, where $P^{*}_{b,t}$ ($P^{*}_{a,t}$) is the strike price at which the buyer (seller) sets the best price of the limit order. If traders are aware of the arrival of a favorable (unfavorable) signal that increases (reduces) the precision of their reservation value, such that they become more aggressive (patient), then they will tend to be more (less) concerned about non-execution risk and less (more) concerned about adverse selection risk. In contrast, traders on the opposite side will tend to be more (less) concerned about adverse selection risk and less (more) concerned about non-execution risk. Consequently, more (fewer) own side limit orders will shift to the prevailing best quoted price, and fewer (more) opposite side limit orders will shift to the prevailing best quoted price.

We should simultaneously consider the interactive change in the number of orders amongst the best five quote and trading prices to capture the shifting behavior of all orders; this provides us with an order aggressiveness spectrum from the aggressive submission of orders to the aggressive cancellation of orders. It could be argued that the difference in aggressiveness between submitting a limit order between the 3rd and the 4th bids and submitting the same order between the 4th

and the 5th bids might appear to be negligible. Hence, we analyze 5-level spectrum (market orders over the best quotes, market orders inside the quotes, limit orders at the best quotes, limit orders between best quotes and 3rd quotes, and limit orders between 3rd quotes and 5th quotes) and 6-level spectrum (market orders over the best quotes, market orders inside the quotes, limit orders at the best quotes, limit orders between best quotes and 3rd quotes, limit orders between 3rd quotes and 5th quotes, and canceling limit orders). The results are similar. We define the price setting ($P^*_{b,t}$) of new arriving limit buy orders by the following fifteen calibrations:

$$j = \begin{cases} 0 & if & submitting\,order & ask_{3,t-1} \leq P^*_{b,t} \\ 1 & if & submitting\,order & ask_{1,t-1} < P^*_{b,t} < ask_{3,t-1} \\ 2 & if & submitting\,order & P^*_{b,t} = ask_{1,t-1} \\ 3 & if & submitting\,order & bid_{1,t-1} < P^*_{b,t} < ask_{1,t-1} \\ 4 & if & submitting\,order & P^*_{b,t} = bid_{1,t-1} \\ 5 & if & submitting\,order & bid_{2,t-1} \leq P^*_{b,t} < bid_{1,t-1} \\ 6 & if & submitting\,order & bid_{3,t-1} \leq P^*_{b,t} < bid_{2,t-1} \\ 7 & if & submitting\,order & bid_{4,t-1} \leq P^*_{b,t} < bid_{3,t-1} \\ 8 & if & submitting\,order & bid_{5,t-1} \leq P^*_{b,t} < bid_{4,t-1} \\ 9 & if & submitting\,order & P^*_{b,t} < bid_{5,t-1} \\ 10 & if & canceling\,order & bid_{5,t-1} \leq P^*_{b,t} < bid_{4,t-1} \\ 11 & if & canceling\,order & bid_{4,t-1} \leq P^*_{b,t} < bid_{3,t-1} \\ 12 & if & canceling\,order & bid_{3,t-1} \leq P^*_{b,t} < bid_{2,t-1} \\ 13 & if & canceling\,order & bid_{2,t-1} \leq P^*_{b,t} < bid_{1,t-1} \\ 14 & if & canceling\,order & P^*_{b,t} = bid_{1,t-1} \end{cases} \qquad (1)$$

Here, $bid_{q,t-1}$ ($ask_{q,t-1}$) is the best q^{th} bid (ask) quote at time $t-1$ to determine the order aggressiveness of a new arriving limit order at time t. (Sell orders have the same calculation.) The order aggressiveness calibration follows the more (less) aggressive and smaller (larger) calibration; yet, we cannot observe the quotes below (above) the best 5th bid (ask), and so the unobservable orders are substituted by the cancelled orders. Intuitively, an investor is likely to be more willing to forego trading relating to the cancellation of the higher (lower) price order of a limit buy (sell) order as compared to the cancellation of the lower (higher) price of a limit buy (sell), and thus the foregoing of trades is likely to be the most aggressive in the cancellation of the limit buy (sell) order of the best first bid (ask). Hall and Hautsch

(2006) also include cancelled orders in their study of the determinants of order aggressiveness. For robustness, we also analyze the effect of order aggressiveness without cancellation of orders on price limits. Since the empirical results for these two order aggressiveness calculations are very similar, we present only the order aggressiveness with cancellation of orders in Section 5.

In order to identify the level of market aggregate order aggressiveness during each call auction, we standardize the order aggressiveness on both sides by rounding up the weighted average value of order aggressiveness. The market aggregate order aggressiveness (*MAOA*) for side *i* at time *t* is as follows:

$$MAOA_{i,t} = round\left(\sum_{j=0}^{14} jW_{i,j,t}\right), \quad W_{i,j,t} = \frac{NOA_{i,j,t}}{TNOA_{i,t}}, \tag{2}$$

$$i = buy, sell \quad side,$$

where $NOA_{i,j,t}$ is the number of orders (submitted or cancelled orders) in the order aggressiveness calibration j; $TNOA_{i,t} = \sum_{j=0}^{14} NOA_{i,j,t}$; and $j = 0,1,...., 14$.

2.2   Hypotheses on the Heating/Cooling-off Effects on Price Limits

For simplification we assume that uninformed traders are characterized by their scant information, represent the majority of market participants, and tend to be the main suppliers of liquidity in an order-driven market. Conversely, informed traders are characterized by the preciseness of their information, are in the minority of market participants, and tend to be the main demanders of liquidity in an order-driven market. Informed traders with precise information are more concerned with non-execution risk, whereas uninformed traders with no private information are more concerned with adverse selection risk (Glosten, 1994; Foucault, 1999; Liu, 2009; Handa *et al.*, 2003).

With the approach of upper limits, informed buyers concerned with any likely impediment to trading will face higher non-execution risk, leading to them becoming more aggressive (Abad and Pascual, 2007; Kim and Sweeney, 2002), whereas uninformed buyers concerned with the potential loss arising from information asymmetry will face higher adverse-selection risk, leading to them

becoming more patient (Arak and Cook, 1997; Chan *et al.*, 2005; Li *et al.*, 2014). This phenomenon in buy market behavior may be the result of informed buyers becoming more aggressive and uninformed buyers becoming more patient, with uninformed buyers outnumbering informed buyers; the outcome of this is an increase in the price of executed orders, but a reduction in the limit prices of most limit buy orders. Thus, the market aggregate order aggressiveness value rises with changes in auctions, meaning that most market participants will become more patient, with more buy side orders leaving from the prevailing best quoted price; clearly, the market behavior in this case leads to a rise in returns accompanied by a fall in order aggressiveness. Our analysis of the market aggregate order aggressiveness of informed and uninformed buyers therefore suggests that upper price limits lead to a cooling-off effect (a reduction of order aggressiveness) amongst all market buyers when uninformed buyers outnumber informed buyers.

Hypothesis 1:   *Upper price limits lead to a cooling-off effect amongst market buyers.*

With the approach of lower price limits, informed buyers will face lower non-execution risk, thereby encouraging them to become more patient, whereas uninformed buyers will face lower adverse-selection risk, thereby encouraging them to become more aggressive. Many theoretical and empirical studies suggest that limit orders may be motivated by informed trading, while market orders may be motivated by uninformed trading (Kaniel and Liu, 2006; Bloomfield *et al.*, 2005; Foucault *et al.*, 2005). This phenomenon in buy market behavior may be the result of informed buyers becoming more patient and uninformed buyers becoming more aggressive, with uninformed buyers outnumbering informed buyers; the outcome of this is a reduction in the price of executed orders, but an increase in the limit prices of most limit buy orders. Thus, market behavior in this case leads to a fall in returns accompanied by a rise in order aggressiveness. The above analysis of the market aggregate order aggressiveness of informed and uninformed buyers therefore suggests that lower price limits lead to a heating effect (an increase of order aggressiveness) amongst market buyers when uninformed buyers outnumber informed buyers.

Hypothesis 2:   *Lower price limits lead to a heating effect amongst market buyers.*

With the approach of lower (upper) price limits, informed sellers will face higher (lower) non-execution risk, leading to them becoming more aggressive (patient), whereas uninformed sellers will face higher (lower) adverse-selection risk, leading to them becoming more patient (aggressive). Thus, we derive the following sell-side null hypotheses.

Hypothesis 3:   *Lower price limits lead to a cooling-off effect amongst market sellers.*

Hypothesis 4:   *Upper price limits lead to a heating effect amongst market buyers.*

3   Methodology

We extend the methodology of Griffiths *et al*. (2000), in which ordered probit regressions are used to analyze order aggressiveness in a continuous market. Within ordered probit regressions, the observed $MAOA_{buy,t}$ ($MAOA_{sell,t}$) denotes outcomes representing the market aggregate order aggressiveness categories on the buy (sell) side. The observed response for each of the sample stocks is modeled by considering a latent variable $y^{*}_{i,t}$ that is linearly dependent on the explanatory variable x_{t-1}:

$$y^{*}_{i,t} = x'_{t-1}\beta_i + \varepsilon_{i,t}, \quad i = buy, sell, \tag{3}$$

where $\varepsilon_{i,t}$ is a random variable. The observed category for $MAOA_{buy,t}$ ($MAOA_{sell,t}$) is based on $y^{*}_{buy,t}$ ($y^{*}_{sell,t}$) according to the rule:

$$MAOA_{i,t} = \begin{cases} 0 & if & y^{*}_{i,t} \leq \gamma_{i,1} \\ 1 & if & \gamma_{i,1} < y^{*}_{i,t} \leq \gamma_{i,2} \\ 2 & if & \gamma_{i,2} < y^{*}_{i,t} \leq \gamma_{i,3} \\ & \vdots & \\ 14 & if & \gamma_{i,14} < y^{*}_{i,t} \end{cases}, \quad i = buy, sell \tag{4}$$

Here, $\gamma_{i,j}$ is the best bid (ask) quote. We follow the above equation to distinguish the bid (ask) order aggressiveness. The best five quote prices of buyer and seller sides disclosed by the trading system are noted from the comparison. The method of Griffiths *et al*. (2000) is divided into 14 levels. In this study we stress that the actual values selected to represent the categories in $MAOA_{i,t}$ are completely arbitrary, with the

model requiring larger category values to correspond to larger latent variable values. In order to capture the heating and cooling-off effects of price limits, we estimate the piecewise linear regressions on 'market aggregate order aggressiveness' under an ordered probit model, which allows for two changes in the slope coefficient on the daily returns. Cho *et al*. (2003) exclude the stock returns at the price limits, essentially because once a price has reached its limit, it can either stay there or move in only one direction, hence exhibiting unusual dynamics. We also exclude all data within three ticks before the price limits, because once the price is very close to its limit, the most aggressive traders will be unable to submit more aggressive orders, thereby leading to a biased value of market aggregate order aggressiveness.

We classify the observations within our entire sample into three groups in order to facilitate our empirical investigation: (i) 'normal distance', which refers to the overnight returns, at the current market price between −3% and +3%, relating to those stocks whose prices do not close at their limits; (ii) 'upper distance', which refers to the overnight returns, at the current market price between +3% and +7%, relating to those stocks that close at their upper price limits; and (iii) 'lower distance', which is the overnight returns, at the current market price between −3% and −7%, relating to those stocks that close at their lower price limits. Our overall aim is to attempt to determine whether there are structural changes in the relationships existing between market aggregate order aggressiveness and the 'normal distance', 'upper distance', and 'lower distance' groups. Hence, we define the *Return* variable, with the dummy variables *DF* (price floor) and *DC* (price ceiling), as $Return_{i,t-1}$ = the return of mid-quote at the $t-1$ auction based upon the closing price of the previous trading session.

We use the following variables to estimate and report our piecewise linear regressions to revise the ordered probit model:

$$
\begin{aligned}
y_{i,t}^* = {} & \alpha_1 return_{i,t-1} + \alpha_2 DF_{i,t-1}\left(return_{i,t-1} + 3\%\right) \\
& + \alpha_3 DC_{i,t-1}\left(return_{i,t-1} - 3\%\right) + x_{t-1}'\beta_i + \varepsilon_{i,t},
\end{aligned}
\tag{5}
$$

where i = buy, sell; and x_{t-1} are the control variables from the limit order book that include prior order aggressiveness, price movement, order imbalance, relative spread, the speed of the trading process, timeframe, price volatility, and trading volume.

The piecewise ordered probit regression of market aggregate order

aggressiveness on returns allows for changes in the slopes at −3% and +3%; however, the theoretical justification for these particular numbers is not very strong. In their study of the effects of the 7% price limits on TSE, Cho *et al.* (2003) set the threshold at ± 3% for their definition of the ceiling and floor; thus, we follow Cho *et al.* (2003) to use ± 3% as the threshold in our examination of the heating and cooling-off effects of price limits purely for reasons of consistency.

If structural changes do exist in order-submission behavior as prices approach their limits, the expected possible relationships between *MAOA* and the returns of the mid-quote in the $t - 1$ auction based on the last closing price (*Return*) are respectively illustrated in Figure 1 as 'inverted-N' ('N') shapes for sell (buy) side.
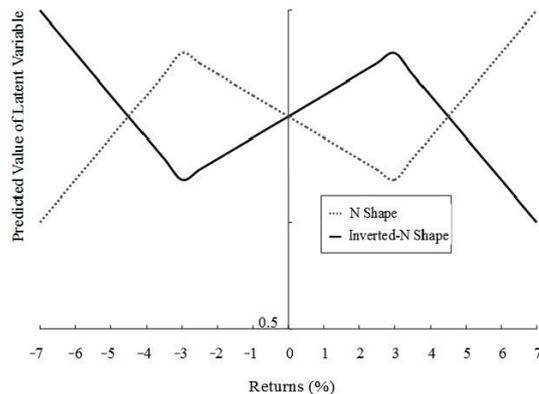
Figure 1.   Relationship between the Market Aggregate Order Aggressiveness of Latent Variables and Market Price Returns to the Last Session's Closing Price

4   Market Structure and Data

4.1   Background to Price Limits and the Structure of TSE

Lee *et al*. (2004) analyze the trading behaviors of individuals, domestic institutions, and foreign institutions using data from the Taiwan Stock Exchange (TSE). They show that the number of orders and shares of individual traders overwhelmingly outnumber those of the other two institutions. Most importantly, the evidence

indicates that large domestic institutions conduct the most informed trades and that large individuals are uninformed traders. We suggest that the TSE market is a good sample for researching the main issue of this paper.

Daily price limits have been imposed within TSE ever since its establishment in 1962, initially being set at 5% for much of the period before 1989; however, from October 11, 1989, the daily price limits were relaxed to 7%[1] for both upward and downward movements. Stocks may not currently be traded at prices that are 7% higher or lower than the offer price or the preceding day's closing price, with this price limit being imposed on all stocks in both the primary and secondary markets.

4.2   Dataset

The data used in this study are drawn from the Taiwan Economics Journal (TEJ) database. All of the information within our dataset is available to market participants in real time through a computerized information dissemination system, with all brokers being directly connected to this system. Our sample comprises 25 of the most highly liquid stocks in the Taiwan Stock Exchange covering the period from March 2003 to June 2007. As we noted earlier that there was no huge economic change during this period, it provides a good opportunity for examination. The dataset contains the full limit order book history on these 25 stocks for a period in excess of four years, reporting the stock code, auction time, execution price, volume in number of shares exchanged (in lots of 1,000), trading time, the best five bid and ask prices, and the total number of shares demanded or offered at each of the five bid and ask quotes (in lots of 1,000) for each auction.

We generate the variables required to examine the relationship between market aggregate order aggressiveness and distance from the market price to the price limits for each observation. For each auction, we calibrate the order aggressiveness of each order, sorted under 15 different order strategies, and then calculate the market aggregate order aggressiveness by the weighted-average of the order aggressiveness of each order; hence, the market aggregate order aggressiveness has 15 possible outcomes. The unconditional relative frequency and the percentages for market

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[1]Since Jun. 1, 2015, the price limit for TSE has been relaxed from 7% to 10%, but this new limit does not cover the period of our study.

aggregate order aggressiveness are reported in Table 1 for the buy side and Table 2 for the sell side, along with details of the total number of auctions for our sample stocks over the whole sample period.

The largest of the market aggregate order aggressiveness values (14) indicates that the market is inclined to be extremely patient towards trading, while the smallest of the values (0) indicates that the market is inclined to be extremely aggressive towards trading. We find that the most frequently occurring calibrations for *MAOAbuy* are 4 and 10, with respective relative frequencies of 23.33% and 23.23%. A similar finding for *MAOAsell* appears, where calibrations 4 and 10 again occur regularly, with respective relative frequencies of 21.54% and 23.91%.

We generate the variables employed in our analyses according to the details extracted from the database, with the variable definitions including 'prior order aggressiveness', 'order imbalance', 'speed', 'relative spread', 'volatility', 'volume', 'momentum factor', and 'timeframe'. The definitions of the control variables (x_{t-1}) in the limit order book constructed in our analysis are as follows.

a. *Prior Order Aggressiveness* (*Own Side and Opposite Side*): Sellers = $MAOA_{sell,t-1}$ and Buyers = $MAOA_{buy,t-1}$.

b. *Order Imbalance:* OI_{t-1} refers to the degree of order imbalance on the buy and sell sides in call auction $t-1$.

c. *Speed:* $Speed_{t-1}$ is elapsed time in seconds during the auction at time $t-1$.

d. *Relative Spread:* $RSpread_{t-1}$ is the relative quoted spread of the best ask and best bid in call auction $t-1$.

e. *Volatility:* $Volatility_{t-1}$ is the standard deviations of the last 20 mid-quote returns at time $t-1$.

f. *Volume:* $Volume_{t-1}$ is trading volume in the auction at time $t-1$.

g. *Momentum Factor:*

$$MidquoteReturn_{t-1} = \frac{Midquote_{t-1} - Midquote_{t-2}}{Midquote_{t-2}} . \qquad (6)$$

$$Momentum_{t-1} = \prod_{i=t-1}^{t-20} (1 + MidquoteReturn_{t-1}) - 1 \cdot \qquad (7)$$

h. *Timeframe:*

$$\text{Timeframe}_{t-1} = \begin{array}{llll} 1 & if & 9:00am. \leq t-1 < 9:30am. & or & 1:00pm. \leq t-1 < 1:30pm. \\ 2 & if & 9:30am. \leq t-1 < 10:00am. & or & 12:30pm. \leq t-1 < 1:00pm. \\ 3 & if & 10:00am. \leq t-1 < 10:30am. & or & 12:00noon. \leq t-1 < 12:30pm. \\ 4 & if & 10:30am. \leq t-1 < 11:00am. & or & 11:30am. \leq t-1 < 12:00noon. \\ 5 & if & 11:00am. \leq t-1 < 11:30am. & or \end{array} \qquad (8)$$

Table 1.   Buy-side Frequency of Market Aggregate Order Aggressiveness

This table presents the unconditional relative frequency and percentages for buy-side market aggregate order aggressiveness along with details of the total number of auctions for the 25 stocks over the full sample period. The order aggressiveness of each order is calibrated for each auction, sorted under 15 different order strategies. Market aggregate order aggressiveness is then calculated by the weighted average of the order aggressiveness of each order; hence, market aggregate order aggressiveness has 15 possible outcomes. The largest of the market aggregate order aggressiveness values (14) indicates that the market is inclined to be extremely patient towards trading, while the smallest of the values (0) indicates that the market is inclined to be extremely aggressive towards trading.

Sample Stock	No. of Obs.	Buy-side Market Aggregate Order Aggressiveness														
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Asia Cement	426,719	0.04	0.47	20.48	5.50	20.30	6.55	3.75	2.97	3.49	5.67	26.43	0.93	0.88	1.19	1.34
Formosa Plastics	545,867	0.02	0.26	16.34	9.05	28.21	10.90	5.39	3.75	3.69	3.86	14.46	0.92	0.86	1.02	1.28
Formosa Chemicals & Fibre	537,304	0.02	0.24	17.26	8.53	26.79	10.50	5.30	3.72	3.74	4.09	15.58	0.92	0.87	1.10	1.34
Far Eastern Textile	532,160	0.03	0.49	19.23	8.22	24.39	8.71	4.83	3.79	4.02	5.95	16.01	1.09	0.96	1.06	1.21
China Steel	572,363	0.01	0.11	13.05	13.16	32.30	15.68	7.14	4.39	3.53	3.73	3.97	0.87	0.68	0.65	0.73
Delta Electronics	78,411	0.06	0.68	20.17	8.76	23.25	8.22	4.66	3.79	3.87	6.31	16.70	0.83	0.78	0.94	0.98
Compal Electronics	544,860	0.03	0.40	18.05	9.22	26.38	9.41	5.05	3.76	3.88	5.34	14.77	0.88	0.84	0.89	1.09
Asustek Computer	564,260	0.03	0.27	15.07	10.87	27.98	12.19	6.42	4.46	4.24	4.97	9.58	0.96	0.87	0.95	1.13
Chunghwa Telecom	517,701	0.02	0.22	17.87	6.95	26.17	9.48	4.55	3.16	3.41	3.25	20.87	0.81	0.80	1.09	1.36
Catcher Technology	501,663	0.04	0.47	14.60	8.90	20.34	10.25	6.60	4.97	5.15	7.03	16.29	1.25	1.15	1.37	1.59
Fubon FHC	520,371	0.03	0.35	19.74	7.43	25.25	7.77	4.34	3.48	3.99	5.14	18.98	0.87	0.72	0.84	1.06
Cathay FHC	556,193	0.02	0.28	16.42	9.65	28.37	11.01	5.49	4.11	4.25	4.63	11.43	1.12	0.93	1.02	1.28
China Development FHC	557,527	0.00	0.15	14.66	9.40	28.87	12.72	6.12	3.96	3.17	3.83	12.10	1.11	1.19	1.29	1.44
Yuanta FHC	557,527	0.00	0.15	14.66	9.40	28.87	12.72	6.12	3.96	3.17	3.83	12.10	1.11	1.19	1.29	1.44
Taishin FHC	553,202	0.00	0.12	13.07	6.88	20.97	7.83	4.07	2.87	2.49	3.23	35.31	0.70	0.71	0.77	0.98
SinoPac FHC	512,863	0.01	0.12	14.47	4.60	18.50	5.52	2.90	2.10	2.08	2.82	43.84	0.58	0.64	0.78	1.06
Chinatrust FHC	553,998	0.02	0.25	19.01	9.14	29.13	9.27	4.89	3.68	3.86	4.63	12.69	0.87	0.75	0.78	1.02
First FHC	522,096	0.01	0.23	18.36	8.19	25.80	9.68	4.97	3.51	3.42	4.70	16.57	1.02	1.00	1.17	1.38
Novatek Microelectronics	535,198	0.01	0.14	10.60	7.12	18.01	9.55	5.64	3.90	3.56	4.45	32.17	1.11	1.08	1.25	1.41
Far EasTone Telecoms	410,188	0.02	0.28	20.85	4.66	20.90	5.94	3.25	2.65	3.18	5.39	29.21	0.72	0.74	1.01	1.20
Formosa Petrochemical	397,383	0.02	0.24	17.43	5.46	22.68	8.86	4.57	3.16	3.45	3.69	26.00	0.89	0.83	1.18	1.53
Foxconn Technology	440,524	0.05	0.54	14.93	8.26	20.03	9.45	5.89	4.59	4.86	6.63	19.34	1.27	1.12	1.42	1.61
Inotera Memories	192,583	0.07	0.56	12.40	6.54	17.56	6.82	3.76	2.93	2.92	4.88	39.11	0.70	0.60	0.56	0.59
InnoLux Display	102,724	0.03	0.28	5.81	3.59	9.28	3.82	2.40	1.89	1.78	2.61	67.14	0.34	0.31	0.33	0.37
Nan Ya Printed Circuit Board	141,352	0.01	0.11	7.47	5.01	13.01	7.05	4.45	3.34	2.83	3.48	50.04	0.85	0.84	0.77	0.74
Average	455,001	0.02	0.30	15.68	7.78	23.33	9.20	4.90	3.56	3.52	4.57	23.23	0.91	0.85	0.99	1.17

Table 2.   Sell-side Frequency of Market Aggregate Order Aggressiveness

This table presents the unconditional relative frequency and percentages for sell-side market aggregate order aggressiveness along with details of the total number of auctions for the 25 stocks over the full sample period. The order aggressiveness of each order is calibrated for each auction, sorted under 15 different order strategies. Market aggregate order aggressiveness is then calculated by the weighted average of the order aggressiveness of each order; hence, market aggregate order aggressiveness also has 15 possible outcomes. The largest of the market aggregate order aggressiveness values (14) indicates that the market is inclined to be extremely patient towards trading, while the smallest of the values (0) indicates that the market is inclined to be extremely aggressive towards trading.

Sample Stock	No. of Obs.	Buy-side Market Aggregate Order Aggressiveness														
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Asia Cement	426,719	0.05	0.63	21.92	5.21	18.10	6.13	3.91	3.27	3.65	5.79	27.78	0.80	0.79	0.92	1.06
Formosa Plastics	545,867	0.03	0.33	18.99	8.60	25.81	10.00	5.18	3.69	3.68	3.99	16.21	0.82	0.75	0.85	1.07
Formosa Chemicals & Fibre	537,304	0.03	0.32	18.84	7.58	24.42	9.51	5.18	3.74	3.86	4.19	18.73	0.80	0.76	0.88	1.15
Far Eastern Textile	532,160	0.04	0.61	21.41	8.12	22.48	8.23	4.99	4.05	4.20	6.09	16.43	0.92	0.77	0.79	0.89
China Steel	572,363	0.01	0.15	16.17	13.40	30.77	13.96	6.84	4.36	3.35	3.77	4.60	0.71	0.62	0.58	0.70
Delta Electronics	78,411	0.10	1.04	23.18	8.52	20.92	7.28	4.55	3.68	3.76	6.39	17.93	0.72	0.62	0.61	0.71
Compal Electronics	544,860	0.04	0.53	21.04	9.44	24.41	9.03	5.12	3.97	4.07	5.40	13.83	0.84	0.70	0.72	0.87
Asustek Computer	564,260	0.03	0.37	16.91	10.91	26.38	11.88	6.59	4.63	4.27	5.08	9.71	0.86	0.73	0.74	0.91
Chunghwa Telecom	517,701	0.01	0.16	17.87	6.99	25.42	9.40	4.82	3.38	3.45	3.36	21.19	0.74	0.74	0.99	1.48
Catcher Technology	501,663	0.05	0.61	16.32	8.94	19.19	9.93	6.73	5.09	5.08	7.00	16.77	1.06	0.97	1.04	1.20
Fubon FHC	520,371	0.03	0.40	21.76	7.71	23.57	7.41	4.41	3.58	3.90	5.10	19.23	0.67	0.64	0.69	0.90
Cathay FHC	556,193	0.03	0.32	18.18	9.93	27.06	10.98	5.74	4.19	4.15	4.79	11.25	0.84	0.75	0.80	1.01
China Development FHC	557,527	0.00	0.21	19.13	10.51	26.64	11.80	6.23	4.18	3.27	3.73	10.54	0.91	0.90	0.90	1.05
Yuanta FHC	557,527	0.00	0.21	19.13	10.51	26.64	11.80	6.23	4.18	3.27	3.73	10.54	0.91	0.90	0.90	1.05
Taishin FHC	553,202	0.01	0.19	15.25	6.23	19.04	6.67	3.82	2.81	2.52	3.23	37.50	0.61	0.64	0.68	0.81
SinoPac FHC	512,863	0.01	0.15	16.49	5.06	17.30	5.93	3.41	2.50	2.32	2.94	41.33	0.52	0.53	0.66	0.85
Chinatrust FHC	553,998	0.02	0.31	21.81	9.13	27.41	8.57	4.72	3.71	3.77	4.75	12.82	0.68	0.68	0.65	0.96
First FHC	522,096	0.01	0.34	21.07	7.88	23.44	8.84	5.03	3.75	3.52	4.63	17.96	0.84	0.84	0.84	1.00
Novatek Microelectronics	535,198	0.01	0.19	11.85	7.30	16.88	9.32	5.90	4.15	3.74	4.45	32.32	0.93	0.90	0.98	1.07
Far EasTone Telecoms	410,188	0.03	0.38	21.41	4.25	18.14	4.82	2.90	2.55	3.37	5.59	33.37	0.70	0.64	0.85	1.00
Formosa Petrochemical	397,383	0.02	0.29	20.07	5.45	21.21	8.14	4.40	3.26	3.80	3.79	26.05	0.81	0.68	0.92	1.11
Foxconn Technology	440,524	0.07	0.65	16.68	8.07	18.47	9.31	6.23	4.73	4.90	6.80	19.65	1.06	1.01	1.14	1.25
Inotera Memories	192,583	0.08	0.89	16.63	6.23	15.18	5.00	3.08	2.43	2.64	4.40	41.52	0.52	0.46	0.47	0.49
InnoLux Display	102,724	0.06	0.42	8.34	3.65	7.96	3.44	1.97	1.59	1.66	2.55	67.37	0.29	0.25	0.21	0.24
Nan Ya Printed Circuit Board	141,352	0.01	0.14	9.84	4.56	11.61	5.23	3.87	2.70	2.86	3.19	53.11	0.80	0.69	0.72	0.67
Average	455,001	0.03	0.39	18.01	7.77	21.54	8.50	4.87	3.61	3.56	4.59	23.91	0.78	0.72	0.78	0.94

Table 3 describes the limit order book characteristics for our sample stocks. The average *MAOAbuy*, at 5.97, and *MAOAsell*, at 6.06, imply that the buyers of the sample stocks frequently submit a limit order at a specified price between the second and third bid prices and the sellers of the sample stocks frequently submit a limit

order at a specified price close to the third ask price. The *Momentum* factor, at 0.092%, indicates that the short-term returns are slightly positive.

Table 3.   Summary Statistics of the Information Content of the Limit Order Book

This table presents the summary statistics of the information content of the limit order book averaged over the full sample period. *MAOAbuy* is the buy-side market aggregate order aggressiveness; *MAOAsell* is the sell-side market aggregate order aggressiveness; *Momentum* is the average return of the last 20 mid-quote returns; *OI* is the number of lots of 1,000 shares on the best ask divided by the sum of the number of lots of 1,000 shares on the best ask and the number of lots of 1,000 shares on the best bid; *RSpread* is the spread divided by the mid-quote; *Speed* is the time elapsed (in seconds) between one auction and the next; *Timeframe* is an indicator of an auction occurring in a particular period of time (a smaller *Timeframe* indicates that the trading time is close to the open or the close); *Volatility* is the standard deviation in the last 20 mid-quote returns; and *Volume* is the number of trades, in lots of 1,000 shares, in each call auction.

Sample Stock	MAOAbuy	MAOAsell	Momentum	OI	RSpread	Speed	Timeframe	Volatility	Volume
Asia Cement	6.14	6.13	0.00074	0.49765	0.00351	39.980	2.717	0.00181	16.874
Formosa Plastics	5.46	5.46	0.00015	0.49651	0.00345	31.248	2.784	0.00059	20.769
Formosa Chemicals & Fibre	5.65	5.54	0.00017	0.49391	0.00352	31.931	2.781	0.00065	20.262
Far Eastern Textile	5.50	5.59	0.00066	0.49381	0.00316	32.060	2.772	0.00209	34.280
China Steel	4.77	4.85	0.00010	0.49655	0.00234	29.855	2.806	0.00054	84.556
Delta Electronics	5.55	5.74	0.00051	0.49995	0.00282	33.196	2.764	0.00129	13.220
Compal Electronics	5.31	5.47	0.00012	0.48995	0.00253	31.538	2.782	0.00085	28.880
Asustek Computer	5.21	5.29	0.00013	0.49681	0.00330	30.377	2.797	0.00077	20.853
Chunghwa Telecom	5.78	5.75	0.00001	0.50779	0.00416	33.148	2.771	0.00043	17.783
Catcher Technology	5.88	5.98	0.00170	0.49342	0.00325	34.149	2.756	0.00259	9.377
Fubon FHC	5.56	5.65	0.00019	0.49070	0.00246	32.745	2.770	0.00094	27.597
Cathay FHC	5.25	5.37	0.00021	0.49924	0.00354	30.750	2.794	0.00075	37.884
China Development FHC	5.15	5.45	0.00021	0.47302	0.00432	30.714	2.792	0.00101	60.764
Yuanta FHC	5.93	6.38	0.00051	0.48503	0.00435	42.580	2.705	0.00155	27.795
Taishin FHC	6.60	6.56	0.00034	0.48411	0.00325	20.487	2.789	0.00115	44.444
SinoPac FHC	6.76	6.96	0.00023	0.50010	0.00400	22.280	2.768	0.00099	40.529
Chinatrust FHC	5.17	5.26	0.00017	0.49673	0.00232	31.023	2.791	0.00089	47.514
First FHC	5.53	5.59	0.00020	0.47816	0.00303	32.706	2.771	0.00096	55.664
Novatek Microelectronics	6.66	6.75	0.00135	0.49189	0.00421	24.915	2.778	0.00241	11.950
Far EasTone Telecoms	6.42	6.24	0.00006	0.50355	0.00245	40.640	2.722	0.00072	13.317
Formosa Petrochemical	6.02	6.14	0.00013	0.50335	0.00388	34.472	2.746	0.00052	14.394
Foxconn Technology	6.02	6.11	0.00172	0.49611	0.00388	38.706	2.738	0.00281	7.267
Inotera Memories	6.74	6.80	0.00059	0.48294	0.00157	16.615	2.781	0.00135	25.482
InnoLux Display	8.20	8.30	0.01250	0.48716	0.00213	7.461	2.795	0.00399	22.778
Nan Ya Printed Circuit Board	8.10	8.06	0.00031	0.48513	0.00247	16.403	2.756	0.00113	4.112
Average	5.97	6.06	0.00092	0.49294	0.00320	29.9991	2.7690	0.00131	28.3338

The average order imbalance (*OI*) is 0.49 for the sample stocks, which indicates

that the buy depth and sell depth are almost equal. The average *RSpread* for the sample stocks, at 0.32%, exceeds that of the Switzerland's Stock Exchange (SWX) market, which Ranaldo (2004) shows to be 0.17%. This is hardly surprising, given that our sample stocks are smaller than the stocks of SWX. The average *Speed* amongst the sample stocks is 29.999 seconds, with the trades frequently occurring at 10:00a.m. to 10:30a.m. and from 12:00 noon to 12:30 p.m. for all of the sample stocks (*Timeframe* = 2.769). The average *Volatility* is 0.131%, which is also higher than the average for SWX at 0.0482%. The average trading volume over the whole market is 28.3338.

5   Empirical Results

5.1   Results of the Relationship between Order Aggressiveness and Price Distance

Table 4 presents the results for most of the control variables, including *MAOAbuy* (buy-side: 100% positive at the 1% significance level; sell-side: 76% negative), *MAOAsell* (76% negative; 100% positive), *Momentum* (40% positive; 52% positive), *OI* (100% positive; 96% negative), *RSpread* (52% positive; 60% positive), *Speed* (52% negative; 84% negative), *Timeframe* (40% negative; 40% negative), *Volatility* (60% negative; 60% negative), and *Volume* (100% positive; 100% positive), all of which are consistent with our expectations, as well as being consistent with the findings within much of the prior literature.

Table 4.   Summary of Piecewise Ordered Probit Model of Market Aggregate Order Aggressiveness

This table presents the ordered probit regressions of the market aggregate order aggressiveness (*MAOA*) for each of the 25 stocks over the full sample period. *MAOA* is the dependent variable, ranked from the most aggressive trading to the most aggressive foregoing submission. The regressors are the key variables of the limit order book of the call auction at time $t-1$; *MAOAsell* is the sell-side order aggressiveness; *MAOAbuy* is the buy-side order aggressiveness; *Momentum* refers to the last 20 mid-quote returns; *OI* is the number of lots of 1,000 shares on the best ask divided by the sum of the number of lots of 1,000 shares on the best ask and the number of lots of 1,000 shares on the best bid; *RSpread* is the spread divided by the mid-quote; *Speed* is the time elapsed (in seconds) between one auction and the next; *Timeframe* is an indicator of an auction occurring in a particular period of time (a smaller *Timeframe* indicates that the trading time is close to the open or the close); *Volatility* is the standard deviation in the last 20 mid-quote returns; *Volume* is the number of trades, in lots of 1,000 shares, in each call auction; *Return* is the market price to closing price return in the last trading session; *DF* is a dummy variable that takes a value of 1 when the *Return* is between −7% and −3% and a value of zero when the *Return* is not between −7% and −3%; *DC* is a dummy variable that

takes a value of 1 when the *Return* is between +3% and +7% and a value of zero when the *Return* is not between +3% and +7%; and *Count* is the number of stocks, with *%* referring to the proportion of *Count* to the 25 stocks. A positive 1% significance indicates the number of coefficients that are significantly positive at the 1% level, and a negative 1% significance indicates the number of coefficients that are significantly negative at the 1% level.

| Variables | Positive | | | | | Negative | | | | |
| | 1% Significant | | | Insignificant | | 1% Significant | | | Insignificant | |
	Coeff.	Total No.	%	Coeff.	%	Coeff.	Total No.	%	Coeff.	%
Panel A: Sell Side										
MAOAbuy ($t-1$)	0.035	6	24		–	−0.021	19	76		–
MAOAsell ($t-1$)	0.037	25	100		–	–	–			–
Momentum ($t-1$)	0.240	13	52	0.0524	16	−0.629	5	20	−0.108	12
OI ($t-1$)		–	–		–	−0.432	24	96	−0.016	4
Rspread ($t-1$)	18.065	15	60	0.7467	12	-34.398	6	24	−0.927	4
Speed ($t-1$)	0.0001	1	4	0.0001	4	−0.001	21	84		–
Timeframe ($t-1$)	0.008	7	28	0.0011	24	−0.007	10	40	−0.002	8
Volatility ($t-1$)	1.390	3	12	0.3067	4	−0.989	15	60	−0.256	24
Volume ($t-1$)	0.001	25	100		–	–	–			–
Return ($t-1$)		–	–		–	−5.631	25	100		–
DF ($t-1$)	4.685	25	100		–	–	–			–
DC ($t-1$)	6.244	1	4	1.2944	4	-16.060	23	92		–
Panel B: Buy Side										
MAOAbuy ($t-1$)	0.043	25	100		–	–	–			–
MAOAsell ($t-1$)	0.033	6	24		–	−0.018	19	76		–
Momentum ($t-1$)	0.546	10	40	0.0551	12	−0.291	7	28	−0.084	20
OI ($t-1$)	0.405	25	100		–	–	–			–
Rspread ($t-1$)	14.329	13	52	1.4351	8	-22.829	9	36	−0.651	4
Speed ($t-1$)	0.0003	6	24	0.0003	4	−0.001	13	52		–
Timeframe ($t-1$)	0.006	8	32	0.0007	16	−0.009	10	40	−0.002	12
Volatility ($t-1$)	0.932	5	20	0.3423	8	−1.451	15	60	−0.451	12
Volume ($t-1$)	0.0003	25	100		–	–	–			–
Return ($t-1$)	3.855	24	96	0.1956	4		–	–		–
DF ($t-1$)		–	–		–	−4.404	24	96	−0.361	4
DC ($t-1$)	9.715	23	92		–	−1.656	1	4	−0.269	4

Table 4 mainly presents the results of the relationship between order aggressiveness and distance from the market price to the price limits based on daily returns. The coefficients on the sell-side *Return* variable are significantly negative in

all of the sample stocks. As for the sell-side price limit dummy variables, all of the sample stocks have significantly positive coefficients on the price floor dummy variable (*DF*), while 92% of the sample stocks have significantly negative coefficients on the price ceiling dummy variable (*DC*). All of these findings are largely in line with Hypotheses 3 and 4, whereby sellers are inclined to be patient when the market price approaches its lower price limit and aggressive when the market price approaches its upper price limit. For sellers, this implies that the price floor has a cooling-off effect, whereas the price ceiling has a heating effect.

InAs regards to the buy-side price limit variables, the coefficients of the *Return* variable are significantly positive in 96% of the sample stocks. The buy-side price floor dummy variable (*DF*) has a significantly negative coefficient in 96% of the sample stocks, whilest the buy-side price ceiling dummy variable (*DC*) has a significantly positive coefficient in 92% of the sample stocks. This provides strong evidence in support of our Hypotheses 1 and 2, wherebythat buyers are inclined to be aggressive when the market price approaches its lower price limits, and patient when the market price approaches its upper price limits. For buyers, this also implies that the price floor has a heating effect, whereas the price ceiling has a cooling-off effect.

5.2 Relationship Shapes between Order Aggressiveness and Price Distance

In this sub-section we focus on the 'N' and 'inverted-N' shapes in the relationship between order aggressiveness and the distance between the market price and price limits. The coefficients in the ordered probit regression of the control variables and price limit variables, *Return*, *DF*, and *DC*, for the sell (buy) side of each stock are shown in Panel A (Panel B) of Table 4. We take the average values of the control variables in Table 3 (according to the coefficients of the ordered probit regression on the buy and sell sides) into the order probit regression of Table 4 to obtain the intercept terms for each stock. Using the intercept terms and the coefficients of the price limit variables in the ordered probit regressions, we then calculate the possible values of the latent variables for market aggregate order aggressiveness, with the *Return* variable being flexible within the range of -7% to $+7\%$.

The estimated relationship between sell-side market aggregate order

aggressiveness (*MAOAsell*) and the return from the market price to the last closing price (*Return*) in Figure 2 clearly reveals an 'inverted-N' shape for sellers, providing evidence of the heating effect of upper price limits and the cooling-off effect of lower price limits. The estimated relationship between buy-side market aggregate order aggressiveness (*MAOAbuy*) and the return from the market price to the last closing price (*Return*) in Figure 3 clearly reveals an 'N' shape for buyers, providing evidence of the cooling-off effect of upper price limits and the heating effect of lower price limits.

The 'inverted-N' shape on the sell side and the 'N' shape on the buy side provide sound justification for the unilateral application of price limits by the regulatory authorities of many emerging stock markets as a device for curbing excessive price swings. The cooling-off effect of the upper (lower) price limit mechanism for buyers (sellers) may indeed reduce the market overreaction by uninformed buyers (sellers) in an upward (downward) market. Furthermore, the heating effect of the lower (upper) price limit mechanism of uninformed buyers (sellers) could neutralize the market overreaction of uninformed sellers (buyers) in a downward (upward) market. Policymakers know that uninformed traders, as the majority of investors, are easily manipulated by the mechanism of price limits to conquer market overreaction, but informed traders, as the minority, are not. Hence, the more astute policymakers in emerging markets can count on price limits to manage disordered market behavior stemming from uninformed traders.
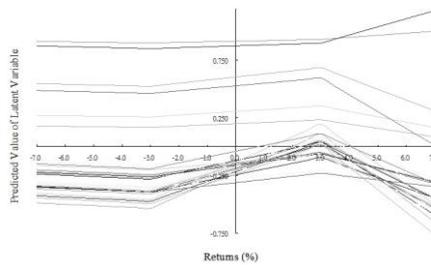
Note: * The figure shows the 'inverted N-shaped' relationship between the predicted values of the market aggregate order aggressiveness latent variable for sellers and the market price returns to the closing price of the last session for the 25 sample stocks estimated by the piecewise linear order probit regression.

Figure 2.   Inverted N-shaped Relationship between the Predicted Values of the Latent Variables and the Market Price Returns to the Last Session's Closing Price
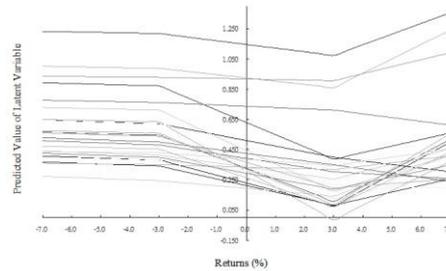
Note: * The figure shows the 'N-shaped' relationship between the predicted values of the market aggregate order aggressiveness latent variable for buyers and the market price returns to the closing price of the last session for the 25 sample stocks estimated by the piecewise linear order probit regression.

Figure 3. N-shaped Relationship between the Predicted Values of the Latent Variables and the Market Price Returns to the Last Session Closing Price

6   Conclusions

This study examines the relationship between market aggregate order aggressiveness and the distance between the market price and price limits. Market overreaction creates unwelcome excess volatility; thus, provided the gains outweigh the costs, any market mechanism that might reduce such overreaction would benefit both individual investors and financial market regulators. Hence, numerous stock markets around the world restrict daily stock price movements by applying price limit rules. The motivation behind the imposition of such limit rules is to prevent overreaction and panic by providing a time-out period that gives investors an interval to cool off.

Our methodology decomposes the effects of price limits into two forces as an effective means of correcting irrational market behavior. First, the evidence presented herein confirms the variability of the cooling-off effect of lower (upper) price limits for uninformed sellers (buyers) who are seen as irrational sources in a downward (upward) market. Second, the heating effect of upper (lower) price limits for uninformed sellers (buyers), who are essentially manipulated by policymakers, could neutralize the overreaction behavior of uninformed buyers (sellers) in an upward (downward) market.

We therefore highlight the fact that within the market there are co-existing cooling-off effects for irrational traders on one side and heating effects for irrational

traders on the other side. This goes some way toward explaining why policymakers in emerging markets firmly believe that price limits are effective for uninformed traders (the majority) in terms of keeping overreaction under some degree of control with their executed orders, because the behavior of informed traders (the minority) cannot be manipulated by a price limit policy.

Finally, our findings support the viability of price limits in terms of the majority of market participants. We cannot say that our evidence is entirely inconsistent with that of prior empirical studies, such as Cho *et al.* (2003) and Chan *et al.* (2005), with regards to the minority of market participants. However, we do state that our evidence fills the gap in the literature on the effects of price limits as they related to limit order traders. Our evidence therefore helps to explain why the regulatory authorities of many emerging markets apply price limits as a device for curbing excessive price swings.

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