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Do Behavioral Biases Affect Order Aggressiveness?*

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Abstract

We extend previous studies on the effect of behavioral biases on investor hold/sell decisions, and examine whether behavioral biases affect the order submission strategies. We use a unique database provided by the Shanghai Stock Exchange, which contains order submissions and executions as well as trading records of all investors. We find investors are less aggressive in submitting sell orders for stocks that experienced losses, and more aggressive in submitting sell orders for stocks that experienced gains. The sell order aggressiveness is negatively related to the size of losses, but has a quadratic relationship with the size of gains. Results are consistent with the combination of the disposition and the house money effects.

JEL classification: G12, G14, G18

Keywords: Order submission, Order aggressiveness, Disposition effect

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1. Introduction

Major global equity markets (e.g., NYSE, NASDAQ, Paris Bourse, Hong Kong, Shanghai) currently rely on limit order books to provide liquidity. Investors can provide liquidity by submitting limit orders, or consume liquidity by submitting market orders. A key research question in the limit order market is what determines the order aggressiveness of investors in their submission strategies. In submitting a limit order, the trader indicates the prices at which he or she is willing to buy or sell. The higher the limit order price to buy or the lower the limit order price to sell, the more aggressive the investor in consuming liquidity. The most aggressive strategy is for the trader to simply submit a market order and ensure it will be immediately executed at the best quote available. Previous studies suggest that investors' order aggressiveness is affected by the status of the limit order book at the time of submission, or the investors' expectation of incoming order flows and the trader's valuation of the traded stock.[1] This literature typically assumes that order submission decisions are based on a rational expectations framework and on forward-looking information, such as future price volatility and cash flows. However, there is extensive empirical evidence that investors exhibit behavioral biases, where prior investment outcomes can affect their subsequent trading decisions. One example is the disposition effect (Shefrin and Statman, 1985), in which investors show a greater propensity to sell stocks trading at a gain rather than a loss. Thus, whether investment outcomes also affect the order aggressiveness of their submission strategies is an important question.

There is no consensus in the theoretical literature on what drives the observed relationship between prior investment outcomes and subsequent risk-taking behavior. One common explanation for the disposition effect is the prospect theory (Kahneman and Tversky, 1979) which postulates that the utility function is concave within the domain of wealth gained, and convex within the domain of wealth lost, so that investors will tend to sell stocks that experience a gain rather than a loss. However, some theoretical studies (e.g., Barberis and Xiong, 2009; Kaustia, 2010) show that the prospect theory does not necessarily lead to the disposition effect. But while there is no agreement on theoretical reasoning, there is widespread empirical evidence that prior investment outcomes affect the subsequent risk-taking decisions of investors, although not necessarily in the form of the relationship predicted by the prospect theory (see Odean, 1998; Grinblatt and Keloharju, 2001; Liu *et al.*, 2010; Ben-David and Hirshleifer, 2012).

This paper complements previous studies by examining how previous trading gain/loss affects the order submission strategies. We are not aware of any studies on relating prior investment consequences to the order aggressiveness. The closest one is by Coval and Shumway (2005) who examine the trading behavior of market makers in CBOT T-bond futures. They find that the CBOT market makers tend to increase their risk exposures after morning losses compared with morning gains. This finding is consistent with the disposition effect. On the other hand, Liu *et al.* (2010) conduct a similar experiment using data on market makers in Taiwan's index options markets and find contrary evidence that investors tend to decrease their risk exposures after morning losses. Our study extends the study in Coval and Shumway (2005) by directly linking investors' order-type choices to their previous trading outcomes. It differs from prior studies in at least two aspects. First,

1 For details, please see Biais, Hillion, and Spatt (1995), Parlour (1998), Foucault (1999), Griffiths *et al.* (2000), Ranaldo (2004), Hollifield, Miller, and Sandas (2004), and Goettler, Parlour, and Rajan (2005).

we investigate not only the actual trades, but all the orders being submitted to the market. We are therefore able to investigate whether prior gain/loss affects the order aggressiveness. Second, our analysis includes all investors rather than market makers only. Our results thus shed light on the effects of behavioral biases on order submission strategies in limit order markets, which has not been examined before, but yet important in the studies of market microstructure.

To investigate the influence of prior investment outcomes on order submission strategies, data on both executed and unexecuted order flows are required. However, most databases of tick-by-tick transactions and brokerage trading records only include executed orders. In this study, we use a unique database provided by the Shanghai Stock Exchange (SSE), which holds real-time records of the order submissions of all investors trading securities that are listed on the exchange, along with their end-of-day stock holdings. This enables us to track order submissions and executions for every investor trading stocks listed on the Shanghai stock market. Similar to other markets, there is extensive evidence that Chinese investors are subject to behavioral biases (e.g., Feng and Seasholes, 2004, 2005; Shumway and Wu, 2006; Xiong and Yu, 2011). The Chinese equity market is therefore an ideal place to examine the potential effect of behavioral biases on order submission strategies.

We focus on sell order submissions and analyze the relationship between the investment outcomes and order aggressiveness. We construct order aggressiveness measures by comparing the order price with the limit order book at the time of submission. Consistent with the disposition effect, we find that investors are more aggressive in submitting sell orders for stocks with gains than for those with losses. Further analysis of the effect of gains/losses on order aggressiveness measures finds that the relationship between sell order aggressiveness and losses is significantly negative, but between sell order aggressiveness and gains is quadratic—order aggressiveness first increases with gains, and then declines after a certain level is reached.

The asymmetric relationship between prior investment outcomes and subsequent order aggressiveness for winner and loser stocks is not entirely consistent with the disposition effect, as we find that investors become less aggressive in selling a winner stock after it has reached a certain level of profit. However, the combination of the disposition effect and the house money effect could explain our result that order aggressiveness first increases with gains when the disposition effect is dominant, and then declines after the gains reach a certain level when the house money effect becomes dominant.

To corroborate our findings, we conduct additional tests, using only executed orders. We examine how the size of gains/losses can affect the hazard ratios associated with the investor's decision to sell/hold stocks. First, the hazard ratio is significantly above one for winner stocks, and significantly below one for loser stocks, which is a clear evidence of the disposition effect. Second, for loser stocks, similar to the effect of order aggressiveness, the size of losses is negatively related to the hazard ratio, indicating that investors are more reluctant to sell stocks of bigger losses. Third, for winner stocks, again similar to the effect of order aggressiveness, the hazard ratio first increases with gains and subsequently declines. These results show that the combination of the disposition effect and the house money effect is evident in both the order aggressiveness and the sell/hold decision.

To show that our results are not caused by the short-sale restrictions in the Chinese when investors could short sell their stocks. We show that our main results of asymmetric relationship between order aggressiveness and prior gains/losses remain unchanged in these alternative data samples.

A number of previous studies have already shown that Chinese investors are subject to behavioral biases.[2] The major contribution of our paper is, however, to show that the behavioral biases also affect the order submission strategies, which has not been documented previously. Even if investors have desire to sell the stocks, but if their propensity to sell is low and they are not aggressive enough in the sell order submission, they will end up with the hold decision. With our unique dataset, we are able to investigate the propensity to sell the stocks based on all sell orders being submitted (including those that are not executed). The paper illustrates that the risk attitudes of the investors embedded in limit orders to be time-varying.

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The study is organized as follows. Section 2 gives a brief overview of order aggressiveness in the limit order market. Section 3 describes the dataset and presents the preliminary statistics. Section 4 introduces the empirical methodology and variables used to explain the order aggressiveness. Section 5 presents the empirical results, and Section 6 presents the robustness test results. Section 7 summarizes the main findings of the study.

2. Previous Studies on Order Aggressiveness and Behavioral Biases

2.1 Order Aggressiveness

A distinguishing feature of the limit order markets is that investors can provide liquidity by submitting limit orders, or consume liquidity by submitting market orders. Limit orders specify a price and the number of shares available for sale or purchase. The price is prespecified, so they cannot always be matched with orders on the other side upon arrival. They are then stored in a limit order book while waiting to be executed. Market orders are executed with certainty at the best available quoted prices on the market.

Biais, Hillion, and Spatt (1995) document the intra-day order flows on the Paris Bourse. Instead of simply comparing limit orders with market orders, they classify orders in terms of their “aggressiveness,” l1ngg

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A number of studies set up dynamic models of trading and investigate the determinants of investors' choices between more aggressive market and less aggressive limit orders (e.g., Cohen *et al.*, 1981; Parlour, 1998; Foucault, 1999; Foucault, Kadan, and Kandel, 2005; Large, 2007; Roşu, 2009). Most of these studies find that the choice between limit orders and market orders is based on a trade-off between the gain of a limit order (a price improvement relative to standing quotes) and the cost of non-execution. Other studies suggest that limit orders are exposed to the risk of being "picked off," as traders submitting market orders may be better informed on the payoff of a risky security than traders submitting limit orders (Glosten, 1994). Foucault (1999) suggests that higher volatility in the market creates a greater risk that limit orders can be picked off by informed traders. Therefore, investors tend to use less aggressive limit orders for a higher compensation reward when the volatility is higher, and vice versa. Handa and Schwartz (1996) also show that investors intend to submit less aggressive limit orders in the presence of higher short-term fluctuations in transaction prices.

2.2 Behavioral Biases

Market microstructure models typically assume a rational expectations framework, under which traders remain risk neutral and their beliefs are rational, based on available information regarding future cash flows. However, behavioral finance shows that investors are subject to psychological biases, causing them to make decisions based on prior investment performance. For example, the prospect theory proposed by Kahneman and Tversky (1979) states that the utility function for gains is concave, and convex for losses. Shefrin and Statman (1985) claim that the prospect theory can explain the disposition effect, in which investors become more risk averse and tend to sell stocks for cash after the price appreciates, but after the stock price declines they are less risk averse and tend to hold the stock. The disposition effect for retail traders regarding financial markets (Odean, 1998; Grinblatt and Keloharju, 2001) and the real estate market (Genesove and Mayer, 2001) is well-documented. Coval and Shumway (2005) document the disposition effect in the trading behaviors of professional market makers as well.

Recent studies have also suggested that gains/losses might affect subsequent sell/hold decisions in a different way than the disposition effect does (e.g., Barberis and Xiong, 2009; Kaustia, 2010) Tversky and Kahneman (1981) also point out that a decision frame can cause the prospect theory not to function well in dynamic contexts. Kumar and Lim (2008) provide evidence by showing that investors trading less consecutively exhibit stronger disposition effect because they are likely to disaggregate each gain (trade in a narrower frame). Similarly, Thaler and Johnson (1990) argue that individuals might segregate gains instead of using a broad decision frame that combines all gains. They find that individuals may show an increasing tolerance to risk as their previous wealth gained exceeds some reference point, a tendency they call the house money effect. The house money effect is contrary to the disposition effect in that it predicts that traders become less risk averse after winning.

Overall, the previous literature on prospect theory suggests that behavioral biases will influence the hold/sell decisions of investors. In this paper, we investigate the willingness of investors to sell the stocks based on all orders being submitted, which affects their liquidity provision decisions. If the prior investment gains/losses can influence the hold/sell decisions of investors, as what have been documented in the disposition effect in previous studies, they should also affect the aggressiveness of investors in submitting sell orders.

3. Description of the Market and Dataset

3.1 The Open Limit Order System of the SSE

The main trading mechanism of the SSE is an order-driven continuous auction. The trading time is from 9:30 to 15:00, with a lunch break from 11:30 to 13:00. Every trading day starts with an opening call auction, and orders to be filled are submitted between 9:15 and 9:25. The opening price is chosen, so the transaction volume at the market opening is maximized for all existing submitted orders. Unexecuted orders are automatically stored in an electronic consolidated open limit order book (COLOB) for continuous trading, which begins at 9:30.

During the continuous trading session, each incoming order is automatically matched against the best standing limit order in the COLOB,engf9.4(c)13c72.6(Un)81.7(t)0(s)260.9(w)14(282(i)16.

as they may be concerned about losing the opportunity to trade stocks at target prices. We therefore remove order submissions from our sample if the particular stocks hit one of their price limits on that trading day. Second, we remove the orders submitted during the first 15 min of each trading day, as this is when the call auction process takes place, rather than a continuous trading session. Third, if the time between the COLOB snapshot and the order submission record is more than 30 s, we drop the order, as the limit order book information is updated at 10–30 s intervals for Chinese individual investors, who constitute the majority of investors in our sample. Therefore, the COLOB information from more than 30 s before the order submission cannot proxy for the order book status at the time of submission.

Our database includes the accounts for all investors who trade SSE securities. However, using all of the data is beyond the SSE's computational capability. We therefore extract a random sample of 500,000 retail investors, together with all institutional investors, and analyze only the data for the year of 2008. We examine only A-share stocks traded by domestic investors and exclude investors who obtained stocks from non-trade stock transfers, bequests, or IPO allocations, as we cannot determine the purchase prices for these stocks. To examine how representative our sample is relative to the whole market, we calculate both the trading volume in shares and in yuan for each stock traded for our sample accounts in 2008, and per-where Bid1 is the best bid quote at the time of order submission and Order_Price is the price that the investor submits on the sell order. Aggressive_1 is similar to the measure used by Harris and Hasbrouck (1996). The best bid quote represents the potential price at which the investor can immediately sell some of the shares. If the investor submits a sell order price higher than the best bid, he or she risks not being able to execute the order immediately, or at all. An investor who intends to assume less risk and to sell the stocks quickly will submit a more aggressive order with an Order_Price close to or even lower than Bid1. The higher Aggressive_1, the more eager the investor is to sell and the more aggressive the order submission. If investors submit a market order, we take the Bid1 equal to or higher than the Order_Price as the order will be executed at the best bid price. Thus, a positive value for Aggressive_1≥0 indicates a market order,[4] and a negative value for Aggressive_1<0 means a limit order.

We note that the aggressiveness measure is calculated with respect to the best bid quote. In the unreported analysis, we also construct the aggressiveness measure with respect to the mid-quote, and find that all of our empirical results remain qualitatively the same.

We should also note that Bid1 may not be the only potential selling price for an investor who intends to sell immediately. Bid1 equals a unique selling price only if the order size is smaller than or equal to the depth at Bid1, so the full order can be executed at the best bid quote. We will later consider the analysis when the sell order size is greater than the depth at the best bid quote.

(ii) Aggressive_2: The second sell order aggressiveness measure is based on Biais, Hillion, and Spatt (1995), whose definition of aggressiveness is based on the status of the current order book. They categorize order aggressiveness by determining whether the order price is below or at the best quote on the other side of the market, and if the order price is within the best ask–bid quote, or is higher than the current best quote on the same side of the market. The most aggressive sell (buy) orders are those that seek immediate executions by offering prices that hit or go lower (higher) than the best bid (ask) quote on the opposite side of the market. The least aggressive sell (buy) orders are those offering prices higher (lower) than, or those that are furthest away from, the best ask (bid) quote. A similar categorization is adopted in Griffiths *et al.* (2000) and Ranaldo (2004).

We develop the second-order aggressiveness measure for the sell orders submitted (Aggressive_2). This is constructed by comparing the sell order price with each of the multiple quoted ask and bid prices in the limit order book at the time of the submission. The calculation involved is as follows:

$$\begin{aligned}\text{Aggressive\_2} &= 1 \text{ if Ask5} \leq \text{Sell\_Order\_Price}\\ &= 2 \text{ if Ask4} \leq \text{Sell\_Order\_Price} < \text{Ask5}\\ &= 3 \text{ if Ask3} \leq \text{Sell\_Order\_Price} < \text{Ask4}\\ &= 4 \text{ if Ask2} \leq \text{Sell\_Order\_Price} < \text{Ask3}\\ &= 5 \text{ if Ask1} \leq \text{Sell\_Order\_Price} < \text{Ask2}\\ &= 6 \text{ if MIDQUOTE} \leq \text{Sell\_Order\_Price} < \text{Ask1}\\ &= 7 \text{ if Sell\_Order\_Price} < \text{MIDQUOTE},\end{aligned}$$

where Ask1, Ask2, Ask3, Ask4, and Ask5 are the five best-quoted ask prices in the order book, and MIDQUOTE is the average of the best ask and bid quotes at the time of the

4 In this study, it is most likely a marketable limit order.

order's submission. We also assume the Aggressive_2 = 7 for the market order. Similar to Aggressive_1, the higher Aggressive_2, the more eager the investor is to sell and the more aggressively she places the sell order.

Shanghai investors can submit market orders, which are to be execut(cu)148.9(e5h,)60(t)-24750(t)0gh

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negatively related to the market depth at the best bid, and positively related to the market depth at the best ask quote.

(iii) Short-term volatility: Foucault (1999) and Handa and Schwartz (1996) show that higher volatility in the market implies that investors who place limit orders face a greater "picking-off" risk from informed traders. Traders will submit less aggressive orders when the short-term volatility is high and when they assess the "picking-off" risk as high. We compute the short-term volatility (RISK) over the 30 min before an order's submission as

$$\mathrm{RISK} = \left(\left(\frac{1}{N-1}\right)\sum_{i=1}^{N}\left(R_i - \bar{R}\right)^2\right)^{1/2},$$

where N equals 30 and R_i is the return of the ith 1-min return during the 30-min interval. $\bar{R}$ is the average of R_i over the 30 min. That is, RISK is calculated as the standard deviation of the 1-min return over the 30-min interval prior to the order submission. We also calculate short-term volatility as the sum of the squared 1-min return over the 30-min interval. Based on previous studies, if short-term volatility represents a higher "picking-off" risk, we should observe a negative relationship between RISK and the order aggressiveness measure.

(iv) Price level: Price level is an inverse measure of the transaction cost. For sell orders, order aggressiveness is measured as the cost of immediacy that the investor is willing to pay to sell the stocks quickly. For our two aggressiveness measures, the cost of immediacy is determined in terms of yuan amount, as Aggressive_1 is equal to the difference between the best bid quote and the sell order price, and Aggressive_2 is an indicator of the order's status in the limit order book, which is measured in terms of the number of ticks. Therefore, the investor looks at the cost of immediacy relative to the price level. The higher the stock price level, the more willing the investor is to pay for the cost of immediacy. We measure the stock price level using the mid-quote (MIDQUOTE), based on the average of the best bid and ask prices at the time of order submission. We expect order aggressiveness to be positively related to the mid-quote.

(v) Amihud measure: The Amihud measure (Amihud, 2002) measures the price impact driven by each dollar trading volume. We calculate the Amihud measure as the average of the daily Amihud measure for the prior 30 days

$$\mathrm{AMIHUD}_t = \sum_{i=1}^{30}\frac{|R_{t-i}|}{30 * \mathrm{Dvol}_{t-i}}$$

R_{t-i} is the holding period return of stock on day $t-i$, and Dvol_{t-i} is the yuan trading volume (in ¥10,000) of on day $t-i$. The AMIHUD assesses liquidity in the form of price impact. It is the average of absolute return per yuan in daily trading volume for the prior 30 trading days. A large AMIHUD is an indication of low liquidity because it suggests that the average daily price movement of the security per unit of trading volume is large. We expect the relationship between order aggressiveness and the AMIHUD to be positive.

(vi) Short-term momentum: Short-term return measures are important indicators for investors who make trading decisions on trends or other technical indicators. We compute the prior half-hour's return (MOMENTUM) as the return over the 30 min prior to the order submission. If sellers believe there is momentum in returns, after the stock price goes up (down) they will revise the valuation of the stock upward (downward), and be less

Table I. Statistics of order aggressiveness measures and explanatory variables

Panels A, B, and C of this table report the mean (Mean), median (Median), standard deviation (Std), minimum (Min), and maximum (Max) of the two order aggressiveness measures, gains/losses measures, and the other control variables. All variables are Winsorized at 95%.

Aggressive_1 is defined as

$$\text{Aggressive\_1} = \text{Bid1} - \text{Sell\_Order\_Price},$$

where Bid1 is the best quoted bid price at the time of order submission and Sell_Order_Price is the (sell) order price submitted.

Aggressive_2 is constructed by comparing the (sell) order price with each of the multiple quoted ask and bid prices in the limit order book at the time of submission.

$$\begin{aligned}\text{Aggressive\_2} &= 1 \text{ if } \text{Ask5} \le \text{Sell\_Order\_Price}\\ &= 2 \text{ if } \text{Ask4} \le \text{Sell\_Order\_Price} < \text{Ask5}\\ &= 3 \text{ if } \text{Ask3} \le \text{Sell\_Order\_Price} < \text{Ask4}\\ &= 4 \text{ if } \text{Ask2} \le \text{Sell\_Order\_Price} < \text{Ask3}\\ &= 5 \text{ if } \text{Ask1} \le \text{Sell\_Order\_Price} < \text{Ask2}\\ &= 6 \text{ if } \text{MIDQUOTE} \le \text{Sell\_Order\_Price} < \text{Ask1}\\ &= 7 \text{ if } \text{Sell\_Order\_Price} < \text{MIDQUOTE},\end{aligned}$$

where Ask1, Ask2, Ask3, Ask4, and Ask5 are the five best-quoted ask prices in the order book. Sell_Order_Price is the (sell) order price submitted. MIDQUOTE is the average of the best-quoted ask and bid prices at the time the order is submitted.

The dollar values (in yuan) of the PGs measure (PG)/PLs measure (PL) are calculated based on the difference between Bid1 and the reference price:

$$\text{PG} = \text{Max}\ [0,\ \text{Bid1} - \text{Reference}],$$
$$\text{PL} = \text{Max}\ [0,\ \text{Reference} - \text{Bid1}],$$

where Reference is the reference price, which is the share-weighted average purchasing price. When the outstanding best bid quote (Bid1) is higher than the reference price, PG is assigned the absolute value of the difference and PL is assigned the value of zero. Conversely, when the current best bid price is lower than the reference price, PG is assigned the value of zero and PL is assigned the absolute value of the difference.

The control variables include the relative bid–ask spread (SPREAD), which is the ratio of the difference between the market best ask and bid quotes divided by the average of those quotes; the best ask market depth (ADEPTH) and the best bid market depth (BDEPTH), which are the yuan quantities of the market depth over the best ask and bid quotes; the average of best-quoted ask and bid prices (MIDQUOTE); the standard deviation of the 1-min best bid price return over the previous 30-min interval (RISK); the average ratio of the absolute stock return to the daily Yuan trading volume over the previous 30 days (AMIHUD), and the stock best bid price SK); an5rin9245.5(pri1t)-288.4(3enc)--326(it)-280.9(interva1)-275.4MOMENenc4(TUM)nce.)TJ0-2.2677TD(T

Table I. Continued

	Mean	Median	Std	Min	Max
PL (in yuan)	1.07	0.20	1.66	0	5.88
PANEL C: Control variables					
SPREAD (%)	0.17	0.14	0.11	0.05	0.45
ADEPTH (in million yuan)	0.23	0.08	0.36	0.004	1.38
BDEPTH (in million yuan)	0.22	0.07	0.35	0.003	1.34
MIDQUOTE	11.40	9.24	7.07	3.57	29.79
RISK	0.003	0.002	0.001	0.001	0.005
AMIHUD	0.009	0	0.013	0	0.071
MOMENTUM	0.004	0.003	0.02	−0.03	0.04

It is noted that Aggressive_1 is a continuous variable that measures investors' trade-off between the benefits and costs of immediate order execution. Aggressive_2, however, is a discrete response variable indicating where an order price ranks in the limit order book. To better understand the characteristics of this variable, Figure 2 plots the bar charts for Aggressive_2. We note that Aggressive_2 does not follow a continuous distribution. This multiple-response discrete distribution is therefore not suitable for an OLS regression.

Panel B of Table I contains summary statistics for the PGs and PLs measures, using the share-weighted average purchase price as the reference price. The mean (median) of PL is 1.07 yuan (0.2 yuan) and the mean (median) of PG is 0.22 yuan (0 yuan). Investors therefore sell stocks with smaller magnitudes of gains than of losses. This finding appears to support the disposition effect, in which investors are more likely to sell winning stocks than losing stocks.

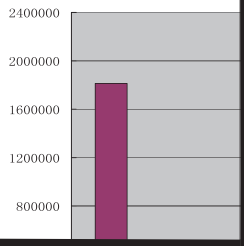
Panel C of Table I gives the statistics of the control variables used in the empirical analysis in the next subsection. The mean (median) relative bid–ask spread is 0.17% (0.14%), the mean (median) market depth at the best ask is 230,000 (80,000) yuan, and the mean (median) market depth at the best bid is 220,000 (70,000) yuan, which indicates a highly liquid market for our sample period.

5. Tests of Order Aggressiveness in Response to Gains and Losses

In this section, we conduct regression analyses to examine whether and how the investment outcomes affect subsequent order aggressiveness. We start with a correlation analysis of the behavioral bias variables and other explanatory variables. The results in Table II show that, in general, the explanatory variables are not highly correlated. This finding suggests that there is little evidence of a multicollinearity problem among the variables in explaining the order aggressiveness measures.

5.1 Regression Analysis Based on Dummy Variable for Gains versus Losses

We first estimate a regression exploring the extent to which investors prefer to submit more aggressive orders to realize profits. We relate the order aggressiveness measures to the indicator variable regarding whether investors are selling at a gain or a loss. We construct a dummy variable that is equal to 1 if the stocks are sold at a PG, and zero if sold at a PL.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We then conduct a regression analysis of the order aggressiveness measures on this dummy variable and other explanatory variables:

$$\begin{aligned}\text{AGGRESSIVE}_t = \alpha &+ \gamma_1\text{GAIN\_DUMMY}_t + \gamma_2\text{SPREAD}_t + \gamma_3\text{ADEPTH}_t + \gamma_4\text{BDEPTH}_t \\ &+ \gamma_5\text{MIDQUOTE}_t + \gamma_6\text{AMIHUD}_t + \gamma_7\text{RISK}_t + \gamma_8\text{MOMENTUM}_t \\ &+ \sum_{i=1}^{7}\beta_i D_i + \varepsilon_t\end{aligned} \tag{1}$$

where AGGRESSIVE_t is one of the two order aggressiveness measures at time t (Aggressive_1 and Aggressive_2); GAIN_DUMMY_t is a dummy variable that is equal to 1 if the stock is sold at a PG (with the stock's market best bid price at time t being higher than the share-weighted average purchase price), and zero otherwise; SPREAD_t is the relative bid–ask spread at time t; ADEPTH_t and BDEPTH_t are the depth (in million yuan) at the best ask and bid quotes, respectively; AMIHUD_t is the average daily Amihud measure for the prior 30 days. MIDQUOTE_t is the average of the best bid and ask prices at time t; RISK_t is the short-term volatility during the half hour prior to time t; MOMENTUM_t is the stock return during the half hour prior to time t; and D_i is a dummy variable for the ith 30-min interval between 9:30 (market opening) and 14:30 of that day.[5]

All of the observations are pooled in the estimation, but partitioned by individual investors and institutional investors. We use OLS to estimate the regression using Aggressive_1 as the dependent variable, and conduct an ordered probit regression to examine the relation between Aggressive_2 and the explanatory variables. The statistical significance reported for both regressions is based on robust standard errors that are adjusted for clustering at two levels, first by each stock and then by each trading day.[6] As it is computationally intensive to perform the order probit regression using the whole sample and beyond the capability of the computers at the SSE, we divide the whole sample into three sub-samples for the ordered probit regression. Two of the sub-samples consist of individual investors, with 250,000 accounts each, and the other consists of institutional investors, with 21,611 accounts.

Table III presents the regression results. For both the OLS and ordered probit regressions, the coefficients of GAIN_DUMMY (γ_1) are significantly positive, for both individual and institutional traders. The coefficients are 0.02 (OLS regression) and 0.08 (ordered probit regression) for the individual investors sub-samples, for example, and 0.01 (OLS regression) and 0.07 (ordered probit regression) for the institutional investors sub-sample, with all of the coefficients being statistically significant.

To illustrate the economic significance of these results, we can see that a coefficient of 0.02 in the OLS regression indicates that an average investor selling a stock at a PG instead of a PL will be more aggressive, lowering the ask price by about two cents. Given that the tick size on the SSE is usually one cent, this suggests that the investor walks down the limit

5 To avoid perfect collinearity, we omit the dummy variable for the last 30-min interval of the trading day.

6 We tried several alternative methods of clustering standard errors. Feng and Seasholes (2005) report results based on robust standard errors adjusted for clustering by each individual investor, for example. Compared with other studies, our method provides the largest standard error, and thus the smallest t-value in the estimation. Switching to other methods only makes our coefficients more significant.

Table III. Regressions of the order aggressiveness measures on the gain indicator variables and control variables

This table presents regressions relating the order aggressiveness measures to various explanatory variables. The regression equation is as follows:

$$\begin{aligned}\mathrm{AGGRESSIVE}_t = \alpha + \gamma_1 \mathrm{GAIN\_DUMMY}_t + \gamma_2 \mathrm{SPREAD}_t + \gamma_3 \mathrm{ADEPTH}_t + \gamma_4 \mathrm{BDEPTH}_t \\ + \gamma_5 \mathrm{MIDQUOTE}_t + \gamma_6 \mathrm{AMIHUD}_t + \gamma_7 \mathrm{RISK}_t + \gamma_8 \mathrm{MOMENTUM}_t \\ + \sum_{i=1}^{7} \beta_i D_i + \varepsilon_t,\end{aligned}$$

Panel A presents the pooled OLS regression results with Aggressive_1 as the dependent variable. Panel B presents the ordered probit regression results with Aggressive_2 as the dependent variable. For the ordered probit regressions, the whole sample is divided into three sub-samples due to computer capability constraints, with two individual trader sub-samples and one institutional trader sub-sample. The two individual trader sub-samples each contain 250,000 accounts and the institutional trader sample contains 21,611 accounts.

All variables are winsorized at the 5th and 95th percentile levels. The *t*-values are reported in parentheses below the coefficients. The robust standard errors are adjusted for clustering first by each individual stock, and then by each trading day. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	A: Aggressive_1, OLS regressions		B: Aggressive_2, ordered probit regressions		
	Individual	Institution	Individual 1	Individual 2	Institution
GAIN_DUMMY	0.02 ***	0.01 ***	0.08 ***	0.08 ***	0.06 ***
(1 if gains positive, 0 otherwise)	(17.97)	(6.74)	(6.93)	(7.06)	(3.38)
SPREAD	−8.77 ***	−10.45 ***	−36.61 ***	−47.48 ***	−45.36 ***
	(−15.22)	(−13.06)	(−12.67)	(−18.86)	(−6.53)
ADEPTH	0.006 ***	−0.001	0.08 ***	0.10 **	0.03
	(4.58)	(−0.61)	(6.53)	(9.05)	(1.30)
BDEPTH	0.001 *	−0.002	−0.13 ***	−0.11 ***	−0.08 ***
	(0.72)	(−1.05)	(−8.92)	(−8.54)	(−3.84)
MIDQUOTE	−0.003 ***	−0.002 ***	0.001 *	−0.001	−0.003 *
	(−29.20)	(−15.92)	(1.67)	(−1.05)	(−1.83)
AMIHUD	0.05 ***	0.32 ***	3.12 ***	3.66	2.25
	(15.02)	(4.92)	(9.87)	(10.69)	(2.60)
RISK	−1.64 ***	−0.05	9.75 **	4.75 **	24.92 ***
	(−4.65)	(−0.09)	(2.75)	(1.37)	(3.40)
MOMENTUM	−0.21 ***	−0.35 ***	−7.64 ***	−7.46 ***	−9.45 ***
	(−9.09)	(−9.34)	(−39.93)	(−41.38)	(−24.06)
Intercept	0.01 ***	0.02 ***			
	(3.41)	(6.92)			

order book by two ticks. This will further show effect on several market liquidity measures, such as the effective spread. Overall, the evidence shows that the previous investment gains and losses of a stock have opposite effects on sell order aggressiveness, with investors submitting more aggressive orders to sell stocks that have encountered gains instead of losses.

Our finding indicates that Mainland Chinese investors exhibit behavioral biases in their order submissions: investors are more aggressive in selling stocks that encounter gains and seek to close out those stock positions, but are less aggressive in selling stocks that have encountered losses and are more willing to hold on to those positions. This is consistent with Coval and Shumway (2005) who find that CBOT market makers in the T-bond futures market tend to take on more risks in the afternoon after morning losses. Our findings also help to explain the order aggressiveness continuation in Biais, Hillion, and Spatt (1995), who find that limit (market) orders tend to follow other limit (market) orders. When the market goes up, most stocks gain profits, and we therefore expect to see market (sell) orders dominate, as traders want to lock-in their profits. When the market goes down we expect to see less aggressive limit (sell) orders to be submitted continuously, as investors become less aggressive in selling the loser stocks.

Table III also presents the regression coefficients of other explanatory variables. The coefficient estimate of SPREAD is significantly negative in both the OLS regression and ordered probit regression, indicating investors submit fewer aggressive orders when the relative bid–ask spread is wider. The coefficient of MOMENTUM is also significantly negative in both regression models, indicating that investors are more reluctant to sell momentum stocks that have continuously experienced price appreciation. The signs of the coefficients of other variables (ADEPTH, BDEPTH, MIDQUOTE, AMIHUD, and RISK) are less consistent and are not statistically significant in all of the regression models.

5.2 Regression Analysis Based on Size of Gains and Losses

The results in Table III show that prior investment outcomes can affect subsequent order aggressiveness in a way consistent with the disposition effect. In this subsection, we further explore the relationship between the size of investment results and the investors' order submission strategies. Instead of using GAIN_DUMMY, we use the size of gains/losses as the explanatory variable in regression Equation (2):

$$\begin{aligned}\mathrm{AGGRESSIVE}_t = \alpha + \gamma_1 PG_t + \gamma_2 \mathrm{PL}_t + \gamma_3 \mathrm{SPREAD}_t + \gamma_4 \mathrm{ADEPTH}_t + \gamma_5 \mathrm{BDEPTH}_t \\ + \gamma_6 \mathrm{MIDQUOTE}_t + \gamma_7 \mathrm{AMIHUD}_t + \gamma_8 \mathrm{RISK}_t + + \gamma_9 \mathrm{MOMENTUM}_t \\ + \sum_{i=1}^{7} \beta_i D_i + \epsilon_t,\end{aligned} \tag{2}$$

where PG_t is the PGs and PL_t is the PLs for the stock, with gains and losses calculated using the share-weighted average purchase price and best bid price at time t. These results suggest investors become more risk averse after gains and submit more aggressive orders, and a positive γ_1 and a negative γ_2 is expected. This change in risk perception is thought to cause the disposition effect (Kaustia, 2010).

We estimate regression model (2) using one of the two aggressiveness measures. Similar to regression model (1), we use the OLS and ordered probit regressions. Table IV presents the regression results. We find that the coefficients for PL (γ_2) are consistently and significantly negative across all investor groups, with the absolute magnitude of t values ranging from 4.20 for the sub-sample of institutional investors in the OLS regression, to around 20 for the sub-sample of individual investors in the ordered probit regressions. The signs of the coefficients for PG (γ_1) do however vary among the regressions, and are insignificant in some of the regression specifications. The results are not entirely consistent with the disposition effect, as although losses make investors less aggressive in their sell order submissions, gains do not cause them to be more aggressive in their order submissions, at least not in a monotonic fashion.

5.3 Regressions with PG, PG^2, and PL

To further understand the non-monotonic relationship between order aggressiveness and gains, we split our sample into two sub-samples, one comprising gains below the mean and the other with gains equal to or above the mean. We repeat the regression model (2) for the two-subsamples. The results, which are not reported here, show that the coefficient of γ_1 is positive for the sub-sample with gains below the mean, and negative for the sub-sample with gains above the mean. This preliminary analysis suggests that investors display different risk-taking behavior according to the size of their gains, with order aggressiveness increasing with the size of gains only when prior gains are relatively small. This analysis suggests that the disposition effect is present only for small gains. To capture the relationship, we add the squared term of gains to allow for a quadratic relationship between order aggressiveness and gains, as per Equation (3):

$$\begin{aligned}\text{AGGRESSIVE}_t = \alpha + \gamma_1\text{PG}_t + \gamma_2 PG_t^2 + \gamma_3\text{PL}_t + \gamma_4\text{SPREAD}_t + \gamma_5\text{ADEPTH}_t \\ +\gamma_6\text{BDEPTH}_t + \gamma_7\text{MIDQUOTE}_t + \gamma_8\text{AMIHUD}_t + \gamma_9\text{RISK}_t \\ +\gamma_{10}\text{MOMENTUM}_t + \sum_{i=}^{7}\beta_i D_i + \epsilon_t, (3)\end{aligned} \tag{3}$$

where PG$_t$ and PG$_t^2$ are the unit and squared terms of PGs, respectively, and PL$_t$ is the PLs for the stock, with gains and losses calculated using the share-weighted average purchase price and best bid price at time t.

The results for Equation (3) are presented in Table V. The coefficient of PL (γ_3) remains significantly negative in all of the regression models across all investor groups. The coefficient of PG (γ_1) is significantly positive in all of the regression models and the coefficient of PG^2 (γ_2) is significantly negative. Therefore, the quadratic relationship is a good fit between the order aggressiveness measures and the size of gains. The evidence suggests that investors tend to submit more aggressive orders when the gains are small and less aggressive orders once the gains exceed a certain level. However, investors consistently submit less aggressive orders for stocks sold at a loss. In Table V, we also choose an alternative control variable, the effective spread, to replace the relative bid–ask spread in the regressions. The effective spread is calculated as the intraday average of the difference between the most recent transaction price and the average of market best bid and ask quotes, normalized by the outstanding average of the market best ask and bid quotes. We can see that the choice of effective spread do not affect the main results.

Overall, the evidence confirms that the investment performance of the stock affects the risk attitude of investors. Results in Table V also support findings in Linnainmaa (2010) that limit orders are associated with higher disposition effect estimates. We find that some investors do submit less aggressive limit orders to sell winner stocks.

Table IV. Regressions of the order aggressiveness measures on PG, PL, and the control variables

This table presents regressions that relate the order aggressiveness measures to various explanatory variables. The regression equation is as follows:

$$\begin{aligned}\text{AGGRESSIVE}_t = \alpha + \gamma_1\text{PG}_t + \gamma_2\text{PL}_t + \gamma_3\text{SPREAD}_t + \gamma_4\text{ADEPTH}_t + \gamma_5\text{BDEPTH}_t \\ + \gamma_6\text{MIDQUOTE}_t + \gamma_7\text{AMIHUD}_t + \gamma_8\text{RISK}_t \\ + \gamma_9\text{MOMENTUM}_t + \sum\nolimits_{i=1}^{7}\beta_i D_i + \epsilon_t,\end{aligned}$$

Panel A presents the pooled OLS regression results with Aggressive_1 as the dependent variable. Panel B presents the ordered probit regression results with Aggressive_2 as the dependent variable. For the ordered probit regressions, the whole sample is divided into three subsamples due to computer capability constraints, with two individual trader sub-samples and one institutional trader sub-sample. The two individual trader sub-samples each contain 250,000 accounts and the institutional trader sample contains 21,611 accounts.

All variables are winsorized at the 5th and 95th percentile levels. The *t*-values are reported in brackets below the coefficients. The robust standard errors are adjusted for clustering first by each individual stock, and then by each trading day. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	A: Aggressive_1, OLS regressions		B: Aggressive_2, ordered probit regressions		
	Individual	Institution	Individual 1	Individual 2	Institution
PG	0.002 *	0.0002	−0.08 ***	−0.08 ***	−0.03
	(1.81)	(0.08)	(−8.79)	(−9.22)	(−1.41)
PL	−0.006 ***	−0.003 ***	−0.06 ***	−0.06 ***	−0.03 ***
	(−18.03)	(−4.23)	(−19.65)	(−20.26)	(−5.04)
SPREAD	−8.97 ***	−10.55 ***	−42.62 ***	−42.02 ***	−43.10 ***
	(−16.19)	(−13.49)	(−16.45)	(−16.33)	(−6.39)
ADEPTH	0.006 **	−0.001	0.10 ***	0.10 ***	0.03
	(4.69)	(−0.62)	(8.18)	(8.17)	(1.27)
BDEPTH	0.001 *	−0.002	−0.11 ***	−0.11 ***	−0.08 ***
	(0.77)	(−1.11)	(−8.01)	(−8.01)	(−3.87)
MIDQUOTE	−0.003 ***	−0.002 ***	0.006 ***	0.007 ***	0.004
	(−26.04)	(−13.23)	(6.43)	(6.78)	(0.21)
AMIHUD	0.52 ***	0.34 ***	3.91 ***	3.95 ***	2.54 ***
	(15.36)	(5.15)	(10.99)	(11.04)	(2.87)
RISK	−1.40 **	0.13	12.25 ***	12.12 ***	25.65 ***
	(−2.26)	(0.23)	(3.49)	(3.46)	(4.01)
MOMENTUM	−0.17 ***	−0.33 ***	−7.49 ***	−7.48 ***	−9.35 ***
	(−7.19)	(−8.82)	(−38.60)	(−38.63)	(−23.75)
Intercept	0.02 ***	0.03 ***			
	(9.53)	(8.76)			

Table V. Regressions of the order aggressiveness measures on PG, PG^2, PL, and the control variables

This table presents regressions that relate the order aggressiveness measures to various explanatory variables. The regression equation is as follows:

$$\text{AGGRESSIVE}_t = \alpha + \gamma_1 PG_t + \gamma_2 PG_t^2 + \gamma_3 PL_t + \gamma_4 \text{SPREAD}_t + \gamma_5 \text{ADEPTH}_t + \gamma_6 \text{BDEPTH}_t + \gamma_7 \text{MIDQUOTE}_t + \gamma_8 \text{AMIHUD}_t + \gamma_9 \text{RISK}_t + \gamma_{10} \text{MOMENTUM}_t + \sum_{i=1}^{7} \beta_i D_i + \varepsilon_t,$$

Panel A presents the pooled OLS regression results with Aggressive_1 as the dependent variable. Column 1 and Column 2 present results for the individual investors and institutional investors. Column 3 presents regression results for the whole sample, while using the effective spread (ESPREAD) as a control variable instead of the quoted spread. The ESPREAD is calculated as the intraday average of the difference between the most recent transaction price and the average of market best bid and ask quotes, normalized by the outstanding average of the market best ask and bid quotes, from the beginning of the day to the time of submission. We then take the average of all the Panel B presents the ordered probit regression results with Aggressive_2 as the dependent variable. For the ordered probit regressions, the whole sample is divided into three sub-samples due to computer capability constraints, with two individual trader sub-samples and one institutional trader sub-sample. The two individual trader sub-samples each contain 250,000 accounts and the institutional trader sample contains 21,611 accounts. Panel C presents the pooled OLS regression results with the volume-based aggressiveness measure, defined as the fraction of the holding that the investor wants to liquidate, as the dependent variable.

All variables are winsorized at the 5th and 95th percentile levels. The *t*-values are reported in brackets below the coefficients. The robust standard errors are adjusted for clustering first by each individual stock, and then by each trading day. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	A: Aggressive_1, OLS regressions			B: Aggressive_2, ordered probit regressions		
	Individual	Institution	Whole sample	Individual 1	Individual 2	Institution
PG	0.04 ***	0.03 ***	0.04 ***	0.08 ***	0.09 ***	0.19 ***
	(17.80)	(5.81)	(22.10)	(2.88)	(3.28)	(2.63)
PG^2	−0.03 ***	−0.02 ***	−0.03 ***	−0.13 ***	−0.15 ***	−0.17 ***
	(−20.52)	(−5.77)	(−25.04)	(−7.60)	(−8.47)	(−3.45)
PL	−0.01 ***	−0.002 ***	−0.005 ***	−0.05 ***	−0.05 ***	−0.03 ***
	(−15.73)	(−3.23)	(−15.84)	(−19.80)	(−18.55)	(−4.31)
SPREAD	−8.65 ***	−10.35 ***		−40.60 ***	−40.55 ***	−41.73 ***
	(−15.37)	(−13.07)		(−15.53)	(−15.67)	(−6.19)
ESPREAD			−1.74			
			(−1.60)			
ADEPTH	0.006 ***	−0.001	0.006 ***	0.10 ***	0.10 ***	0.03
	(4.70)	(−0.60)	(5.31)	(8.19)	(9.16)	(1.30)
BDEPTH	−0.001	−0.002	0.001	−0.10 ***	−0.10 ***	−0.08 ***
	(−0.87)	(−1.06)	(1.14)	(−8.04)	(−8.49)	(−3.86)
MIDQUOTE	−0.003 ***	−0.002 ***	−0.002 ***	0.01 ***	0.01 ***	0.001
	(−25.49)	(−14.72)	(−23.00)	(7.05)	(5.44)	(0.37)

(continued)

Table V. Continued

	A: Aggressive_1, OLS regressions			B: Aggressive_2, ordered probit regressions		
	Individual	Institution	Whole sample	Individual 1	Individual 2	Institution
AMIHUD	0.52 ***	0.33 ***	0.38 ***	3.94 ***	4.01 ***	2.53 ***
	(15.25)	(5.11)	(9.86)	(11.04)	(11.35)	(2.86)
RISK	−1.33 ***	0.20	−2.30 ***	12.42 ***	11.07 ***	26.16 ***
	(−3.80)	(0.36)	(−6.62)	(3.54)	(3.25)	(4.07)
MOMENTUM	−0.19 ***	−0.35 ***	−0.18 ***	−7.57 ***	−7.35 ***	−9.46 ***
	(−8.00)	(−9.11)	(−7.85)	(−39.11)	(−41.28)	(−23.69)
Intercept	0.01 ***	0.02 ***	−0.001			
	(6.98)	(7.33)	(−0.77)			

5.4 Tests for the Behavioral Biases in Hold/Sell Decisions

The previous analysis shows that certain behavioral biases affect the aggressiveness of investors' order submission strategies, although the relationship is not totally explained by the disposition effect. In this section, we examine whether a similar relationship on the hold/sell decision of the investors is observed. For this, we focus on the executed orders and conduct a survival analysis, as in Feng and Seasholes (2005), who extend the disposition measures of Odean (1998) by including the holding period as one of the determinants of the trade decisions, and conduct a survival analysis to calculate the hazard ratio as a measure of the disposition effect in Chinese investors. A hazard ratio greater than 1 indicates an increase in the conditional probability of a sale, and less than 1 indicates a decrease in the conditional probability. The disposition effect exists if the hazard ratios are greater than 1 for stocks with gains and less than 1 for stocks with losses, indicating a greater propensity among investors to sell winner stocks and a reluctance to sell loser stocks.

A survival analysis of the entire dataset would be extremely computationally intensive and is beyond the capability of the computers at the SSE. Therefore, we randomly choose a subsample of 100,000 investor accounts. Table VI presents results of the survival analyses, with the hazard function categorized by either the Weibull regression or the Cox regression. The left-hand side variable takes a value of zero each day the individual holds a stock, and one each day he sells a stock. Reg 1 and 3 of Panel A are based on the trading gain indicator (TGI), which takes a value of 1 for every day a stock trades at a gain (relative to the share-weighted average purchase price), and Reg 1 and 3 of Panel B are based on the trading loss indicator (TLI), which takes a value of 1 for every day a stock trades at a loss (relative to the share-weighted average purchase price). The results show that the hazard ratios are well below 1 for stocks at a loss and well above 1 for stocks at a gain. These findings provide strong evidence of the disposition effect for mainland Chinese investors, who are eager to sell stocks that show gains and reluctant to sell those showing losses.

To explore the possible non-monotonic relationship between gains/losses and selling decision, we construct dummy variables for nonzero trading gains/losses in five percentiles: below the 20th percentile, between the 20th and the 40th percentile, between the 40th and

Table VI. Survival analyses on executed trade flows

This table presents the hazard ratios associated with the average individual's decision to sell/hold stocks at a loss/gain. The left-hand variable of the regression takes a value of zero for each day the individual holds a stock, and a value of 1 for every day she sells a stock. Trading gains or trading losses are equal to the sell price minus the stock's share-weighted average purchase price if the stock is sold. If the investor does not sell (she holds the stock position at the end of the day), we determine whether the stock is trading at a paper gain or a paper loss. If a stock's daily low is above its share-weighted average purchase price, it is counted as a "paper gain" (in other words, the investor could have sold at a gain at any time during the day). In this case, the trading gain equals the daily low minus its share-weighted average purchase price and the trading losses is zero; conversely, if a remaining stock's daily high is below its original share-weighted average purchase price, it is counted as a "paper loss" (the investor could only have sold for a loss that day). Its trading loss equals the daily high minus its share-weighted average purchase price. Its trading gain equals zero.

The TGI takes a value of 1 for every day a stock is trading at a gain or could be traded at a gain (relative to the share-weighted average purchase price), and zero otherwise. The TLI takes a value of 1 for every day a stock is trading at a loss or could be traded at a loss (relative to the share-weighted average purchase price), and zero otherwise.

We construct dummy variables for nonzero trading gains below the 20th percentile, between the 20th and the 40th percentile, between the 40th and the 60th percentile, between the 60th and the 80th percentile, and above the 80th percentile. We construct a similar dummy variable for the trading loss brackets. We interact these trading gains/losses dummy variables with the TGI or the TLI to measure differences in investors' propensity to sell wecner/loser stocks given changes in gains/losses.

We use two methods to calculate the hazard ratios. The first regression uses a Weibull distribution with the parameter "*p*" for the hazard function. A parameter value of $p = 1$ indicates an exponential hazard rate. A parameter value of $p < 1$ indicates a decreased hazard rate over time. The second regression uses a COX model that does not specify any distribution for the underlying variables.

The data sample contains a random sample of 100,000 investor accounts from the whole sample of 521,116 accounts. The data are from January to December 2008 and are provided by the SSE. The *Z*-statistics are based on robust standard errors that allow for clustering by each stock. The *Z*-statistics are shown in brackets below the hazard ratios.

	Weibull hazard model		COX hazard model	
	Reg 1	Reg 2	Reg 3	Reg 4
Panel A: Regressions with TGI				
Disposition effect variables				
TGI	8.90		7.39	
(*Z*-stat)	(76.65)		(82.99)	
Gains ∈ (0, 20%]×TGI		8.93		7.24
(*Z*-stat)		(83.25)		(86.98)
Gains ∈ (20%, 40%]×TGI		10.22		8.35
(*Z*-stat)		(90.84)		(97.88)
Gains ∈ (40%, 60%]×TGI		9.38		7.78
(*Z*-stat)		(77.09)		(84.21)
Gains ∈ (60%, 80%]×TGI		8.54		7.18
(*Z*-stat)		(63.52)		(68.55)

(continued)

Table VI. Continued

	Weibull hazard model		COX hazard model	
	Reg 1	Reg 2	Reg 3	Reg 4
Gains ∈ (80%, 100%]×TGI		6.51		5.65
(*Z*-stat)		(41.67)		(45.11)
Parameters				
p-parameter	0.62	0.62		
(standard error)	(0.0041)	(0.0042)		
Panel B: Regressions with TLI				
Disposition effect variables				
TLI	0.23		0.28	
(*Z*-stat)	(−53.40)		(−53.05)	
Losses ∈ (0, 20%]×TLI		0.63		0.67
(*Z*-stat)		(−19.43)		(−19.68)
Losses ∈ (20%, 40%]×TLI		0.27		0.32
(*Z*-stat)		(−33.96)		(−33.00)
Losses ∈ (40%, 60%]×TLI		0.14		0.17
(*Z*-stat)		(−42.76)		(−41.81)
Losses ∈ (60%, 80%]×TLI		0.08		0.11
(*Z*-stat)		(−47.94)		(−45.42)
Losses ∈ (80%, 100%]×TLI		0.06		0.07
(*Z*-stat)		(−52.89)		(−46.05)
Parameters				
p-parameter	0.61	0.69		
(standard error)	(0.0039)	(0.0043)		

the 60th percentile, between the 60th and the 80th percentile, and above the 80th percentile. We then interact these trading gains dummy variables with TGI, and trading losses dummy variables with TLI, and examine the hazard ratio associated with each interaction variable. The results are shown under Reg 2 and Reg 4 of Panels A and B. For the interaction terms involving TGI (Panel A) the hazard ratios are all significantly above 1, although they first increase until the (20th–40th) percentile, then subsequently decrease. Therefore, consistent with the relationship exhibited in order aggressiveness associated with gains, there is also a quadratic relationship between the size of gains and the willingness to sell stocks. For the interaction terms involving TLI (Panel B), the hazard ratios are all significantly below 1, and decrease monotonically across higher loss percentiles. This is also consistent with the relationship exhibited in order aggressiveness associated with losses, in which a negative relationship between the size of losses and the willingness to sell stocks is present.

Out results show there is also a quadratic relation between prior gains and the decisions to sell stocks. Again, one explanation for this phenomenon is the combination of the disposition effect and the house money effect (Thaler and Johnson, 1990). The house money effect suggests that investors might increase their risk-exposure once they think they are investing with money gained. However, when prior gains are relatively small, the disposition effect dominates so that investors are more willing to sell stocks. But when prior gains are relatively large, the house money effect dominates so that investors are more willing to hold stocks. It is thus shown that the combination of these two effects affects the aggressiveness of investors in submitting orders, as well as their sell/hold decisions seen in executed trades.

Overall, our results are similar to those of Kaustia (2010) and Barber and Odean (2013), based on Finnish data. The authors find that Finnish investors show a propensity to sell winner stocks and to hold loser stocks, whereas the hold/sell decisions remain relatively insensitive to the size of losses.

6. Robustness Tests

We conduct robustness tests on our findings from the previous section. In this section, we discuss additional tests based on alternative specifications, different time periods, and alternative explanatory variables.

6.1 Regressions for the Sub-samples of Different Periods

We also investigate whether the relationship between the order aggressiveness measures and gains/losses applies for different sub-sample periods. Our full sample covers the whole of 2008. As the market in the latter part of the year was volatile, we ensure our conclusions are not over-influenced by observations from this period. We use three methods to partition our data into different sub-samples. First, we split the full sample in two, with one sub-sample containing the order submissions on days with positive market returns and the other containing submissions on days with negative returns. We then estimate the regression model into up-market and down-market sub-samples. Second, we split the whole sample into 12 months and estimate the regression model for selected months. Third, we split the whole sample into daily sub-samples, with each containing order submissions within one trading day. We then conduct a Fama–MacBeth type regression (Fama and MacBeth, 1973) by first estimating the regression with the data for each trading day and then tabulating the cross-sectional average for the coefficients from each daily sub-sample.

Table VII presents the estimation results of regressing Aggressive_1 on the explanatory variables for the different sub-samples. Panel A shows the results for the up-market and down-market sub-samples. The onset of the financial crisis occurred in 2008, so the up-market sub-sample contains fewer observations than the down-market sub-sample. Approximately 44% of the days in 2008 show positive market returns, with 56% showing negative returns. Panel B gives the monthly sub-samples. To save space, we report the results for May and November as two representative months. The regressions using sub-samples for other months are qualitatively and quantitatively similar. Panel C reports the Fama–MacBeth regression results. Overall, regardless of the method, the regression coefficients are qualitatively similar to the regression coefficients for the entire sample shown in Table V, with the coefficient of PG being significantly positive, the coefficient of PG^2 being significantly negative, and the coefficient of PL being significantly negative. This reinforces the conclusion that investors' sell order submission strategies are subject to both the disposition and the house money effects, and this is not driven by observations from one specific period.

6.2 Alternative Measures of Potential Selling Price and Reference Price

In constructing Aggressive_1, we take the market best bid quote (Bid1) as the potential price at which an investor can sell if she wants to execute her order without any delay. However, the

Table VII. Regressions for the down-market and up-market sub-samples, the November and May observations sub-samples, and Fama–MacBeth regressions

This table presents regressions that relate Aggressive_1 to gains, the squared term of gains, losses, and other control variables. The regression equation is as defined in Equation (3).

Panel A presents the pooled OLS regression results for the up-market sub-sample when the daily market return is positive or zero, and for the down-market sub-sample when the daily market return is negative. Panel B presents the pooled OLS regression results for the sub-sample comprising data for May and November. Panel C presents the Fama–MacBeth (FM) type regression results. The FM regressions are conducted by first running OLS regressions day-by-day and then by averaging the coefficients across trading days.

All variables are winsorized at the 5th and 95th percentile levels. The *t*-values are reported in brackets below the coefficients. The robust standard errors are adjusted for clustering first by each individual stock, and then by each trading day. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	A: Aggressive_1 OLS regressions		B: Aggressive_1 OLS regressions		C: Aggressive_1 FM regressions
	Up-market	Down-market	May	November	
PG	0.04 ***	0.04 ***	0.05 ***	0.04 ***	0.05 ***
	(15.17)	(14.04)	(8.97)	(8.80)	(21.65)
PG^2	−0.03 ***	−0.03 ***	−0.04 ***	−0.03 ***	−0.04 ***
	(−16.43)	(−17.87)	(−10.63)	(−8.69)	(−25.09)
PL	−0.01 ***	−0.005 ***	−0.004 ***	−0.01 ***	−0.001 ***
	(−12.69)	(−11.15)	(−4.82)	(−16.90)	(−4.08)
SPREAD	−8.25 ***	−9.08 ***	−11.65 ***	−3.93 ***	−8.46 ***
	(−12.26)	(−14.94)	(−21.75)	(−5.86)	(−25.12)
ADEPTH	0.006 ***	0.006 ***	0.005 ***	0.004 ***	0.001 ***
	(4.80)	(4.18)	(3.01)	(2.95)	(5.33)
BDEPTH	−0.0004	0.002	0.003	−0.001 ***	−0.003 ***
	(−0.37)	(1.75)	(0.16)	(−0.85)	(−10.02)
MIDQUOTE	−0.003 ***	−0.002 ***	−0.002 ***	−0.004 ***	−0.003 ***
	(−23.46)	(−21.69)	(−17.67)	(−11.70)	(−24.19)
AMIHUD	0.50 ***	0.54 ***	0.62 ***	0.30 ***	0.45 ***
	(13.88)	(13.24)	(7.47)	(10.45)	(11.02)
RISK	−1.46 **	−1.34 ***	−1.62	−2.19 ***	−3.15 ***
	(−3.31)	(−3.03)	(−1.58)	(−3.97)	(−18.42)
MOMENTUM	−0.05 *	−0.30 ***	−0.27 ***	0.01	−0.02
	(−1.79)	(−12.21)	(−5.54)	(0.15)	(−1.58)
Intercept	0.0 ***	0.01 ***	0.01 ***	0.01 ***	0.02 ***
	(5.26)	(6.35)	(3.18)	(3.35)	(18.69)

success of this sale assumes that the order size is equal to or less than the market depth at the best bid quote. For the overall sample, we find that 83% of orders have sizes equal to or smaller than the market best bid depth. Therefore, for the remaining 17% of the orders, sellers must either walk through the order book on the bid side and execute the sales at lower bid prices, or let their bids be stored in the book to wait for more incoming buy orders. Investors can also choose to withdraw their orders if they cannot be fully executed in a timely fashion.

Investors may specify that if orders cannot be executed, they must be automatically removed from the market or stored in the ask side of the order book at the best bid quote, and in this case the potential selling price is simply the best bid quote (Bid1). However, if investors require their orders to walk through the book and be executed at prices inferior to the best bid quote, then their potential selling price is the share-weighted average of the several bid quotes covered by the orders. We therefore calculate the potential selling price as the share-weighted average of five bid quotes as an alternative approach, using the number of shares executed at each bid quote level as the weighting. We then adopt this alternative selling price in calculating Aggressive_1 and the PG and PL variables.

Our empirical analyses so far assume that the share-weighted average purchase price is the reference (purchase) price. We additionally construct three alternative purchase prices: the initial purchase price, the most recent purchase price, and the highest purchase price. We also use these alternative measures for the reference purchase price in re-calculating the PG and PL measures.

Table VIII presents the empirical results when the alternative selling price (share-volume weighted bid quotes) is used to compute Aggressive_1 with the alternative measures of reference purchase prices previously mentioned. The results are qualitatively similar to those presented in Table V. Thus, our conclusions are robust to alternative measures of potential selling prices and reference prices.

6.3 Effects of "Fleeting" Limit Orders

The term "fleeting" limit orders refers to "the fast submission and cancellation of limit orders" (Hasbrouck and Saar, 2009) made with the objective of price manipulation. For example, if a manipulator wants to buy stocks, he might first submit many sell orders at Ask1. Other investors may interpret this as negative stock information, and may also try to sell. The manipulator avoids his sell orders being executed by canceling (or withdrawing) the orders within a very short time (usually 2–3 s, according to Hasbrouck and Saar, 2009), and then resubmitting them. These unexecuted sell orders may still put downward pressure on the stock price. The manipulator then cancels all of his sell orders and buys from the other side of the market. Thus, the concept of "fleeting orders" is an alternative influence on order aggressiveness. However, "fleeting orders" are less of a concern, as there were no algorithmic or high-frequency traders in the Shanghai market in 2008, and in our sample, less than 0.1% of orders submitted are withdrawn within 5 s. When we remove these orders, the results remain quantitatively and qualitatively similar.

6.4 Evidence from Samples Comprising Stocks that can be Sold Short

The dataset being analyzed so far are obtained from the SSE and during the year of 2008, when the short-sale is prohibited in the Chinese stock market China officially introduced short-sale into its stock market around April 2010. Since then, CSRC has maintained an adjustable list of stocks eligible for short-sales. We are unable to expand the dataset obtained from SSE to after 2010. To examine whether the short-sale restriction affects our main results, we obtain account-level data from a year after 2010, when the short-sale is allowed in China, and repeat our analyses before.

We obtain account-level order submission and equity holding data from a leading web-based trading platform in China. Starting from 2013, the growing popularity of e-commerce in China made it convenient for software companies to develop web-based trading platforms for investors. We obtain the complete records of order submission, order execution, and end-of-day equity holding data for roughly 97,119 accounts from a national web-based trading platform. The data sample covers a period of 13 months from July 2014

Table IX. Order aggressiveness and explanatory variables during an alternative sample period when short-sale is allowed

This table presents regressions that relate Aggressive_1 to gains, the squared term of gains, losses, and other control variables. The potential selling price is defined as the highest bid quote. The reference price is defined as the share-weighted average purchase price, respectively. The time period in this table is from July 2014 to July 2015. The data sample comprises of nearly 200,000 accounts from a national web-based trading platform in China. We limit our data sample to Shanghai stocks only.

Panel A presents summary statistics for the aggressiveness measure and other control variables. Two control variables related to the short-sale activities include the ratio of market value of outstanding borrowed shares to the market capitalization of all tradable shares for each stock (SHORT), and the stock's average increasing rate of the outstanding borrowed stock value for the previous 30 days (S_RATE). All variables are winsorized at the 5th and 95th percentile levels. Panel B presents the results from pooled regressions. The regression equation is as defined in Equation (3). Column 1 uses the whole data sample with the same control variables as in Equation (3). Columns 2 and 3 use the whole dataset, while including the two short-sale-related variables (SHORT and S_RATE), respectively. Column 4 only comprises the stocks that are eligible for short-sales, whereas Column 5 only comprises stocks not eligible for short-sales.

The *t*-values are reported in brackets below the coefficients. The robust standard errors are adjusted for clustering first by each individual account, and then by each trading day. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Summary statistics				
	Mean	Median	Std	Min	Max
Aggressive_1	−0.03	0.00	0.09	−0.86	0.20
PG (in yuan)	0.63	0.10	1.15	0.00	10.27
PL (in yuan)	0.42	0.00	1.05	0.00	12.73
SPREAD (%)	0.11	0.09	0.07	0.02	0.64
ADEPTH (in million yuan)	0.99	0.35	1.49	0.01	2.35
BDEPTH (in million yuan)	1.03	0.32	3.74	0.01	21.26
MIDQUOTE	17.75	14.36	11.62	2.99	74.03
RISK	0.003	0.002	0.002	0.0001	0.013
AMIHUD	0.001	0.0004	0.003	0.00003	0.11
MOMENTUM	0.002	0	0.017	−0.082	0.122
SHORT	0.01	0.005	0.01	0	0.07
S_RATE	0.03	0.01	0.05	−0.06	1.51

	Panel B: Pooled regressions				
	1	2	3	4	5
PG	0.02 ***	0.02 ***	0.02 ***	0.02 ***	0.03 ***
	(14.61)	(14.70)	(14.60)	(10.54)	(12.30)
PG^2	−0.01 ***	−0.01 ***	−0.01 ***	−0.01 ***	−0.01 ***
	(−6.07)	(−6.15)	(−6.06)	(−4.37)	(−8.93)
PL	−0.01 ***	−0.01 ***	−0.01 ***	−0.01 ***	−0.02 ***
	(−20.99)	(−20.80)	(−20.94)	(−17.29)	(−13.23)
SPREAD	−8.61 ***	−8.59 ***	−8.62 ***	−6.18 ***	−15.11 ***

(continued)

Table IX. Continued

	Panel B: Pooled regressions				
	1	2	3	4	5
	(−30.48)	(−30.42)	(−30.63)	(−18.41)	(−39.36)
ADEPTH	0.001 **	0.001 **	−0.001	0.001 **	0.002 **
	(24.88)	(24.71)	(24.90)	(23.66)	(15.31)
BDEPTH	−0.0003 **	−0.0003	−0.003 ***	−0.0003 **	0.00003 **
	(−4.88)	(−5.01)	(−4.88)	(−4.43)	(0.03)
MIDQUOTE	0.05 ***	0.05 ***	0.05 ***	0.05 ***	0.08 ***
	(29.02)	(−28.93)	(28.64)	(23.46)	(33.59)
AMIHUD	−0.09 **	−0.09 **	−0.10 **	−0.10 *	−0.14 **
	(−2.20)	(−1.98)	(−2.23)	(−1.76)	(−2.47)
S_RATE		0.01 ***			
		(6.19)			
SHORT			−0.005		
			(−0.30)		
RISK	−0.01 **	−0.01 *	−0.01 ***	−0.01 **	−0.01 **
	(−39.29)	(−39.32)	(−39.43)	(−36.93)	(−24.39)
MOMENTUM	−0.44 *	−0.44 ***	−0.44 ***	−0.44 *	−0.44 *
	(−47.95)	(−47.91)	(−47.97)	(−43.75)	(−29.79)
Intercept	−0.18 ***	−0.18 ***	−0.18 ***	−0.18 ***	−0.22 ***
	(−39.16)	(−39.15)	(−39.07)	(−35.65)	(−39.19)

aggressiveness measures, prior gains/losses measure, and other control variables. Panel A of Table IX presents summary statistics of these variables. We can see that, Aggressive_1 is on average negative, which is consistent with the statistics in year 2008. PG and PL are more balanced relative to their counterparts in 2008, probably because the overall stock market was increasing from 2014 to 2015, while decreasing in 2008. This is also evidenced by the fact that the largest bid depth is nearly ten times of the ask depth, showing that more buy volume are await in the market. We also add two variables directly related to the short sell activities, namely, the ratio of market value of outstanding shorted shares to the market capitalization of tradable shares (SHORT), and the average increasing rate of the shorted stock value for the previous 30 days (S_RATE). Both variables measure the extent to which people borrow stocks (to sell).

Table IX presents the empirical results of relating order aggressiveness measure to prior gains/losses measures. Similar to our results in Table V, we find the order aggressiveness measures show a quadratic relation with respect to prior gains, and a negative relation with prior losses. This effect remains unchanged even we divide the whole dataset into only stocks that can be sold short and stocks that cannot be sold short. The coefficients on S_RATE are significantly positive, showing that investors tend to submit more aggressive orders for stocks that have increasingly shares being borrowed (for sold short). However, adding the short-sale-related variables do not change our main results from Table V qualitatively.

7. Conclusion

This study makes use of a unique database provided by the SSE to examine how prior investment outcomes affect the aggressiveness of order submission strategies. Our finding is in general consistent with the prospect theory in that prior investment outcomes can affect order aggressiveness. In line with the disposition effect, we do find that investors are more aggressive in submitting sell orders for a stock that experiences gains and less aggressive in submitting sell orders for stocks with losses, and the results are economically significant. We further analyze the relationship between the size of gains/losses and several order aggressiveness measures. Although the relationship between sell order aggressiveness and losses is significantly negative, the relationship between sell order aggressiveness and gains is quadratic, as the order aggressiveness first increases with gains, but then declines after the gains reach a certain level. The results apply to both individual investors and institutional investors, and are robust to various regression analyses. Our evidence is consistent with the co-existence of the disposition effect and the house money effect, and indicates that behavioral biases can affect investors' liquidity provision decisions. The study also suggests that future theoretical models may incorporate behavioral biases when modeling order submission strategies.

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