Do Behavioral Biases Affect Order Aggressiveness?

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Keywords: Order aggressiveness, Disposition effect, House money effect

JEL number: G12, G14, G18

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We investigate whether behavioral biases affect the order submission strategies of investors. We take advantage of a very unique database provided by the Shanghai Stock Exchange, which allows us to track order submissions and executions for every investor, and compare with their trading performance of individual stocks. Consistent with previous studies, we find that investors exhibit disposition effect whereby they are more likely to sell stocks that experience gains than losses. The disposition effect will affect the sell order submission strategies, as investors are less (more) aggressive in submitting the sell order for a stock that experiences paper losses (gains). Consistent with the house money effect, investors are more willing to assume more risk and become more patient in selling the winner stocks after the paper profits reach a certain level.

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I. Introduction

Extensive empirical evidence has demonstrated that investors exhibit behavioral biases during their decision making processes. One prominent example is the disposition effect (Shefrin and Statman (1985)) that investors tend to hold loser stocks for too long and sell winner stocks too soon. The disposition effect has been well documented in the financial markets (Odean (1998)) as well as in the real estate market (Genesove and Mayer (2001)). The most popular explanation for the disposition effect has been the *prospect theory* (Kahneman and Tversky (1979)), which postulates that utility is determined not by the level of wealth, but by the change in wealth relative to a reference point. According to this explanation, the utility function is concave in the domain of gains and convex in the domain of losses. This utility function shape impacts the risk-taking behaviors subsequent to the gains/losses. As a result, after the stock price appreciates, investors become more risk averse and tend to sell the stocks; after the stock price declines, however, investors become less risk averse and prefer to continue holding their stock positions.

Despite the widely documented evidence on behavioral biases, very few papers investigate directly how the biases affect the trading behavior of investors. One exception is Coval and Shumway (2005), who examine the behavior of proprietary traders in the CBOT T-bond futures during 1998. Evidence indicates that the traders are highly loss averse, and they assume greater afternoon risk following morning losses by submitting more orders, purchasing contracts at higher prices, and selling contracts at lower prices. However, the behavior is completely reversed with morning gains. Their findings are consistent with the prospect theory. In another study, Liu, Tsai, Wang, and Zhu (2010) conduct a similar experiment using data from the market participants in Taiwan's index options markets. Contrary to Coval and Shumway, they find that investors assume higher subsequent (afternoon) risks after morning gains. Their results, however, are inconsistent with the loss aversion explanation for the disposition effect, but are consistent with the house money effect. House money was suggested by Thaler and Johnson (1990) and refers to the phenomenon that gamblers are risk-takers when they have won and play with the money they have won. In this paper, we examine how behavioral biases affect investors' order submission strategies. We make use of a very unique database provided by the Shanghai Stock Exchange. This database keeps real-time records for the order submissions and executions for all investors trading securities listed in SSE, as well as records of their stock holdings. The database allows us to track order submissions and executions for every investor in doing trading of securities listed in the Shanghai market.

We focus on the order submission strategies of selling stocks. Specifically, we focus on the order aggressiveness proposed by Biais, Hillion, and Spatt (1995). As discussed above, previous studies find that investors exhibit disposition effect, whereby investors tend to hold assets on which they have experienced prior (unrealized) losses, but they tend to sell assets on which they have experienced prior (unrealized) gains. We therefore examine whether the prior gains and prior losses associated with selling stocks will affect the order aggressiveness in the submission strategies. We argue that, after controlling for other factors that affect order submission strategies, investors are less (more) aggressive in submitting the sell order for a stock that experiences prior losses (gains). Conditional on selling loser stocks, the higher the prior (unrealized) losses, the less aggressive the investors are in submitting the sell orders.

Besides the disposition effect, we conjecture that the house money effect (e.g. Thaler and Johnson (1990) and Liu, Tsai, Wang and Zhu (2010)) will affect the order submission strategies of selling stocks as well. While house money effect might not affect the order submission strategies of selling loser stocks, it will affect the strategies of selling winner stocks. We conjecture that after the prior gains reach a certain level, investors will become willing to assume more risks and more patient in selling the winner stocks. Combining the disposition effect and house money effect, it implies that for winner stocks, order aggressiveness will first increase with the prior gains as the disposition effect dominates.

We examine the effect of behavioral biases on order aggressiveness using a very unique and

comprehensive dataset available at the Shanghai Stock Exchange (SSE). This dataset is distinct from the account-level trading data used in prior studies in that it has detailed records of when and by which trader-account (in SSE) each order is submitted, cancelled, or executed on which security and at what price and volume. This dataset also contains continuous information of the five best ask and bid quoted prices and volumes of the open limit order book for each security during the trading time. Because SSE runs a pure order-driven market, the dataset provide us with unique advantages in examining whether potential gains and losses can affect order submission strategies in a limit order market. To our best knowledge, no prior research has investigated this important question.

We construct three order aggressiveness measures for each sell order submitted by SSE investors on A share stocks, which are either based on comparison of the price of each sell order submitted with the status of the limit order book at the time of submission, or based on the size of the sell order in relationship with the investor's holding balance for the stock. We use the market best bid price at the time of submission as the potential selling price and calculate the prior gains (losses) by comparing the prior selling price with the price at which the stock was purchased before. We then examine how the prior gains and losses affect measures of order aggressiveness, after controlling for other factors that are documented to affect the order aggressiveness, such as the bid-ask spread (Foucault (1999), and Biais, Hillion, and Spatt (1995)), market best bid or ask depth (Parlour (1998) and Griffiths, Smith, Turnbull, and White (2000)), short-term return volatility (Foucault (1999)), and short-term stock momentum.

Our results indicate that the prior gains and losses of the stock that the investor plans to sell have significant impact on the aggressiveness of the sell order. We find that the order aggressiveness measure is positively and significantly related to prior gains, and negatively and significantly related to the squared term of prior gains and the prior losses. Even after adding other explanatory variables, these behavioral bias measures remain statistically significant, and more significant than most of the control variables. The results are robust to both the ordinary least squares and the ordered probit regression analysis. We also show that the results are robust to the choice of alternative potential selling prices and alternative purchase prices, or sub-sample analyses.

Because of the data uniqueness, our project represents the first attempt to examine how the behavioral biases of individual investors affect the order submission strategies. Although the study is based on the Chinese stock markets in which a lot of investors have no trading experience and suffer from behavioral biases (Feng and Seasholes (2005), Shumway and Wu (2006), Chan, Wang, and Yang (2008), Xiong and Yu (2011)), the evidence should have economic implications for other developed markets as well. Even in the well-developed U.S. equity markets, research has documented the existence of various behavioral biases (e.g. Odean (1998, 1999), Barber and Odean (2007)). At the same time, as the electronic limit order book has become more popular around the globe, there have been more theoretical and empirical research on the limit order trading as well (e.g. Parlour (1998), Foucault (1999), Goettler, Parlour, and Rajan (2005), Handa and Schwartz (1996), Harris and Hasbrouck (1996)). However, most of the theoretical work assumes that investors are rational in formulating order submission strategies. This paper illustrates that the order submission is influenced by behavioral biases as well.

The rest of the paper is organized as follows: Section II contains a brief overview of the related literature in order aggressiveness in the limit order market, and develops the hypotheses in this study. Section III describes the Shanghai stock market and the dataset, and presents preliminary statistics, Section IV discusses the empirical methodologies and introduces the order aggressiveness measures. Section V presents empirical results. Section VI summarizes the main findings of this paper.

II. Overview of Order Aggressiveness in Limit Order Markets

Many of the world's major equity markets, such as the New York Stock Exchange, NASDAQ, Paris Bourse, Tokyo Stock Exchange, and Hong Kong Stock Exchange are operated based on order-driven trading mechanism. In an order-driven market, an investor can choose to post either a limit order or a market order. While limit orders are stored in a limit order book waiting for executions, market orders are executed with certainty at the posted prices in the market. Traders face a dilemma in choosing between a limit order and a market order. The submission of limit order entails uncertainty because they are executed only if enough market orders on the opposite side of the order book arrive in the future to execute those limit orders with priority ahead of them in the queue, so traders bear the risk of non-execution or delayed-execution as well as the risk of being "picked off" by the incoming informed traders. On the other hand, there is no execution risk for market orders, but traders have to pay for the price of immediacy (Chacko, Jurek, and Stafford (2008)). Biais, Hillion, and Spatt (1995) characterize this trade-off from the perspective of order flow by introducing the classification of *order aggressiveness*. According to them, investors with higher time preferences will be more aggressive in their order submissions, demanding liquidity from investors with lower time preferences. Based on this classification scheme, the most aggressive order is a market order which is allowed to be executed immediately, whereas the least aggressive order is the limit order furthest from the best quote on the opposite side of the book.

A number of theoretical papers have explored the determinants of investors' choices between market versus limit orders. Parlour (1998) shows that an increase in the buy-side (sell-side) market depth reduces the execution probability of the buy (sell) limit orders and induces incoming buyers (sellers) to submit more aggressive buy (sell) market orders. On the opposite side, sellers (buyers) observe the increase of buy-side (sell-side) market depth and rationally expect a higher execution probability of sell (buy) limit orders and thus have incentives to submit less aggressive sell (buy) orders to enjoy the more favorable prices. Foucault (1999) suggests that higher volatility in the market implies a greater "picking-off" risk for limit order submitters by future informed traders. Thus, limit order traders will demand a larger compensation for the higher "picking-off" risk, which in turn results in a wider spread and a higher cost of trading for market orders. Hence, the model predicts that investors tend to use less (more) aggressive limit orders when the volatility and spread is higher (lower).

Similar to Foucault (1999), Handa and Schwartz (1996) show that investors intend to submit less aggressive limit orders in the presence of higher short-term fluctuation in transaction prices because they worry about losses through trades with informed traders, and intend to submit more aggressive market

orders when market depth is high and they assess the "picking-off" risk (by informed traders) is low. Kaniel and Liu (2004) provide both theoretical explanation and empirical evidence that the expected horizon is critical for the order submission strategy. As a result, although limit order has execution risk, the risk will become lower if the expected horizon of private information increases.

Empirical work has provided evidence to the theories above on the choice between market versus limit orders. Biais, Hillion, and Spatt (1995) study the interaction between the order book and the order flow in the Paris Bourse and find evidence that a wide bid-ask spread increases the probability of price-improving limit orders and reduces the probability of market orders. Ahn, Bae, and Chan (2001) provide empirical evidence of a dynamic interaction among market depth, volatility, and order choice, as suggested by Handa and Schwartz (1996), using data from the Hong Kong stock market. Griffiths, Smith, Turnbull, and White (2000) and Ranaldo (2004) develop econometric techniques to study order submission strategies in limit order markets. They find short-term volatility, bid-ask spreads, and the depth on both the same and the opposite side of the limit order book are important determinants of order aggressiveness.

The above research all assume that investors in the economic setting are rational and able to choose optimal decisions in any circumstances. However, extensive literature has demonstrated that Chinese investors are subject to behavioral biases (see Feng and Seasholes (2005), Chan, Yang, and Wang (2008)). Similar to the risk-cost tradeoff tackled in the framework above, we can characterize the decision on order submission strategies from the perspectives of prior gains and losses. Suppose an investor intends to sell a stock that has experienced an appreciation (prior gain) relative to her purchase price, the disposition effect predicts that she would become more risk-averse and want to realize the gains quickly. On the contrary, if the stock has experienced a price depreciation (prior loss), the disposition effect predicts that the investor would be willing to assume more risks and hold the loser stock for longer. Because investors are more eager to sell stocks that have prior gains than those that have prior losses, investors are more (less) aggressive in submitting the sell orders for the stocks with prior gains (losses). This consideration leads to the following hypothesis.

Hypothesis I: order aggressiveness increases with the size of prior gains, and decreases with the size of prior losses from the stock that is planned to be sold.

Also affecting the order submission is the house money effect, (e.g. Thaler and Johnson (1990) and Liu, Tsai, Wang and Zhu (2010)). While house money effect might not affect the order submission strategies of selling loser stocks, it will affect the strategies of selling winner stocks. We conjecture that after the prior gains reach a certain level, investors will become willing to assume more risks and be more patient in selling the winner stocks. Combining the disposition effect and house money effect, it implies that for winner stocks, order aggressiveness will first increase with the prior gains as the disposition effect dominates.

Hypothesis II: order aggressiveness first increases with the size of prior gains but after a certain threshold, will decrease with the size of prior profits.

III. Description of the Market and Dataset

A. The Open Limit Order System of the Shanghai Stock Exchange

The main trading mechanism of the Shanghai Stock Exchange (SSE) is the 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. Orders to be filled at the opening call auction are submitted between 9:15 and 9:25. The opening price is chosen such that the transaction volume at the market open is maximized for all existing submitted orders. Unexecuted orders are automatically stored in an electronic consolidated open limit order book (COLOB) for the continuous trading that begins at 9:30.

During the continuous trading session, an incoming order is automatically matched against the best standing limit order in the COLOB, in accordance with the price-time priority principle. If the order

cannot be matched, then it is added to the COLOB. Like most other order-driven markets around the world, SSE does not have designated market makers. During the continuous trading session, investors can submit both market orders and limit orders. Market orders are executed at the best market quotes available, whereas limit orders are submitted with specific prices to be executed at. Investors also need to specify, at the time of submissions, whether they want to withdraw the order or store the order in COLOB should the order size is larger than depth at the intended transaction price. Investors are allowed to cancel or revise their orders at any time prior to matching.

B. Data and Preliminary Statistics

Our data comes from three files contained in a database at SSE. The first data file is an order submission (ORDER) file that contains record of order submissions and cancellations for all investors, and tracks the status of each order submitted to the SSE, indicating whether and when the order is executed, modified, or withdrawn. The second file is an equity holding (HOLD) file consisting of end-of-day stock holdings for each investor in the SSE stocks. The third file is the COLOB file that contains time series of the snapshots of the five best quoted bid and ask prices and volumes, most recent transaction prices and trading volumes for each SSE stock at every 3~6 second interval. The COLOB file is available for all participants in the stock market during the trading time. The data are extracted from a very comprehensive database located at the research center of SSE. This database is very accurate and contains no errors. Only the research center employees or special-term academic professors visiting the exchange have access to the database. However, they are not allowed to copy or download any data from the database and take the data away from the exchange, nor can they print any computer output due to the confidentiality policy controlled by SSE. Researchers can only work with the data in a designated computer in the center during the working hours, not including the lunch break, between 9:00 and 17:00 from Monday to Friday. All computations must be done at the computer under careful inspections by the data manager. At the end of the project, the researchers need to submit a report to the exchange and can take the report out of SSE. They are not allowed to take any data out away, even after the data have been processed. So, working with the data files for our paper is extremely labor intensive and we are the first to conduct in-depth and comprehensive

analyses to the database provided by SSE.¹

To construct the sample used in this study, we first merge the ORDER file with the COLOB file by matching each order submitted with the most recent order book snapshot (to the seconds). The order book snapshot acts as proxy for the limit order book information at the time of order submission. We then merge the data with the HOLD file to recover the holding balance and prior gains/losses for each stock right before submission. By merging the three files together, we produce the trading records of every investor, keep track of the profits/losses for each stock, and monitor all the orders being submitted. We then combine the trading records for each stock with the stock's daily highest, lowest, and closing prices on every day it is held by at least one investor account. We acquire the stock price data from the public source: RESSET Inc., a leading data provider for academic studies in Beijing.² We then focus on the sell orders submitted. The combination of public data and private data from SSE allows us to investigate how the trading history and prior gains/losses affect investors' sell order submission strategies. Since securities laws in China allow an investor to open only one account per citizen ID, our data can track the status of the entire portfolio for each investor in the sample period.

We apply a few filters to our data sample. First, the Chinese Securities Regulatory Commission (CSRC) imposes a 10% limit on daily price increase or decrease of any stock traded in China. Investors might decide to buy or sell stocks when stock prices approach their daily limits, as they worry losing the opportunities to trade stocks at desired prices. Since the stock prices getting close to the daily limits may affect the investors' selling decision as well, we remove order submissions during the same days when the stocks hit their price limits from our sample. We add these observations back to our sample, and repeat all the empirical analyses in the following sections. The results are qualitatively the same.

In addition, we remove all the market (sell) order submissions from our data. Market orders were introduced in SSE in July 2006. According to the statistics from SSE, only less than 1% of the orders

¹ Other papers that also use data from SSE include Bailey, Cai, Cheung, and Wang (2009), Seasholes and Wu (2006), and Choi, Jin, and Yan (2012).

² RESSET is headquartered at Tsinghua university. For more information, please see http://www.resset.cn/en/.

submitted are market orders, and most of the market orders are not on stocks.³ Market orders do not specify execution prices. Thus, we are unable to quantitatively determine their order aggressiveness and calculate their prior gains and losses, which are required for our analysis. Investors who want to execute their orders immediately can submit marketable limit orders. In our study, marketable limit orders are treated as market orders. Marketable limit (sell) orders refer to limit (sell) orders with order prices equal to or less than the best bid quotes of the order book. Marketable limit orders function like market orders in that they can be executed immediately.

Third, we remove order submissions associated with stale quotes, which are easily recognized through zero depth. We also drop order submission data from our sample where the time between the COLOB snapshot and order submission record is more than 30 minutes. Finally, we remove the orders submitted during the first fifteen minutes of each trading day in our sample because this period contains a call auction process instead of a continuous trading session.

Although the database includes accounts for all investors trading SSE securities, it is very computationally intensive to merge all the data together. We extract a random sample of 500,000 retail investors, together with all institutional investors, and we perform the analysis using only the data in 2008. We examine only A-share stocks that are traded by domestic investors and exclude investors that obtained stocks from non-trade stock transfers,⁴ bequests, or IPO allocations as we are unable to determine their purchase prices of stocks. To examine how our sample is representative of the whole market, we calculate the trading volume in shares and yuan trading volume for each stock in the sample in 2008, and run cross-sectional correlation tests between our trading volume figures with the corresponding trading volume figures reported for the aggregate market in the same year. The correlation is very high, with 96% for trading volume in shares and 97% for yuan trading volume, respectively. Thus, the sample is quite representative of the whole market. The final sample contains the detailed order submission and trading

³ More information on order statistics in SSE can be found in the market quality report at http://www.sse.com.cn. Most market orders were on equity warrants.

⁴ In China, if both parties are agreed to transfer the ownership of stocks within themselves. They can go directly to the exchange to transfer the ownership, without declaring the transferring prices to the exchange.

history for the total of 521,611 Chinese investors in the Shanghai stock market (among which 500,000 are retail investors) investing into 855 Shanghai stocks during the 250 trading days in 2008.

Insert Table I about Here

Table I presents summary statistics of orders submitted in our sample. The average time between the snapshot of limit order book and the time for order execution is around 5 seconds, with the maximum being 30 seconds. This fairly short interval guarantees that our sample can accurately represent the order book information at the time of order submission.⁵ The average sell order price submitted is 12.238 yuan, with the minimum and maximum values being 1.05 yuan and 290 yuan. The dollar value of the sell order submitted ranges from 2.40 yuan to 46.553 million yuan. For most of the stocks in our sample, the average dollar spread is about one tick size (0.01yuan). The average (median) spread is 0.185 percent (0.144 percent) of the average value of the best ask and best bid quotes. The average (median) relative bid-ask spread is lower than spreads in many developed markets. For example, Anh, Bae, and Chan (2001) report an average spread of 0.47%, and Angel (1997) reports the median percentage spread of Dow Jones Industrial Average Index stocks to be 0.32%. The average (median) monetary quantity (market depth) is 2.568 million (0.88 million) over the five best ask quotes, and 2.202 million (0.771 million) over the five best bid quotes. These numbers are much higher than the market depth of 1.18 million HK dollar for the bid and ask sides together in the Hong Kong Stock market (Ahn, Bae, and Chan (2001)). These results indicate that our sample include highly liquid stocks with high market depths. The data statistics in Table I also suggests the presence of some extreme observations for those variables. Later in this study, we will winsorize the data to remove the noise from those extreme observations, without affecting the main conclusions.

We also presents summary statistics related to the holding histories before order submission in Table 1 On average, the time between an investor first purchase a stock and the investor submit a sell order is about 36 days, with the minimum being 1 day because Chinese buyers of stocks suffer from a one-day lockup and cannot sell their shares until the next trading day (Bian, Su, and Wang (2012)).

⁵ The limit order book information is updated at every 15-30 seconds in China for retail investors, who account for the majority in our sample.

IV. Empirical Methodology and Variables

In this section, we discuss the methodology that we employ to construct the order aggressiveness measures, as well as the behavioral bias variables and the control variables being used to explain the cross-sectional difference of the order aggressiveness.

A. Order Aggressiveness Measures

The first order aggressiveness measure, *Aggressive_1*, is similar to the measure used by Harris and Hasbrouck (1996). It is calculated as the difference between the market best bid quote and the (sell) order price submitted.

Aggressive_1 = Bid1 – Order_Price

where *Bid1* is the best bid quote at the time of order submission and *Order_Price* is the (sell) order price submitted. The best bid quote represents the potential selling price, the price below which the market is willing to provide liquidity. *Aggressive_1* represents the compensation (premium) the investor requires for being willing to bear the non-execution risk. An investor who intends to assume less risk and sell the stocks quickly will submit a more aggressive order with the *Order_Price* close to or even lower than *Bid1*. The higher the *Aggressive_1*, the more eager the investors would like to sell, and the more aggressive the orders submitted, with *Aggressive_1* ≥ 0 usually indicates a marketable limit order and *Aggressive_1* < 0 means a limit sell order.

It is noted that the potential selling price is based on Bid1, rather the mid-quote ((Ask1 + Bid1)/2), where Ask1 and Bid1 represent the current market best ask and bid quote, respectively. This is because best bid price (Bid1), rather than the mid-quote, represents the highest compensation that a seller is likely to receive if she wants her orders to be executed without any delay. Nevertheless, as quoted bid-ask spread usually stays only around the tick size, Bid1 is very close to the mid-quote. In unreported tables, we

repeat all empirical tests in this study, but using the mid-quote as the potential selling price instead, we find all our empirical results remain qualitatively the same.

It should be mentioned that *Bid1* might not be the only potential selling price once the investor intends to sell immediately. *Bid1* equals the unique selling price only if the order size is smaller than or equal to the depth at *Bid1* so that the full order could be executed at the best bid quote. In section V, we consider the situation where the sell order size is greater than the depth at the best bid quote.

Many studies have suggested that order size will affect the order aggressiveness. They, however, have reached inconsistent conclusions. For example, Biais, Hillion, and Spatt (1995) suggest that the larger the order size, the more aggressive the order because aggressive traders tend to buy or sell quickly. Yet Lo and Sapp (2010) find that more aggressive orders tend to be smaller in size because smaller orders have higher probabilities to get quick executions.

We also construct a second measure of order aggressiveness (*Aggressive_2*) by comparing the order size with the stock holding of the investor right before the order submission. The second aggressiveness measure (*Aggressive_2*) is defined as the following:

Aggressive_2=
$$\frac{Order_Vol}{Hold_Bal}$$

where *Order_Vol* is the share volume size of the (sell) order submitted, and *Hold_Bal* is the share balance of the stock held by the trader right before the submission. *Aggressive_2* measures the fraction of the holding submitted to sell. It reflects how much the investor wants to liquidate her stock holdings, which in turn reflects her attitude toward risk-taking behaviors. As a result, the higher the *Aggressive_2*, the more risk averse the investor is, and the more aggressive the submitted order.

Biais, Hillion, and Spatt (1995) also define aggressiveness 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, within the best ask-bid quote, or higher than the current best quote on the same side of the market. The most aggressive sell (buy) orders are those with prices hitting or being lower (higher) than the best bid (ask) quote on the opposite side of the market to get immediate executions, whereas the least aggressive sell (buy) orders are those with prices higher (lower) than, and furthest away from, the best ask (bid) quote. Similar categorization is adopted in Giriffiths, Smith, Turnbull, and White (2000) and Renaldo (2004).

In our study, we extend the idea in Biais, Hillion, and Spatt (1995) to develop the third order aggressiveness measure. This measure takes the unique advantage of the data in our study that provides the complete COLOB information at the time of submission. *Aggressive_3* 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.

$$\begin{array}{l} Aggressive_3 = 1 \text{ if } Ask5 \leq Order_Price \\ = 2 \text{ if } Ask4 \leq Order_Price < Ask5 \\ = 3 \text{ if } Ask3 \leq Order_Price < Ask4 \\ = 4 \text{ if } Ask2 \leq Order_Price < Ask3 \\ = 5 \text{ if } Ask1 \leq Order_Price < Ask2 \\ = 6 \text{ if } Mid_Quote \leq Order_Price < Ask1 \\ = 7 \text{ if } Order_Price < Mid_Quote \end{array}$$

where *Ask1*, *Ask2*, *Ask3*, *Ask4*, and *Ask5* are the 5 best quoted ask prices in the order book, and *Mid_Quote* is the average of best ask and bid quotes at the time of orders submission. Similar to *Aggressive_1* and *Aggressive_2*, the higher the *Aggressive_3*, the more risk averse the investor and the more eager she would like to sell, and the more aggressive she places the sell orders, with *Aggressive_3* equal to 7 indicating a marketable limit order and *Aggressive_3* less or equal to 6 indicating a limit sell order.

B. Prior Gains / Losses

Most prior studies test the disposition effect using measures calculating various ratios of sales for gains and sales for losses. These measures are first introduced by Odean (1998), and later implemented and extended by Dhar and Zhu (2006) and Feng and Seasholes (2005), etc. In this study, we construct similar gains/losses measures examining the disposition effect in order aggressiveness.

Each time whenever a sell order is submitted, we compare the potential selling price (*Bid1*) for each stock sold to the reference purchase price (*Reference*) to determine whether that stock is sold for a prior gain or a prior loss. We calculate the dollar value of Prior Gains measure (*PG*) / Prior Losses measure (*PL*) in yuan as follows:

When the outstanding best bid quote (Bid1) is higher than the reference price, PG is assigned the absolute value of the difference while 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 while PL is assigned the absolute value of the difference.

We define the reference price as the price at which the investor purchases the stock. In case that the stock is purchased at different prices, we calculate the reference price as the share-weighted average of prior purchase prices. In section V, we will consider calculation of PG and PL based on the alternative reference prices.

C. Control Variables

Given previous studies offer alternative explanations for order aggressiveness, we introduce a few control variables to examine the incremental explanatory power of our *PG* and *PL* measures.

Short-Term Volatility: We compute the short-term volatility (*RISK*) over the 30 minutes before order submission as $((1/(N-1))\sum_{i=1}^{N}(R_i - \overline{R})^2)^{1/2}$, where N equals 30 and R_i is the return of the *i*th 1-minute return during the 30-minute interval. \overline{R} is the average of R_i over the 30 minutes. That is, *RISK*

is calculated as the standard deviation of the 30 1-minute return prior to the order submission. We also calculate short-term volatility as the summation of the squared 1-minute return over the 30-minute interval, as documented in Ahn, Bae, and Chan (2001). Given that the high frequency intraday return is typically close to zero, these two volatility measures are very similar and would not affect our results. According to Foucault (1999), an increase in volatility reflects greater information uncertainty, and traders will be less aggressive in order submission. This leads to a negative relationship between *RISK* and order aggressiveness. On the other hand, higher volatility might also suggest greater uncertainty on the execution of limit orders. The risk-averse investors might be more aggressive in order submissions to reduce the execution risk, leading to a positive relationship between *RISK* and order aggressiveness.

Relative Bid-Ask Spread: We compute the relative bid-ask spread (*SPREAD*) as (*Ask1-Bid1*)/*Mid-Quote*, where *Ask1* is the market best ask quote and *Bid*1 is the market best bid quote, and *Mid-Quote* is the average of *Ask1* and *Bid1*. The relative spread measures the cost of immediate execution. On one hand, a wider bid-ask spread implies that there is more room for the sellers to improve the quote. In this sense, we expect investors to submit more aggressive orders following a widening of spread to induce the spread to return to its equilibrium value. On the other hand, a larger spread could imply there is greater uncertainty in the market, as the size of spread reflects the disagreement of valuation among various market participants on the same stock (Handa, Schwartz and Tiwari (2003)). In that case, we expect investors to be less aggressive in order submissions when spread is higher.

Depth at the Best Ask/Bid Quote: We calculate the depth at the ask side (*ADEPTH*) and the bid side (*BDEPTH*) based on the monetary quantities quoted at the best ask and the best bid quotes (in terms of 1 million yuan) at the time of order submission. According to Parlour (1998), as the lengthening of the queue at one level decreases the execution probability of further limit orders at the same level, the probability of observing a limit buy (sell) order after the arrival of a limit buy (sell) order is smaller than the probability of observing a limit buy (sell) order after the execution of a market buy (sell) order. That is, an increase in depth available at the best bid (ask) quote implies that the seller (buyer) can become less aggressive by posting a higher ask (lower bid), waiting for the buy (sell) orders to walk through the order

book to hit the seller's (buyer's) order. On the other hand, an increase in depth available at the best ask (bid) price implies that the seller (buyer) has to be more aggressive by posting a lower ask (higher bid) quote in order for the sell (buy) order to be executed. Therefore, we expect the market depth on the best quote of the same market to be positively related to the order aggressiveness, and the market depth on the best quote of the opposite market to be negatively related to the order aggressiveness.

Short-Term Momentum: We compute the prior half-hour return (*MOMENTUM*) as return over the 30 minutes prior to the order submission. If sellers believe there are momentum in returns so that after the stock price goes up (down), they will revise the valuation of the stock upward (downward), and be less (more) aggressive in posting the quotes for the sell orders. So, we expect the prior half-hour return to be negatively related to the order aggressiveness.

Half-hourly Dummy: Both Lo and Sapp (2010) and Duong, Kalev, and Krishnamurti (2009) find the order aggressiveness measures vary intra-daily. This may be due to the fact that the asymmetry of information is the widest at the market open and narrows as trading updates the dealer's information set (Bloomfield, O'Hara, and Saar (2004)).

Te examine the intraday variation of order aggressiveness measures in our sample, we sort all the three measures by the time the sell orders are submitted and then calculate the mean for each measure over each of 30-minute intervals during the time when the market is open, i.e. 9:30 - 10:00, 10:00 - 10:30, 10:30 - 11:00, 11:00 - 11:30, 13:00 - 13:30, 13:30 - 14:00, 14:00 - 14:30, and 14:30 - 15:00. We then plot the means in each time intervals in Figure 1.

Insert Figure 1 about Here

Part A and Part C of Figure 1 show that both *Aggressive_1* and *Aggressive_3* in general increase from the market open in the morning to the market close in the afternoon. This suggests that investors who want to sell stocks are the least aggressive at the market open, but the most aggressive at the market close. Panel B, however, shows a different pattern regarding *Aggressive_2*, which is higher when market opens at the morning and decreases after that. One explanation is that while the investors would try to sell a bigger

portion of their holdings in the morning than in the afternoon, they anticipate that not all their order would be executed as they are less aggressive in posting bid and ask prices in the morning. But as the market is near the close, in order to guarantee order executions, investors will be aggressive in posting bid and ask prices but submitting smaller orders in the afternoon.

Figure 1 reveals predictable intraday patterns in all three order aggressive measures. To capture the intraday variation, we introduce intraday dummy variables as the control variables. As there are altogether four trading hours at SSE, from 9:30-11:30 am and 1:00-3:00pm, we create eight half-hourly dummies (*DUMMY1* to *DUMMY8*) to capture differences in the order aggressiveness over the trading day.

V. Empirical Results

A. Evidence of Behavioral Biases on Investment Decisions

There is strong evidence that Chinese investors display behavioral biases, like the disposition effect. Using a small sample from a local brokerage house in Mainland China, Feng and Seasholes (2005) examine various factors that influence investors' decisions to trade, and confirm the impact of disposition effect on investors' buy-sell decisions. They also find that more sophisticated traders, as reflected by trading experience, are less prone to the disposition effects. Shumway and Wu (2006) show that disposition drive momentum in Mainland China, and that small and less active traders are more affected by the disposition effect. In this subsection, we first repeat previous studies to examine whether Chinese investors in the Shanghai stock market show disposition effect in their investment decisions.

Previous studies have proposed a couple of measures to test for the disposition effect. One is based on the ratio of unrealized profits to the sum of unrealized and realized profits (referred to as "*PGR*") and the ratio of unrealized losses to the sum of unrealized and realized losses (referred to as "*PLR*"), calculated for the market in aggregate, as defined in Odean (1998). Dhar and Zhu (2006) extend these two ratios at

the investor level, and calculate the disposition effect for each individual investor. The other is proposed by Feng and Seasholes (2005) who adopt survival analysis to test the average disposition effect. We employ both methodologies to test the disposition effect. Similar to Feng and Seasholes (2005), we define a position as one investor-stock-day cycle held by investors in Shanghai. A position starts when an investor first purchases a given stock and ends when either the holding balance goes to zero or at the end of the data sample period.

Following prior studies, we remove those positions that are not closed-out by the end of the sample period. We also combine multiple sells in one day into a one sell with share-weighted sell price if no buys take place in the same day. We obtain a very rich dataset, with more than 2 million positions. The median number of positions taken per investor in the dataset is 5, with the time between the initial purchase and the first sell of the same stock being 15.96 days. The number of position per investor and the days from initial purchase to the first sell match the data reported in Feng and Seasholes (2005). We replicate our analysis without removing incomplete positions and combining multiple intraday sells and find qualitatively similar results.

First, we follow Odean (1998) and Dhar and Zhu (2006) and compute *PGR* and *PLR* for both the entire data set and for each individual investor and then average them up for the whole sample. As mentioned above, *PGR* and *PLR* are defined as

PGR = Realized Gain / (Realized Gain + Paper Gain) PLR = Realized Loss / (Realized Loss + Paper Loss)

We count the number of "Realized Gain/Loss" and "Paper Gain/Loss" each time an individual sells a stock. A sale is recognized a realized gain/loss if the selling price is higher/lower than the stock's share-weighted average purchase price. For other stocks in the same portfolio held by the investor, each stock will be recognized as a paper gain (loss) if the daily highest (lowest) price of the stock is lower (higher) than the share-weighted average purchase price. We remove observations from our sample if the investor has only 1 stock in her portfolio. The disposition effect is defined as the difference between *PGR* and *PLR*

Disposition Effect (DE) = PGR - PLR

A positive *DE* is evidence that the average investor is more likely to realize gains than losses in her portfolio.

Insert Table II about Here

For all the observations of paper gain, paper loss, realized gain, and realized loss, we count the number for each type, and compute *PGR*, *PLR*, as well as *DE*, for both the entire data set and each individual account, respectively. The results are in Table II. For the entire data set, the *PGR* and *PLR* are 0.671 and 0.390, with the *DE* being 0.281. The mean (median) across individual accounts for *PGR*, *PLR*, and *DE* are 0.791 (0.870), 0.457 (0.429), and 0.335 (0.373). Both *DE* in Panel A and Panel B are statistically significant at 1% level (p-value less than 0.001). We also present the distribution of *DE* for all investors in our sample in Figure 2. The *DE* measure is widely distributed with minimum of -1 and maximum of 1. We can see the distribution is highly skewed, with over 90% of investors showing the disposition effect (*DE* >0). Overall, Table II and Figure 2 indicate a very strong disposition effect among the investors in our sample during 2008.

Insert Figure 2 about Here

Next, we follow Feng and Seasholes (2005) and conduct survival analyses to test the average disposition effect in the data set. An advantage of survival analysis is that it takes into consideration the holding length of the stock when calculating the measure of disposition effect. Feng and Seasholes (2005) show that different investors with different holding lengths can have very distinct incentives to sell winner stocks, even both investors share the same *PGR* and *PLR* ratios.

Following Feng and Seasholes (2005), we define two indicator variables. The first variable is the "Trading Loss Indicator" or *TLI*. This variable takes a value of one if the stock is sold at a price lower than the stock's share-weighted average purchase price, and zero otherwise. For a stock not sold during the day, *TLI* takes a value of one if the highest daily trading price is below the share-weighted average purchase price, and zero otherwise. The second variable is the "Trading Gain Indicator" or *TGI*. This variable takes a value of one if the stock is sold at a price higher than the stock's share-weighted average purchase price, and zero otherwise. For a stock not sold during the day, *TGI* takes a value of one if the stock is sold at a price higher than the stock's share-weighted average purchase price, and zero otherwise. For a stock not sold during the day, *TGI* takes a value of one if the

lowest daily trading price is above the share-weighted average purchase price, and zero otherwise. Both the *TLI* and *TGI* are time-series variables indicating the gain/loss status of each stock in the position at a daily basis. We then construct another dummy variable, which takes a value of one if the stock is sold during the day, and a value of zero if the stock stays in the portfolio for the entire day. We will then regress this holding status dummy variable on either *TLI* or *TGI*. We cannot put both *TLI* and *TGI* as the independent variables simultaneously since stocks are trading either at a loss or a gain. We use maximum likelihood method and report the hazard ratios associated with *TLI* and *TGI*. The hazard ratio measures the possibility that the investor will sell the stock if the stock is trading at a loss (*TLI* = 1), or trading at a gain (*TGI*=1), relative to the baseline function where *TLI* or *TGI* equals zero, respectively. A hazard ratio less than one for the *TLI* indicates investors are less likely to sell a stock at a loss than the baseline hazard function indicates.

The survival analysis of the entire data set is very computationally intensive, and beyond the computational capability of the computer at SSE. We divide the entire sample of the 521,611 investor accounts into six subsamples, with five subsamples of individual investors (each containing 100,000 investor accounts) and one subsample for institutional investors (containing 21,611 investor accounts). We pool all the observations together in each subsample, and adopt two separate approaches to perform the maximum likelihood tests. First, we use the parametric regression, assuming the baseline holding follows a *Weibull* distribution. Then, we use the Cox regression for proportional hazard models, without assuming distribution for the baseline holding. Panel A of Table III reports the hazard ratios on *TLI* and *TGI*. We observe the very low (high) value of the *TLI* (*TGI*) hazard ratio, an indication that the average investor is prone to the disposition effect. The hazard ratio of *TGI* of about 13 or 8 indicates that the average investor is more than 10 times (retail investors) or about 8 times (institutional investors) likely to sell the stock once the stock could be sold at a gain (transaction price higher than the share-weighted average purchase price), and the hazard ratio of *TLI* indicates that the average investor is less than 20% (retail investors) or 30% (institutional investors) likely to sell the stock once the stock could be sold at a gain (transaction price higher than the share-weighted average purchase price). Similar results could be

found in Panel B using Cox regression method. The findings provide very strong evidence that Shanghai investors in our sample show disposition effect in their investment decisions, eager to sell stocks with gains instead of losses. Table 3 also shows that the disposition effect exists for both retail and institutional investors, although the institutional investors show a smaller disposition effect.

Insert Table III about Here

B. Preliminary Analysis of Aggressiveness Measures, PG/PL, and other Control Variables

In the previous subsection, we introduce the three order aggressiveness measures, the prior gains (PG) and prior losses (PL) measures. This section will present preliminary statistics of the aggressiveness measures, the PG and PL measures, and other explanatory variables. We also conduct some preliminary analysis of the relationship between aggressiveness measures and PG and PL.

As Table I shows, the raw dataset has a few extreme observations. To remove outlier observations for our empirical analysis, we winsorize all the variables used in the following studies at the 95% level. Since we have an extremely rich sample of data from the exchange, we still have a very large sample even with 5% winsorization. We have also tried winsorization at 1% and 10% and the results in our study do not change qualitatively.

Insert Table IV about Here

Panel A of Table IV reports the summary statistics for the three order aggressiveness measures in our study. The mean (median) of *Aggressive_1* is -0.067 (-0.010), which suggests that average investors submit sell orders higher than the most recent market bid price, storing their orders in COLOB. This is consistent with the mean (median) of *Aggressive_3*, which is equal to 4.527 (5). The non-negative *Aggressive_1* or the *Aggressive_3* equal to seven are regarded as aggressive (marketable limit) orders because investors want to quickly execute their orders by selling at current best bid prices or lower, forfeiting the potential premium by waiting for better prices. We estimate from our sample that a considerable portion of the total orders can be categorized as aggressive orders. Similar conclusion can be

drawn from *Aggressive_2*. The median of *Aggressive_2* equal to 1 suggests that in over half of the sells in our sample investors intend to liquidate their current holdings in one time, which indicates strong eagerness to sell.

Insert Figure 3 about Here

We also plot the bar charts for *Aggressive_3* in Figure 3. *Aggressive_3* is the discrete response variable that directly indicates where in the book the order price hits. A unique feature for *Aggressive_3* is that this variable does not follow a continuous distribution. Nearly 38% of observations are with *Aggressive_3* equal to 7, which can be regarded as the most aggressive orders. The multiple-response discrete distribution is not suitable for ordinary least-square (OLS) regressions, which require both dependent and independent variables to follow continuous distributions.

Panel B of Table IV contains summary statistics for the prior gains (*PG*) and prior losses (*PL*) measures, using the share-weighted average purchase price as the reference price. We note that *PL* are on average much higher than *PG*, with the mean (median) of *PL* equal to 1.068 yuan (0.200 yuan) and the mean (median) of *PG* equal to 0.218 yuan (0 yuan). This finding provides support to the disposition effect as the investors tend to hold on to stocks with large losses than stocks with small gains.

Panel C of Table IV computes the statistics of the control variables used in the empirical analysis in the next subsection. The control variables include the relative bid-ask spread, the monetary quantities at the best ask/bid price, the standard deviation of the 30 1-minute returns prior to the order submission, and the return over the 30 minute prior to the order submission. As in Table I, the average (median) relative bid-ask spread of 0.173 (0.144) indicates a highly liquid market in our data sample. It should be noted that we do not use the depth over all the bid and ask quotes available to investors. This is because an important determinant in order aggressiveness is whether the order could be executed immediately at the best quote on the other side of the market. Even for aggressive sellers, they do not need to submit sell orders at bid price below *Bid1*.

Insert Figure 4 about Here

We further compute the mean of the three order aggressiveness measures for different subgroups of data

to gain deeper understanding of these measures. We split our sample into two subsamples, one with positive Prior Gains (about 41% of orders submitted), and the other with positive Prior Losses (about 59% of the orders submitted). We divide each subsample into four quartiles according to their *PG* (*PL*) measure if the *PG* (*PL*) value is positive, with the *PG*(*PL*) value in the 4th quartile being the largest. We then compute the mean of *Aggressive_1*, *Aggressive_2*, and *Aggressive_3* for each of the quartile and subsample, respectively. Figure 4 plots the mean of the three order aggressiveness measures over the subsamples and quartiles for *PG* > 0 and *PL* > 0, respectively. We can see that the means of the three aggressiveness measures show a clear bell-shape pattern, with the measure first increasing as the *PG* gets larger and then decreasing after *PG* reaches certain level. On the other hand, the means of the three measures in general show a decreasing trend as the *PL* measure gets larger in each subsample. The only exception is the mean of *Aggressive_3* first slightly increases from *PL* = 0 to the first quartile when *PL* > 0, and then consistently decreases as *PL* keeps getting larger. The patterns of the means in different subsamples are consistent with our hypotheses.

C. Regressions of Aggressiveness Measures on Behavioral Variables and Controls

In this subsection, we examine whether the investors who have encountered prior gains in their stock holding will tend to submit more aggressive selling orders, after controlling for other explanatory variables. We also check the robustness of our results by testing for alternative explanations.

We start with a correlation analysis of behavioral biases and other explanatory variables. Table V show that, in general, the explanatory variables are not highly correlated. All correlation coefficients are below 0.3 in absolute values, except for the correlation between PG and PL (0.362), and between the market depth at the ask quote and the market depth at the bid quote (0.335). This suggests that there is less of the multicollinearity problem among the explanatory variables in explaining the order aggressiveness measures.

Insert Table V about Here

We conduct regression analysis of the order aggressiveness measures on various explanatory variables, including the prior gains and prior losses. We then use the first two order aggressiveness measures as the dependent variable in the regressions. The following is the regression equation (1):

$$AGGRESSIVE_{t} = \alpha + \gamma_{1}PG_{t} + \gamma_{2}PG_{t}^{2} + \gamma_{3}PL_{t} + \gamma_{4}SPREAD_{t} + \gamma_{5}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{t}$$

$$(1)$$

where $AGGRESSIVE_t$ is the order aggressiveness measure at time t, PG_t is the prior gains (based on the share-weighted average purchase price) at time t, PG_t^2 is the squared term of the prior gains at time t, PL_t is the prior losses (based on the share-weighted average purchase price) at time t, $SPREAD_t$ is the relative bid-ask spread at time t, $ADEPTH_t$ and $BDEPTH_t$ are the depth (monetary quantity) at the best ask and bid quotes, respectively, $RISK_t$ 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, D_i is the dummy variable indicating whether the order is submitted during the i^{th} 30-minuter interval between 9:30 AM (the market open) and 2:30 PM of the day.⁶

We first pool all the observations together and run regressions. We run OLS regression for *Aggressive_1* and *Aggressive_2*. The statistical significance reported in various tables is based on robust standard errors that are adjusted for clustering at two levels: first by each stock and then by each trading day.⁷ We also run regressions in the style of Fama-Macbeth (1973) in which we conduct trader-by-trader regressions and average the coefficients across traders, and we conduct day-by-day regressions and average the coefficients across traders, and we conduct day-by-day regressions, we remove from our sample if the investor submits less than 100 orders in the whole year of 2008. The Fama-Macbeth regressions serve to test whether our results are driven more by particular traders or by particular days.

⁶ We do not include the dummy variable for the last 30-minute interval of the trading day to avoid perfect collinearity.

⁷ We have tried several alternative ways for clustering standard errors. For example, Feng and Seasholes (2005) report results based on robust standard errors adjusted for clustering by each individual investor. Our current method, however, provides the largest standard error, and thus the smallest t-value, in estimation. Switching to other methods will only make our coefficients more significant. We download STATA program code to run regression reporting robust standard errors that allow for clustering by two dimensions from Michell Petersen's website at

http://www.kellogg.northwestern.edu/faculty/petersen/htm/papers/se/se_programming.htm.

The estimation results are reported in Table VI and Table VII, respectively.

Insert Table VI about Here

Table VI presents regression results when using Aggressive_1 as the dependent variable. In Model 1 when Aggressive_1 is regressed on behavioral bias measures, the coefficient of PG (γ_1) is significantly positive, the coefficient of $PG^2(\gamma_2)$ is significantly negative, and the coefficient of $PL(\gamma_3)$ is significantly negative. The coefficients are also economically significant: a one standard deviation change in PG (PL) can induce a 10% (9%) change in the standard deviation of Aggressive_1. The results show that order aggressiveness measures is negatively related to PL, but positively related to PG when PG is small and negatively related to PG when PG is large. This indicates that investors become more risk-averse after small previous gains and submit more aggressive sell orders, and become more risk-taking when gains accumulate to a certain level and submit less aggressive sell orders. They also submit less aggressive sell order when they encounter prior losses. In Model 2 when the only explanatory variable is SPREAD, the coefficient estimate of SPREAD is significantly negative, which shows that investors submit less aggressive limit orders when the spread is bigger. In Model 3 when the explanatory variables are the depth variables, while the coefficient estimate of the best ask depth (ADEPTH) is significantly positive, the coefficient estimate of the best bid depth (BDEPTH) is not significant. The positive sign for ADEPTH is consistent with the "crowding out" effect in Palour (1998), as after an increase in market depth at the best ask price, investors need to submit more aggressive selling orders to increase the probability of execution. However, there is no such "crowding out" effect for best bid depth. In Model 4 where the only explanatory variable is short-term volatility (RISK), the coefficient estimate of RISK is negative and significant. The evidence is therefore consistent with Foucault (1999) that higher volatility increases the "picking-off" risk, so that investors tend to submit less aggressive limit orders. In Model 5 where the only explanatory variable is MOMENTUM, the coefficient is significantly negative, indicating that investors are less reluctant to sell stocks that are in momentum and experience price appreciation recently. In Model 6 where all explanatory variables are included, we find that PG, PG^2 , and PL remains significant even after all control variables and the half-hour dummy variables. The explanatory power of the behavioral variables (PG, PG^2 , and PL) appears to be robust in that their coefficients are more statistically

significant than all other control variables (except for the half-hour dummies). In Model 7 and Model 8, we can see both Fama-MacBeth trader-by-trader and day-by-day regressions generate results similar to the pooled OLS regression in Model 6. Overall, the evidence is consistent with the hypothesis that investors exhibit both disposition effect and house money effect in their order submission strategies

Insert Table VII about Here

Table VII shows a similar relation between the second order aggressiveness measures (*Aggressive_2*) and behavioral bias variables. The coefficient estimate of PG is positive and the coefficients estimate of PG^2 is negative, showing that investors will be more aggressive in submitting sell order when potential profit is small, but less aggressive in submitting sell order when potential profit is large. The negative coefficient estimate associated with *PL* means that investors are reluctant to sell the stocks if they have experienced losses. Again, the results are robust after adding various control variables.

D. Ordered Probit Regression

As we have seen in Figure 2, *Aggressive_3* follows a discrete response distribution, and we cannot adopt OLS regression on *Aggressive_3*. Following previous tests in Griffiths, Smith, Turnbull, and White (2000) and Ranaldo (2004), we argue that the latent continuous variable related to order aggressiveness determine the responses of *Aggressive_3*. As a result, we can model *Aggressive_3* as the ordered response of the latent aggressiveness measure, and perform Ordered Probit regression to examine the relation between *Aggressive_3* and the explanatory variables. The regression equation is as (2):

$$Z_{t} = \gamma_{1}PG_{t} + \gamma_{2}PG_{t}^{2} + \gamma_{3}PL_{t}$$

+ $\gamma_{4}SPREAD_{t} + \gamma_{5}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t}$
+ $\sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{t}$ (2)

where Z_t is the latent order aggressiveness measure at time t, PG_t is the prior gains (based on the share-weighted average purchase price) at time t, PG_t^2 is the squared term of the prior gains at time t, PL_t is the prior losses (based on the share-weighted average purchase price) at time t, $SPREAD_t$ is the

relative bid-ask spread at time t, $ADEPTH_t$ and $BDEPTH_t$ are the depth (monetary quantity) at the best ask and bid quotes, respectively, $RISK_t$ 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, D_i is the dummy variable indicating whether the order is submitted during the i^{th} 30-minuter interval between 9:30 AM (the market open) and 2:30 PM of the day. We do not include the dummy variable for the last 30-minute interval of the trading day to avoid perfect collinearity.

Insert Table VIII about Here

Table VIII shows the results of Ordered Probit analysis. Since the Ordered Probit analysis of the whole sample is beyond the computational capability of the computers at the exchange, we divide the whole sample into three subsamples: two retail trader subsample with 250,000 accounts each and one institutional trader subsample with 21,611 accounts. The dependent variable is *Aggressive_3*, and the explanatory variables include the three behavioral bias variables, the explanatory variables including *RISK*, *SPREAD*, *ADEPTH*, *BDEPTH*, *MOMENTUM*, as well as half-hour dummies. Again, the coefficients for *PG*, *PG*², and *PL* are significant and the signs are similar to the OLS regression results presented in Table VI and VII. The evidence once again shows that investors are more likely to submit aggressive sell orders after she has accumulated small gains, but more likely to submit less aggressive sell orders after he has accumulated large gains, or after she has encountered losses in the investments. The statistical significance of the t-value reported next to the coefficients is based on robust standard errors that are adjusted for clustering at two levels: first by each stock and then by each trading day. Table VIII also shows that the behavioral biases affect order aggressiveness for both retail and institutional traders.

E. Robust Tests

In this section, we conduct various robust tests by (i) splitting the full-sample into four sub-samples; (ii) constructing alternative measures of potential selling prices and reference purchase prices; (iii) excluding the "fleeting" limit orders suggested by Hasbrouck and Saar (2009); (iv) adding back market orders into our sample; and (v) adding squared term for the potential loss measures in the regression

equation.

E.1 Regressions for the Four Quarters of 2008

To examine how robust our results are, we split the full sample into four sub-sample period, with each sub-sample period comprising data from one quarter of the year 2008. We repeat our empirical estimations in each of the sub-samples, and find similar results as analyses using the whole dataset. This shows that our conclusion is robust in each quarter of the year 2008.

E.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 selling price that the investor can get should she want to execute her orders without any delay. This procedure assumes that the order size is equal to or less than the market depth at the best bid quote. For the sample period, we find that 83% of orders have sizes equal to or smaller than the market best bid depth. Therefore, for the remaining 17% orders, they will either walk through the book on the bid side and be executed at inferior bid prices, or be store in the book to wait for more incoming buy orders, depending on the investors' preference. The investor can also choose to withdraw the orders if they cannot be fully executed.

If investors specify that the size of orders that cannot be executed will be automatically removed from the market or stored in the ask side of the book at the best bid quote, then the potential selling price is just the best bid quote (*Bid1*). On the other hand, if the investors require the orders to walk through the book and be executed at prices inferior to the best bid quote, then the potential selling price is the share-weighted average of the several bid quotes the orders cover. Therefore, as an alternative, we calculate the potential selling price as the share-weighted average of five bid quotes (public to each investor), while using number of shares executed at each bid quote level as the weightings. We then adopt this alternative selling price in calculating $Aggressive_1$, as well as PG and PL variables.

In addition, our empirical analysis so far assume the share-weighted average purchase price as the reference (purchase) price. We also construct alternative purchase prices, namely, the initial purchase price, the most recent purchase price, and the highest purchase price. We use these alternative measures of reference purchase price in re-calculating PG and PL measures as well.

Table IX presents the empirical results when we use alternative selling price (share-volume weighted bid quotes) and different measures of reference purchase prices (initial purchase price, most recent purchase price, and the highest purchase price). We use either *Aggressive_1* or *Aggressive_2* as the dependent variable. The results are quantitatively and qualitatively similar to the results in Table VI, VII, and VIII, with the significance levels for the behavioral bias measures comparable as well. Thus, our conclusion is robust to alternative measures of potential selling prices and reference prices.

Insert Table IX about Here

E.3 Effects of "Fleeting" Limit Orders

The "fleeting" limit orders refer to "the fast submission and cancellation of limit orders" (Hasbrouck and Saar (2009)), with the objective of price manipulation. For example, if the manipulator wants to buy stocks, he might first submit a lot of sell orders at *Ask1*. This might be interpreted by other investors as negative information about the stock so that they will try to sell as well. To avoid their sell orders get executed, the manipulator will cancel (or withdraw) their orders within a very short time period (usually within 2-3 seconds, according to Hasbrouck and Saar (2009)) and resubmit. After this downward pressure drives down the stock price, they will cancel all their sell orders and buy from the other side of the market. Thus, the existence of "fleeting orders" provides an alternative explanation that can affect the order aggressiveness. However, in our sample, this phenomenon is rare, as less than 0.01% orders submitted withdrawn within 5 seconds. This is possibly due to the trading restriction in Chinese market (for example, the selling lockup) and the stringent inspection from CSRC. Anyhow, even after we remove those orders that are withdrawn within 5 seconds of their submissions, we find the results remain qualitatively similar.

E.4 Effects of Market Orders

In our analysis, we remove from our sample the market (sell) orders submitted because market orders do not specify the order prices, so we cannot compute *Aggressive_1* and *Aggressive_3*. We can, however, include the market orders in our analysis if we assume the order prices for the market orders. Because market sell orders are required to be executed at the best bid quotes immediately, we can assume the order prices of market orders to be *Bid1*(or the share-weighted average of five bid quotes if the order size exceeds the depth at the best bid quote). This will give us the *Aggressive_1* equal to or greater than zero or *Aggressive_3* equal to 7. In our sample, market orders are very rare, less than 0.5%. We find the results remain qualitatively similar after we add the market orders back into our sample and assume orders prices to them.

E.5 Additional Effects of Prior Losses

Our analysis so far has been assuming that investors will be more risk-taking when they experience prior losses. The empirical evidence also shows that there is a negative relationship between order aggressiveness and prior loss. However, according to Thaler and Johnson (1990), the effect of prior loss on risk aversion is not necessarily monotonic. This is because other than the original formulation of prospect theory, whether investors will seek more risk or not in the presence of losses depends on whether they can get back to the original reference or "break-even" point (Kahneman and Tversky (1979)). When the prior loss is large, they need to be more risk-seeking in order to break even. But when the prior loss is small, they do not necessarily to be more risk-seeking to break even. This "break-even" point implies that the effect of prior loss on risk aversion will be positive when the prior loss is small, but becomes negative when the prior loss is large. To investigate this possibility, we introduce squared term of PL in the regression for explaining various order aggressive measures. Regardless of which order aggressive measure we use, the coefficient estimate of PL remains negative, while the coefficient estimate of squared term of PL is either negative or positive. Therefore, even after allowing for the possibility of "break-even" point, the effect of prior loss on the risk aversion remains negative even when the prior loss is small.

VI. Conclusions

This paper examines the role of behavioral biases in order submission strategies in the Shanghai stock market, which uses a computerized limit-order trading system. Taking advantage of a unique database provided by SSE, we examine how the order aggressiveness is being affected by the behavioral biases. We show that the sell order aggressiveness is strongly affected by disposition effect. When the investor sells a stock that has depreciated relative to the purchase price, the bigger the losses, the less aggressive he will be in the order submission. When the investor sells a stock that has appreciated relative to the purchase price, the bigger the losses, the less aggressive he will be in the order submission. When the investor sells a stock that has appreciated relative to the purchase price, the bigger the profits, the more aggressive he will be in the order submission. However, the investor will also be affected by the housing money effect, so that for the stocks that he is making profits, after the profits reach a certain level, he becomes less aggressive in the order submission.

Our paper marks the first attempt to relate behavioral bias measures to order submission strategies. Previous studies examining the order submission strategies are based on the rational framework. An important contribution of our paper is that based on a very unique dataset, we show that psychological biases can affect how aggressive investors are in the order submission.

We believe that our results are relevant not only for an emerging stock market like China, which is has a lot of less experienced retail investors, but should have implications for developed markets as well. There is a lot of evidence that investors in the developed markets exhibit behavioral biases as well, at both retail investor level (Odean (1999)) and professional investor level (Haigh and List (2005)). Research has also shown that the introduction of electronic trading system and the ensuing decrease in trading costs have induced more traders to participate in trading as well. And it is not surprising that these investors are easily subject to behavioral biases through their investment decision making processes. With more detailed trading account available for individual investors in different markets, it will be interesting to examine how these behavioral biases will affect other trading decisions as well.

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Table I Summary Statistics

This table reports the mean (Mean), median (Median), standard deviation (Std), minimum (Min), and maximum (Max) of various variables on stocks in our sample. Our sample contains the full history of limit orders submitted by 521,611 investors on 855 stocks from January to December of 2008. The sample is further restricted to those observations in days when stock prices do not hit their price limits. The time to execution is the seconds between the record of the snapshot of the limit order book and submission of the sell order. Order price and order size are the price and yuan volume submitted in an order. Relative Spread is the ratio of the difference between market best ask and bid quotes divided by the average of the market best ask and bid quote when the limit order book is recorded. Ask Depth is the yuan quantities of the market depth over the five bid quotes when the limit order book is recorded. Bid Depth is the yuan quantities of the days between the date of the first purchase and the date of the sell order submission.

Variable	Mean	Median	Std	Min	Max
Time to Execution (seconds)	5.368	4.000	4.627	1.000	30
Order Price (yuan)	12.238	9.330	10.798	1.050	290
Order Size (1,000 yuan)	32.415	8.200	154.217	0.0024	46,553
Relative Spread (%)	0.185	0.144	0.165	0.0001	15.503
Ask Depth (1,000,000 yuan)	2.568	0.880	6.273	0.001	330.737
Bid Depth (1,000,000 yuan)	2.202	0.771	4.899	0.0002	263.414
Holding Period (days)	35.651	10.000	59.154	1.000	355

Table II Tests for the Disposition Effect

This table presents the results of testing the Disposition Effect on investment decisions for investors in our sample. The proportion of gains realized (PGR) and the proportion of losses realized (PLR) are defined as

PGR = Realized Gains / (Realized Gains + Paper Gains) PLR = Realized Losses / (Realized Losses + Paper Losses)

The number of "Realized Gains/Losses" and "Paper Gains/Losses" is counted each time an individual sells a stock. A sale is defined as a realized gain/loss if the selling price is higher/lower than the stock's share-weighted average purchase price. For other stocks in the same portfolio held by the investor, a holding is defined as a paper gain (loss) if the daily highest (lowest) price of the stock is lower (higher) than the share-weighted average purchase price. The disposition effect is defined as the difference of each investor's *PGR* and *PLR*

Disposition Effect (DE) = PGR - PLR

Panel A calculates *PGR*, *PLR*, and *DE* for the entire Data set. Panel B calculates *PGR*, *PLR*, and *DE* for each investor (account), and then reports the mean and median across investors. We remove observations from our data set if the investor has only 1 stock in her portfolio. The sample includes 521,611 investor accounts. Data are from January to December 2008 and are provided by SSE.

	Mean						
PGR	0.671						
PLR	0.390						
DE	0.281						
Panel B: The Disposition Effect for Individual Investors							
	Mean	Median					
PGR	0.791	0.870					
PLR	0.457	0.429					
DE	0.335	0.373					

rallel A. The Disposition Effect for the Entitle Data Se	Panel A:	The Dis	position	Effect	for the	Entire	Data	Se
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Table III Tests for the Disposition Effect (Survival Analysis)

This table presents hazard ratios associated with the average individual's decision to sell/hold stocks at a loss/gain. The left-hand side variable of the regression takes a value of zero every day the individual holds a stock, and takes the value of one every day she sells a stock. In the first regression, the independent variable is an indicator that takes a value of one every day a stock is trading at a loss (relative to the purchase price) and zero otherwise. In the second regression, the independent variable is an indicator that takes a value of one every day a stock is trading at a gain (relative to the purchase price) and zero otherwise. Panel A uses a *Weibull* distribution with parameter "p" to parameterize 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. Panel B runs a Cox regression without specifying any distribution for the underlying holding variable.

Data are from January to December 2008 and are provided by SSE. Z-stats are based on robust standard errors that allow for clustering by each stock. Z-stats are shown in parenthesis below the hazard ratios. Individual1 to individual5 are subsamples each containing 100,000 retail accounts. And Institution is the subsample containing 21,611 institutional investors. Panel A: Hazard Ratio, Parametric (*Weibull*) Regression

	Indivi	dual1	Indivi	dual2	Individual3		Individual4		Individual5		Institution		
TLI	0.159		0.159		0.158		0.159		0.158		0.283		
(Z-stat)	(-78.01)		(-73.62)		(-81.28)		(-75.93)		(-78.41)		(-37.90)		
TGI		12.905		12.868		13.002		12.917		12.954		8.416	
(Z-stat)		(99.31)		(95.70)		(102.58)		(98.29)		(101.04)		(60.12)	
p-parameter	0.635	0.637	0.633	0.634	0.636	0.638	0.636	0.638	0.635	0.636	0.689	0.689	
(std error)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	
	Panel B: Hazard Ratio, Cox Regression												
TLI	0.1	.91	0.1	91	0.1	189	0.1	91	0.190		0.331		
(Z-stat)	(-75	.95)	(-71	.37)	(-77	.68)	(-73	.25)	(-79	9.19)	(-36	.18)	
TGI	11.	154	11.1	119	11.227		11.149		11.188		7.709		
(Z-stat)	(102	2.25)	(97.	86)	(104	4.13)	(100	.19)	(102.99)		(61.	(61.85)	

Table IV Statistics of Order Aggressiveness Measures and Explanatory Variables

Panel A, B, and C of this table report the mean (Mean), median (Median), standard deviation (Std), minimum (Min), and maximum (Max) of the three order aggressiveness measures, prior gains / losses measures, and other control variables, a of order aggressiveness measures according to prior gains/losses.

where *Bid1* is the best quoted bid price at the time of order submission and *Order_Price* is the (sell) order price submitted. *Aggressive_2* is defined as

$$Aggressive_{2} = \frac{Order _Vol}{Hold \ Bal}$$

where *Order_Vol* is the share volume size of the (sell) order submitted, and *Hold_Bal* is the share balance of the stock held by the trader right before the submission. *Aggressive_3* 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.

$$Aggressive_3 = 1$$
 if $Ask5 \leq Order_Price$ $= 2$ if $Ask4 \leq Order_Price < Ask5$ $= 3$ if $Ask3 \leq Order_Price < Ask4$ $= 4$ if $Ask2 \leq Order_Price < Ask3$ $= 5$ if $Ask1 \leq Order_Price < Ask2$ $= 6$ if $Mid_Quote \leq Order_Price < Ask1$ $= 7$ if $Order_Price < Mid_Quote$

where *Ask1*, *Ask2*, *Ask3*, *Ask4*, and *Ask5* are the 5 best quoted ask prices in the order book. *Order_Price* is the (sell) order price submitted *Mid_Quote* is the average of best quoted ask and bid prices at the time the order is submitted.

The dollar value (in yuan) of Prior Gains measure (PG) / Prior Losses measure (PL) are calculated based on the difference between *Bid1* and the reference price:

PG = Max [0, Bid1 - Reference]PL = Max [0, Reference - Bid1]

When the outstanding best bid quote (*Bid1*) is higher than the reference price, Reference is the reference price, which is the share-weighted average purchase price. PG is assigned the absolute value of the difference while 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 while PL is assigned the absolute value of the difference.

The control variables include the relative bid-ask spread (*SPREAD*), the best ask market depth (*ADEPTH*), the best bid market depth (*BDEPTH*), the standard deviation of the 1-minute best bid price return over the previous 30-minute interval (*RISK*), and the stock best bid price return over the prior 30-minute interval (*MOMENTUM*)

	Mean	Median	Std	Min	Max					
PANEL A: Order Aggressiveness Measures										
Aggressive_1	-0.067	-0.010	0.131	-0.490	0.020					
Aggressive_2	0.690	1.000	0.349	0.091	1.000					
Aggressive_3	4.527	5.000	2.403	1.000	7.000					
PANEL B: Prior Gains / Losses										
PG (in yuan)	0.218	0	0.387	0	1.373					
PL (in yuan)	1.068	0.200	1.663	0	5.880					
PA	NEL C: Control	Variables								
SPREAD (%)	0.173	0.144	0.107	0.047	0.445					
ADEPTH (in million Yuan)	0.233	0.079	0.357	0.004	1.378					
BDEPTH (in million Yuan)	0.222	0.074	0.346	0.003	1.340					
RISK	0.003	0.002	0.001	0.001	0.005					
MOMENTUM	0.004	0.003	0.018	-0.026	0.041					

Table V Explanatory Variable Correlations

This table presents the correlations among all candidate explanatory variables for the cross-sectional variation in order aggressiveness measures. These explanatory variables include two behavioral bias measures: the prior gains measure (PG) and the prior losses measure (PL), the relative bid-ask spread (SPREAD), the monetary quantities of the best ask depth (ADEPTH), the monetary quantities of the best bid depth (BDEPTH), the standard deviation of the 1-minute best bid price return over the previous 30-minute interval (RISK), and the stock best bid price return over the prior 30-minute interval (MOMENTUM).

	PG	PL	SPREAD	ADEPTH	BDEPTH	RISK	MOMENTUM
PG	1	-0.362	-0.188	0.042	0.035	0.009	0.125
PL		1	-0.011	-0.021	-0.011	0.037	-0.054
SPREAD			1	-0.112	-0.104	0.237	-0.0003
ADEPTH				1	-0.335	-0.123	0.043
BDEPTH					1	-0.144	-0.022
RISK						1	-0.239
MOMENTUM							1

Table VI Order Aggressiveness: Aggressive_1 and Competing Explanations

This table presents regressions that relate Aggressive_1 to various explanatory variables. The regression equation is:

 $AGGRESSIVE_{t} = \alpha + \gamma_{1}PG_{t} + \gamma_{2}PG_{t}^{2} + \gamma_{3}PL_{t} + \gamma_{4}SPREAD_{t} + \gamma_{5}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{t}$

where $AGGRESSIVE_t$ is the order aggressiveness measure at time t, PG_t is the prior gains (based on the share-weighted average purchase price) at time t, PR_t^2 is the squared term of the prior gains at time t, PL_t is the prior losses (based on the share-weighted average purchase price) at time t, $SPREAD_t$ is the relative bid-ask spread at time t, $ADEPTH_t$ and $BDEPTH_t$ are the depth (monetary quantity) at the best ask and bid quotes, respectively, $RISK_t$ 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, D_i is the dummy variable indicating whether the order is submitted during the i^{th} 30-minuter interval between 9:30 AM (the market open) and 2:30 PM of the day. We do not include the dummy variable for the last 30-minute interval of the trading day to avoid perfect collinearity.

Panel A presents pooled OLS regression results. Panel B presents Fama-Macbeth (FM) regression results. FM regressions are conducted first trader-by-trader and average the coefficients across trading days. For FM trader-by-trader regressions, investors each submitting less than 100 orders in the whole year of 2008 are removed from the sample.

The number of observation in our dataset is 7,299,636. All variables are winsorized at the 5th and 95th percentile levels. The t-values are reported in the parenthesis below the coefficients. The robust standard errors are adjusted for clustering first by each individual stock, and then by each trading day. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

									Half-Hour	
Model	PG	PG^2	PL	SPREAD	ADEPTH	BDEPTH	RISK	MOMENTUM	Dummy	α
		I	Panel A: Pooled	OLS regression	ns, Dependent V	ariable: Aggress	ive_1			
	0.033***	-0.041***	-0.007***							-0.060***
1, Prior gains/Losses	(12.66)	(-21.97)	(-19.25)						No	(-46.90)
				-0.576						-0.067***
2, Spread				(-0.72)					No	(-36.47)
					0.005***	0.001				-0.070***
3, Market Depth					(2.96)	(0.60)			No	(-58.50)
							-4.299***			0.057***
4, Short-Term Volatility							(-8.70)		No	(-30.13)
								-0.192***		-0.067***
5, Short-Term Momentum								(-7.52)	No	(-52.53)
	0.035***	-0.042***	-0.008***	-0.323	0.003**	-0.001	0.451	-0.179***		-0.023***
6, All Explanatory Variables	(13.82)	(-24.05)	(-21.45)	(-0.46)	(2.42)	(-0.70)	(1.09)	(-7.03)	Yes	(-14.89)
		Pa	nnel B: Fama-M	acbeth regression	ons, Dependent	Variable: Aggres	sive_1			
	0.044***	-0.051***	-0.001***	-1.704***	0.006***	0.002*	-2.870***	0.095***		-0.031***
1, FM by trader	(25.14)	(-9.95)	(-9.91)	(-12.84)	(22.05)	(1.78)	(-29.23)	(11.88)	Yes	(-48.47)
	0.035***	-0.042***	-0.008***	-4.488***	0.002***	-0.002***	-5.576***	-0.015***		-0.038***
2, FM by trading date	(16.23)	(-28.24)	(-41.60)	(-10.22)	(5.78)	(-5.25)	(-22.76)	(-7.05)	Yes	(-35.13)

Table VII Order Aggressiveness: Aggressive_2 and Competing Explanations

This table presents regressions that relate Aggressive_2 to various explanatory variables. The regression equation is:

$$AGGRESSIVE_{t} = \alpha + \gamma_{1}PG_{t} + \gamma_{2}PG_{t}^{2} + \gamma_{3}PL_{t} + \gamma_{4}SPREAD_{t} + \gamma_{5}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{t}$$

where $AGGRESSIVE_t$ is the order aggressiveness measure at time t, PG_t is the prior gains (based on the share-weighted average purchase price) at time t, PG_t^2 is the squared term of the prior gains at time t, PL_t is the prior losses (based on the share-weighted average purchase price) at time t, $SPREAD_t$ is the relative bid-ask spread at time t, $ADEPTH_t$ and $BDEPTH_t$ are the depth (monetary quantity) at the best ask and bid quotes, respectively, $RISK_t$ 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, D_i is the dummy variable indicating whether the order is submitted during the i^{th} 30-minuter interval between 9:30 AM (the market open) and 2:30 PM of the day. We do not include the dummy variable for the last 30-minute interval of the trading day to avoid perfect collinearity.

Panel A presents pooled OLS regression results. Panel B presents Fama-Macbeth (FM) regression results. FM regressions are conducted first trader-by-trader and average the coefficients across trading days. For FM trader-by-trader regressions, investors each submitting less than 100 orders in the whole year of 2008 are removed from the sample.

The number of observation in our dataset is 7,299,636. All variables are winsorized at the 5^{th} and 95^{th} percentile levels. The t-values are reported in the parenthesis below the coefficients. The robust standard errors are adjusted for clustering first by each individual stock, and then by each trading day. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

									Half-Hour	
Model	PG	PG^2	PL	SPREAD	ADEPTH	BDEPTH	RISK	MOMENTUM	Dummy	α
		I	Panel A: Pooled	OLS regression	s, Dependent Va	riable: Aggressi	ve_2			
	0.286***	-0.186***	-0.035***							-0.702***
1, Prior gains/Losses	(21.98)	(-21.86)	(-27.21)						No	(-181.28)
				-9.167***						-0.706***
2, Spread				(-5.29)					No	(-117.85)
					-0.002	0.005				0.689***
3, Market Depth					(-0.47)	(1.18)			No	(184.22)
							-6.339***			0.707***
4, Short-Term Volatility							(-3.62)		No	(208.08)
								-2.524***		0.701***
5, Short-Term Momentum								(-31.20)	No	(184.90)
	0.338***	-0.217***	-0.034***	-6.034***	-0.001	0.004*	2.762***	-3.167***		0.681***
6, All Explanatory Variables	(26.50)	(-25.83)	(-29.62)	(-6.44)	(-0.50)	(1.41)	(2.60)	(-43.06)	Yes	(122.57)
		Pa	anel B: Fama-Ma	acbeth regressio	ns, Dependent V	/ariable: Aggres.	sive_2			
	0.365***	-0.300***	-0.024***	5.322***	0.011***	0.024***	3.552***	-1.593***		0.629***
1, FM by trader	(21.27)	(-8.45)	(-36.74)	(18.36)	(13.30)	(9.77)	(13.50)	(-83.89)	Yes	(206.23)
	0.397***	-0.277***	-0.031***	0.114	-0.003***	0.004***	8.636***	-3.026***		0.686***
2, FM by trading date	(31.32)	(-29.38)	(-33.00)	(0.32)	(-3.48)	(4.44)	(12.93)	(-63.94)	Yes	(169.41)

Table VIII. Ordered Probit analysis of Aggressive_3 and competing explanations

This table shows the Ordered Probit analysis of sell orders submitted in SSE during 2008. The dependent variable is the latent order aggressiveness measure, of which *Aggressive_3* is the ordered response. *Aggressive_3* is classified into seven different levels of aggressiveness levels. The regression equation is as the following:

$Z_{t} = \gamma_{1}PG_{t} + \gamma_{2}PG_{t}^{2} + \gamma_{3}PL_{t} + \gamma_{4}SPREAD_{t} + \gamma_{5}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{7}\beta_{i}D_{i} + \varepsilon_{i}ADEPTH_{t} + \gamma_{8}ADEPTH_{t} + \gamma_{8$

where Z_t is the latent order aggressiveness measure at time t, PG_t is the prior gains (based on the share-weighted average purchase price) at time t, PG_t^2 is the squared term of the prior gains at time t, PL_t is the prior losses (based on the share-weighted average purchase price) at time t, $SPREAD_t$ is the relative bid-ask spread at time t, $ADEPTH_t$ and $BDEPTH_t$ are the depth (monetary quantity) at the best ask and bid quotes, respectively, $RISK_t$ 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, $MOMENTUM_t$ is the stock return during the half-hour prior to time t. D_i is the dummy variable indicating whether the order is submitted during the i^{th} 30-minuter interval between 9:30 AM (the market open) and 2:30 PM of the day. We do not include the dummy variable for the last 30-minute interval of the trading day to avoid perfect collinearity. α_i for i = 1-6, refers to the probit thresholds. The whole sample is divided into three subsamples with two retail trader sample and one institutional trader sample. The two retail trader sample each contains 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 the parenthesis below the coefficients. The robust standard errors are adjusted for clustering first by each individual stock, and then by each trading day. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Depen	dent Variable: Agg	gressive_3		
	Retail 1	Retail 2	Institutional		
No. Traders	250,000	250,000	21,611		
	0.090***	0.100***	0.186***		
PG	(3.33)	(3.75)	(2.65)		
	-0.113***	-0.128***	-0.175***		
PG^2	(-6.37)	(-7.29)	(-3.45)		
	-0.050***	-0.050***	-0.026***		
PL	(-17.22)	(-15.89)	(-4.46)		
	-40.689***	-39.978***	-34.363***		
SPREAD	(-12.18)	(-11.67)	(-3.77)		
	0.076***	0.080***	0.016***		
ADEPTH	(6.00)	(7.46)	(0.76)		
	-0.129***	-0.128***	-0.091***		
BDEPTH	(-8.22)	(-8.68)	(-4.35)		
	14.289***	12.969***	29.063***		
RISK	(3.99)	(3.72)	(4.79)		
	-7.591***	-7.380***	-9.428***		
MOMENTUM	(-39.32)	(-41.43)	(-23.70)		
Half – Hour Dummy	Yes	Yes	Yes		
Partition boundaries					
	-0.997***	-0.984***	-1.242***		
$\alpha_{_{1}}$	(-66.56)	(-65.52)	(-41.59)		
-	-0.899***	-0.887***	-1.139***		
α_{2}	(-66.56)	(-59.70)	(-38.64)		
2	-0.764***	-0.754***	-1.001***		
α_{2}	(-51.85)	(-50.95)	(-34.00)		
3	-0.531***	-0.522***	-0.780***		
α.	(-36.47)	(-35.73)	(-26.73)		
4	-0 031**	-0.026**	-0 326***		
a.	(-2.41)	(-1.85)	(-11.69)		
~5	0 041***	0.045***	-0 245***		
	0.071	0.040	0.273		
a	(2.94)	(3.26)	(-9.02)		

Table IX Order Aggressiveness and Explanatory Variables: Alternative Potential Selling Prices and Reference Prices

This table presents OLS regressions that relate *Aggressive_1* and *Aggressive_2* to explanatory variables. Potential selling price is defined as share-weighted average of five bid quotes. Reference price is defined as the initial purchase price, the most recent purchase price, and the highest purchase price, and the share-weighted average purchase price, respectively. The regression equation is:

$$AGGRESSIVE_{t} = \alpha + \gamma_{1}PG_{t} + \gamma_{2}PG_{t}^{2} + \gamma_{3}PL_{t} + \gamma_{4}SPREAD_{t} + \gamma_{5}ADEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{\prime}\beta_{i}D_{i} + \varepsilon_{6}BDEPTH_{t} + \gamma_{6}BDEPTH_{t} + \gamma_{7}RISK_{t} + \gamma_{8}MOMENTUM_{t} + \sum_{i=1}^{\prime}\beta_{i}D_{i} + \varepsilon_{6}BDEPTH_{t} + \gamma_{8}BDEPTH_{t} + \gamma_{8}BDEP$$

where $AGGRESSIVE_t$ is the order aggressiveness measure at time t, PG_t is the prior gains (based on the share-weighted average purchase price) at time t, PR_t^2 is the squared term of the prior gains at time t, PL_t is the prior losses (based on the share-weighted average purchase price) at time t, $SPREAD_t$ is the relative bid-ask spread at time t, $ADEPTH_t$ and $BDEPTH_t$ are the depth (monetary quantity) at the best ask and bid quotes, respectively, $RISK_t$ 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, D_i is the dummy variable indicating whether the order is submitted during the i^{th} 30-minuter interval between 9:30 AM (the market open) and 2:30 PM of the day. We do not include the dummy variable for the last 30-minute interval of the trading day to avoid perfect collinearity.

The number of observation in our dataset is 7,299,636. All variables are winsorized at the 5^{th} and 95^{th} percentile levels. The t-values are reported in the parenthesis below the coefficients. The robust standard errors are adjusted for clustering first by each individual stock, and then by each trading day. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

									Half-Hour	
Model	PG	PG^2	PL	SPREAD	ADEPTH	BDEPTH	RISK	MOMENTUM	Dummy	α
Panel A: Dependent variable: Aggressive_1, Potential Selling price = Share-weighted average of five bid quotes										
	0.041***	-0.045***	-0.005***	0.019	0.003**	0.003**	-0.061	-0.141***		-0.026***
Initial purchase price	(15.42)	(-24.49)	(-21.16)	(0.03)	(2.56)	(2.12)	(-0.14)	(-5.55)	Yes	(-15.74)
	0.050***	-0.064***	-0.005***	-0.090	0.003**	0.003**	-0.015	-0.138***		-0.025***
Highest purchase price	(15.65)	(-24.75)	(-21.10)	(-0.12)	(2.55)	(2.11)	(-0.03)	(-5.46)	Yes	(-15.63)
	0.015***	-0.025***	-0.010***	-1.246*	0.003**	0.002*	0.340	-0.160***		-0.024***
Most recent purchase price	(7.03)	(-20.03)	(-21.14)	(-1.80)	(2.58)	(1.82)	(0.84)	(-6.60)	Yes	(-15.87)
Share-weighted average	0.035***	0.042***	-0.008***	-0.323	0.003**	-0.001	0.451	-0.179***		-0.023***
purchase price	(13.82)	(-24.05)	(-21.45)	(-0.46)	(2.42)	(-0.70)	(1.09)	(-7.01)	Yes	(-14.89)
	Panel	B: Dependent	variable: Aggres	sive_2, Potential	Selling price =	Share-weighted	average of five	e bid quotes		
	0.339***	-0.235***	-0.035***	-7.868***	-0.001	0.005*	2.775**	-2.941***		0.708***
Initial purchase price	(30.14)	(-30.98)	(-41.23)	(-8.86)	(-0.16)	(1.82)	(2.84)**	(-40.70)	Yes	(146.5)
	0.466***	-0.324***	-0.033***	-5.050***	-0.002	0.005*	2.408	-3.090***		-0.697***
Highest purchase price	(34.76)	(-30.28)	(-41.76)	(-5.66)	(-0.69)	(1.73)	(2.60)	(-41.94)	Yes	(-147.87)
	0.468***	-0.030***	-0.009***	-10.648***	0.002	0.004	0.640	-2.726***		0.683***
Most recent purchase price	(5.73)	(-7.44)	(-6.04)	(-8.30)	(0.41)	(1.13)	(0.41)	(-39.90)	Yes	(98.56)
Share-weighted average	0.338***	-0.217***	-0.034***	-6.034***	-0.001	0.004*	2.762**	-3.167***		0.681***
purchase price	(26.50)	(-25.83)	(-29.62)	(-6.44)	(-0.50)	(1.41)	(2.60)	(-43.06)	Yes	(122.57)

Figure 1 Aggressiveness Measure Variations during the Course of a Trading Day

This figure presents the mean of *Aggressive_1*, *Aggressive_2*, and *Aggressive_3* for every 30-minute interval during the course of a trading day. *Aggressive_1* is defined as the best bid price in COLOB minus submitted sell price. *Aggressive_2* is defined as the submitted order volume divided by the share balance before submission. *Aggressive_3* is the multiple response variables indicating where in the book the order price hits. All observations are winsorized at 95%.









Figure 2 Distribution of Disposition Effect (DE) of All Investors

This figure presents the histogram of disposition effect for all investors in our data sample. The disposition effect is defined as the difference of each investor's proportion of gains realized (PGR) and the proportion of losses realized (PLR):

Disposition Effect
$$(DE) = PGR - PLR$$

PGR and PLR are defined as

PGR = Realized Gains / (Realized Gains + Paper Gains) PLR = Realized Losses / (Realized Losses + Paper Losses)

The number of "Realized Gains/Losses" and "Paper Gains/Losses" is counted each time an individual sells a stock. A sale is defined as a realized gain/loss if the selling price is higher/lower than the stock's share-weighted average purchase price. For other stocks in the same portfolio held by the investor, a holing is defined as a paper gain (loss) if the daily highest (lowest) price of the stock is lower (higher) than the share-weighted average purchase price. We remove observations from our data set if the investor has only 1 stock in her portfolio. The sample includes 521,611 investor accounts. Data are from January to December 2008 and are provided by SSE.



Figure 3 Distribution of Aggressive_3

This figure reports the distribution of *Aggressive_3*. *Aggressive_3* is defined as a discrete-response variable where a unique value is given when Order Price falls within the specific range on the order book.

$$\begin{array}{l} Aggressive_3 = 1 \ if Ask5 &\leq Order \ Price \\ &= 2 \ if \ Ask4 &\leq Order \ Price < Ask5 \\ &= 3 \ if \ Ask3 &\leq Order \ Price < Ask4 \\ &= 4 \ if \ Ask2 &\leq Order \ Price < Ask3 \\ &= 5 \ if \ Ask1 &\leq Order \ Price < Ask2 \\ &= 6 \ if \ Mid_Quote &\leq Order \ Price < Ask1 \\ &= 7 \ if \ Order \ Price < Mid_Quote \end{array}$$

where *Ask1*, *Ask2*, *Ask3*, *Ask4*, and *Ask5* are the 5 best ask prices in the order book, respectively, and *Mid_Quote* is the average of best ask and bid quotes, at the time the sell orders are submitted.



Figure 4 Order Aggressiveness Measures when Prior gains/Losses Measures are zero or positive

This figure presents the mean of $Aggressive_1$, $Aggressive_2$, and $Aggressive_3$ when PG and PL are either positive or zeros. We split our sample into two subsamples, one with positive Prior Gains (about 41% of orders submitted), and the other with positive Prior Losses (about 59% of the orders submitted). We divide each subsample into four quartiles according to their PG (PL) measure if the PG (PL) value is positive, with quartile 1 value being the smallest and quartile 4 value being the largest. We then compute the mean and median of Aggressive_1, Aggressive_2, and Aggressive_3 for each of the quartile and subsample, respectively. Aggressive_1 is defined as the best bid price in COLOB minus submitted sell price. Aggressive_2 is defined as the submitted order volume divided by the share balance before submission. Aggressive_3 is the multiple response variables indicating where in the book the order price hits. All observations are winsorized at 95%.



A: Mean of Order Aggressiveness Measures when Prior gains are zero or positive

A: Mean of Order Aggressiveness Measures when Prior losses are zero or positive







Aggressive_3