Do Behavioral Biases Affect Order Aggressiveness?

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This Draft: April, 2013

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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. We provide the first evidence that prior investment outcomes can affect subsequent order aggressiveness, which is consistent with the prospect theory. We further show that the investors' order aggressiveness is subject to both the disposition effect and the house money effect. 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.

Keywords: Order aggressiveness, Disposition effect, House money effect

JEL number: G12, G14, G18

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I. Introduction

Extensive empirical evidence has demonstrated that investors exhibit behavioral biases. These biases are purported to be related to a number of market anomalies, with a considerable amount of such biases relating the prior investment outcomes to subsequent investor behaviors. Among them, the most prominent example is the disposition effect (Shefrin and Statman (1985)) that investors tend to hold loser assets for too long and sell winner assets 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 such a phenomenon 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. Such a shape of the utility function impacts the risk-taking behaviors subsequent to the gains/losses: after the stock price appreciates, investors become more risk averse and tend to sell the stocks，whereas after the stock price declines, investors become less risk averse and prefer to continue holding their stock positions. In a more recent study, Barberis and Xiong (2009) have narrowed down the application the prospect theory in generating the disposition effect. They show that only when investors are assumed to derive utility from realizing gains / losses can they generate risk-taking behaviors consistent with the disposition effect. Otherwise, investors may seek to increase their risk taking after prior gains, instead of losses.

Despite the widely documented evidence on the impact of behavioral biases on investment decisions, very few papers investigate directly how the biases affect the trading behaviors 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 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 disposition effect. 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 findings provide evidence to the analysis by Barberis and Xiong (2009). They offer several possible explanations to their findings and find out that their results are more consistent with the house money effect, which is suggested by Thaler and Johnson (1990) and refers to the phenomenon that gamblers are will to take more risks when they have won and play with the money they have won.

This paper extends the analysis on the relationship between prior investment outcomes and trading behaviors to investigate whether behavioral biases affect traders' order submission decisions. Order submission decisions are among the most important choices traders make. Many of the most influential equity markets around the world are now operated based on the order-driven trading mechanism. These markets include the New York Stock Exchange, NASDAQ, Paris Bourse, and Hong Kong Stock Exchange. In an order driven market, a trader typically must decide whether to submit a market order or a limit order to trade. In this sense, the market order refers to either the order that is sure to be executed immediately at the best current quotes available or the limit order that could be executed without any delay, whereas the limit order refers to the order that would be added to the order book and waits to be executed. Parlour (1998) and Foucault (1999) model the limit order versus market order choice problem based on the trade-off between transaction price and execution risk: On one hand, limit orders are risky because they are only executed 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. On the other hand, there is no non-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) also characterize this trade-off by examining the interaction between the order book and the order flow in the Paris Bourse market. They introduce the *order aggressiveness* to quantitatively categorize each order submitted, with the order intended to be executed soonest being most aggressive. Investors with extreme time preferences will be more aggressive in the order submission, demanding liquidity from investors with less extreme time preferences. Linking these two views, we note that order aggressiveness reflect investors' patience in bearing the non-execution risks. If, according to the Prospect Theory, behavior biases can potentially affect investors' risk-taking behaviors, we should expect prior investment consequences to affect investors' order choices as well.

Unfortunately, we lack direct evidence on how behavior biases affect investors' order submission behaviors in practice. Producing such evidence would require order submission data not only for executed orders, but also for the orders that are withdrawn or revised by investors who submit them before, and for orders that are automatically removed from the market at the end of the trading day by the exchange. Previous empirical studies investigating the relationship between prior investment outcomes and subsequent trading behaviors typically examine executed orders only (e.g. Coval and Shumway (2005), Liu, Tsai, Wang, and Zhu (2010)). So, it seems that more direct evidence on the relationship between prior investment outcomes and subsequent order submission behaviors are needed.

In this paper, we examine how prior investment outcomes affect the order submission aggressiveness for both individual and institutional investors. We make use of a very unique database provided by the Shanghai Stock Exchange (SSE). This database keeps real-time records of order submissions and executions for all investors trading securities listed in SSE, as well as records of their stock holdings. This dataset is distinct from the account-level trading data used in prior studies in that it contains information for not only the executed orders, but the orders that have not been executed as well. Specifically, the dataset 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. Thus, the database allows us to track order submissions and executions for every investor in doing trading of securities listed in the Shanghai market. 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.

Using this unique order submissions database and the trading history for each account provided by SSE, we find that the prior investment consequences significantly affect investors' order submission behaviors at the Shanghai Stock Exchange. We first perform ratio tests (Odean (1998)) and survival analyses (Feng and Seasholes (2005)) to confirm that Shanghai investors' investment decisions are subject to behavioral biases. Then, we focus on the order aggressiveness proposed by Biais, Hillion, and Spatt (1995). We construct an indicator variable for each sell order submitted to show whether the investors is selling at gains / losses by comparing the potential selling price with the average purchase price. We then relate these indicator variables to order aggressiveness measures calculated by comparing the potential selling prices with the status of the limit order books at the time of submissions. Regression analysis shows that investors are more aggressive in submitting sell orders when they have encountered gains, instead of losses, and the results are both statistically and economically significant. These findings provide direct evidence to the prospect theory in that prior investment outcomes can affect order submission choices. The disposition effect seems to offer an explanation to this phenomenon: because investors are more eager to sell stocks that have experienced gains than those that have experienced losses, they are more aggressive in submitting the sell orders for the winner stocks.

We then analyze the relationship between the size of prior gains / losses and the order aggressiveness measures. We calculate the prior gains (losses) for each stock to be sold, and show that both the sizes of gains and the sizes of losses can significantly affect the aggressiveness of the sell order submitted. We find that for the stocks that have encountered prior gains, the relationship is significantly positive between the order aggressiveness measures and the prior gains and significantly negative between the order aggressiveness measures and the squared terms of the prior gains; for the stocks that have encountered prior losses, the relationship is significantly negative between order aggressiveness measures and prior losses, and not significant between the order aggressiveness measures and the squared terms of prior losses. These findings are consistent with theoretical studies showing that the relationship between prior outcomes and subsequent risk taking is complex, as documented by previous studies that investors could either become more risk averse and intend to sell assets quickly after gains (Coval and Shumway (2005)) or become less risk averse and choose to hold assets for longer (Liu, Tsay, Wang, Zhu (2010)). We claim that the disposition effect, together with the house money effect, can explain the relationship between the order aggressiveness measures and prior investment consequences: Suppose an investor intends to sell a stock that has experienced an appreciation（prior gains）relative to her purchase price，the disposition effect predicts that she would become more risk-averse and submit more aggressive orders to realize the gains quickly. On the contrary，if the stock has experienced a price depreciation（prior losses），the disposition effect predicts that the investor would be willing to assume more risks and submit less aggressive orders to hold the loser stock for longer. Also affecting the order submission is the house money effect. 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，and then later decrease with the prior gains as the house money effect dominates. Our results are robust to both the ordinary least squares and the ordered probit regression analysis，as well as after controlling for competing hypotheses regarding the determinants of order aggressiveness. We also show that the results do not change qualitatively using 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 investors affect the order submission strategies. 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, these theoretical works are all set in a rational economic framework and assume that investors are able to choose optimal order submission strategies in any circumstances. In this paper, we find that both individual and institutional traders are susceptible to psychological factors when deciding their order submission choices. Our results shed some light on how to incorporate behavioral biases when future theories model investor trading behaviors and market equilibrium.

Although this study is based on the Chinese stock market in which a lot of investors are supposed to have less 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)), and these biases can significantly affect traders' behaviors and asset prices (Coval and Shumway (2005)). The unique database provided by SSE can help us clearly identify the effect of behavioral biases on investors' order submission choices. Our findings can help us better understand the factors affecting the trading and order submission behaviors in other equity markets 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. Description of the Market and Dataset

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

The main trading mechanism of the 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 COLOB, in accordance with the price-time priority principle. If the order cannot be matched, then it is added to 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 execution.

B. Data and Preliminary Statistics

Our major dataset 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 on average 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, researchers are not allowed to copy or download any data from the database or 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 designated 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 microstructure level 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 combine the trading records for each stock with the stock's daily highest, lowest, and closing prices (provided by SSE.) on every day it is held by at least one investor account. We then focus on the sell orders submitted. The dataset in this study 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 from our sample during the same days when the stocks hit their price limits. 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

[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).

introduced in SSE in July 2006. According to the statistics from SSE, only less than 1% of the orders submitted are market orders, and most of the market orders are not on stocks.[2] 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 zero quoted volumes. We also drop order submission data from our sample where the time between the COLOB snapshot and order submission record is more than 30 seconds. This is because the limit order book information is updated at every 15-30 seconds in China for individual investors accounting for the majority in our sample, and at a higher frequency for institutional investors, so the COLOB information more than 30 seconds prior to the order submission cannot proxy for the current order book status at the time of submissions. 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,[3] 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

[2] 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.
[3] 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.

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 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 COLOB 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. The average sell order price submitted is 12.24 yuan, with the minimum and maximum values being 1.05 yuan and 290 yuan, respectively. The dollar value of the sell order submitted ranges from 2.40 yuan to 46.55 million yuan. The very small order size is due to the fact that Chinese investors can sell any number of shares they own, whereas when they buy stocks, they can only buy at least 100 shares on each individual stock they choose. For most of the stocks in our sample, the average dollar spread is about one tick size (0.01yuan). The average (median) spread is 0.19 percent (0.14 percent) of the average value of the best ask and 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 2.57 million (0.88 million) over the five best ask quotes, and 2.20 million (0.77 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 statistics in Table I also suggests the presence of some extreme observations for many variables. For example, the lowest relative spread is only 0.0001 percent of the average value of the best bid and ask quotes of the stock, while the largest relative spread being 15.5 percent of that value. Also, the maximum values of order size, ask depth, and bid depth are more than 19 million, 300 thousand, and 1.2 million times their minimum values, respectively. Such a wide distribution may result from the great heterogeneity of investors' characteristics in our data sample comprising investors from the whole market. However, because the extreme observations could add noises to our analysis and blur the major relationship between the order submission variables and behavioral bias 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)).[4]

III. Order Aggressiveness Measures, Behavioral Bias Variables, and Control Variables

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

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

[4] This restriction does not affect our empirical results in that the lockup is only imposed on stock buyers. For investors who sell stocks in China's stock market, they can buy any stocks after their selling at any time.

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 $Aggressive\_1 \geq 0$ 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.

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 Girifiths, Smith, Turnbull, and White (2000) and Renaldo (2004).

In our study, we extend the idea in Biais, Hillion, and Spatt (1995) to develop the second order aggressiveness measure for the sell order submitted. This measure takes the unique advantage of the data in our study that provides the complete COLOB information at the time of submission. *Aggressive_2* is constructed by comparing the (sell) order price with each of the multiple quoted ask and bid prices in the limit order book at the time of the submission.

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

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*, the higher the *Aggressive_2*, 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_2* equal to 7 indicating a marketable limit order and *Aggressive_2* 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 Lease, Lewellen, and Schlarbaum (1974), Schlarbaum, Lewellen, and Lease (1978), and Schlarbaum, Lewellen, and Lease (1978), and recently implemented and extended by Odean (1998), 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 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:

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

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

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 from Alternative Explanations

A number of theoretical and empirical papers have explored the determinants of investors' choices among orders with different aggressiveness other than the behavioral bias variables. We thus construct a few control variables to examine the incremental explanatory power of our *PG* and *PL* measures.

***Bid-Ask Spread*:** Handa, Schwartz, and Tiwari (2003) show that a larger bid-ask spread could imply a greater uncertainty in the market, as the size of spread in an order driven market reflects the disagreement of valuation among various market participants on the same stock. This suggests that investors tend to submit less aggressive limit orders because they worry about losses through trades with more informed traders. Similarly, Biais, Hillion, and Spatt (1995) study 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 more aggressive (market) orders.

We compute the 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 spread measures the cost of immediate execution. According to rationale above, we expect investors to submit less aggressive orders when the spread is higher because of the higher uncertainty in market and the higher probability to obtain better executed prices. However, a wider bid-ask spread might well imply that there is more room for the sellers to improve the quote. In this sense, we could also expect investors to submit more aggressive orders following a widening of spread to induce the spread to return to its equilibrium value.

***Depth at the Best Ask/Bid Quote*:** Parlour (1998) describes the interaction between the order submission strategies and the market depths: 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.

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. 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 Volatility**:** Foucault (1999) and Handa and Schwartz (1996) show that higher volatility in the market implies a greater "picking-off" risk for limit order submitters by future informed traders. Traders will demand a larger compensation for the risk, which in turn results in a wider spread and a higher cost of trading for market orders. Thus, traders intend to submit less (more) aggressive orders when the short-term volatility is high (low) and they assess the "picking-off" risk is high (low).

We compute the short-term volatility ($RISK$) over the 30 minutes before order submission as $\left((1/(N-1))\sum_{i=1}^{N}\left(R_i-\overline{R}\right)^2\right)^{1/2}$, 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. On the one hand, if short-term volatility represents higher "picking-off" risk, we should observe a negative relationship between *RISK* and the order aggressiveness measure. 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 the order aggressiveness measure.

Mid-Quote: Previous research has shown that tick size has important impact on investors' trading behaviors. For the majority of investors in an order driven market, they tend to submit limit orders with the smallest costs available. And this can explain, for most stocks, the average spread is just the tick size, in order driven markets such as Hong Kong and Shanghai. However, investors submit orders for stocks with larger fundamental values (usually measured by the average of the best bid and ask prices) typically assume a larger tick size. This will cause orders submitted for stocks with larger (smaller) average prices of market current best bid and ask prices to be less (more) aggressive.

We compute the mid-quote (*MQUOTE*) as the average of the best bid and ask prices at the time of order submission. As investors typically tend to bid lower when the current mid-quote is higher, we expect the mid-quote to be negatively related to the order aggressiveness.

***Short-Term Momentum*:** Short-term return measures are important indicators for investors making trading decisions on trends or other technical indicators. 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 the two measures by the time the sell orders are submitted and then calculate the mean for each measure over each of the 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 B of Figure 1 show that both *Aggressive_1* and *Aggressive_2* 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. Figure 1 reveals predictable intraday patterns in the two 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.

D. Preliminary Analysis of Order Aggressiveness Measures, PG/PL, and Control Variables

In this subsection, we present preliminary statistics of the order aggressiveness measures, the *PG* and *PL* measures, and other explanatory variables.

As Table I shows, the raw dataset has a few extreme observations that could make us difficult to identify the major relationship between order aggressiveness measures and PG/PL measures. 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 II about Here

Panel A of Table II reports the summary statistics for the two order aggressiveness measures in our study. The mean (median) of *Aggressive_1* is -0.07 (-0.01), which suggests that average investors submit sell orders higher than the most recent market bid prices, storing their orders in COLOB. This is consistent with the mean (median) of *Aggressive_2*, which is equal to 4.53 (5). This means that on average investors submit less aggressive orders and wait for executions in the future. On the other hand, orders with non-negative *Aggressive_1* or the *Aggressive_2* equal to seven are regarded as most aggressive (marketable limit) orders and are to be executed immediately. Based on the measure of *Aggressive_1* and *Aggressive_2*, we estimate from our sample that a considerable portion (about 35%) of the total orders can be categorized as the most aggressive orders. These measures indicate that some investors do want to quickly execute their orders by selling at current best bid prices or lower, forfeiting the potential premium by waiting for better prices. Our results show that investors in our sample express various degrees of aggressiveness in submitting sell orders. In the sections following, we will try to offer explanations to this variation observed.

Insert Figure 3 about Here

We note that *Aggressive_2* is a discrete response variable that directly indicates where in the limit order book the order price hits. To better understand the characteristics of this variable, Figure 3 plots the bar charts for *Aggressive_2*. A unique feature for *Aggressive_3* is that this variable does not follow a continuous distribution. This multiple-response discrete distribution is not suitable for many regression analyses (including the OLS regression) that require both dependent and independent variables to follow continuous distributions. We need to design a suitable econometric methodology to analyze the relationship between *Aggressive_2* and its determinants.

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 1.07 yuan (0.2 yuan) and the mean (median) of *PG* equal to 0.22 yuan (0 yuan). This finding seems to support the prospect theory that equal-magnitude gains and losses do not have symmetric impacts on decision making and that losses hurt investors more than gains satisfy. Thus, Shanghai investors on average submit orders to sell their stocks with smaller magnitude of gains than losses.

Before we move to more rigorous investigation on the effect of prior gains/losses on order aggressiveness, we run some preliminary analysis in this subsection. We split the sample into two sub-samples, with one sub-sample comprising all the order submissions with *PG* greater than zero and the other including order submissions with *PL* greater than zero. We then compare the means of *Aggressive_1* and *Aggressive_2* in each of the sub-samples. Our estimations show that the mean of *Aggressive_1* (*Aggressive_2*) in the sub-sample with *PG* greater than zero is -0.06 (4.59), and with *PL* greater than zero is -0.07 (4.50), with these two numbers being statistically different. These results show that investors tend to submit less aggressive sell orders for stocks that have encountered losses instead of gains (in terms of *Aggressive_1*, this means order price with one cent higher). This finding provides further evidence to the prospect theory.

Panel C of Table II 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 average quote of the best the ask/bid prices, 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 0.17 (0.14) indicates a highly liquid market in our data sample. It should be noted that we do not use the depth over all the five 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 prices below *Bid1*.

IV. Empirical Results

In this section, we conduct regression analyses to examine whether and how the prior investment outcomes affect subsequent order aggressiveness. We check the robustness of our results by controlling for alternative explanations.

A. *Evidence of Prior Investment Outcomes on the Selling Decisions*

Before we move to the analyses relating order aggressiveness measures to the *PG* and *PL* variables, we first examine whether the prior investment outcomes affect the selling decisions made by the Shanghai investors in our sample. Previous studies have provided evidence that Chinese investors are subject to the effects of these variables in their decision making processes (Feng and Seasholes (2005), Shumway and Wu (2006)). We note that the order submission choice is an integral part of the investment decision an investor makes. As a natural inference, we should expect prior gains / losses histories affect Shanghai investors' selling decisions making if we claim that those variables can affect these invests' order submissions decisions,

To examine the behavioral biases in Chinese investors' investment decisions, we remove those stock holdings that are not closed-out by the end of the sample period. We also combine multiple sells within a day into one sell with the share-weighted sell price if no buys take place in the same day. We replicate our analysis without removing incomplete positions and combining multiple intraday sells and find qualitatively similar results.

We employ two methods to examine whether Shanghai investors are subject to behavioral biases when making investment decisions. We first use the ratio tests used by Odean (1998) and Dhar and Zhu (2006). The two ratios we examine are "*PGR*" and "*PLR*", which measures the proportion of realized gains and losses, respectively. If *PGR* is significantly higher than *PLR*, we claim that investors' decisions are subject to behavioral biases and show the disposition effect. Next, we follow Feng and Seasholes (2005) to include the holding length as a determinant of the degree of the behavioral biases, and conduct the survival analysis to calculate the hazard ratio as a measure of the magnitude of the disposition effect. A hazard ratio greater (less) than 1 indicates a greater propensity to sell (hold) stocks. The disposition effect exists if we find hazard ratios significantly greater than 1 for stocks with prior gains and significantly less than 1 for stocks with prior losses, indicating investors' great propensity to sell winner stocks and reluctance to sell loser stocks. For details of the ratio tests and survival analyses, please refer to Odean

(1998), Dhar and Zhu (2006), and Feng and Seaasholes (2005).

Insert Table III about Here

Table III presents estimation results for the ratio tests. For the entire data set, the *PGR* and *PLR* are 0.67 and 0.39, with the difference being significantly positive at 0.28. The mean (median) across individual accounts for *PGR* and *PLR* are 0.79(0.87) and 0.46 (0.43), and the mean (median) difference is significantly positive at 0.34 (0.37). We also present the distribution of the difference between *PGR* and *PLR* for all investors in our sample in Figure 2. The difference measure shows a skewed distribution, with over 90% of investors showing a positive difference between *PGR* and *PLR* (disposition effect). Overall, Table III and Figure 2 indicate a very strong disposition effect among the investors' selling decisions in our sample.

Insert Figure 2 about Here

Table IV presents the results of survival analyses. The survival analysis of the entire data set is very computationally intensive, and beyond the computational capability of the computers at SSE. So we divide the entire sample of the 521,611 investor accounts into six sub-samples, with five sub-samples of individual investors (each containing 100,000 investor accounts) and one sub-sample for institutional investors (containing 21,611 investor accounts). Both panel A and panel B of Table III report the hazard ratios well below 1 when the stock is sold (could be sold) at a loss and well above 1 when the stock is sold (could be sold) at a gain. And this conclusion holds for both individual and institutional investors, albeit the institutional investors show a somewhat smaller disposition effect. The findings provide further evidence that Shanghai investors take into consideration of prior gains / losses in their in their investment decision makings, eager to sell stocks with gains instead of losses.

Insert Table IV about Here

B. Regressions Analyses

Our analyses above provide evidence that the prior investment outcomes can affect Shanghai investors' decisions on whether to sell / hold stocks, In this subsection, we further test whether prior gains / losses affect investors' aggressiveness in submitting sell orders, and whether the magnitudes of the gains or losses are related to the order aggressiveness measures. We start with a regression that relates the order aggressiveness measures to the indicator variables that whether investors are selling at gains or losses.

B.1 Regressions with Gain_Indicator Variables

Encouraged by our findings that *PG* and *PL* have asymmetric effects on the magnitude of order aggressiveness, with investors more prone to sell stocks with *PG* greater than zero, we construct a dummy variable to indicate whether the investor is trading at a gain or at a loss. The variable equals one if the stocks have encountered prior gains when investors submit sell orders, and equals zero if those stocks have encountered prior losses. We then conduct regression analysis of the order aggressiveness measures on this dummy variable and other various explanatory variables. We use the two order aggressiveness measures as the dependent variables in the regressions, respectively. The following is the regression equation:

$$\begin{aligned} AGGRESSIVE_t = {} & \alpha + \gamma_1 GAIN\_DUMMY_t \\ & + \gamma_2 SPREAD_t + \gamma_3 ADEPTH_t + \gamma_4 BDEPTH_t + \gamma_5 MIDQUOTE_t + \gamma_6 RISK_t + \gamma_6 MOMENTUM_t \\ & + \sum_{i=1}^{7} \beta_i D_i + \varepsilon_t \end{aligned} \quad (1)$$

where $AGGRESSIVE_t$ is the order aggressiveness measure at time *t*, $GAIN\_DUMMY_t$ is the dummy variable equal to one if the stock's market best bid price at time *t* is higher than the share-weighted average purchase price, and zero otherwise, $SPREAD_t$ is the relative bid-ask spread at time *t*, $ADEPTH_t$ and $BDEPTH_t$ are the depth (monetary quantity) at the best ask and bid quotes, respectively, $MIDQUOTE_t$ is the average of the best bid and ask prices at the time *t*. $RISK_t$ is the short-term volatility during the half-hour prior to time *t*, $MOMENTUM_t$ is the stock return during the half-hour prior to time *t*, 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.[5]

We first pool all the observations together and run regressions with *Aggressive_1* as the dependent variable. Because the *Aggressive_2* follows a discrete response distribution, we cannot adopt OLS regression on *Aggressive_2*. Then, 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_2*. As a result, we can model *Aggressive_2* as the ordered response of the latent aggressiveness measure, and perform *Ordered Probit* regression to examine the relation between *Aggressive_2* and the explanatory variables. It should be noted that 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.[6]

Insert Table V about Here

Table V presents regression results for equation (1). We run the two aggressiveness measures on the dummy and the explanatory variables for the individual and institutional investors, respectively. Since the ordered probit analysis of all the individual traders in the whole sample is beyond the computational capability of the computers at the exchange, we divide the whole sample into three sub-samples for the ordered probit regressions: two retail trader sub-sample with 250,000 accounts each and one institutional trader sub-sample with 21,611 accounts. We note that, for both OLS regressions and the ordered probit regressions, the coefficients of *GAIN_DUMMY* (γ_1) are significantly positive for either individual or

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

institutional traders. For example, the coefficients are 0.02 (OLS regression) and around 0.08 (ordered probit regression) for the individual investors sub-sample, and 0.01 (OLS regression) and 0.07 (ordered probit regression) for the institutional investors sub-sample, with all coefficients being statistically significant. The results are also of economic significance. For example, the coefficient of 0.02 when regressing *AGGRESSIVE_1* on *GAIN_DUMMY* and other variables means that (on average) selling winner stocks, instead of loser stocks or stocks with zero gains,[7] will cause individual investors to lower down their ask prices (submitting more aggressive orders) by about 2 cents. Given that quoted prices in SSE usually differ by one cent (which is also the tick size), this suggests the order walking through the limit order book by two ladders, e.g. the order price changes from *Ask1* to *Ask3*. Such a change in order aggressiveness will cause significant changes on the transaction costs incurred and the profits to the sellers. Overall, our results provide strong supports to the *prospect theory* in that prior investment consequences have asymmetric effect on subsequent risk-taking trading behaviors. Investors intend to submit more aggressive orders to sell stocks that have encountered gains instead of losses.

Table V also presents regression coefficients for the explanatory variables from competing hypotheses. The coefficient estimate of *SPREAD* is significantly negative, which shows that investors submit less aggressive limit orders when the spread is bigger. The coefficient estimates for *ADEPTH* are significantly positive except for the OLS regression relating institutional investors (which is not significant), and for *BDEPTH* are significantly negative. 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, sellers need to submit more aggressive orders to increase the probability of execution. However, there is no such “crowding out” effect for *BDEPTH*. On the contrary, an increase in the best bid depth will increase the probability that sell orders will be executed at desired prices, thus give sellers less incentives to submit aggressive orders. The coefficient of *MIDQUOTE* is significantly negative for all investor groups, which suggests that investors tend to submit less aggressive sell orders for larger stocks because they take for granted that the

[7] There is a small portion (less than 1%) of the observations where the stock’s market best bid price is equal to its share-weighted average purchase price. We remove these observations from our sample, retaining only order submissions with positive gains or positive losses, and repeat regression specified in equation (1). The results are qualitatively and quantitatively very similar.

tick size for larger stocks are also larger. The coefficients for *RISK* are not consistent among different investor groups in OLS and ordered probit regressions. The coefficient of *MOMENTUM* is significantly negative for all investors in both regression models, indicating that investors are less reluctant to sell stocks that are in momentum and experience price appreciation recently. We note that the coefficients for *GAIN_DUMMY* are consistently significantly positive after controlling for alternative hypotheses. Overall, our findings suggest that the conclusion that prior investment consequences can affect order aggressiveness is fairly robust.

B.2 Regressions with Prior Gains and Prior Losses

Our results in Table V show that prior investment outcomes are able to affect subsequent order aggressiveness, which is consistent with the prediction by the prospect theory. In this subsection, we further explore the relationship between the prior investment consequences and subsequent risk taking behaviors (order submission behaviors) of Shanghai investors in our sample. Although Shefrin and Statman (1985) show that the prospect theory could explain the disposition effect that investors become more risk averse after prior gains and risk seeking after prior losses, Baberis and Xiong (2009) show that it is also possible that investors show the reverse disposition effect, i.e. becoming more risk seeking after prior gains and more risk averse after prior losses. To examine this question, we need to separate prior gains from prior losses. We replicate the regression specification in (1), replacing *GAIN_DUMMY* with the prior gains / losses. The following is the regression equation (2):

$$
\begin{aligned}
AGGRESSIVE_t = {} & \alpha + \gamma_1 PG_t + \gamma_2 PL_t \\
& + \gamma_3 SPREAD_t + \gamma_4 ADEPTH_t + \gamma_5 BDEPTH_t + \gamma_6 RISK_t + \gamma_7 MIDQUOTE_t + \gamma_8 MOMENTUM_t \\
& + \sum\nolimits_{i=1}^{7} \beta_i D_i + \varepsilon_t
\end{aligned}
\tag{2}
$$

where PG_t is the prior gains and PL_t is the prior losses based on the share-weighted average purchase price at time *t*, and other variables are as defined in equation (1). If the previous investment consequences affect investors' subsequent investment behaviors through the disposition effect as documented by Coval and Shumway (2005), we should expect investors become more (less) risk averse after prior gains (losses) and submit more (less) aggressive orders, thus a positive γ_1 and a negative γ_2.

Insert Table VI about Here

In regressions with equation (2), similarly as with (1), we run the two aggressiveness measures on the *PG* / *PL* and other explanatory variables for both the individual and institutional investor sub-samples, employing the pooled OLS and ordered probit regression, respectively. Table VI presents the regression results. We find coefficients for *PL* (γ_2) to be consistently and significantly negative across all investor groups, with *t* values ranging from 4.20 for institutional investors with OLS regressions to 20.26 for individual investors with ordered probit regressions after allowing the standard errors to be clustered first by each stock and then by each trading day. On the other hand, the signs and significance levels of the coefficients for *PG* (γ_1) vary among different regressions. For example, γ_1 is 0.002 for OLS regression involving individual investors with the *t*-value of 1.90, and is insignificant at 0.0004 for the OLS regression comprising institutional investors with a t-value of only 0.16. This result suggests that, while the relationship between prior losses and order aggressiveness is consistent with the disposition effect, the relationship between prior gains and order aggressiveness is not.

Table VI seem to suggest that investors may have different risk-taking behaviors after prior gains. We further explore this possibility. According to Liu, Tsai, Wang, and Zhu (2010), the squared terms of prior gains affect investors' risk-taking behaviors. We thus add the squared prior gains in the regression equation above, and rerun all the OLS and ordered probit regressions. The following is the regression equation (3):

$$
\begin{aligned}
AGGRESSIVE_t = {} & \alpha + \gamma_1 PG_t + \gamma_2 PG_t^{\,2} + \gamma_3 PL_t \\
& + \gamma_4 SPREAD_t + \gamma_5 ADEPTH_t + \gamma_6 BDEPTH_t + \gamma_7 MIDQUOTE_t + \gamma_8 RISK_t + \gamma_9 MOMENTUM_t \\
& + \sum_{i=1}^{7} \beta_i D_i + \varepsilon_t
\end{aligned} \tag{3}
$$

where PG_t^2 is the squared term of the prior gains at time *t*, and other control variables as defined in equation (1) and equation (2).

Insert Table VII about Here

Regression results with equation (3) are presented in Table VII. After controlling for alternative hypotheses, we find the coefficient of *PG* (γ_1) is significantly positive and the coefficient of *PL* (γ_3) is significantly negative in all regression models across all investor clientele groups. These findings are robust in that we have controlled for other alternative hypotheses. The coefficients are also of economic significance in that one standard deviation of *PG* (*PL*) is able to cause 10% (9%) of the changes of one standard deviation of *Aggressive_1*. As in Liu, Tsay, Wang, and Zhu (2010), we find the coefficient of PG^2 (γ_2) is significantly negative. This suggests a quadratic relationship between order aggressiveness measures and the size of prior gains. This finding seems to suggest that investors tend to submit more aggressive orders when the prior gains are small and submit less aggressive orders after the sizes of prior gains exceed a hurdle level, while consistently submitting less aggressive orders when encountered losses in their previous investments on the stocks to be sold.

We can also interpret the results above base on the prospect theory. Liu et al (2010) document a reverse disposition effect for stocks with prior gains in the Taiwan Index Options market. They find investors with morning gains are likely to be more risk seeking in the afternoon. They claim that their findings are consistent with the *House Money Effect,* and provide evidence to the complex relationship between prior investment outcomes and subsequent risk-taking behaviors analyzed in Barberis and Xiong (2009). House money effect is proposed by Thaler and Johnson (1990), and refers to phenomenon that gamblers are risk-takers when they have won and play with the money they have won. We find that the house money effect, together with the disposition effect, can also explain the quadratic relationship between the order aggressiveness measures and the size of prior gains: When investors plan to trade in the stock market of limit orders, they are faced with the risk that their orders will not be executed by end of the day.

According to the prospect theory, the prior investment outcome history is going to affect their risk attitude at the time of the decision making. When the size of the prior gains is small, the disposition effect will dominate, investors tend to become more risk averse and then submit more aggressive sell orders; however, when the stock prior gain grows, investors will become concern about the risk involved as they feel that the money are investing with do not belong to them at the beginning, which is predicted by the house money effect. After the size of prior gains exceeds a benchmark level, the house money effect will dominate, and investors become less risk averse, thus submit less aggressive sell orders.

Evidence form an Alternative Order Aggressiveness Measure

The current aggressiveness measures are based on the comparison between the order price and the various quoted prices in the COLOB at the time of order submissions. There is another type of order aggressiveness measures that concerns the order size (volume) instead of the price. It is noted that more aggressive sellers typically try to liquidate a higher fraction of their stock holdings at once. Lacking investors' stock holding data prior to order submissions, researchers have focused on the submitted quoted volumes. For example, Biais, Hillion, and Spatt (1995) suggest that the larger the order size, the more aggressive the order is, whereas 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. Given that we show that the house money effect and the disposition effect can jointly affect the relationship between prior investment outcomes and subsequent order aggressiveness measured by matching order prices with prices on the limit order book, our findings can be substantially corroborated if we find similar results using aggressiveness measures involving not only prices, but also quantities.

Combining the stock holding data and order history for each investor provided by SSE, we construct the unique dataset comprising the sell order volume for each stock submitted and the number of shares held for that stock prior to the submission. We thus compute a measure of order aggressiveness by comparing the order size with the stock holding right before the order submission. This aggressiveness measure is defined as the following:

$$Aggressive\_Vol = \frac{Order\_Vol}{Hold\_Bal}$$

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_Vol* 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, similar to *Aggressive_1* and *Aggressive_2*, the higher the *Aggressive_Vol*, the more risk averse the investor is, and the more aggressive the submitted order.

We then run OLS regressions relating *Aggressive_Vol* to explanatory variables and present results in panel C of Table VII. As we expect, we find qualitatively similar results as in Panel A & B, where *PG* is significantly positive, PG^2 is significantly negative, and *PL* is significantly negative, after controlling for alternative hypotheses. This result further supports our conclusion that prospect theory can explain the relationship between prior investment outcomes and order submission strategies through a combination of the disposition and the house money effect.

As a natural extension and comparison with the regression equations above, we add the squared term of the size of prior loss in the equation. Regression equation is as follows:

$$\begin{aligned} AGGRESSIVE_t = {} & \alpha + \gamma_1 PG_t + \gamma_2 PG_t^{\,2} + \gamma_3 PL_t + \gamma_4 PL_t^{\,2} \\ & + \gamma_4 SPREAD_t + \gamma_5 ADEPTH_t + \gamma_6 BDEPTH_t + \gamma_7 MIDQUOTE_t + \gamma_8 RISK_t + \gamma_9 MOMENTUM_t \\ & + \sum\nolimits_{i=1}^{7} \beta_i D_i + \varepsilon_t \end{aligned} \tag{4}$$

where $PL_t^{\,2}$ is the squared term of the prior losses at time *t*, and other control variables as defined in equation (1), (2), and (3).

We note that house money effect does not support a nonlinear relationship between the order aggressiveness measures and the size of prior losses because the house money effect describes the difference in the risk attitudes for gamblers gambling with their own money and with the money they have won (not their own money originally). An alternative explanation that might offer an explanation of why the squared term of prior losses may affect the risk attitude of investors rests in the "Break-Even Hypothesis".

Thaler and Johnson (1990) raise a possibility that the effect of prior losses 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. This intuition suggests γ_3 to be positive and γ_4 to be negative.

Insert Table VIII about Here

Regression results of equation (4) are presented in Table VIII. We note that the only two investor clienteles that show positive γ_3 and negative γ_4 are OLS and Ordered Probit regressions with institutional investors. However, γ_3 in both regressions are not significant and γ_4 in the OLS regression with institutional investors are not significant as well. For other regressions, regardless of which order aggressiveness measure we use, the coefficients estimate of PL remains negative while the coefficient estimates of squared term of PL is either negative or positive. Therefore, we lack evidence that Shanghai investors change their risk averse attitude along with the change of the size of prior losses.

Overall, our empirical results lead to the conclusion that behavioral biases could affect investors' order aggressiveness, and this effect could be explained using prospect theory. Consistent with the disposition effect and the house money effect, we find that the order aggressiveness first increases when the prior gains are small, and then decreases after the gains pass a certain level, whereas the order aggressiveness decreases as the prior losses get larger. This suggests that investors show disposition effect in their order aggressiveness for stocks with small prior gains or with prior losses, and show the house money effect for stocks with large prior gains. We also find that both individual and institutional investors are subject to these behavioral biases in their order submission behaviors.

C. Robust Tests

Because the relationship between order aggressiveness measures and prior gains and losses could depend on the choice of sample time period, potential selling prices and purchase prices, and whether to include market orders or orders that have been withdrawn within a very short period of time after submissions, we evaluate the robustness of our conclusion be conducting a variety of robust tests.

C.1 Regressions for the sub-samples of different time periods

Our sample comprises the data covering the whole year of 2008. Because this year is typically regarded as a period with dramatic market fluctuations as it marks the onset of the recent global financial crisis, it is imperative to show that our empirical conclusion is not driven by observations only from part of the time period. To show this robustness, we employ three methods to split our data sample into different sub-samples. We first split the full-sample into one sub-sample containing only order submissions when the daily market returns are positive and one sub-sample containing order submissions from days when daily market returns are negative. In the second method, we split the whole sample into twelve sub-samples, each containing observations in one month. We then repeat the regression analyses as specified in Table VII with *Aggressive_1* as the dependent variable for each of the sub-samples. In the third method, we split the whole sample into multiple sub-samplesss, with each sub-sample containing order submissions within one trading day. We then conduct a Fama-MacBath type regression by first run regressions with data in each trading day, and then calculate the cross-sectional average for the coefficients from each sub-sample.

Table IX presents the estimation results by regressing *Aggressive_1* on explanatory variables in different sub-samples. Panel A split the whole sample into positive daily market return sub-sample (upmarket sub-sample) and negative daily market return sub-sample (downmarket sub-sample) and run regressions in each of the sub-samples. As people would probably think 2008 as a down-market year due to the financial crisis, we find that the upmarket sub-sample contains fewer observations than the downmarket sub-sample. There are about 46% of the days in 2008 are with positive market returns, and 54% with negative market returns.[8] In panel B, we split the sample into twelve sub-samples with each sub-sample containing data for one month and run regressions for each sub-sample. To save space, we report the results for two months (November and June). Regressions with sub-samples for other months are qualitatively and quantitatively similar. We present the Fama-MacBeth regression results in panel C. We note that both the regression coefficients in Panel A and B and the average coefficients in Panel C show qualitatively very similar to the regression coefficients with the entire sample in Table VII, with the prior gains being significantly positive, the squared terms of prior gains being negative, and the prior losses being negative. This result implies that our conclusion that the Shanghai investors' submission strategies are subject to both the disposition effect and house money effect holds is not driven by observations from any specific time period when the market probably experiences dramatic fluctuations.

Insert Table IX about Here

C.2 Alternative Measures of Potential Selling Price, 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'

[8] No observations in our whole sample are with zero market returns.

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 analyses 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 X presents the empirical results when we use alternative selling price (share-volume weighted bid quotes) to compute *Aggressive_1* and employ different measures of reference purchase prices (initial purchase price, most recent purchase price, and the highest purchase price). The results are quantitatively and qualitatively similar to the results in Table VII, 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 X about Here

C.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 0.1% 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.5 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 some 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 method causes the *Aggressive_1* equal to or greater than zero and *Aggressive_2* equal to 7 in practice. We can now add these market orders submissions observations back into our sample and run regressions again. In our sample, market orders are very rare, less than 0.5%. We find the regressions results remain qualitatively similar as before after we add the market orders back into our sample and assume orders prices to them.

V. 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 that allows us to track the history of each order submitted, we examine how the order aggressiveness is being affected by the behavioral biases. We show that the aggressiveness of sell orders is strongly affected by prior investment outcomes, which is consistent with the prospect theory. Further analyses reveal that Shanghai investors' order aggressiveness is subject to both the disposition effect and the house money effect. According to the 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 to reluctantly realize the losses. 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 to quickly realize the gains. 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 as he becomes more willing to take the non-execution risks with the money he has won. We perform both the ordinary least squares and the ordered probit regression analyses, and show that our results are robust after controlling for competing hypotheses regarding the determinants of order aggressiveness and using alternative potential selling prices and alternative purchase prices, or sub-sample analyses.

Our paper marks the first attempt to relate behavioral bias measures to order submission strategies. Current 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. Our results shed some light on how to incorporate behavioral biases when future theories model investor trading behaviors and market equilibrium.

We believe that our results are relevant not only for an emerging stock market like China, which is known to have 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 through their investment decisions at both the retail investor level (Odean (1999)) and the professional investor level (Haigh and List (2005)). It is noted 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, median, standard deviation, minimum, and maximum of various variables 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 open 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, Ask Depth, and Bid Depth are information extracted from the snapshots of the open limit order book. Relative Spread is the ratio of the difference between market best ask and bid quotes divided by the average of those quotes. Ask Depth is the yuan quantities of the market depth over the five ask quotes. Bid Depth is the yuan quantities of the market depth over the five bid quotes. Holding Period is 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)	5.37	4.00	4.63	1.00	30.00
Order Price (yuan)	12.24	9.33	10.80	1.05	290.00
Order Size (1,000 yuan)	32.41	8.20	154.21	0.0024	46,553
Relative Spread (%)	0.19	0.14	0.17	0.0001	15.50
Ask Depth (1,000,000 yuan)	2.57	0.88	6.27	0.001	330.74
Bid Depth (1,000,000 yuan)	2.20	0.77	4.90	0.0002	263.41
Holding Period (days)	35.65	10.00	59.15	1.00	355.00

Table II Statistics of Order Aggressiveness Measures and Explanatory Variables

Panel A, B, and C of this table report the mean, median, standard deviation, minimum, and maximum of the two order aggressiveness measures, prior gains / losses measures, and other control variables. *Aggressive_1* is defined as

$$Aggressive\_1 = BID1 - Order\_Price$$

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 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.

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

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:

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

where *Reference* is the reference price, which is the share-weighted average purchase price. 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.

The control variables include the relative bid-ask spread (*SPREAD*), the best ask market depth (*ADEPTH*), the best bid market depth (*BDEPTH*), the average of best quoted ask and bid prices (*MIDQUOTE*), 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	-0.07	-0.01	0.13	-0.49	0.02
Aggressive_2	4.53	5.00	2.40	1.00	7.00
PANEL B: Prior Gains / Losses					
PG (in yuan)	0.22	0	0.39	0	1.37
PL (in yuan)	1.07	0.20	1.66	0	5.88
PANEL C: Control Variables					
SPREAD (%)	0.17	0.14	0.11	0.05	0.45
ADEPTH (in million Yuan)	0.23	0.08	0.36	0.004	1.38
BDEPTH (in million Yuan)	0.22	0.07	0.35	0.003	1.34
MIDQUOTE	11.40	9.24	7.07	3.57	29.79
RISK	0.003	0.002	0.001	0.001	0.005
MOMENTUM	0.004	0.003	0.02	-0.03	0.04

Table III 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.

Panel A: The Disposition Effect for the Entire Data Set

	Mean
PGR	0.67
PLR	0.39
DE	0.28

Panel B: The Disposition Effect for Individual Investors

	Mean	Median
PGR	0.79	0.87
PLR	0.46	0.43
DE	0.34	0.37

Table IV 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 of each panel, the independent variable is an indicator that takes a value of one every day a stock is trading at a loss or could be traded 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 or could be traded 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 sub-samples each containing 100,000 Individual accounts. And Institution is the sub-sample containing 21,611 institutional investors.

Panel A: Hazard Ratio, Parametric (*Weibull*) Regression

	Individual1		Individual2		Individual3		Individual4		Individual5		Institution	
TLI	0.16		0.16		0.16		0.16		0.16		0.28	
(Z-stat)	(-78.01)		(-73.62)		(-81.28)		(-75.93)		(-78.41)		(-37.90)	
TGI		12.91		12.87		13.00		12.92		12.95		8.42
(Z-stat)		(99.31)		(95.70)		(102.58)		(98.29)		(101.04)		(60.12)
p-parameter	0.64	0.64	0.63	0.63	0.64	0.64	0.64	0.64	0.64	0.64	0.69	0.69
(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

	Individual1	Individual2	Individual3	Individual4	Individual5	Institution
TLI	0.19	0.19	0.19	0.19	0.19	0.33
(Z-stat)	(-75.95)	(-71.37)	(-77.68)	(-73.25)	(-79.19)	(-36.18)
TGI	11.15	11.12	11.23	11.15	11.19	7.71
(Z-stat)	(102.25)	(97.86)	(104.13)	(100.19)	(102.99)	(61.85)

Table V Regressions of Order Aggressiveness Measures on Gain Indicator Variables and Control Variables

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

$$AGGRESSIVE_t = \alpha + \gamma_1 GAIN\_DUMMY_t + \gamma_2 SPREAD_t + \gamma_3 ADEPTH_t + \gamma_4 BDEPTH_t + \gamma_5 MIDQUOTE_t + \gamma_6 RISK_t + \gamma_7 MOMENTUM_t + \sum_{i=1}^{7} \beta_i D_i + \varepsilon_t \quad (1)$$

where $AGGRESSIVE_t$ is the order aggressiveness measure at time *t*, $GAIN\_DUMMY_t$ is the dummy variable equal to one if the stock's market best bid price at time *t* is higher than the share-weighted average purchase price, and zero otherwise, $SPREAD_t$ is the relative bid-ask spread at time *t*, $ADEPTH_t$ and $BDEPTH_t$ are the depth (monetary quantity) at the best ask and bid quotes, respectively, $MIDQUOTE_t$ is the average of the best bid and ask prices at the time *t* $RISK_t$ is the short-term volatility during the half-hour prior to time *t*, $MOMENTUM_t$ is the stock return during the half-hour prior to time *t*, 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 with *Aggressive_1* being the dependent variable. Panel B presents ordered probit regression results with *Aggressive_2* being the dependent variable. For the ordered probit regressions, the whole sample is divided into three sub-samples with two individual trader sub-sample and one institutional trader sub-sample. The two individual trader sub-sample each contains 250,000 accounts and the institutional trader sample contains 21,611 accounts.

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The total number of observation in our dataset is 7,299,639. 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.

	A: *Aggressive_1*, OLS regressions				B: *Aggressive_2*, ordered porbit regressions					
	Individual		Institution		Individual1		Individual2		Institution	
GAIN_DUMMY	0.02	***	0.01	***	0.08	***	0.08	***	0.07	***
(1 if Prior Gains positive, 0 otherwise)	(18.21)		(6.95)		(6.92)		(7.09)		(3.75)	
SPREAD	-7.2	***	-9.6	***	-28.81	***	-28.56	***	-39.22	***
	(-12.22)		(-11.42)		(-9.60)		(-9.41)		(-5.11)	
ADEPTH	0.003	**	-0.002	*	0.08	***	0.08	**	0.02	
	(2.37)		(-1.61)		(6.45)		(7.41)		(0.81)	
BDEPTH	-0.002	*	-0.003	*	-0.13	***	-0.13	***	-0.09	***
	(-1.59)		(-1.99)		(-9.46)		(-10.02)		(-4.26)	
MIDQUOTE	-0.003	***	-0.003	***	0.001	*	-0.001		-0.003	*
	(-30.60)		(-17.44)		(1.42)		(-1.05)		(-1.59)	
RISK	-1.12	***	0.29		10.61	***	9.12	**	24.87	***
	(-3.09)		(0.52)		(3.05)		(2.69)		(3.91)	
MOMENTUM	-0.21	***	-0.35	***	-7.65	***	-7.46	***	-9.44	***
	(-9.16)		(-9.29)		(-40.26)		(-42.55)		(-24.02)	
Intercept	0.02	***	0.024	***						
	(25.31)		(8.11)							

Table VI Regressions of Order Aggressiveness Measures on *PG*, *PL*, and Control Variables

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

$$AGGRESSIVE_t = \alpha + \gamma_1 PG_t + \gamma_2 PL_t + \gamma_3 SPREAD_t + \gamma_4 ADEPTH_t + \gamma_5 BDEPTH_t + \gamma_6 MIDQUOTE_t + \gamma_7 RISK_t + \gamma_8 MOMENTUM_t + \sum_{i=1}^{7} \beta_i D_i + \varepsilon_t \quad (2)$$

where PG_t is the prior gains and PL_t is the prior losses based on the share-weighted average purchase price at time *t*, and other variables are as defined in equation (1).

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

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The total number of observation in our dataset is 7,299,639. 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.

	A: *Aggressive_1*, OLS regressions				B: *Aggressive_2*, ordered porbit regressions					
	Individual		Institution		Individual1		Individual2		Institution	
PG	0.002	*	0.0004		-0.08	***	-0.09	***	-0.03	
	(1.90)		(0.16)		(-8.97)		(-9.13)		(-1.28)	
PL	-0.01	***	-0.003	***	-0.06	***	-0.06	***	-0.003	***
	(-17.42)		(-4.20)		(-20.26)		(-19.28)		(-4.24)	
SPREAD	-7.35	***	-9.66	***	-29.82	***	-29.57	***	-37.33	***
	(-12.68)		(-11.76)		(-10.00)		(-9.72)		(-3.53)	
ADEPTH	0.003	**	-0.002	*	0.08	***	0.08	***	0.02	
	(2.34)		(-1.68)		(6.59)		(7.49)		(0.76)	
BDEPTH	-0.002	*	-0.004	**	-0.13	***	-0.13		-0.09	***
	(-1.65)		(-2.11)		(-8.99)		(-9.49)		(-4.34)	
MIDQUOTE	-0.003	***	-0.002	***	0.01	***	0.01***	***	-0.001	
	(-27.31)		(-15.00)		(5.50)		(5.10)		(-0.61)	
RISK	-0.81	**	0.47		16.17	***	14.81	***	27.93	***
	(-2.26)		(0.87)		(4.61)		(4.34)		(4.37)	
MOMENTUM	-0.18	***	-0.33	***	-7.48	***	-7.25	***	-9.34	***
	(-7.43)		(-8.75)		(-39.27)		(-41.48)		(-23.76)	
Intercept	0.02	***	0.03	***						
	(11.57)		(10.13)							

Table VII Regressions of Order Aggressiveness Measures on *PG*, PG^2, *PL*, and Control Variables

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

$$AGGRESSIVE_t = \alpha + \gamma_1 PG_t + \gamma_2 PG_t^2 + \gamma_3 PL_t + \gamma_4 SPREAD_t + \gamma_5 ADEPTH_t + \gamma_6 BDEPTH_t + \gamma_7 MIDQUOTE_t + \gamma_8 RISK_t + \gamma_9 MOMENTUM_t + \sum_{i=1}^{7} \beta_i D_i + \varepsilon_t \tag{3}$$

where PG_t^2 is the squared term of the prior gains at time *t*, and other variables are as defined in equation (1) and (2).

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

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The total number of observation in our dataset is 7,299,639. 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.

	A: *Aggressive_1*, OLS regressions				B: *Aggressive_2*, ordered porbit regressions						C:*Aggressive_Vol*, OLS regressions			
	Individual		Institution		Individual1		Individual2		Institution		Individual		Institution	
PG	0.04	***	0.03	***	0.08	***	0.09	***	0.19	***	0.34	***	0.11	***
	(17.63)		(5.88)		(3.06)		(3.44)		(2.67)		(27.38)		(3.16)	
PG^2	-0.03	***	-0.03	***	-0.14	***	-0.15	***	-0.18	***	-0.23	***	-0.1	***
	(-19.95)		(-5.78)		(-7.56)		(-8.39)		(-3.46)		(-26.50)		(-4.03)	
PL	-0.01	***	-0.002	***	-0.06	***	-0.06	***	-0.03	***	-0.04	***	-0.02	***
	(-15.69)		(-3.20)		(-19.79)		(-18.63)		(-4.29)		(-32.16)		(-10.17)	
SPREAD	-7.03	***	-9.47	***	-28.41	***	-28.04	***	-35.07	***	-0.98		-10.9	***
	(-11.85)		(-11.38)		(-9.53)		(-9.22)		(-4.95)		（-1.34)		(-4.54)	
ADEPTH	0.003	**	0.002	*	0.08	***	0.08	***	0.02	***	-0.003		0.03	***
	(2.47)		(1.66)		(6.62)		-7.53		-0.77		(-1.19)		(3.28)	
BDEPTH	-0.002		-0.004	**	-0.13	***	-0.13	***	-0.09	***	0.003		0.05	***
	(-1.48)		(-2.06)		(-9.04)		(-9.57)		(-4.35)		(1.07)		(5.40)	
MIDQUOTE	-0.003	***	-0.002	***	0.01	***	0.01	***	-0.003	***	0.002	***	0.004	***
	(-26.74)		(-14.72)		(5.81)		(5.44)		(-0.18)		（8.18)		(7.47)	
RISK	-0.82	**	0.54		16.46	***	15.1	***	28.78	***	3.43	***	5.72	**
	(-2.24)		(1.00)		(4.69)		-4.43		-4.52		(3.47)		(2.41)	
MOMENTUM	-0.19	***	-0.34	***	-7.56	***	-7.35	***	-9.44	***	-3.18	***	-2.71	***
	(-8.05)		(-9.04)		(-39.77)		(-42.08)		(-23.67)		(-43.10)		(-18.92)	
Intercept	0.07	***	0.03	***							0.66	***	0.41	***
	(9.62)		(8.58)								(123.19)		(30.91)	

Table VIII Regressions of Order Aggressiveness Measures on *PG*, PG^2, *PL*, PL^2, and Control Variables

This table presents regressions that relate order aggressiveness measures to various explanatory variables. The regression equation is equation (3)

$$AGGRESSIVE_t = \alpha + \gamma_1 PG_t + \gamma_2 PG_t^{\,2} + \gamma_3 PL_t + \gamma_4 PL_t^{\,2} + \gamma_4 SPREAD_t + \gamma_5 ADEPTH_t + \gamma_6 BDEPTH_t + \gamma_7 MIDQUOTE_t + \gamma_8 RISK_t + \gamma_9 MOMENTUM_t + \sum_{i=1}^{7} \beta_i D_i + \varepsilon_t \qquad (4)$$

where $PL_t^{\,2}$ is the squared term of the prior losses at time *t*, and other variables are as defined in equation (1) , (2), and (3).

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

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The total number of observation in our dataset is 7,299,639. 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.

	A: *Aggressive_1*, OLS regressions				B: *Aggressive_2*, ordered porbit regressions					
	Individual		Institution		Individual1		Individual2		Institution	
PG	0.04	***	0.04	***	0.07	***	0.079	***	0.26	***
	(20.57)		(7.05)		(3.16)		(3.46)		(3.50)	
PG^2	-0.03	***	-0.028	***	-0.13	***	-0.14	***	-0.22	***
	(-22.60)		(-6.63)		(-8.55)		(-9.40)		(-4.237)	
PL	-0.01	***	0.001		-0.06	***	-0.06	***	0.02	
	(-4.93)		(0.40)		(-6.78)		(-6.89)		(0.81)	
PL^2	-0.001		-0.01		0.001		0.002		-0.01**	**
	(-0.69)		(-1.64)		(0.80)		(1.05)		(-2.09)	
SPREAD	-7.03	***	-9.47	***	-28.47	***	-28.12	***	-35.00***	***
	(-11.91)		(-11.38)		(-9.63)		(-9.34)		(-4.93)	
ADEPTH	0.003	**	0.002		0.08	***	0.08	***	0.02	
	(2.46)		(1.61)		(6.62)		(7.54)		(0.82)	
BDEPTH	-0.002		-0.003*	**	-0.13	***	-0.13	***	-0.09	***
	(-1.47)		(-2.01)		(-9.04)		(-9.58)		(-4.29)	
MIDQUOTE	-0.003	***	-0.002	***	0.01	***	0.01		-0.0003	
	(-26.74)		(-14.76)		(5.82)		(5.46)		(-0.19)	
RISK	-0.82	**	0.48		16.62	***	15.33	***	27.84***	***
	(-2.24)		(0.87)		(4.72)		(4.48)		(4.36)	
MOMENTUM	-0.19	***	-0.34	***	-7.57	***	-7.36	***	-9.40***	***
	(-8.05)		(-9.01)		(-39.69)		(-42.03)		(-23.84)	
Intercept	-0.07	***	0.03	***						
	(-9.62)		(8.35)							

Table IX Regressions for Sub-Sample of Downmarket and Upmarket, of Sub-Sample with November and June's Observations, and Fama-MacBeth Regressions

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

Panel A presents pooled OLS regression results for an Upmarket sub-sample when daily market return is positive or zero and the Downmarket sub-sample when daily market return is negative. Panel B presents pooled OLS regression results for the sub-sample comprising data for November and the sub-sample comprising data for June. Panel C presents Fama-Macbeth (FM) type regression results. FM regressions are conducted by first running OLS regressions day-by-day and then averaging the coefficients across trading days.

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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.

	A: *Aggressive_1* OLS Regressions				B: *Aggressive_1* OLS Regressions				C: *Aggressive_1* FM Regressions	
	Upmarket		Downmarket		June		November			
PG	0.04	***	0.04	***	0.04	***	0.41	***	0.05	***
	(15.30)		(13.84)		(4.89)		(9.11)		(24.74)	
PG^2	-0.03	***	-0.03	***	-0.03	***	-0.03	***	-0.04	***
	(-16.06)		(-17.35)		(-5.79)		(-8.95)		(-26.59)	
PL	-0.01	***	-0.02	***	-0.004	***	-0.01	***	-0.001	***
	(-12.55)		(-11.25)		(-5.51)		(-17.39)		(-3.08)	
SPREAD	-6.57	***	-7.53	***	-8.77	***		***	-8.66	***
	(-9.28)		(-11.61)		(-14.25)		(-3.23)		(-26.80)	
ADEPTH	0.003	**	0.003	**	0.001		0.001		0.002	***
	(2.49)		(2.19)		(0.55)		(0.85)		(6.16)	
BDEPTH	-0.003	**	-0.001		-0.001		-0.004	***	-0.004	***
	(-2.92)		(-0.36)		(-0.51)		(-2.99)		(-12.32)	
MIDQUOTE	-0.003	***	-0.003	***	-0.003	***	-0.004	***	-0.003	***
	(-24.40)		(-22.81)		(-15.76)		(-12.30)		(-23.09)	
RISK	-0.97	**	-0.74	*	-0.28		-1.55	***	-3.18	***
	(-2.15)		(-1.67)		(-0.36)		(-2.69)		(-18.76)	
MOMENTUM	-0.06	*	-0.23	***	-0.32	***	0.01		-0.02	
	(-1.90)		(-12.32)		(-6.44)		(0.11)		(-1.28)	
Intercept	0.02	***	0.02	***	0	***	0.02	***	0.02	***
	(7.20)		(8.36)		(4.59)		(5.55)		(20.83)	

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

This table presents regressions that relate *Aggressive_1* to prior gains, the squared term of prior gains, the prior losses, and other control variables. Potential selling price is defined as share-weighted average of the five bid quotes. Reference price is defined as the initial purchase price, the most recent purchase price, the highest purchase price, and the share-weighted average purchase price, respectively. The regression equation is defined as in equation (3).

The number of observation in each column is 7,299,639. 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.

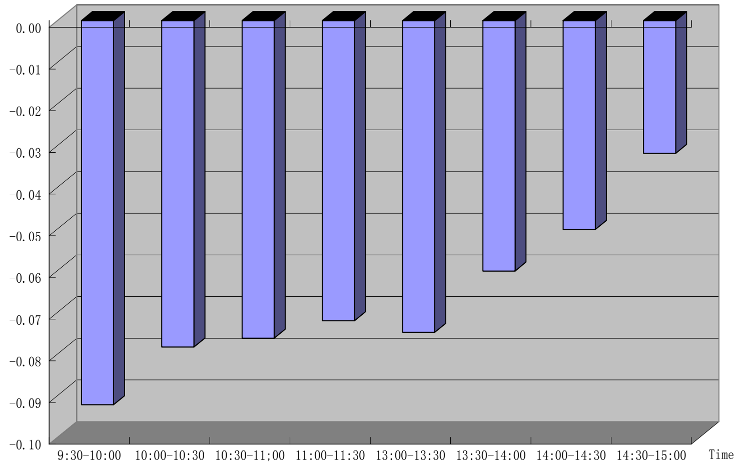
Aggressive_1 OLS Regressions

	Initial Purchase Price		Highest Purchase Price		Most Recent Purchase Price		Average Purchase Price	
PG	0.04	***	0.047	***	0.019	***	0.04	***
	(18.11)		(17.6)		(11.23)		(18.00)	
PG^2	-0.03	***	-0.03	***	-0.02	***	-0.03	***
	(-19.56)		(-19.64)		(-16.75)		(-20.18)	
PL	-0.004	***	-0.004	***	-0.01	***	-0.01	***
	(-18.73)		(-18.60)		(-11.02)		(-15.36)	
SPREAD	-7.44	***	-7.50	***	-7.81	***	-7.46	***
	(-12.54)		(-12.66)		(-13.16)		(-12.51)	
ADEPTH	0.003	**	0.003	**	0.003	**	0.003	**
	(2.47)		(2.46)		(2.20)		(2.37)	
BDEPTH	0.001		0.001		0.001		0.001	
	(0.99)		(0.97)		(0.83)		(0.87)	
RISK	-1.24	***	-1.18	***	-0.96	**	-1.07	**
	(-3.53)		(-3.35)		(-2.66)		(-3.02)	
MOMENTUM	-0.16	***	-0.158	***	-0.17	***	-0.18	***
	(-6.81)		(-6.75)		(-7.92)		(-7.80)	
MIDQUOTE	-0.003	***	-0.003	***	-0.003	***	-0.003	***
	(-28.05)		(-27.64)		(-25.84)		(-27.52)	
Intercept	0.02	***	0.02	***	-0.06	***	0.02	***
	(10.18)		(10.19)		(-33.18)		(9.44)	

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

This figure presents the mean of *Aggressive_1* and *Aggressive_2* 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 the multiple response variables indicating where in the book the order price hits. All observations are winsorized at 95%.

A. Mean of *Aggressive_1*



B. Mean of *Aggressive_2*

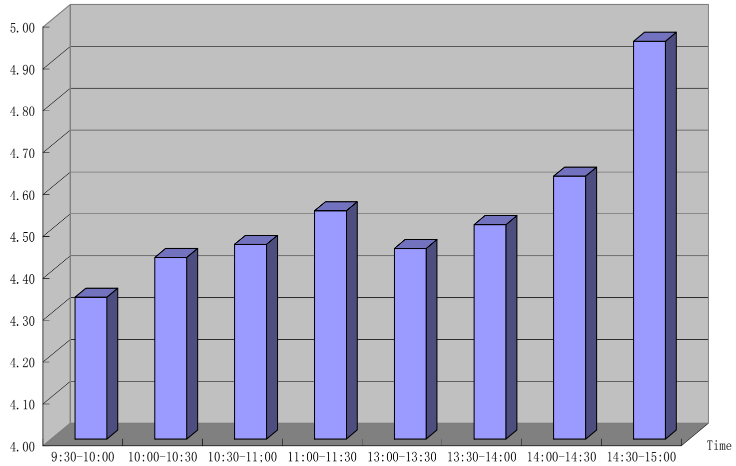


Figure 2 Distribution of *Aggressive_2*

This figure reports the distribution of *Aggressive_2*. *Aggressive_2* 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.

$$\begin{aligned} Aggressive\_3 &= 1 \text{ if } Ask5 \leq Order\ Price \\ &= 2 \text{ if } Ask4 \leq Order\ Price < Ask5 \\ &= 3 \text{ if } Ask3 \leq Order\ Price < Ask4 \\ &= 4 \text{ if } Ask2 \leq Order\ Price < Ask3 \\ &= 5 \text{ if } Ask1 \leq Order\ Price < Ask2 \\ &= 6 \text{ if } Mid\_Quote \leq Order\ Price < Ask1 \\ &= 7 \text{ if } Order\ Price < Mid\_Quote \end{aligned}$$

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.

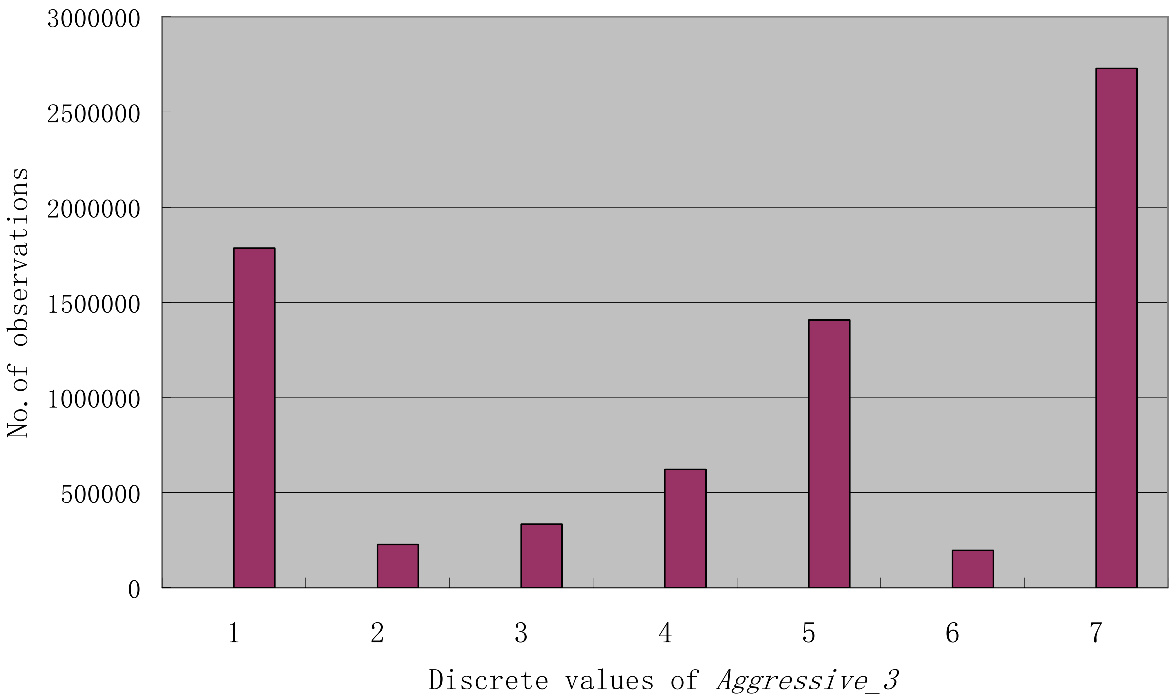


Figure 3 Distribution of Disposition Effect (*DE*) of All Investors

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.