V-shape Disposition Effect and Rank Effect in Chinese Stock Market

ABSTRACT:

This paper analyzes whether do V-shape disposition effect and rank effect exist in Chinese stock market. We use a sample of 5,000 individual investors with more than 2 million transactions from January 2007 to May 2009, which enable us to compare individuals' trading behavior during the booming, crashing, and recovering period. After controlling for firm-specific information, holding period or the level of returns itself, we find that V-shape disposition does not exist in our result. Rank effect is also different in Chines market. Compared with investors in the US market, Chinese investors are more likely to sell a position with extreme good (the best) performance, and followed by the 2^{nd} best position, but reluctant to sell the salience of extreme bad portfolio positions. This result is robust under different specifications, for example, different modelling method, extreme portfolio situation, measurement of rank and limit-down limitation, etc., and consistent in different time periods.

Keywords: Behavioral finance; Chinese market; Financial crisis; Disposition effect; Rank effect

1. Introduction

In traditional economics and finance, the majority of the research have been built on the assumption that human beings are rational, which means they are unbiased and efficient processors of relevant information and that their decisions are consistent with utility maximization. Markowitz (1952) describes how to choose a portfolio with the minimum possible risk for the given expected return but assumes that all investors are rational and risk adverse. However, a large number of empirical studies growing over the last twenty years indicate that investors do not behave the way that is predicted. They suffer from many behavioral biases, for example, they fail to behave rationally in even quite simple situations (Elton, *et al.*, 2004), using too simple diversification portfolio (Benartzi and Thaler, 2001; Goetzmann and Kumar, 2008), buying stocks they are familiar with (Massa and Simonov, 2006), influenced by limited attentions (Seasholes and Wu, 2007; Barber and Odean, 2008), using mental accounting to evaluate stocks (Thaler, 1985), trading too much due to overconfidence (Barber and Odean, 2000), keeping loser and selling winner – known as disposition effect (Shefrin and Statman, 1985; Odean, 1998). All these biases contribute to the over-performance or under-performance of investors in the real world than in the ideal model.

Among all the researches of disposition effect, Ben-David and Hirshleifer (2012) exam the relationship between the magnitude of gain or loss and disposition effect. They find no evidence of a jump for short-term prior holding periods. The probability of selling as a function of profit is V-shaped, and investors are more likely to sell big losers than small ones. Meanwhile, by using data from Finnish market, Kaustia (2010b) get similar result.

Hartzmark (2015) further develops these theories and find a new stylized fact about how investors trade assets, named rank effect. It shows that investors compare the returns of stocks in their portfolio when consider selling and they are more willing to sell stocks with extreme winning and extreme losing positions. The most crucial contribution of rank effect is that it considers the comparison within one's portfolio when he/she is making decision of selling. In previous studies, although most researches successfully explain investors' behavior to some extent, but most of them suffer from a stock-by-stock bias, which they assume that investors consider stocks one-by-one and ignore the comparison between stocks in the portfolio. However, it has been proven in psychology that people consider what they have as a whole in the decision-making process. Therefore, comparison in one's own portfolio should be added as a factor when analyzing the decision making of an investor. Furthermore, rank effect causes damage to the profit of investors since both stocks with large unrealized gains and losses outperform other stocks (An, 2017).

In this paper, we explore V-shape disposition effect and rank effect in Chinese stock market. Based on a very unique and large database, we test whether rank effect exists in Chinese stock market. If yes, we further examine to what extent do investor characteristics affect rank effect, in different overall market condition and in different selling-orders.

The data is collected from a large brokerage firm in China[1]. It contains more than 3 million accounts and 2 billion daily stock dealing records over the period of January 2007 to May 2009. Due to the consideration on the cost of computation, we use a sample of 5,000 investors in this paper. Both the market and the time period of the dataset are worth noting. China is an ideal laboratory to study behavioral finance among investors. Due to its successful economic transition in the last three decades, Chinese market has become the world's second largest stock market in value since 2014 and has been added to MSCI Emerging Markets Index since 2017, indicating its increasing importance in global economy. However, Chinese stock market starts later (only from 1990s) and has generally been viewed as under-developed market with high degree of asymmetric information, due among other things to its unsound financial system and its weak shareholders' protection, as well as its weak corporate governance system. The time period of the dataset in this research is from 2007 to 2009, which cover the financial crisis period. In China, although not mainly caused by the world financial crisis, there was also a huge bubble in 2007 and experiencing significant stock price

[1] Most of the previous studies (Odean, 1998; Feng and Seasholes, 2005; Dhar and Zhu, 2006, etc.) in this area do not disclose the specific name of the brokerage for confidentiality reasons, neither do my research.

falling in 2008. The changes of the investor emotion and behavior when they face large profits and losses along with risks are interesting to research. This adds more value to the dataset and this research.

In this paper, we significantly update the time period of researches in disposition and rank effect. We find that from 2007 to 2009, in Chinese stock market, disposition effect exists among individual investors. However, V-shape disposition does not appear in our result. Investors tends to sell a close-to-zero stock when it is a loss. In gain side, the relationship between magnitude of gain and probability of selling is not significant. When consider the comparison of stocks in one portfolio, for rank effect, Chinese investors are more likely to sell a position with better performance. Best positions (position with largest return) have the largest probability of being sold. 2^{nd} best positions follow. The probability of selling among middle, 2^{nd} worst and worst positions have no significant difference. The rank effect in Chinese market is not the same as it is in US market. Surprisingly, investors do not trade very differently before, during or over financial crisis. The extreme risk market condition in financial crisis does not change the behaviour of individual investors a lot. Our results are the same under different time periods and market conditions.

The rest of this paper is organized as follows. Section 2 reviews the relevant literatures. Section 3 introduces the dataset, data processing and Chinese stock market during this period. Section 4 discusses the main empirical results, while robustness tests are presented in Section 5. Section 6 concludes.

2. Literature Review

In the early stage, expected utility (also known as von Neumann-Morgenstern utility) theory dominates the analysis of investors' decision making under uncertainty. It states that the expected utility of any decision may be expressed as a linear combination of the utilities of the outcomes, with the weights being the respective probabilities. This theory has a normative interpretation which researchers particularly used to think applies in many situations, for example, stock investment, to rational agents and individuals. However, investors are generally viewed as irrational when they make decisions and this violates the axioms of this theory, and therefore invalidate expected utility model. Among all the critiques, Kahneman and Tversky (1979) develop an alternative model, called prospect theory, to describe decisions making under risk. Prospect theory states that the propensity to sell a stock declines as its price moves away from the purchase price in either direction. Since then, the biases of the investor behavior have been widely discussed. Among these, disposition effect (the tendency to hold losers too long and sell winners too soon), pioneered by Shefrin and Statman (1985), is the most well-known one.

Odean (1998) is the first to provide empirical result of disposition effect. The result demonstrates that investors realize their gains more readily than their losses. These investors demonstrate a strong preference for realizing winners rather than losers. After his findings in US market, disposition effect is widely examined in many countries and areas, for instance, Israel (Shapira and Venezia, 2001), Finland (Grinblatt and Keloharju, 2001a), China (Feng and Seasholes, 2005; Sumway and Wu, 2005), Taiwan (Barber, et al., 2009), Germany (Lukas, et al., 2017), Korea (Choe and Eom, 2009), etc. These papers show that investor's behavior bias occurs in a wide range of markets. Prospect theory is most commonly used to explain the disposition effect. Barberis and Xiong (2009) model the trading behavior of an investor with prospect theory preferences and show that, if gains and losses are evaluated when they are realized, a disposition effect obtains. Therefore, a S-shaped curve in the probability of selling as a function of profit is expected. However, Ben-David and Hirshleifer (2012) find that the curve is actually V-shaped. They also document that gains or losses is not the only issue when analyze disposition effect. How much is the gains or losses is a question as well. Meanwhile, using the data from Finnish market, Kaustia (2010b) supports this result. Attention trading (Barber and Odean, 2008) provides a possible reason for the V-shape disposition since stocks with large gains or losses catch more attention of investors.

(Insert Figure 1)

However, most of the findings on V-shaped disposition effect are based on the data from developed countries. Ben-David and Hirshleifer (2012) use the same dataset as Odean (1998) which is from U.S. stock market and the period is from January 1990 through December 1996. Kaustia (2010b)'s data source is from Finish market from December 27, 1994 through May 26, 2000. The relationship between the selling behavior and the magnitude of gains (losses) in emerging market is under researched. In addition, investors trading behavior under an updated time period, especially under extreme market conditions such as financial crisis, is still ambiguous and lack of research. In this paper, we use a dataset from Chinese stock market from 2007 to 2009 to discuss these questions.

Research Question 1: What is the relationship between the selling behavior and the magnitude of gains (losses) in Chinese market? Is it a V-shape relation similar as US market?

Research Question 2: Does V-shape disposition effect behave differently before, during and after financial crisis? Do Chinese investors trade differently under different market situation?

Rank effect (Hartzmark, 2015) further develops these findings into a new investor trading bias effect that individuals are more likely to sell the extreme winning and extreme losing positions in their portfolio. He criticizes that the previous studies have considered investor trading preliminary on a stock-by-stock bias and ignore the portfolio problem in its entirety. Using data from a large retail brokerage in US stock market from 1991 to 1996, Hartzmark (2015) shows that on a day an investor sells a position in their portfolio, the investor has a 31% chance of selling the stock with the highest return in the portfolio and a 26% chance of selling the stock with the lowest return, after controlling for a number of factors. Hartzmark (2015) also fits Logit regression model used by Ben-David and Hirshleifer (2012) with adding the rank dummy variable. The best-ranked stock (*Best*) is 15.7% more likely to be sold, and the worst-ranked stock (*Worst*) is 10.7% more likely to be sold, both significant with large t-statistics. After including the two dummy variables for rank, the *Loss*Return* and *Gain*Return* coefficients, which indicate the disposition effect, are becoming insignificant and the *Gain* dummy coefficient decreases. This means that rank effect is at least as strong as disposition effect. After these, An (2016) finds asset pricing value based on V-shape disposition effect and rank effect by showing that stocks with both large unrealized gains and large unrealized losses outperform others in the following month.

In this paper, we significantly update the time period of the data to 2007 to 2009. We also discuss the rank effect in a brand-new market, Chinese market, which is a large and emerging market in a developing country. Since the year 2007 to 2009 cover the financial crisis, we also analyze rank effect in the extreme market condition.

Research Question 3: Does rank effect exist in Chinese market? Do Chinese investors evaluate a given stock differently based on what else is in their portfolio?

Research Question 4: Does rank effect behave differently before, during and after financial crisis?

3. Background and the Dataset

2.1 Chinese Stock Market in 2007-2009

The year of 2008 saw a sequence of adverse financial news in the world and triggered the US credit crunch and market crisis. And it soon became the worldwide financial crisis. This poor external financial environment should have a great impact on Chinese stock markets. However, although there was indeed an extreme volatility of stock prices that signified a market bubble appearing and bursting in Chinese market, the story began at the start of 2007 before the financial crisis.

Due to the Split-Share Structure Reform[2] in China, the entire year of 2007 is a crazy year of Chinese stock market (see Fig.2). The biggest bull market came to Chinese

[2] Liao, *et al* (2014) and Lehkonen (2010) introduce the reform in detail.

stock markets in the beginning of 2007. The Shanghai Composite Index surged over 3,500 points from 2715.72 at the start of the year to 6,124 on October 16, which reached the peak, with the rise of 140%. And then it plunged all the way, felling back to roughly 2000 points in November 2008, with the loss near to 70%. On 4th November 2008, it got the lowest point, which is 1706. Then the index got back to steady growth till the end of 2009. In sharp contrast, during the same time period, the Chinese real economy grew at average more than 10% per year.

(Insert Figure 2 here)

Chinese stock market provides an interesting and unique research environment in terms of the market emotion and investor behavior. At the start of the bubble, with the extreme bullish market, both domestic and foreign investors were enticed to buy whatever shares were on offer without carefully analyzing the real performance and growth potential of the listed firms. The whole market was under the emotion of over-confidence and over-optimistic. Then when the bubble burst, all investors were facing extraordinary loss and risk. The overall emotion turns to fear and lack of confidence.

We also introduce some criteria related to our research in Chinese stock market during 2007 to 2009. In that time, one investor can only open one trading account in agent. Therefore, our data for one investor is the entire trading behavior of this investor in the market which helps us to get a more comprehensive understanding of the investor. There is a limit up and limit down restriction, in the magnitude of 10% as well. In Chinese market, the short sale constraint existed until 2010. There are no short-selling records in our data.

3.2 The Data

This paper is based on a very large database collected from a large nationwide brokerage firm in China, with more than 3 million accounts and 2 billion daily dealing records over the period of January 2007 to May 2009[3]. Due to the computational capacity limitations, we use a random sample of 5,000 investors and 2 million records sub-data to build our model. The dataset is formed with 4 sub-datasets that are customer file, account file, stock file and transaction file. Customer file contains the information of each customer. Account file contains balance information of customer's account on daily basis. Stock file contains information of each stocks held by each customer on daily basis. Transaction file contains each deal's information. Customer ID is used to merge all files. We also get the stock price information from CSMAR (China Stock Market & Accounting Research Database).

Each row in the stock file indicates the holding record of one investor for one stock at the end of one trading day and it composes our main data table. The transaction file provides us the trading amount and price of each trades. There is also a column shows "selling" when the transaction record is a sell. The customer file shows the gender, account open date and birthday. All investors are individual investors and there is no foreign investor. Since all data is based on the ending data of each trading day, the trading sequence of multiple trades of one investor in one day cannot be observed.

There are totally 2,264,950 holding records in stock file from the 5000 customers sample. After deleting duplicated records, 2,234,204 records remain in dataset. Some of the records have a very small numbers of shares holding by one person one day. We think it is caused by mistake. We keep holding records with more than (equal to) 100 shares per investor per day and 2,152,700 remain in the dataset. Since the data is based on the shares one investor hold at the end of one trading day, if investor sells all his shares that day, there is no record for him in that day. However, these records should be involved in our model. We add these rows by finding corresponding records from transactions record file. We only add roughly less than 1% data.

The current price is the stock price at the end of a trading day when investor keeps this stock or sells part of his holding shares of that stock. And it is the stock price at the last trade when investor liquidated. Since the stock price in one day does not change

[3] There are three missing months, which are April 2007, May 2007 and March 2008.

too much, this setting is reasonable in our data. The cost price is calculated as the share weighted average buying price for multiple buying behavior for one stock. The return is current price minus cost price.

We drop positions with unclear buying price. This is because the buying behavior is before the start date of our data. We accomplished this by deleting positions that are holdings in the first day. This drop roughly 8.8% of all records. The initial dataset includes some records from HK market and other market. We only keep records from Chinese stock market. This drops no more than 1%. There are also little records with 0 purchase price or current price. It is from some recording error. We drop this part and it is a little more than 1%.

In rank effect theory, investors are more likely to sell best-performance stock and worst-performance stock. Therefore, if one holds too few stocks one day, these records should not be included since there is no best, worst and comparison. We follow Hartzmark's (2015) method to keep records with at least 5 stocks in one's portfolio one day. Since our data size is very large, we still have enough data to build the model. Also, since investors with more number of stocks in their portfolio are thought to be more sophisticated, this is a question to discuss further.

Also following the method of Hartzmark (2015), we only consider portfolios in days that investors do sell at least one stock that day (a sell day). Since we discuss the comparison of stocks in one's portfolio when he considers selling a position, if the investor does not sell any position one day, he is considered to be inactive that day. After all the cleaning process, there are 67,288 records remain in our data.

4. V-shape Disposition in Chinese Market

4.1 The Model

To test the impact of on selling by the magnitude of the gain and loss in Chinese market during financial crisis, we estimate a similar model as Ben-David and Hirshleifer (2012) and Hartzmark (2015) do:

$$Sell = Constant + a_1(Gain) + a_2(Gain * Return) + a_3(Loss * Return) + a_4(Rank\ Variables) + a_5(Control\ Variables)$$

The model is on day-investor-stock level. Each observation is a position that one investor holds one stock in one day. The model is fitted as a Logit model by maximum likelihood. The dependent variable is a dummy variable, equals to 1 if the stock is sold that day by that investor and 0 otherwise. Both partial selling and liquidation are involved. *Return* is the unit share return of position which is calculated based on the buying price (trading cost involved and is weighted average price by shares in case of multiple purchase) and the current price of that stock at that day. *Gain* is a dummy variable that takes the value of 1 if the unit return of the position is positive and 0 otherwise. *Loss* is the opposite of *Gain*. Including the interaction terms of *Gain (Loss)* and *Return* allows us to analyze the relationship between the probability of selling and the magnitude of gain and loss separately. To further test rank effect, we add 5 rank variables into the model. The details of these 5 rank variables will be introduced in chapter 5.2.

For control variables, since our data is not continuous, it is hard to get the exact holding period of a position. We do not introduce holding period as control variable in our model. *Gender* is a dummy variable that takes value of 1 for female and 0 for male. *Root_age* is the square root of the investor's age[4]. To control the experience of investor, we introduce a dummy variable *New_investor*, which equals to one if the investor opened account in this brokerage after the start of our data period and zero otherwise. It is worth noting that at that time, in Chinese market, one individual can only open one account in the whole market. This makes our experience more powerful. *Root_tradetimes* is the square root of times of trading an investor made in our data period. It can indicate the activation of an investor in some degree.

Since our data cover the financial crisis in China, we further introduce two dummy

[4] We use the date difference between investor's birthday and May 31st 2009, which is the last day of our dataset.

variables to control the time and market condition. We divide our data period, Jan 2007 to May 2009, into three parts, from Jan 1st 2007 to Oct 16th 2007 as bull market, from Oct 17th 2007 to Nov 4th 2008 as bear market, from Nov 5th 2008 to May 31st 2009 as steady growth market. We define the three sub time period by the value of Shanghai Composite Index, which has been discussed in detail in the early part of this paper (part 2.1). We introduce dummy variable *Bull_mar*, equals to 1 if the position is in bull market period, and *Bear_mar*, equals to 1 if the position is in bear market period. We set the steady period as benchmark.

(Insert table 1 here)

In table 1, we present the summary statistics of variables we use in our model. After all cleaning, there are total 67,288 records (positions). For dummy variable (binomial variable), we present the number of 1. For dependent variable *Sold,* there are 11,779 positions that are sold in the end of the day. Since we only include positions that at least one stock in the portfolio is sold in that day. This number is reasonable. As for independent variables, the numbers of 1 in *Best, 2nd best, 2nd worst, Worst* are the same (8,548). By the definition of rank variables, there should be 1 best position, 1 2nd best position, 1 2nd worst position and 1 worst position in 1 portfolio. So, the numbers of 1 are the same for these variables. This also shows that there are 8,548 portfolio-day in our model. 1 portfolio can include more than 1 middle rank positions. And the number of 1 in *Middle* variable is 33,096. Since our data cover financial crisis, there are more loss positions than gains in our model. The number of positions held by new investors is 12,783. Our data is also balance in gender and in all three sub-market conditions. For numerical variables, due to financial crisis, the average of loss per loss position is larger than gain per gain position. The average age is 49.87 and *Root_age* is 7.0219. The average *Root_tradetimes* is 27.9682.

4.2 Empirical Results of the Impact of Magnitude of Gain and Loss

Table 2 presents the marginal effect of the Logit regression model. Since then observations are related to each other, we apply the clustered standard error instead of the simple standard error. Ben- David and Hirshleifer (2012) suggest clustering the standard error by investor. In our data, clustering in investor level or date level are both reasonable. Therefore, we fit the model in both method and compare the performance.

(Insert Table 2 here)

Table 2 presents the marginal effect of a logit regression model to examine the impact of magnitude of gain and loss on selling. As it is shown in column 1, a position is 9.32% more likely to be sold if it is a gain with a very large t-statistics value. It confirms the disposition effect in Chinses stock market. Since the marginal effect of *Gain*Return* is in negative sign and insignificant, the increase of magnitude of gain does not lead to an increase probability of selling in Chinses market, as it does in US market. The relationship between the magnitude of gain and probability of selling is still unclear. The marginal effect of *Loss*Return* is significant in our result, but the sign is positive. Since all of the *Loss*Return* terms should be nonpositive, this means that in loss case, the probability of selling is increasing when the return is close to zero. An increase of magnitude of loss does not lead to an increase of probability of selling. It is contrary to the result of Ben- David and Hirshleifer (2012) in US market. The V-shape disposition is not suitable in Chinese market from 2007 to 2009.

Column 2 shows the results when the standard errors are clustered by date. By comparing with results in column 1 which the standard errors are clustered by investor, most of the t-statistics in column 2 are larger than column 1, but the differences are not large, and all of the significant levels of our main variables stay the same. This indicate that both method suggest a similar result. Since the relation between positions from one investor is more reasonable than the relation between dates, we follow the method from Ben- David and Hirshleifer (2012) and use standard error clustered by investor in the rest of this paper.

To consider the performance of investors' characteristics control variables, in column 1, all of these variables are insignificant, *New_investor* is insignificant in column 2 as well. The investors' heterogeneity may not play an important role in individuals' decision of selling. However, since our dataset is large, we do not suffer from a luck of degree of freedom by adding these variables. Adding them benefits to the robustness level of our results.

4.3 The Impact of Magnitude of Gain and Loss in Different Market Condition

Since our data covers the financial crisis, analyzing how individual investors performance under financial crisis and extreme market condition adds more value to our data and research. Chinese market did not suffer seriously from the worldwide financial crisis in 2008. However, there is an extreme volatility of stock prices that signified a market bubble appearing and bursting in Chinese market during 2007 and 2008[5]. The Shanghai Composite Index was around 2700 at the beginning of 2007. It surged and reached the peak at 6124 on 16th October 2007. And then it went all the down to 1706 on 4th November 2008, which is the lowest point in 2008. After that the Shanghai Composite Index enter a steady growth period in 2009. Based on this we split our dataset into 3 subsets: 1st January 2007 to 16th October 2007, called bull market, 17th October 2007 to 4th November 2008, called bear market, and 5th November 2008 to 31st May 2009, called steady market. We fit the same model in table 2 in these time periods separately to test the impact of magnitude of gain and loss on selling in Chinese market before, under and over financial crisis.

(Insert Table 3 here)

In table 3, since the observations of these time periods are on the same level our data is balance to this split. In column 1, under bull market, Chinese individual investors are 8.41% (with t-statistics 6.839) more likely to sell a gain position, which shows a significant disposition effect. However, the relationship between magnitude of gain and the probability of selling is weak since *Loss*Return* is insignificant. *Gain*Return* has

5 We discuss in detail in part 2.1 of this paper.

a significant and positive result. This means that if the position is a gain, investors are more likely to sell it if it is close to zero. However, this tendency is not strong since the result is less than 0.1%. What is unexpected is that the bear market condition shares the same result with bull market condition. In column 2, the power of disposition effect is 9.82%. In the gain part, the impact of return on selling is also insignificant. And in the loss part, investors are more likely to sell a close-to-zero stock with less than 1% tendency. The results in steady growth period is slightly different. In column 3, in steady market condition, disposition effect is still significant and in loss part, investors are still slightly more willing to sell a stock with a small loss. However, *Gain*Return* is negative and significant, which indicate that investor is also more likely to sell a close-to-zero position when it is a gain. This shows a slightly reverse V-shape in the relation of probability of selling and return.

Individual investors in Chinese market performance similarly before, under and over financial crisis. The difference is very small. They show a strong disposition effect in all three market conditions. And they also performance the same when a position is a loss, which they are more slightly likely to sell it if it is a small loss. When a position is a gain, in bull and bear market conditions, there is no impact of magnitude of gain on probability of selling. But in steady growth market condition, inventors are more willing to sell a gain position when it is close to zero. As a conclusion, disposition effect is all strong before, under and after financial crisis. However, the V-shape do not exist in all three market conditions. In Hoffmann, et al. (2013) and Gerrans, et al. (2015), both of them state that although individual investors change their expectation of return and risk tolerance during financial crisis, their trading behavior do not change significantly. Our result support their argument in Chinese market.

5. Rank Effect

5.1 The Univariate T-test Result

By a similar method with Hartzmark (2015), we rank the positions in one's portfolio by the unit share return as best, 2nd best, worst, 2nd worst and middle. A position is ranked best if it has the highest unit share return in the portfolio of that particular investor in that particular day. 2^{nd} best, worst and 2^{nd} worst are defined in a similar way. Middle includes all positions not ranked in the top or bottom two positions. For investors, only days that at least one stock is sold are included as sell day (active day). The observations are at day-investor-stock level. We define *Best%* as:

$$Best\% = \frac{\#Best\ Sold}{\#Best\ Sold + \#Best\ Not\ Sold}$$

#Best Sold is the number of best stocks that had their number of shares decreased. *#Best Not Sold* is the number of best stocks that had their number of shares increased or remained the same. *2^{nd} Best%, Middle%, 2^{nd} Worst%* and *Worst%* are defined in a similar way. To calculate the t-statistics, we cluster the data by investor and date and calculate the average.

(Insert Table 4 here)

In Table 4, we present the result in this large whole dataset. In Chinese stock market, the order of probability of selling from large to small is the same order of the rank of return. A best position with a 32% probability of selling is 7.05% more likely to be sold than a 2^{nd} best position, with a very large t-statistics. In a similar way, a 2^{nd} best position is more likely to be sold than a middle one, a middle position is more likely to be sold than a 2^{nd} worst one and the worst position has the lowest probability to be sold. However, when we compare the difference between ranks, although all differences pass statistic test, the difference between best and 2^{nd} best is 7.05% and the difference between 2^{nd} best and middle is 6.89%. These two differences are more than 2 times larger than the rest two differences. In further results, when control variables are added, the differences among middle, 2^{nd} worst and worst become insignificant. The best stock is the one that is most likely to be sold by Chinese investors, and the 2^{nd} best stock follows. The rest stocks, middle, 2^{nd} worst and worst, are treated similarly. As a conclusion, Chinese investors during financial crisis are more likely to sell a position with better performance. In Hartzmark (2015), the US investors are more likely to sell best and worst positions than the middle one. Our result in Chinese market is significantly different.

To compare with results from Hartzmark (2015), the average probability of selling for all stocks is 12.1%. Our result is 19.67%. All other selling percentage is larger as well. This is not because that Chinese investors are more likely to trade. This is because both of the papers only include selling day position, which means on each day that is included, at least one position is sold. Since the average portfolio size of Chinese investor is significant smaller than US investor and at least one stock is sold in one portfolio one day, the average selling probability in Chinese market is of course larger than it is in US.

5.2 Rank Effect in Regression Models

To test the rank effect in Chinese market with control variables, we run a similar logit model with Hartzmark (2015) which is similar to our model in Section 4. We add 5 rank variables into the model in Section 4.2. *Best* is a dummy variable that equals to 1 if the position is in 1st rank in one's portfolio on a particular day when we rank the positions in portfolio by the unit share return[6] since purchase. This means the best stock has the largest unit share return in the portfolio. *2nd Best*, *2nd Worst* and *Worst* are defined similarly to indicate the 2nd best, 2nd worst and worst position in one's portfolio on a particular day. If one position is not *Best, 2nd Best, 2nd Worst* nor *Worst*, it is defined as middle, which has a value of 1 in dummy variable *Middle*.

Hartzmark (2015) states a rank effect in US market, which is investors are more likely to sell best and worst positions rather than middle positions. Therefore, he uses *Middle* as his benchmark in his model. Based on our result in chapter 4.1, we find out that worst position has the least probability to be sold. This means *Worst* is another benchmark that is suggested ton be chosen. In our model, we compare the result when *Middle* or *Worst* is the benchmark.

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6 The method of calculation unit share return is discussed in part 3.1

(Insert Table 5 here)

Table 5 presents the results of rank effect from the logit model. In column 1, best, worst and middle positions are included, and worst is chosen as the benchmark. Best positions are 6.33% more likely to be sold than worst positions with a very large t-statistics (6.578). Middle positions are 4.37% less likely to be sold than worst positions. However, when changing the benchmark to middle, as it is shown in column 2, best positions are still significantly more likely to be sold but the probability of selling a worst position is not significantly difference with the probability of selling a middle one. To further discuss this question, we introduce *2nd Best* and *2nd Worst* in column 3 and 4. In column 3, a best position is 10.12% more likely to be sold than a worst one and a 2nd best position is 6.41% more likely to be sold than a worst one. These are the top 1 and 2 positions to be sold. The difference of probability of selling is insignificant between middle positions and worst positions and between 2nd worst positions and worst positions. In column 4, when middle is the benchmark, the results of best and 2nd best positions are similar to they are in column 3. The difference of probability of selling between middle and worst positions is insignificant and the difference between 2nd worst and worst positions is significant in 5% confidence level but insignificant in 1%. Therefore, when adding 2nd best and 2nd worst positions into our model, we find that there is no significant difference among the probability of selling of middle, 2nd worst and worst positions. How to choose the benchmark position does not change this result. We will use worst positions as benchmark in further results of this paper.

Based on these result, we can conclude that in Chinese market during 2007 to 2009, The best position, the position that has the largest return in one's portfolio, has the largest chance to be sold and the 2nd best position follows. The results of probability of selling of middle, 2nd worst and worst positions may need more evidence. But based on the result for now, we can infer that Chinese individual investors do not treat them in a large magnitude of difference. The performance of Chinese investors during 2007 to

2009 is difference to the performance of US investors as it is in result of Hartzmark (2015). Chinese investor does not follow the rank effect.

5.3 Rank Effect in Different Market Conditions

Since the particularity of our data period, we test rank effect before, during and after financial crisis. The market condition changed dramatically during financial crisis. Under financial crisis, when all investors are facing extreme loss and risk, the mind and selling choice of investors may change. Similar to chapter 3.3 and 4.2, we depart data time period into three parts that represent three market conditions: bull market, bear market and steady market.

(Insert Table 6 here)

Table 6 shows the marginal effect of rank effect in different market conditions. In table 6 column 1, under bull market, individual investors are 10.34% more likely to realize best-ranked positions than worst-ranked (benchmark in this model) positions. They are also 7.04% more likely to realize 2nd best-ranked positions. The probabilities of realizing middle and worst positions do not appear a significant difference. But the probability of selling 2nd worst positions is larger than selling worst positions. Results during financial crisis are shown in column 2. Best and 2nd best ranked positions still get the largest and second largest probability of being sold. There is no significant difference among 2nd worst and worst positions. However, for middle positions, individual investors are 3.48% less likely to sell them than worst positions. This is different from column 1. In column 3, after financial crisis, investors in Chinese market are 10.08% more likely to sell best positions and 8.34% more likely to sell 2nd best positions. They treat middle, 2nd worst and worst positions similarly when considering the selling choice. Based on these results, the behaviors of individual investors before, under and after financial crisis are similar. Rank effect in Hartzmark (2015) does not appear in Chinese market. Chinese investors are more likely to sell best and 2nd best positions. But in general, they do not discriminate middle, 2nd worst and worst positions when they consider selling a position. Their selling behavior before, during and after financial crisis do not change very much. This result is similar as it is in chapter 4.3 of this paper and also support the result from Hoffmann, et al. (2013) and Gerrans, et al. (2015).

6. Robustness Test

In addition of many control variables we include in our model, we also to several robustness test to empower our result.

6.1 V-shape Disposition Test by Probit Regression

To further control for the influence of methodology, we run the same model as in table 2 but based on a probit regression method. Table 7 presents the marginal effect of the probit model. The results are similar to the results in logit model. If the position is a gain, the probability of selling this position by Chinese individual investor is increased by 9.59%, which indicate a significant disposition effect. The *Gain*Return* term is also negative and insignificant, which is the same as it is in logit model in table 2. The magnitude of gain does not impact the probability of selling. In the loss side, *Loss*Return* is positive and significant, which means that when a position is a loss and close to zero, it is more likely to be sold. The V-shape disposition is not suitable in Chinese market from 2007 to 2009. This result is consistent with the result in logit regression. Our result is robust with different modeling methodology.

(Insert Table 7 here)

6.2 V-shape Disposition Test Measured by Rate of Return

Investor may consider the magnitude of gain or loss in other measurement rather than unit stock return. In this part, we consider the rate of return, which equals to (current price per share – purchase price per share) / purchase price per share. This measurement is commonly used in stock analysis. In table 8, we show the result of our logit regression.

When using rate of return to measure the magnitude of gain or loss, investors are 7.35% more likely to sell a gain position. The *Gain*Rate_return* term is insignificant, so there is no significant relationship between magnitude of gain and probability of selling. *Loss*Rate_return* term is positive and significant, which indicate that when a position is a loss, investors are more likely to sell in when it is close to 0. This result also shows that V-shape disposition effect does not appear in Chinese market.

(Insert table 8 here)

6.3 Rank Effect by Probit Model

For rank effect, in order to control the influence of modeling methodology, we run a test similar with our model in rank effect by probit model. Table 9 presents the result from probit model. In Chinese market, a best rank position is 10.51% more likely to be sold than a worst position (benchmark). A 2^{nd} best position is 6.60% more likely to be sold than a worst position. The differences among middle, 2^{nd} worst and worst positions are insignificant. The disposition effect is significant (coefficient of *Gain* is positive and significant) and the V-shape disposition is insignificant (coefficient of *Gain*Return* is insignificant, and *Loss*Return* is positive). The results from porbit model is the same as results from logit model. Our results are robust with the choice of model.

(Insert Table 9 here)

6.4 Rank Effect in All Gain/ Loss Portfolios

In order to research rank effect in extreme condition and the relation between rank effect and disposition effect, we estimate a similar logit model that restricts the portfolios into all gain portfolios and all loss portfolios. In all gain portfolios, all positions in this portfolio at that day are gain. These positions are at very good situation and may lead investors to overconfidence. In all loss portfolios, everything is the opposite. This test provides a more precise control for the disposition effect and contributes to explain the disappear of V-shape disposition effect in Chinese market.

(Insert Table 10 here)

Table 10 shows the results of rank effect in all gain/loss portfolios in logit model. When all positions in a portfolio is gains, in column 1, investors are 13.74% (with significant t value 5.524) more likely to sell a best position than a worst one and 12.23% more likely to sell a 2^{nd} best position. The probabilities of selling middle and 2^{nd} worst positions are slightly large with t values significant in 5% confidence level but not significant in 1%. The differences among middle, 2^{nd} worst and worst positions are not strong. When all positions come to a loss, in column 2, the probabilities of realizing best and 2^{nd} best positions are still significantly larger than the probability of worst positions. The differences among middle, 2^{nd} worst and worst positions are insignificant. Our result that Chinese investors are more likely to sell best and 2^{nd} best positions and treat other positions equally is found in both all gain and all loss portfolios. Since in all loss portfolios, this result is stronger, it leads to an interpretation of our result in V-shape disposition effect. The magnitude of loss influences the decision of selling more than magnitude of gain. And for a loss position, investors are more likely to sell it if it is close to zero.

6.5 Rank Effect in No Limit-Down Portfolios

The influence of government policy is strong in Chinese stock market. The limit-down policy was established 1996. A limit-down stock is a stock that decrease more than 10% in one day, which means (today's price – yesterday's price) / yesterday's price is less than -10%. If a stock becomes a limit-down stock in a particular day, the policy limits the lower bound of its price by -10% rate of return, so it cannot be traded in a lower price. Therefore, the possibility of selling limit-down positions is limited and it may influence the probability of selling bad-performance positions in our model. Thus, it can affect how investors sell their portfolios.

(Insert table 11 here)

To control this, we use portfolios with no limit-down stocks in our data. In table 11, when a portfolio has no limit-down position, a best-ranked position is 10.57% more likely to be sold than a worst one, with a very large t-value (7.611). The probability of selling a 2nd best position is also significantly larger than selling a worst position. The probabilities of selling middle, 2nd worst and worst positions have no significant difference. This result is similar to our result in rank effect model. Our result is robustness to the policy of limit-down stock.

6.6 Rank Effect Measured by Rate of Return

In this paper, we use return of a position per share to measure the rank effect. In the real world, there are many factors that may draw investors' attention. Thus, these factors can lead investors to rank positions in their portfolio by other measurements. To test this, we change the measurement of rank into rate of return. We use the same calculation method as in chapter 6.2.

(Insert table 12 here)

When using rate of return as the measurement of rank, in table 12, we find that the result is robust to our main result. Best rank stock has the largest probability to be sold, which is 12.15% more likely than worst with t-value 10.424. 2nd best stock follows with a 9.23% more likely to be sold than worst stock and also large t-value. The probability of selling a middle stock is not significantly different than a worst one. However, for 2nd worst stock, the result is slightly different from the main result. Instead of insignificant difference, 2nd worst stock is 2.35% more likely to be sold than worst stock with a t-value 3.243. But 2.35% is much smaller than 12.15% and 9.23%. This indicate that we can still say our result is robust when we change the measurement of rank from return to rate of return.

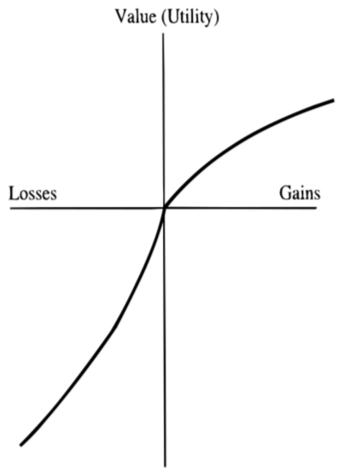
7. Conclusions

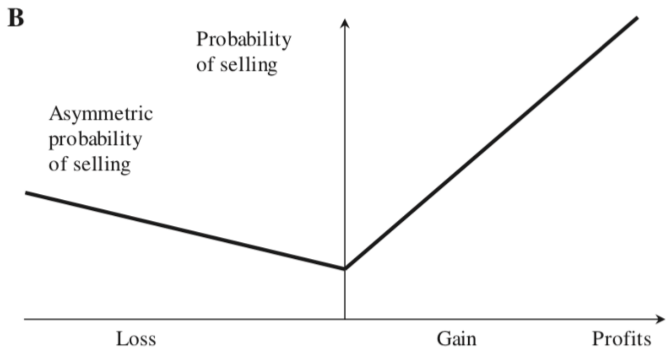
In this paper, we test V-shape disposition effect and rank effect among individual investors in Chines stock market before, during and after financial crisis. We find that disposition effect is significant in China, but V-shape disposition effect is not. If the position is a gain, the relationship between probability of selling and magnitude of gain is not significant. While in loss part, investors are more likely to sell a position if it is close to zero. We also indicate that except the slightly difference, this result is similar before, during and after financial crisis. Investors do not behave differently in different market conditions.

The rank effect in Chinese market is different from US market. The positions with best performance in one's portfolio have the largest probability to be sold. The 2nd best on follows. However, the probabilities of selling middle, 2nd worst and worst positions are not significantly different. In general, investors want to sell positions with better return. This result is also similar in different market conditions.

In our study, we want to discover how investor choose which position to sell when they want to sell their stocks. We find investors are more willing to sell positions with better performance. However, how they treat bad positions has not been discovered totally. In addition, since investors do not behave significant differently before, during and after financial crisis, how to explain this and how to explain the tiny difference in different market conditions are also good questions.

Figure 1: S-shape Disposition and V-shape Disposition





Source: Figure 1 from Odean (1998) and Figure 2B from Ben-David and Hirshleifer (2012)

Figure 2: S&P500 v.s. SEE Composite Index

Source: S&P500 index and SSE composite index

Table 1
Summary Statistics of Variables

Observation	67,288

Dummy variable	Number of 1 in data
Sold	11,779
Best	8,548
2^{nd} best	8,548
Middle	33,096
2^{nd} worst	8,548
Worst	8,548
Gain	25,880
Gender	33,875
New_investor	12,783
Bull_mar	21,443
Bear_mar	25,912
Steady_mar	19,933

Numerical variable	Average
Gain*Return	0.8624
Loss*Return	-2.2745
Root_tradetimes	27.9682
Root_age	7.0219

Note: This table presents the summary statistics of variables in our model. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. All variables are defined in part 3.1 in this paper.

Table 2
The Impact of Magnitude of Gain and Loss on Selling

	Dependent Variable: Dummy of Selling the Position	
Clustering standard error by:	Investor	Date
	(1)	(2)
Gain	0.0932***	0.0932***
(t-statistics)	(11.667)	(21.947)
Gain*Return	-0.000002	-0.00002
	(-0.032)	(-0.019)
Loss*Return	0.0066***	0.0066***
	(5.041)	(9.776)
Root_tradetimes	0.0003	0.0003**
	(0.599)	(2.343)
Gender	-0.0152	-0.0152***
	(-1.042)	(-5.954)
Root_age	-0.0055	-0.0055***
	(-0.797)	(-3.382)
New_investor	0.0037	0.0037
	(0.225)	(1.133)
Bull_mar	-0.0153	-0.0153***
	(-1.419)	(-3.808)
Bear_mar	0.0198**	0.0198***
	(2.315)	(4.451)
Observations	67,288	67,288
Pseudo R^2	0.02713	0.02713

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. The dependent variable is a dummy variable equal to one if a stock is sold. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is applied. The first column shows the results with standard errors clustered by investor. The second column shows the results with standard errors clustered by date. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 3

The Impact of Magnitude of Gain and Loss on Selling in Different Market Condition

	Dependent Variable: Dummy of Selling the Position		
Market Condition:	Bull	Bear	Steady
	(1)	(2)	(3)
Gain	0.0841***	0.0982***	0.1260***
(t-statistics)	(6.839)	(9.981)	(12.114)
Gain*Return	0.0002**	-0.0007	-0.0131**
	(1.981)	(-0.915)	(-2.209)
Loss*Return	0.0025	0.0062***	0.0068***
	(0.487)	(3.757)	(3.839)
Root_tradetimes	0.0014***	0.0005	-0.0095**
	(2.772)	(0.979)	(-2.364)
Gender	-0.0169	-0.0183	0.0019
	(-0.748)	(-1.319)	(0.155)
Root_age	-0.0122	-0.0077	0.0057
	(-1.374)	(-0.918)	(0.849)
New_investor	0.0287**	0.0108	-0.0183
	(2.180)	(0.572)	(-1.186)
Observations	21,443	25,912	19,933
Pseudo R^2	0.01422	0.03131	0.04597

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Column 1 is from data from bull market and the time period is from Jan 1st 2007 to Oct 16th 2007. Column 2 is from bear market condition and the time period is from Oct 17th 2007 to Nov 4th 2008. Column 3 is the steady market condition and the time period is from Nov 5th 2008 to May 31st 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. The dependent variable is a dummy variable equal to one if a stock is sold. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. The standard error is clustered by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 4
The Univariate Test of Rank Effect

	(1)
Best%	0.3189
2nd Best%	0.2484
Middle%	0.1795
2nd Worst%	0.1404
Worst%	0.1194
All	0.1967
Best% - 2nd Best%	0.0705***
	(10.3105)
2nd Best% - Middle%	0.0689***
	(12.4040)
Middle% - 2nd Worst%	0.0391***
	(8.1051)
2nd Worst% - Worst%	0.0210***
	(4.1094)
Observations	8,625

Note: This table presents the t-test result of rank effect. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Best% is calculated as the ratio of best positions that are sold divided by all best positions. Others are defined in a similar method. The data is clustered by investor and date. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included. In the second half of this table, the top number is the difference in average, and the lower number in parentheses is the t -statistic. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 5
The Test of Rank Effect

	Dependent Variable: Dummy of Selling the Position			
benchmark:	Worst	Middle	Worst	Middle
	(1)	(2)	(3)	(4)
Best	0.0633***	0.0894***	0.1012***	0.1128***
(t-statistics)	(6.578)	(10.256)	(7.286)	(12.166)
2ndbest			0.0641***	0.0757***
			(6.103)	(11.817)
Middle	-0.0437***		-0.0120	
	(-6.684)		(-1.155)	
2ndworst			0.0079	0.0192**
			(1.135)	(2.355)
Worst		-0.0046		0.0089
		(-0.512)		(0.905)
Gain	0.0733**	0.0708***	0.0614***	0.0611***
	(7.934)	(7.581)	(6.939)	(6.907)
Gain*Return	-0.0005	-0.0004	-0.0007	-0.0007
	(-0.159)	(-0.141)	(-0.221)	(-0.221)
Loss*Return	0.0065***	0.0057***	0.0052***	0.0052***
	(5.378)	(4.445)	(4.204)	(4.152)
Control Variables	Yes	Yes	Yes	Yes
Observations	67,288	67,288	67,288	67,288
Pseudo R^2	0.03807	0.03520	0.04021	0.04018

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. The dependent variable is a dummy variable equal to one if a stock is sold. 5 dummy rank variables are included to test rank effect. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 6
Rank Effect in Different Market Conditions

	Dependent Variable: Dummy of Selling the Position		
Market Condition:	Bull	Bear	Steady
	(1)	(2)	
Best	0.1034***	0.1049***	0.1080***
(t-statistics)	(6.416)	(6.475)	(5.026)
2ndbest	0.0704***	0.0486***	0.0834***
	(4.610)	(3.265)	(4.584)
Middle	0.0124	-0.0348***	-0.0010
	(0.758)	(-2.626)	(-0.063)
2ndworst	0.0357***	-0.0079	0.0015
	(3.320)	(-0.701)	(0.100)
Gain	0.0589***	0.0616***	0.0946***
	(5.327)	(7.116)	(10.896)
Gain*Return	0.000006	-0.0030***	-0.0232***
	(0.468)	(-2.620)	(-5.506)
Loss*Return	0.0002	0.0045***	0.0053***
	(0.040)	(3.080)	(2.914)
Control Variables	Yes	Yes	Yes
Observations	21,443	25,912	19,933
Pseudo R^2	0.02241	0.05060	0.05943

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Column 1 is from data from bull market and the time period is from Jan 1st 2007 to Oct 16th 2007. Column 2 is from bear market condition and the time period is from Oct 17th 2007 to Nov 4th 2008. Column 3 is the steady market condition and the time period is from Nov 5th 2008 to May 31st 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. The dependent variable is a dummy variable equal to one if a stock is sold. 5 dummy rank variables are included to test rank effect. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 7
The Impact of Magnitude of Gain and Loss on Selling by Probit Model

	Dependent Variable: Dummy of Selling the Position
Modeling Method:	Probit
	(1)
Gain	0.0959***
(t-statistics)	(12.174)
Gain*Return	-0.000003
	(-0.038)
Loss*Return	0.0056***
	(5.209)
Root_tradetimes	0.0002
	(0.512)
Gender	-0.0162
	(-1.109)
Root_age	-0.0057
	(-0.814)
New_investor	0.0032
	(0.192)
Bull_mar	-0.0147
	(-1.355)
Bear_mar	0.0194**
	(2.325)
Observations	67,288
Pseudo R^2	0.02689

Note: This table presents the marginal effect from probit regressions. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. The dependent variable is a dummy variable equal to one if a stock is sold. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 8

The Impact of Magnitude of Gain and Loss (Measured by Rate of Return) on Selling

	Dependent Variable: Dummy of Selling the Position
Measurement:	Rate of return
	(1)
Gain	0.0735***
(t-statistics)	(8.772)
Gain*Rate_return	-0.0114
	(-1.103)
Loss*Rate_return	0.2361***
	(9.710)
Root_tradetime	-0.000006
	(-0.013)
Gender	-0.0135
	(-0.977)
Root_age	-0.0039
	(-0.593)
New_investor	0.0026
	(0.165)
Bull_mar	-0.0244**
	(-2.198)
Bear_mar	0.0135
	(1.521)
Observations	67,288
Pseudo R^2	0.03199

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. The dependent variable is a dummy variable equal to one if a stock is sold. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Rate_return is the unit share rate of return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 9
Rank Effect by Probit Model

	Dependent Variable: Dummy of Selling the Position
Modeling Method:	Probit
	(1)
Best	0.1051***
(t-statistics)	(8.619)
2ndbest	0.0660***
	(6.574)
Middle	-0.01116
	(-1.176)
2ndworst	0.0074
	(1.115)
Gain	0.0620***
	(9.054)
Gain*Return	-0.0001
	(-0.695)
Loss*Return	0.0044***
	(4.326)
Control Variables	Yes
Observations	67,288
Pseudo R^2	0.04020

Note: This table presents the marginal effect from probit regressions. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. The dependent variable is a dummy variable equal to one if a stock is sold. 5 dummy rank variables are included to test rank effect. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 10
Rank Effect in All Gain/Loss Portfolios

	Dependent Variable: Dummy of Selling the Position	
Portfolios:	Gain	Loss
	(1)	(2)
Best	0.1374***	0.1227***
(t-statistics)	(5.524)	(7.271)
2ndbest	0.1223***	0.0901***
	(5.496)	(6.014)
Middle	0.0468**	0.0124
	(2.308)	(0.762)
2ndworst	0.0491	0.0047
	(2.413)	(0.342)
Control Variables	Yes	Yes
Observations	3,772	12,814
Pseudo R^2	0.02249	0.02143

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. If the whole portfolio of one investor in one day are gain positions, the data is included in column 1. If the whole portfolio of one investor in one day are loss positions, the data is included in column 2. The dependent variable is a dummy variable equal to one if a stock is sold. 5 dummy rank variables are included to test rank effect. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 11
Rank Effect from Portfolios with No Limit-Down Stocks

	Dependent Variable: Dummy of Selling the Position
Subsample:	No limit-down stocks in portfolio
	(1)
Best	0.1057***
(t-statistics)	(7.611)
2ndbest	0.0695***
	(6.728)
Middle	-0.0086
	(-0.854)
2ndworst	0.0100
	(1.397)
Gain	0.0609***
	(6.973)
Gain*Return	-0.0005
	(-0.146)
Loss*Return	0.0051***
	(4.025)
Control Variables	Yes
Observations	62,987
Pseudo R^2	0.04057

Note: This table presents the marginal effect from logit regression. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. If the whole portfolio of one investor has no limit-down stock, the data is included. The dependent variable is a dummy variable equal to one if a stock is sold. 5 dummy rank variables are included to test rank effect. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 12
Rank Effect Measured by Rate of Return

	Dependent Variable: Dummy of Selling the Position
Subsample:	No limit-down stocks in portfolio
	(1)
Rate_best	0.1215***
(t-statistics)	(10.424)
Rate_2ndbest	0.0923***
	(8.716)
Rate_middle	0.0081
	(0.831)
Rate_2ndworst	0.0235***
	(3.243)
Gain	0.0551***
	(7.817)
Gain*Return	-0.0001
	(-0.146)
Loss*Return	0.0051***
	(4.323)
Control Variables	Yes
Observations	67,758
Pseudo R^2	0.04318

Note: This table presents the marginal effect from logit regression. The data contains daily holding records of 5,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included, and an investor must hold at least five stocks to be included in the model. The dependent variable is a dummy variable equal to one if a stock is sold. 5 dummy rate_rank variables (measured by rate of return instead of return) are included to test rank effect. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the unit share return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. The top number is the marginal effect, and the lower number in parentheses is the t -statistic. Clustered standard error is by investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

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Appendix:

This list contains items in the data given by a brokerage firm from January 2007 to September 2009, which are stored in four sub-datasets. Customer file contains the information of each customer. Account file contains balance information of customer's account on daily basis. Stock file contains information of each stocks held by each customer on daily basis. Transaction file contains each deal's information. All files are linked by Customer Id and Datadate.

ITEM NAME	ITEM EXPALANTION
KEYS	
CUSTOMER ID	Unique series number for each investor
DATADATE	Date of each record
CUSTOMER FILE	
SEX	0 for male and 1 for female
BIRTH	Birthday
CITY	City where the personal id issued
BRANCH	Branch where account was opened and held
CORPORATE IDENTIFIER	0 for individual investor, 1 for corporate investor
NATIONALITY	0 for china, and 1 for other countries
CURRENCY TYPE	0 for RMB, 1 for USD
ACCOUNT FILE	
ACCOUNT OPEN DATE	The first date of account opening
CASH	Cash balance in customer account
STOCK COST	Historical total stock value that customer paid
STOCK VALUE	Current total stock value that customer holds
STOCK VOLUME	Total amount of shares that customer holds
STOCK FILE	
STOCK PRICE(COST)	Historical stock price that customer paid at purchase
STOCK VOLUME	Current number of shares of each stock that customer holds
STOCK VALUE (CURRENT)	Market value of each stock that customer holds
TRANSACTION FILE	
STOCK CODE	Stock code, which is 6-digit used in Chinese stock markets
STOCK PRICE(COST)	Stock price (cost) is the stock price that customer actually paid or sold
STOCK VOLUME	Amount of shares that customer traded, positive value for purchase and negative value for sale
STOCK VALUE(COST)	Stock value (cost) equals stock price (at transaction) times stock volume(cost)
COMMISSION FEE	Commission fees that customer paid to broker. As this data is acquired from one broker, the commission is 0.0033 for all transaction
STAMP DUTY	Stamp duty is tax that customer paid to the government and stock exchange, equals 0.0033 for all deals
PROFIT	Profit is realized gains from a sale, equals the stock value of sale minus historical stock value (cost) of initial purchase.