

Selling the Best: Rank Effect in Chinese Individual Investors

(A preliminary version)

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ABSTRACT:

This paper shows individuals are more likely to sell the top-performance stock in their portfolio than other stocks. We analyze the existence of rank effect in Chinese stock market by applying a dataset of 100,000 individual investors with more than 56 million daily holding records from January 2007 to May 2009. We find that Chinese investors are more likely to sell a position with extreme good (the best) performance, and followed by the 2nd best position, but reluctant to sell the salience of extreme bad portfolio positions, which is different from result in US (sell both the best and the worst). When the investor is aggressive, the market is under recovery period or the holding period of position is short, the decrease in selling relative under-performing positions is moderated. This result leads to three possible mechanisms, investor characteristics and culture feature, market condition and holding strategy. The difference between the two countries can also be attributed to the distribution of investors in the two datasets. This result is robust under different modelling methods, extreme portfolio situation, measurement of rank and limit-down limitation, etc.

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

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This paper shows individuals are more likely to sell the top-performance stock in their portfolio than other stocks. We analyze the existence of rank effect in Chinese stock market by applying a dataset of 100,000 individual investors with more than 56 million daily holding records from January 2007 to May 2009. We find that Chinese investors are more likely to sell a position with extreme good (the best) performance, and followed by the 2nd best position, but reluctant to sell the salience of extreme bad portfolio positions, which is different from result in US (sell both the best and the worst). When the investor is aggressive, the market is under recovery period or the holding period of position is short, the decrease in selling relative bad-performance positions is moderated. This result leads to three possible mechanisms, investor and culture heterogeneity, market condition and holding strategy. The difference between the two countries can also be attributed to the distribution of investors in the two datasets. This result is robust under different modelling methods, extreme portfolio situation, measurement of rank and limit-down limitation, etc.

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1. Introduction

In the study of behavioral finance, although most research successfully explain investors' behavior to some extent, how investors treat their own portfolio, how investors compare positions in their portfolio and how they choose when they want to sell are still questions.

To answer this, Hartzmark (2015) develops these theories and finds 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 considering 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 research 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). And in unshown result, we also find rank effect hurt investor's profit in Chinese market.

However, there is still a lack of empirical evidence of rank effect due to the limited availability of detailed account-level data on trading activities. In this paper, we explore rank effect in Chinese stock market. Based on a very unique and large database, we find a different rank effect exists in Chinese stock market, which is individuals are more likely to sell best and 2nd best performance positions.

Furthermore, to discover the reasons of the difference between US investors (selling both best and worst positions) and Chinese investors (only selling best position), we analyze the

culture difference between US and China. In the literature of culture difference, the most widely discussed topic is that US is the typical individualistic culture while China is the typical collectivistic culture (Zhang and Neelankavil, 1997; Zha, *et al.*, 2010; Jackson and Wang, 2013). Guess (2004) further document that people from individualistic culture are more willing to take risk than people from collectivistic culture when they make decision, which means US investors are more willing to take risk than Chinese investors. Therefore, the preference on selling the worst position in their portfolio from US investors could be attributed to their preference on risk seeking. Since one typical risk seeking behavior of investors is their willing to gamble, we then test if Chinese investors are willing to sell the worst position when they are gambling in the market. We find that when the position is under a gambling situation (short period, low unit price and high volatility), the probability of selling the worst is close to the probability of selling the 2nd best. And when we further limit portfolios from young, male and new investors, investors are willing to sell the worst in China. Young, male and new investors are over-confidence and have less patient to their loss. Investors have less patient to gambling positions as well. When an aggressive investor holds a gambling position and it performs badly, the probability of selling this position is significantly high. Since the US data is dominated by male investors while our data is balanced, the reason could also be the difference on investor distributions.

The second reason for the difference in rank effect between China and US could be the data period of the studies. Hartzmark (2015) applies individual investors data from 1991 to 1996 in the US market. The market was stable at that time. However, the data in this paper is from 2007 to 2009 in Chinese market. The data covers the financial crisis. When we separate the data into bull (before bubble), bear (bubble crushing) and steady recovery (after bubble). We find the in a steady recovery market, investors are more willing to sell the worst position. Since this result is similar to the previous result from the US, we argue that although the best position is always the first selling choice, when the market is stable, individual investors are more willing to sell

the worst position.

The third reason for the difference could be the impact of holding period of the position. Ben-David and Hirshleifer (2012) and Kaustia (2010b) show that the impact of past profit on disposition is closely related to holding period. Therefore, holding period can also play an important role on rank effect. Short-term, midrange and long-term positions may indicate different trading strategies as well. However, Hartzmark (2015) does not discuss this issue. In our study, we find that investors are more willing to sell the worst position when the holding period of the position is short. Holding period can influence rank effect.

In some recent studies, Frydman and Wang (2020) discuss rank effect in Chinese market. However, they only use extreme rank instead of distinguishing best and worst. They find Chinese investors are more likely to sell extreme rank positions. We suggest that this preference is dominated by the preference of selling the best instead of selling the worst, which is the focus of this paper. Barber, et al (2022) document the attention-induced trading of Robinhood Users. As an online trading platform, Robinhood makes trading gamification and simplicity to individuals. The preference on attention grabbing trades on Robinhood is consistent with our result that the preference of US investors on gambling trading is one of the reasons why US investors behave differently to Chinese investors.

The data is collected from a large brokerage firm in China¹. 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 100,000 investors in this paper. The time period of the dataset in this research covers 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 falling in 2008. The changes of the investor emotion and behavior when they face large profits and losses along with risks are interesting

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 our research.

to research. This adds more value to the dataset and this research.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the dataset, data processing and Chinese stock market during this period. Section 4 document the model. Section 5 discusses the main empirical results, while robustness tests are presented in Section 6. Section 7 concludes.

2. Literature Review

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 these biases, disposition effect is one of the most well-known and widely discussed topics. 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 invalidates 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 decline 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; Bian, et al., 2018), 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, an 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 in the short-term positions. They also document that gains or losses are 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 on the gain side, while he finds the probability of selling on the loss side is constant. Since Kaustia (2010b) does not control holding period and Ben-David and Hirshleifer (2012) suggest that V-shape appears in positions with short holding period and it perform differently in long-term positions, the impact of holding period on V-shape disposition is also worth noting. Additionally, 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 here)

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 consider 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 the *Loss*Return* and *Gain*Return*, which indicate the disposition effect, their coefficients 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. In addition, we also discuss rank effect on positions with different holding period and rank effect with investor heterogeneity.

3. Background and the Dataset

3.1 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 Reform² 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 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.

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

(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%. This means the rate of increase and decrease of stock trading price in one day can be no larger than 10%. In Chinese market, the short sale constraint existed until 2010. There are no short-selling records in our data. Furthermore, there is no tax of profit in stock market. Therefore, there is no motivation of tax-selling in China.

3.2 The Database

This paper is based on a very large database collected from a large nationwide brokerage firm in China, with 100,000 accounts and more than 56 million daily dealing records over the period of January 2007 to May 2009³. The dataset is formed with 3 sub-datasets that are customer file, stock file and transaction file. Customer file contains the information of each customer. Stock file contains information about each stock held by each customer on daily basis. Transaction

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

file contains each deal's information. Customer ID, stock ID and date are used to merge all files. We also get the stock price and volatility 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 with the trading amount and price of each trade. There is also a column shows "selling" when the transaction record is a sale. The customer file shows the gender, account open date and birthday. Most of the investors are individual investors and there are no foreign investors. Since all data is based on the end of each trading day, the trading sequence of multiple trades of one investor in one day cannot be observed. Day traders are not included as well.

There are in total 56,561,915 holding records in the stock file from the 100,000 customers. Following the method of Ben-David and Hirshleifer (2012) and Hartzmark (2015), we only consider portfolios on days that investors do sell at least one stock that day (active selling 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. To execute this, we compare the holding amount of one position with the position being held by the same investor in the previous trading day. If the holding amount decreases, we consider that the investor sells this position that day. Also, since the data is based on the shares one investor holds at the end of one trading day, if investor sells all his shares of one stock that day (liquidation), there is no record for him on that day. Therefore, we add these records to our data and mark them by liquidation. After duplication, only positions in which at least one stock is sold (liquidated) are included in our data. There are 7,554,613 observations remaining (roughly 13%).

Since our data also contains some records from September and October 2009, but June, July and August 2009 are missing, we delete records after May 2009. We roughly delete 5% observations. 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 held on the first day and positions with the same investor and same stock with these positions. This drops roughly 8% of all records. We furthermore delete extreme records and mistake records. We drop positions with trading price smaller than 0, number of shares smaller than 100. The initial dataset includes some records from HK market and other markets. We only keep records from Chinese stock market (Shanghai exchange and Shenzhen exchange). There are 42 institutional investors among these 100,000 investors. We only focus on individuals and delete positions held by these investors. There are no foreign investors. Some of the records have a very small number 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. There are also some records that have 0 turnover rate in customer file, we drop them as well. We also delete positions with extreme rate of return (>100 or <-100) and extreme capital gains or losses (>200 or <-200).

When dealing with stock disclosure data, we delete data from the IPO day, trade suspension day and the first day of trading after continuously 20 suspension day. We believe trading in these days is probably abnormal. When matching stock disclosure data with our holding records data, we drop positions on these days (approximately 11%). Since we use the stock price variance over last year to control the volatility⁴, we also delete positions with stock IPO within 50 trading days. This deletes 2% of the data.

When calculating holding period, we match our holding data with transaction data to get the first buying date of every position. However, there are approximately 12% of positions that cannot find their first buying date in transaction data or have their first buying date after the positions record date. This is probably because of some bugs in this data. To discuss this, while we still delete this part of data in our main data in order to calculate holding period, we also

⁴ See more details in Section 4.

employ a robust test that keep this part⁵.

When we delete these positions above, we may delete positions that are sold that day. And if this is the only position that is sold that day in the portfolio, there is no position that is sold in this portfolio remaining in our data and that day is not an active selling day of this investor anymore. Since we only want to keep portfolios that at least one stock is sold (the day is an active selling day of that investor), we check this again and delete roughly 11% observations.

The current price is the stock price at the end of a trading day when the 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 the investor liquidates. Since the stock price in one day does not change 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.

As we are discussing the selling preference, investors need to have at least two positions in their portfolio to be able to choose. Therefore, we include records with at least 2 stocks in one's portfolio. There are 3,881,310 observations and 42,453 investors remaining. Furthermore, in rank effect theory, investors are more likely to sell best-performance stock and worst-performance stock. For similar reason, we follow Hartzmark's (2015) method to keep records with at least 5 stocks in one's portfolio one day. Since investors with a larger portfolio size are thought to be more sophisticated, this process is biased to some extent. After all the cleaning process, there are 2,130,348 records and 18,610 investors remain in our data to analyze rank effect. More details of the data preparation process are shown in table 1 below:

(Insert Table 1 here)

⁵ See more details in Appendix B.

4. The Model

To test the rank effect and top effect in Chinese market during financial crisis, we estimate a similar model as Ben-David and Hirshleifer (2012) and Hartzmark (2015) and is listed below as Equation 1:

$$Sell = Constant + a_1(Rank\ Variables\ or\ Top\ Variables) + a_2(Gain) + a_3(Gain * Return) + a_4(Loss * Return) + a_5(Control\ Variables) + \epsilon \quad (1)$$

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. This controls the disposition effect. *Loss* is the opposite of *Gain*. Including the interaction terms of *Gain (Loss)* and *Return* allows us to control the relationship between the probability of selling and the magnitude of gain and loss separately.

When analyzing rank effect, we add a set of 5 rank variables into the model. we rank the positions in one's portfolio by the unit share return as best, 2nd best, worst, 2nd worst and middle. *Best* is a dummy variable that equals to 1 if the position is in 1st rank in one's portfolio on a particular day. 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* (not ranked in the top or bottom two), it is defined as middle, which has a value of 1

in dummy variable *Middle*. When examining top effect, we employ a set of 2 top variables instead of rank variables. A position is *Top* when it performs the best in one's portfolio, and *Other* otherwise.

For control variables, we also follow the choice of these two papers. The effect due to holding period and volatility are controlled for. To control the days a position is held from purchase to sell, the square root of the holding days (*Root_holding_period*) and interaction terms with gain dummy and return (*Root_holding_period*return*gain*) and loss dummy by return (*Root_holding_period*return*loss*) are included. To control the stock variance, we also calculate the return variance of a stock over the last year (the variance of stock price over preceding 250 trading days, if there are at least 50 non-missing records). We include the interaction term *Variance*gain* and *Variance*loss* in our model.

In addition to the control variables choice in Ben-David and Hirshleifer (2012) and Hartzmark (2015), we further add investor characteristic control variables to control the investor heterogeneity influence. *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 age⁶. 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. *Portfolio_size* is the number of stocks in one's portfolio that day.

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

⁶ We use the date difference between investor's birthday and May 31st 2009, which is the last day of our dataset.

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 3.1). 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 2 here)

In table 2, we present the summary statistics of data we use in our model. After all cleaning, there are total 2,130,348 records (positions). For dummy variable (binomial variable), we present the number of 1. For dependent variable Selling, there are 568,590 positions that are sold by 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. Since our data cover financial crisis, there are more loss positions than gains in our model. The number of gain positions is 779,494. The numbers of positions held by new investors and old investors are balanced. There are 1,117,368 positions held by new investors. Our data is also balance in gender. For numerical variables, due to the financial crisis, the average return is negative, which is -0.08. And the mean of stock variance is 0.86. On average, the square root of days a position is held is 6.81 and the square root of portfolio size is 9.04. The average the square root of age is 6.67. The average the square root of trading times in the data period is 30.33.

5. Main Result

5.1 Empirical Study of Rank Effect

We employ the model in section 3 to examine rank effect in Chinese stock market. For investors, only days that at least one stock is sold are included as sell day (active day). An

investor needs to hold at least 5 stocks to be included as well. The observations are at day-investor-stock level. All results are presented as marginal effects.

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. Following his method, we set *Middle* as benchmark as well. We explore the it into *Worst* and *2nd worst* as well. In our model, we compare the result when *Middle*, *Worst* or *2nd worst* is the benchmark.

(Insert Table 3 here)

Table 3 presents the results of rank effect from the logit model. In column 1, when using *Middle* as benchmark, a best position is 12.92% (t-statistics 33.8272) more likely to be sold than a middle one and a 2nd best position is 5.51% (t-statistics 25.5293) more likely to be sold than a middle one. These are the top 1 and 2 positions to be sold. 2nd worst position is 0.52% (t-statistics -2.4782) less likely to be sold than a middle one. The difference of probability of selling is insignificant between middle positions and worst positions. In column 2, when *Worst* is the benchmark, the results of best and 2nd best positions are similar to they are in column 1. The difference of probability of selling between middle and worst positions is insignificant. The probably of selling a 2nd worst position is significantly smaller then selling worst position. While in column 3, when *2nd worst* is the benchmark, the results of best and 2nd best positions are still constant. The probability of selling a middle position is 0.52% (t-statistics 2.4699) larger than selling a 2nd worst one. And the probability of selling a worst position is 0.74% (t-statistics 3.8345) larger than selling a 2nd worst one. As a conclusion, Chinese investors during financial crisis are more likely to sell a position with better performance (best, 2nd best) and the probability of selling other positions (middle, 2nd worst and worst) do not have a large gap. 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.

At the same time, since in column 3, 2nd worst positions appear to have the smallest probability of selling. We will use 2nd worst positions as benchmark in further results of this paper. Meanwhile, *Gain* is positive and significant in all three columns. This result is constant with previous studies and indicates a strong disposition effect in China. However, by adding rank variables, the sign of *Gain*return* turns is negative while *Loss*return* is insignificant. The V-shape disposition effect is insignificant after including rank variables. This shows the explanatory power of rank variables. Rank effect is at least as strong as disposition effect.

Based on these results, 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 rank of probability of selling in China should be: *Best* >> 2nd *best* >> *worst* >= *middle* >= 2nd *worst*. 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 share the same rank effect with US investors.

In addition, to consider the performance of investors' characteristics control variables, all these variables except *New_investor* is significant. This indicate that the investors' heterogeneity plays an important role in individuals' decision of selling. These variables should be included in this model. Furthermore, since our dataset is large, we do not suffer from a lack of degree of freedom by adding these variables. Adding them benefits to the robustness level of our results.

5.2 Rank Effect under 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, we depart data time period into three parts that represent three market conditions: bull market, bear market and steady market.

(Insert Table 4 here)

Table 4 shows the marginal effect of rank effect in different market conditions. In table 4 column 1, under bull market, individual investors are 11.94% more likely to realize best-ranked positions than 2nd worst-ranked (benchmark in this model) positions. They are also 7.09% more likely to realize 2nd best-ranked positions. The selling probability of middle positions is 1.79% larger than 2nd worst positions. And the probabilities of realizing worst and 2nd worst positions do not appear a significant difference. 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. However, different from bull market, there is no significant difference among 2nd worst and middle positions. And for worst positions, individual investors are 0.94% more likely to sell them than 2nd worst positions. In column 3, after financial crisis, investors in Chinese market are 12.77% more likely to sell best positions and 6.54% more likely to sell 2nd worst positions. They are also more likely to sell middle and worst positions than 2nd worst positions with percentage 0.83% and 1.08% respectively.

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 the same in Chinese market. Chinese investors are more likely to sell best and 2nd best positions while their behavior on other positions are still not clear enough. But in general, they do not discriminate between

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.

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 results support their argument in Chinese market. This result may also be explained by the macroeconomic situation in China from 2007 to 2009. The GDP of China grew on average 10% during this period. This can lead Chinese individual investors to have confidence on their local companies and stocks even if their performance on the stock market is not good.

5.3 Rank Effect by Different Holding Period

Ben-David and Hirshleifer (2012) show that V-shape disposition is closely related to holding period. Therefore, holding period can also play an important role on rank effect. Short-term, midrange and long-term positions may indicate different trading stagey as well. Because of that, we analyze rank effect on different holding period positions. We split our data into three sub-data: holding period from 1 to 20 days, from 21 to 250 days and more than 250 days. We fit the same model on three sub-datasets separately to analyze rank effect in Chinese market for different holding period positions. Due to multicollinearity, wo do not include holding period control variables this time.

(Insert Table 5 here)

In table 5, column 1 shows results of short-term positions (holding period from 1 to 20 days). Individuals are 13.61% more likely to sell a best-ranked position than 2nd worst-ranked position with a very large t-statistics. They are also 5.66% more likely to sell a 2nd best position. The difference between middle positions and 2nd worst positions is not significant. And the

preference of selling worst positions than 2nd worst is relatively small, only 1.56%. Meanwhile, for midrange positions (holding period from 21 to 250 days), in column 2, investors are also more likely to sell best and 2nd best positions. Both the preferences of selling middle and worst positions than 2nd worst positions are smaller than 1% and not significant on 1% level. In column 3, we present results from long-term positions (holding period larger than 250 days). The performance of best and 2nd best positions are similar; both have large preference of selling. The probability of selling middle positions than 2nd worst positions is 2.05%. There is no significantly difference between selling of worst positions and 2nd worst positions.

To sum up, the Chinese choices, best and 2nd best positions, perform constantly strong among all holding period positions. The results of middle, worst and 2nd worst positions are also similar. There is no large difference among these three positions. None of the results has a preference larger than 2.5%. Not as it is for V-shape disposition, rank effect is robust with holding periods of positions. This result can also improve the robustness power of our result on Chinese rank effect.

5.4 Impact of Investor Heterogeneity on Rank Effect

Goetzmann and Massa (2002) and Dhar and Kumar (2002) finds significant heterogeneity in investor beliefs and trading styles. List (2003), Dhar and Zhu (2006) and Feng and Seasholes (2005) discover influence of investor characteristics on disposition effect. In this section, we are going to discuss the impact of investor heterogeneity on rank effect. We do this by introducing interaction term of rank term and characteristics term into our main model.

(Insert table 6 here)

In our model, we apply two measurements of age, a continuous variable square root of age and age groups. In table 6 column 1, we display the first measurement of age as well as other

investor characteristics. Although aged investors are more likely to best positions, we can hardly find strong influence of age on other rank variables. Since gender is 1 for female, female investors have larger probability of selling a best or a 2nd best position than male. Thus, they perform follow rank effect. Comparing with new investors, experienced investors are more likely to sell best, 2nd best and middle positions. They are rank effect traders. Investors with less trading frequency are more likely to behave follow rank effect as well. On the other side, in column 2, while other characteristics stay the same, we use age group to test effect of age. Old investors (age ≥ 55) like to sell best position and do not like sell a worst one. Old investors are rank traders in China.

Since trading follow rank effect causes damage to investor's profit (An, 2017), we treat rank effect as a trading bias together with disposition effect. Combining with results in Chinese market from Feng and Seasholes (2005), female and old investors are more likely to trade follow rank effect as well as disposition effect. We also find that years since one open an account cannot improve their performance on defending rank effect. But trading more helps.

5.5 Gambling, Investor Heterogeneity and Mechanism of the New Rank Effect

Since Chinese investors only sell the best-performance position while US investors sell both the best and the worst position, we want to discover what causes the difference. Based on a data driven logic, we build many different sub-groups to find in what situations investors in China sell both best and worst positions, that consistent to US investors.

(Insert 7 Table Here)

In this table, we examine the situations when Chinese investors also sell worst positions. In column 1, we include positions that is short period (holding days less than 20), low on unit price (unit price less than 30 percental of all stocks price that day) and high on volatility (return

variance of last 250 days above 70 percental of all stocks that day). We find that when position is under these situations, the probability of selling a worst position rather than a 2nd worst one is almost 2%, and it is close to the probability of selling a 2nd best one. Since the criteria of short period (indicate high trading frequency and high turnover rate), low price and high volatility is close to the criteria of gambling stocks (Kumar, 2009 and Liao, Liang and Zhang, 2016) in both US and Chinese market, we define these positions as gambling positions. Furthermore, young, male and new investors are aggressive investors and more likely to gamble in Chinese market (Liao, Liang and Zhang, 2016), we apply these criteria in column 2. However, we find aggressive investors perform similar to the whole population. They are more likely to sell best and 2nd best positions. Furthermore, we combine the criteria in column 1 and column 2 together. In column 3 the probability of selling worst position is greater than the probability of selling 2nd worst. When the position is a gambling position and it is held by an aggressive investor, Chinese investors also sell the worst position, which is the same as US investors.

Young, male and new investors are over-confidence and have less patient to their loss. Investors have less patience in gambling positions as well. When an aggressive investor holds a gambling position and it performs badly, the probability of selling this position is significantly high. Since the previous paper on rank effect is based on Odean's data in US (Hartzmark, 2015) and Odean's data is dominated by male investors, we doubt that rank effect is biased by investors' characteristic.

As a typical collectivistic culture, Chinese people care more on face-losing. It drives them away from realize the under-performing position in their portfolios. There is no capital gain tax in China during our data period. But as Hartzmark (2015) discusses different tax type accounts from US market and find similar results, we do not suggest tax is one of the main reasons of the difference between our results and US market results.

6. Robustness Test

6.1 Rank Effect with Small Size Portfolios

One main limitation of rank effect is that it requires investors to have at least 5 stocks in their portfolio. We enhance it by developing rank effect into top effect that only requires at least 2 stocks. To further test rank effect in small size portfolios, we run a model similar to our main model in three sub-samples, portfolio contains 2, 3 or 4 positions. When portfolio size is 2, we employ Best variable and use Worst as benchmark, this is also the same model as top effect. When portfolio size is 3, we employ Best and Middle variables and use Worst as benchmark. And when portfolio size is 4, we employ Best, 2nd best, Worst variables and use 2nd worst as benchmark, which follow the benchmark choice of rank effect model in our main result.

(Insert table 8 here)

Table 8 present the results of rank effect in small size portfolios. All of the three sub-samples follow our result in rank effect that investors are most likely to sell best position and also like to sell 2nd best position (middle is also 2nd best in a 3 stocks portfolio). Our result is robust in small portfolios.

6.2 Rank Effect by Probit Model

For rank effect, in order to control the influence of modeling methodology, we apply a test similar with our model in rank effect by probit model. Table 10 presents the result from probit model. In Chinese market, a best rank position is 12.65% more likely to be sold than a 2nd worst position (benchmark). A 2nd best position is 5.95% more likely to be sold than a 2nd worst position. With preference smaller than 1%, a middle position is 0.44% more likely to be sold and for worst position, the preference is 0.68%. Chinese individual investors have larger

preference on selling best and 2nd best positions and the preferences on selling middle, worst and 2nd worst positions are very small. 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)

6.3 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. By doing this, we also consider the robustness of the overall performance of the portfolio. In all gain portfolios, all positions in this portfolio at that day are gains. 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.

(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 11.00% (with significant t value 3.732) more likely to sell a best position than a 2nd worst one and 4.78% more likely to sell a 2nd best position. The probabilities of selling middle and worst positions are not larger than selling 2nd worst positions significantly. The differences among middle, 2nd worst and worst positions are not strong. When all positions come to a loss, in column 2, the probabilities of realizing best and 2nd best positions are still significantly larger than the probability of 2nd worst positions. Both of the preferences on selling middle and worst positions rather than 2nd worst positions are smaller than 1%. Our result that Chinese investors are more likely to sell best and

2nd best positions and treat other positions similarly is found in both all gain and all loss portfolios.

Since our result is robust in all gain and all loss portfolios, we suggest that disposition effect cannot explain our result. Furthermore, since when the portfolio is all gain (or loss), the overall portfolio is guaranteed to be a gain (or loss), the portfolio-driven disposition effect (An, et al, 2024) cannot explain our results.

6.4 Rank Effect with Liquidation

In our main model, we test the probabilities of selling of different rank positions. Selling here contains both partial sale and liquidation. Since liquidation can indicate a different strategy rather than selling, we use dummy of liquidation as dependent variable in our model rather than selling in this section.

(Insert table 11 here)

The result of liquidation is shown in table 11. Individuals are 6.77% more likely to liquidate a best position than a 2nd worst one and 2.59% more likely to liquidate a 2nd best one. These results are similar to our main result. The only different is that when it comes to worst position, an investor is more likely to liquidate a worst position as well. However, the preference of liquidating a worst position is no more than half of a 2nd best one and also significantly smaller than a best one. Our main result that investors are more likely to sell best and 2nd best positions than others is generally robust when we use liquidation.

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 $(\text{today's price} - \text{yesterday's price}) / \text{yesterday's price}$ 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 12 here)

If there is a limit-down stock in one portfolio, it can influence the selling choice of the whole portfolio. Therefore, we delete the whole portfolio. In this part, only portfolios without limit-down stocks are included. We employ the same logit model in table 3 using these portfolios. In table 13, when a portfolio has no limit-down position, a best-ranked position is 12.18% more likely to be sold than a 2nd worst one, with a very large t-value (26.191). The probability of selling a 2nd best position is also significantly larger than selling a 2nd worst position. The preferences of selling middle and worst positions than 2nd worst positions are very tiny, smaller than 1%. This result is similar to our result in the rank effect model. Our result is robustness to the policy of limit-down stock.

7. Discussions and Conclusions

In this paper, we test rank effect among individual investors in Chinese stock market before, during and after financial crisis. We further develop rank effect into top effect and discuss in what situation investor sell bad-performance positions. We also support that disposition effect is significant in China.

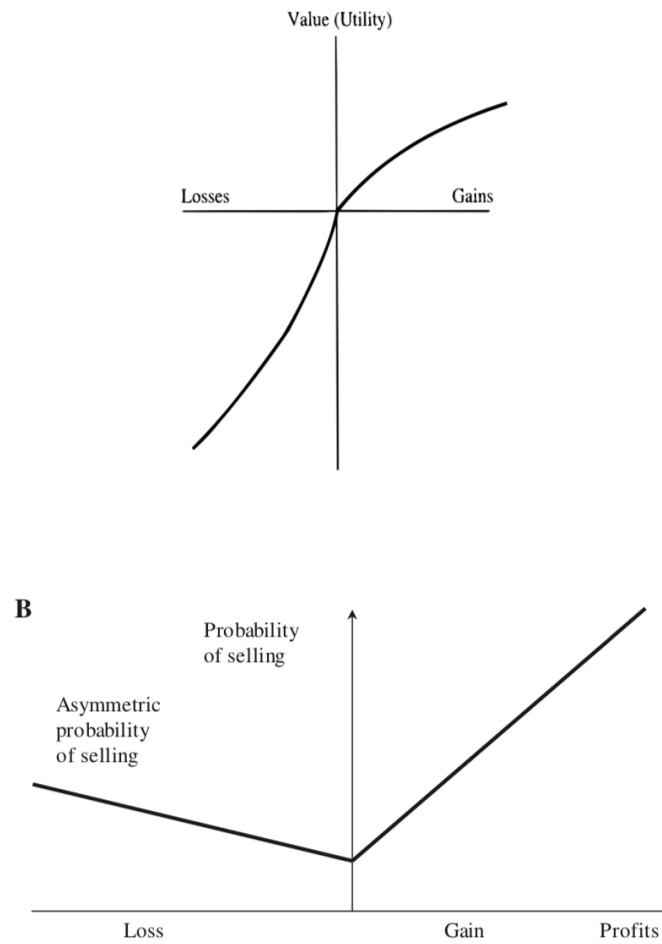
The rank effect in Chinese market is different from US market. The positions with best performance in one's portfolio have the largest probability to be sold. The 2nd best on follows. However, the probabilities of selling middle, 2nd worst and worst positions are not significantly

different. In general, investors want to sell positions with better return. This result is also similar in different market conditions and on different holding period positions. We also document that senior, female investors with long trading experience and less trading frequency are more likely to sell good rank positions.

Since one main limitation of rank effect is that it requires at least 5 stocks in the portfolio, we introduce top effect and significantly improve this number to 2. When there are more than 1 stocks in investors' portfolio which means they can choose when selling, investors have a significant preference of choosing the top one performance position. The top one is choices of selling.

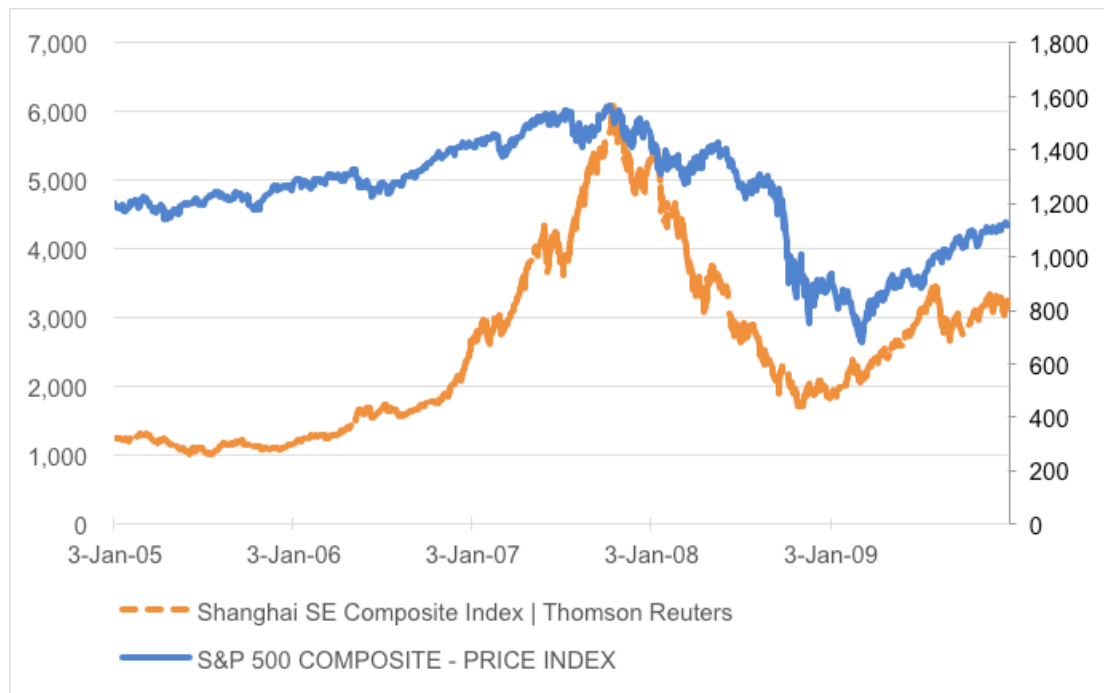
In our study, we try to discover how investor choose which position to sell when they want to sell their stocks. We find investors are more willing to sell positions with better performance, especially the top one position. In further studies, we aim to employ all the models we run on rank effect to test top effect. We will try to find more evidences and reasons of top effect. 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: Data Preparation Process

	Data Preparation Process
Original	56,561,915
(percentage remain)	(100%)
Active selling-day (at least one stock is sold on that day in the portfolio)	7,554,613
	(13.36%)
Date before 2009-06-01	7,140,349
	(94.52%)
Delete positions form the first day	6,565,088
	(91.94%)
Delete trading price smaller or equals to 0	6,271,589
	(95.53%)
Delete number of shares in a position < 100	6,071,948
	(96.82%)
Delete positions not in Shanghai and Shenzhen exchange	6,028,922
	(99.29%)
Delete institutional investors	6,023,504
	(99.91%)
Delete positions with extreme Returns and capital gains or losses	6,023,153
	(99.99%)
Delete positions with inappropriate stock disclosure information	5,352,998
	(88.87%)
Delete investors with 0 turnover rate in customer file	5,352,886
	(approximately 100.00%)
Delete positions which stock variance over last year is null value	5,220,901
	(97.53%)
Delete positions which cannot Calculate holding period	4,597,484
	(88.06%)
Keep active selling-day again	4,065,588
	(88.43%)
Portfolio contains at least 2 stocks (to test top effect)	3,881,310
	(95.47%)
Portfolio contains at least 5 stocks (to test rank effect)	2,130,348
	(54.89%)

Note: This table presents the process of data preparation. The data contains daily holding records of 100,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. The details of each step are described in section 3.2 in this paper. The top number is the number of observations(positions) after executing the particular data cleaning step. The lower number in parentheses is percentage of observations remain after this step.

Table 2: Summary Statistics

Data after Cleaning							
Observation	2,130,348						
Dummy variable	Percentage of value 1						
Selling	26.69%				Bull_mar	17.26%	
Gain	36.59%				Bear_mar	45.32%	
Gender	48.67%				Steady_mar	37.43%	
New_investor	52.45%						
Numerical variable	Average	S.D.	P1	P25	P50	P75	P99
Return	-0.08	0.23	-0.68	-0.15	-0.02	0.02	0.37
Sqrt_holding_period	6.81	6.37	0	2	4.58	10.25	23.81
Variance	0.86	2.74	0.01	0.10	0.23	0.66	9.45
Portfolio_size	9.04	5.51	5	6	7	10	32
Sqrt_tradetimes	30.33	18.61	7.68	17.49	25.32	37.74	98.77
Sqrt_age	6.67	0.87	4.72	6.05	6.65	7.32	8.67

Note: This table presents the summary statistics of variables in our model. The data contains daily holding records of 100,000 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 on which a stock is sold are included. An investor must hold at least five stocks to be included in the data. All variables are defined in section 3.1 in this paper.

Table 3: The Test of Rank Effect

Portfolio size	Dependent Variable: Dummy of Selling the Position							
	5+				2+		5+	
	2nd Worst	2nd Worst	2nd Worst	2nd Worst	Middle	Worst	Others	Others
Benchmark	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Best	0.1314***	0.1195***	0.1288***	0.1169***	0.1234***	0.1247***		
(t-statistics)	(27.28)	(31.98)	(26.66)	(28.73)	(28.36)	(25.38)		
2 nd best	0.0660***	0.0576***	0.0644***	0.0561***	0.0580***	0.0593***		
	(20.60)	(20.31)	(18.56)	(17.58)	(24.69)	(15.78)		
Middle	0.0080***	0.0043*	0.0075***	0.0039		0.0013		
	(3.90)	(1.91)	(3.16)	(1.61)		(0.41)		
2 nd worst					-0.0080***	-0.0066***		
					(-3.90)	(-3.15)		
Worst	0.0066***	0.0094***	0.0066***	0.0092***	-0.0013			
	(3.15)	(4.91)	(2.68)	(4.12)	(-0.41)			
Top							0.1343***	0.1046***
							(39.16)	(28.68)
Gain	0.0774***	0.0870***	0.0766***	0.0857***	0.0774***	0.0774***	0.0827***	0.0903***
	(14.01)	(18.52)	(12.91)	(17.79)	(14.01)	(14.01)	(13.66)	(15.73)
Gain*return	-0.0027*	-0.0017	-0.0044**	-0.0036*	-0.0027*	-0.0027*	0.0056***	-0.0013
	(-1.65)	(-1.06)	(-2.09)	(-1.88)	(-1.65)	(-1.65)	(3.34)	(-0.80)
Loss*return	-0.0020	0.0056***	0.0015	0.0077***	-0.0020	-0.0020	-0.0062**	0.0010
	(-0.07)	(4.64)	(0.50)	(6.03)	(-0.07)	(-0.07)	(-2.39)	(0.37)
Day Fixed	No	Yes	No	Yes	No	No	No	No
Stock Fixed	No	No	Yes	Yes	No	No	No	No
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,130,348	2,098,285	2,130,348	2,098,285	2,130,348	2,130,348	3,881,306	2,130,348
Pseudo R ²	0.0587	0.0681	0.0617	0.0718	0.0587	0.0587	0.0759	0.0567

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Column 1-4 test the rank effect with different fixed effects. Column 4-6 test the rank effect with different benchmarks. Column 7 and 8 explore the rank effect to involve more portfolios with smaller size. 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 return rate of a single position since purchase. Other variables are control variables and are defined in section 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 4: Rank Effect in Different Market Conditions

Portfolio Size Market Period	Dependent Variable: Dummy of Selling the Position					
	5+			2+		
	Bull	Bear	Steady	Bull	Bear	Steady
	(1)	(2)	(3)	(4)	(5)	(6)
Best	0.1205***	0.1397***	0.1331***			
(t-statistics)	(18.71)	(17.45)	(30.10)			
2 nd best	0.0688***	0.0620***	0.0739***			
	(13.36)	(11.95)	(20.61)			
Middle	0.0149***	0.0019	0.0130***			
	(3.19)	(0.65)	(4.58)			
Worst	0.0092**	0.0052**	0.0100***			
	(2.27)	(2.02)	(3.32)			
Top				0.1295***	0.1418***	0.1303***
				(21.94)	(25.43)	(28.15)
Gain	0.0734***	0.0686***	0.0801***	0.0793***	0.0714***	0.0880***
	(12.21)	(6.16)	(12.27)	(10.83)	(6.29)	(9.56)
Gain*return	-0.0014	-0.0010	-0.0061**	0.0037**	0.0081**	0.0115***
	(-0.80)	(-0.29)	(-2.04)	(2.00)	(2.13)	(3.73)
Loss*return	-0.0080*	-0.0013	0.0140***	-0.0235***	-0.0083**	0.0033*
	(-1.65)	(-0.33)	(6.34)	(-4.21)	(-2.09)	(1.73)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	367,633	965,387	797,328	728,197	1,720,871	1,432,238
Pseudo R ²	0.0356	0.0504	0.0852	0.0610	0.0742	0.0929

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Column 1 is the test of rank effect using middle positions as benchmark. Column 2 uses worst positions as benchmark. Column 3 uses 2nd worst positions as benchmark. 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 section 3.1 in this paper. All control variables except market condition variables (bull_market, bear_market) are included. 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 5: Rank Effect by Different Holding Period

Portfolio Size Holding Period (day)	Dependent Variable: Dummy of Selling the Position					
	5+			2+		
	1-20	21-250	250+	1-20	21-250	250+
	(1)	(2)	(3)	(4)	(5)	(6)
Best	0.1320***	0.1411***	0.1245***			
(t-statistics)	(23.24)	(21.90)	(15.19)			
2 nd best	0.0580***	0.0744***	0.0872***			
	(11.95)	(15.37)	(14.37)			
Middle	-0.0008	0.0096***	0.0260***			
	(-0.22)	(4.06)	(7.16)			
Worst	0.0191***	0.0027*	-			
	(5.72)	(1.32)	(-2.72)			
Top				0.1295***	0.1566***	0.1380***
				(29.48)	(41.43)	(26.31)
Gain	0.0872***	0.0664***	0.0376***	0.0820***	0.0711***	0.0494***
	(13.03)	(5.28)	(4.29)	(10.93)	(5.35)	(5.15)
Gain*return	-	-	-	0.0027*	0.0121***	-
	0.0066***	0.0112***	0.0125***	(1.30)	(-12.67)	(-8.94)
	(-3.54)	(-11.83)	(-6.50)			
Loss*return	0.0040**	0.0060***	0.0031***	-0.0053***	0.0068***	0.0047***
	(2.42)	(7.07)	(4.29)	(-3.82)	(7.51)	(6.08)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,052,893	803,870	273,585	2,190,293	1,310,578	380,435
Pseudo R ²	0.0359	0.0522	0.0725	0.0469	0.0908	0.1093

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Column 1 is from positions that their holding period is less than 20 days. Column 2 is from positions with holding period 21-250 days. Column 3 is from positions that had been held for more than 250 days. 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 section 3.1 in this paper. All control variables except holding period variables (root_holding_period, root_holding_period*return*gain, root_holding_period*return*loss) are included. 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 and Investor Characteristics

	Dependent Variable: Dummy of Selling the Position	
	Continuous age	Age group
	(1)	(2)
Best	0.1337***	0.2096***
(t-statistics)	(6.7547)	(18.8585)
2 nd best	0.0563***	0.0859***
	(3.7228)	(11.3848)
Middle	0.0142	-0.0033
	(1.2953)	(-0.6279)
Worst	0.0334***	-0.0042
	(2.7184)	(-0.8083)
Gain	0.0872***	0.0872***
	(17.6649)	(17.6642)
Gain*return	-0.0035**	-0.0036**
	(-2.0299)	(-2.0465)
Loss*return	-0.0001	-0.0001
	(-0.0457)	(-0.0440)
Best*root_age	0.0083***	
	(3.3344)	
2 nd best*root_age	0.0035*	
	(1.7299)	
Middle*root_age	-0.0014	
	(-0.8351)	
Worst*root_age	-0.0041**	
	(-2.5194)	
Best*young		-0.0159***
(age<35)		(-2.8671)
2 nd best*young		0.0066
(age<35)		(-1.3256)
Middle*young		0.0101*
(age<35)		(1.8679)
Worst*young		0.0168***
(age<35)		(2.7254)
Best*middle-age		-0.0075*
(35<= age<55)		(-1.9162)
2 nd best*middle-age		-0.0035
(35<= age<55)		(-1.0082)
Middle*middle-age		0.0102***

Table 7 (Continued)	(1)	(2)
(35<= age<55)		(2.6155)
Worst*middle-age		0.0102**
(35<= age<55)		(2.0566)
Best*gender	0.0292***	0.0293***
	(6.9775)	(6.9803)
2 nd best*gender	0.0192***	0.0192***
	(5.6920)	(5.6907)
Middle*gender	0.0042*	0.0044*
	(1.6707)	(1.7819)
Worst*gender	-0.0031	-0.0031
	(-1.2063)	(-1.1953)
Best*new_investor	-0.0281***	-0.0297***
	(-6.6580)	(-7.0213)
2 nd best*new_investor	-0.0234***	-0.0241***
	(-6.3741)	(-6.5712)
Middle*new_investor	-0.0105***	-0.0113***
	(-3.6177)	(-3.8356)
Worst*new_investor	0.0029	0.0023
	(1.0193)	(0.7922)
Best*root_trade_times	-0.0018***	-0.0018***
	(-7.4812)	(-7.5189)
2 nd best*root_trade_times	-0.0005***	-0.0005***
	(-2.8404)	(-2.8352)
Middle*root_trade_times	0.0001	0.0001
	(0.9667)	(1.1206)
Worst*root_trade_times	0.0000	0.0000
	(0.4878)	(0.0658)
Root_age	-0.0104***	-0.0086***
	(-5.9640)	(-5.4330)
Gender	-0.0175***	-0.0176***
	(-5.2383)	(-5.2418)
New_investor	0.0257***	0.0266**
	(4.8767)	(4.9075)
Root_trade_times	0.0020***	0.0020***
	(4.6741)	(4.6744)
Control Variables	Yes	Yes
Observations	2,130,354	2,130,354
Pseudo R ²	0.0586	0.0586

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of

100,000 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. We employ a continuous variable the square root of age to measure age in column 1. We use age group 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 section 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 date and investor. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Table 7: Rank Effect with Gambling Positions and Aggressive Investors

	Dependent Variable: Dummy of Selling the Position		
	Gambling Positions	Aggressive Investors	Gambling Positions & Aggressive Investors
	(1)	(2)	(2)
Best	0.0900***	0.1277***	0.1461**
(t-statistics)	(3.8176)	(15.9853)	(2.2086)
2 nd best	0.0260	0.0559***	0.0728
	(1.2768)	(9.1048)	(1.1526)
Middle	-0.0232	0.0017	0.0676
	(-1.3479)	(0.4291)	(1.2468)
Worst	0.0191	0.0180***	0.1154
	(0.7499)	(3.6865)	(1.6227)
Gain	0.1292***	0.0796***	0.0694
	(5.1520)	(11.2871)	(0.7418)
Control variables	Yes	Yes	Yes
Observations	7,145	196,225	853
Pseudo R ²	0.0732	0.0441	0.0741

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. A portfolio needs to have at least 2 positions to be included. If a position is short period (holding days less than 20), low on unit price (unit price less than 30 percental of all stocks price that day) and high on volatility (return variance of last 250 days above 70 percental of all stocks that day), it is defined as a gambling position and is included in column 1. In column 2, we only include aggressive traders (<35, male and new investor). In column 3, based on requirements in column 1 and 2, we combine them together. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included. The dependent variable is a dummy variable equal to one if a stock is sold. Rank variables are dummy variables equal to 1 if the position is that particular rank in the portfolio. Gain is a dummy variable indicating a positive return. Other variables are control variables and are defined in section 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: Rank Effect with Small Size Portfolios

Portfolio Size:	Dependent Variable: Dummy of Selling the Position		
	2	3	4
	(1)	(2)	(3)
Best	0.1305***	0.1524***	0.1339***
(t-statistics)	(23.346)	(30.220)	(30.142)
2 nd best			0.0429***
			(16.694)
Middle		0.0466***	
		(16.035)	
Worst			-0.0196***
			(-6.941)
Gain	0.0799***	0.0813***	0.0850***
	(11.767)	(12.510)	(13.270)
Gain*return	0.0383***	0.0147***	0.0055***
	(10.934)	(6.630)	(2.660)
Loss*return	-0.0267***	-0.0162****	-0.0107***
	(-9.237)	(-5.165)	(-3.528)
Control variables	Yes	Yes	Yes
Observations	526,458	635,012	589,494
Pseudo R ²	0.0394	0.0277	0.0282

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. If a portfolio contains 2 stocks, it is included in column 1. If a portfolio contains 3 stocks, it is included in column 2. If a portfolio contains 4 stocks, it is included in column 3. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included. The dependent variable is a dummy variable equal to one if a stock is sold. Rank dummy 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 section 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	
	(1)
Best	0.1265***
(t-statistics)	(31.602)
2 nd best	0.0595***
	(19.539)
Middle	0.0044**
	(2.539)
Worst	0.0068***
	(4.152)
Gain	0.0846***
	(18.749)
Gain*return	-0.0052***
	(-3.349)
Loss*return	0.0010
	(0.474)
Control variables	Yes
Observations	2,130,354
Pseudo R ²	0.0575

Note: This table presents the marginal effect from probit regressions. The data contains daily holding records of 100,000 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 section 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

Portfolios:	Dependent Variable: Dummy of Selling the Position	
	All gain	All loss
	(1)	(2)
Best	0.1100***	0.1142***
(t-statistics)	(3.732)	(31.757)
2 nd best	0.0478***	0.0555***
	(3.543)	(17.997)
Middle	0.0094	0.0083***
	(0.838)	(3.624)
Worst	-0.0096	-0.0024
	(-1.147)	(-0.887)
Return	0.0034	0.0003
	(0.619)	(0.201)
Control Variables	Yes	Yes
Observations	78,302	378,843
Pseudo R ²	0.0239	0.0447

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 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. Return is the unit share return since purchase. Other variables are control variables and are defined in section 3.1 in this paper. Control variables in this table includes root_holding_period, root_holding_period*return, stock variance, market condition variables and demographic variables. 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 Examining Liquidation Rather than Selling

	Dependent Variable: Dummy of Liquidation
	(1)
Best	0.0677***
(t-statistics)	(13.361)
2 nd best	0.0259***
	(7.050)
Middle	-0.0032
	(-1.635)
Worst	0.0097***
	(4.843)
Gain	0.0588***
	(13.661)
Gain*return	-0.0090***
	(-4.632)
Loss*return	0.0029
	(0.946)
Control variables	Yes
Observations	2,130,354
Pseudo R ²	0.0696

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 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 liquidated. 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 section 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 from Portfolios without Limit-Down Stocks

Dependent Variable: Dummy of Selling the Position	
	(1)
Best	0.1218***
(t-statistics)	(26.191)
2 nd best	0.0580***
	(16.709)
Middle	0.0055***
	(2.795)
Worst	0.0077***
	(3.972)
Gain	0.0817***
	(17.545)
Gain*return	-0.0050***
	(-3.085)
Loss*return	-0.0012
	(-0.384)
Control variables	Yes
Observations	2,011,191
Pseudo R ²	0.0562

Note: This table presents the marginal effect from logit regression. The data contains daily holding records of 100,000 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 section 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 date. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

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Appendix A: Empirical Results of the Impact of Magnitude of Gain and Loss (V-shape Disposition)

We calculate the marginal effect of a model similar to our main model to get empirical results of the impact of magnitude of gain and loss (V-shape disposition) in Chinese market. Since the observations are related to each other, we apply the clustered standard error of investor and date instead of the simple standard error.

(Insert Appendix A Table here)

Appendix A table presents the marginal effect of a logit regression model to examine the impact of magnitude of gain and loss on selling. A position is 12.51% more likely to be sold if it is a gain with a very large t-statistics value. It confirms the disposition effect in Chinese stock market. Since the marginal effect of Gain*Return is in positive sign and significant, the increase of magnitude of gain leads to an increase probability of selling in Chinese market, which is similar to the US market (Ben-David and Hirshleifer, 2012). The marginal effect of Loss*Return is negative and insignificant. Since all of the Loss*Return terms should be nonpositive, this means that in loss case, the probability of selling is insignificantly increasing when the magnitude of loss is large. The probability of selling a loss position is relatively constant. It is different with the result of Ben-David and Hirshleifer (2012) in US market. The V-shape disposition is only suitable on the gain side in Chinese market from 2007 to 2009.

This result is similar to Kaustia (2010b)'s result from Finnish market that the probability of selling is approximately constant over a wide range of losses and increasing over a wide range of gains. Furthermore, we add the sources of the disposition effect and test whether it reflects realization preference in our model. When comparing with the result in Bian, et al. (2018), that the probability of selling is constant both on gain and loss side, our model introduces more control variables.

Appendix A Table: The Impact of Magnitude of Gain and Loss on Selling

	Dependent Variable: Dummy of Selling the Position
	(1)
Gain	0.1251***
(t-statistics)	(19.6698)
Gain*return	0.0154***
	(8.1766)
Loss*return	-0.0042
	(-1.5897)
Root_holding_period	0.0019
	(1.4763)
Root_holding_period	-0.0022***
*return*gain	(-11.7796)
Root_holding_period	0.0011***
*return*loss	(4.1766)
Variance*gain	-0.0020***
	(-4.3430)
Variance*loss	0.0030***
	(8.8587)
Portfolio_size	-0.0371***
	(-26.8021)
Bull_market	-0.0145***
	(-3.9052)
Bear_market	0.0270
	(1.0482)
Root_trade_times	0.0016***
	(3.3342)
Gender	-0.0102***
	(-4.4628)
Root_age	-0.0102***
	(-7.8144)
New_investor	0.0052
	(1.4007)
Observations	4,065,596
Pseudo R ²	0.0863

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 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. 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 price return since purchase. Other variables are control variables and are defined in section 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 by date and investor. The first column shows the results with all variables. The second column shows the results without holding period. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Appendix B: The Robust Test of Deleting Data that cannot Calculate Holding Period

In section 3.2, we document that when calculating holding period, there are 12% data cannot calculate holding period. In this chapter, we discuss the robustness of deleting these 12% observations. We run a model that is similar to our model in appendix A but it does not contain holding period variables. We fit the model with our main data (deleting these 12%) and the data keep this 12% observations separately.

(Insert Appendix B Table here)

As shown in appendix table B, in column 1, it is result from our main data, and in column 2, it is from data with these 12%. The results from these two datasets are very similar. They both have large positive and significant coefficient on *Gain*. At the same time, they also both have negative and significant on *Gain*return* and positive and significant on *Loss*return*. These results demonstrate that the deleting of these 12% data does not influence our result.

Appendix B Table: The Robust Test of Deleting Data that cannot Calculate Holding Period

Data:	Dependent Variable: Dummy of Selling the Position	
	Data used in our model	Keep data that cannot calculate holding period
	(1)	(2)
Gain	0.1201***	0.1210***
(t-statistics)	(18.187)	(19.169)
Gain*return	-0.0019**	-0.0030***
	(-2.286)	(-4.418)
Loss*return	0.0092***	0.0074***
	(19.845)	(16.927)
Control Variables	Yes	Yes
Observations	4,065,596	4,622,237
Pseudo R ²	0.0851	0.0861

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 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. Column 1 uses data we use in our model (around 10% of data that their holding period cannot be calculated correctly). Column 2 uses data that include this 10% data. 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 price return since purchase. Other variables are control variables and are defined in part 3.1 in this paper. All control variables except holding period variables (root_holding_period, root_holding_period*return*gain, root_holding_period*return*loss) are included. The top number is the marginal effect, and the lower number in parentheses is the t-statistic. Clustered standard error is applied by date. The first column shows the results with all variables. The second column shows the results without holding period. ***, **, * indicate statistical significance at the 1% level, 5% level and 10% level respectively.

Appendix C: The Univariate T-test Result of Rank Effect

By a similar method with Hartzmark (2015), we run a similar t-test to test the rank effect based on a random sample of 5,000 investors. 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. 2nd best, worst and 2nd 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. *2nd Best%*, *Middle%*, *2nd 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 Appendix C Table here)

In Appendix C table, we present the result. 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 2nd best position, with a very large t-statistics. In a similar way, a 2nd best position is more likely to be sold than a middle one, a middle position is more likely to be sold than a 2nd 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 2nd best is 7.05%

and the difference between 2nd 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, 2nd worst and worst become insignificant. The best stock is the one that is most likely to be sold by Chinese investors, and the 2nd best stock follows. The rest stocks, middle, 2nd 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.

Appendix C Table: The Univariate Test of Rank Effect

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

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.

Appendix D: The Statistics of Dataset

Table 1: The Summary Statistics of Dataset

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.

Table 2: Summary of Customer Profiles

This table provides the summary of customers' information given by a big brokerage firm from January 2007 to September 2009. The total number of customers is 3.667 million. Number and percentage of all traders are reported for customers' sex, nationality, age, and years of trading. Age and years of trading are based on 15th November 2009. Years of trading are the number of years since the first day account is opened.

Number of Customer: 3,667,274				
Sex	Male	Female	Missing	
Number	1,953,438	1,662,570	51,266	
Percent	53.3%	45.3%	1.4%	
Nationality	Chinese	Other Countries		
Number	3,471,849	195,425		
Percent	94.7%	5.3%		
Age	<=25	26~35	36~45	
number	227,012	836,091	1,083,845	
percent	6.2%	22.8%	29.6%	
	46~55	56~65	>65	Missing
number	803,440	413,129	236,087	67,670
percent	21.9%	11.3%	6.4%	1.8%
Years of trading	0~3	4~7	8~11	>=12
number	1,778,986	237,667	786,819	611,102
percent	48.4%	6.5%	21.4%	16.6%

Appendix E: 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, which equals to (current price per share – purchase price per share) / purchase price per share. This measurement is commonly used in stock analysis.

(Insert Appendix E Table here)

When using rate of return as the measurement of rank, in table 13, we find that the result is robust to our main result. Best rank stock has the largest probability to be sold, which is 12.18% more likely than 2nd worst with t-value 26.191. 2nd best stock follows with a 5.80% more likely to be sold than worst stock and also large t-value. The preferences of selling middle and worst positions than 2nd worst positions are very tiny, smaller than 1%. This indicates that our result is robust when we change the measurement of rank from return to rate of return.

Appendix E Table: Rank Effect Measured by Rate of Return

Dependent Variable: Dummy of Selling the Position	
	(1)
Rate_best	0.1313***
(t-statistics)	(33.141)
Rate_2 nd best	0.0660***
	(22.046)
Rate_middle	0.0080***
	(4.424)
Rate_worst	0.0066***
	(3.463)
Gain	0.0774***
	(17.392)
Gain*return	-0.0027*
	(-1.807)
Loss*return	-0.0002
	(-0.076)
Control variables	Yes
Observations	2,130.354
Pseudo R ²	0.0587

Note: This table presents the marginal effect from logit regression. The data contains daily holding records of 100,000 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 section 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.

Appendix F: Developing Rank Effect into Top Effect

Due to the result of rank effect in China, best-performance position has the largest probability of being sold. Rank effect requires a portfolio to at least have 5 positions, but a portfolio needs only at least 2 positions to have a best-performance position. Therefore, the question raises: when the condition expands and becomes at least 2 positions in a portfolio instead of 5, do the result of the best (top) performance have the largest probability of being sold still exist? To explore this question, we employ portfolios with at least 2 stocks and name a dummy variable Top (equals to 1 when the position has the largest unit share return in the portfolio) into our model. In this case, we are using positions that do not have the largest unit share return as benchmark.

(Insert Appendix F Table Here)

Appendix F table presents the marginal effect of logit regression. In column 1, the portfolio size is larger or equal to 2. Individual investors are 13.53% more likely to sell a position when it is a top (best) performance one. And they are 9.00% more likely to sell a gain position as well. If the portfolio has at least 5 stocks, it is included in column 2, this is also the condition of rank effect. In column 2, investors are still more likely to sell top stock and gain stocks. These results indicate that no matter the portfolio size, our result that individual investors are more likely to sell the top 1 performance stock in their portfolio always exist. Disposition effect is strong in China as well.

These results show the choice of individual investors when they want to sell a position is the top 1 performance stock. We name this preference of investors the top effect. Due to the comparison of marginal effects of top effect and disposition effect, we can say in general, top effect is strong among Chinese investors and it is at least as strong as disposition effect.

Appendix F Table: The Examine of Top Effect

Portfolio size:	Dependent Variable: Dummy of Selling the Position	
	2+	5+
	(1)	(2)
Top	0.1353***	0.1083***
(t-statistics)	(35.3203)	(32.4736)
Gain	0.0900***	0.0980***
	(15.5655)	(19.1316)
Gain*return	0.0040**	-0.0030*
	(2.4118)	(-1.7687)
Loss*return	-0.0063**	0.0010
	(-2.3354)	(0.3658)
Control variables	Yes	Yes
Observations	3,881,318	2,130,354
Pseudo R ²	0.0747	0.0560

Note: This table presents the marginal effect from logit regressions. The data contains daily holding records of 100,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. If the portfolio size of an investor is larger or equal to 2, it is included in column 1. If the portfolio size of an investor is larger or equal to 5, it is included in column 2. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included. The dependent variable is a dummy variable equal to one if a stock is sold. If the position has the largest unit share return in the portfolio, the dummy variable top takes value of 1. Otherwise, it is classified into other and is applied as benchmark here. 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 section 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.

Appendix G: Robust Test of Fixed Effect

To further control the time and market condition, we apply fixed effect to rank effect and top effect. Due to the size of our dataset and computation capability, we only discuss day fixed effect here. Our result is robust after controlling for day fixed effect.

(Insert Appendix G Table here)

Appendix G Table: Rank Effect and Top Effect by Fixed Effect

	Dependent Variable: Dummy of Selling the Position	
	Rank Effect	Top Effect
	(1)	(2)
Best	0.1200***	
(t-statistics)	(28.5009)	
2 nd best	0.0506***	
	(16.5505)	
Middle	0.0009	
	(0.4339)	
Worst	0.0110***	
	(6.3896)	
Top		0.1253***
		(37.8873)
Gain	0.0979***	0.1032**
	(20.7448)	(18.1111)
Control variables	Yes	Yes
Day FE	Yes	Yes
Observations	2,098,291	3,809,888
Pseudo R ²	0.0670	0.0814

Note: This table presents the marginal effect from logit regressions controlled by day fixed effect. The data contains daily holding records of 100,000 investors from a large nationwide brokerage in the period from January 2007 to May 2009. Column 1 examines rank effect. Column 2 examines top effect. Each position is an observation which is at investor-stock-day level. Only days in which a stock is sold are included. If the position has the largest unit share return in the portfolio, the dummy variable top takes value of 1. 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 section 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.