Before and After: The Impact of a Real Bubble Crash on Investors' Trading Behavior in the Lab†

Pan Deng[a]
School of Economics, Fudan University, China

Binglin Gong[b]
School of Management, Fudan University, China

Vivian Lei[c]
Department of Economics, University of Wisconsin-Milwaukee, USA

Abstract

We report the results of an experiment designed to study whether or not having experienced booms and crashes in naturally occurring asset markets affects subjects' trading behavior in the lab. Active investors in the Shanghai Stock Exchange were recruited to participate in either the Boom treatment, conducted in June 2007 after the Shanghai Stock Exchange had had a bull market for almost two years, or the Crash treatment, conducted in August 2008 after the SSE Composite Index had plummeted almost 60 percent from its high reached in October 2007. We find that, compared to those in the Crash treatment, subjects in the Boom treatment were much more active when participating in our experimental asset markets in that they preferred to make bigger trades and hold more shares than cash. These behavioral differences cannot be explained by the overconfidence hypothesis.

JEL classification: C91, C93, G01, G11
Keywords: Experiment, asset market, experience.

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†Binglin Gong thanks the Shanghai Education Development Foundation for research support under grant 2007CG018. We are particularly grateful to the School of Economics and Finance at Shanghai Jiaotong University for providing its economics laboratory.

[a] School of Economics, Fudan University, Shanghai 200433, China; e-mail: pandeng@fudan.edu.cn.
[b] Corresponding author. School of Management, Fudan University, Shanghai 200433, China; phone: 86-21-25011080; fax: 86-21-65642411; and e-mail: blgong@fudan.edu.cn.
[c] Department of Economics, University of Wisconsin-Milwaukee, Bolton Hall 818, Milwaukee, WI53211; e-mail: vlei@uwm.edu.

1. Introduction

When making decisions, individuals tend to make quick inferences that relate the current situation with similar experiences which occurred in the past. These conscious or even subconscious recalls and evaluations not only are disproportionately influenced by peaks and ends of historical events, but also tend to trigger emotions that turn out to play crucial roles in the decision making process (see, for example, Forgas (1995), Fredrickson (2000), Isen (2000), Loewenstein et al. (2001), Nagel and Malmendier (2011), Schwarz (1990), and Zajonc (1980)).

Recognizing the psychological influence of dramatic historical moments on decision making, this paper investigates whether or not experiencing a market boom vs. a market crash occurred in the naturally occurring world would have different spillover effects on subjects' laboratory trading behavior. Note that there have been a few studies that investigate the behavior of professional traders in controlled laboratory settings (see, for example, Alevy et al. (2007), Haigh and List (2005, 2010), Smith et al. (1988)). Our paper differs from these studies in that we had a unique opportunity to recruit subjects who not only had trading experience from a naturally occurring market but, more importantly, had encountered dramatically different episodes—a market boom vs. a market crash—before they came participate in our study. By doing so, we were able to address the following research question: compared to those who have recently experienced a market boom in the field, do investors who have experienced a market crash trade more conservatively in the lab? We adopted a between-subject design and recruited investors who had been actively participating in the Shanghai Stock Exchange to participate in our laboratory experiment. We conducted our first treatment, called Boom, in June 2007 after the Shanghai Stock Exchange had had a bull market for almost two years. The

second treatment, called Crash, was conducted in August 2008 after the SSE Composite Index had plummeted almost 60 percent from its high. To create similar boom-and-crash market conditions in our laboratory asset markets, we introduced price patterns that were constructed using the weekly data from the Nasdaq and Taiwan Stock Exchanges. Subjects, taking the price information as given, had to decide when and how much (in blocks of 100 shares) they would like to buy or to sell. Finally, a lottery-choice test and an exit survey were conducted at the end of the experiment to elicit subjects' general risk preferences and information such as trading experience in the Shanghai stock market and self-assessment on their relative performance in the experiment.

Based on Nagel and Malmendier (2011) who utilize the data from the Survey of Consumer Finances between 1964 and 2004 and find that birth-cohorts that have experienced high stock market returns report lower risk aversion and have a tendency to invest a higher fraction of liquid wealth in stocks later in their life, we hypothesize that our subjects would behave in the same way in the lab. In other words, not only we expect that field experience would transcend beyond the boundary of naturally occurring markets but, more importantly, we expect that those who have encountered a more depressed market in the field would be less willing to take financial risk even in a laboratory setting that has comparatively less stakes involved.

Several measures are employed to investigate subjects' trading behavior. The first measure is based on decisions made in a lottery-choice task similar to Holt and Laury (2002). The second measure is the number of trades executed in the laboratory asset markets. The third measure concerns the size of an average trade. For this measure, we look at the number of

blocks per trade (the absolute size of trade) as well as the percentage of cash used to purchase shares or the percentage of shares sold to obtain cash in one single transaction (the relative size of trade). The fourth measure is the proportion of liquid assets in the form of cash. As a robustness check, we also investigate the percentage of time a given individual holds more than 80% of his liquid assets in shares. Except the first one, all other measures are comparable with most of the risk-taking measures adopted in Nagel and Malmendier (2011).[1]

Results reported in Section 3 support our hypothesis. We find evidence indicating that, after demographic characteristics and years of trading experience in the Shanghai Stock Exchange are being controlled for, subjects in the Crash treatment are more risk averse in the lottery-choice task. Although we don't find them making less trades than those in the Boom treatment, we do find that they have a tendency to make smaller trades, hold a larger proportion of liquid assets in cash, and spend less time holding more than 80% of liquid assets in stocks.

A further data investigation suggests that the above behavioral differences are mainly driven by the behavior of those who can be categorized, ex post, as overconfident or unbiased traders. This result seems to be inconsistent with the finding by Odean (1999) and Barber and Odean (2000) that overconfident traders, defined as those who systematically overestimate the precision of their information and therefore have unrealistic beliefs about their expected trading profits, tend to trade too much. Yet, we argue that, since overconfident traders in our study are defined as those who overestimate their performance ranking in the exit survey, the result that overconfident traders in the Crash treatment tend to trade more conservatively may

[1]Nagel and Malmendier (2011) adopt the following four measures of risk-taking: (1) responses to a survey question about individuals' willingness to take financial risk, (2) stock market participation, (3) the proportion of liquid assets invested in stocks or mutual funds, and (4) the proportion of liquidity assets other than stock that are invested in bonds.

have more to do with a belief formed based on their field experience that such a trading approach would help reduce their exposure to risks and thus generate more wealth than an average person. While our data do not suggest that the overconfident/unbiased traders in the Crash treatment accumulate significantly more wealth than their underconfident counterparts, they do indicate that, in market N, these traders accumulate more wealth than the same type of traders in the Boom treatment. In other words, the belief suggested above may not be entirely unjustified.

The rest of our paper is organized as follows. Section 2 describes the experimental design and procedures. The results are reported in Section 3, and Section 4 concludes with a brief summary and discussion.

2. The Experiment

The experiment consisted of 8 sessions that were conducted at Shanghai Jiao Tong University (SJTU). A total of 103 subjects (72 students and 31 non-students; 49 in 2007 and 54 in 2008) were recruited via SJTU BBS. The average age is 23.9 for students and 40.1 for non-students. Although none of the subjects had any experience in a similar laboratory experiment, they all had been participating in the Shanghai Stock Exchange before coming to our experiment. Specifically, subjects who were recruited in 2007 for the first treatment had an average of 1.36 years of trading experience in the Shanghai Stock Exchange, whereas those who were recruited in 2008 for the second treatment had 1.47. A ranksum test suggests that the

difference is significant at the 1% level.[2]

Sessions lasted about 90 minutes including instructions, a trial period and cash payment to subjects. The experiment was conducted in an experimental currency that was converted to RMB at a predetermined conversion rates.[3] Student and non-student subjects earned an average of 44.12 RMB (5.95 USD) and 124.52 RMB (16.88 USD), respectively.

To study how market experience in the field affects trading behavior in the lab, we conducted two treatments in the experiment. Our first treatment, called Boom, was conducted in June 2007, during a bull market of the Shanghai Stock Exchange. As a comparison, the second treatment, called Crash, was conducted in August 2008 after the SSE Composite Index had plunged almost 60 percent from its high that was reached in October 2007. The overall pattern of the Shanghai Stock Exchange Composite Index from mid 2006 to late 2008 is presented in Figure 1.

[Figure 1: About Here]

In each treatment, subjects were asked to make investment decisions in two trading rounds. There were two stocks, one in each round, in which subjects could invest. Subjects were told that the two stocks were completely unrelated to each other. A cash endowment of 100,000 experimental dollars was given to each subject at the beginning of each trading round. For each stock, subjects were given its market information including the current and historical prices and trading volumes. The percentage change in price was also provided.

[2]In the data analysis reported in Section 3, we exclude 17 subjects whose lottery choices are not considered as rational. As a result, the number of years trading experience becomes 1.58 in the Boom treatment (2007) and 1.35 in the Crash treatment (2008). As reported in Table 2, this difference is only marginally significant.

[3] The conversion rate was 10,000 experimental dollars to 3 RMB for students and 10 RMB for non-students. The exchange rate was about 1 USD = 7.64RMBin June 2007 and 6.84RMB in August 2008.

To create price patterns similar to what subjects had experienced in the field, we exogenously imposed the stocks' trading prices that were constructed using weekly data from the Nasdaq Stock Exchange and the Taiwan Stock Exchange between May 8, 1995 and April 12, 2005. Figures 2 and 3 present the price patterns of these two markets, called market N and market T, respectively. There were 500 data points of the price and quantity pair for each stock. The first 100 data points, represented in dashes in the figures, were shown all at once to subjects before trading started. The market information was then updated every 5 seconds until the rest of the 400 data points were released. This process took approximately 33 minutes.

[Figures 2 and 3: About Here]

During each trading round, the specific decision that subjects were asked to make was when and how much (in blocks of 100 shares) to buy or to sell at the current price level. There were no interactions among subjects. In addition to the market information, the computer screen also showed the personal account information such as one's cash balance, stock holding, total wealth at the current price level (cash balance plus the value of stock holding), the maximum number of blocks that one could buy given the current price and cash balance (see Figure 4). The personal account information was updated after each transaction took place or after each new data point was released. A transaction tax of 0.5%, equivalent to the average transaction cost in the Shanghai Stock Exchange, was also imposed on each trade. At the end of each round, the value of one's stock holding, calculated at its ending price, was added to the subject's final cash balance as her/his total earnings in that round.

[Figure 4: About Here]

To elicit subjects' general risk preferences, we implemented a lottery-choice test, similar to the one used in Holt and Laury (2002), after the second trading round was completed. In this test, subjects were asked to indicate a preference between lotteries A and B for each of the nine paired lottery choices shown in Table 1. For example, in the first decision, lottery A pays either 20RMB or 16RMB, whereas lottery B pays 38.5RMB or 1RMB. Since the probability of the higher payoff in both cases is 0.1, the difference between the two lotteries' expected payoffs is 11.6. Therefore, a risk neutral person would choose A over B in the first decision. As the probability of the higher payoff increases, the incentive to pick A becomes smaller. The far right column that summarizes the differences in expected payoffs implies that a risk neutral individual would choose lottery A for the first four decisions but B for the rest. For a risk averse individual, the crossover point would occur later. And of course, the more risk averse this person is, the later she would switch from A to B. After subjects completed the test, the computer randomly picked one of the nine pairs for each person and played her lottery choice that determined her earnings for this part of the experiment.

[Table 1: About Here]

The timing of activities in a session was as follows. Upon arriving at the experiment, subjects were randomly assigned computer terminals by the experimenter. Once everyone was seated, the instructions were read aloud for the subjects who followed along with their own copy of the text. Subjects were then given 5 minutes to practice how to use the interface.[4] The practice round was followed by the two trading rounds, the lottery-choice test and a questionnaire that surveyed their demographic information, investment experience,

[4] The price pattern in the practice round involved no bubbles and crashes.

expectations about the Shanghai Stock Exchange, and assessment on their own performance in the experiment. To minimize the impact of wealth effects, subjects were asked to flip a coin to determine which trading round would be counted toward their final earnings. Finally, subjects received their final earnings which included the trading earnings from one of the two rounds and the payment from the lottery of their choice privately while leaving the lab one by one.

3. Results

In the lottery-choice test, a rational subject should either stay with one of the two lotteries throughout or switch from A to B at most once. Thus in the following data analysis, we include decisions made only by those subjects whose lottery choices satisfy this rationality criterion.[5] The summary statistics of their demographic information is provided in Table 2. Also, for market T, we only analyze the data from the first bubble-and-crash market phase, indicated as T1 in Figure 3, to avoid treatment effects being confounded by learning effects associated with the existence of two bubbles in that market.

[Table 2: About Here]

3.1 General Risk Preference

We use the crossover point or the first time that lottery B is chosen in the lottery-choice test to determine subjects' general risk preference. For instance, we assign an index number 5 to a risk neutral choice pattern AAAABBBBB and 1 to a pattern of straight Bs. A pattern of straight As is assigned an index

[5] As a result, we have to exclude decisions made by 17 irrational subjects. Including the 17 subjects does not significantly change the summary statistics or the treatment effects on the number of trades, the absolute or relative size of trade, the cash holding, and the percentage of time holding more than 80% liquid assets in stock reported later in the paper. It does make the treatment effect on the total value of liquid assets (or wealth) more significant (at the 10% level) for market T1. The difference in the total value of liquid assets between the two treatments remains insignificant for market N.

number 10. The statistical summary reported in Table 3 shows that the risk preference index is, on average, higher in Crash than in Boom, suggesting that subjects who had just recently experienced a downward adjustment in the Shanghai Stock Exchange were slightly more risk averse. A simple ranksum test suggests that this difference is not statistically significant. Nevertheless, when we employ a robust IRLS (iteratively reweighted least squares) model that controls for years of trading experience in the Shanghai Stock Exchange, gender, age, and student identity, the estimated coefficient on the Crash treatment, as reported in Table 4, becomes significantly positive, suggesting that, after all the above factors are being controlled for, subjects in the Crash treatment were more risk averse in terms of their general risk preference than those in the Boom treatment.[6]

[Tables 3 and 4: About Here]

3.2 Number of Trades

One of the most important aspects of trading behavior is trading frequency. The statistical summary of the average number of trades in either one of the two markets is given in Table 3. For instance, in market N, the mean number of trades is 25.51 in the Boom treatment and 28.29 in the Crash treatment. A non-parametric ranksum test indicates that trading frequencies in the two treatments are not significantly different in market N. A similar result is also found in market T1.

A robust IRLS model is used again as a more rigorous approach to investigate the treatment effect. The explanatory variables included in the model are a dummy variable that equals 1 for the Crash treatment, a dummy variable that describes the order of the two markets

[6] Since the distribution of errors is heavy-tailed, we employ robust IRLS models instead of simple OLS models for all regression analysis in the paper.

in which subjects' participated, subjects' general risk preference from the lottery-choice test, years of trading experience in the Shanghai Stock Exchange, gender, age, and student identity.[7] Taking each subject as an independent observation, the estimated coefficients on the Crash dummy variable reported in Table 4 are 3.03 and -0.92 for market N and market T1, respectively. Neither estimate is significant, suggesting that subjects who had experienced a dramatic crash in the Shanghai Stock Exchange did not trade more or less frequently in the lab than those who had a completely opposite field experience.

3.3 Size of Trade

Knowing that there is no significant difference in the trading frequency between the two treatments, our next focus is on the size of trade. In the following, we first discuss the absolute size of trade, defined as the average number of blocks (100 shares) per trade, and for a robustness check, we also look at the relative size of trade, defined as the percentage of cash used to purchase shares or the percentage of shares sold to obtain cash in one single transaction.

Table 3 provides the average number of blocks (100 shares) per transaction. In market N, the number of blocks per transaction is about 36 in the Boom treatment and 24 in the Crash treatment. The numbers are very similar in market T1. Both differences are significant according to non-parametric ranksum tests. In other words, even though subjects in the Crash treatment executed almost the same number of trades as those in the Boom treatment, they purchased or sold significantly less shares in an average transaction. This trading pattern is supported by the regression results reported in Table 4 which indicate that, after factors such as

[7] The dummy variable for the order of the markets equals 1 if market N was played first and 0 otherwise.

the order of the two laboratory markets in which subjects participated, field trading experience, general risk preference and demographic characteristics are being controlled for, the difference between the two treatments is about -7.17 blocks in market N and -8.12 blocks in market T1 per transaction. These estimates are significant at the 5% level.

As mentioned above, the relative size of trade is defined as the percentage of cash used to purchase shares or the percentage of shares sold to obtain cash in one single transaction. Therefore, it is the relative size of trade compared to the total cash or asset holding. The statistical summary and the results from IRLS regression models reported in Tables 3 and 4 provide further evidence suggesting that investors tended to make smaller trades in the Crash treatment than in the Boom treatment.

3.4 Cash Holding

Another sign that indicates a more conservative or risk-averse trading approach is the investors' unwillingness to hold stock shares. Two measures are considered here: the proportion of liquid assets that is in the form of cash and the percentage of time a subject held more than 80% of her liquid assets in stock.[8] Note that liquid assets consist of cash and stock holding here.

Since there were 400 data points (price plus trading volume) released every 5 seconds, we first calculate the percentage of cash holding at the end of every 5-second interval and then compute the average across all intervals in market N and market T1. As shown in Table 3, subjects in the Crash treatment held a significantly larger proportion of liquid assets in cash

[8] We chose 80% as the cutoff point because it was a reasonably large percentage of shares holding in our view. Nevertheless, we have also tried several other cutoff points for robustness check and the results are similar to what we report here.

than those in the Boom treatment. The IRLS regression results reported in Table 4 estimates that the difference is about 10.05 percentage points in market N and 15.78 percentage points in market T1, significant at the 10% and 1% level, respectively.

To minimize exposure to risk, it is likely that conservative investors not only wish to hold, percentage-wise, fewer shares in their liquid assets, but also wish to reduce the amount of time they hold large quantities of shares. To investigate such a dynamic adjustment, we calculate the percentage of time investors had over 80% of their liquid assets invested in shares. Tables 3 and 4 clearly indicate that it is much less likely for investors to hold a large proportion of liquid assets in shares in the Crash treatment. This result provides further support that subjects who had experienced a crash in the Shanghai Stock Exchange had a tendency to behave more cautiously in our laboratory asset markets than those who had just experienced a boom.

3.5 Liquidity Assets or Wealth

The average value of subjects' liquid assets, cash plus the value of stock holding, as indicated in Table 3, is slightly higher in the Boom treatment than in the Crash treatment. This is true for both market N and market T1. While a ranksum test indicates that the difference between the two treatments is not significant in either market, the IRLS regression results reported in Table 4 suggest that the difference is significant for market T1.

The observation that subjects adopted different trading strategies but at the end accumulated almost the same or slightly less assets seems intriguing. After further scrutinizing the data, we find that, when either market N or market T1 was on a rising trend, a more

conservative approach did not allow subjects in the Crash treatment to accumulate as much wealth as those in the Boom treatment. But when the market was plummeting, the same approach could help prevent them from losing as much as their counterparts. Taken together, a more cautious, risk-averse trading strategy turned out to make subjects almost equally well off.

3.6 Self-assessment Bias

One might suspect the fact that subjects in the Boom treatment traded more actively in our laboratory asset markets was because, after having gone through a prolonged bull market in the Shanghai Stock Exchange, they were more confident, perhaps overconfident, about the market in general or about their own ability to beat the market. This viewpoint is certainly consistent with, for example, Odean (1999), Barber and Odean (2000), Statman, Thorley, and Vorkink (2006), and Glaser and Weber (2007) that find that excess trading is positively related to investor overconfidence.

To see if overconfidence explains our findings, we compute subjects' self-assessment biases based on their responses to one of the questions from the exit survey. In that question, we asked subjects to estimate their ranking in terms of their accumulated wealth within their group on a scale of 1 (top 20%) to 5 (bottom 20%). A trader is said to be overconfident/underconfident if his self-assessment bias, defined as his actual ranking minus his own estimation, is positive/negative. A trader is said to be unbiased if his actual ranking is the same as his own estimation. Based on this categorization, we have 32 (37.2%) overconfident, 25 (29.1%) unbiased, and 29 (33.7%) underconfident traders in our study.

We modify the robust IRLS model reported in Table 4 by including a dummy variable

that equals 1 for overconfident and unbiased traders and an interaction term between the Crash and the overconfident/unbiased dummy variables.[9] Table 5 reports the new estimation results. The estimated coefficients on Crash are no longer significant. The estimated coefficients on the interaction of Crash and the overconfident/unbiased dummy are, on the other hand, all consistent with the results reported earlier, implying that the trading patterns we observe in the Crash treatment are mainly driven by the behavior of those who can be categorized ex post as overconfident or unbiased traders. This result appears to contradict the notion that overconfidence, defined either as systematic overestimation of the prevision of one's information or unrealistic, positive evaluation of one's own ability, is positively correlated with trading volume. Yet we argue that, since the self-assessment bias in our study is constructed based on subjects' responses in the exit survey, the result that overconfident traders in the Crash treatment tend to trade more conservatively might reflect more or less a belief formed based on their field experience that such a trading approach would help reduce their exposure to risks and thus generate more wealth than an average person. Although we do not find from Table 5 that these traders accumulate more wealth than their underconfident counterparts in the Crash treatment, we do find that they make significantly more wealth, at least in market N, than the same type of traders in the Boom treatment, partially supporting the belief suggested above.

4. Conclusion

In this paper, we study whether or not experiencing a market boom vs. a market crash

[9] We took the advice from one of the referees and conducted all the regression analysis for overconfident, unbiased and underconfident traders separately. We found that the estimated treatment effects for overconfident and unbiased traders were rather comparable and thus decided to pool these two groups of traders together in all the regression results reported in Table 5.

occurred in the naturally occurring world would have different impact on subjects' laboratory trading behavior. We recruited investors who had been actively participating in the Shanghai Stock Exchange to participate in the Boom treatment that was conducted in June 2007 after the Shanghai Stock Exchange had had a bull market for almost two years, and the Crash treatment that was conducted in August 2008 after the SSE Composite Index had plummeted almost 60 percent from its high. We find that, compared to those who had gone through a completely different episode in 2007, subjects who had experienced the crash in the Shanghai Stock Exchange in 2008 were more cautious and risk averse in our experimental asset markets. They exhibited a tendency to make smaller trades, hold a larger proportion of liquid assets in cash, and spend less time holding more than 80% of liquid assets in stocks. All these trading patterns are consistent with Nagel and Malmendier's (2011) finding that, based on the data from the Survey of Consumer Finances between 1964 and 2004, birth-cohorts that have experienced high stock market returns report lower risk aversion and have a tendency to invest a higher fraction of liquid wealth in stocks later in their life.

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Table 1: Lottery Choices in Risk Test

Lottery A		Lottery B		EVA	EVB	Difference
p(¥20)	p(¥16)	p(¥38.5)	p(¥1)			
0.1	0.9	0.1	0.9	16.4	4.8	11.6
0.2	0.8	0.2	0.8	16.8	8.5	8.3
0.3	0.7	0.3	0.7	17.2	12.3	4.9
0.4	0.6	0.4	0.6	17.6	16.0	1.6
0.5	0.5	0.5	0.5	18.0	19.8	-1.8
0.6	0.4	0.6	0.4	18.4	23.5	-5.1
0.7	0.3	0.7	0.3	18.8	27.3	-8.5
0.8	0.2	0.8	0.2	19.2	31.0	-11.8
0.9	0.1	0.9	0.1	19.6	34.8	-15.2

Table 2: Demographic Characteristics of Subjects Included in the Data Analysis

Variable	Treatment	Mean	S.D.	*p*-value (Rank-sum)
Years of Trading Experience in Shanghai Stock Exchange	Boom	1.58	2.43	0.070
	Crash	1.35	1.40	
Female %	Boom	30.55	0.47	0.686
	Crash	26.53	0.45	
Age	Boom	29.56	11.54	0.147
	Crash	27.55	6.22	
Student %	Boom	72.97	0.45	0.451
	Crash	65.31	0.48	

Table 3: Summary Statistics of Risk Attitude, Trading Behavior and Self-assessment Bias

Variable	Market	Treatment	Mean	S.D.	*p*-value (Rank-sum)
General Risk Index		Boom	6.14	2.19	0.222
		Crash	6.71	2.10	
Number of Trades	N	Boom	25.51	20.61	0.397
		Crash	28.29	20.79	
	T1	Boom	13.03	11.07	0.694
		Crash	11.84	11.19	
Absolute Size of Trade	N	Boom	35.65	21.01	0.005
		Crash	24.43	14.98	
	T1	Boom	32.07	12.40	0.040
		Crash	25.82	14.94	
Relative Size of Trade (% of Total Cash or Shares)	N	Boom	75.34	18.22	0.004
		Crash	62.40	21.29	
	T1	Boom	77.77	17.31	0.118
		Crash	67.93	24.50	
Cash Holding (% of Liquid Assets)	N	Boom	45.76	22.19	0.031
		Crash	56.03	22.79	
	T1	Boom	41.48	22.76	0.001
		Crash	57.54	21.66	
% of Time Holding over 80% of Liquid Assets in Shares	N	Boom	43.66	21.80	0.005
		Crash	28.10	22.99	
	T1	Boom	50.86	29.33	0.000
		Crash	25.61	27.34	
Liquid Assets (or Wealth)	N	Boom	134,938	76,415	0.358
		Crash	131,581	49,238	
	T1	Boom	125,526	25,976	0.122
		Crash	115,940	21,375	

Table 4: Estimated Coefficients from Robust IRLS Regression Models

	General Risk Preference Index	Number of Trades		Absolute Size of Trade		Relative Size of Trade (% of Total Cash or Shares)	
		Mkt N	Mkt T1	Mkt N	Mkt T1	Mkt N	Mkt T1
Crash	0.92*	3.03	-0.92	-7.17**	-8.12**	-13.09***	-9.48*
	(0.51)	(3.93)	(2.31)	(3.51)	(3.45)	(4.79)	(5.09)
Order		5.40	0.45	4.35	0.26	4.10	-0.30
		(3.79)	(2.22)	(3.39)	(3.33)	(4.62)	(4.83)
Risk Index		-0.54	-0.43	-0.01	1.07	-1.23	-1.63
		(0.91)	(0.53)	(0.81)	(0.79)	(1.11)	(1.18)
Experience	-0.11	1.08	-0.37	-2.89**	-1.95	-3.50**	-4.30**
	(0.18)	(1.36)	(0.80)	(1.22)	(1.19)	(1.66)	(1.73)
Female	0.85	-0.92	-3.24	-7.23*	0.09	-9.52*	-12.61**
	(0.55)	(4.23)	(2.49)	(3.79)	(3.70)	(5.17)	(5.52)
Age	0.08	-0.43	0.01	0.56*	-0.03	0.63	0.62
	(0.05)	(0.37)	(0.22)	(0.33)	(0.32)	(0.45)	(0.49)
Student	1.40*	1.64	1.37	6.19	-2.90	2.70	0.04
	(0.84)	(6.44)	(3.78)	(5.76)	(5.62)	(7.85)	(8.20)
Constant	2.67	30.78**	13.73	15.26	31.56**	69.68***	81.84***
	(1.84)	(14.24)	(8.37)	(12.73)	(12.39)	(17.37)	(19.41)
Adj. R^2	0.038	-0.007	-0.039	0.113	0.042	0.130	0.105

Standard errors in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 4 (cont'd): Estimated Coefficients from Robust IRLS Regression Models

	Cash Holding (% of Liquid Assets)		% of Time Holding over 80% of Liquid Assets in Shares		Liquid Assets (or Wealth)	
	Mkt N	Mkt T1	Mkt N	Mkt T1	Mkt N	Mkt T1
Crash	10.05*	15.78***	-14.57***	-26.66***	3601.49	-10255.06**
	(5.09)	(5.02)	(4.87)	(7.05)	(10121.92)	(4777.28)
Order	-10.47**	2.66	9.98**	0.77	-17982.14*	12201.08***
	(4.91)	(4.84)	(4.70)	(6.80)	(9760.02)	(4606.47)
Risk Index	1.78	1.05	-1.73	-0.35	2432.34	2509.49**
	(1.18)	(1.16)	(1.13)	(1.63)	(2340.00)	(1104.42)
Experience	2.46	2.88	-3.32*	-4.04	1325.33	-1464.19
	(1.77)	(1.74)	(1.69)	(2.45)	(3513.39)	(1658.23)
Female	14.74***	1.07	-18.00***	-7.91	-11408.37	-4229.38
	(5.49)	(5.41)	(5.26)	(7.60)	(10911.80)	(5150.08)
Age	-0.04	-0.24	0.29	0.62	85.85	-558.33
	(0.48)	(0.48)	(0.46)	(0.67)	(960.11)	(453.15)
Student	-9.06	-16.24*	12.56	15.80	17901.48	-2151.62
	(8.34)	(8.23)	(7.99)	(11.56)	(16587.48)	(7828.85)
Constant	39.71**	47.01**	42.13**	32.49	98915.76***	121390.10***
	(18.46)	(18.20)	(17.67)	(25.57)	(36697.53)	(17320.27)
Adj. R^2	0.199	0.229	0.300	0.189	0.023	0.135

Standard errors in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 5: Estimated Coefficients from Robust IRLS Regression Models with Self-Assessment Bias Included

	Number of Trades		Absolute Size of Trade		Relative Size of Trade (% of Total Cash or Shares)	
	Mkt N	Mkt T1	Mkt N	Mkt T1	Mkt N	Mkt T1
Crash	-0.64	-6.25	3.48	3.27	5.34	1.37
	(6.54)	(3.91)	(5.41)	(5.66)	(7.49)	(8.45)
Overconfident/Unbiased Dummy	4.16	-4.67	0.97	5.03	9.37	3.37
	(6.06)	(3.62)	(5.02)	(5.17)	(6.95)	(7.83)
Crash × Overconfident/Unbiased	6.41	8.13*	-17.25**	-17.50**	-30.39***	-17.82*
	(7.90)	(4.72)	(6.54)	(6.82)	(9.05)	(10.25)
Order	3.57	-0.21	6.10*	0.80	7.95*	0.91
	(3.70)	(2.21)	(3.07)	(3.20)	(4.24)	(4.80)
Risk Index	-0.41	-0.30	-0.00	1.29*	-1.11	-1.64
	(0.88)	(0.53)	(0.73)	(0.76)	(1.01)	(1.17)
Experience	1.31	-0.54	-2.86**	-1.79	-3.44**	-4.16**
	(1.33)	(0.79)	(1.10)	(1.13)	(1.52)	(1.72)
Female	-0.47	-2.72	-9.29***	-1.06	-11.82**	-13.55**
	(4.16)	(2.48)	(3.44)	(3.57)	(4.77)	(5.54)
Age	-0.56	-0.00	0.60**	0.01	0.62	0.56
	(0.36)	(0.22)	(0.30)	(0.31)	(0.41)	(0.49)
Student	-0.90	0.49	7.63	-2.17	3.83	-0.67
	(6.23)	(3.72)	(5.16)	(5.34)	(7.14)	(8.08)
Constant	33.04**	17.40**	12.13	24.35*	61.00***	81.00***
	(14.60)	(8.72)	(12.09)	(12.49)	(16.74)	(20.11)
Adj. R^2	0.024	-0.034	0.283	0.133	0.297	0.137

Standard errors in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 5 (cont'd): Estimated Coefficients from Robust IRLS Regression Models with Self-Assessment Bias Included

	Cash Holding (% of Wealth)		% of Time Holding over 80% of Wealth in Shares		Liquid Assets (or Wealth)	
	Mkt N	Mkt T1	Mkt N	Mkt T1	Mkt N	Mkt T1
Crash	9.28	-3.36	-3.52	0.02	-14140.79	-2453.90
	(8.97)	(8.04)	(8.17)	(11.44)	(16279.44)	(8451.86)
Overconfident/Unbiased Dummy	1.38	-14.73*	2.54	19.64*	-46225.50***	5648.93
	(8.32)	(7.46)	(7.58)	(10.62)	(15104.44)	(7841.83)
Crash × Overconfident/Unbiased	1.28	29.36***	-18.18*	-39.70***	25208.60	-11105.35
	(10.83)	(9.71)	(9.87)	(13.82)	(19669.36)	(10211.81)
Order	-10.33**	1.70	11.09**	0.98	-20714.45**	13093.77***
	(5.08)	(4.55)	(4.63)	(6.48)	(9219.59)	(4786.57)
Risk Index	1.78	0.91	-1.43	-0.23	1821.83	2572.96**
	(1.21)	(1.09)	(1.10)	(1.55)	(2201.55)	(1142.98)
Experience	2.44	2.50	-3.01*	-3.52	820.42	-1158.54
	(1.82)	(1.63)	(1.66)	(2.32)	(3301.69)	(1714.15)
Female	14.84**	2.83	-19.48***	-9.46	-9030.87	-4651.4
	(5.70)	(5.11)	(5.19)	(7.28)	(10351.77)	(5374.36)
Age	-0.06	-0.29	0.27	0.76	403.47	-572.31
	(0.50)	(0.44)	(0.45)	(0.63)	(898.93)	(466.70)
Student	-9.38	-17.97**	12.80	18.35*	22391.33	-1617.59
	(8.55)	(7.66)	(7.79)	(10.91)	(15521.96)	(8058.59)
Constant	39.33*	61.44***	38.66**	11.74	125673.50***	116143.40***
	(20.02)	(17.95)	(18.24)	(25.55)	(36356.90)	(18875.54)
Adj. R^2	0.175	0.319	0.340	0.261	0.145	0.116

Standard errors in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Figure 1: Shanghai Stock Exchange Composite Index

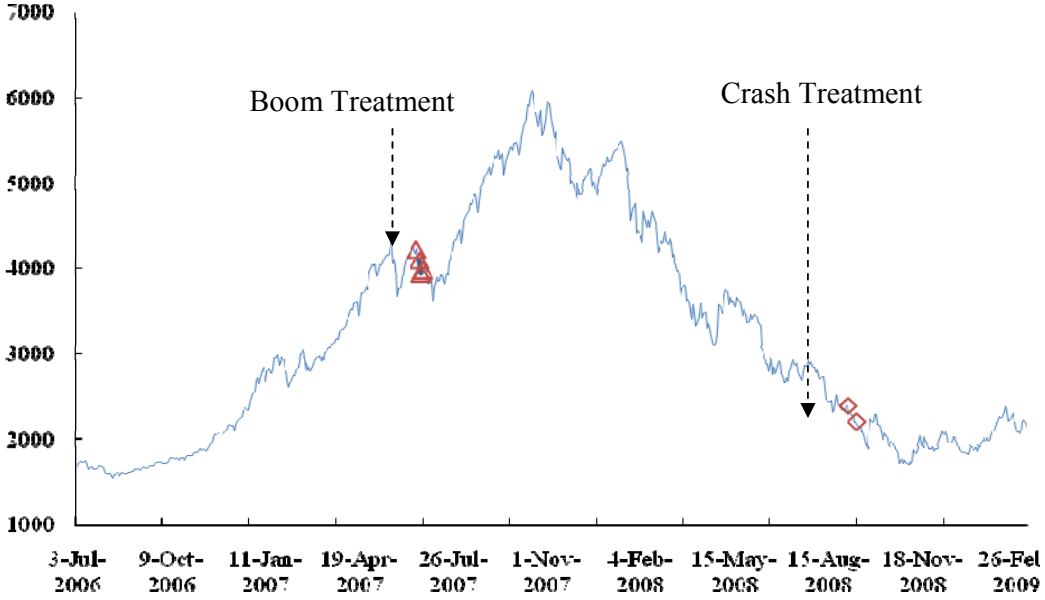


Figure 2: The Price Pattern of Market N

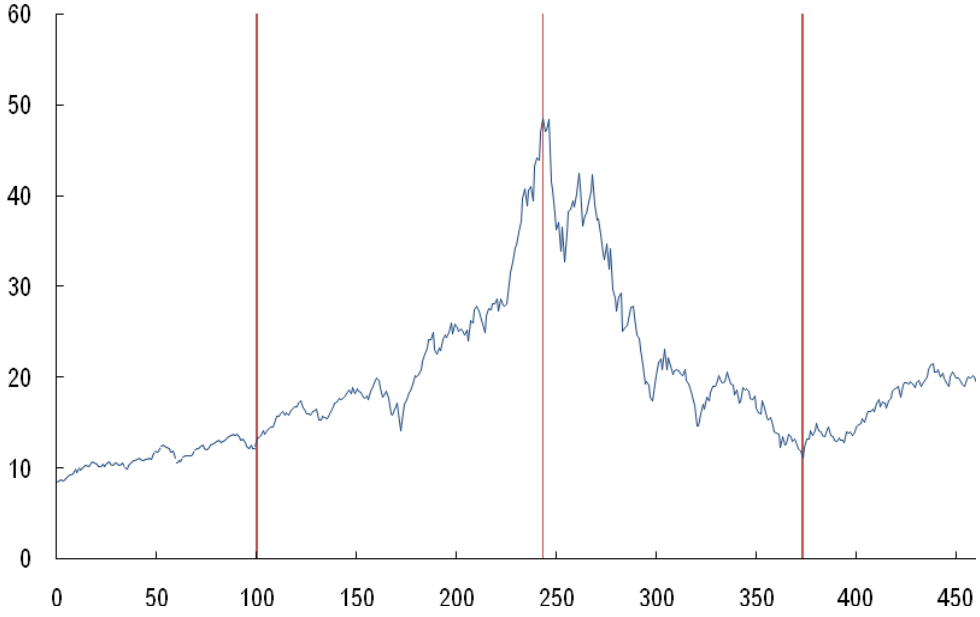


Figure 3: The Price Pattern of Market T

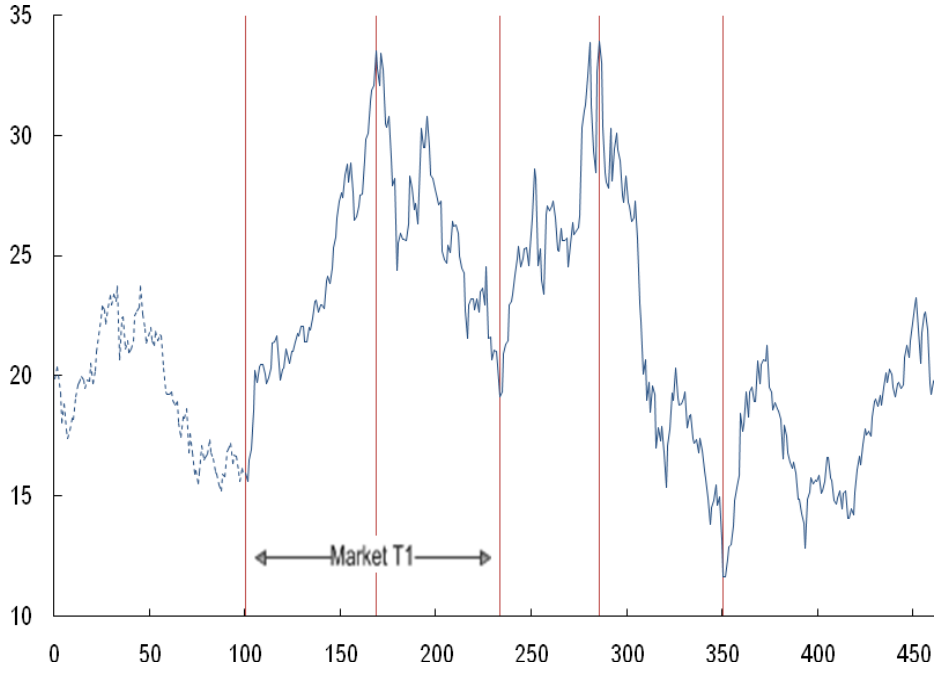
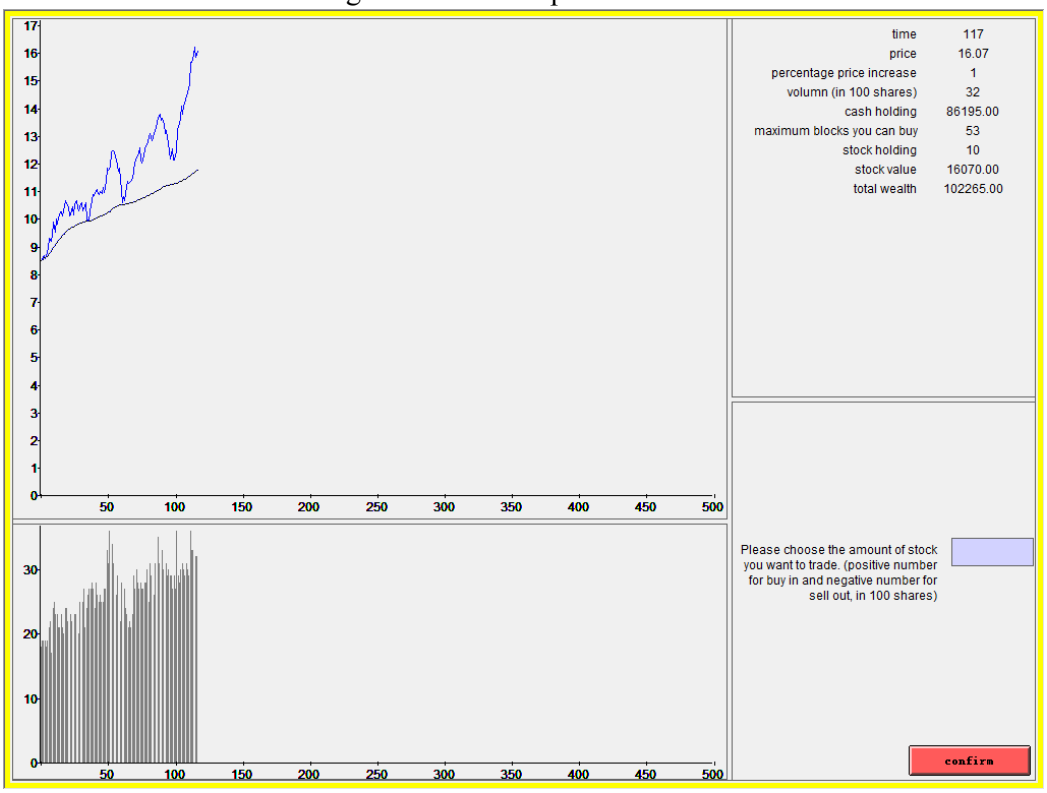


Figure 4: The Computer Interface



Appendix: Instructions for the Experiment

Please read the instructions carefully. Please do not talk to other participants. Please raise your hand if you have questions and we will come to you.

You are now in a laboratory stock market. In this market, you are going to make two rounds of investment. Each round will last for around 33 minutes. When each round begins, you will get an endowment of 100,000 laboratory dollars, which you can use to invest on a stock. There is no correlation between the prices of the stock in round 1 and those of the stock in round 2. You can consider the two stocks available in the two rounds as two completely different stocks in different markets.

On the screen, you will see two graphs. The first graph plots the historical stock prices and the average price up to each time point. The second graph is a histogram reporting trade volume at each time point. At the beginning of each round, price and volume on 100 time points will be presented in the graphs. Then, the stock price and volume will change every five seconds and these new data will be added to the graphs. A total of 400 updates will take place in each round. The price and volume are exogenously given and there is no interaction among participants.

On the upper right corner of the screen, you can see the current stock price, the price change, the trade volume, your cash holding, the maximum number of hands (hundred shares) you can buy, your current stock holding, the current value of your stock holding, and your total asset. The maximum number of hands you can buy equals your cash holding divided by the current price of one hundred shares, rounded to the biggest integer below. Your total asset equals your cash holding plus the current value of your stock holding. All these numbers will

also be updated every five seconds.

On the bottom right corner of the screen, you can input the number of hands you want to trade. A positive number means buying in and a negative number means selling out. The unit of transaction is hand, which means one hundred shares. The size of your trade should be between (-1)×your current stock holding and the maximum number of hands you can buy. For example, if you currently hold 5 hands (500 shares) and the maximum number of hands you can buy is 20, you can input any integer between -5 and 20. If you enter "10", it means you want to buy 10 hands (1,000 shares). If you input "-3", it means you want to sell 3 hands (300 shares). If you enter any number that is smaller than -5 or bigger than 20, an error message will appear. In that case, you can click "OK" and change your input. Once you enter the number of hands you want to trade and click "confirm", the transaction is made. (Note the clicking "confirm" twice will result in duplicate transactions.) You can buy or sell stocks at any time during a round. You need to pay a 0.5% tax for every transaction, no matter buying or selling. This tax will be deducted from your cash holding. When a round ends, you will see your endowment, your final total asset and earning in this round.

After a little rest, you will enter the next round. After both rounds have ended, please fill in a questionnaire and flip a coin to determine which round of investment is paid to you in cash (head for round 1 and tail for round 2). (Note that the value of your stock holding at the ending price is included in your final total asset. Therefore, your payoff does not depending on whether you sell your stocks or not in the last 5 seconds.) Every 1,000 experimental dollars are exchanged into 1RMB. For example, if your final total asset equals 150,000 experimental dollars in the first round and 200,000 experimental dollars in the second round, and your coin

flip results in round two being paid, then your payoff would be 200RMB. After getting paid and sign a receipt, you can leave the laboratory.

Before the two formal rounds begin, you have 5 minutes to practice how to use the interface. Please raise your hand if you have questions during the practice periods. After that, the first round begins. The stock prices for the practice period come from historical data in the Shanghai Stock Exchange and have nothing to do with the stock prices in the two formal rounds.

You can click “Continue” to start practice now if you do not have questions.