# The Impact of Stock Market Crashes and Recoveries on Investor Expectations and Disposition Effects——A Lab-in-the-field Experiment

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**Abstract:**

Existing studies have shown that experience can affect price expectation and investment behavior, but most studies focus on the effects of bubbles rather than crash. In this lab in the field experiment, we adapt the experimental design of Gong et al. (2013) and change the two bubble-and-crash markets setting to two crash-and-recovery markets. We recruit real individual investors to investigate how they behave in a laboratory asset market crash and whether they form different price expectations and behave differently after experiencing a crash and its recovery, especially in terms of disposition effects. The experimental results indicate that after experiencing a laboratory crash-and-recovery, investors tended to hold higher expectations on future market prices, leading to a reduction in the duration of holding both profitable and loss-incurring stocks. Overall, experienced investors' expectations for future stock prices become more optimistic, and the disposition effect is mitigated. The increase in expectations also weakens the impact on the disposition effect of investors.

Keywords: experience, expectation, disposal effect, investor behavior, experiment

Abstract

# 1. Introduction

## (1) Research Background and Significance

### 1) Research Background

When making investment decisions, individuals frequently draw on past experiences to interpret current situations, whether consciously or subconsciously. These evaluations are significantly shaped by historical peaks and troughs, which, in turn, evoke emotions crucial to the decision-making process(Forgas,1995). Behavioral finance posits that anomalous events can affect investor emotions and behavior, thereby influencing the stock market(Liu, 2020). Investors' decisions are shaped by a range of psychological, emotional, and cognitive factors, leading to distinct behavioral patterns such as herd behavior(Olsen, 2008), emotion-driven trading, and information dissemination. These patterns not only contribute to short-term market fluctuations but also have significant implications for long-term market stability and efficiency. In the face of substantial market volatility—such as crashes or bubbles—individual investors often display irrational behaviors influenced by factors such as their level of education, access to information, and professional expertise(Chen, 2022).

In China, as reported by the latest Shanghai Stock Exchange Statistical Yearbook, individual investors accounted for 51.68% of the total market value of shares by the end of 2022(Shanghai stock exchange, 2020). This figure is particularly noteworthy, as it indicates that over half of the active capital in the Chinese stock market is driven by individual investors. Consequently, understanding the behavior of these investors is critical to comprehending the overall dynamics of the market. In 2022, both the Shanghai and Shenzhen stock indices experienced declines exceeding 20%, with frequent fluctuations in individual stock prices(Yu, 2011). Stocks whose closing prices deviate by more than 20% across three consecutive trading days are categorized as exhibiting abnormal price volatility.

In this context, it becomes imperative to investigate how individual investors' past experiences with market crashes and subsequent recoveries influence their emotions and decision-making processes. Analyzing the behavioral responses of investors to market downturns can shed light on the underlying psychological mechanisms and decision-making frameworks that shape investor actions. This, in turn, can provide more accurate insights and forecasts for market trends, contributing to a more comprehensive understanding of stock market operations.

Historically, numerous speculative trading phases have led to rapid price escalations in specific commodities or financial assets, followed by sudden and dramatic crashes(Chancellor, 1999 and Kindleberger, 2001). A prominent example, frequently cited by economists, is the Dutch tulip mania of 1637(Garber, 2000), during which the prices of certain tulip bulbs rose to levels several times higher than the average individual's annual income, only to collapse precipitously to nearly zero(Dash, 1999). Existing studies suggest that the behavior of investors who have lived through market downturns or crashes tends to change, potentially mitigating the formation of market bubbles at the macro level and fostering greater caution at the individual level. Investors with recent experiences of a market crash, or those who have encountered similar episodes, are generally more averse to investing in the same types of assets that contributed to their previous losses. In most cases, investors fail to anticipate such patterns before experiencing a market downturn firsthand.Research shows that investors learn from their experiences, and as their familiarity with the market increases, the disposition effect—whereby investors are more likely to sell assets that have gained in value while holding onto those that have lost value—diminishes significantly. While previous studies indicate that experience plays a role in shaping investors' expectations for future market movements, empirical evidence often struggles to precisely capture these expectations. This gap can be addressed through experimental designs, wherein learning effects derived from trading experiences can help reduce the disposition effect.

This study utilizes account-level data from a major Chinese securities firm, which unfortunately does not allow for a clear distinction between the impacts of market crashes and subsequent recoveries. To overcome this limitation, the paper employs an experimental design to expose investors to controlled market crash scenarios, quantifying their expectations and disposition effects. Through this approach, the research aims to analyze the influence of these market experiences on investors' future expectations and behavioral patterns.

### 2) Research Significance

#### a. Theoretical Significance

By employing experimental methods to investigate the impact of market crashes and recoveries on investor expectations and behaviors, this research provides a more refined and controlled environment, allowing for an in-depth exploration of the mechanisms through which experiential factors influence decision-making. The experimental approach offers insights into how investors adjust their market expectations both before and after experiencing crashes and recoveries, generating quantitative data that is often difficult to capture in empirical studies. This approach helps to reveal the underlying psychological processes that shape investor behavior, thereby contributing to a more robust theoretical framework in the domain of behavioral finance.

#### b. Practical Significance

Researching the effects of crash and recovery experiences on investors can offer valuable insights into how investors understand and navigate market downturns. The disposition effect, an irrational investment behavior that impedes investors from maximizing returns, is a key factor in this analysis. By identifying the factors that influence this behavior, investors can make more informed decisions, ultimately improving their market outcomes. Moreover, this research can enhance the understanding of market behaviors among financial practitioners, enabling them to more accurately predict and explain market fluctuations. It can also provide a scientific foundation for financial regulation, facilitating the development of more effective policies aimed at maintaining market stability.

### (2) Research Content and Methods

#### 1) Research Content

This paper examines the impact of investors' experiences on their future investment behavior, drawing on advanced theories and methodologies from both domestic and international research. By utilizing experimental methods, it aims to analyze how investors adjust their expectations, disposition effects, and other behaviors following a market crash, offering fresh insights to improve decision-making and support the efficient functioning of financial markets. The study is structured into five chapters:

Chapter 1: Introduction – This chapter provides an overview of the research background, emphasizing the gap in quantifying investor expectations and the largely unexplored mechanisms by which crash and recovery experiences affect both expectations and disposition effects. It proposes the use of experimental methods to examine how market crashes impact investor behavior and discusses the theoretical and practical significance, methodologies, and innovations of the research.

Chapter 2: Literature Review – It reviews the existing literature on how experience influences investor behavior, the methods for measuring the disposition effect, and the impact of experience on this effect. This chapter synthesizes prior studies to establish a theoretical framework that will inform the subsequent analysis and experimental design.

Chapter 3: Experimental Design and Implementation – This chapter outlines the experimental model, introduces three key hypotheses derived from the research objectives, and provides a detailed explanation of the experimental design and procedures, setting the stage for the analysis in the following chapters.

Chapter 4: Analysis of Experimental Results – Using descriptive statistics and regression analysis, this chapter assesses the influence of experience on investor behavior, with a focus on trading patterns, expectations, and disposition effects. The hypotheses are tested, and the corresponding conclusions are drawn based on the experimental data.

Chapter 5: Conclusions and Outlook – Building on the previous analysis, this chapter discusses how market crashes shape investor behavior. It provides theoretical insights and practical recommendations for investors, financial professionals, and regulators, suggesting ways to enhance future decision-making and policy formulation.

### 2) Research Methods

#### a. Literature Review Method

This method involves conducting a systematic review and analysis of literature related to behavioral and experimental economics, utilizing databases such as CNKI. The objective is to enhance the understanding of the theoretical framework, measurement techniques, and empirical research surrounding key concepts like experience, expectations, and disposition effects. By synthesizing existing studies, this approach ensures that the research questions are grounded in both scientific rigor and contemporary advancements, thereby maintaining the relevance and innovation of the study within the broader academic discourse.

### b. Controlled Experiment Method

This method simulates a real investment environment through a laboratory-based stock market experiment using the zTree program(Dufwenberg et al., 2005). Real investors from diverse age groups and experience levels are recruited to participate. The experiment replicates market conditions by constructing price patterns based on weekly data from the NASDAQ and Taiwan Stock Exchange, thereby generating external stock trading prices that reflect both market crash and recovery scenarios. These simulated market conditions serve as critical parameters for analyzing investor behavior, providing controlled insights into how different experience levels influence expectations and decision-making in volatile market environments.

### c. Questionnaire Survey Method

Following the experiment, a questionnaire survey is administered to participants to gather detailed information and feedback regarding their investment decisions and psychological responses during the simulated market conditions. This data is then systematically analyzed to provide deeper insights into participants' behaviors, including their expectations, risk perceptions, and disposition effects. The combination of experimental results and survey responses allows for a comprehensive understanding of how investors' experiences influence their actions in market crash and recovery scenarios.

#### d. Statistical Analysis Method

Finally, this study utilizes statistical analysis to process the collected data and build analytical models. Tools such as Excel and Stata are employed to examine variations in investor responses and wealth conditions in the aftermath of significant market declines and recoveries. Both qualitative and quantitative methods are applied to assess the impact of market crashes and recoveries on investor behavior, thereby validating the proposed hypotheses. This comprehensive analysis aims to provide robust evidence on how different market conditions influence investor decision-making and behavioral patterns.

### (3) Innovations of This Study

This study may include the following innovative aspects:

1） **Observation of Price Expectations through Controlled Experiments**

By employing controlled experiments, this research directly measures investors' price expectations and links them to the disposition effect. This experimental approach overcomes the limitations of real-world data, which often lack detailed information on investor expectations following market crashes. This method provides a more precise understanding of how market events influence expectations.

2） **Investigation of Experience's Influence on the Disposition Effect**

The study uses controlled experiments to examine how investors' past experiences with market crashes and recoveries impact the disposition effect. This approach offers a clearer and more focused analysis of this psychological phenomenon, providing insights that cannot be easily observed in non-experimental settings.

3） **Exploration of Stock Market Crashes and Recoveries within a Behavioral Finance Framework**

By focusing on the effects of market crashes and recoveries on investor behavior, this research contributes to the behavioral finance literature. It offers valuable insights into how such events shape investor decision-making processes, helping to better understand the psychological and behavioral responses to market volatility.

## 2. Literature Review

### (1) The Impact of Experience on Investment Behavior

Psychological literature indicates that personal experiences, particularly recent ones, have a stronger impact on individual decision-making than abstract statistical knowledge or formal education (Nisbett and Lee D., 1980; Weber et al., 1993; Hertwig et al., 2004). When investors experience market crashes or bubbles firsthand, their investment behaviors tend to shift accordingly. Economic literature suggests that the cultural and political environment in which individuals grow up influences the formation of their preferences and beliefs, such as their trust in financial institutions, participation in the stock market, and preferences for social policies(Guiso et al., 2004; Alesina et al., 2007; Osili et al., 2008). Beginning with the foundational work of Vernon L. Smith et al. (1988), laboratory experiments have demonstrated that speculative bubbles are more likely to emerge among inexperienced traders, while traders with multiple exposures to similar market conditions tend to avoid such phenomena.

Dufwenberg et al. (2005) found that introducing experienced traders into experimental asset markets can mitigate or even eliminate bubbles. This is coincident with findings from Haruvy et al. (2007), who explored the relationship between traders' future price expectations and the formation of bubbles and crashes. Their experiments revealed that most first-time participants did not foresee potential downward trends, emphasizing the significant role of experience in shaping market expectations and behavior.

Further empirical evidence comes from Nagel and Malmendier (2011), who discovered that between 1960 and 2007, investors who had experienced periods of low returns on stocks or bonds exhibited a reluctance to invest in these assets, particularly those who had recently encountered negative returns. Similarly, Gong et al. (2013) conducted field experiments with individual investors in Shanghai during the 2007 stock market boom and the subsequent crash of 2008. They found that investors who had experienced the 2008 bubble collapse on the Shanghai Stock Exchange were more cautious in laboratory asset markets, particularly as price takers, underscoring the role of personal experience in shaping investment behavior.

This body of research contributes to a deeper understanding of how investors' behavior evolves after experiencing specific market events, providing critical empirical support for theories of investor decision-making. Gong and Su (2022) further highlighted the divergent behaviors of investors following stock market declines: those inclined to follow market trends may quickly cut losses during price drops, while contrarian investors may seize declining prices as opportunities to buy.

### (2) The Disposition Effect and Its Measurement

The disposition effect, an irrational investment behavior first introduced by Shefrin and Statman (1985), refers to the tendency of investors to sell winning stocks too early while holding on to losing stocks for too long. Shefrin and Statman analyzed the duration of investors' holdings under conditions of gains and losses to verify the existence of this effect. Odean (1998) further refined the measurement of the disposition effect by comparing the percentage of profitable stocks sold (the "proportion of gains realized" or PGR) with the percentage of losing stocks sold (the "proportion of losses realized" or PLR). This method provides a clear and intuitive measure of investor behavior across different market conditions, offering valuable insights for a deeper understanding of the psychological factors driving the disposition effect(Winne, 2021).

The method of measuring PGR and PLR is based on realized and unrealized gains and losses. Realized income is calculated as the difference between the selling price and the purchase price, multiplied by the number of shares sold. Realized losses follow a similar calculation but account for selling below the purchase price. Book gains and losses represent the difference between the purchase price and the current market price during the holding period. By calculating the difference between PGR and PLR, researchers can generate a Disposition Effect (DE) measure, providing a quantitative understanding of this behavioral bias. This approach offers important reference value for practical applications in investment behavior analysis, especially when dealing with individual investors' decision-making under varying market conditions.

$$\frac{Realized\ Gains}{Realized\ Gains + Paper\ Gains} = PGR \qquad (1)$$

$$\frac{Realized\ Losses}{Realized\ Losses + Paper\ Losses} = PLR \qquad (2)$$

$$\mathrm{DE} = \mathrm{PGR} - \mathrm{PLR} \qquad (3)$$

**(3) The impact of experience on disposal effects**

Academic research has long explored the formation of investor expectations. For instance, studies by Clarke and Meir (1998), as well as Fisher and Meir (2000), have investigated how expectations develop among market participants. There is evidence suggesting that investor expectations can be predictive of future price trends (Lee et al., 2002; Lee et al., 2002) , and that deviations in market pricing from underlying fundamentals may occur as a result (Brown et al., 2005).

The influence of varying expectations on market activity has been extensively studied. For example, research by Brown and Robert H.(1989), Grundy and Maureen (1989), Hua and Jiang (1995), and Barberis et al. (1998) has shed light on how different investor expectations shape trading dynamics and market behavior.

Meng and Weng (2018) introduced reference point models for analyzing the disposition effect, emphasizing the role of the adjustment speed of reference points in shaping investor decisions. They defined the reference point as the lagged expected final wealth and argued that loss aversion is a key factor leading to the emergence of the disposition effect, which is notably influenced by how quickly investors adjust their reference points. Their research explained changes in both expectations and the disposition effect within the framework of this reference point model.

While the literature has discussed the measurement of expectations and the disposition effect in detail, there is still a significant gap in the understanding of how experience influences expectations and the interplay between expectations and the disposition effect. Liu (2020) conducted an empirical analysis showing that investors can learn from their past trading experiences. As experience accumulates, the learning effect increases, leading investors to reduce their holdings of loss-making stocks, decrease the likelihood of selling profitable stocks, and significantly mitigate the disposition effect(Pastor and Veronesi, 2009). Notably, Liu found that the impact of experience does not differ significantly across different age groups and genders.

This study seeks to focus on the relationship between experience, expectations, and the disposition effect by employing experimental methods. By doing so, it aims to refine the understanding of how experience influences investor behavior and expectations, addressing the current gaps in the literature and contributing to a more comprehensive understanding of investor decision-making processes.

## 3. Experimental design and implementation

### (1) Experimental basic model

This article enhances the experimental model proposed by Gong et al. (2013) to better align with the objectives of this experiment. In the modified model, it is assumed that each investor possesses an initial capital of A units of currency, with each investment spanning T periods. The stock price at time t is denoted as $P_t$, and the investor's position consists of H×100 shares (where 100 shares constitute one transaction). The investor's expectation of future stock prices is represented by $EP_{ti}$, and their risk preference by $R_i$.

During the $t<=500$ period, investors make buy or sell decisions based on the prevailing market price $P_t$. Upon completing a transaction involving the purchase of H shares, the investor's new holding becomes H shares, while their remaining currency balance is $A-H\times P_t-H\times0.5\%$ (with a 0.5% transaction tax applied to each trade). After selling H shares, the investor receives additional funds calculated as $H\times P_t'-H\times0.5\%$, where $P_t'$ is the price at which the shares are sold.

For every 100 transactions completed, investors are required to predict the stock price for the next 100 transactions in order to estimate $EP_{ti}$, their expectation of future prices. They are rewarded based on the accuracy of their predictions, receiving a reward of $2000-|P_t-EP_{ti}|\times 20$ units of experimental currency. This reward mechanism is designed to encourage precise forecasting of future price trends and to simulate real-world investment decision-making processes, providing valuable insights into how expectations and risk preferences influence investor behavior in volatile markets.

### (2) Research hypothesis

This study assumes that participants will approach their choices rationally—that is, each experimental participant will weigh potential risks and benefits based on the specific context of the experiment, comprehensively considering various factors, and making decisions they believe will maximize their expected utility. However, experimental economics has shown that individuals typically make decisions that reflect a blend of rational and irrational behavior. Based on existing literature and the experimental objectives and design of this study, the following research hypotheses are proposed:

**H1: Experiencing the full cycle of market collapse and recovery will make investors more cautious in their investments.**

Some studies have pointed out that the presence of experienced investors in the market reduces or even eliminates market bubbles (e.g., Dufwenberg, Lindqvist, and Moore, 2005) and that such investors are less likely to reinvest in low-performing stocks (Nagel and Malmendier, 2011). Thus, this study uses the context of a stock market crash and recovery to investigate the effects of this experience on investor behavior. After going through a market collapse and subsequent recovery, investors are expected to become more cautious, which would be evident in lower trading frequency, reduced trading volume, and higher cash holdings. This hypothesis suggests that, following a crash, investors will exhibit more conservative behavior, reflecting increased caution in their investment decisions. Therefore, it is predicted that investors who have experienced a crash will decrease both their trading frequency and volume, while increasing cash holdings.

**H2: Experiencing the full cycle of market collapse and recovery will affect investors' expectations of future market performance.**

Existing research indicates that investors often fail to anticipate market downturns before they occur (Haruvy, Lahav, and Noussair, 2007). This study expects that investors' experience with market crashes will influence their future price predictions. After enduring a market collapse, investors may experience emotional shifts—such as a loss of confidence—which could lower their expectations for future market performance. Thus, investors who have experienced a crash are expected to hold more conservative price expectations than those who have not, potentially diminishing their overall optimism about the market's future prospects.

**H3: Experiencing the full cycle of market collapse and recovery will weaken the disposition effect, making investors more rational.**

Previous literature has identified a learning effect among investors in financial markets, suggesting that they become more rational over time (Liu Ying, 2020). This study posits that investors who have experienced both market crashes and recoveries will exhibit altered behavior with regard to the disposition effect. The disposition effect refers to the tendency for investors to sell winning stocks too quickly and hold losing stocks too long. Investors who have gone through a crash may accelerate the sale of profitable stocks while continuing to hold onto loss-making ones, thereby reflecting a stronger disposition effect. This research hypothesizes that historical experience, particularly of crashes and recoveries, will influence investor behavior, leading to a reduction in irrational behavior and a more measured approach to their investment strategies.

### (3) Experimental Design

To conduct an in-depth investigation into the multifaceted effects of experience on expectations, the disposition effect, and investor behavior, this study employed a dual-market experiment using the zTree software platform. The entire experiment lasted approximately 90 minutes, which included computer equipment setup, explanation of the experiment, execution of the formal experimental process, completion of a questionnaire, and calculation and payment of compensation.

In order to simulate a stock market crash scenario, this research utilized weekly data from the NASDAQ and Taiwan Stock Exchanges, covering the period from May 8, 1995, to April 12, 2005. These datasets allowed for the formation of stock market crashes and recoveries through price reversals. Figures 3-1 and 3-2 display the stock price trends in these two markets, referred to as Market N (NASDAQ) and Market TW (Taiwan Stock Exchange), respectively. Each market consists of 500 periods of stock price and quantity data. To aid participants in predicting future market trends, the first 100 periods were presented in their entirety before the formal start of the experiment. Subsequently, market information was updated every 5 seconds, with the entire trading session comprising 400 transactions over 33 minutes, with an additional 7 minutes dedicated to reading predictions and reviewing experimental instructions.

At the beginning of the experiment, each participant received 100,000 units of experimental currency and comprehensive market information, including key stock data such as current prices, historical price trends, trading volumes, and percentage price changes. Importantly, there was no correlation between the stock prices in the first and second rounds. Participants were randomly assigned to two simulated markets, where they independently decided when to buy or sell shares and in what quantities (in units of 100 shares). For each trade, participants incurred a 0.5% transaction tax, mirroring the average transaction cost on the Shanghai Stock Exchange.

Before the markets opened at periods 100, 200, 300, and 400, participants were required to predict the stock prices for the next 100 periods using the historical data they had been provided. Figure 3-3 illustrates the user interface participants encountered during the experiment. In the interface, participants could enter the desired number of shares to trade in the lower right corner. Positive numbers represented buying, while negative numbers indicated selling. The system automatically imposed a transaction tax of 0.5% per trade.

At the end of the experiment, the experimental currency was converted into Chinese yuan based on a preset exchange rate. For student participants, every 10,000 units of experimental currency were converted into 3 RMB, while for non-student participants, every 10,000 units were exchanged for 10 RMB. The September 2024 exchange rate used for this conversion was 1 USD to 7.11 RMB.

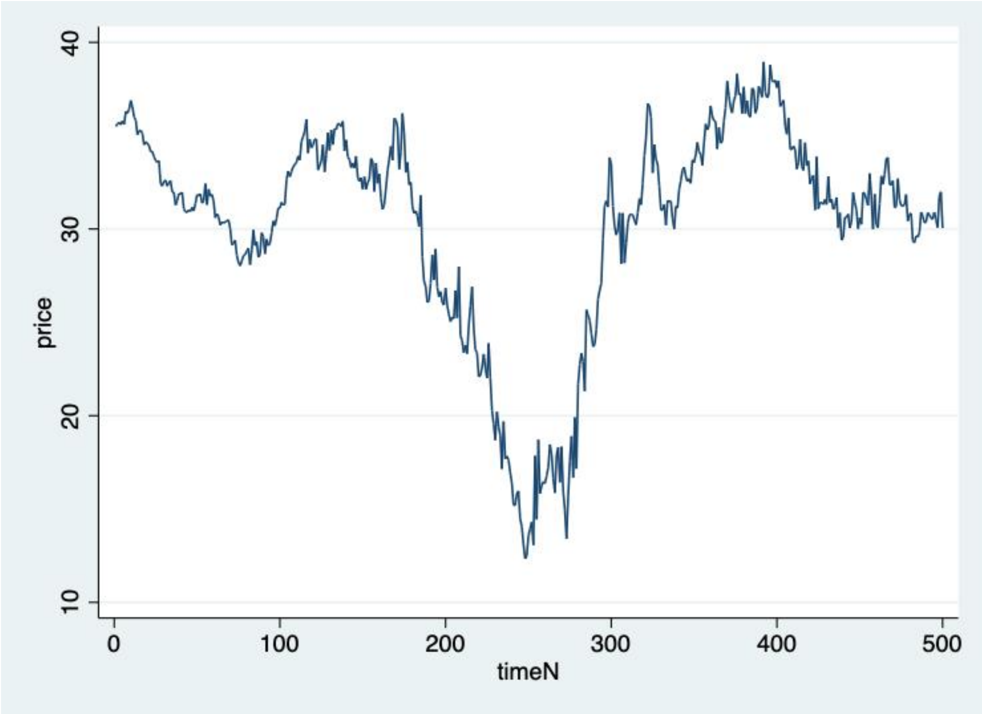


Figure 3-1 The price pattern of market N

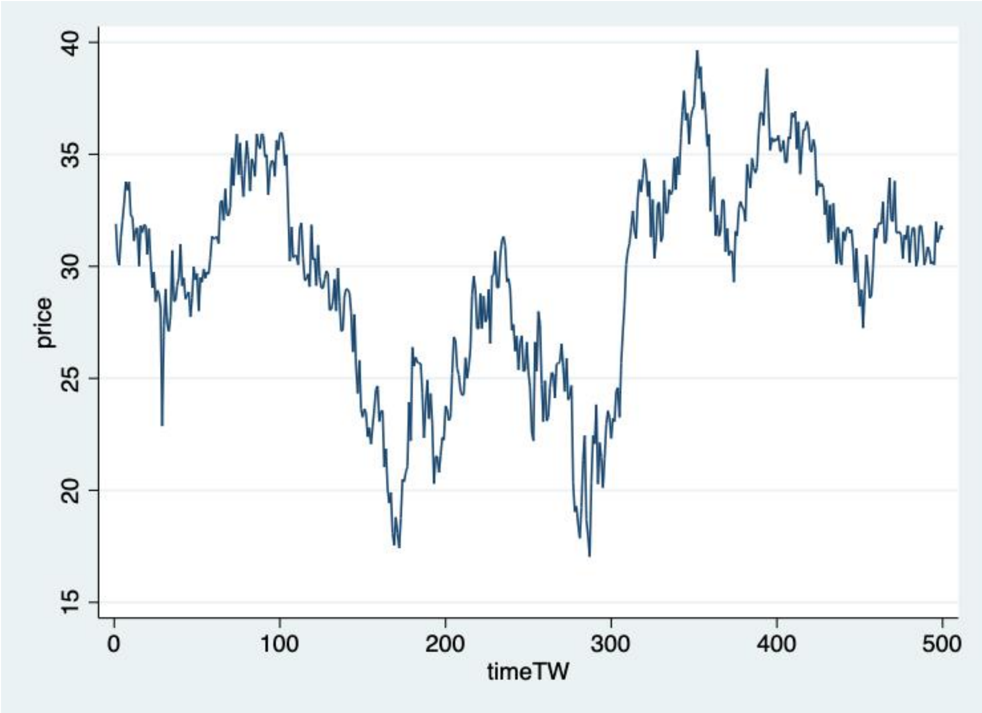


Figure 3-1 The price pattern of market N

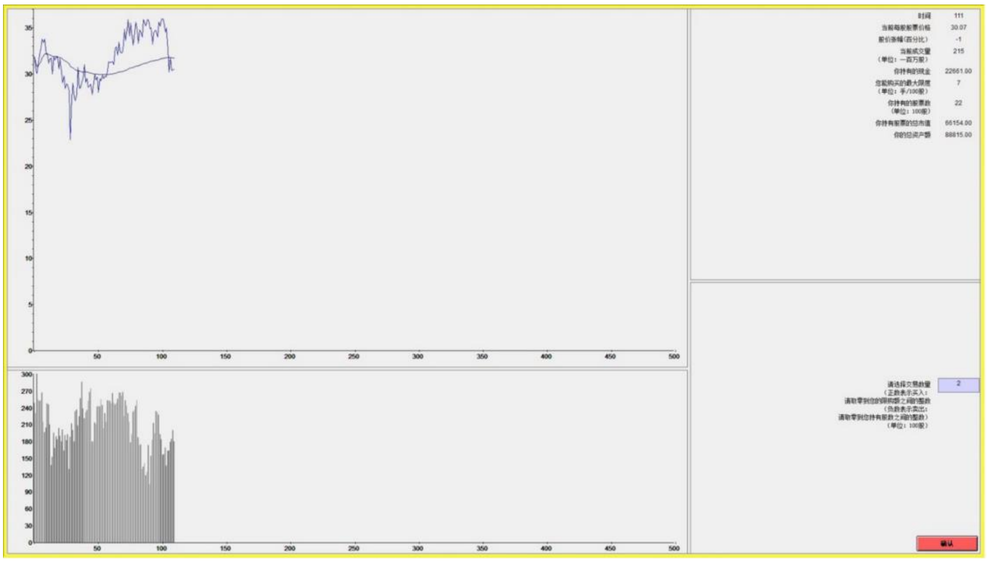

Figure 3-3 The computer interface

After participants complete the simulated trading in two markets, they will participate in a lottery selection experiment, modeled after Holt and Laury's (2002) framework, to assess their risk preferences. In this task, participants will be presented with 9 pairs of lottery choices, as shown in Table 3-1, and they must select one lottery from each pair, making a total of 9 lottery decisions.

Each lottery pair offers two options: Lottery A and Lottery B. For instance, in the second pair, Lottery A offers an 80% chance of winning 4.8 yuan and a 20% chance of winning 6 yuan, while Lottery B presents an 80% chance of winning 0.3 yuan and a 20% chance of winning 11.4 yuan. Both options have a 20% probability of higher returns, yet the expected value of Lottery A is 5.04 yuan, while for Lottery B, it is 2.52 yuan. A risk-neutral participant, considering only the expected returns, would opt for Lottery A over Lottery B in this decision.

However, as the probability of obtaining higher returns increases across the pairs, participants' preferences may shift. Initially, they might favor Lottery A, with more stable returns, but they may become inclined toward Lottery B as the probability of high payoffs rises. This transition will reflect participants' varying degrees of risk aversion or risk-seeking behavior, which is a key factor in analyzing their decision-making processes in the context of market crashes and recoveries.

By incorporating the lottery selection experiment, the study captures a more comprehensive understanding of how risk preferences influence investor behavior in financial markets.

Table 3-1 Lottery Experiment Table

| | A | | B | |
|---|---|---|---|---|
| 序号 | 4.8 元 | 6 元 | 0.3 元 | 11.4 元 |
| 1 | 90% | 10% | 90% | 10% |
| 2 | 80% | 20% | 80% | 20% |
| 3 | 70% | 30% | 70% | 30% |
| 4 | 60% | 40% | 60% | 40% |
| 5 | 50% | 50% | 50% | 50% |
| 6 | 40% | 60% | 40% | 60% |
| 7 | 30% | 70% | 30% | 70% |
| 8 | 20% | 80% | 20% | 80% |
| 9 | 10% | 90% | 10% | 90% |

After the lottery selection test, participants will complete a survey questionnaire. This survey will gather personal information, participants' self-assessment of their performance during the computer simulation investment, their personal judgment of the current stock market situation, and details about their household's involvement in stock market trading.

## 4. Experimental implementation

After collecting data from a simulated investment experiment, a total of 114 participants (including 32 non students and 82 students) completed a 90 minute simulated investment process. In the N market, 46 people worked in the N market before the TW market, and 68 people worked in the TW market before the N market; In the TW market, there are 46 people who first work in the N market and then in the TW market, and 68 people who first work in the TW market and then in the N market. In the statistical sample, the average age of students is 24.1 years old and they receive an average compensation of 45.6 yuan, while the average age of non students is 30.6 years old and they receive an average compensation of 119.4 yuan. Table 3-2 records the investment experience, gender, and age distribution of the participants.

Table 3-2 Summary Statistics on Subject Characteristics

| Variable | Mean | S.D. | Min | Max |
|---|---|---|---|---|
| Experience | 0.90 | 2.98 | 0 | 25 |
| Female | 0.42 | 0.50 | 0 | 1 |
| Age | 25.90 | 5.975 | 19 | 50 |

According to the data presented in Table 3-2, participants in the experiment had an average stock market trading experience of 0.9 years, with a variance of 2.98. The range of investment experience varied widely, with the shortest being 0 years and the longest 25 years. Female participants made up 42% of the total, with a standard deviation of 0.5 in the gender distribution. In terms of age, the average was 25.9 years, with a standard deviation of 5.975, where the youngest participant was 19 years old, and the oldest was 50 years old.

Table 3-3 further breaks down the demographic composition of participants with and without investment experience. Among inexperienced investors, ages ranged from 19 to 30 years, with 33% being female, and all participants were students. In contrast, among experienced investors, ages ranged from 21 to 50 years, with women accounting for 57% and students representing 24%. This segmentation provides important insights into how different demographic factors, such as age, gender, and student status, may relate to investment experience and behavior in the study.

Table 3-3 Basic Information Description of Experienced Investors

| Experience | Variable | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|
| 0 | Female | 0.33 | 0.46 | 0 | 1 |
| | Age | 24.36 | 3.83 | 19 | 30 |
| | student | 1 | 0 | 1 | 1 |
| 1 | Female | 0.57 | 0.51 | 0 | 1 |
| | Age | 28.52 | 7.86 | 21 | 50 |
| | student | 0.24 | 0.43 | 0 | 1 |

## 5. Analysis of experimental results

After the experiment, this study conducted a comparative analysis of the data collected from the aforementioned experiments. Based on the purpose of the experimental design and the experimental design, this article analyzes and discusses the collected experimental data using descriptive statistics and regression analysis methods. The experimental results mainly focus on investors' trading frequency, trading scale, trading price, price expectation, and total assets, in order to analyze how experience affects investors' investment behavior and expectations.

### (1) Variable definition

To ensure accuracy and clarity in data analysis, a range of key variables have been constructed to align with the experimental design and research objectives. These variables are categorized as dependent, independent, control, and additional variables, each contributing to the detailed analysis of how experience influences investor behavior and expectations.

Dependent variable:

1. Expectation Difference (EPD): EPD represents the difference between the prices predicted by investors and the actual market prices. Investors make price predictions every 100 periods, and the average of these 4 predictions per market is used to calculate their expectations.

2. Trade: The shares of stocks that investors buy or sell in each transaction.

3. Number of Trades: The number of transactions an investor completes in each simulated market.

4. Relative Size of Trade: The proportion of trading volume to position held by investors in a simulated stock market.

5. Ending Wealth: The total assets held by investors at the conclusion of the experiment.

6. DE: This is calculated as the difference between the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR), serving as a measure of investors' disposition effect.

7. Order: Indicates the sequence in which the investors participate in the two markets. If an investor experiences the local market first and then the non-local market, the value is 1; otherwise, it is 2.

Control variables:

8. Market: Denotes the market type in the experiment. The NASDAQ market is coded as 1, and the Taiwan market is coded as 2.

9. Age of investors: The age of each investor is included as a control variable to assess its impact on investment behavior.

10. Female: Investor gender composition, if 1, the investor is female, otherwise it is male.

11. Duration: The duration of an investor's past participation in real stock market trading, measured in years.

12. Risk: Risk preference. Based on risk testing, select the position where lottery A changes to lottery B for the first time as the risk value. If there are multiple changes, take the average of the positions where lottery A changes to B multiple times as the risk value. The higher the value of Risk, the more averse it is to risk.

13. Confidence Level: The difference between the ranking of total assets in two markets and the investor's perceived ranking, with a higher value indicating less confidence.

Other variables:

14. Irrational: In the risk test, if the lottery value only changes once, take 0; otherwise, take 1

15. PGR(Proportion of Gains Realized): the proportion of realized income to total realized and book income.

16. PLR(Proportion of Losses Realized): the proportion of realized losses to total realized and recorded losses.

**(2) Investor behavior analysis**

Table 4-1 shows the data of trading frequency, trading volume size, trading volume to position ratio, cash holding ratio, and year-end assets of different experienced investors in two markets. This article conducted rank sum tests on them respectively. The experimental results show that after experiencing a market crash, investors increase their trading frequency, decrease their absolute trading volume, decrease their relative trading volume, increase their cash holdings, and increase their total assets at the end of the period.

Table 4-1 presents data on the trading frequency, trading volume, trading volume-to-position ratio, cash holdings ratio, and year-end assets of investors with varying levels of experience across two markets. Rank-sum tests were conducted for these variables. The experimental results reveal that after experiencing a market crash and recovery, investors increase their trading frequency while reducing their absolute trading volume and relative trading volume-to-position ratio. Moreover, they tend to hold more cash, investors' total assets at the end of the period show an increase. These results underscore the influence of market crashes on investor behavior, reflecting heightened risk aversion and a shift towards more prudent investment strategies.

Table 4-1 Investor Investment Behavior Analysis

| Variable | Market | Order | Mean | S.D. | Min | Max | Rank-sum test P-value |
|---|---|---|---|---|---|---|---|
| Number of Trades | N | 1 | 11.26 | 19.69 | 0 | 76 | 0.155 |
| | | 2 | 17.55 | 30.62 | 0 | 207 | |
| | TW | 1 | 11.16 | 27.57 | 0 | 208 | 0.727 |
| | | 2 | 19.71 | 43.52 | 0 | 404 | |
| Absolute Size of | N | 1 | 11.21 | 10.02 | 0 | 75 | 0.001*** |
| | | 2 | 8.66 | 11.51 | 0 | 97 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Trade | TW | 1 | 9.78 | 12.33 | 0 | 136 | 0.313 |
| | | 2 | 9.66 | 10.64 | 0 | 66 | |
| Relative Size of Trade | N | 1 | 0.43 | 0.34 | 0 | 1 | 0.000*** |
| | | 2 | 0.37 | 0.34 | 0 | 1 | |
| | TW | 1 | 0.43 | 0.33 | 0 | 1 | 0.000*** |
| | | 2 | 0.28 | 0.41 | 0 | 1 | |
| Cash Holding% | N | 1 | 0.66 | 0.37 | 0 | 1 | 0.317 |
| | | 2 | 0.67 | 0.32 | 0 | 1 | |
| | TW | 1 | 0.69 | 0.37 | 0 | 1 | 0.489 |
| | | 2 | 0.71 | 0.36 | 0 | 1 | |
| Ending Wealth | N | 1 | 120234.70 | 47566.61 | 65303 | 285220 | 0.010*** |
| | | 2 | 129040.50 | 31770.55 | 10000 | 239926 | |
| | TW | 1 | 117491.30 | 24553.66 | 78528.5 | 199686 | 0.028** |
| | | 2 | 126474.50 | 22632.91 | 78183.5 | 203428 | |

Note: The data in the table is sourced from experimental data, where *, * *, and * * * represent p-values<0.1,<0.05, and<0.01, respectively.

The results of the rank-sum test indicate that in the N market, investors' trading volume significantly decreases. Additionally, the relative trading volume (the ratio of trading volume to holdings) significantly declines in both markets, while total assets at the end of the period show a notable increase. These findings suggest that the experience of a market crash makes investors more cautious, and this increased caution tends to improve their overall returns. Thus, Hypothesis 1 is supported by the data.

**(3) Price expectation analysis**

Table 4-2 shows the expected outcomes of investors with different experiences in two markets. EPD represents the total difference between the price predicted by investors and the actual price: Investors make a prediction of the price for the next 100 periods every 100 periods in each market, and the average of 4 predictions in each market is selected as the investor's expectation in that market. In the N market, investors generally underestimate future price trends, and experienced investors have reduced their underestimation of future prices. In the TW market, experienced investors tend to overestimate future prices. However, from the perspective of absolute price fluctuations, the market experience of collapse and recovery will increase investors' expectations for future prices, which is consistent with the conclusion of hypothesis 2.

Table 4-2 Expectations of Price Analysis

| Variable | Market | Order | Mean | S.D. | Min | Max | P-value |
|---|---|---|---|---|---|---|---|
| EPD | N | 1 | -1.81 | 2.80 | -4.42 | 2.75 | 0.238 |
| | | 2 | -0.47 | 2.74 | -7.50 | 6.25 | |
| | TW | 1 | -0.38 | 3.47 | -9.73 | 6.25 | 0.381 |
| | | 2 | 0.72 | 1.82 | -2.00 | 2.88 | |

Note: The data in the table is sourced from experimental data, where *, * *, and * * * represent p-values<0.1,<0.05, and<0.01, respectively.

**(4) Disposal effect analysis**

Table 4-3 presents the data on PLR (Proportion of Losses Realized), PGR (Proportion of Gains Realized), and DE (Disposition Effect) for investors with different levels of experience in two markets. PLR represents the ratio of realized losses to the total of realized and paper losses, while PGR represents the ratio of realized gains to the total of realized and paper gains. DE is calculated as the difference between PLR and PGR.

From the perspective of PLR, investors with crash experience tend to have a lower PLR. In the N market, this decrease is significant, while in the TW market, the decrease is not statistically significant. This indicates that the proportion of losses realized by investors relative to total losses is declining, meaning that investors are holding onto losing positions for a longer period of time.

Regarding PGR, the rank sum test results show that, at a significance level of 0.01, experienced investors in both markets exhibit lower PGR compared to inexperienced investors. This suggests that the proportion of realized gains to total realized and book gains is decreasing for experienced investors, resulting in a reduction in their realized returns.

Table 4-3 Disposition Effect Analysis

| Variable | Market | Order | Mean | S.D. | Min | Max | P-value |
|---|---|---|---|---|---|---|---|
| PLR | N | 1 | 0.016 | 0.041 | 0 | 0.164 | 0.002*** |
| | | 2 | 0.0039 | 0.016 | 0 | 0.088 | |
| | TW | 1 | 0.0079 | 0.031 | 0 | 0.176 | 0.750 |
| | | 2 | 0.0077 | 0.023 | 0 | 0.092 | |
| PGR | N | 1 | 0.033 | 0.077 | 0 | 0.436 | 0.000*** |
| | | 2 | 0.015 | 0.039 | 0 | 0.205 | |
| | TW | 1 | 0.025 | 0.036 | 0 | 0.145 | 0.000*** |
| | | 2 | 0.014 | 0.031 | 0 | 0.126 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| DE | N | 1 | 0.045 | 0.11 | -0.44 | 0.164 | 0.000*** |
| | | 2 | 0.025 | 0.046 | -0.21 | 0.088 | |
| | TW | 1 | 0.037 | 0.051 | -0.15 | 0.172 | 0.000*** |
| | | 2 | 0.020 | 0.039 | -0.13 | 0.092 | |

Note: The data in the table is sourced from experimental data, where *, * *, and * * * represent p-values<0.1,<0.05, and<0.01, respectively.

Overall, in the N market, the average DE (Disposition Effect) of inexperienced investors is 0.045, while that of experienced investors is 0.025, with a P-value of less than 0.01, indicating statistical significance. In the TW market, the average DE of inexperienced investors is 0.037, compared to 0.020 for experienced investors, and the rank sum test also shows significance at the 0.01 level. These results suggest that experience significantly reduces the Disposition Effect among investors, meaning that experienced investors exhibit less tendency to hold onto losing stocks and sell winning stocks prematurely. This finding aligns with hypothesis 3.

## 6. Regression analysis

### (1) Model construction

To achieve the research objectives, this study plans to construct three models, each focusing on the impact of experience on investor behavior, expectations, and the influence of experience on the disposition effect. Since participants were randomly assigned to conduct experiments in two markets in sequence, and individual characteristics or other factors affecting the experimental outcomes were entirely independent, this design avoids issues related to omitted variable bias or endogeneity. In the subsequent analysis, investor behavior, expectations, and disposition effect will be used as dependent variables, with experience serving as the independent variable for regression analysis. Additionally, control variables such as age, investor risk preference, historical market experience, and gender will be included. Based on an in-depth investigation of how experience and expectations jointly influence investor behavior, this study will construct a multiple linear regression model as follows:

$$Behavior_i = \alpha_0 + \alpha_1 Order_i + \lambda_1 \Sigma x_i + \varepsilon_i \qquad (4)$$

$$Expc_i = \beta_0 + \beta_1 Order_i + \lambda_2 \Sigma x_i + \varepsilon_i \qquad (5)$$

$$DE_i = \gamma_0 + \gamma_1 Order_i + \lambda_3 \Sigma x_i + \varepsilon_i \qquad (6)$$

**(2) Regression analysis**

Table 4-4 presents the results of a regression analysis on four aspects of investor behavior, with experience as the key explanatory variable.

Table 4-4 Regression Analysis of Investor Behavior

| Variables | Number of Trades | | Absolute Size of Trade | | Relative Size of Trade | | Cash Holding | |
|---|---|---|---|---|---|---|---|---|
| | N | TW | N | TW | N | TW | N | TW |
| Order | 5.44 | 14.46 | -4.41*** | -4.47*** | -0.94 | -3.90* | 0.58 | 2.63*** |
| | (7.44) | (15.67) | (0.53) | (0.60) | (2.27) | (2.08) | (2.07) | (1.88) |
| Experience | -0.78 | -2.18 | -0.31* | -0.66** | 1.32* | -1.63** | 0.96 | -0.69 |
| | (4.89) | (10.50) | (0.16) | (0.23) | (0.65) | (0.79) | (0.63) | (0.74) |
| Female | 5.72 | -4.73 | 0.31*** | -1.53** | 0.05 | 1.02 | 1.24*** | 1.08 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (10.63) | (22.84) | (0.59) | (0.75) | (2.48) | (2.57) | (0.23) | (2.38) |
| Risk | -4.13* | -1.78 | 0.51*** | -0.80* | -0.34 | -0.03*** | 0.66 | 2.16*** |
| | (2.41) | (5.18) | (0.12) | (0.16) | (0.50) | (0.01) | (0.48) | (0.51) |
| Age | -0.86 | -2.70 | 0.45*** | 0.38*** | 0.93*** | 0.52** | -0.69*** | 0.13 |
| | (2.77) | (5.85) | (0.05) | (0.07) | (0.22) | (0.27) | (0.19) | (0.23) |
| conlevel | 2.94 | -6.24 | -0.29 | -2.23*** | -5.06*** | -2.38*** | 5.47*** | 3.72*** |
| | (2.63) | (5.52) | （0.20） | (0.20) | (0.89) | (0.68) | (0.78) | (0.64) |
| constant | 53.02 | 127.45 | 9.01*** | 2.48*** | 19.41*** | 32.24*** | 64.43*** | 44.27*** |
| | (60.54) | (126.77) | (1.40) | (1.90) | (5.94) | (6.82) | (5.42) | (6.01) |
| Adj.$R^2$ | 0.011 | 0.114 | 0.111 | 0.152 | 0.051 | 0.034 | 0.084 | 0.031 |

Note: The data in the table is sourced from experimental data, where *, * *, and * * * represent p-values<0.1,<0.05, and<0.01, respectively.

In the first regression, the dependent variable is the Number of Trades, while in the second regression it is the Absolute Size of Trade. The third regression uses the Relative Size of Trade as the dependent variable, and the fourth focuses on Cash Holding. The results demonstrate that experience with market collapse is significantly positively correlated with the trading volume of investors. In the TW market, experience is significantly negatively correlated with relative trading volume and significantly positively correlated with the cash holding ratio. These findings are consistent with the results from the analysis of investor behavior in Table 4-1, particularly regarding trading volume, trade size, and cash holding ratio.

Table 4-5 presents the OLS regression analysis for expectations, showing that in the N market, experience is significantly positively correlated with expectations. Experiencing market collapse and recovery leads investors to increase their price expectations, causing them to overestimate future stock values. However, this effect is not significant in the TW market.

Table 4-5 Regression Analysis of Expectation

| | Expectation | |
|---|---|---|
| Market | N | TW |
| Order | 1.75*** | 0.34 |
| | (0.32) | (0.24) |
| Experience | 0.40*** | 0.99*** |
| | (0.05) | (0.05) |
| Female | 0.81** | -2.31*** |
| | (0.34) | (0.28) |
| Risk | 0.32* | 0.33*** |
| | (0.05) | (0.06) |
| Age | -0.25*** | -0.49*** |
| | (0.21) | (0.21) |
| conlevel | 0.26*** | -0.38*** |
| | (0.08) | (0.08) |
| constant | 0.75 | 0.11 |
| | (0.48) | (0.48) |
| Adj.R2 | 0.328 | 0.744 |

Note: The data in the table is sourced from experimental data, where *, * *, and * * * represent p-values<0.1,<0.05, and<0.01, respectively.

For the insignificant results, this article speculates that the differences may be related to the distinct market patterns between the two markets, as depicted in Figure 3-1 and Figure 3-2. In the N market, investors experience one market crash followed by one market recovery. However, in the TW market, investors experience two market crashes, one small-scale recovery, and one relatively complete recovery.

To explore whether different market patterns influence the effect of experience on expectations, this article categorizes investors in the TW market based on their trading periods, focusing on two specific time points: time=234 and time=351. Investors trading between time=234 and time=351 have experienced one crash and recovery, and for ease of description, they are referred to as "crash recovery investors." Those trading after time=351, who have experienced two crashes and two recoveries, are defined as "crash recovery second investors." A regression analysis was conducted on these two groups of investors, with the results displayed in Table 4-6.

Table 4-6 Regression Analysis of Expectation（Investor 1&2）

| | Expectation | |
|---|---|---|
| TW Market | Investor 1 | Investor 2 |
| Order | -0.45 | 1.58*** |
| | (0.39) | (0.22) |
| Experience | 0.91*** | 0.80*** |
| | (0.09) | (0.10) |
| Female | -2.11*** | -5.33*** |

| | | |
|---|---|---|
| | (0.46) | (0.25) |
| Risk | 0.33*** | 1.23*** |
| | (0.10) | (0.06) |
| Age | -0.45*** | -0.75*** |
| | (0.03) | (0.02) |
| conlevel | -0.39*** | -0.61*** |
| | (0。15) | (0.07) |
| constant | 10.11*** | 11.23*** |
| | (0.78) | (0.48) |
| Adj.R2 | 0.659 | 0.986 |

Note: The data in the table is sourced from experimental data, where *, * *, and * * * represent p-values<0.1,<0.05, and<0.01, respectively.

The regression analysis results in Table 4-6 reveal that the experience of investors who have encountered a single crash and recovery does not significantly influence their expectations. However, investors who have experienced two crashes and recoveries demonstrate a significant positive impact on their expectations, aligning with the results observed in the N market. Investors in the N market, having undergone two market crashes and recoveries, show similar behavioral patterns to B-class investors in the TW market, who have also experienced one crash and recovery in each market. Altogether, these investors have encountered two crashes and recoveries. The article hypothesizes that this cumulative experience of multiple market crashes and recoveries significantly shapes investor expectations.

Table 4-7 presents the OLS regression analysis of disposition effect data. The findings suggest a negative correlation between experience and the disposition effect across both markets, with significance at the 0.01 level. After facing market crashes and recoveries, investors tend to hold profitable stocks for a longer duration and sell loss-making stocks more quickly in subsequent trades, reducing the disposition effect. This result aligns with the disposition effect analysis presented in Table 4-3.

Table 4-7 Regression Analysis of Disposition Effect

| | DE | |
|---|---|---|
| Market | N | TW |
| Order | -2.03*** | -2.38*** |
| | (0.32) | (0.30) |
| Experience | 0.34*** | 0.17 |
| | (0.10) | (0.12) |
| Female | 0.05 | 0.97*** |
| | (0.36) | (0.38) |
| Risk | -0.31*** | -0.045 |
| | (0.07) | (0.082) |
| Age | -0.11*** | -0.19*** |
| | (0.03) | (0.04) |
| conlevel | -0.74*** | -0.38*** |
| | (0.12) | (0.10) |
| constant | -0.99 | 4.91*** |

| | | |
|---|---|---|
| | (0.84) | (0.96) |
| Adj.R2 | 0.189 | 0.114 |

Note: The data in the table is sourced from experimental data, where *, * *, and * * * represent p-values<0.1,<0.05, and<0.01, respectively.

When investors' expectations shift, their emotions and trading behavior may also be affected. The regression analysis presented in Table 4-8 indicates a significant negative correlation between expectations and the disposition effect (DE), with results significant at the 0.01 level. As investor expectations rise, their disposition effect diminishes, leading them to hold onto profitable stocks for longer periods and sell loss-making stocks more quickly. This suggests that heightened expectations may enhance rational decision-making in stock trading.

Table 4-8 Regression Analysis of Expectation Disposition Effect

| | DE | |
|---|---|---|
| Market | N | TW |
| EPD | -0.46*** | -1.03*** |
| | （0.04） | （0.04） |
| Experience | 0.48*** | -0.48*** |
| | （0.04） | （0.07） |
| Female | -0.59*** | 0.05 |
| | （0.21） | （0.03） |
| Risk | 0.31*** | 0.41*** |
| | （0.04） | （0.06） |
| Age | -0.16*** | 0.21*** |

| | | |
|---|---|---|
| | （0.02） | （0.03） |
| conlevel | 0.26*** | 0.39*** |
| | （0.07） | （0.08） |
| constant | 0.45 | -10.38*** |
| | （0.32） | （0.61） |
| Adj.R2 | 0.430 | 0.713 |

Note: The data in the table is sourced from experimental data, where *, * *, and * * * represent p-values<0.1,<0.05, and<0.01, respectively.

## 7. Conclusion and Suggestions

### (1) Conclusion

After experiencing market crashes and recoveries, investors' behavior and expectations undergo notable shifts. This article draws on data from two stock market investment experiments characterized by both downturns and recoveries, examining variables such as investor expectations and trading volume. The data analysis reveals the following findings:

**Behavioral Changes:** Investors exhibit significant behavioral changes following market crashes and recoveries, marked by a notable reduction in trading volume, increased cash holdings, and more conservative investment decisions.

**Expectations Shift:** After enduring two market crashes and subsequent recoveries, investors tend to hold more optimistic expectations regarding future stock prices. For those initially underestimating market prices, their forecasts become more aligned with actual prices post-crash, whereas overestimating investors tend to increase their degree of overvaluation.

**Disposition Effect:** Investors reduce the holding periods for both profitable and loss-making stocks following market crashes and recoveries. However, the overall disposition effect declines, which is also closely linked to their future price expectations. As expectations rise, the disposition effect further decreases.

**(2) Policy recommendations**

In the context of frequent market fluctuations, investors are advised to adopt a conservative investment strategy. This includes reducing the frequency of trades and maintaining a higher cash reserve (such as 20% to 30% of the investment portfolio), which can significantly enhance overall returns.

Investors' expectations tend to rise following experiences of stock market crashes and recoveries. To better adapt to market dynamics, they should consider lowering their expectations by 1% to 2%, even if their initial expectations remain unchanged.

After encountering a market crash and recovery, investors typically become more rational in their decision-making. If they perceive a shift in their investment strategy, they should maintain discipline and resist the urge to adjust their holdings based solely on market trends. Moreover, avoiding excessive trading and continuously refining their investment strategy will be key to long-term success.

**(3) Further prospects**

Due to time constraints and the limitations of this research, there are several shortcomings and areas requiring further investigation. First, the participants in this study may not fully represent the broader stock market population, as the sample was selectively recruited and might not encompass the diverse characteristics and behaviors of all market participants. Second, the simplified simulation models used in the controlled laboratory environment cannot fully capture the complexity of real-world stock market conditions, potentially leading to differences between experimental outcomes and actual market behavior.

Additionally, the experimental results from the N market differed from those of the TW market, possibly due to the existence of two distinct crash and recovery phases in the TW market. Future research should consider disentangling different crash and recovery processes, while controlling empirical factors within a more focused range. For example, when analyzing the impact of crashes and recoveries on expectations, this study considered the overall effect without differentiating between the crash and recovery phases. Investors experiencing crashes might develop more pessimistic expectations, while those witnessing recoveries could become more optimistic. Further research could explore these nuances in greater detail.

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