



Research Paper

Booms, busts, and beliefs[☆]Qian Cao^a, Jun Luo^{b,*}, Xiaofei Niu^{c,*}, Wenhua Wang^c^a School of Business Administration, Nanjing University of Finance & Economics, Nanjing, China^b School of Economics and Center for Economic Behavior and Decision-Making, Zhejiang University of Finance & Economics, Hangzhou, China^c School of Economics/Institute for the Study of Brain-Like Economics, Shandong University, Jinan, China

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ABSTRACT

Despite the prevalence of booms and busts, little is known about how investors learn from financial information during these cycles. We prime financial professionals with either a boom or a bust scenario and find that boom-primed professionals exhibit asymmetric learning from positive and negative information, while bust-primed professionals do not. This procyclical learning asymmetry is absent among professionals without bubble-crash experience and among nonfinancial professionals, highlighting the pivotal role of experience, particularly bubble-crash experience. One potential explanation for the procyclical learning asymmetry is emotion-driven associative memory. Our findings shed light on the dynamics of belief formation over the business cycle.

1. Introduction

Booms and busts are recurring phenomena in financial markets. For example, the U.S. stock market experienced five major bull and bear markets in the twentieth century, averaging once every twenty years (Barsky and De Long, 1990). Similarly, the Chinese stock market has experienced two bubble-crash episodes since its inception in 1991, averaging once every fifteen years (An et al., 2022).¹

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¹ The definition of boom-bust and bubble-crash varies in the literature. However, a common feature of boom-bust and bubble-crash is that the price of an asset rises for a period of time and then falls, reversing much of the rise (for more discussion on boom-bust and bubble-crash, see Brunnermeier and Oehmke, 2013; Barberis, 2018).

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Despite the prevalence of financial booms and busts, little is known about how investors form beliefs during such cycles. Consider a scenario in which an investor receives either good or bad news about a stock during a market boom and another scenario in which the investor receives such news about the same stock during a market downturn. Do investors learn from positive and negative information in the same way during booms and busts?

The existing literature does not provide a complete answer to this question. [Kuhnen's \(2015\)](#) seminal paper shows that investors exhibit asymmetric learning from positive and negative information, generally forming pessimistic beliefs in response to negative information.² However, the question of whether this learning asymmetry or pessimism bias persists during both boom and bust periods remains unanswered.

A major challenge in answering this question is to identify *ceteris paribus* variations in financial market trends. Actual market data may not be ideal because good and bad news are endogenous to boom and bust markets, with good news abundant in booms and bad news excessive in busts. Consequently, it is difficult to determine whether changes in beliefs are driven by market cycles or by the uneven distribution of positive and negative information.

To circumvent this issue, we adopted the approach of [Cohn et al. \(2015\)](#) by manipulating financial market trends in a controlled experimental setting. Participants were primed with either a stock market boom or bust by being shown a graph of asset prices that resembled a boom or bust, depending on their priming condition. We then asked them condition-specific general questions about their investment strategy during a boom or bust. This priming activated the concept of a financial boom or bust, allowing us to examine its psychological impact on participants' beliefs.³

Following the priming manipulation, we elicited participants' beliefs in a learning task developed by [Kuhnen \(2015\)](#). Participants observed the dividends paid by a stock and provided an estimate of the probability that the stock paid from either a good or bad distribution. As in [Kuhnen \(2015\)](#), we manipulated the stock dividends. The stock offered only positive payoffs in the gain domain and only negative payoffs in the loss domain. Participants faced the same learning problem in both domains, the only difference being the sign of the dividend paid by the stock ($-/+$).

We use this design to conduct a series of online experiments with both financial and nonfinancial professionals. Our results show that when primed with a boom, professionals exhibit a pessimism bias: Their subjective probability estimates that the stock is paying from a good distribution are lower in the loss domain than in the gain domain. This difference remains statistically significant even after controlling for the objective Bayesian posterior probability. In contrast, when professionals are primed with a bust, the pessimism bias, or the wedge between subjective beliefs in the loss and gain domains, disappears. These findings suggest that professionals' asymmetry in learning from positive and negative information is procyclical, reflecting a pattern of procyclical learning asymmetry.

Further analysis indicates that this procyclical learning asymmetry is primarily driven by bust-primed professionals reacting less to high dividends in gain trials compared to boom-primed professionals. As a result, subjective beliefs in the gain domain are more pessimistic in bust priming than in boom priming, while beliefs in the loss domain remain the same across priming conditions.

Our results also show that professionals with bubble-crash experience exhibit procyclical learning asymmetry, whereas those without such experience do not. Moreover, nonprofessionals show no evidence of procyclical learning asymmetry. These findings highlight the critical role of experience, particularly experience with bubble-crash episodes, in shaping procyclical learning asymmetry. We also provide evidence that emotion-driven associative memory may be a mechanism underlying the procyclical learning asymmetry.

Our paper contributes to the literature in several ways. Prior experimental work in finance documents that student participants exhibit asymmetry in learning from positive and negative information ([Kuhnen, 2015](#)).⁴ We show that this learning asymmetry extends beyond student samples and is robust among both professional and nonprofessional participants. More importantly, we find a procyclical learning asymmetry: the asymmetry emerges only when professionals are primed with a boom scenario and disappears when they are primed with a bust scenario.⁵

² Beyond the financial literature, research in economics and neuroscience suggests that individuals tend to process information asymmetrically when it pertains to personal characteristics and future life outcomes, giving more weight to good news and less weight to bad news ([Eil and Rao, 2011](#); [Sharot et al., 2011](#)). This optimism bias is typically associated with updating beliefs about the "self". In contrast, [Kuhnen's \(2015\)](#) study documents a pessimism bias that corresponds to the formation of beliefs about the "future state of the world".

³ Priming is a well-established and widely used technique in social psychology that refers to the activation of mental concepts by subtle situational cues ([Dai et al., 2023](#)). Priming often involves activating seemingly unrelated mental concepts through specific tasks, with the primed concepts then "spilling over" into subsequent tasks. By examining and comparing such spillover effects, it is possible to examine the impact of primed concepts on individual behavior. Priming has also been widely used in recent economic and financial literature (e.g., [Cohn et al., 2015 and 2017](#); [Kirchler et al., 2018](#); [Colonnelli et al., 2024](#); for a review, see [Cohn and Maréchal, 2016](#)).

⁴ In a parallel strand of the economic literature, the evidence from laboratory experiments on learning asymmetries in other contexts is inconclusive, with some studies finding evidence of asymmetries (e.g., [Eil and Rao, 2011](#)) and others finding no support (e.g., [Barron, 2021](#)). For a detailed discussion of learning asymmetries, see [Benjamin \(2019\)](#), who calls for further research on whether and under what circumstances asymmetries exist. We add to this literature by examining asymmetric learning from positive and negative information across the business cycle.

⁵ Our findings add to the growing literature on the behavior of financial professionals ([Cohn et al., 2015, 2017](#); [Kirchler et al., 2018](#); [Weitzel et al., 2020](#); [Cao et al., 2022](#); [Niu et al., 2023](#)). Recent experimental evidence shows that in some situations, financial professionals behave in the same way as students, while in other situations their behavior differs from that of students. For example, the impact of time pressure and cognitive control on the disposition effect is robust across professionals and students ([Cao et al., 2022](#); [Niu et al., 2023](#)). However, compared to students, professionals have stronger preferences for relative performance ([Kirchler et al., 2018](#)) and are responsible for less frequent and less severe bubbles in experimental asset markets ([Weitzel et al., 2020](#)).

In this regard, our study relates to the literature on how risk-taking and beliefs vary across booms and busts. Using a similar priming method, [Cohn et al. \(2015\)](#) show that exposing financial professionals to a bust scenario, as opposed to a boom scenario, significantly reduces risk-taking, providing evidence of countercyclical risk aversion. Instead of priming, [Kieren et al. \(2023\)](#) induce boom- or bust-like environments by manipulating positive and negative returns. They conduct two experiments: the first restricts learning to exclusively positive (boom) or exclusively negative (bust) domains, following [Kuhnen \(2015\)](#), while the second uses mixed-outcome distributions with either positive (boom) or negative (bust) expected returns. Across both experiments, they find that participants exposed to bust environments form more pessimistic beliefs than those in boom environments. These belief differences reduce willingness to take investment risks under ambiguity but not under risk.

We add to this literature by distinguishing the effects of boom-bust scenarios and gain-loss domains on learning from financial information.⁶ We show that financial professionals learn similarly from negative information in boom and bust scenarios, but they react to positive information more pessimistically in a bust than in a boom. As a result, the pessimism bias induced by negative information persists in a boom scenario but not in a bust scenario. We also show that emotional memory serves as a mechanism underlying learning from financial information in booms and busts.⁷

Our paper also relates to the literature on experience effects, particularly the impact of bubble-crash experience. Prior work has examined how personal exposure to recessions ([Malmendier and Nagel, 2011](#)) and inflation ([Malmendier and Nagel, 2016](#)) shapes risk-taking and beliefs (for an overview, see [Malmendier, 2021](#)). [Heinke et al. \(2024\)](#) examine how prior experiences influence subsequent investment decisions in a laboratory experiment. They find that participants who previously encountered high (low) outcomes tend to invest more (less) in a risky asset, even in situations where these experiences offer no new information and should be disregarded.

We extend this literature by providing experimental evidence on how bubble-crash experience influences belief formation across the business cycle. We also show that professionals, but not nonprofessionals, exhibit procyclical learning asymmetry, highlighting the critical role of experience in shaping beliefs in booms and busts.

2. Experiments with financial professionals

2.1. Design for experiments 1 and 2

2.1.1. Basic design

Experiments 1 and 2 consisted of two parts.⁸ The first part included some icebreaker questions and the experimental manipulation of financial market trends (adapted from [Cohn et al., 2015](#)). Participants were randomly assigned to one of the three market trend conditions (i.e., *Baseline*, *Boom*, or *Bust*). In the *Baseline* condition, participants faced a calm stock market. In the *Boom* condition, participants faced a booming stock market, while in the *Bust* condition, participants faced the opposite situation, a stock market bust (see [Fig. 1](#)). The participants then answered four questions about their investment strategy. For example, in the *Boom* condition, participants were asked, “Imagine you are in a stock market boom and you expect it to continue as indicated by the arrow in the picture. Would you buy or sell stocks? Briefly explain your answer.” In the *Baseline* or *Bust* condition, participants answered an analogous set of questions.

The second part of the experiment was a belief task (adapted from [Kuhnen, 2015](#)). Participants could earn money in the belief task where they were asked to learn about the distribution of a stock. The belief task consisted of the gain and loss domains (i.e., *Gain* and *Loss* conditions). In the *Gain* condition, the stock provided positive payoffs, +2 or +10 Chinese yuan (i.e., CNY). In the *Loss* condition, the stock provided negative payoffs, −10 or −2 CNY. In the *Gain* or *Loss* condition, the stock paid dividends from either a good or a bad distribution. The good distribution was one in which the high dividends occurred with a probability of 70 % and the low dividends occurred with a probability of 30 %. The bad distribution was one where these probabilities were reversed: The high dividends occurred with a probability of 30 %, and the low dividends occurred with a probability of 70 %. The high dividends in the *Gain* and *Loss* conditions are +10 CNY and −2 CNY, respectively.

The experiment comprised 24 trials, grouped into four blocks of six trials each. In each trial, participants were presented with the payoffs paid by the stock and then asked to estimate the probability that the stock paid payoffs from either the good or bad distribution. The probability estimates for each distribution were counterbalanced, meaning that participants reported their estimates for the good

⁶ Our study also relates to the literature on bubbles and financial crises. Existing theoretical work focuses primarily on explaining stock market bubbles and crashes, such as expectation-based extrapolative and diagnostic bubbles ([Barberis et al., 2018](#); [Bordalo et al., 2021](#); for a detailed discussion of the explanations of bubbles and financial crises, see [Brunnermeier and Oehmke, 2013](#)). Survey studies provide suggestive evidence that investors are optimistic in booms and pessimistic in busts ([Amromin and Sharpe, 2014](#)). We add to this literature by examining the dynamics of belief formation over the business cycle.

⁷ The existing literature in economics and finance largely attributes belief biases to selective memory shaped by similarity and interference ([Hartzmark et al., 2021](#); [Bordalo et al., 2023](#); [Enke et al., 2024](#); [Jiang et al., 2025](#)). In contrast, our study focuses on emotional memory.

⁸ All experiments reported in our study are pre-registered at AsPredicted (i.e., #74383, #80569, #93187, and #137107). Please note that our pre-registrations were basic and provided only essential information (i.e., research question, treatment design and sample size). We did not pre-register details of the planned analysis (e.g., primary analysis, secondary analysis and exploratory analysis). This is because our analysis mainly follows [Kuhnen \(2015\)](#). We also make it clear that we have not selectively reported the most favorable analysis.

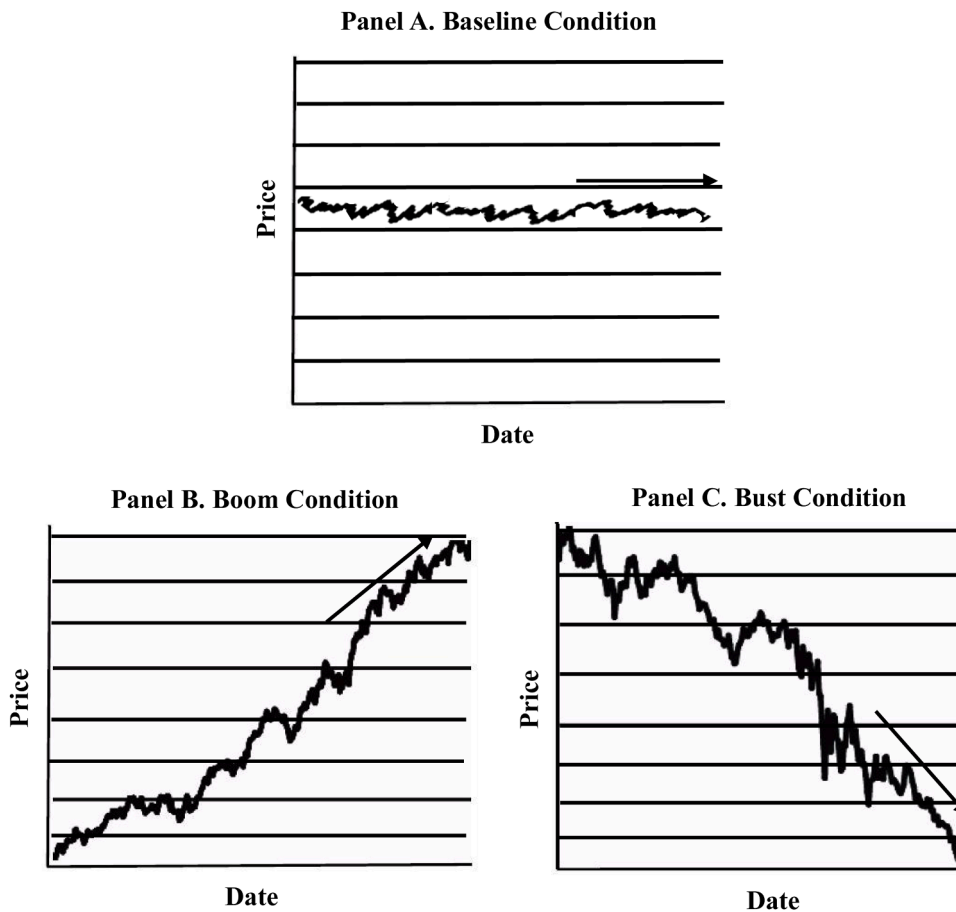


Fig. 1. Manipulation of financial market trends used in Experiments 1 and 2. Panels A, B, and C present the market trends in the *Baseline*, *Boom*, and *Bust* conditions, respectively. We intentionally did not label the time and price axes to prevent participants from thinking about a specific stock market event, but about booms and busts in general. The arrows were used to illustrate that the market trends were not expected to reverse in the near future.

distribution in some blocks and for the bad distribution in others. Probability estimates for the bad distribution were inverted so that higher estimates indicated more optimistic beliefs. Each block of six trials involved the same learning task, with the stock paying payoffs from either the good or bad distribution.

At the beginning of each learning block, the computer randomly determined whether the good or bad distribution would be used in the following six trials, with a 50 %-50 % probability. It is important to note that participants were explicitly informed that the prior probability of the stock paying payoffs from either the good or bad distribution was 50 % for each learning block. The experiment began only after participants confirmed their understanding of this 50 % prior. To verify that participants were aware of the prior probability, we asked them to report the 50 % prior at the beginning of each learning block. Using the 50 % prior, along with the dividend displayed on each trial, participants estimated the probability that the stock was paying from the good or bad distribution in that block. Panels A and B in Fig. 2 depict the time course of a typical block for the *Gain* and *Loss* conditions, respectively.

All participants were presented with the same set of realized dividends, but they observed them in different blocks. The order of blocks and realized dividends can be found in Table A1 in Appendix A. To minimize potential order effects, we varied the order of blocks for each session of a treatment, ensuring that each session had a unique block order within that treatment.

The value of the objective Bayesian posterior that the stock is paying from the good or bad distribution can be calculated. For example, after observing t high dividends in n trials so far, the Bayesian posterior that the stock is paying from good distribution is $\frac{1}{1 + \frac{1-p}{p} \times \left(\frac{q}{1-q}\right)^{n-t}}$, where $p = 50\%$ is the prior that the stock would pay dividends from the good distribution (before any dividends are

observed in that learning block) and $q = 70\%$ is the probability that the stock with a good distribution pays high (rather than the low) dividends in each trial. Appendix B provides the value of the objective Bayesian posterior for all $\{n, t\}$ possible pairs. Using this Bayesian posterior, we can measure how close the participants' expressed probability estimate is to the objectively correct value and

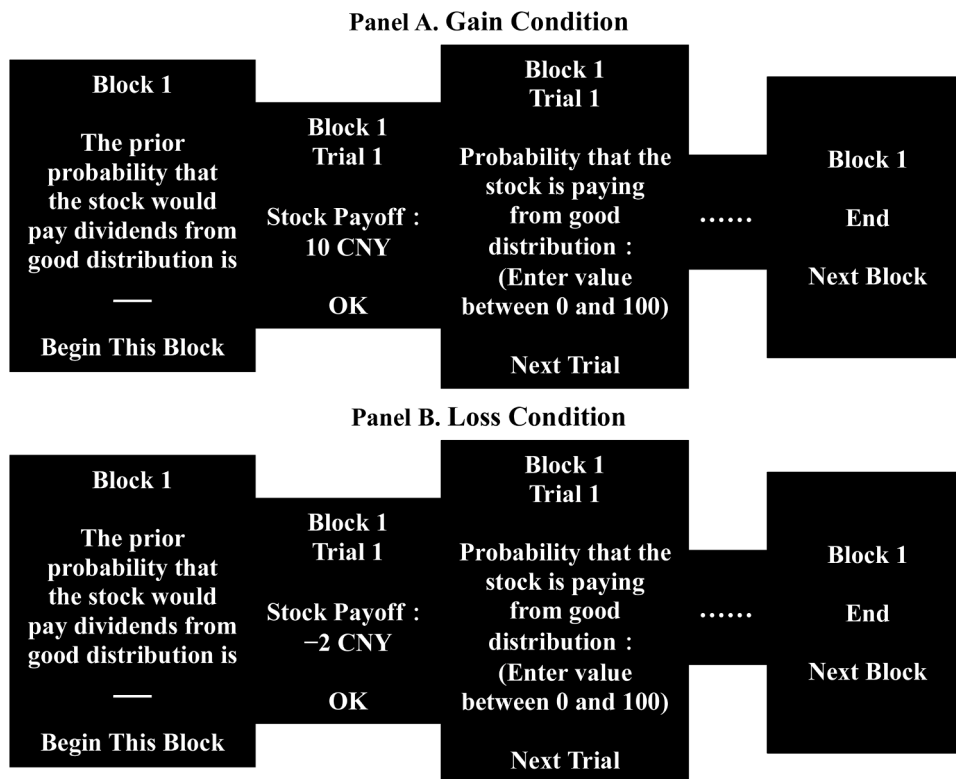


Fig. 2. Belief task used in Experiments 1 and 2. This Fig. shows an example of a gain condition block (Panel A) and a loss condition block (Panel B). In both types of blocks, participants were asked to report the 50 % prior at the beginning of each learning block. Participants observed the payoff paid by the stock in each trial of that block. They were then asked to provide an estimate of the probability that the stock paid from the good or bad distribution. The block ended when participants had completed six trials.

how well the participants' belief update tracks the objective update on each trial based on the new dividend information. We added 10 CNY to participants' earnings each time they provided us with a probability estimate that was within 5 % of the correct value. To avoid feedback effects, the accuracy of each participant's probability estimate and the corresponding earnings were provided at the end of the experiment. This information was common knowledge.

Our experiment ended with several questionnaires about the participants' socioeconomic background, such as age, gender, education level, monthly income, and years of work in the financial industry. We also included a financial literacy test.⁹

2.1.2. Design differences

There are three main design differences between Experiments 1 and 2.

First, in Experiment 1, the financial market trends and gain-loss domains are between-subject designs. There are three market trend conditions (i.e., *Baseline*, *Boom*, and *Bust*) and two gain-loss conditions (i.e., *Gain* and *Loss*), resulting in six treatments (i.e., BASE-GAIN, BASE-LOSS, BOOM-GAIN, BOOM-LOSS, BUST-GAIN, BUST-LOSS) in a 3×2 design, as shown in Panel A of Table 1. In Experiment 2, the market trend condition is a between-subject design, and the gain-loss condition is a within-subject design, generating two treatments (i.e., BOOM and BUST) in a 2×1 design, as shown in Panel B of Table 1. We believe that a combination of between-subject and within-subject designs can provide us with more convincing evidence of changes in subjective beliefs during financial booms and busts.

Second, in Experiment 1, participants were not endowed with the stock, and their payoffs depended only on the accuracy of their probability estimates. In Experiment 2, participants were endowed with the stock, and their payoffs depended on the dividends of the stock and the accuracy of their probability estimates. Note that in our experiment, stock ownership is exogenously assigned to

⁹ Following Kuhnén (2015), we asked participants to calculate the expected value of the portfolio, and multiple-choice responses allowed us to detect whether they lacked an understanding of probabilities, the difference between net and gross returns, or the difference between stocks and savings accounts. This resulted in a financial literacy score of zero to three, depending on whether the participant's response showed an understanding of none, one, two, or all three of these concepts.

participants, not by their choice.¹⁰ Recent experimental evidence shows that stock ownership affects how participants learn from financial information (Hartzmark et al., 2021). We test whether our experimental results are robust to stock ownership.

Third, the set of realized dividends in Experiments 1 and 2 is different (see Panels A and B of Table A1 in Appendix A). It is possible that the observed change in subjective beliefs during financial booms and busts is due to a particular set of realized dividends. Therefore, we change the set of realized dividends in Experiment 2.

2.1.3. Professionals

To study the behavior of real financial market participants, we recruited financial professionals who were regularly faced with investment and trading decisions in their daily work. The professionals came from major financial institutions in China, such as wealth management, portfolio management, fund management, and investment banking. We used several channels to invite professionals to participate in our experiment. The main channel through which we advertised our experiment was by circulating a link to our experiment website on the WeChat platform, which is one of the largest social networks in China. We also posted an advertisement along with the link of the experiment webpage on the official accounts. The link of the experiment webpage was generated through a professional platform called “Wenjuanxing”, which provides functions equivalent to Qualtrics. We used a consistent strategy to recruit participants and the same platform to run experiments.

For Experiment 1, we recruited 480 professionals, 448 of whom correctly answered the control questions about the experimental instructions. As pre-registered, we excluded 32 professionals who failed the control questions. A total of 24 experimental sessions (4 sessions per treatment) were conducted from September 12 to October 2, 2021. There were 20 professionals in each session. For Experiment 2, we recruited 200 professionals, and 15 professionals failed the control questions, resulting in a final sample of 185 professionals. In total, we conducted 8 experimental sessions (4 sessions per treatment) from October 3 to October 12, 2021. Each session had 25 professionals. Each professional participated in only one session of Experiment 1 or Experiment 2. The professionals completed the experiments via their mobile phones. The English translation of the experimental instructions can be found in Appendix J.

Panels A and B of Table A2 in Appendix A present summary statistics for our sample of 448 and 185 financial professionals in Experiment 1 and Experiment 2, respectively. For professionals in Experiment 1, 44.8 % were female; their age ranged from 28 to 51 years, and the average age was 37.02 years; 33.5 % had a college degree; they had worked in the financial industry for an average of 7.38 years; their average monthly income was 11,064 CNY; and 22.1 % answered the financial literacy test question correctly.¹¹ For the professionals in Experiment 2, their demographic characteristics were basically the same as those in Experiment 1. We used Mann-Whitney tests or χ^2 tests in the case of binary variables to test whether the random assignment successfully produced a balanced sample. The results show that we cannot reject the null hypotheses that the socioeconomic and financial backgrounds of the professionals in Experiments 1 and 2 are balanced across treatments based on conventional significance levels.

Professionals in Experiment 1 received an average payoff of 73.64 CNY with a standard error of 1.59. Professionals in Experiment 2 received a mean payoff of 55.78 CNY with a standard error of 2.43. To increase participants' earnings in Experiment 2, we added a fixed payoff of 26 CNY, which was common knowledge. The average durations of Experiments 1 and 2 were 35 and 30 minutes, respectively.¹² Due to budget constraints, we randomly selected 20 percent of the professionals for actual payment.¹³ This method of payment was common knowledge.

2.2. Results for experiments 1 and 2

2.2.1. Subjective probability estimate

We begin by examining the belief wedge between the gain and loss domains in terms of its business cycle dynamics. Fig. 3 plots the average of the subjective probability estimates that the stock is paying from the good distribution by market trend condition for Experiment 1 (Panels A1, A2, and A3) and Experiment 2 (Panels B1 and B2). The x-axis represents each value of the objective Bayesian posterior belief that is encountered in the experiment. The y-axis represents the subjective probability estimates provided by the professionals for each level of the objective Bayesian posterior. If the professionals' subjective posteriors were Bayesian, they would be

¹⁰ In Kuhnen's (2015) original design, participants were required to complete two tasks, an active task and a passive task. In the active task, participants were asked to choose whether to invest in a risky or a riskless security while learning about the dividend distribution of the risky security (i.e., the stock). In the passive task, participants were only asked to provide the probability estimate that the stock pays from the good distribution. The belief task in our Experiment 1 is identical to the passive task. However, our Experiment 2 differs from the active task. Recent experimental evidence shows that prior investment choices influence participants' learning from financial information (Kuhnen et al., 2017). To rule out the confounding factor of prior choices, in Experiment 2 we endowed participants with the stock at the beginning of the experiment.

¹¹ Our sample of financial professionals is representative of their counterparts in China, who are generally young, have 3–10 years of experience in the financial industry, and exhibit relatively low levels of financial literacy.

¹² Professionals reported an average monthly income of (approximately) 11,000 CNY. Based on an 8-hour workday, each person earned approximately 46 CNY per hour. The average hourly payoffs in Experiment 1 were approximately 125 CNY, $(73/35) \times 60 = 125.14$, which amounted to 2.72 times the average hourly wage of professionals. The average hourly payoffs in Experiment 2 were approximately 112 CNY, $(56/30) \times 60 = 112$, which amounted to 2.43 times the average hourly wage of professionals. Therefore, the monetary incentive is sufficient in our experiments.

¹³ Payment schemes with random components are commonly used in experimental finance (Cohn et al., 2015; Kirchler et al., 2018), and there is solid evidence that these schemes do not change behavior (Cubitt et al., 1998).

Table 1

Experimental design for Experiments 1 and 2. Panels A and B show the design for Experiments 1 and 2, respectively.

Panel A. The 3 × 2 design for Experiment 1			
3 × 2 design		Gain or Loss Condition	
		Gain	Loss
Market Trend Condition	Baseline	BASE-GAIN (4 sessions, 75 professionals)	BASE-LOSS (4 sessions, 74 professionals)
	Boom	BOOM-GAIN (4 sessions, 76 professionals)	BOOM-LOSS (4 sessions, 73 professionals)
	Bust	BUST-GAIN (4 sessions, 74 professionals)	BUST-LOSS (4 sessions, 76 professionals)
Panel B. The 2 × 1 design for Experiment 2			
2 × 1 design		Gain and Loss Condition	
Market Trend Condition		Boom	BOOM (4 sessions, 95 professionals)
		Bust	BUST (4 sessions, 90 professionals)

equal to the objective probabilities and thus perfectly aligned along the 45° line. However, we find that this is not the case; in both the gain and loss domains, the subjective probability estimates deviate from the objective value.

In the *Baseline* condition of Experiment 1, we replicate the findings of [Kuhnen \(2015\)](#) and find that professionals' subjective beliefs in the loss domain are overly pessimistic relative to the gain domain (see Panel A1). Importantly, the pessimism bias, or the wedge between subjective beliefs in the loss and gain domains, is still present in the *Boom* condition (see Panel A2) but disappears in the *Bust* condition (see Panel A3). Similar results are found in Experiment 2 (see Panels B1 and B2).

In [Table 2](#), we regress professionals' subjective probability estimates on dummies for the *Loss*, *Boom*, and *Bust* conditions. Panels A and B in [Table 2](#) show the regressions for Experiments 1 and 2, respectively. Controlling for objective Bayesian probability, the first column of Panel A shows that across trials, professionals' subjective probability estimates that the stock is paying from the good distribution are on average 3.330 % lower in the *Loss* condition than in the *Gain* condition ($t = -6.73$). This result indicates that professionals' subjective beliefs are more pessimistic in the loss domain than in the gain domain. The second, third, and fourth columns of Panel A show that the difference between subjective beliefs expressed in the loss relative to the gain domain is significant in the *Baseline* (-3.718 %, $t = -5.24$) and *Boom* (-5.484 %, $t = -6.27$) conditions but not in the *Bust* condition (-0.805 %, $t = -0.86$). Therefore, bust priming eliminates the wedge between subjective beliefs in the loss and gain domains. That is, asymmetric learning from positive and negative information is procyclical.

The first column of Panel A in [Table 2](#) also shows that across trials, professionals' beliefs are 1.110 % higher in the *Boom* condition ($t = 1.95$) and 1.420 % lower in the *Bust* condition ($t = -2.39$), indicating that professionals are more optimistic when primed with a boom and more pessimistic when primed with a bust.¹⁴ This result is consistent with existing survey and experimental evidence suggesting that investors have procyclical beliefs ([Amromin and Sharpe, 2014](#); [Kieren et al., 2023](#)).

Importantly, the last two columns of Panel A show that the effects of the *Boom* and *Bust* conditions on professionals' subjective probability estimates are significant in the *Gain* condition ($t = 2.40$ and $t = -3.71$, respectively) but not in the *Loss* condition ($t = 0.27$ and $t = 0.02$, respectively). Thus, bust priming reduces professionals' subjective beliefs, while boom priming increases their beliefs, and these effects are primarily present in the gain domain. That is, in gain trials, bust priming induces pessimistic beliefs, and boom priming induces optimistic beliefs. This result indicates that professionals learn more pessimistically from positive information in busts than in booms, and they learn the same from negative information in both booms and busts.

The regression results of Experiment 1 are also found in Experiment 2, where the professionals are endowed with the stock and the gain-loss condition is a within-subject design. Panel B in [Table 2](#) shows that across all trials, professionals' beliefs are on average 3.854 % lower in the *Loss* condition than in the *Gain* condition ($t = -6.23$); the pessimism bias is more pronounced in the *Boom* condition (-6.887 %, $t = -7.95$) than in the *Bust* condition (-0.653 %, $t = -0.87$); the *Bust* condition significantly reduces the subjective probability estimates (-3.320 %, $t = -5.05$), and this effect is present in the *Gain* condition ($t = -8.37$) but not in the *Loss* condition ($t = -0.21$). Thus, our findings are robust to stock ownership and to the within-subject design and are not due to the particular set of realized dividends.

Professionals may update their beliefs differently depending on their individual characteristics, such as differences in socioeconomic status and differences in financial literacy ([Kuhnen and Miu, 2017](#); [Das et al., 2020](#)). Table A3 in Appendix A adds the subject fixed effects to account for such differences, and the results are similar in this specification.

2.2.2. Change in probability estimate

We then examine how professionals' probability estimates evolve from trial to trial so that they exhibit procyclical learning

¹⁴ In an ambiguity task framed as drawing balls of different colors, [Cohn et al. \(2015\)](#) ask financial professionals to guess the share of yellow balls, which serves as a measure of their beliefs. They find that priming a boom or bust scenario does not affect these beliefs. In contrast, using the same priming but a different task, our study shows that it influences professionals' beliefs. We argue that differences in the task environment may explain these inconsistent results. Unlike the ambiguity task, our belief elicitation task is set in a stock market context ([Kuhnen, 2015](#)). In such an environment, professionals may rely more heavily on their prior experiences of the stock market, making the priming more salient and influential.

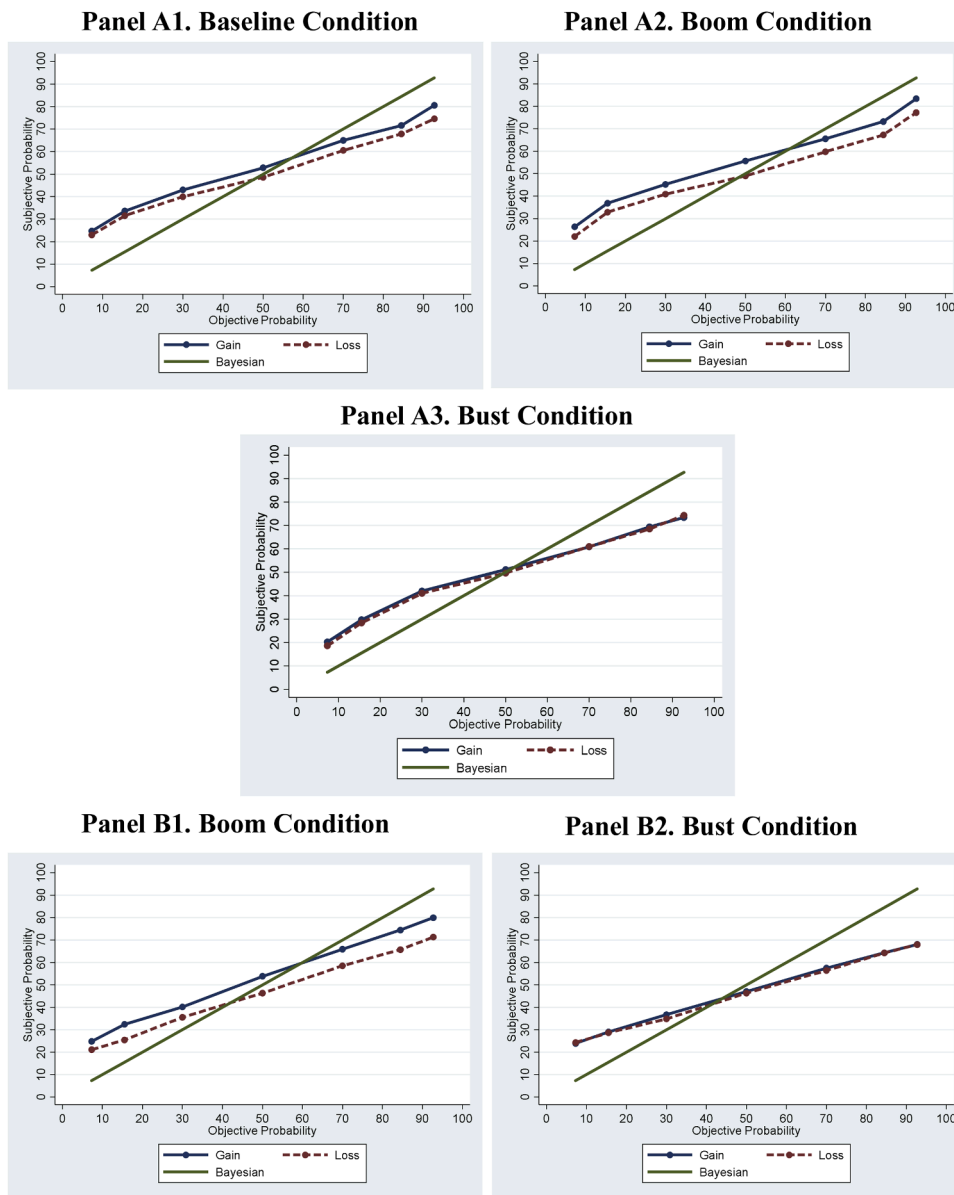


Fig. 3. Average subjective probability estimates in Experiments 1 and 2. Panels A1, A2, and A3 show the data from Experiment 1. Panels B1 and B2 show the data from Experiment 2. Panel A1 presents the belief data from the *Baseline* condition. Panels A2 and B1 present the belief data from the *Boom* condition. Panels A3 and B2 present the belief data from the *Bust* condition. The objective Bayesian posteriors that the stock is paying from a good distribution are listed in Appendix B, along with the various combinations of high and low dividends observed during a learning block that lead to such posteriors. If the subjective posteriors were Bayesian, they would be equal to the objective probabilities and thus would lie on the 45° line. Participants' subjective probability estimates for each level of the objectively correct Bayesian posterior are shown as dotted lines for the *Loss* condition and as dotted solid lines for the *Gain* condition.

asymmetry. To this end, for each professional i and trial t , we compute the change from trial t to trial $t+1$ in the probability estimate, namely, the difference between the subjective posterior and the prior belief that the stock pays from the good distribution. We then compute the average change in subjective probability estimates for the *Gain* and *Loss* condition split by high and low dividends. The results are reported in Panel A and Panel B of Table 3 for Experiment 1 and Experiment 2, respectively.

We find that in the *Baseline* and *Boom* conditions, professionals' asymmetric learning from financial information is due to reacting

Table 2

Regression analysis of the subjective probability estimate for Experiments 1 and 2. Panels A and B show the regressions for Experiments 1 and 2, respectively. The regression uses a linear probability model. Standard errors are clustered by subject, and *t*-statistics are in parentheses. The dependent variable in the regression models below, *Probability Estimate_{it}*, is the subjective posterior belief that the stock is paying from the good distribution that participant *i* expressed in trial *t*. *Loss_t* is a dummy variable equal to one if trial *t* is in a *Loss* condition and zero otherwise. *Boom_t* is a dummy variable equal to one if trial *t* is in a *Boom* condition and zero otherwise. *Bust_t* is a dummy variable equal to one if trial *t* is in a *Bust* condition and zero otherwise. Objective Posterior indicates fixed effects for each level of the objective Bayesian posterior probability that the stock pays from the good distribution, given the 50 % prior and the history of stock dividends.

Panel A. Experiment 1						
Dependent variable	<i>Probability Estimate_{it}</i>					
	All trials	Trials in Baseline condition	Trials in Boom condition	Trials in Bust condition	Trials in Gain condition	Trials in Loss condition
<i>Loss_t</i>	−3.330 (−6.73)	−3.718 (−5.24)	−5.484 (−6.27)	−0.805 (−0.86)		
<i>Boom_t</i>	1.110 (1.95)				1.972 (2.40)	0.206 (0.27)
<i>Bust_t</i>	−1.420 (−2.39)				−2.891 (−3.71)	0.021 (0.02)
Objective Posterior	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10752	3576	3576	3600	5400	5352
Clusters	448	149	149	150	225	223
R ²	0.536	0.541	0.551	0.521	0.553	0.516
Panel B. Experiment 2						
Dependent variable	<i>Probability Estimate_{it}</i>					
	All trials	Trials in Boom condition	Trials in Bust condition	Trials in Gain condition	Trials in Loss condition	
<i>Loss_t</i>	−3.854 (−6.23)	−6.887 (−7.95)	−0.653 (−0.87)			
<i>Bust_t</i>	−3.320 (−5.05)			−6.437 (−8.37)	−0.203 (−0.21)	
Objective Posterior	Yes	Yes	Yes	Yes	Yes	
Observations	4440	2280	2160	2220	2220	
Clusters	185	95	90	185	185	
R ²	0.551	0.586	0.518	0.585	0.521	

Table 3

Average change in probability estimates from trial to trial after observing high and low dividends in Experiments 1 and 2. Panels A and B show the data from Experiments 1 and 2, respectively. *Probability Estimate_{t+1} – Probability Estimate_t* is the change from trial *t* to trial *t*+1 in participants' subjective posterior belief that the stock is paying from the good distribution. *t*-statistics are in parentheses.

Panel A. Experiment 1						
	<i>Probability Estimate_{t+1} – Probability Estimate_t</i>					
	Baseline condition		Boom condition		Bust condition	
	High dividend in trial <i>t</i> + 1	Low dividend in trial <i>t</i> + 1	High dividend in trial <i>t</i> + 1	Low dividend in trial <i>t</i> + 1	High dividend in trial <i>t</i> + 1	Low dividend in trial <i>t</i> + 1
Loss condition	9.059 %	–10.348 %	9.082 %	–11.196 %	9.668 %	–11.520 %
Gain condition	11.424 %	–11.68 %	11.532 %	–11.871 %	9.153 %	–10.350 %
Loss–Gain	–2.365 % (–2.97)	1.332 % (1.48)	–2.450 % (–3.61)	0.675 % (0.84)	0.515 % (0.75)	–1.171 % (–1.35)
Panel B. Experiment 2						
	<i>Probability Estimate_{t+1} – Probability Estimate_t</i>					
	Boom condition		Bust condition			
	High dividend in trial <i>t</i> + 1	Low dividend in trial <i>t</i> + 1	High dividend in trial <i>t</i> + 1	Low dividend in trial <i>t</i> + 1		
Loss condition	8.568 %	–10.052 %	6.714 %	–8.189 %		
Gain condition	11.847 %	–11.737 %	5.033 %	–7.315 %		
Loss–Gain	–3.208 % (–2.95)	1.684 % (1.57)	1.680 % (1.28)	–0.874 % (–0.81)		

less to high dividends in the loss domain than in the gain domain.¹⁵ Critically, we find that in gain trials, professionals primed with a bust react significantly less to high dividends than those primed with a boom, such that bust priming leads to more pessimistic beliefs in the gain domain than boom priming, thereby eliminating the belief wedge between the loss and gain domains.

Specifically, Panel A of Table 3 shows that in the *Baseline* condition, observing a high dividend significantly increases the probability estimates of professionals that the stock is paying from good distribution by 2.365 % ($t = -2.97$) less in the *Loss* condition than in the *Gain* condition. This result also holds in the *Boom* condition, where the difference between the *Loss* and *Gain* conditions in terms of the effect of a high dividend on the change in probability estimates is -2.450 % ($t = -3.61$). However, in the *Bust* condition, after observing a high dividend, the average change in professionals' probability estimates does not differ between the *Loss* and *Gain* conditions (difference = 0.515 %, $t = 0.75$).

Importantly, in gain trials, after observing a high dividend, the average change in professionals' probability estimates is significantly lower in the *Bust* condition relative to the *Baseline* (difference = -2.171 %, $t = -3.10$) and *Boom* conditions (difference = -2.379 %, $t = -3.57$), but the latter two do not differ (difference = -0.108 %, $t = -0.16$). In the loss trials, after observing a high dividend, the average change in probability estimates of the professionals does not differ across the three market trend conditions (all absolute t values < 1.0). After observing a low dividend, the differences in the average change in professionals' beliefs between the *Loss* and *Gain* conditions are not significant in any of the three market trend conditions (all absolute t values < 1.50).

Panel B of Table 3 shows that the main results of Experiment 2 are consistent with the findings of Experiment 1. That is, in gain trials, after observing a high dividend, the average change in professionals' probability estimates is significantly lower in the *Bust* condition than in the *Boom* conditions (difference = -6.814 %, $t = -5.833$). In the loss trials, after observing a high dividend, the average change in probability estimates does not differ between the *Bust* and *Boom* conditions (difference = -1.854 %, $t = -1.481$).¹⁶

Table A4 in Appendix A confirms our key results by regressing the change in beliefs from trial to trial on *High Dividend_t*, a dummy variable equal to one if the dividend is 10 or -2 in trial t and zero otherwise, the dummy variables *Boom_t* and *Bust_t*, and two interactions (*High Dividend_t* $\times$ *Boom_t* and *High Dividend_t* $\times$ *Bust_t*). The regression shows that in the *Gain* condition, the interaction of *High Dividend_t* with *Bust_t* is significantly negative (all absolute t values > 2.50); in the *Loss* condition, the coefficient on *High Dividend_t* $\times$ *Bust_t* is not significant ($t = 1.08$) in Experiment 1, and it is significant ($t = -2.37$) in Experiment 2, but this interaction effect is much smaller than that in the gain trials.

2.2.3. Probability estimation error

Finally, we test the effect of market trend priming on professionals' absolute probability estimation error, which represents the gap between the subjective estimate of the probability that the stock is paying from the good distribution and the objective Bayesian probability. In the *Baseline* condition of Experiment 1, consistent with Kuhnen (2015), we find that the pessimism induced by the loss domain leads to more probability estimation errors, namely, the probability estimation error is higher in the BASE-LOSS treatment compared to the BASE-GAIN treatment. The probability estimation error in the BOOM-LOSS treatment is also higher than that in the BOOM-GAIN treatment. However, the probability estimation error in the BUST-LOSS treatment is basically the same as that in the BUST-GAIN treatment. Similar results can be found in Experiment 2.

To provide statistical support for the treatment differences, we run several regression analyses for Experiment 1 (Panel A) and Experiment 2 (Panel B) in Table 4. The first column of Panel A shows that across trials, the error in subjective probability estimates is 0.889 % larger in the *Loss* condition than in the *Gain* condition ($t = 2.74$). The second and third columns of Panel A show that in the *Baseline* and *Boom* conditions, the difference in the probability estimation error between the *Loss* and *Gain* conditions is 1.497 % ($t = 2.67$) and 1.542 % ($t = 2.75$), respectively. In the *Bust* condition, however, this difference is -0.361 % and not significant ($t = -0.65$) (see the fourth column of Panel A). Thus, bust priming eliminates the difference in the probability estimation error between the loss and gain domains.

Importantly, the pessimism induced by bust priming in gain trials leads to larger probability estimation errors. The first column of Panel A in Table 4 shows that across all trials, the error in subjective probability estimates is 0.764 % larger in the *Bust* condition ($t = 1.92$), indicating that professionals' probability estimation error is significantly increased when they are primed with a financial bust. The last two columns of Panel A show that the effect of the *Bust* condition on the probability estimation error of professionals is significant in the *Gain* condition ($t = 3.09$) but not in the *Loss* condition ($t = -0.28$). The *Boom* condition has no significant effect on the probability estimation error (all t values < 0.30). Thus, bust priming significantly increases professionals' probability estimation errors, and this effect is mainly present in the gain domain, echoing our previous findings that professionals' beliefs are more pessimistic in gain trials when they are primed with a bust.

These regression results are robustly present in Experiment 2 (see Panel B of Table 3). Table A5 in Appendix A shows that our results are not altered when we control for the subject fixed effects in the regressions.

¹⁵ This differs from the results of Kuhnen (2015), who finds that student participants' asymmetric learning is due to reacting more to low dividends in the loss domain relative to the gain domain. These results suggest that both students and professionals exhibit asymmetric learning from financial information, but they react differently to high and low dividends.

¹⁶ One difference from Experiment 1 is that in Experiment 2, in both gain and loss trials, the average change in professionals' probability estimates after observing a low dividend is significantly lower in the *Bust* condition than in the *Boom* condition (all absolute t values > 1.64). However, this result is not robustly present in Experiment 3, which replicates Experiment 2 (see Appendix D).

Table 4

Regression analysis of the probability estimation error for Experiments 1 and 2. Panels A and B show the regressions for Experiments 1 and 2, respectively. The regression uses a linear probability model. Standard errors are clustered by subject, and *t*-statistics are in parentheses. The dependent variable in the regression models, *Absolute Probability Error_{it}*, represents the gap between the subjective estimate of the probability that the stock is paying from the good distribution and the objective Bayesian probability. *Loss_t* is a dummy variable equal to one if trial *t* is in a *Loss* condition and zero otherwise. *Boom_t* is a dummy variable equal to one if trial *t* is in a *Boom* condition and zero otherwise. *Bust_t* is a dummy variable equal to one if trial *t* is in a *Bust* condition and zero otherwise.

Panel A. Experiment 1						
Dependent variable	<i>Absolute Probability Error_{it}</i>					
	All trials	Trials in Baseline condition	Trials in Boom condition	Trials in Bust condition	Trials in Gain condition	Trials in Loss condition
<i>Loss_t</i>	0.889 (2.74)	1.497 (2.67)	1.542 (2.75)	−0.361 (−0.65)		
<i>Boom_t</i>	0.089 (0.22)				0.072 (0.12)	0.116 (0.22)
<i>Bust_t</i>	0.764 (1.92)				1.700 (3.09)	−0.159 (−0.28)
Observations	10752	3576	3576	3600	5400	5352
Clusters	448	149	149	150	225	223
R ²	0.003	0.005	0.006	0.001	0.006	0.001
Panel B. Experiment 2						
Dependent variable	<i>Absolute Probability Error_{it}</i>					
	All trials	Trials in Boom condition	Trials in Bust condition	Trials in Gain condition	Trials in Loss condition	
<i>Loss_t</i>	1.115 (4.02)	1.795 (4.64)	0.397 (1.03)			
<i>Bust_t</i>	1.108 (2.21)			1.806 (3.17)	0.409 (0.72)	
Observations	4440	2280	2160	2220	2220	
Clusters	185	95	90	185	185	
R ²	0.006	0.007	0.001	0.008	0.001	

Table 5

The role of bubble-crash experience in Experiment 3. Data are split by bubble-crash experience reported by professionals (i.e., without and with bubble-crash experience). The regression uses a linear probability model. Standard errors are clustered by subject, and *t*-statistics are in parentheses. The dependent variable, *Probability Estimate_{it}*, is the subjective posterior belief that the stock is paying from the good distribution that professional *i* expressed in trial *t*. *Loss_t* is a dummy variable equal to one if trial *t* is in a *Loss* condition and zero otherwise. *Bust_t* is a dummy variable equal to one if trial *t* is in a *Bust* condition and zero otherwise. Objective Posterior indicates fixed effects for each level of the objective Bayesian posterior probability that the stock pays from the good distribution, given the 50 % prior and the history of stock dividends.

Dependent variable	<i>Probability Estimate_{it}</i>							
	Without bubble-crash experience				With bubble-crash experience			
	Trials in Boom condition	Trials in Bust condition	Trials in Gain condition	Trials in Loss condition	Trials in Boom condition	Trials in Bust condition	Trials in Gain condition	Trials in Loss condition
<i>Loss_t</i>	−6.852 (−6.04)	−1.672 (−2.28)			−5.414 (−9.29)	0.559 (1.15)		
<i>Bust_t</i>			−7.117 (−8.10)	−1.938 (−2.65)			−5.615 (−7.95)	0.358 (0.62)
Objective Posterior	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312	336	324	324	816	816	816	816
Clusters	13	14	27	27	34	34	68	68
R ²	0.887	0.821	0.851	0.857	0.872	0.825	0.848	0.851

2.3. Multiple hypothesis testing

A potential concern with the analysis of our experimental data is that, due to the multiple treatments in Experiment 1, we are simultaneously testing multiple null hypotheses. We address this concern using the multiple hypothesis correction procedure developed by List et al. (2019). We also compare our results with those obtained using the classical Bonferroni and Holm multiple testing procedures. The corrected results show that our main findings are robust to adjusting for multiple hypothesis testing. See Appendix C for detailed results of the correction for multiple hypothesis testing.

3. Role of experience

In this section, we investigate the role of experience, with a particular focus on bubble-crash experience. We further examine whether the procyclical learning asymmetry observed among financial professionals extends to nonprofessionals.

3.1. Bubble-crash experience

Previous work in finance and economics documents lasting effects of personal experience (Malmendier, 2021). For example, Malmendier and Nagel (2011, 2016) find that expectations of stock returns and inflation are disproportionately shaped by past experience, highlighting the role of personal experience in belief updating. Accordingly, when primed with booms and busts, professionals with bubble-crash experience may exhibit procyclical learning asymmetry, while those without it may not.

To test the role of bubble-crash experience, we conducted Experiment 3 with 100 professionals. Five professionals did not correctly answer the control questions, leaving 95 professionals (36 female, mean age 39.69 years) for data analysis. Panel C of Table A2 in Appendix A shows the socioeconomic and financial backgrounds of the professionals, which indicates that the demographic characteristics are basically the same as in Experiments 1 and 2. The professionals received an average payoff of 43.16 CNY. Experiment 3 was conducted in July 2023.

To measure bubble-crash experience, at the end of Experiment 3, professionals were told that the Chinese stock market had experienced two notorious bubble-crash episodes (i.e., the 2007–2008 and 2014–2015 market bubble crashes).¹⁷ They were then asked whether they had personally experienced such episodes. Other experimental design and procedures were the same as in Experiment 2. The percentage of professionals who reported experiencing the 2014–2015 bubble-crash episode is 71.58 % (68/95). The difference in the percentage of professionals who experienced the 2014–2015 bubble-crash episode between the *Boom* and *Bust* conditions was not significant (Mann-Whitney test, $p = 0.871$). No professional reported experiencing the 2007–2008 bubble-crash episode.

Experiment 3 replicates the results of Experiments 1 and 2, further demonstrating that professionals exhibit a procyclical learning asymmetry. Experiment 3 also shows that the procyclical learning asymmetry is mainly driven by bust-primed professionals reacting less to positive high outcomes than boom-primed professionals (see Appendix D for detailed results).

Importantly, the regression analysis in Table 5 shows that when primed with a bust, professionals with bubble-crash experience exhibit procyclical learning asymmetry, while those without bubble-crash experience do not. The regression results of Table 5 are basically the same when we control for subject fixed effects (see Table A6 in Appendix A). Therefore, bubble-crash experience plays a crucial role in procyclical learning asymmetry.¹⁸

3.2. Experiment with nonprofessionals

A key difference between professionals and nonprofessionals is their experience with financial markets. Nonprofessionals are less exposed to market booms and busts and thus have limited experience with bubbles and crashes. Drawing on the role of bubble-crash experience in procyclical learning asymmetry among professionals, we predict that nonprofessionals' lack of such experience may eliminate this asymmetry when primed with booms and busts. To test this, we conducted an online experiment with nonprofessionals (Experiment 4).

The experimental design and procedure of Experiment 4 were identical to those of Experiment 2. We recruited 160 nonprofessionals, and 12 did not answer the control questions correctly, leaving 148 nonprofessionals (48 female, mean age 37.07 years) for data analysis. The nonprofessionals came from nonfinancial institutions in China, such as information technology, textiles, retail, manufacturing, medical, and public services. An equal number of nonprofessionals were randomly assigned to the *Boom* and *Bust* conditions (i.e., 74 nonprofessionals).

The percentage of nonprofessionals with stock trading experience was 14.8 %. The percentage of nonprofessionals who answered the financial literacy test question correctly was 12.8 %, which was significantly lower than the percentage of financial professionals (Mann-Whitney test, all p values < 0.01). This result suggests that nonprofessionals have less financial market experience than

¹⁷ The Shanghai Stock Exchange was established on November 26, 1990, and it is the largest stock market in mainland China in terms of total market capitalization and trading volume. The Chinese stock market index has experienced two notorious bubble-crash episodes, namely, the 2007–2008 market rise and collapse and the 2014–2015 market bubble crash.

¹⁸ We also provide indirect evidence that bubble-crash experience plays a role in procyclical learning asymmetry by using data from Experiment 1 to test for individual heterogeneity in years of work in the financial industry. See Appendix E for a detailed analysis.

professionals. Other demographic variables of the nonprofessionals were basically the same as those of the professionals (see Panel D of Table A2 in Appendix A). Nonprofessionals received an average payoff of 49.73 CNY with a standard error of 1.57. Experiment 4 was conducted in November–December 2021.

We find that the pessimism bias, or the wedge between subjective beliefs in the loss and gain domains, is present in both the Bust and Boom conditions. That is, nonprofessionals exhibit asymmetric learning from financial information, but their learning asymmetry is not eliminated by priming with a bust. Thus, nonprofessionals do not exhibit procyclical learning asymmetry.¹⁹ Detailed results for Experiment 4 can be found in Appendix F.

4. Exploring the mechanisms

We demonstrate that financial professionals exhibit procyclical learning asymmetry, with experience, particularly bubble-crash experience, playing a crucial role. Moreover, the procyclical learning asymmetry is primarily driven by the fact that bust-primed professionals react less to positive high outcomes than boom-primed professionals. In this section, we explore a potential mechanism. Specifically, we ask why bust priming causes professionals to react less to high dividends in the gain domain compared to boom priming.

4.1. Memory

Memory plays an important role in the formation of beliefs. When people update their beliefs, they tend to retrieve information from memory. Associative memory refers to an increased tendency to recall information that is cued by context (Kahana, 2012). In our experiments, boom and bust priming may trigger different memorable contexts. Specifically, boom priming may evoke a context characterized by positive returns and substantial price increases. Conversely, bust priming may evoke a context characterized by negative returns and significant price declines. As a result, in the gain domain, bust-primed professionals may recall fewer high dividends than boom-primed professionals, leading them to react less to positive high dividends in busts than in booms.

To test this, we included a recall question during the belief task in Experiment 1. Each participant was randomly assigned a trial and asked to recall the dividend on the previous trial. For example, in *Block 1*, after seeing a dividend in *Trial 4*, participants were taken to a separate page and asked to recall the dividend in *Trial 3*. This recall question always came as a surprise. The recall measure was financially incentivized: Participants earned 10 CNY for correct recall.

Consistent with our prediction, we find that in the gain domain, bust priming significantly reduces recall of high dividends relative to boom priming. An exploratory mediation analysis provides suggestive evidence that recall of high dividends partially explains the effect of bust priming on subjective probability estimates in the gain domain. In the loss domain, recall of high dividends is the same between bust and boom priming. A detailed analysis of memory in Experiment 1 is provided in Appendix G1.

4.2. Emotion

An important question is why priming with booms and busts leads to associative memory. To answer this question, we conducted Experiments 5 and 6. Previous work in cognitive psychology has suggested that emotions not only determine what information is encoded in memory but also play a crucial role in memory retrieval (LaBar and Cabeza, 2006). Levine and Edelman (2009) have shown that people often exhibit memory narrowing, where they have excellent memory for information that is central to an emotional event but poorer memory for peripheral details. When professionals are primed with booms and busts, emotional memory narrowing may make different memorable contexts accessible in their minds, thereby generating associative memory processes (Cohn et al., 2015; Levine and Edelman, 2009).

Therefore, we test whether the priming elicits different emotional responses and promotes memory narrowing, leading to associative memory (i.e., emotion-driven associative memory). In summary, we propose that emotion-driven associative memory may serve as a mechanism for the procyclical learning asymmetry. Appendix G2 provides a detailed exposition of this mechanism.

4.2.1. Priming, emotion, and memory

Experiment 5 examines the role of financial market trend priming in emotional responses and memory narrowing. We recruited 150 financial professionals, and 18 professionals did not correctly answer the control questions, leaving 132 financial professionals (42 female, mean age 37.98 years) for data analysis. The professionals were randomly assigned to one of the two market trend treatments, BOOM_EMOTION (65 participants) and BUST_EMOTION (67 participants). They were paid 20 CNY each for their participation in the experiment. Panel E of Table A2 in Appendix A shows the descriptive statistics of the socioeconomic and financial background of the professionals. Experiment 5 was conducted in April 2022.

After priming, professionals were asked to report the valence of their emotional responses to the priming, ranging from very negative (coded as “−4”) to very positive (coded as “4”), and they were also asked to choose which of six descriptions of emotional

¹⁹ Evidence from priming experiments shows that financial professionals behave differently when their professional identity is made less salient (Cohn et al., 2014 and 2017). Thus, one potential explanation for this result is that nonprofessionals lack a professional identity in the financial industry, which may cause their subjective beliefs to differ from those of professionals when primed with a bust. However, professional identity cannot explain why professionals without bubble-crash experience do not exhibit procyclical learning asymmetry.

experiences best captured their feelings (i.e., Afraid/Scared/Anxious, Bored/Jaded/Uninterested, Neutral/No Emotional Reaction, Excited/Eager/Enthusiastic, Sad/Gloomy/Depressed, and Calm/Relaxed/Peaceful; Andrade et al., 2016). To measure memory narrowing, we included a recall task that was not financially incentivized. Professionals were asked to recall a stock they remembered and answer two questions: “What happened to the price of this stock during the financial market cycle displayed in the graph? (sharp increases, slight increases, sharp declines, slight declines, or others)” and “Does this stock have positive or negative returns during the financial market cycle displayed in the graph?”.²⁰

Consistent with Cohn et al. (2015), we find that boom and bust priming can induce positive and negative emotions in professionals, respectively. The average emotional valence in the BOOM_EMOTION treatment is 2.231 (SE = 0.135), which is significantly higher than −0.940 (SE = 0.239) in the BUST_EMOTION treatment (Mann-Whitney test, $p < 0.001$). When professionals are primed with a boom, 83.07 % of them report that “Excited/Eager/Enthusiastic” best captures their feelings. When primed with a bust, 79.10 % of professionals report that “Afraid/Scared/Anxious” best captures their feelings. Importantly, boom and bust priming can promote memory narrowing. When professionals are primed with a boom, 90.77 % and 84.62 % of them recall that a stock they remember has positive returns and sharp price increases, respectively. When primed with a bust, 89.55 % and 91.04 % of professionals recall that a stock they remember has negative returns and sharp price declines, respectively. Table A7 in Appendix A shows that the BUST_EMOTION treatment has a significantly negative effect on emotional valences and recall of positive returns, but a significantly positive effect on recall of sharp price declines.

4.2.2. Emotion and memory

Experiment 6 examines the effect of emotions on associative memory. We recruited 120 financial professionals, and 18 professionals did not correctly answer the control questions, leaving us with 102 professionals (32 female, mean age 37.46 years) for data analysis. Professionals received an average payoff of 33.15 CNY with a standard error of 0.86. Panel F of Table A2 in Appendix A shows the descriptive statistics of the socioeconomic and financial background of the professionals.

In Experiment 6, we used the belief task of Experiment 2 but did not elicit the beliefs of the professionals. The professionals were only asked to observe the dividends of the stocks they owned and were not required to provide an estimate of the probability that the stock was paying from the good or bad distribution. At the beginning of each trial, professionals viewed a picture that was unrelated to the stock dividends (Kuhnen and Knutson, 2011). The pictures were used to exogenously manipulate the emotional states of the professionals. Experiment 6 had two treatments, POSI_EMOTION (50 participants) and NEGA_EMOTION (52 participants). In the POSI_EMOTION treatment, professionals saw only the positive pictures (e.g., cat), whereas in the NEGA_EMOTION treatment, they saw only the negative pictures (e.g., spider). The pictures used in the experiment were drawn from the International Affective Picture System (IAPS) (Lang et al., 2008).²¹ Table A8 in Appendix A shows the description of the IAPS stimuli (numbers) used in Experiment 6.

After the belief task, we measured the emotional states of the professionals by asking them to rate the pictures: arousal and valence. Arousal measures how energized or activated professionals feel at a given moment, and valence indicates how positively or negatively professionals feel at a given moment. Arousal was measured on a scale of 1 to 9, while valence was measured on a scale of −4 to 4.²²

The professionals were then asked to perform an unrelated real effort task that needed them to enter multiple combinations of letters and numbers. They were given 10 minutes to enter as many combinations as possible. For each correctly completed task, they received 1 CNY. Because associative memory is thought to operate on long-term memory, we included a 10-minute distraction task. We then asked the professionals to recall how often the stock paid 2, 10, −2, and −10 CNY in the belief task. This recall task was not announced beforehand. Professionals earned 10 CNY if they made a correct recall. We forced professionals’ responses in the recall task to always add up to twelve positive dividends and twelve negative dividends (the true total number of observed positive and negative dividends, respectively). Experiment 6 was conducted in May 2022.

In the POSI_EMOTION treatment, professionals rate positive pictures as more positive and arousing (valence: $M = 2.08$, $SE = 0.142$; arousal: $M = 6$, $SE = 0.257$), and in the NEGA_EMOTION treatment they rate negative pictures as more negative and arousing (valence: $M = -1.384$, $SE = 0.184$; arousal: $M = 5.077$, $SE = 0.209$) (Mann-Whitney test, all p values < 0.01). This result indicates that the emotional state is successfully manipulated exogenously.

Importantly, we find that the negative emotion manipulation leads to fewer high dividend recalls and lower recall accuracy in gain trials compared to the positive emotion manipulation. In gain trials, the average number of high dividends recalled in the NEGA_EMOTION treatment is 3.788 ($SE = 0.165$), which is significantly lower than 6.62 ($SE = 0.209$) in the POSI_EMOTION treatment (Mann-Whitney test, $p < 0.001$); the percentage of recall accuracy in the NEGA_EMOTION treatment is 0.096 ($SE = 0.041$), which is also significantly lower than in the POSI_EMOTION treatment ($M = 0.24$, $SE = 0.061$) (Mann-Whitney test, $p = 0.052$). In loss trials, the differences in recall of high dividends and recall accuracy between the NEGA_EMOTION and POSI_EMOTION treatments are not

²⁰ In Experiment 5, we included a manipulation check, asking professionals to judge which of the financial cycles best describes the stock market index shown in the graph (i.e., boom, bust, or I don’t know). We find that when professionals are primed with a boom, all of them judge that the stock market displayed in the graph is in a boom period; otherwise, all of them judge that the stock market displayed in the graph is in a bust period. This result indicates that our manipulation of financial market trends is successful.

²¹ The IAPS is a large set of emotionally evocative, internationally accessible, color photographs that contain content across a wide range of semantic categories (Lang et al., 2008).

²² Low valence scores indicate that professionals feel slow, quiet, or unenergized, while high valence scores indicate that professionals feel highly activated, charged, or energized, physically or mentally. Valence is negative when professionals feel unhappy, upset, irritated, frustrated, angry, sad, anxious, or depressed, and it is positive when they feel happy, pleased, satisfied, competent, proud, satisfied, or delighted.

significant (Mann-Whitney test, all p values > 0.50). Table A9 in Appendix A shows that the NEGA_EMOTION treatment has a significant negative effect on recall of high dividends and recall accuracy in gain trials but no effect in loss trials.

Moreover, in Experiment 4, we asked nonprofessionals to report their emotional responses after priming, and following the belief task, they completed a surprise recall task. We find that when primed with a bust, nonprofessionals report the same level of emotional responses as those primed with a boom. Associative memory does not differ between bust and boom priming (see Appendix G3 for details).

4.3. Other mechanisms

Although we have shown that emotion-driven associative memory could explain why bust-primed professionals react less to positive high outcomes than boom-primed professionals, we argue that it cannot fully explain our experimental results. In the gain domain, we find that professionals asymmetrically recall high dividends in booms and busts. The flip side of this result is that there is an asymmetry in the recall of positive low dividends in booms and busts (i.e., fewer positive low dividends are recalled in booms than in busts). This cannot explain the observation that professionals react equally to positive low dividends across priming conditions. Moreover, in the loss domain, our results are also somewhat inconsistent with the prediction based on theoretical work on associative memory (Kahana, 2012; Enke et al., 2024). According to this prediction, in loss trials, bust-primed professionals would recall more low dividends, and boom-primed professionals would recall fewer low dividends, resulting in a difference in recall of negative low or high dividends across priming conditions. However, we find that in the loss domain, both bust-primed and boom-primed professionals recall more low dividends, leading to no difference in recall of negative low or high dividends across priming conditions (see Appendix G1 for details).

These inconsistencies suggest that while emotion-driven associative memory offers a compelling explanation for our findings, it alone is not sufficient. Other mechanisms, such as attention, cognitive uncertainty, the representativeness heuristic, and efficient encoding, may also play a role. Working in combination, these mechanisms could help account for our experimental results. Accordingly, we note that our evidence for the mechanism underlying the procyclical learning asymmetry (i.e., emotion-driven associative memory) is suggestive rather than conclusive.

Based on neuroscience research that has highlighted the interactions between emotion and attention in influencing memory and learning (Dolcos et al., 2020), we speculate that emotion-attention interactions may moderate the influence of associative memory on beliefs, as evidenced by our experimental results. Specifically, in gain trials, the positive emotions elicited by boom priming, as opposed to the negative emotions induced by bust priming, may lead professionals to pay more attention to both high and low dividends during booms relative to busts (Levine and Edelstein, 2009). This may strengthen the effect of asymmetric recall of positive high dividends on the reaction to information but eliminate the effect of asymmetric recall of positive low dividends. Thus, in the gain domain, professionals react asymmetrically to high dividends, but equally to low dividends across priming conditions. In loss trials, professionals may pay more attention to low dividends in booms than in busts, perhaps due to the higher salience of negative low outcomes in booms (Bordalo et al., 2022). This may lead boom-primed professionals to increase their recall of negative low dividends. As a result, in the loss domain, recall of low or high dividends does not differ between booms and busts. We encourage future studies to clarify the effects of emotion-attention interactions on memory and learning.

In addition to emotion-attention interactions, cognitive uncertainty and the representativeness heuristic may also interact to influence memory and learning. Because probability estimation in our belief task is difficult, professionals may exhibit cognitive uncertainty: subjective uncertainty about what the value of an objective Bayesian posterior probability is (Enke and Graeber, 2023). When professionals are cognitively uncertain, they may make probability estimates based on the representativeness heuristic, which refers to the tendency to judge as likely events or instances that are merely representative (Tversky and Kahneman, 1972).

Recent theoretical work shows that the representativeness heuristic may arise from the selective retrieval of information cued by context and that information that closely matches the given context (i.e., is representative of the context) is more likely to be retrieved than less representative information (Kahana et al., 2024). Boom-primed professionals may perceive positive and high dividends as representative, whereas bust-primed professionals may perceive negative and low dividends as representative. Therefore, in the gain domain, bust priming leads to less recall of high dividends and less reaction to high dividends relative to boom priming, thereby resulting in procyclical learning asymmetry.

Finally, efficient encoding may also play a role. People encode stimuli more accurately when they expect to encounter them more often (Frydman and Jin, 2022). After boom priming, it is natural for the brain to expect to encounter high dividends and therefore encode them more accurately, making them easier to recall. Conversely, after bust priming, the brain does not expect to encounter high dividends and may therefore encode them inaccurately, leading to less accurate recall. This may lead to less recall of high dividends in the gain domain when primed with a bust.

5. Conclusion and discussion

In this paper, we examine how investors learn from positive and negative information over the business cycle. In particular, we aim to test whether the learning asymmetry or pessimistic bias induced by negative information persists throughout boom and bust periods. To this end, we conduct six pre-registered online experiments with over 1100 financial and nonfinancial professionals. In the experiments, we prime professionals with either a financial boom or a financial bust scenario and elicit their subjective beliefs in the gain and loss domains.

The results from our experiments show that boom-primed professionals exhibit asymmetric learning from positive and negative information, whereas when professionals are primed with a bust, the pessimistic bias or belief wedge between the loss and gain

domains disappears. This procyclical learning asymmetry is mainly driven by the fact that bust-primed professionals react less to high outcomes and form more pessimistic beliefs in gain trials relative to boom-primed professionals. Moreover, this reduction in reaction to high outcomes in gain trials leads to more probability estimation errors in bust priming than in boom priming.

We also find that professionals without bubble-crash experience and nonprofessionals do not exhibit procyclical learning asymmetry, suggesting that experience (especially bubble-crash experience) plays a crucial role in procyclical learning asymmetry.²³ We further provide evidence that emotion-driven associative memory may be a mechanism underlying the procyclical learning asymmetry.

The procyclical learning asymmetry we document here can shed light on the dynamics of belief formation over the business cycle, and may provide an explanation for countercyclical risk aversion and sluggish recovery from recessions. Therefore, our findings have broad implications for the business cycle, risk-taking, and asset pricing. A detailed discussion of these implications is provided in Appendix I.

In particular, our study has implications for the equity risk premium, which is countercyclical and tends to be higher in busts than in booms. One explanation is countercyclical risk aversion: during financial busts investors become more risk averse and hence less willing to purchase risky assets (Cohn et al., 2015). Another explanation is learning asymmetry (Kuhnen, 2015; Kieren et al., 2023), especially the procyclical learning asymmetry documented in our study.²⁴ The lower willingness to purchase risky assets during busts may arise because investors' beliefs become more pessimistic, particularly when updating from positive information.

Both explanations imply that the equity risk premium should increase during financial busts, either because investors demand greater compensation for bearing risk when they are more risk averse, or because they form more pessimistic beliefs about risky-asset payoffs when updating from positive information in busts. We argue that the procyclical learning asymmetry documented here offers a complementary mechanism to the preference-based account of countercyclical risk premia, and suggests that belief formation may play an equally important role as risk preferences in explaining the observed dynamics of asset prices.

We note that the replicability of priming studies is controversial in the social psychological literature. Several papers report failures to replicate influential priming studies (e.g., Rahwan et al., 2019), while meta-analytic studies show that priming can produce replicable effects on individuals' behavior (e.g., Dai et al., 2023). Despite the controversy surrounding priming techniques in social psychology, we believe that priming has merit, a viewpoint that is also supported by several economists and social psychologists (e.g., Cohn and Maréchal, 2016; Sherman and Rivers, 2021; Dai et al., 2023). Sherman and Rivers (2021, p. 9) argue that: "We should have more ambitious goals than merely testing the reliability of particular effects. We should aim for a broader theoretical understanding of the moderators and mechanisms underlying priming in order to better predict when, why, and how priming occurs."²⁵

This is what our study aims to do. We show that experience, particularly bubble-crash experience, plays a critical role in our priming effects. We also show that emotion-driven associative memory may be a mechanism underlying our priming effects, consistent with early literature suggesting that priming is an unconscious form of human memory (Tulving and Schacter, 1990). We speculate that personal experience with financial booms and busts may moderate the role of emotion-driven associative memory in procyclical learning asymmetry. This moderating influence of personal experience on emotion and memory has also been proposed in previous literature examining other forms of belief formation (Laudenbach et al., 2019).

Moreover, priming allows researchers to study the psychological impact of specific economic events (e.g., booms and busts) while holding constant a variety of other fundamental factors that naturally covary with the events (Cohn and Maréchal, 2016). In our experiments, we made the state of boom or bust more salient in the minds of professionals. This priming ensures that there are no observable or unobservable differences between boom and bust conditions. Actual booms and busts are likely to be much more powerful primes, and investors will have stronger emotional responses to primes in the field. Thus, it seems plausible that the influence of real booms and busts may be even larger.

Finally, although priming is typically observed only under controlled experimental conditions, similar conditions often occur naturally outside the laboratory. For example, the spread and dynamics of popular narratives (e.g., the Great Recession of 2007–9) can activate human implicit memory through priming, thereby affecting belief formation (Tulving and Schacter, 1990; Shiller, 2017). It is therefore reasonable to assume that priming is a ubiquitous occurrence in everyday life.

Declaration of competing interest

None.

²³ Using a sample of financial professionals in China, we replicate the findings of Cohn et al. (2015) and provide experimental evidence of countercyclical risk aversion (see Appendix H for details). In contrast, König-Kersting and Trautmann (2018), using a sample of student participants, do not replicate this countercyclical pattern in risk aversion. Based on our findings, these inconsistent results may be explained by differences in experience, especially bubble-crash experience, as nonprofessionals, including students, lack stock market experience.

²⁴ We thank an anonymous reviewer for pointing this out.

²⁵ Sherman and Rivers (2021) show that the conversation about priming effects on behavior has created and stereotyped a new, pejorative category of research called social priming. They challenge this nomenclature, arguing that not only are many of the relevant studies not particularly social in nature, but other robust priming effects that are clearly social in nature do not count as social priming.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.jebo.2026.107488](https://doi.org/10.1016/j.jebo.2026.107488).

Data availability

Data will be made available on request.

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