INVESTOR MEMORY AND BIASED BELIEFS: EVIDENCE FROM THE FIELD*

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We survey a large, representative sample of retail investors in China to elicit their memories of stock market investments and their return expectations. We merge these survey data with administrative transaction data to test a model in which investors selectively recall past experiences to form their beliefs. Our analysis uncovers new facts about investor memory and highlights similarity-based recall as a key mechanism of belief formation in financial markets. A rising market prompts investors to recall their past experiences more positively, leading to more optimistic forecasts of future returns. Recalled experiences can explain cross-investor variation in return expectations and, in our setting, dominate actual experiences in their explanatory power. In the transaction data, we confirm that recalled experiences are reflected in investors' trading decisions through a belief channel. *JEL codes:* D14, D91, G41.

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I. Introduction

Beliefs are central to economic decision making, yet recent research increasingly challenges the full-information rational expectations (FIRE) benchmark. Mounting evidence documents systematic deviations from this benchmark, prompting further investigations into the mechanisms that shape belief formation.[1] A growing theoretical literature proposes that memory can help reconcile many puzzles about beliefs and choices (Mullainathan 2002; Gennaioli and Shleifer 2010; Malmendier, Pouzo, and Vanasco 2020; Bordalo et al. 2021, 2023; Wachter and Kahana 2024). This literature highlights two key principles of memory that shape belief formation. First, memory is limited and selective: not all experiences are equally likely to be stored, and not all memories are retrieved at any given time. Second, because memory is associative, retrieval is often triggered by contextual, emotional, or narrative cues. In parallel, empirical work has begun to examine memory mechanisms in the lab or through surveys (Zimmermann 2020; Andre et al. 2024; Colonnelli et al. 2024; Enke, Schwerter, and Zimmermann 2024; Gödker, Jiao, and Smeets 2025; Graeber, Roth, and Zimmermann 2024). Yet field evidence on how memory shapes belief formation and decisions remains scarce.[2]

In this article, we study how memory shapes investor beliefs in financial markets. We view financial markets as an ideal testing ground for the role of memory, given their real financial stakes, strong incentives, and the potential for substantial gains or losses. We survey a nationally representative sample of over 17,000 Chinese retail investors and, for a subsample, merge their survey responses with detailed trading records. Compared with

1. Examples include underreaction at the consensus level (Coibion and Gorodnichenko 2015), overreaction at the individual level (Bordalo et al. 2020), extrapolative beliefs (Greenwood and Shleifer 2014), and overconfidence (Glaser and Weber 2007; Liu et al. 2022). Some of the proposed mechanisms focus on psychological biases, while others emphasize information frictions and bounded rationality. See Barberis (2018) for a review of the possible microfoundations of extrapolation.

2. For example, when reviewing the evidence on the experience effect, Malmendier and Wachter (2024, 2239) state that "there is little direct evidence on that link [between experience-induced choices and memories of those experiences]. It would be interesting to apply some of the techniques eliciting 'retrieval' from the laboratory studies on memory to individuals exposed to measurable experiences from years and decades ago as explored in the field studies."

existing survey and experimental settings, our approach is closer to everyday decision making along several key dimensions. First, our sample consists of real investors actively trading in a major market, including high-net-worth individuals, who are typically difficult to survey. Second, the decision domain we examine is high stakes: for many of the Chinese retail investors we survey, stock investment constitutes a significant fraction of their total financial wealth.[3] Third, when studying the cued nature of memory, we rely on cues that naturally occur in financial markets, rather than those introduced by experimenters. Fourth, by combining survey data with detailed transaction records, we observe investors' past trading experiences and future trading behavior, allowing us to more directly link memory, beliefs, and behavior.

To guide our empirical analysis, we begin with a memory-based model of belief formation based on Bordalo et al. (2025). We assume an investor has accumulated a database of past investment experiences and forecasts future returns in two steps. In the first step, called recall, she retrieves past experiences based on the rule of similarity—experiences similar to the present cue are more likely to be recalled—using returns, perhaps the most ubiquitous stimulus in financial markets, as the cue. The model can also be extended to include other memory forces, such as recency and salience. In line with memory research (Kahana 2012), the model predicts that positive recent returns trigger the recall of past experiences that are also associated with positive returns. In the second step, called simulation, the investor uses retrieved experiences to simulate a distribution of future returns, which guides her forecasts. Positive recalls are thus associated with higher average return forecasts and lower crash probability forecasts. The model implies return extrapolation as a consequence of cued recall: high recent returns prompt more positive recalls, leading to more optimistic forecasts.

In the baseline survey, we design two theory-driven question blocks to elicit investor memory. The first block, *FreeRecall*, asks investors to (i) recall a market episode that first comes to mind and (ii) then recall the market return during that episode. As the name suggests, this block mirrors the well-established experimental paradigm of free recall to capture the market episode that an investor immediately thinks of when looking at past

3. In our sample, the median fraction of wealth invested in stocks is around 36%.

trading experiences (e.g., Murdock 1962; Kahana 2012).[4] To minimize confounding effects, all respondents begin with the *FreeRecall* block. The second block, *ProbedRecall*, asks investors to recall their own return in the stock market over a given horizon (from "yesterday" to "past five years"). The survey also collects information on investor beliefs, including expectations of market and own returns and perceived crash probabilities, and other individual characteristics such as the Big Five personality traits, measures of social activities, and demographics. After applying filters, our main sample consists of approximately 17,000 valid responses. More than a quarter of these responses are merged with detailed transaction-level data from our collaborating institution, forming the merged sample.

With these data in hand, we confirm that investors were indeed making a conscious effort when completing the recall tasks. We show that recalled experiences, on average, are highly correlated with the actual experiences observed in the market data and transaction data. For example, in *FreeRecall*, where investors are asked to recall market returns for episodes that first come to mind, the correlation between the *recalled* return and the *actual* return is 0.57. A positive correlation is also observed in *ProbedRecall* between recalled own returns and actual own returns. Overall, the survey-elicited experiences are strongly correlated with investors' objective experiences, supporting the validity of our survey design.

Next we document new stylized facts about investor memory. For example, when prompted to recall a past market episode, investors tend to retrieve both recent episodes and distant episodes featuring dramatic market movements, such as bubbles and crashes. This non-monotonic recall pattern suggests that to realistically capture investors' memory structure, it is insufficient to treat the effect of past experiences as simply decaying over time. Instead, features of the experiences themselves, such as salience, also play an important role in investor recall (e.g., Bordalo et al. 2023; Wachter and Kahana 2024).

After documenting basic facts about investor memory, we test our model, following Figure I, which outlines the logical chain

4. Free recall is also analogous to the idea of "what comes to mind," which can account for biases in judgment and decision making (Gennaioli and Shleifer 2010).

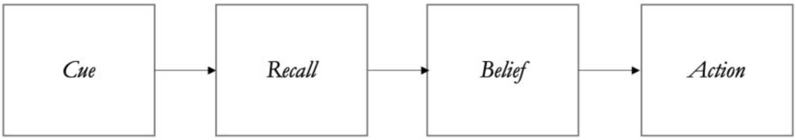


FIGURE I

Chain from Cue to Recall, Belief, and Action

from cue to recall, belief, and finally action. Our subsequent analysis examines each of these links in turn.

We start by testing the first part of our model, recall, by examining how recalled experiences relate to recent market returns. Our empirical strategy relies on the gradual rollout of the survey over six weeks, enabling us to analyze how variation in market returns influences retrieved memories for both recall blocks. In *FreeRecall*, when the stock market rises on the survey day, investors who recall more recent episodes—spanning no more than the past five years—are more likely to retrieve an episode featuring a bullish market. For example, a 1 percentage point increase in the market return on the survey day is associated with a 2.5 to 4.1 percentage point increase in the recalled episode return, depending on the precise specification. However, this cued recall result holds only for investors with recent recalls and not for the full sample. In *ProbedRecall*, when the market goes up today, investors tend to recall their past performance more positively, even after controlling for their actual performance. Specifically, a 1 percentage point increase in the survey day's market return is associated with a 52 basis point increase in the recalled own return for the previous day. Together, the two results support the model's predictions on cued recall. Memory is not a static representation of past experiences; instead, it is much more fluid, shaped by the available cues in the current context and varying over time as the context changes.

We proceed to test the second part of the model, simulation, by examining the relationship between recalls and beliefs. In both recall tasks in our survey, retrieved memories are strongly correlated with return expectations, even after controlling for an extensive list of demographic variables and other investor characteristics. The economic significance is large. For example, as investors' recalled past one-month own returns increase from the 25th to the 75th percentile, their return expectations for the next month and the next year increase by 0.7 and 1.8 percentage points, respectively.

We analyze additional properties of the simulation process. First, it exhibits horizon dependence, meaning there is alignment between the forecasting horizon and the recall horizon. For example, when the forecasting horizon is one year, investors' return expectations rely more on their recalled past one-year returns than on their recalled one-month returns. Second, in a series of horse races between the explanatory power of actual versus recalled experiences for beliefs, recalled experiences consistently dominate. This suggests that at least in our setting, the internal, subjective representation of experiences—shaped by selective and cued recall—may play a larger role than objective experiences in belief formation. The weakened correlation between past returns and return expectations after controlling for recalled experiences further supports a memory-based microfoundation for return extrapolation. Third, a single variable based on recalled own return demonstrates similar explanatory power, as measured by the adjusted R^2, to that of an exhaustive list of individual characteristics combined. Fourth, when linking retrieved memories to forecast errors, we find a similarly positive relationship. Thus, investor memory not only explains overall return expectations but also contributes to forecast errors.

While the robust relationship between recalls and beliefs documented above is consistent with simulation, we also consider alternative explanations. The first is anchoring—that is, people may base their answer to a later question on their answer to an earlier one. To address this, we consider three types of anchoring that may arise in our setting: anchoring on numbers, anchoring due to similarity in wording, and anchoring due to similarity in answer options. Overall, the evidence from additional belief questions and alternative elicitation methods does not support the view that these forms of anchoring drive our results.

Second, to address concerns about priming—eliciting memory before beliefs potentially overstating the role of memory—we conduct an additional survey that varies the order of survey blocks. The results show that the relationship between recalls and beliefs remains largely unchanged regardless of the order of the survey blocks. Note that we ask survey participants not to refer to external sources when answering our questions. Although this leads to a more faithful description of their investing memories, it may also lead to a stronger correlation between memories and beliefs than would be observed in some real-world settings. As such, our results may be more relevant for less sophisticated investors, who make less formal use of external sources in their decisions.

Third, we examine other explanations, such as the use of default options driven by cognitive uncertainty (Enke and Graeber 2023) and consistency bias (Falk and Zimmermann 2013) and argue that these are unlikely to fully account for our findings. We discuss the limitations of our setting—for instance, eliciting both recall and belief in the same survey may lead respondents to infer a connection between the two, potentially introducing an experimental artifact—and suggest ways future research can improve the design.

Finally, we validate our belief measures by showing that more optimistic investors increase their equity holdings shortly after the survey. This positive correlation between beliefs and actions is particularly strong for the return expectations explained by recalls, consistent with a belief channel through which memory influences trading decisions. This final piece of evidence completes the chain of relationships illustrated in Figure I.

This article provides new facts about investor memory in the field. Consistent with Malmendier and Nagel (2011, 2016), memory in our data exhibits a strong recency effect. We show, however, that memory is not simply a function of time elapsed since an event; it is also shaped by the characteristics of the experiences. In particular, salient events, such as sharp run-ups and crashes, are more likely to be recalled, consistent with the predictions from Wachter and Kahana (2024). Moreover, memory is not static—it is influenced by the environment one is currently in, as demonstrated by our analysis of cued recall. Therefore, to the extent that experience can affect decisions through memory, models that incorporate key features of the human memory system, such as context retrieval and similarity-based recall, can explain a wider range of behaviors, as shown in work by Wachter and Kahana (2024) and Bordalo et al. (2023, 2025). Charles (2022, 2025) also presents field evidence demonstrating that associative memory can affect trading behavior and asset prices at the market level. Our approach is different: we directly elicit investor memories, examine their properties, and link them to beliefs and trading behavior at the individual level.

Our analysis highlights the importance of memory in belief formation. The strong and robust relationship between recall and expectations is consistent with the notion of simulation—that is, the idea that investors form expectations about the future by retrieving past experiences (Bordalo et al. 2025). Notably, in our setting, the mental representation of past experiences in memory, shaped by selective and cued recall, has more explanatory power for beliefs than actual experiences do. Furthermore, we contribute to the literature on investor heterogeneity by showing that memory can significantly enhance the explanatory power of individual characteristics for cross-sectional variation in beliefs (Giglio et al. 2021; Jiang, Peng, and Yan 2024).

Last, our article contributes to the growing literature that combines survey data with observational data (Giglio et al. 2021; Liu et al. 2022). Previous studies have used surveys to collect investors' expectations and trading motives. In contrast, we collect investors' recalls and expectations, merging the survey data with information on their actual trading behaviors.

The rest of the article is organized as follows. Section II presents a simple model that serves as our conceptual framework. Section III explains the survey design and other data sources and documents key stylized facts about investor memory. Sections IV and V empirically test the two parts of the model: recall and simulation. Section VI concludes.

II. A Conceptual Framework

II.A. Setup

To guide our empirical analysis, we present a model of belief formation in financial markets based on Bordalo et al. (2025). Suppose that in the current period T, an investor observes that the return on her portfolio is r_T. She has accumulated a trading experience in each period t ($1 \leqslant t \leqslant T$). In reality, this experience is characterized by multiple attributes (e.g., time, location, and experienced return), but for simplicity, we assume that the period t experience is fully characterized by the experienced return, r_t. Later we discuss how relaxing this assumption can generate additional predictions. For these T experienced returns, we assume that each is a random draw from a normal distribution with a mean of μ and a variance of σ^2, with a probability density function (PDF) denoted by $f(\cdot)$. To simplify calculations, for most of our analysis, we assume that T is sufficiently large so that the

PDF $f(\cdot)$ closely approximates the empirical distribution of the T experienced returns.

II.B. Cued Recall

1. *Free Recall.* When asked to recall an experience that first comes to mind, in the absence of additional prompts or cues, the investor engages in "free recall" by drawing from all of her past experiences. Memory is associative (Schacter 1996; Kahana 2012; Baddeley 2020). Various attributes of the current environment—such as location, narrative, story, image, and emotion—and the individual's current internal context can trigger the recall of certain past experiences.[5]

To incorporate cued recall into the model, we need to specify both the cue and the mechanism through which it affects recall. First, we focus on the current return r_T as the cue. In Section IV.A we provide a detailed rationale for this choice. Second, following Bordalo et al. (2025), we assume that memory retrieval is guided by the rule of similarity: experiences with attributes similar to the cue are more likely to be retrieved. Let $s(r_t, r_T)$ denote the similarity between the experienced return r_t and the cue r_T, where a larger value indicates higher similarity and consequently a higher probability of retrieval. As a result, the recalled experience is no longer a random draw from the distribution $f(\cdot)$. Instead, it is drawn from the following "cued" PDF:

$$f^*(r|r_T) = f(r) \times s^*(r, r_T), \tag{1}$$

where

$$s^*(r, r_T) = \frac{s(r, r_T)}{\int_z f(z) \times s(z, r_T)dz}. \tag{2}$$

The denominator, $\int_z f(z) \times s(z, r_T)dz$, normalizes the PDF so that the total probability equals one.

For simplicity, we focus on the following similarity function:

$$s(r, r_T) = \exp\left(-\frac{(r - r_T)^2}{2\sigma_s^2}\right), \tag{3}$$

5. There is also growing evidence in the economics literature studying the role of cues. For example, Enke, Schwerter, and Zimmermann (2024) shows that experiment participants are more likely to remember news cued by the current environment. Wachter and Kahana (2024) present a retrieved-context model to explain various findings in the finance literature.

where σ_s captures the strength of cued recall. According to equation (3), experienced returns closer in magnitude to r_T have higher similarity measures and are therefore more likely to be recalled. A larger σ_s indicates weaker influence from the cue (for example, if the investor perceives the cue to be less relevant). In the extreme case where $\sigma_s \to +\infty$, $s(r, r_T)$ approaches one, and f^* becomes equal to f; that is, the cue does not affect the recall process at all.

With equation (3) as the similarity function, the mean of the investor's free-recalled return, $\overline{R}_{\text{free}}(r_t|r_T)$, corresponds to the mean of random draws from the cued distribution f^*. We show in Online Appendix A1 that

$$\overline{R}_{free}(r|r_T) = (1-\alpha)\mu + \alpha r_T, \tag{4}$$

where $\alpha = \frac{\sigma^2}{\sigma^2+\sigma_s^2}$.[6] Therefore, the investor assigns a weight of $1-\alpha$ to the objective mean, μ, and the remaining weight, α, to the cue, r_T. This leads to the following prediction about free recall.

PREDICTION 1. (Cue effect on free recall) The mean of an investor's free-recalled return, $\overline{R}_{free}(r|r_T)$, is increasing in the current period's return r_T.

2. *Probed Recall.* Suppose the investor is asked to recall specifically her experienced return in period t. Such a prompt may trigger the investor to consciously search for a specific experience stored in her memory database. We refer to such a recall process as "probed recall." We assume that with probability θ, the investor correctly retrieves the target experience r_t. However, with probability $1-\theta$, retrieval is unsuccessful, and she engages in free recall instead; that is, her recalled experience is a random draw from the "cued" PDF in equation (1), with the mean given by equation (4).[7] Hence, the mean of the investor's recalled period

6. Specification (3) is mathematically equivalent to the investor using the current return r_T as a "signal" to infer r_t in a Bayesian fashion. Specifically, the investor has prior belief about r_t, where $r_t \sim N(\mu, \sigma^2)$, and treats r_T as a signal of r_t: $r_T = r_t + \epsilon$, with $\epsilon \sim N(0, \sigma_s^2)$. She follows Bayes's rule to obtain the following posterior distribution: $r_t|r_T \sim N((1-\alpha)\mu + \alpha r_T, \sigma_q^2)$, where $\sigma_q^2 = \frac{\sigma^2\sigma_s^2}{\sigma^2+\sigma_s^2}$.

7. Although the specifications for free recall and probed recall differ in form, they can be reconciled under a unified memory framework. Specifically, probed recall can be seen as recall triggered by more structured cues. If each experience is defined by both its return and the period in which it occurred, then probed recall involves two cues: (i) the current market return, and (ii) the prompted time

t return is given by

$$\overline{R}_{probed}(r_t|r_T) = \theta r_t + (1-\theta)[(1-\alpha)\mu + \alpha r_T]. \quad (5)$$

As before, the recalled return in this probed recall task remains influenced by the memory cue—the current return. This leads to a second, related prediction about cued recall.

PREDICTION 2. (Cue effect on probed recall) The mean of the recalled return for period t, $\overline{R}_{probed}(r_t|r_T)$, is increasing in the current period's return r_T.

II.C. From Recalls to Beliefs

After specifying the recall process, we turn to the formation of beliefs. We consider a generic belief-formation problem in which the investor needs to make forecasts about next period's return, r_{T+1}. Following Bordalo et al. (2025), we assume that the investor makes forecasts through "simulation"—using retrieved experienced returns (i.e., r_1,..., r_T) to simulate a distribution of future returns. Under this assumption, the investor's expected return for the next period is simply the average of his free recalled returns, $\overline{R}_{free}(r|r_T)$, which is given by equation (4). Hence, simulation naturally leads to return extrapolation based on the current return:

PREDICTION 3. (Return extrapolation) The investor's average forecast of the return for period $T+1$ is increasing in the current period's return r_T.

Four clarifications are worth noting. First, to highlight the role of simulation in belief formation, we assume that returns are independent and identically distributed and show that extrapolation arises even in this simple environment. In a more general setting where the returns are auto-correlated, a rational decision maker would extrapolate, and simulation amplifies the extrapolation by giving recent returns even higher weights in belief formation. Second, the current experience, r_T, is only one of T experiences, so its direct effect on belief formation is limited and

window. Including the time window as part of the cue increases the likelihood of retrieving experiences from that period—consistent with our assumption that investors correctly recall returns for that window with some probability. For parsimony, we model experiences as one-dimensional and use a reduced-form specification for probed recall, but both recall types are conceptually consistent with a single cue-based retrieval process.

vanishes as T approaches infinity. However, its indirect effect remains significant because, due to the cue effect, experiences with higher similarity to r_T are more likely to be sampled in the simulation process. Third, because cues affect both free recall and probed recall, return extrapolation arises regardless of whether the investor retrieves experiences using free recall or probed recall.

Fourth, because the simulation process pertains to the entire distribution of future returns, not just the average return, it has additional implications for the perception of crash risk. Let $r_{T+1} < \underline{r}$ denote a crash event, defined as a market return falling below the threshold $\underline{r}$. Our model predicts that the investor's perceived crash probability, $\Pr(r_{T+1} < \underline{r})$, decreases with the current return, r_T. This result, combined with Predictions 1 and 2, implies that the perceived crash probability also decreases with the average recalled return, $\overline{R}(r_t|r_T)$. Intuitively, higher current returns shift the perceived return distribution to the right, increasing the average expected return and lowering the perceived crash probability. This leads to the following prediction.

PREDICTION 4. (Perceived crash risk) The investor's perceived crash probability for period $T+1$, $\Pr(r_{T+1} < \underline{r})$, is decreasing in both the averaged recalled return $\overline{R}(r_t|r_T)$ and the current return r_T.

II.D. Extensions

1. *Recency and Salience.* So far, the model focuses solely on the cued recall aspect of memory. Two other well-documented aspects of memory—recency and salience effects—can also play significant roles. We illustrate that recency and salience can be easily incorporated into our framework.

First, to capture the recency effect, we follow the contiguity principle dating back to Bower (1972). Because the contextual state evolves gradually, recent experiences often share a similar context with the current state, making them more likely to be recalled. To capture this formally in reduced form, we define the recency measure as follows. For the period-t experience r_t, its recency measure $r(r_t)$ is given by $\exp(-\sigma_r(T-t))$, where a higher recency measure indicates a higher probability of being recalled. The parameter σ_r determines the speed of decay for recency: a higher σ_r indicates faster decay and therefore stronger recency effects. Second, to measure salience, we follow Bordalo, Gennaioli, and Shleifer (2022) by assuming that a return is more salient if it contrasts more sharply with other returns and adopt the following salience measure: $a(r_t) = \exp(\sigma_a(r_t - \mu)^2)$. According to this specification, returns that deviate more from the mean are more salient and are more likely to be recalled. The parameter σ_a captures the strength of salience: a higher σ_a means a disproportionally high probability of recall for salient returns.

To capture all three aspects of memory, we specify the retrieval probability for the experience in period t as

$$p_t = \frac{s(r_t, r_T)r(r_t)a(r_t)}{\sum_{\tau=1}^{T} s(r_\tau, r_T)r(r_\tau)a(r_\tau)}, \tag{6}$$

where the denominator normalizes the probabilities so that they sum to one. In Online Appendix A1, we use a numerical example to illustrate that all three effects jointly characterize the recall process and the relative strength of each effect is determined by the three σ parameters. In particular, even after incorporating both recency and salience effects, the cued recall phenomenon still emerges.

2. *Horizon Dependence.* So far, each experience in the database has been characterized solely by the return experienced in a given period. In reality, the meaning of a period varies across contexts, and an investor can represent an experience with any arbitrary time span. For instance, an investor may remember both her return in March 2020 (when the market initially plummeted due to COVID-19) and her overall return in 2020 (when the market as a whole rose substantially).

When an experience is characterized by both its return and its time span, the way return expectations are elicited can affect the recall process due to similarity. In particular, the forecasting horizon specified in the prompt can serve as a semantic cue, making experiences with similar features more likely to be retrieved. For example, when asked to forecast the return for the next year, the investor may naturally draw on her past experiences of yearly returns rather than, say, monthly returns. Due to recency, the most recent yearly return will play a disproportionately large role. Similarly, when prompted to forecast the return for the next month, the investor's simulation would be based more on her recalled return over the past month. This implies a form of "horizon dependence" in belief formation: a longer forecasting horizon is associated with the use of more distant experiences.

III. Survey Design and Stylized Facts

We begin by elaborating on the survey design in Section III.A. Section III.B details the implementation of the survey and the other data sources used in the article. Section III.C reports the summary statistics of key variables. Section III.D presents new stylized facts about investor memory.

III.A. Survey Design

1. *Recall.*

i. FreeRecall. The original survey is in Chinese; see Online Appendix A2 for an English translation. The survey starts with a block called *FreeRecall*, named after the well-established experimental paradigm of free recall (e.g., Murdock 1962; Kahana 2012). This survey block is designed to elicit a period of market movement that first comes to mind when an investor thinks about past stock market movements. By "free," we mean that the task imposes minimal restrictions on the period to be recalled.

For *FreeRecall*, we consider three treatments: *Neutral*, *Happy*, and *Painful*. In the *Neutral* treatment, we ask an investor to "first think about the overall stock market movement since you opened an account." We ask, "What is the episode of market movement that first comes to your mind? Please enter the starting month and ending month of this episode." This phrasing limits the recall episodes to those the investors have experienced themselves.[8] After entering the market episode that first comes to mind, investors are immediately asked three questions about that episode: (i) "How much did the market (the Shanghai Composite Index) move during this period?" (ii) "What was your total RMB investment during this period?" and (iii) "What was your total RMB return during this period?"[9] Because it may be difficult to recall an exact number, we offer multiple choices for each ques-

8. Episodes not directly experienced, such as the Great Depression for Baby Boomers or the tech bubble for Gen Z investors, can also be recalled and affect belief formation. However, we focus exclusively on experience-based recall. In a survey conducted for a different project, we modify the *FreeRecall* type of question in two significant ways. First, we experiment with different phrasing to elicit the episode that first comes to mind. Second, we instruct investors not to limit their recall to periods they have personally experienced. We discuss these results in the Online Appendix A4 and A6.2.

9. These responses are elicited after investors have specified their recall episodes. Therefore, they are no longer entirely "free," as they are now conditional on the recalled episodes. By *FreeRecall*, we mean that the recall task of specify-

tion, with each choice covering a fixed range of values (e.g., 0% to 5%).[10]

In addition to the *Neutral* treatment, which does not impose any specific conditions on the type of episode to be recalled, we consider two other treatments, each with a specific condition. In the *Happy* treatment, we ask investors to recall a pleasant episode that first comes to mind. In the *Painful* treatment, we ask investors to recall a painful episode that first comes to mind. As before, immediately after recalling an episode, investors are asked to answer the same three questions regarding the market return and their own returns during the recalled episode. Investors are randomly assigned to one of the three treatments with equal probability. We later use the *Happy* and *Painful* treatments to test for anchoring in survey responses.

ii. ProbedRecall. After *FreeRecall*, investors move on to the second recall block, called *ProbedRecall*. We ask them to recall their past own returns in the stock market for a given horizon. By "probed," we emphasize that these questions are more specific and detailed than those in *FreeRecall*, both the type of memory elicited (own return) and the time period specified (one day to five years). This mirrors the differences between free and probed recall in the model. When an investor enters *ProbedRecall*, we ask: "To the best of your recollection, what was the cumulative return rate of your equity investment over: (1) the last trading day; (2) the last month; (3) the past year; and (4) the past five years?" As before, we design these questions to be multiple-choice, with each choice covering a fixed range of values.

In our model of simulation, investors repeatedly sample past experiences to form expectations. In the survey, we are limited to the above two types of recalls. Despite their appearance as one-shot elicitations, we believe these two types are highly relevant for simulation. *FreeRecall* captures the first thoughts that come to mind, which is crucial because, while the model assumes repeated sampling, investors often reach conclusions based on limited sampling (Gennaioli and Shleifer 2010). Although the free-recalled

ing the episode imposes minimal restrictions and involves little interference from other sections of the survey.

10. We also have a similar set of questions at the stock level, and the response rate is substantially lower. Because we primarily focus on expectations at the market level, we do not discuss the results of stock-level recall in the remainder of the article.

episode refers to a single period the investor chooses to recall, this period may encompass multiple events and returns. In this sense, it represents a subset of the investor's memory database that they are likely to sample from when forming expectations. Similarly, *ProbedRecall* reflects a sequence of experiences—spanning from a specific point in the past up to yesterday—capturing recent and potentially relevant information for decision making.

2. *Expectation.* After the two recall blocks, investors enter the third block, *Expectation*. This block elicits beliefs about both the market and the investor's own portfolio. For the market, we ask about the mean return and the probability of a crash. As with the previous questions, these use a multiple-choice design and are phrased similarly to those in earlier studies (Giglio et al. 2021; Liu et al. 2022). For example, when eliciting beliefs about the mean market return over the next month, we ask: "What do you expect the cumulative return rate of the Shanghai Composite Index to be over the next 30 days?" When eliciting beliefs about crash probability, given that the Shanghai Composite Index hovered mostly between 3,500 and 3,600 during the sample period, we focus on two potential crash events: the index dropping below 3,000 within a month and the index dropping below 2,500 within a year. Investors are asked to report a percentage number between 0% and 100% as their subjective probability of a crash.

Throughout the main survey, we follow the order of survey blocks as *FreeRecall*, *ProbedRecall*, and *Expectation*, based on two considerations. First, starting with *FreeRecall* minimizes any confounding effects that the other blocks might have on investors' free-recall process. Second, placing *Expectation* after the two recall blocks helps avoid the influence of motivated reasoning (Bénabou and Tirole 2002, 2004), which could lead investors to alter their recall answers to align with their reported beliefs. A potential concern with eliciting recalls before beliefs is that it may make the recalls more salient, prompting investors to rely more heavily on them when forming beliefs. In Section V.E, we address this concern with an additional survey in which we vary the order of the survey blocks to show that our analysis is robust to different orderings of survey blocks.

3. *Other Blocks.* At the beginning of the survey, investors are explicitly instructed to rely solely on memory and not to check their brokerage account or search the internet when answering

FIGURE II

Organization of Survey Blocks

the survey questions. Although we cannot verify whether an investor strictly follows our instructions, around 60% complete the entire survey within 10 minutes, which leaves limited time for such checking. In addition, since the survey is not incentivized with money, investors lack the incentive to make an effort to search for the precise answers.[11] Even if some investors did check online, such behavior would likely introduce an attenuation bias in most of our analyses.

At the beginning of the survey, investors must complete a comprehension check, which includes questions about basic finance concepts such as dollar investment and dollar return. Investors who do not pass this check are excluded from our analysis. After passing the comprehension check, investors proceed to one of the three treatments in *FreeRecall* (*Neutral*, *Happy*, and *Painful*), before moving on to *ProbedRecall* and then *Expectation*. After *Expectation*, investors complete a personality block, which includes 20 questions designed to measure the Big Five personality traits (Jiang, Peng, and Yan 2024). At the end of the survey, a standard questionnaire is used to collect demographics and other information, including name, date of birth, age, gender, wealth, income, and social activities. Figure II illustrates the design of the survey blocks.

III.B. Survey Implementation and Other Data Sources

1. *Main Sample.* We administered the survey through a large financial institution in China, which maintains close relationships with all major Chinese brokerage firms and has access

11. The survey is not monetarily incentivized due to regulatory concerns, which significantly reduces participants' motivation to tailor their answers to perceived expectations. In addition, the online survey platform eliminates direct interaction between researchers and respondents, further minimizing any inclination to cater to the experimenters.

to the trading records of all retail investors. This partnership allowed us to randomize our sample across the branch offices of China's 60 largest brokers. The number of branch offices selected in each province was proportional to the trading volume from that province. Specifically, we selected 2,993 branch offices across 30 provinces (and regions) and our collaborating institution requested that each branch office collect at least 10 valid responses.

The survey was conducted between November 29, 2021, and January 9, 2022. To expose investors to different market conditions during the survey period, we conducted the survey in three waves, each lasting two weeks. Investors could complete the survey using either their personal computers or smartphones, with the vast majority opting for smartphones. An investor's response is considered invalid if they spent less than 175 seconds (the 5th percentile) to finish the survey, failed the comprehension check, or recalled an episode spanning longer than 10 years in *FreeRecall*.[12] Table I details the sample construction process. Our main sample consists of 17,324 valid responses, although missing data reduce the sample size in subsequent analyses. By design, investors are evenly distributed across the 60 brokers and the three *FreeRecall* treatments.

The distributions of demographics are plotted in Figure III. Overall, the sample is young, well educated, and affluent: the median age is around 35, 61% hold a bachelor's degree, and 34% have wealth above 1 million RMB.[13] In Online Appendix A3.1, we plot the distribution of survey respondents by day and by hour. Most responses are recorded during trading hours when the market is open. The correlation between the number of responses and daily market return is close to zero, indicating that market conditions do not significantly affect participation in the survey.

12. We drop investors whose recalled episode spans more than 10 years, as the Chinese stock market only became active in the 1990s, and a recall covering roughly 30% of its entire history is less informative. This excludes a substantial fraction of the sample, possibly because some investors reported their entire trading history as their response. Given the potential noise in these investors' answers to other questions, we exclude these observations entirely from the analysis.

13. To limit the influence of extreme observations that are more likely to be noise, we winsorize all variables at the 5th and 95th percentiles. Our communications with the collaborating institution suggest that investors taking our survey tend to have closer ties with their account managers at the brokerage firm. This implies that our sample represents investors who are more socially active, better connected to their broker, and possess higher net worth.

TABLE I
SAMPLE CONSTRUCTION PROCESS

Filter	Sample size
Initial sample	37,921
Drop if an investor spent < 175 seconds (5th percentile) on the survey	36,164
Drop if an investor fails the two comprehension check questions	27,799
Drop if an investor's recalled episode > 10 years in *FreeRecall*	17,324
Main sample	17,324
Treatment *Neutral*	6,214
Treatment *Happy*	5,805
Treatment *Painful*	5,305
Merged sample	5,154

Notes. We survey 37,921 retail investors in China. To ensure response quality, we impose the following filters to create our main sample: (i) the time spent to complete the survey must be at least 175 seconds (5th percentile); (ii) at the beginning of the survey, respondents must correctly answer two questions related to the concept of dollar investment and dollar return; (iii) in response to the question about the episode that comes to mind in the *FreeRecall* block, the length of the recalled episode must be no longer than 10 years. After imposing these three filters, we arrive at a main sample of 17,324 investors. In the *FreeRecall* block, investors are randomly assigned to one of the three treatments—*Neutral*, *Happy*, and *Painful*—which ask respondents to recall a past market episode that first comes to mind, that is the happiest, and that is the most painful, respectively. The number of qualified responses is 6,214, 5,805, and 5,305 for the three treatments, respectively. Finally, we are able to merge the survey responses with respondents' actual trading records for a subsample of 5,154 observations. These responses constitute our merged sample.

2. *Merged Sample*. For 5,154 investors, we are able to merge their survey responses with their detailed transaction data accessed through the collaborating institution, which contains the entire trading history of all stocks listed on one of the two main exchanges in China. As before, missing data may further reduce the sample size. The main requirement for a successful merge is that the name and date of birth reported by the investor uniquely identify the same individual in the transaction data. In Online Appendix A3.2, we compare observable characteristics between the merged sample and the unmerged sample, finding that the differences, if any, are generally small in magnitude. Online Appendix A3.3 further shows the trading characteristics of the investors in the merged sample. The average year-to-date maximum investment amount is 224,000 RMB, with a standard deviation of 380,000 RMB, indicating a wide range of investors across different wealth brackets. The average monthly turnover is 81%, suggesting that investors in our sample trade frequently, reshuffling their entire portfolio almost once every month. The average monthly raw return is 0.26%, and after accounting for fees and taxes, the average monthly net return is 0.07%.

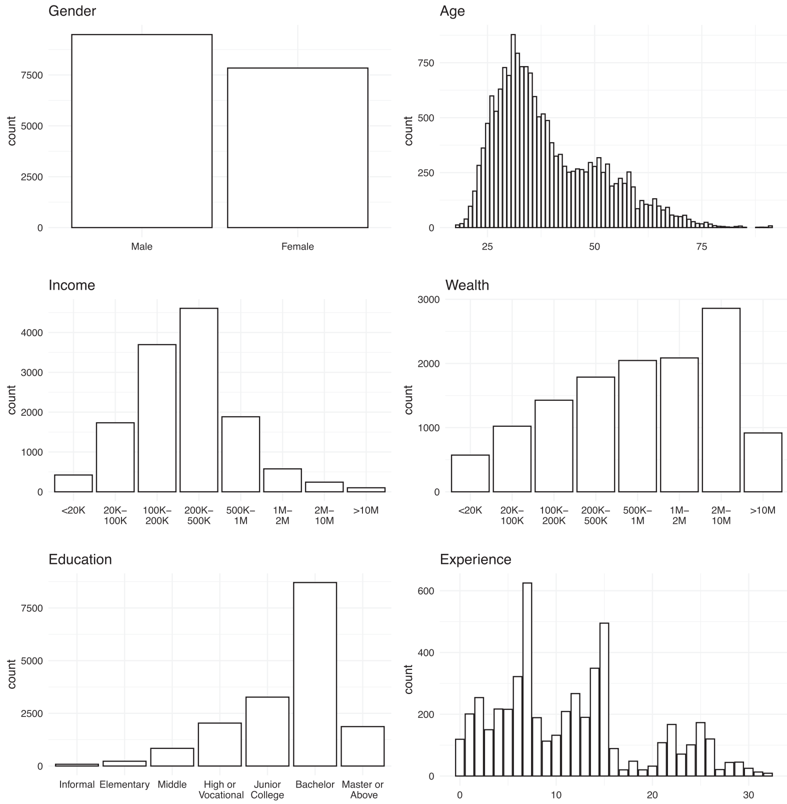


FIGURE III

Distribution of Demographic Variables

This figure reports the distribution of gender, age, annual income, wealth, education, and experience for survey respondents. The variable experience is defined as the number of years since an investor opens a trading account and is only available for the merged sample. All other variables are based on the main sample. The y-axis represents the number of observations.

III.C. Summary Statistics

Our analysis focuses on three types of variables: recalls, expectations, and realized values. To simplify notation, throughout this article, we use $\mathbb{R}$ to denote recall and $\mathbb{E}$ to denote expectation. Unless specified otherwise, a variable without $\mathbb{R}$ or $\mathbb{E}$ represents the realized value.

TABLE II

Summary Statistics of Recalled and Realized Returns

	N	Mean	Std. dev.	P5	P25	Median	P75	P95
Panel A: Main sample, the *FreeRecall* block								
$\mathbb{R}[\mathrm{MktRet}_{\mathrm{episode}}]$	13,791	4.2%	36.5%	−50.5%	−17.5%	0.0%	12.5%	100.0%
Neutral	5,087	5.6%	38.8%	−50.5%	−19.5%	0.0%	15.5%	100.0%
Happy	4,511	23.4%	33.6%	−8.5%	2.5%	9.5%	30.5%	100.0%
Painful	4,193	−18.1%	21.3%	−50.5%	−32.5%	−15.5%	−3.5%	8.5%
Panel B: Main sample, the *ProbedRecall* block								
$\mathbb{R}[\mathrm{OwnRet}_{\mathrm{1D}}]$	10,432	−0.3%	5.5%	−13.5%	−2.5%	−0.5%	2.5%	10.5%
$\mathbb{R}[\mathrm{OwnRet}_{\mathrm{1M}}]$	9,957	−0.2%	6.5%	−13.5%	−4.5%	0.5%	4.5%	10.5%
$\mathbb{R}[\mathrm{OwnRet}_{\mathrm{1Y}}]$	10,440	1.8%	13.2%	−22.5%	−6.5%	1.5%	8.5%	32.5%
$\mathbb{R}[\mathrm{OwnRet}_{\mathrm{5Y}}]$	9,325	4.3%	24.3%	−39.5%	−9.5%	2.5%	10.5%	70.5%
Panel C: Main sample, the *Expectation* block								
$\mathbb{E}[\mathrm{MktRet}_{\mathrm{1M}}]$	12,786	2.0%	3.8%	−5.5%	0.0%	1.5%	4.5%	9.5%
$\mathbb{E}[\mathrm{MktRet}_{\mathrm{1Y}}]$	12,356	5.2%	6.7%	−6.5%	0.0%	4.5%	9.5%	20.5%
$\mathbb{E}[\mathrm{OwnRet}_{\mathrm{1M}}]$	9,375	6.1%	7.7%	−5.5%	2.5%	4.5%	9.5%	28.5%
$\mathbb{E}[\mathrm{OwnRet}_{\mathrm{1Y}}]$	9,602	16.0%	23.4%	−5.5%	4.5%	9.5%	19.5%	99.4%
Panel D: Merged sample								
$\mathrm{OwnRet}_{\mathrm{1D}}$	2,759	0.3%	2.5%	−3.0%	−0.9%	0.2%	1.4%	4.0%
$\mathrm{OwnRet}_{\mathrm{1M}}$	2,936	3.2%	10.1%	−10.5%	−2.0%	2.6%	7.3%	18.6%
$\mathrm{OwnRet}_{\mathrm{1Y}}$	3,309	8.0%	28.0%	−24.1%	−6.8%	3.5%	16.9%	52.1%

Notes. This table reports summary statistics for recalled and actual experiences in the *FreeRecall* and *ProbedRecall* blocks. In the *FreeRecall* block, investors are randomly assigned to one of the three treatments, *Neutral*, *Happy*, or *Painful*, which ask respondents to recall a past market episode that first comes to mind, that is the happiest, and that is the most painful, respectively. Respondents are then asked to recall the market return, labeled $\mathbb{R}[\mathrm{MktRet}_{\mathrm{episode}}]$ during the recalled episode. The *ProbedRecall* block asks investors to recall returns of their own portfolios over the past one day, one month, one year, and five years, labeled as $\mathbb{R}[\mathrm{OwnRet}_{\mathrm{1D/1M/1Y/5Y}}]$. The *Expectation* block asks investors to predict future returns of the market and their own portfolios in the next month and next year, labeled as $\mathbb{E}[\mathrm{MktRet}_{\mathrm{1M/1Y}}]$ and $\mathbb{E}[\mathrm{OwnRet}_{\mathrm{1M/1Y}}]$. In Panels A–C, we report the summary statistics of these variables in the main sample. For a subsample of respondents for whom we can observe their transactions (the merged sample), we also calculate their *actual* portfolio returns over the same period of time, denoted by $\mathrm{OwnRet}_{\mathrm{1D/1M/1Y/5Y}}$, and report the summary statistics in Panel D.

1. *Recalls. FreeRecall* asks investors to recall a market episode that first comes to mind when thinking about past stock market movements. For simplicity, we refer to an investor's answer to this question as the "recalled episode" or just "episode." In addition, investors are asked to recall the market return during the recalled episode, which we denote as $\mathbb{R}[\mathrm{MktRet}_{\mathrm{episode}}]$. Table II, Panel A reports the summary statistics of $\mathbb{R}[\mathrm{MktRet}_{\mathrm{episode}}]$, first for all three *FreeRecall* treatments combined, and then for each treatment separately.

First we consider all three treatments combined. The standard deviation of $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ is large, indicating substantial variation in the types of market conditions investors recall. Indeed, more than 10% of investors recall an episode during which the market doubles in value or shrinks by half. The median of $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ is around zero, suggesting that overall, investors are not selectively recalling more positive or negative experiences. We compare across the three treatments using the *Neutral* treatment as a benchmark. By design, the distribution of $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ shifts to the right for the *Happy* treatment and to the left for the *Painful* treatment. Within each treatment, there is again sizable variation in $\mathbb{R}[\text{MktRet}_{\text{episode}}]$, indicating substantial heterogeneity in what comes to mind for each investor.

ProbedRecall asks investors to recall their own returns on their equity investment over a given horizon. We label these recalls $\mathbb{R}[\text{OwnRet}]$ and use a subscript to specify the recall horizon (e.g., $\mathbb{R}[\text{OwnRet}_{1\text{D}}]$ for recalled own return from yesterday). Table II, Panel B reports the summary statistics of $\mathbb{R}[\text{OwnRet}]$. There is significant variation in $\mathbb{R}[\text{OwnRet}]$ for all recall horizons, with the amount of variation increasing as the recall horizon lengthens. Comparing the mean and median across recall horizons, we observe that a longer recall horizon is associated with more positive recalls.

2. *Expectations.* Table II, Panel C reports the summary statistics for four measures of beliefs: expectations ($\mathbb{E}$) of the market return (MktRet) or one's own return (OwnRet) over the next month (1M) or year (1Y). Even when investors are asked about the same variable of market return, we observe substantial heterogeneity in their subjective beliefs. When comparing return expectations for the market and their own returns over the same horizon, we observe that expectations of own returns are generally higher than those of market returns, consistent with the notion of overconfidence.

3. *Realizations.* Table II, Panel D reports the summary statistics of actual own returns, denoted by OwnRet, over various horizons for the merged sample. For horizons between one day and one year, $\mathbb{R}[\text{OwnRet}]$ is generally lower than OwnRet for the same period, indicating a conservative bias in recall. When the horizon extends to five years (not shown), however, there is suggestive evidence of positively biased recall: the median recalled

TABLE III
CORRELATIONS BETWEEN RECALLED AND ACTUAL RETURNS

	$\mathbb{R}[\text{MktRet}_{\text{episode}}]$	$\mathbb{R}[\text{OwnRet}_{1D}]$	$\mathbb{R}[\text{OwnRet}_{1M}]$	$\mathbb{R}[\text{OwnRet}_{1Y}]$
$\text{MktRet}_{\text{episode}}$	0.57***			
	(0.01)			
OwnRet_{1D}		0.10***		
		(0.02)		
OwnRet_{1M}			0.25***	
			(0.02)	
OwnRet_{1Y}				0.32***
				(0.02)

Notes. This table reports the correlation coefficients between recalled and corresponding actual returns in the *FreeRecall* for the main sample and in the *ProbedRecall* for the merged sample. For example, the top left cell shows the correlation coefficient between the recalled and actual market episode return ($\mathbb{R}[\text{MktRet}_{\text{episode}}]$ and $\text{MktRet}_{\text{episode}}$). Standard errors are in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$.

own return is 2.5%, and the median actual own return is around 0.9%. One possible explanation is that long-term performance is harder to recall, leaving more room for investors to positively bias their memories of past performances—a form of motivated reasoning.

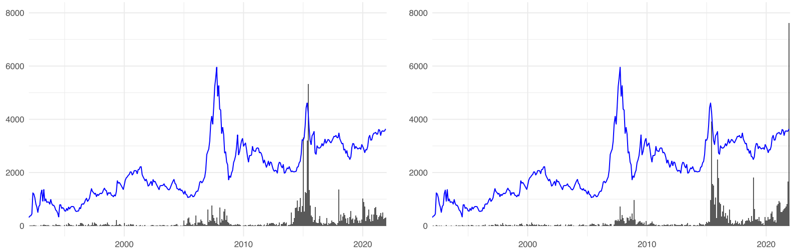
4. *Recalls and Realizations.* To examine the accuracy of investor recalls, Table III reports the correlation between the recalled and realized values of the same variable. For *FreeRecall*, the correlation between $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ and $\text{MktRet}_{\text{episode}}$ is 0.57. For *ProbedRecall*, the correlation between $\mathbb{R}$[OwnRet] and OwnRet ranges from 0.10 to 0.32. All of these coefficients are highly statistically significant. Overall, the positive correlations confirm that investors made a conscious effort when completing the recall tasks.

III.D. Stylized Facts

We present several stylized facts about investor memory by examining the basic structure of the memories investors report, such as the types of episodes they recall and their content. This serves as a baseline characterization of the memory database. In contrast, in Section IV, we explore how memory varies systematically with external market cues.

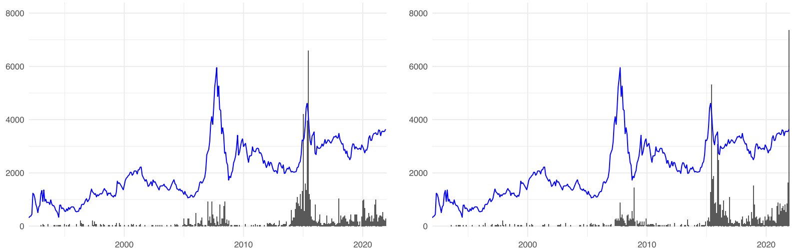
To analyze the properties of *FreeRecall*, Figure IV, Panel A plots the distribution of the start and end months of the recalled episodes against the Shanghai Composite Index for the *Neutral*

Panel A: Main sample



Distribution of start months *Distribution of end months*

Panel B: Excluding investors who entered the market during the past year



Distribution of start months *Distribution of end months*

FIGURE IV

Distribution of Recalled Market Episodes in *FreeRecall*

In the *Neutral* treatment of the *FreeRecall* block, investors are asked to recall a past market episode that first comes to mind. We plot the distribution of start and end months of the reported episodes. The solid blue line represents the Shanghai Composite Index. The solid black bars represent the frequency of responses. The legends on the y-axes represent the level of the Shanghai Composite Index. Panel A is based on the main sample. Panel B is based on a subsample that excludes investors who started trading stocks during the last year of our sample (2021).

treatment. The gray bars represent the frequency of responses, and the blue line represents the index. Two patterns immediately emerge in Figure IV. First, recalls display a strong recency effect: a disproportionally large number of responses concern recent periods, especially for the end month. This result mirrors the recency effect documented in free recall experiments conducted by memory psychologists, where items that participants saw most recently are more likely to be recalled (Kahana 2012). In our setting, one potential driver of the recency effect is investor experience: as the question explicitly instructs investors to recall only experiences since they started trading, new investors will mechanically report more recent periods. To rule out this alternative force, Figure IV, Panel B replots the distribution of recalled episodes but excludes investors who entered the market during the past 12 months. If recency plays no role, then all the months during the past year should be equally likely to be recalled. However, Panel B shows a cluster of recalled episodes for the most recent month.

A second pattern that emerges in Figure IV is that a substantial fraction of recalled market episodes tilt toward two bubble-and-crash episodes, one in 2007–8 and another in 2014–15. Therefore, unlike the specification used in models of experience effects (Malmendier and Nagel 2011), the probability of recalling an episode is not merely a function of time elapsed. Instead, features of the experience, such as the extremeness and rarity of the event, can influence investor recall. There are several potential explanations for the salience effect, one being attention. It has been observed that market run-ups are eye-catching events, drawing attention from retail investors whose active trading eventually leads to a trading frenzy (Scheinkman and Xiong 2003; Xiong and Yu 2011; Barberis et al. 2018; Liao, Peng, and Zhu 2022). Because more mental resources were devoted to tracing and monitoring the stock market at the time—a process through which experiences are encoded into memory—these experiences are subsequently more likely to be recalled (Mullainathan 2002). This observation also supports the retrieved-context model by Wachter and Kahana (2024), which allows for stronger encoding of experiences that are more extreme.

In Online Appendix A4, we conduct a variety of robustness checks for the recency and salience effects. First, we plot the distribution of recalled episodes for two subsamples split by age. Both recency and salience effects are observed in the two subsamples, with the recency effect being more pronounced in the younger sample. Second, we consider an alternative phrasing for the *FreeRecall* block that allows for recalling episodes not personally experienced, and we find similar patterns of recency and salience. One remaining issue with our phrasing is that asking for an “episode of market movement” may prompt investors to recall more turbulent periods. More generally, eliciting market experiences without inadvertently encouraging attention to dramatic events is inherently challenging, as even alternative wordings—such as asking about a “return,” “period,” or “condition”—are likely to cue respondents toward more salient, volatile episodes. Developing new elicitation methods to minimize the influence of question wording on recall remains an important direction for future research. Third, our simulations show that the documented salience and recency effects cannot be attributed to the mechanical consequence of inflows of new investors. Fourth, recency and salience are observed across investors with varying trading intensities. Together, these additional results suggest that recency and salience effects are robust to alternative explanations.[14] Last, it is worth noting that the coexistence of recency and salience effects is reminiscent of the "peak-end" rule, whereby people evaluate an experience primarily based on how they felt at its peak and its end (Fredrickson and Kahneman 1993; Kahneman et al. 1993).

IV. Cued Recall

This section tests the first part of the model, recall, by studying how return cues affect the dynamics of investor memory over time. This corresponds to the link between "cue" and "recall" shown in Figure I. In Section IV.A, we discuss how the survey generates variation in return cues. In Sections IV.B and IV.C, we examine the relationship between return cues and the memories elicited by the two recall blocks.

IV.A. Return as the Cue

The complexity of the stock market gives rise to many potential cues—for example, location, experienced returns, media narratives—all of which could affect investor recall. Our empirical design focuses on returns as the cue for several reasons. First, return is by far the most salient feature of the stock market. It is frequently cited and discussed in the media, drawing significant attention from investors. Second, from an investor's perspective, return is directly linked to fluctuations in wealth, creating a monetary incentive to closely monitor their brokerage account. While many other cues, such as media narratives, can also influence investor recall, they are often constructed based on the latest market movements and are unlikely to operate independently of returns.

14. In Online Appendix A5, we further document an age effect in recall: older investors generally tend to recall a more bullish episode. We further show that this phenomenon is more consistent with selective recall, rather than biased recall.

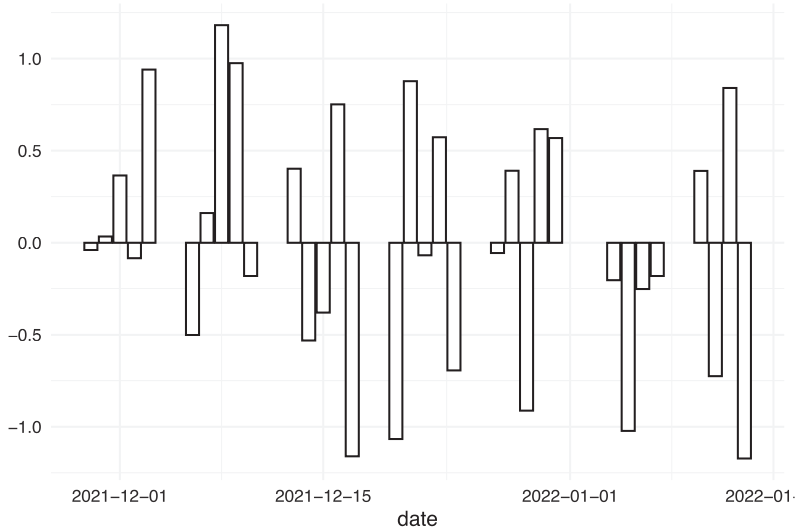


FIGURE V

Distribution of Daily Returns During the Survey Period

The figure plots the daily stock market return (in %) for the Shanghai Composite Index during our survey period, November 29, 2021, to January 9, 2022.

We hypothesize that returns—returns of the entire market and returns in one's own portfolio—can cue investors to think of past trading experiences. This hypothesis directly corresponds to Predictions 1 and 2, which argue for cued recall in *FreeRecall* and *ProbedRecall*. While market returns and own returns are highly correlated and attention-grabbing, the mechanism through which they attract attention may differ: market returns attract attention because they are salient and frequently discussed in the news, while own returns draw attention because they are directly linked to individual wealth.

When distributing the survey to investors, we rolled it out in three waves over six weeks to obtain significant variation in daily market returns in our sample period. Figure V shows the evolution of daily returns during this period. The maximum daily return was 1.18%, the minimum was −1.16%, and the standard deviation was 0.66%. The survey platform recorded the precise time when an investor began taking the survey. Therefore, even for investors taking the survey on the same day, the intraday returns they experienced could differ as the market fluctuates throughout the day. When examining own returns as a cue, our analysis is restricted to the merged sample, for which we can observe detailed transaction data.

IV.B. Testing Cued Recall in the FreeRecall Block

According to Prediction 1, a positive return can trigger the retrieval of an episode featuring a booming market. To test this, we use the following main specification (for notational simplicity, we omit the subscript i, which indexes investor i):

$$\begin{aligned}\mathbb{R}[\mathrm{MktRet}_{\mathrm{episode}}] = \beta_0 + \beta_{\mathrm{D}}\mathrm{MktRet}_{\mathrm{today}} + \beta_{\mathrm{M}}\mathrm{MktRet}_{\mathrm{1M}} \\ + \beta_{\mathrm{Y}}\mathrm{MktRet}_{\mathrm{1Y}} + X + \epsilon.\end{aligned} \tag{7}$$

On the left side, $\mathbb{R}[\mathrm{MktRet}_{\mathrm{episode}}]$ denotes an investor's recalled episode market return in *FreeRecall*. On the right side, $\mathrm{MktRet}_{\mathrm{today}}$ represents the cumulative market return today up to the minute when the investor starts the survey; $\mathrm{MktRet}_{\mathrm{1M}}$ ($\mathrm{MktRet}_{\mathrm{1Y}}$) represents the cumulative market return over the last month (year); and X denotes various individual-level controls, including age, gender, education, wealth, income, and measures of social activities. Simply put, specification (7) tests whether market fluctuations today and over the past month or year affect investor recall. Note that if the cue and the recalled episode overlap in the time period they cover, this could create a mechanical positive correlation and bias the estimated coefficients upward. Therefore, we exclude observations where the recalled episode ends in 2021 (the survey was conducted at the end of 2021). This also ensures that *FreeRecall* and *ProbedRecall* (which, as shown later, examine recalled own returns over the past month and year) do not overlap in the periods they cover. To minimize the effects of question phrasing, our main analysis only uses the *Neutral* treatment. Using *Happy* and *Painful* treatments might introduce bias, as investors could be influenced by the specific condition in the question prompt (e.g., recalling a pleasant or painful episode) and the market return.

Table IV, columns (1)–(4) report the results for the full sample in the *Neutral* treatment. For all four regressions, the coefficients on $\mathrm{MktRet}_{\mathrm{today}}$, $\mathrm{MktRet}_{\mathrm{1M}}$, and $\mathrm{MktRet}_{\mathrm{1Y}}$ are close to zero and insignificant.

The null results in columns (1)–(4) may initially appear surprising and counter to the prediction of similarity-based recall.

TABLE IV

TESTS OF CUED RECALL IN THE *FreeRecall* BLOCK

	Dependent variable: $\mathbb{R}[\text{MktRet}_{\text{episode}}]$							
	Main sample				Sample of recent recalls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{MktRet}_{\text{today}}$	0.36			0.74	2.49**			4.09**
	(1.35)			(1.76)	(1.24)			(1.60)
$\text{MktRet}_{1\text{M}}$		−0.51		−0.08		0.94*		1.63***
		(0.57)		(0.65)		(0.48)		(0.60)
$\text{MktRet}_{1\text{Y}}$			1.25	1.32			−1.43	0.25
			(1.21)	(1.27)			(1.19)	(0.86)
Observations	3,503	3,503	3,503	3,503	940	940	940	940
Adjusted R^2	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.02

Notes. We test the effects of cues on *FreeRecall* by regressing recalled market return for the episode, $\mathbb{R}[\text{MktRet}_{\text{episode}}]$, on cues. We consider three types of cues: $\text{MktRet}_{\text{today}}$ is the market return on the day when the survey was completed and is calculated as the cumulative return from the market open to the minute when the investor starts to take the survey; $\text{MktRet}_{1\text{M}}$ ($\text{MktRet}_{1\text{Y}}$) is the market return over the past month (year) before the survey was taken. All results are produced using the *Neutral* treatment. We also exclude observations in which the recalled episode ends in or after December 2020, so that the recalled episode does not overlap with the cues. Columns (1)–(4) are based on the entire *Neutral* treatment; columns (5)–(8) are based on a subset of the *Neutral* treatment in which the recalled episode ending date is within the past one to five years. We control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, and number of WeChat groups. Standard errors, in parentheses, are clustered by date. * $p < .1$; ** $p < .05$; *** $p < .01$.

A closer examination, however, suggests two alternative interpretations. First, as shown in Section III.D, recalled episodes in *FreeRecall* largely capture dramatic events featuring large swings in asset prices. This salience-recall pattern may be partly driven by the design of the question, which asks respondents to recall an episode of market movement, thereby reducing the cuing effect of market returns when they are less extreme. Indeed, according to similarity-based recall (Kahana 2012), for return cues to influence the retrieval of such salient events, the return cues themselves may need to be extreme. However, Figure V shows that although there is some degree of market volatility during our survey period, the overall market lacked dramatic rises or falls in asset prices. As a result, during our sample period, market returns as a cue may not be powerful enough to affect recall in *FreeRecall*. As part of a separate project, we conducted a similar survey during a more volatile market environment and found stronger evidence for cue-driven recall. This alternative survey took place during a period of more dramatic fluctuations—daily returns ranged from -1.6% to 2.6%, and past-month returns from -7.1% to 3.5%—and under these conditions, higher recent returns were significantly associated with a greater likelihood of recalling bullish episodes, suggesting that stronger return cues enhance memory retrieval. The results are presented in Online Appendix A6.2.

Second, similarity is not solely defined by two experiences having similar returns; it also depends on their temporal proximity, meaning that experiences occurring close together in time are mentally associated with each other. Consequently, cuing one experience increases the likelihood of retrieving another that occurred around the same time. In the regressions discussed earlier, we primarily considered recent returns as cues, which may influence the retrieval of more recent experiences but not the more distant ones. To test this possibility, we rerun these regressions on a subsample of investors whose recalled episode in *FreeRecall* ends within the past five years. This five-year cutoff ensures a sufficiently large sample while avoiding earlier bubble-and-crash episodes, but results are robust to several alternative cutoff points; see Online Appendix A5 for these results.

Table IV, columns (5)–(8) reports the regression results based on the subsample. Both today's return and the past one-month return have a much stronger influence on $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ in *FreeRecall*. In column (5), a 1 percentage point increase in today's return increases $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ by 2.5 percentage points. In column (6), a 1 percentage point increase in the past one-month return increases $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ by 0.9 percentage points. In column (8), where all three returns are included, the coefficients remain positive and statistically significant for today's return and the past month's return. The coefficient on the one-year return, however, is not statistically significant.

As argued, our test of cued recall in the *FreeRecall* block only uses the *Neutral* treatment because it does not prime investors with additional conditions. As a robustness check, we conduct the same analysis by pooling all three treatments together while controlling for treatment fixed effects. The results are reported in Online Appendix A6.3 and remain similar. Depending on the specification, a 1 percentage point increase in today's return is associated with a 2.0 to 2.1 percentage point increase in $\mathbb{R}[\text{MktRet}_{\text{episode}}]$.

IV.C. Testing Cued Recall in the ProbedRecall Block

Prediction 2 states that a positive market return on the survey day leads to a more positive recall of one's own returns elicited in *ProbedRecall*. To test this prediction, using data from all three treatments, we run the following regression:

$$\mathbb{R}[\text{OwnRet}] = \beta_0 + \beta_1 \text{MktRet}_{\text{today}} + X + \epsilon. \tag{8}$$

On the left side, $\mathbb{R}$[OwnRet] represents the recalled own return over a specific horizon. Given that Chinese retail investors typically focus on short trading horizons (Liu et al. 2022; Gao et al. 2023), we focus on recall horizons of one day and one month. On the right side, to avoid time overlaps between cues and recalls, we only include $\text{MktRet}_{\text{today}}$. To test for recall biases, it is necessary to control for actual own returns, which are available only in the merged sample. In the main sample, where actual own returns are not observable, we instead use actual market returns, which are highly correlated with own returns. Therefore, when analyzing the main sample, we adjust $\mathbb{R}$[OwnRet] by deducting the actual market return over the same horizon. For the merged sample, we directly control for investors' actual own returns. As before, X represents a set of individual-level controls, including demographics and other personal characteristics.

In Table V, columns (1) and (2) report the regression results for the main sample. A 1 percentage point increase in today's market return is associated with a 52 basis point increase in investors' recalled own return for the previous day and a 113 basis point increase for the past month. Using the merged sample, columns (3) and (4) extend the analysis in column (1) in two ways. First, in column (3), we further control for investors' actual own return from the previous day. The coefficient on today's market return remains significant, suggesting that today's market movement induces a biased recall of yesterday's own return. Second, in column (4), instead of using today's market return as the cue, we use one's own return today ($\text{OwnRet}_{\text{today}}$) as the cue and again find evidence of cued recall, with a positive and significant coefficient on $\text{OwnRet}_{\text{today}}$. In columns (5) and (6), we conduct a similar analysis to that in columns (3) and (4), focusing on recalled own returns over the past month rather than the previous day, and we find comparable results. Together, columns (3)–(6) demonstrate

TABLE V

TESTS OF CUED RECALL IN THE *ProbedRecall* BLOCK

	Main sample		Merged sample			
	$\mathbb{R}[\text{OwnRet}_{1D}]$	$\mathbb{R}[\text{OwnRet}_{1M}]$	$\mathbb{R}[\text{OwnRet}_{1D}]$		$\mathbb{R}[\text{OwnRet}_{1M}]$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MktRet}_{\text{today}}$	0.52**	1.13***	1.04***		0.90*	
	(0.22)	(0.26)	(0.33)		(0.52)	
$\text{OwnRet}_{\text{today}}$				0.28**		0.39***
				(0.11)		(0.10)
OwnRet_{1D}			0.35***	0.31***		
			(0.11)	(0.11)		
OwnRet_{1M}					0.20***	0.20***
					(0.02)	(0.02)
Observations	7,362	7,362	1,348	1,348	1,348	1,348
Adjusted R^2	0.03	0.04	0.06	0.05	0.09	0.10

Notes. We test the effects of cues on *ProbedRecall* by regressing recalled own return yesterday or the last month, $\mathbb{R}[\text{OwnRet}_{1D/1M}]$, on return cues. We consider two types of cues. In columns (1) and (2), which use the main sample, the cue is $\text{MktRet}_{\text{today}}$, the market return on the day when the survey was completed, calculated as the cumulative return from the market opening to the minute when the investor begins the survey. In columns (3)–(6), which uses the merged sample, we consider a second cue, $\text{OwnRet}_{\text{today}}$, which represents an investor's actual portfolio return on the survey day. In the merged sample, we control for actual portfolio return yesterday or the past month, $\text{OwnRet}_{1D/1M}$. For all columns, we control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, and number of WeChat groups. Standard errors, in parentheses, are clustered by date, and we include treatment fixed effects. * $p < .1$; ** $p < .05$; *** $p < .01$.

that both market returns and own returns serve as relevant cues in investors' recall process.[15]

IV.D. Discussion

So far, we have focused on testing current returns as plausible cues for investors' recall process. Notably, our survey never asks investors about the returns they currently see or have recently experienced. As a result, the return cues we investigate occur naturally in investors' information environment, without requiring explicit prompts or priming from the survey or research design. This naturalistic approach contrasts with most previous studies on cued recall, where cues are typically embedded in the

15. We also note that in our setting, probed recall is more sensitive to cues than free recall is. We suspect that the *FreeRecall* block elicits episodes that are buried deeper in investors' minds. As such, the elicited memory is less fluid and sensitive to cues in the environment, possibly capturing the experience effect (Malmendier and Nagel 2011, 2016). A further exploration of different types of memory is left to future research.

research design through direct prompts (e.g., Enke, Schwerter, and Zimmermann 2024). Importantly, our findings demonstrate that naturalistic cues, such as market returns, do influence investors' recall in a field setting.

An alternative interpretation of our cued-recall results is that investors are actually using today's return to make inferences about past returns. Empirically, aggregate market returns are largely unpredictable, especially at daily or monthly horizons. For example, the autocorrelation coefficient in daily stock returns from 2017 to 2021 is nearly zero. In 2021, it is -0.04 (p-value .49); during our survey period, it is -0.09 (p-value .65). Thus, evidence of return predictability is weak, leaving little room for rational inference. It is possible that investors may hold an incorrect mental model of the stock market, falsely believing in positive autocorrelation. However, Liu et al. (2022) finds that only 30%–35% of retail investors in China report believing in trend continuation.[16] Moreover, if these recalls are merely products of inference based on today's return, they should not significantly affect belief formation or trading behavior, especially after controlling for recent market or personal returns. In Section V.F, we show that recalls do affect beliefs and trading behavior. Given these considerations, the evidence in this section aligns best with the interpretation based on cued recall.

While we have established the relevance of returns as cues in investors' recall process, the complexity of a field setting, such as trading in financial markets, suggests that other cues may also influence recall. Although a full exploration of alternative cues is beyond the scope of this paper, in Online Appendix A6.4, we explore the role of media narratives by examining the language used in financial media. Specifically, we test whether investors are more likely to recall episodes of a rising or falling market when terms like "run-up" or "crash" are mentioned more frequently in the media. Overall, we find that the language used by the financial press does not explain investor recall better than market returns do. One possibility is that media language simply reflects market returns and therefore does not provide additional information. Another possibility is that our approach—focusing

16. In addition, cued recall results from *FreeRecall* suggest that today's return can cue experiences from months or even years ago. For inference to have such a strong effect, beliefs in return autocorrelation would need to be implausibly high, which is not supported by survey evidence from Liu et al. (2022).

on specific words rather than broader narratives—may not precisely capture the full impact of media on investor recall. We leave a more thorough investigation of these issues to future research.

V. Recalls, Beliefs, and Actions

In this section, we test the second part of the model, simulation, by examining how investors use recalls to form beliefs. This corresponds to the link between "recall" and "belief" shown in Figure I. In Section V.A, we analyze the statistical relationship between memories elicited in the two recall blocks and expectations elicited in the *Expectation* block. Sections V.B through V.D provide further evidence on this relationship. Section V.E considers alternative explanations. Finally, in Section V.F, we discuss the implications of our results for behavior in the field and connect the elicited beliefs to observed trading behavior in the transaction data. This final exercise, by examining the relationship between "belief" and "action," completes the chain of relationships illustrated in Figure I.

V.A. Correlation Between Recalls and Beliefs

1. *Main Results.* Return expectations show significant and persistent differences across investors, but the underlying causes of this variation are not well understood (Giglio et al. 2021). Differences in how investors mentally account for past events may offer an explanation through the memory channel. To explore this, we examine the relationship between recalls and expectations by conducting a series of cross-sectional regressions. We begin with the following:

$$\mathbb{E}[\text{Ret}] = \beta_0 + \beta_1 \mathbb{R}[\text{MktRet}_{\text{episode}}] + X + \epsilon. \tag{9}$$

The dependent variable is the expected return of the market ($\mathbb{E}[\text{MktRet}]$) or an investor's own portfolio ($\mathbb{E}[\text{OwnRet}]$). We examine these expectations across two horizons: one month (1M) and one year (1Y). The key independent variable is the investor's recalled episode market return ($\mathbb{R}[\text{MktRet}_{\text{episode}}]$) from the *FreeRecall* block. As before, X represents the list of individual-level control variables. We use all three treatments while controlling for treatment fixed effects.

In Table VI, Panel A, each column presents the regression results for a different type of return expectation. Across all four columns, the coefficients on $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ are positive and sta-

TABLE VI

RELATIONSHIP BETWEEN RECALLS AND BELIEFS

	$\mathbb{E}[\text{MktRet}_{1M}]$ (1)	$\mathbb{E}[\text{MktRet}_{1Y}]$ (2)	$\mathbb{E}[\text{OwnRet}_{1M}]$ (3)	$\mathbb{E}[\text{OwnRet}_{1Y}]$ (4)
Panel A: *FreeRecall*				
$\mathbb{R}[\text{MktRet}_{\text{episode}}]$	0.005**	0.01***	0.01***	0.05***
	(0.002)	(0.003)	(0.004)	(0.01)
Observations	5,626	5,626	5,626	5,626
Adjusted R^2	0.01	0.04	0.04	0.07
Panel B: *ProbedRecall*				
$\mathbb{R}[\text{OwnRet}_{1M}]$	0.09***	0.08***	0.20***	0.16*
	(0.01)	(0.02)	(0.03)	(0.09)
$\mathbb{R}[\text{OwnRet}_{1Y}]$	0.02***	0.05***	0.10***	0.38***
	(0.01)	(0.01)	(0.01)	(0.03)
Observations	4,190	4,190	4,190	4,190
Adjusted R^2	0.04	0.05	0.13	0.12

Notes. We explore the relationship between recalls, elicited in the *FreeRecall* and *ProbedRecall* blocks, and beliefs, elicited in the *Expectation* block. The dependent variables are four measures of beliefs: the expected return ($\mathbb{E}$) of the market (MktRet) or the investor's own portfolio (OwnRet) over the next month (1M) or year (1Y). In Panel A, the key independent variable is the recalled market return for the episode, $\mathbb{R}[\text{MktRet}_{\text{episode}}]$, as elicited in *FreeRecall*. To ensure that coefficients are comparable across columns, we exclude investors with any missing values. In Panel B, the independent variables are the recalled own return for either the past month or year, $\mathbb{R}[\text{OwnRet}_{1M/1Y}]$, as elicited in the *ProbedRecall* block. Both panels use the main sample. We control for age, gender, education, wealth, income, frequency of account checks, frequency of news checks, frequency of investment discussions, and the number of WeChat groups. Standard errors, in parentheses, are clustered by date, and we include treatment fixed effects. * $p < .1$; ** $p < .05$; *** $p < .01$.

tistically significant. This suggests that investors who recall more bullish episodes tend to have higher expectations for market performance and their own future returns. In terms of magnitude, the interquartile range in $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ implies a 0.2 percentage point difference in $\mathbb{E}[\text{MktRet}_{1M}]$ and a 0.4 percentage point difference in $\mathbb{E}[\text{MktRet}_{1Y}]$.[17] The effects on expectations for own returns are even larger: the same interquartile range in $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ implies a 0.4 percentage point difference in $\mathbb{E}[\text{OwnRet}_{1M}]$ and a 1.8 percentage point difference in $\mathbb{E}[\text{OwnRet}_{1Y}]$.

In Table VI, Panel B, we rerun the regression using recalled own returns ($\mathbb{R}[\text{OwnRet}]$) from the *ProbedRecall* block as the

17. The recalled episodes can potentially span up to 10 years. The 25th and 75th percentiles of the recalled episode returns are −19.5% and 15.5%, respectively.

independent variables:

$$\mathbb{E}[\text{Ret}] = \beta_0 + \beta_1 \mathbb{R}[\text{OwnRet}_{1\text{M}}] + \beta_2 \mathbb{R}[\text{OwnRet}_{1\text{Y}}] + X + \epsilon. \tag{10}$$

As before, on the left side, we consider expectations for both market returns and own returns over the next month and year. On the right side, we focus on recalled own returns for the same two horizons, 1M and 1Y, as they align with the forecasting horizons in beliefs. In these regressions, return expectations are strongly positively correlated with recalled own returns. Relative to Panel A, the economic effects are larger: the interquartile range of $\mathbb{R}[\text{OwnRet}_{1\text{M}}]$ corresponds to a difference in return expectations between 0.7 and 1.8 percentage points; the interquartile range of $\mathbb{R}[\text{OwnRet}_{1\text{Y}}]$ implies a difference in return expectations between 0.3 and 5.7 percentage points. Together, Panels A and B indicate that memory influences beliefs not only through the retrieval of market-wide events but also through the recall of personal experiences. Therefore, even for investors who have experienced the same period of market movements, differences in their recalled own returns can lead to significant heterogeneity in beliefs.

2. *Horizon Dependence.* Consistent with the hypothesis in Section II.D, Table VI, Panel B shows that when the recall horizon matches the forecasting horizon, the positive correlation between recalls and beliefs strengthens. For instance, comparing columns (1) and (2), which shift from a one-month-ahead forecast to a one-year-ahead forecast, the coefficient on $\mathbb{R}[\text{OwnRet}_{1\text{M}}]$ decreases in magnitude, while the coefficient on $\mathbb{R}[\text{OwnRet}_{1\text{Y}}]$ increases. Similar changes are observed in columns (3) and (4). Thus, when investors form expectations for a specific horizon, they rely more on recalled experiences from the same horizon. This also implies that a long forecasting horizon is associated with the use of more distant experiences.

One alternative explanation for the horizon dependence result is anchoring due to similarity in wording. For instance, when forecasting returns for the next month, investors might anchor their answers to the recalled past month's return because both the expectation and recall questions contain the word "month." Though this interpretation is feasible in principle, it cannot explain our overall evidence.[18] For example, recall elicita-

18. We defer a systematic examination of this anchoring-based explanation to Section V.E.

tion in *FreeRecall* does not specify a horizon, and hence wording-similarity-induced anchoring is absent in this case. Horizon dependence suggests that recent recalls have a stronger influence on short-term expectations, while distant recalls have a stronger influence on long-term expectations. We can test this by splitting the sample based on the recency of the recalled episode. We rerun the regression specification in equation (9) for two subsamples: investors with recall distances below the median and those with distances above the median. Distances are defined as the differences between the midpoints of the recalled episodes in *FreeRecall* and the month of the survey. The results are reported in Online Appendix A7. Overall, we find evidence consistent with horizon dependence in belief formation: recent recalls influence short-term expectations more, while distant recalls have a greater effect on long-term expectations.

V.B. Horse Race Between Actual and Recalled Experience

Our analysis in Section IV suggests that recalled experience is subjective and fluid, varying over time depending on the cues present in the current context. In contrast, actual experience is objective and static. Both actual and recalled experiences can influence beliefs, but which one has greater explanatory power?

We compare their relative impact on beliefs in our setting. We begin by regressing measures of investor beliefs on both $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ and $\text{MktRet}_{\text{episode}}$ simultaneously, where $\text{MktRet}_{\text{episode}}$ represents the actual market return for the recalled episode in *FreeRecall*. The regression results are reported in Table VII, Panel A. The coefficients on $\text{MktRet}_{\text{episode}}$ are either insignificant or significantly negative, while the coefficients on $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ remain positive and significant. Therefore, in our setting, recalled experiences have a stronger influence on explaining investors' expectations than actual experiences.

Next, we conduct a similar horse race between recalled past own returns in *ProbedRecall* and actual past own returns. In this analysis, we face a trade-off between statistical power and model interpretability. Because investors are asked to recall their past own returns in *ProbedRecall*, an apples-to-apples comparison would involve contrasting these recalled past own returns with actual past own returns. However, actual past own returns are only available for the merged sample. In the main sample, we only observe actual past market returns. To strike a balance,

TABLE VII
HORSE RACE BETWEEN ACTUAL AND RECALLED EXPERIENCE IN EXPLANATORY POWER FOR BELIEFS

	(1)	(2)	(3)	(4)
Panel A: *FreeRecall*, main sample				
	$\mathbb{E}[\text{MktRet}_{1M}]$	$\mathbb{E}[\text{MktRet}_{1Y}]$	$\mathbb{E}[\text{OwnRet}_{1M}]$	$\mathbb{E}[\text{OwnRet}_{1Y}]$
$\text{MktRet}_{\text{episode}}$	−0.001	−0.002	−0.01***	−0.02***
	(0.001)	(0.004)	(0.003)	(0.01)
$\mathbb{R}[\text{MktRet}_{\text{episode}}]$	0.005***	0.02***	0.01***	0.06***
	(0.002)	(0.004)	(0.004)	(0.02)
Observations	4,977	4,977	4,977	4,977
Adjusted R^2	0.01	0.04	0.04	0.07
Panel B: *ProbedRecall*, main sample				
	$\mathbb{E}[\text{MktRet}_{1M}]$		$\mathbb{E}[\text{MktRet}_{1Y}]$	
MktRet_{1M}	0.12*	0.09	0.14**	0.10
	(0.06)	(0.06)	(0.07)	(0.07)
MktRet_{1Y}	−0.05	−0.003	−0.19	−0.16
	(0.17)	(0.17)	(0.15)	(0.15)
$\mathbb{R}[\text{OwnRet}_{1M}]$		0.07***		0.07***
		(0.01)		(0.02)
$\mathbb{R}[\text{OwnRet}_{1Y}]$		0.01***		0.05***
		(0.004)		(0.01)
Observations	6,436	6,436	6,287	6,287
Adjusted R^2	0.02	0.04	0.04	0.06
Panel C: *ProbedRecall*, merged sample				
	$\mathbb{E}[\text{OwnRet}_{1M}]$		$\mathbb{E}[\text{OwnRet}_{1Y}]$	
	(1)	(2)	(3)	(4)
OwnRet_{1M}	0.05*	0.01	0.11	0.05
	(0.03)	(0.03)	(0.07)	(0.07)
OwnRet_{1Y}	0.001	−0.03**	0.05	−0.04
	(0.02)	(0.02)	(0.04)	(0.04)
$\mathbb{R}[\text{OwnRet}_{1M}]$		0.18***		0.26
		(0.06)		(0.18)
$\mathbb{R}[\text{OwnRet}_{1Y}]$		0.11***		0.32***
		(0.03)		(0.09)
Observations	1,088	1,088	1,159	1,159
Adjusted R^2	0.03	0.10	0.03	0.08

Notes. We regress measures of subjective beliefs on recalled and actual experiences simultaneously. The dependent variables are four measures of beliefs: the return expectation ($\mathbb{E}$) for the market return (MktRet) or the investor's own portfolio return (OwnRet) over the next month (1M) or year (1Y). In Panel A, the independent variables are the recalled market return for the episode, $\mathbb{R}[\text{MktRet}_{\text{episode}}]$, and the corresponding actual market return, $\text{MktRet}_{\text{episode}}$. In Panel B, the independent variables are the recalled own returns for the past month or year, $\mathbb{R}[\text{OwnRet}_{1M/1Y}]$, and the actual market returns over the same periods, $\text{MktRet}_{1M/1Y}$. In Panel C, the independent variables are the recalled own returns for the past month or year, $\mathbb{R}[\text{OwnRet}_{1M/1Y}]$, and the actual own returns over the same periods, $\text{OwnRet}_{1M/1Y}$. Panels A and B are based on the main sample, and Panel C is based on the merged sample. We control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, and number of WeChat groups. Standard errors, in parentheses, are clustered by date, and treatment fixed effects are included. * $p < .1$; ** $p < .05$; *** $p < .01$.

we conduct a horse race between recalled own returns and actual market returns in the larger main sample, followed by a more direct comparison between recalled own returns and actual own returns in the smaller merged sample.

Table VII, Panel B focuses on the main sample. In column (1), we begin by regressing the one-month market return expectation, $\mathbb{E}[\text{MktRet}_{1M}]$, on two actual past market returns, MktRet_{1M} and MktRet_{1Y}. Consistent with return extrapolation, the coefficient on MktRet_{1M} is positive and significant. However, in column (2), where the two recalled own returns, $\mathbb{R}[\text{OwnRet}_{1M}]$ and $\mathbb{R}[\text{OwnRet}_{1Y}]$, are included, the coefficient on MktRet_{1M} is no longer significant. In contrast, the coefficients on the two recalled returns are positive and significant. Combined, the results in columns (1) and (2) support Prediction 3, which states that return extrapolation can be explained through a cued recall mechanism. Columns (3) and (4) replicate these regressions using $\mathbb{E}[\text{MktRet}_{1Y}]$ as the dependent variable and display the same patterns.

In Table VII, Panel C, we focus on the merged sample. In column (1), we regress the one-month own return expectation, $\mathbb{E}[\text{OwnRet}_{1M}]$, on two actual past own returns, OwnRet_{1M} and OwnRet_{1Y}. Consistent with the idea that investors extrapolate their own past returns to predict future returns, the coefficient on OwnRet_{1M} is positive and marginally significant. However, in column (2), where we control for recalled own returns, the significance disappears, while the coefficients on the two recalled own returns are positive and significant. In columns (3) and (4), where we examine $\mathbb{E}[\text{OwnRet}_{1Y}]$ as the dependent variable, we observe a similar pattern. Together, the results from Table VII point to a stronger link between investor beliefs and recalled returns than with actual returns, at least in our setting. That said, in other contexts, investors may rely more on historical data and less on memory, potentially weakening the relationship between beliefs and recalls.

V.C. R^2

Another way to evaluate the explanatory power of recalls for beliefs is to quantify the amount of variation in beliefs that can be accounted for by recalls. In Table VIII, we regress the four measures of beliefs on demographic variables and recalls and examine the R^2 values of these regressions. In all columns, we

TABLE VIII

Explanatory Power for Cross-Sectional Variation in Beliefs

	$\mathbb{E}[\text{MktRet}_{1M}]$ (1)	$\mathbb{E}[\text{MktRet}_{1Y}]$ (2)	$\mathbb{E}[\text{OwnRet}_{1M}]$ (3)	$\mathbb{E}[\text{OwnRet}_{1Y}]$ (4)
Demographics fixed effects only	0.009	0.025	0.030	0.044
Expanded demographics fixed effects	0.020	0.043	0.047	0.068
Recalled own return only	0.022	0.025	0.080	0.073

Notes. We regress measures of subjective beliefs on either demographic variables or recalled own returns. Each cell reports the adjusted R^2 from regressing expected returns on either recalled own returns alone or demographic fixed effects alone. The dependent variables are four measures of beliefs: the return expectation ($\mathbb{E}$) for the market (MktRet) or the investor's own portfolio (OwnRet) over the next month (1M) or year (1Y). In the first row, we report the adjusted R^2 from regressing a measure of belief on demographic fixed effects, including gender, age, income, wealth, and education. In the second row, we repeat this exercise, adding four additional measures of investors' social activities: frequency of checking stock accounts, frequency of checking news, frequency of discussing investments, and the number of WeChat groups. In the third row, we report the adjusted R^2 from regressing the measure of belief on the recalled own returns over the past period of the same length. For example, the independent variable is the recalled one-month own return ($\mathbb{R}[\text{OwnRet}_{1M}]$) if the dependent variable is the expectation of future one-month market or own returns ($\mathbb{E}[\text{MktRet}_{1M}]$ or $\mathbb{E}[\text{OwnRet}_{1M}]$).

maintain a constant sample size by retaining only observations with nonmissing values across all specifications, ensuring that the R^2 values are comparable across models. We run three sets of regressions. First, we regress beliefs on basic demographic variables, including gender, age, income, wealth, and education dummies, mirroring the specification used in Giglio et al. (2021). Demographics are a natural benchmark for heterogeneity, as they are widely available and have been linked to belief formation in financial markets.[19] Next, we expand the set of demographics to include measures of social activities. Finally, we regress beliefs on recalls. For each specific type of belief, we regress it solely on the recalled own return in *ProbedRecall*, aligning the recall horizon with the belief's forecasting horizon. For instance, when explaining variation in $\mathbb{E}[\text{MktRet}_{1M}]$, we run a univariate regression of $\mathbb{E}[\text{MktRet}_{1M}]$ on $\mathbb{R}[\text{OwnRet}_{1M}]$.

Table VIII reports the adjusted R^2 values for each regression. Comparisons among the three sets of regressions show that on average, the explanatory power of recalled own returns for

19. Prior studies have focused on traits such as wealth, gender, IQ, birthplace, personality, and location (Armona, Fuster, and Zafar 2019; D'Acunto et al. 2019; Das, Kuhnen, and Nagel 2020; Jiang, Peng, and Yan 2024). Although demographics are more objective and memory measures inherently subjective, we believe the comparison is informative given the substantial prior literature, especially the findings in Giglio et al. (2021).

expectations is comparable to, or even greater than, that of demographic variables. Giglio et al. (2021) pose an open question about which variables drive cross-sectional variation in beliefs. Our evidence suggests that the way experiences are processed, stored, and retrieved offers a promising avenue for microfounding belief heterogeneity.[20]

V.D. *Forecast Errors*

In our analysis so far, we have shown that memory is related to investors' overall return expectations. However, since return expectations consist of both rational and biased components, it is unclear whether memory specifically relates to biases in beliefs. To address this question, we examine the relationship between memory and forecast errors, calculated as the difference between an investor's expected market return and the realized future market return over the same period. In Online Appendix A8, we report the results from regressing forecast errors on recalls and find a significantly positive relationship between the two. This suggests that investor memory not only drives return expectations but also contributes to forecast errors at the individual level.

V.E. *Alternative Explanations*

Section V.A showed a strong and robust statistical relationship between recalls and beliefs. Now we discuss a series of alternative explanations for this relationship and argue that the most likely mechanism underlying the documented relationship is simulation—retrieving past experiences to make forecasts about the future.

1. *Anchoring.* In the main survey, the elicitation of recalls precedes the elicitation of beliefs. This raises concerns about a potential anchoring effect: if investors anchor their responses to the belief questions based on their earlier answers to the recall questions, it might create a mechanical positive correlation between recalls and beliefs that is unrelated to the process of simulation. To address this concern, we identify and discuss three types of anchoring that could potentially emerge in our setting.

20. Giglio et al. (2021) include experience as an explanatory variable. However, as we have shown, it is not only the experience itself that matters, but the way it is processed and subsequently recalled that plays a more significant role.

The first type is naive anchoring on numbers. After typing in a number to answer a previous question, that same number may linger in one's mind. When answering a subsequent question, people might instinctively rely on that number as a starting point to formulate their response. Although they may make adjustments, these adjustments are often insufficient, creating a positive serial correlation across answers. If naive anchoring on numbers is responsible for the documented correlations between recalls and beliefs, we would expect to see such relationships persist throughout the survey. For example, $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ is designed to vary drastically across the three treatments in *FreeRecall*, as confirmed in Table II. If naive anchoring on numbers were at play, we would expect significant differences in answers to the immediate next *ProbedRecall* block across the three treatments. Table IX, Panel A compares $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ and $\mathbb{R}[\text{OwnRet}]$ across the three treatments. Column (1) confirms that across the treatments, the mean values of $\mathbb{R}[\text{MktRet}_{\text{episode}}]$ increase monotonically from treatment *Painful*, to treatment *Neutral*, and finally to treatment *Happy*, with values of -18.1%, 5.6%, and 23.4%, respectively. However, columns (2)–(5) show that the average $\mathbb{R}[\text{OwnRet}]$ over various horizons does not follow the same monotonic pattern across the three treatments. Therefore, it does not appear that investors are mechanically anchored to numbers from their previous answers.

The second type of anchoring arises from similarity in wording. For instance, if two questions are phrased similarly—such as one about past-month returns and another about expected future-month returns—respondents might anchor on their earlier answers. In the *ProbedRecall* questions, we asked about portfolio returns over the past month and year, while the crash probability questions referred to the likelihood of a crash over the next month or year. If anchoring on wording were present, we would expect no correlation (due to different wording) or a positive correlation (due to matching time horizons). By contrast, Prediction 4 implies a negative relationship: higher recalled returns should lead to lower perceived crash probabilities via simulation. To test these hypotheses, we estimate:

$$\begin{aligned}\mathbb{E}[\text{CrashProb}] = \beta_0 + \beta_1\mathbb{R}[\text{OwnRet}_{1\text{M}}] + \beta_2\mathbb{R}[\text{OwnRet}_{1\text{Y}}]\\ +X + \epsilon.\end{aligned} \tag{11}$$

TABLE IX

TESTS FOR ANCHORING IN SIMULATION

	(1)	(2)	(3)	(4)	(5)
Panel A: Testing naive anchoring on numbers					
	$\mathbb{R}[\text{MktRet}_{\text{episode}}]$	$\mathbb{R}[\text{OwnRet}_{1D}]$	$\mathbb{R}[\text{OwnRet}_{1M}]$	$\mathbb{R}[\text{OwnRet}_{1Y}]$	$\mathbb{R}[\text{OwnRet}_{5Y}]$
Neutral	5.6%	−0.3%	−0.1%	2.1%	4.9%
Happy	23.4%	−0.2%	−0.4%	1.8%	5.1%
Painful	−18.1%	−0.5%	−0.1%	1.6%	2.8%
Panel B: Testing anchoring due to similarity in question phrasing					
	$\mathbb{R}[\text{CrashProb}_{1M}]$		$\mathbb{R}[\text{CrashProb}_{1Y}]$		
$\mathbb{R}[\text{OwnRet}_{1M}]$	−0.11***	−0.08***		−0.05***	
	(0.02)	(0.02)		(0.01)	
$\mathbb{R}[\text{OwnRet}_{1Y}]$		−0.03***	−0.03***	−0.02***	
		(0.01)	(0.01)	(0.01)	
Observations	7,853	7,853	7,832	7,832	
Adjusted R^2	0.02	0.02	0.03	0.03	
Panel C: Testing anchoring due to similarity in answer options					
	$\mathbb{E}[\text{MktRet}_{1M}]$	$\mathbb{E}[\text{MktRet}_{1Y}]$	$\mathbb{E}[\text{OwnRet}_{1M}]$	$\mathbb{E}[\text{OwnRet}_{1Y}]$	
$\mathbb{R}[\text{OwnRet}_{\text{episode}}]$	0.004***	0.01***	0.01***	0.04***	
	(0.001)	(0.002)	(0.002)	(0.01)	
Observations	5,518	5,518	5,518	5,518	
Adjusted R^2	0.01	0.04	0.04	0.06	

Notes. Each panel tests a different type of anchoring: naive anchoring on numbers, anchoring due to similarity in question phrasing, and anchoring due to similarity in answer options. Panel A tests for naive anchoring on numbers by reporting the mean values of recalled market returns for the episode, $\mathbb{R}[\text{MktRet}_{\text{episode}}]$, and recalled own returns from the past, $\mathbb{R}[\text{OwnRet}_{1D/1M/1Y/5Y}]$, across three treatments: *Neutral*, *Happy*, and *Painful*. In Panel B, we test for anchoring due to similarity in question phrasing by regressing expected crash probability on recalled own returns from the past month or year. During the sample period, the Shanghai Composite Index mostly hovered between 3,500 and 3,600. We consider two potential crash events: the index dropping below 3,000 within a month and the index dropping below 2,500 within a year. Investors are asked to report a percentage between 0% and 100% as their subjective probability of a crash, $\mathbb{E}[\text{CrashProb}_{1M/1Y}]$. In Panel C, we regress measures of subjective beliefs on recalled episode own returns. The dependent variables are four measures of beliefs: the return expectation ($\mathbb{E}$) for the market return (MktRet) or the investor's own portfolio return (OwnRet) over the next month (1M) or year (1Y). The main independent variable is the recalled own return for the episode, $\mathbb{R}[\text{OwnRet}_{\text{episode}}]$. This is elicited by first asking about the total RMB investment and then the total RMB return; the ratio of the RMB return to the investment is the return rate. In Panels B and C, we control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, and number of WeChat groups. Standard errors, in parentheses, are clustered by date, and we include treatment fixed effects. $^{*}\ p < .1$; $^{**}p < .05$; $^{***}\ p < .01$.

As shown in Table IX, Panel B, both coefficients are significantly negative across specifications, supporting the simulation mechanism and ruling out mechanical anchoring on similar wording.

The third type of anchoring stems from similarity in answer formats. Even if questions differ in wording, responses might correlate mechanically if they share units (e.g., percentages). To address this, we examine Table VI, Panel A, where beliefs are related to recalled episode returns. In the *FreeRecall* block, instead of directly eliciting percentage returns, we ask for RMB profit and investment amounts, then compute $\mathbb{R}[\text{OwnRet}_{\text{episode}}]$ as their ratio. In Table IX, Panel C, we find that beliefs remain significantly positively associated with $\mathbb{R}[\text{OwnRet}_{\text{episode}}]$, suggesting that these correlations are not driven by similar answer options.[21]

2. *Priming.* A second concern is priming, which is related to but distinct from anchoring. Suppose that causality runs from memory to beliefs, with investors routinely drawing on memory when forming expectations. Under this causal direction, our survey design may amplify the role of memory: by eliciting expectations immediately after recall, it makes memory especially salient, potentially overstating its influence on beliefs. We fully acknowledge this concern and provide additional evidence below and in Section V.F to help address and partly alleviate it. However, if beliefs also influence memory, then our subsequent test—where beliefs are elicited before recalls—could make expectations salient and induce recall consistent with those expectations. In that case, the priming test described below would not mitigate such concerns.

Specifically, we conduct an additional survey, called *RandomOrder*, in which we vary the order of survey blocks. Details about the survey's implementation can be found in Online Appendix A10.[22] This survey is similarly structured to the main survey and includes three main blocks: *FreeRecall*, *ProbedRecall*, and *Expectation*. For simplicity, we only consider the *Neutral* treatment for *FreeRecall*. Maintaining the requirement that *FreeRecall* must precede *ProbedRecall*, we consider three orderings:

(i) In the *Baseline* treatment, the order is the same as in the main survey: *FreeRecall—ProbedRecall—Expectation*.

21. See Online Appendix A9 for additional anchoring robustness checks.

22. The survey has passed the IRB and AEA RCT pre-registration. IRB no. CUHKSZ-D-20240003; RCT ID: AEARCTR-0013186.

(ii) In the *Reverse* treatment, we elicit beliefs before eliciting recalls: *Expectation—FreeRecall—ProbedRecall*.
(iii) In the *Switch* treatment, we switch the order between *Expectation* and *ProbedRecall*: *FreeRecall—Expectation—ProbedRecall*.

Each respondent is randomly assigned to one of the three treatments with equal probabilities. We start with a target sample size of 1,500 in total, with 500 for each treatment. After applying quality assurance criteria and excluding observations with missing values, the final sample consists of 1,202 investors.

Using *RandomOrder*, we revisit Table VI, Panel B, which showed strong correlations between recalled own returns and beliefs. If this positive correlation results from investors being primed by recall elicitation, we would expect the correlation to weaken or disappear when expectations are elicited before recalls, as in the *Reverse* and *Switch* treatments. To test this hypothesis, we run the following regression for each treatment:

$$\mathbb{E}[\text{MktRet}_{1\text{M}}] = \beta_0 + \beta_1 \mathbb{R}[\text{OwnRet}_{1\text{M}}] + X + \epsilon. \tag{12}$$

Table X, Panel A reports the regression results. In all three treatments, the coefficients on $\mathbb{R}[\text{OwnRet}_{1\text{M}}]$ are positive and statistically significant. Therefore, changing the order of survey blocks does not eliminate the positive correlation between recalls and beliefs.

In Table X, Panel B, we formally test whether the correlation between recalls and beliefs varies with the order of survey blocks. We do this by including two treatment dummies and their interactions with $\mathbb{R}[\text{OwnRet}_{1\text{M}}]$ in the same regression. In column (1), which examines the correlation between $\mathbb{E}[\text{MktRet}_{1\text{M}}]$ and $\mathbb{R}[\text{OwnRet}_{1\text{M}}]$, the two interaction terms are close to zero in magnitude and statistically insignificant. In columns (2) and (3), we consider two other measures of beliefs: $\mathbb{E}[\text{OwnRet}_{1\text{M}}]$ and $\mathbb{E}[\text{CrashProb}_{1\text{M}}]$. The interaction terms are generally close to zero and insignificant; the only significant term is positive, suggesting an even stronger relationship between recalls and beliefs. Overall, even when beliefs are elicited before recalls, the positive correlation between recalls and beliefs remains unchanged, suggesting that the priming effect cannot fully explain our findings. However, we recognize that the survey may place undue emphasis on certain types of memories, such as recalled own returns, which could inflate their impact on belief formation. As a result, we consider

TABLE X

Testing Order Effects in Simulation

	(1)	(2)	(3)
Panel A: Regressing beliefs on recalls by treatment			
		$\mathbb{E}[\text{MktRet}_{1M}]$	
	Baseline	*Reverse*	*Switch*
$\mathbb{R}[\text{OwnRet}_{1M}]$	0.13***	0.16***	0.10**
	(0.03)	(0.03)	(0.04)
Observations	395	429	378
Adjusted R^2	0.04	0.05	0.01
Panel B: Statistical tests of order effects			
	$\mathbb{E}[\text{MktRet}_{1M}]$	$\mathbb{E}[\text{OwnRet}_{1M}]$	$\mathbb{E}[\text{CrashProb}_{1M}]$
$\mathbb{R}[\text{OwnRet}_{1M}]$	0.15***	0.24***	−0.45***
	(0.03)	(0.06)	(0.17)
Reverse	−0.001	−0.42**	−0.71
	(0.33)	(0.21)	(1.03)
Switch	−0.22	−0.60**	1.15
	(0.31)	(0.24)	(1.00)
$\mathbb{R}[\text{OwnRet}_{1M}]$ × *Reverse*	0.02	0.22***	−0.11
	(0.02)	(0.07)	(0.17)
$\mathbb{R}[\text{OwnRet}_{1M}]$ × *Switch*	−0.06	0.09	0.35
	(0.06)	(0.13)	(0.40)
Observations	1,202	1,202	1,202
Adjusted R^2	0.04	0.12	0.01

Notes. To examine the effect of question ordering on the statistical relationship between recalls and beliefs, we conducted a new survey that varies the order of survey blocks. The first treatment, *Baseline*, follows the same order as our baseline survey: *FreeRecall*, *ProbedRecall*, and *Expectation*. The second treatment, *Reverse*, reverses the order: *Expectation*, *FreeRecall*, and *ProbedRecall*. The third treatment, *Switch*, swaps the order between probed recall and beliefs: *FreeRecall*, *Expectation*, and *ProbedRecall*. Each respondent was randomly assigned to one of the three treatments. In Panel A, we regress the expected market return for the next month ($\mathbb{E}[\text{MktRet}_{1M}]$) on the recalled one-month own return ($\mathbb{R}[\text{OwnRet}_{1M}]$) separately for the three treatments. In Panel B, we pool all treatments together and regress expected future returns or crash probability on recalled one-month own returns, along with two dummies indicating the *Reverse* and *Switch* treatments, and interaction terms between the recalled one-month own return and the two dummies. We control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, and the number of WeChat groups. Standard errors, in parentheses, are clustered by date. * $p < .1$; ** $p < .05$; *** $p < .01$.

our estimates to be an upper bound for the effect of recalled own returns on beliefs. This does not necessarily imply that memories play a lesser role in belief formation in real-world settings. Instead, it highlights the importance of other types of memories that may be more influential in field contexts.

3. *Cognitive Defaults.* Another potential explanation for the positive correlation between recalls and beliefs is the use of

cognitive defaults (Enke and Graeber 2023). This mechanism is plausible given that both recall and forecasting are cognitively demanding tasks. For instance, an investor with a fixed belief—say, that stock returns average 1% per month—might report this figure for both questions to minimize effort, thereby inducing a positive correlation. However, as shown in Table II, recalled and actual experiences are highly correlated, suggesting that investors were not responding randomly but instead engaged meaningfully with the recall task. To provide additional evidence against cognitive defaults as the driver of our results, we repeat the analysis in Table VI, Panel B for a subsample of investors whose recalled episode returns are accurate, suggesting they did not rely on cognitive defaults. Specifically, we focus on investors whose recalled episode returns and actual episode returns differ by no more than 10%, indicating clear effort in the survey. The results are reported in Online Appendix A11. In this subsample, we find similar correlations between recalled episode returns and beliefs, suggesting that these correlations are unlikely to be driven by cognitive defaults.

4. *Motivated Reasoning.* Although it is psychologically plausible to expect the direction of causality to flow from memory to expectations, it is also possible that causality operates in the opposite direction—through motivated reasoning. For instance, suppose that expectations are not directly influenced by memory but are instead shaped by some omitted variables. Optimistic investors might then justify their optimism by selectively recalling more positive experiences. Because we do not exogenously vary either expectations or recall, we cannot definitively differentiate between these two possibilities. However, we can analyze one specific version of the motivated-reasoning hypothesis by examining the relationship between past actions and future recall. According to this version, after an investor increases her stock holdings, she might justify her decision by recalling more positive past experiences. To test this possibility, in Online Appendix A12 we regress recalled own returns on recent holding changes, and none of the coefficients are significantly positive. Therefore, we find little evidence that past actions drive recall.

5. *Taste for Consistency.* Sequencing recall and belief questions in the same survey may inflate their correlation if respondents perceive the two to be related and feel some pressure to

answer consistently (Falk and Zimmermann 2013). We acknowledge this is a valid concern, and it is possible that eliciting recall and belief in separate surveys could attenuate the correlation by weakening such perceived links.[23] However, for consistency bias to fully explain our findings, it must overcome two challenges. First, the notion of "consistency" between recalled past returns and expected future returns is inherently ambiguous in financial contexts. Some investors may view high past returns as signaling lower future returns (e.g., due to mean reversion), while others may expect continuation (e.g., due to momentum). As a result, both positive and negative correlations between recall and belief can be construed as consistent, depending on the investor's model of the market. This interpretive flexibility limits the explanatory power of the consistency bias argument in our setting. Second, even well-established financial principles—such as the positive risk–return trade-off—are frequently violated in survey data. As in prior studies (Giglio et al. 2021), we find that many investors simultaneously expect high returns and low risk.[24] If respondents do not feel compelled to align beliefs on this basic and widely taught dimension, it seems unlikely that they would feel bound to align recall and belief—particularly when no clear standard for such consistency exists.

V.F. Relevance to the Field

1. *Discussion of Limitations.* We document a strong and robust relationship between recalled returns and return expectations. Although this evidence is highly consistent with a memory-based channel of belief formation, it does not establish causality from memory to beliefs. A further concern, as noted, is that the survey design may overemphasize the role of memory by instructing participants to recall past returns without consulting external sources. While this restriction is necessary to elicit genuine recalls, it may amplify the apparent influence of memory on belief

23. A potentially fruitful direction for future research is to compare two distinct designs: one in which recall and belief are elicited sequentially in the same survey, and another in which they are elicited separately. The latter setup may yield a different correlation—possibly weaker, either due to reduced consistency bias or because the recall question becomes less salient when decoupled from the belief context—and it would be interesting to quantify these effects.

24. In our survey, the correlation between investors' expected market return and expected crash probability is −0.11 at the 30-day horizon and −0.15 at the one-year horizon. Both correlations are statistically significant at the 1% level.

formation, particularly in a survey setting. In real-world environments, two factors may attenuate the link between memory and beliefs. First, investors can supplement memory with external information, such as historical return data or market commentary. For example, an investor aware of their imperfect memory might check their phone to retrieve past market or portfolio performance. If investors can partially correct for their own memory biases, this would weaken the relationship between memory and beliefs. Second, other belief-formation mechanisms—including model-based inference, extrapolation from observed data, and attention-based filtering—also shape expectations. Institutional investors, for instance, often rely on dedicated research teams that employ forecasting models to generate return projections. When such competing mechanisms are at play, the influence of memory on beliefs may be further reduced. For these reasons, we view our estimates as an upper bound on the effect of recalled personal returns on beliefs. We also conjecture that memory-based mechanisms are particularly relevant for beliefs about the aggregate market, where broad impressions or salient past events may guide expectations. In contrast, for individual stocks or mutual funds—where performance histories are harder to recall and easier to access—investors are more likely to consult external data.

Even when historical data are readily accessible and alternative models are available, memory may continue to influence decision making meaningfully in many circumstances. Investors may not always consult external sources when forming beliefs, especially in situations where time is limited, attention is divided, or decisions are made out of habit. In practice, memory may be a convenient shortcut, particularly for retail investors making quick or repeated portfolio choices. Moreover, memory-based inputs into beliefs need not be limited to numerical returns. Investors may recall episodes of vivid news stories or personal experiences—elements that can shape beliefs in ways not easily captured by return data alone. Although we do not claim that memory dominates all other belief-formation mechanisms, our results suggest that it plays a consistent and detectable role, even when other inputs may also be available.

2. *Trading Behavior.* We analyze the extent to which beliefs and recalls are reflected in trading behavior. To begin, in the merged sample, we regress measures of trading activity observed in the transaction data on return expectations elicited in

TABLE XI

Beliefs, Recalls, and Trading Decisions

	(1)	(2)	(3)
Panel A: Dependent variable NetBuy_{1D}			
$\mathbb{E}[\text{OwnRet}_{1M}]$	26.15*		
	(14.94)		
$\mathbb{E}[\text{MktRet}_{1M}]$	−18.72		
	(22.95)		
$\widetilde{\mathbb{E}}[\text{OwnRet}_{1M}]$		71.16***	79.67**
		(24.49)	(37.52)
OwnRet_{1M}			13.58
			(9.58)
Observations	1,869	1,783	1,088
Adjusted R^2	0.01	0.01	0.00
Panel B: Dependent variable NetBuy_{1M}			
$\mathbb{E}[\text{OwnRet}_{1M}]$	295.52***		
	(146.90)		
$\mathbb{E}[\text{MktRet}_{1M}]$	219.51		
	(368.17)		
$\widetilde{\mathbb{E}}[\text{OwnRet}_{1M}]$		1,141.48***	1,347.80**
		(434.28)	(590.62)
OwnRet_{1M}			243.93
			(158.27)
Observations	1,869	1,783	1,088
Adjusted R^2	−0.01	0.00	−0.01

Notes. We regress measures of future trading behavior on return expectations and actual experiences. The dependent variables are $\text{NetBuy}_{1D/1M}$, the net buy amount (buy minus sell) on the day of the survey or in the month after the survey. The independent variables are $\mathbb{E}[\text{OwnRet}_{1M}]$ and $\mathbb{E}[\text{MktRet}_{1M}]$, return expectations of own portfolios or the market over the next month; $\widetilde{\mathbb{E}}[\text{OwnRet}_{1M}]$, return expectation of own portfolio return in the next month that can be explained by recalled own returns; and OwnRet_{1M}, actual own return over the past month. The test is based on the merged sample. We control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, and number of WeChat groups. Standard errors, in parentheses, are clustered by date. * $p < .1$; ** $p < .05$; *** $p < .01$.

the survey. For trading activity, we consider NetBuy, calculated as the total buy amount minus the total sell amount in Chinese yuan, on the survey day or during the month following the survey. For return expectations, we use the two return expectations over the next month, $\mathbb{E}[\text{OwnRet}_{1M}]$ and $\mathbb{E}[\text{MktRet}_{1M}]$. We run the following cross-sectional regression of net buy amount on the two return expectations, controlling for a variety of individual characteristics:

$$\text{NetBuy} = \beta_0 + \beta_1\mathbb{E}[\text{OwnRet}_{1M}] + \beta_2\mathbb{E}[\text{MktRet}_{1M}] + X + \epsilon. \tag{13}$$

The results are reported in Table XI, column (1). In both specifications, the coefficients on $\mathbb{E}[\text{OwnRet}_{1M}]$ are significantly positive, suggesting that investors who believe in higher own returns tend to increase their holdings both on the survey day and in the subsequent month. A 1 percentage point increase in the one-month own return expectation is associated with an increase of 26 RMB in buying on the survey day and 296 RMB in buying during the next month. Interestingly, the coefficients on $\mathbb{E}[\mathrm{MktRet}_{1\mathrm{M}}]$ are not statistically significant. This comparison suggests that expectations of one's own portfolio returns may have a larger effect on investors' portfolio decisions.[25]

Next we show that memory correlates with trading behavior through beliefs. We first decompose $\mathbb{E}[\mathrm{OwnRet}_{1\mathrm{M}}]$, which is shown to be related to trading, into two components: one driven by memory and one that is not. Specifically, we first regress $\mathbb{E}[\mathrm{OwnRet}_{1\mathrm{M}}]$ on $\mathbb{R}[\mathrm{OwnRet}_{1\mathrm{M}}]$ and $\mathbb{R}[\mathrm{OwnRet}_{1\mathrm{Y}}]$ from *ProbedRecall*, while controlling for the same list of individual characteristics as before; the fitted values are then denoted as $\widetilde{\mathbb{E}}[\mathrm{OwnRet}_{1\mathrm{M}}]$.[26]

We rerun the same cross-sectional regression of net buy amount on $\widetilde{\mathbb{E}}[\mathrm{OwnRet}_{1\mathrm{M}}]$:

$$\mathrm{NetBuy} = \beta_0 + \beta_1 \widetilde{\mathbb{E}}[\mathrm{OwnRet}_{1\mathrm{M}}] + X + \epsilon. \tag{14}$$

The results are reported in column (2). Memory-induced return expectations are positively correlated with trading behavior: a 1 percentage point increase in the one-month memory-induced return expectation is associated with an increase of 71 RMB in buying on the survey day and 1,141 RMB in buying in the subsequent month. These coefficients are much larger in magnitude than before. One possibility is that memory-driven return expectations are more relevant for decision making. Alternatively, it could be that the elicited return expectations contain noise, creating an attenuation bias.

25. Giglio et al. (2021) also examine the link between beliefs and portfolio choices by regressing the equity share on return expectations. However, our transaction data include detailed records of exchange-traded products but do not contain information on cash balances, preventing us from measuring overall equity share. As such, the two exercises are not directly comparable. It is important to recognize that these regression results above do not imply causality. For instance, it could be a case of reverse causality, where planned trades influence reported beliefs, or the result of an omitted variable that jointly affects both trading decisions and return expectations.

26. We include only $\mathbb{R}[\mathrm{OwnRet}_{1\mathrm{M}}]$ and $\mathbb{R}[\mathrm{OwnRet}_{1\mathrm{Y}}]$ as these are the two horizons most frequently used for trading. Other specifications, such as including all four types of recalled own returns in *ProbedRecall*, produce essentially the same results.

Last, in column (3) we further control for actual experience and find that the results are essentially unchanged. This further suggests that it is the recalled experiences, rather than the objective experiences, that affect portfolio decisions through the expectations channel.

VI. Conclusion

There is growing interest in the role of memory in shaping beliefs and choices. Much of the existing discussion has focused on laboratory evidence and the development of memory-based theories of decision making. This article contributes new field evidence to support these theories. Surveying a large, representative sample of retail investors, we elicit their memories of stock market investments and return expectations. By merging these survey responses with administrative transaction records, we validate the memories, examine their properties, and provide new insights into how investor memory shapes belief formation.

Our analysis delivers several key messages. First, memory is not a simple record of past experiences. It oversamples recent and salient events and is shaped by the current environment. This challenges belief-formation models based solely on time-weighted averages of past experiences, where recent experiences receive greater weight (Malmendier and Nagel 2011, 2016). Future models should incorporate salience by assigning more weight to particularly vivid or extreme experiences. Our findings on cued recall further highlight the importance of environmental cues in shaping expectations. Though we focus on returns as a key cue, more comprehensive models must allow for interacting cues with changing significance over time. For example, Taubinsky et al. (2024) show how affect influences recall in the context of inflation expectations, pointing to the need for richer dynamic frameworks.

Second, memory plays a central role in shaping beliefs. Our evidence is consistent with the investors in our study forming expectations by sampling from a subjective distribution of past returns and projecting these samples onto future outcomes. While this process reflects a psychologically realistic mechanism for retail investors, more sophisticated investors may use memory differently—for instance, by recalling past return dynamics or regime shifts. Exploring such uses of memory is a promising direction for future research.

Third, memory-driven expectations meaningfully influence trading decisions. Although our analysis focuses on investment behavior, the broader economic implications of memory are substantial. Recent work has begun to explore how memory affects decisions in other domains, such as consumption. Further investigating these dynamics offers the potential to enrich our understanding of decision making across a wide range of economic contexts.

Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

The data underlying this article are available in the Harvard Dataverse, https://doi.org/10.7910/DVN/MGIDH7 (Jiang et al. 2025).

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