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Investor Memory and Biased Beliefs: Evidence from the Field[*]

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Abstract

We survey a large representative sample of retail investors in China to elicit their memories of stock market investment and return expectations. We merge the survey data with administrative data of transactions to test a model in which investors selectively recall past experiences similar to the present cue to form beliefs. Our analysis uncovers new facts about investor memory and supports similarity-based recall as a key mechanism of belief formation in financial markets. When the market is going up, it cues investors to retrieve episodes of rising markets and recall their past performance more positively. Recalled experiences explain a sizable fraction of cross-investor variation in beliefs and dominate actual experiences in explanatory power. Recalled experiences also drive out the explanatory power of recent returns for expected future returns, ruling in a memory-based foundation for return extrapolation.

JEL codes: D83, D91, C91, G41.

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1 Introduction

Beliefs are key to economic decisions. Traditional models typically assume full information rational expectations (FIRE) whereby the agent uses all relevant information to form expectations, but recent evidence has challenged FIRE by documenting a variety of biases in belief-formation.[1] The underlying mechanisms driving such deviations are less well understood: some explanations are based on psychological biases while others resort to information frictions and bounded rationality.[2] A recent theoretical literature proposes that memory can help reconcile many puzzles on beliefs and choices (Mullainathan, 2002; Gennaioli and Shleifer, 2010; Malmendier et al., 2020; Bordalo et al., 2021, 2022b; Wachter and Kahana, 2021). These models highlight two key principles driving the process of belief formation. First, memory is limited and selective: not all memories get retrieved in any given point. Second, because memory is associative, retrieval is often cued by environmental stimuli such as context, emotion, and narratives. In parallel with these theoretical developments, recent papers examine memory mechanisms in the lab or through surveys (Zimmermann, 2020; Colonnelli et al., 2021; Gödker et al., 2021; Andre et al., 2022; Enke et al., 2022; Graeber et al., 2022). However, there has been little evidence yet from the field on the structure of memory and its connection to belief formation.[3]

In this paper, we study how memory shapes investor beliefs in financial markets. We survey a nationally representative sample of over 17,000 Chinese retail investors and, for a subsample of investors, we merge their survey responses with detailed trading records. Compared to the settings of existing surveys and experiments, ours is closer to everyday decision-making in several important dimensions. First, the sample we study consists of real investors actively trading in a large market. Some of these investors are high-net-worth and typically hard to survey. Second, the decision domain we examine is high-stake: for many of the Chinese retail investors we survey, stock investment constitutes a significant fraction of their total financial wealth. Third,

[1]Examples include underreaction to news at the consensus level (Coibion and Gorodnichenko, 2015), overreaction to news at the individual level (Bordalo et al., 2020), extrapolative beliefs (Greenwood and Shleifer, 2014), and overconfidence (Glaser and Weber, 2007; Liu et al., 2022).

[2]See, for example, Barberis (2018) for a recent review on the possible microfoundations of extrapolation.

[3]For example, when reviewing the evidence on the experience effect, Malmendier and Wachter (2021) state that "at this point, 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."

when studying the cued nature of memory, instead of using cues designed by experimenters, we rely on cues that occur naturally in financial markets to test their impact on recall and beliefs. Fourth, by combining the survey data with detailed transactions data, we can compare recalled experiences from the survey and actual experiences revealed by the transaction data.

To structure our empirical analysis, we start with a memory-based model of belief formation based on Bordalo et al. (2022a). We assume an investor has accumulated a database of investment experiences, and she forecasts future returns in two steps. In the first step, called *recall*, she retrieves cued past experiences according to the rule of similarity: experiences similar to the present cue are more likely to be recalled. While different environmental stimuli can act as cues in different settings, perhaps the most ubiquitous stimulus in financial markets is return: price fluctuations in the stock market and balance changes in one's brokerage account can easily draw an investor's attention. In line with memory research (Kahana, 2012), similarity-based recall then leads to the model's first two predictions. First, seeing positive recent returns triggers the investor to recall past experiences that are also associated with positive returns. Second, such cued recall is stronger when retrieved experiences are more recent. In the second step, called *simulation*, the investor uses retrieved experiences to simulate a distribution of future returns as her forecasts. Combined with cued recall, simulation leads to the model's third prediction, namely return extrapolation: high recent returns make an investor more optimistic about future returns. Therefore, beliefs are based on the selective retrieval of cued past experiences, which may be different from all of the past experiences.

In the baseline survey, we design two theory-driven blocks of questions to elicit investor memory. The first block, *FreeRecall*, asks investors to (1) recall a market episode that first comes to mind and (2) then recall the market return during that episode. As the name suggests, this block mirrors in design the well-established experimental paradigm of free recall to capture the market episode that an investor immediately thinks of when looking back at past trading experiences (e.g., Murdock, 1962; Kahana, 2012).[4] Given the nature of *FreeRecall*, respondents always start with this block to reduce potential confounding effects induced by the survey's other blocks. The second block, *ProbedRecall*, asks investors to recall their own return in the stock market over

[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).

a given horizon (from "yesterday" to "past 5 years"). The survey also collects information on expectations about the market return and one's own portfolio return, perceived crash probabilities, the Big Five personality traits, measures of social activities, and demographics. For more than a quarter of our *main* sample, survey responses can be merged with administrative data of comprehensive transaction records from one of the largest financial institutions; these investors make up the *merged* sample.

With these data in hand, we first confirm that respondents were indeed making a conscious effort when completing the recall tasks. Specifically, we show that recalled experiences, on average, are consistent with actual experiences observed in the market data and transaction data. For example, in *FreeRecall* where investors are asked to recall returns for episodes that first come to mind, the correlation between the *recalled* episode return and the *actual* episode return is 0.53. We observe a similar positive correlation in *ProbedRecall* for recalled own return and actual own return. By and large, survey-elicited experiences are consistent 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 market bubbles and crashes. This non-monotonicity in recall suggests that, to realistically capture investors' memory structure, it is insufficient to treat the impact of past experiences as decaying over time. Instead, features of the experiences themselves such as contexts and salience also play an important role in investor recall (e.g., Bordalo et al., 2022b; Wachter and Kahana, 2021).

After documenting basic facts about investor memory, we test the first part of our model, *recall*, by relating recalled experiences to recent market returns. We conduct the survey in three waves spanning six weeks to examine how market returns on the survey day affect the retrieved memories elicited by the survey. Consistent with cued recall, when the stock market goes up on the survey day, investors tend to retrieve an episode featuring a more bullish market. Similarly, they tend to recall their past performance more positively. These results are particularly strong when the recalled experiences are more recent. Taken together, they support the model's first two predictions on cued recall and recency effects. Therefore, memory is not a static representation of past experiences. Instead, it is much more fluid: it is driven by the available cues in the current environment and varies over time as the context changes.

We proceed to test the second part of the model, *simulation*, by examining the relationship between retrieved memories and beliefs. For both recall tasks in our survey, retrieved memories are highly correlated with expectations, even after controlling for an exhaustive list of demographic variables and other investor characteristics. This is consistent with the idea of simulation, whereby investors rely on retrieved memories to make forecasts about the future.

We then derive additional properties about the simulation process. First, simulation exhibits horizon-dependence, in that there is a mapping between the forecasting horizon and the recall horizon. For instance, when the forecasting horizon goes from next month to next year, investors' return expectations load less on past month's experiences and more on past year's experiences. Second, in a horse race between *actual* experiences and *recalled* experiences in their explanatory power for beliefs, recalled experiences dominate. This suggests that the internal, subjective representation of experiences—processed through selective and cued recall—plays a bigger role than objective experiences in belief formation. Third, a single variable based on recalled own return has similar explanatory power, measured by R-squared, than that of an exhaustive list of individual characteristics combined. Fourth, we further link retrieved memories with forecast errors, and we find a similar relationship. This suggests that investor memory drives not only return expectations themselves, but also biases in beliefs. Using additional treatments and further analyses, we examine other explanations such as anchoring, click-through behavior, and motivated reasoning. We also confirm the validity of the beliefs collected in the survey by showing that more optimistic investors increase their equity holdings shortly after the survey.

Lastly, we relate similarity-based recall to return extrapolation—the tendency that expectations about future returns positively load on past returns. In our data, consistent with extrapolation, higher past returns are associated with more optimistic beliefs about the market and one's own returns going forward. This relationship significantly weakens, however, after we control for recalled own returns. This contrast rules in a memory-based microfoundation for return extrapolation behavior.

Like Malmendier and Nagel (2011, 2016) and Malmendier et al. (2020), memory in our data exhibits a strong recency effect. However, recall is not merely a function of time; it is also determined by features of the experiences themselves. In particular, salient events such as sharp run-ups and crashes are more likely to be recalled, consistent with the prediction from Wachter and Kahana (2021). In addition, recall is not static—it is influenced by the environment one is currently in, as confirmed by our analysis on cued recall. Therefore, to the extent that experience affects decisions through memory, models incorporating 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 recent works by Wachter and Kahana (2021) and Bordalo et al. (2022b,a).

The strong and robust relationship between recall and expectations suggests that investors rely on their memories to imagine the future, consistent with the simulation process of belief formation (Bordalo et al., 2022a). Rather strikingly, the mental representation of past experiences in memory, shaped by selective and cued recall, has more explanatory power for beliefs than one's actual experiences. We also speak to the literature of investor heterogeneity by showing that memory can substantially increase the explanatory power of individual characteristics for cross-sectional variation in beliefs (Jiang et al., 2020; Giglio et al., 2021).

Lastly, our paper is related to a growing literature combining survey data with observational data (Giglio et al., 2021; Liu et al., 2022). Previous papers have used surveys to collect investors' expectations and trading motives. We, however, collect investors' recalls and expectations and merge the survey with data on their actual trading behaviors.

The rest of the paper is organized as follows. Section 2 presents a simple model as our conceptual framework. Section 3 explains the survey design and other data sources. Section 4 documents stylized facts about investor memory. Sections 5 and 6 test the two parts of the model, recall and simulation. Section 7 presents evidence on return extrapolation and overconfidence. Section 8 concludes.

2 A Conceptual Framework

We begin by reviewing theories of memory in Section 2.1; in particular, studies on two important memory mechanisms—selective memory and associative memory. These two features of the human memory system motivate a model of belief formation based on cued recall, presented in Section 2.2.

2.1 Theories of memory

In models of full information rational expectations (FIRE), agents can fully recall and access all past information to make decisions. Self-reflection and introspection, however, would immediately suggest that, in reality, human memory is far from perfect (see Kahana (2012) for a detailed review).

First, memory is selective. At least three forces have been suggested to be driving selective memory. The first is recency: people tend to recall more recent events and are able to describe their details more precisely. The second force is motivated reasoning (Brunnermeier and Parker, 2005; Köszegi, 2006; Zimmermann, 2020), which says that people tend to selectively recall the more positive experiences to maintain a positive image about themselves. The third force has to do with the features of the experience itself: more salient, dramatic experiences are more likely to be recalled.

Second, memory is associative. As a result, recall is cued in nature: different cues in the present environment—time, location, narrative, story, image, emotion, and other stimuli—can trigger recall of different past experiences. One of the principles governing cued recall is similarity: experiences with features that are similar to the active features in the present environment are more likely to be recalled (Kahana, 2012; Wachter and Kahana, 2021; Bordalo et al., 2022b,a).

2.2 A model of cued recall and belief formation

To guide our empirical analysis, we next present a model of belief formation in financial markets based on Bordalo et al. (2022a). The model incorporates both selective recall and cued recall.

Suppose that we are now in period T. An investor faces the task to forecast the return in the next period, $T + 1$. When making this forecast, she first retrieves a distribution of past returns from memory. The goal of our model is to articulate how the investor's experience in period T serves as the cue to influence both recall and belief formation.

In reality, an experience is characterized by multiple attributes, e.g., time, location, and experienced return. For simplicity, however, we assume that the experience in period t is fully characterized by the return during the period, r_t, for $1 \leq t \leq T$. The distribution of those experienced returns can be described by a probability density function (PDF), $f(\cdot)$. For simplicity, we assume that the distribution is normal, with a mean μ and variance σ^2.

2.2.1 Recall

Suppose the investor is prompted to recall her return in period t, for $1 \leq t \leq T-1$. Let $R(r_t|r_T)$ denote the investor's recall of r_t, given the current market cue r_T. We assume that, with probability θ ($0 \leq \theta \leq 1$), the investor correctly recalls the return, i.e., $R(r_t|r_T) = r_t$. With probability $1-\theta$, however, the investor retrieves one of her (many) experienced returns.

In the absence of the market cue r_T, the investor simply randomly chooses one of her experienced returns. How does the market cue influence the retrieval of experienced returns? Following Bordalo et al. (2022a), we assume that the retrieval process follows the rule of *similarity*. That is, experiences with attributes similar to the cue, r_T, are more likely to be retrieved. Let $s(r, r_T)$ denote the similarity between experienced return r and r_T, where a larger value indicates higher similarity. All else being equal, if an experienced return is more similar to the cue, it is more likely to be retrieved. Therefore, the cue alters the distribution of recalled experienced returns, resulting in a "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 numerator, $\int_z f(z) \times s(z, q_T) dz$, normalizes the PDF so that the total probability equals one. Hence, $R(r_t|r_T)$ is a random draw from the cued distribution in equation (1).

For simplicity, we will focus on the following similarity function:

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

where parameter σ_ϵ captures the strength of the cue. Specifically, equation (3) implies that experienced returns closer in magnitude to r_T have higher similarity measures. The cue's influence is weaker if it is perceived to less relevant to the past returns (i.e., σ_ϵ is larger). For example, today's return is likely to be a stronger cue for recalling yesterday's return than for recalling the return of the past year, given that today's and yesterdays' returns are temporally closer to each other. In the extreme case in which σ_ϵ approaches infinity, $s(r, r_T)$ approaches 1 and hence $f^* = f$. That is, the cue has no influence on the investor's recall.

With the similarity function (3), the mean of the investor's recalled period-t return, denoted as $\bar{R}(r_t|r_T)$, is given by

$$\bar{R}(r_t|r_T) = \theta r_t + (1-\theta)\bar{R}^*[r_t|r_T], \tag{4}$$

where $\bar{R}^*[r_t|r_T]$ is the mean of her recalled period-t return if she fails to retrieve the correct memory. Let $\alpha = \sigma^2/(\sigma^2 + \sigma_\epsilon^2)$. We show in the Online Appendix that

$$\bar{R}^*[r_t|r_T] = (1-\alpha)\mu + \alpha r_T. \tag{5}$$

The above equation shows that if the investor fails to retrieve the correct memory, her retrieved return tends to be higher if the market cue, r_T, is higher.[5]

Substituting (5) in (4), we obtain

$$\bar{R}(r_t|r_T) = \theta r_t + (1-\theta)(1-\alpha)\mu + \alpha(1-\theta)r_T. \tag{6}$$

Hence, the average recalled return is increasing in the cue. When the current return r_T is higher, recalled returns tend to be higher as well. This effect is weaker if the cue is perceived to be less relevant. This would the case, for example, if the recalled experience is in the more distant past. These results are summarized in the following two predictions.

Prediction 1. *(Cued recall) Recalled return is increasing in today's market return r_T.*

Prediction 2. *(Recency) The cue's effect is weaker if the cue is perceived to be less relevant, for example, if the recalled experience is in the more distant past.*

[5] In Section C of the Online Appendix, we also show that 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, $r_t \sim N(\mu, \sigma^2)$, and treats r_T as a signal of r_t: $r_T = r_t + \epsilon$, with $\epsilon \sim N(0, \sigma_\epsilon^2)$. She follows Bayes' rule to obtain the following posterior distribution: $r_t|r_T \sim N((1-\alpha)\mu + \alpha r_T, \sigma_q^2)$, where $\sigma_q^2 = \frac{\sigma^2\sigma_\epsilon^2}{\sigma^2+\sigma_\epsilon^2}$. This distribution is identical to the cued distribution implied by equations (1)–(3).

2.2.2 Belief formation

Let $\mathbb{E}[r_{T+1}]$ denote the investor's expectation for the return in period $T+1$. How does the investor form her expectations? Following Bordalo et al. (2022a), we assume that the investor uses her retrieved memories to "imagine the future" through a process called *simulation*. Specifically, she uses her retrieved experienced returns ($R(r_t|r_T)$, for $t = 1, ..., T-1$) as the dataset and draws samples from it repeatedly. Her expectation for the return in $T+1$, $\mathbb{E}[r_{T+1}]$, is given by the sample mean.

Equation (6) implies that this sample mean approaches $\theta\mu + (1-\theta)(1-\alpha)\mu + \alpha(1-\theta)r_T$, when the simulation sample size goes to infinity. Hence, we obtain

$$\mathbb{E}[r_{T+1}] = \mu + \alpha(1-\theta)(r_T - \mu),$$

which leads to the following prediction.

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

3 Survey Design and Data

In this section, we describe the survey and the other sources of data used in the paper. Sections 3.1 to 3.3 elaborate on the design of different blocks of questions. Section 3.4 details the implementation of the survey and the other data sources.

3.1 Survey design: Recall

Examining investors' memory structure requires collecting data on their recall about investment experiences and performance in the past. We design two blocks of questions to elicit investor recall.

3.1.1 *FreeRecall*

The survey starts with a block called *FreeRecall*. As the name suggests, this block is motivated by the well-established experimental paradigm of free recall (e.g., Murdock, 1962; Kahana, 2012) and is designed to elicit a period of market movement that first comes to mind when an investor thinks about stock market movements in the past. By “free,” we intend to give respondents minimal restrictions on what periods to recall. Thus, their answers capture the idea of selective recall and are potentially informative of its determinants.

Once an investor enters the *FreeRecall* block, we start by asking her to “first think about the overall stock market movement since you opened an account.” We then immediately ask the following question: “what is the episode of market movement that first comes to mind? Please enter the starting month and ending month of this episode.” With this question design, we are particularly concerned with recalling episodes that investors have experienced themselves in their trading.[6]

Having just entered the market episode that comes to mind, investors are immediately asked three follow-up questions: 1) “How much did the market (Shanghai Composite Index) move during this period?” 2) “What was your total RMB investment during this period?” and 3) “What was your total RMB return during this period?” Because it would be difficult to recall an exact number for these questions, we offer multiple choices, each choice covering a range of value (e.g., 0% to 5%).[7]

In addition to the main treatment block, *FreeRecall*, we consider two additional treatment blocks; all investors, when starting the survey, are randomly assigned into one of the three treatments—therefore, our results on *FreeRecall* rely on a third of our sample. In the first treatment, called *HappyRecall*, instead of asking participants to free-recall any market episode, we ask them to recall a *pleasant* episode. In the second treatment, called *PainfulRecall*, we ask them to recall a *painful* episode. As before, investors also need to recall the market return during the recalled episode. We discuss results from these two blocks in more detail in Section 6.

[6]It is possible that episodes that are not directly experienced, such as the Great Depression for baby boomers and the tech bubble to Gen Z investors, can also be recalled and have an effect on belief formation; we abstract away from such non–experience-based recall throughout the paper. In a follow-up survey we run for a different project, we amend *FreeRecall* in two significant ways. First, we experiment a different phrasing to elicit the episode that first comes to mind. Second, we ask investors not to restrict their recall of the market to periods they have experienced themselves. We will discuss these results in Section 4.2 of the Online Appendix.

[7]We repeat this set of questions at the stock level, and the response rate is substantially lower. For the sake of brevity and because we primarily focus on expectations at the market level, we do not discuss the results of stock-level recall in the remainder of this paper.

3.1.2 *ProbedRecall*

After *FreeRecall*, investors move on to the second recall block, called *ProbedRecall*. Here, we ask them to recall their own returns in the stock market in the past. By "probed," we highlight the fact that these questions are designed with more elaborate conditions, both in terms of the type of memory elicited (own return) and the time period specified (one day to five years).

When an investor enters the *ProbedRecall* block, we ask: "To the best of your recollection, what was the cumulative return rate of your equity investment over: (1) last trading day; (2) last month; (3) last year; and (4) last five years?" As before, we design these questions to be multiple-choice, with each choice covering a fixed range of values.

3.2 Survey design: Expectation

After the two recall blocks, investors enter the *Expectation* block. We elicit two types of expectations, one about future market returns and one about future own returns. For market returns, we ask about both the mean and tail distributions. Again, these questions are multiple-choice, and the phrasing is similar to that in earlier papers using surveys to elicit expectations (Giglio et al., 2021; Liu et al., 2022). For example, when eliciting the return expectation about the market over the next month, we ask: "What do you expect the cumulative return rate of Shanghai Composite Index to be over the next 30 days?"

In theory, we could randomize the order of blocks. For example, we can start with the expectation block and then proceed to the two recall blocks (*Expectation–FreeRecall–ProbedRecall*) or place the expectation block between the two recall blocks (*FreeRecall–Expectation–ProbedRecall*). The current ordering, however, is our preferred version, for the following reasons. Given the nature of free recall, we prefer to keep *FreeRecall* as the first block to reduce potential confounding effects induced by the survey's other blocks. We place the *Expectation* block after the two recall blocks to avoid the influence of motivated reasoning (Bénabou and Tirole, 2002, 2004). One concern about eliciting memories before eliciting beliefs is that the elicited memories may prime investors. As a result, investors simply copy their previous responses in the two recall blocks to answer questions in *Expectation*. In Section 6.5, we directly address this concern.

3.3 Survey design: Other blocks

At the beginning of the survey, investors are explicitly instructed to purely rely on memory and not to check their brokerage account or search the internet when completing the survey. In reality, we cannot verify whether an investor indeed follows our instructions. However, around 60% investors finish the entire survey within 10 minutes, which leaves limited them time for such checking. In addition, since the survey is not incentivized with money, investors do not have the incentive to get the accurate answer. Even if some of them do check online, their answers would lead to an attenuation bias for most of the results we document.

At the beginning of the survey, investors also need to go through a comprehension check. These questions examine investors' understanding of the concepts such as dollar investment and dollar return. In our analysis, we exclude observations that did not pass the comprehension check. Investors then move on to one of the three treament blocks (*FreeRecall*, *HappyRecall* or *PainfulRecall*) that they are randomly assigned to, *ProbedRecall* , and *Expectation* blocks. After the *Expectation* block, participants do a personality block, which includes 10 questions to measure the Big Five personality traits (Jiang et al., 2020). At the end of the survey, we collect demographics and other information in a standard questionnaire, including age, gender, wealth, income, social activities, and so on. In the remainder of the paper, these variables will mostly be used as control variables. Figure 1 illustrates the design of the survey blocks.

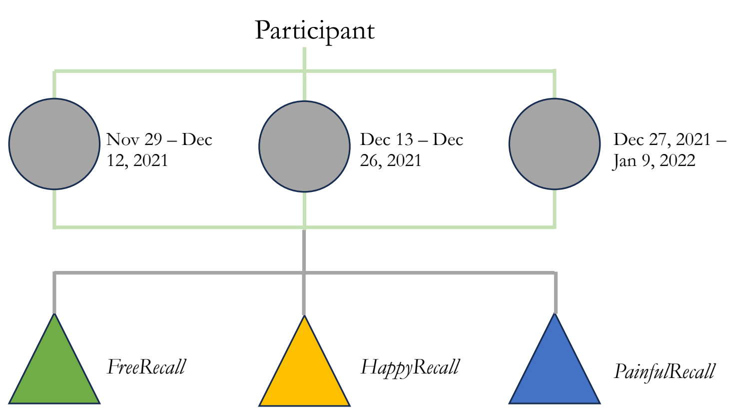
Figure 1: Organization of survey blocks

3.4 Survey implementation and other data sources

We administered the survey through one of the largest financial institutions in China. In a nutshell, we randomized selected target investors across 30 provinces (and regions) in China.

Figure 2 illustrates the implementation timeline. The survey took place between November 29, 2021, and January 9, 2022. There were three waves, each lasting two weeks. An investor's response is considered to be invalid if she spent shorter than 175 seconds (5th percentile) to finish the survey, failed to answered the two comprehension check questions correctly, or recalled an episode spanning longer than 10 years in the *FreeRecall* task. Respondents could open the survey using their personal computers or smartphones; the vast majority completed the survey on their phones. After applying basic filters, we collected an initial sample of around 17,324 respondents. Table 1 details the sample construction process. By design, respondents are evenly distributed across the 60 brokers, with only slight variation. In terms of geographic variation, areas that are more financially developed are more represented. The basic demographic characteristics of our sample can be found in Figure 3. Overall, the sample is young, well-educated, and affluent: the median age is around 35, 61% of them have a bachelor degree, and 34% of them have a wealth above 1 million RMB.

Figure 2: Timeline of survey implementation



In Section A.1 of the Online Appendix, we plot the distribution of survey respondents by day and by hour. Within a day, most of the responses are recorded during trading hours when the market is moving. In addition, when calculating correlation between the number of responses and the daily market return, the relationship is weak and close to zero. Therefore, it does not seem that market returns affect investors' participation in the survey.

For a substantial fraction of the investors answering our survey, we can merge their survey responses with their detailed transaction data at our collaborator, one of the largest financial institutions in China. The main criterion is that name and date of birth allow us to uniquely identify this investor among the investor population. This merging process is close to random in theory, but empirically the merged and unmerged samples exhibit some differences in observable characteristics. These differences, reported in Section **??** of the Online Appendix, are generally small in magnitude. In addition, as we will show later in Table 3, the merging process does not change the distribution of portfolio returns in the merged sample.

4 Stylized Facts about Investor Memory

In this section, we examine survey responses from the two recall blocks to document new stylized facts about investor memory. In Section 4.1, we compare recalled returns in the survey to actual returns in the market data and transaction data. In Section 4.2, we analyze the recalled market episodes in *FreeRecall*. In Section 4.3, we discuss age effects in recall.

4.1 Consistency between recalled return and actual return

4.1.1 *FreeRecall*

The *FreeRecall* block asks investors to recall a market episode that first comes to mind when thinking about stock market movements in the past. In the rest of the paper, we will refer to their answers to this question as "recalled market episodes." We examine the properties of these recalls later in Section 4.2. In addition, respondents are asked to recall the market return during the recalled episode. In the rest of the paper, we will refer to their answers to this question as "recalled episode returns."

Table 2 shows the summary statistics for recalled episode returns and actual episode returns (the actual market returns during the recalled episodes). In Panel A, the standard deviation of recalled episode returns is sizable, suggesting substantial variation in the type of market condition investors recall. Indeed, more than 10% of the investors recall an episode having either gone up by 100% or down by 50%. The median of recall episode returns is around zero, suggesting that, in aggregate, investors do not appear to be selectively recalling more positive experiences. Furthermore, the actual episode return, on average, is higher than the recalled episode return, which means that investors do not seem to recall past episode returns with a positive bias. This, as we will explain in more detail below, is not necessarily inconsistent with motivated reasoning, because motivated reasoning is generally about investors holding overly rosy views about their *own* performances, not about the entire market.

How accurate are these recalled episode returns? Panel B finds their correlation with the actual episode returns to be 0.53. This high correlation further confirms that respondents in our sample are indeed making a conscious effort when completing the survey's recall tasks.

4.1.2 *ProbedRecall*

Table 3 shows the summary statistics of recalls in *ProbedRecall*. In the rest of the paper, we will refer to these recalls as "recalled own returns," in order to differentiate from "recalled episode returns" in *FreeRecall*. Panel A shows the distribution of recalled own returns for different recall horizons. Overall, a longer recall horizon is associated with more positive recalled returns.

Panel B then compares recalled own returns to actual own returns for the merged sample. Three observations are worth noting. First, the distribution of recalled own returns for the full sample in Panel A and for the merged sample in Panel B are similar, suggesting that the merging process does not create selection in investor skills. Second, for horizons between one day and one year, we do not find that recalled own returns are systematically higher than actual own returns. Therefore, at the aggregate level, we do not find evidence that investors recall their past performances with a positive bias for short-term or medium-term horizons. Third, when the look-back horizon is over the longer term of five years, we find more suggestive evidence of positively biased recall: the median recalled own return is 2.5% while the median actual own return is around 0.9%. One possible explanation is that, since performance over the long run is harder to recall accurately, it creates more room for motivated reasoning.

Overall, evidence in support of motivated reasoning is not strong in our setting. This may initially appear surprising, given that, in our setting, retail investors on average overestimate their relative rank based on investment performance in the population. [8]. One way to reconcile this apparent contradiction is through investors' assessment of others' performances. Indeed, if investors are both negatively biased in recalling their *absolute* performance and positively biased in assessing their *relative* rank, it must be that they are underestimating other people's performance, in the spirit of dismissiveness (Eyster et al., 2019).

Panel C shows the correlation between recalled own returns and actual own returns. The correlations are positive and highly significant for all horizons, with the coefficient ranging between 0.07 and 0.40. Interestingly, the correlation is highest for the one-year horizon, suggesting the possibility that investors tend to evaluate and mentally represent their performance on a yearly basis.

4.2 Salience and recency effects in recall

To analyze the properties of recalled market episodes, Figure 4 plots the distribution of start dates and end dates against the Shanghai Composite Index. Although, on average, the market exhibits an upward trajectory over the last three decades, it has also experienced two salient bubble-and-crash episodes, one in 2007–08 and one in 2014–15.

Two patterns immediately emerge in Figure 4. First, recalled episodes display a strong recency effect: a disproportionally large number of answers concern recent periods, especially for the end date. This result mirrors the recency effect documented in free recall experiments conducted by memory psychologists: items that participants most recently saw are more likely to be recalled later. In our setting, however, one mechanical driver of this recency effect is experience: new investors can only recall the more recent experiences, which can mechanically tilt the distribution to recent periods. Figure 5 replots the distribution of recalled episodes but excludes investors who entered the market during the last 12 months. If recency does not matter, then all the 12 months during the past year should be equally likely to be recalled. However, Figure 5 shows a cluster of recalled episodes for the most recent month, confirming that the recency effect is not

[8] Following (Liu et al., 2022), we designed questions to construct measures of investors' overconfidence level. In one of the questions, we ask investors to assess their performance rank among all the A-share market investors. We then calculate their actual performance rank using their trading records. On average, we find investors over-estimate their relative performances.

mechanically driven by the cohort of new investors.

A second pattern in Figure 4 is that a substantial fraction of recalled market episodes tilt towards the two bubble-and-crash episodes, even though they happened 7 and 14 years ago, respectively. Therefore, the probability of recalling a market episode is not merely a function of time elapsed since that episode.

In Section A.3 of the Online Appendix, we plot the distribution of recalled market episodes for two subsamples split by age. Again, both recency and salient effects are observed in the two subsamples, with the recency effect being more pronounced in the younger sample. In Section A.4 of the Online Appendix, we consider an alternative phrasing of the free-recall question.[9] In Section A.5 of the Online Appendix, we simulate a recall distribution under the assumption that investors are equally likely to recall any month they have experienced in the stock market. Under this hypothetical recall structure, we also find both recency and salience effects. However, they are substantially weaker than those documented in Figure 4. Combined, these additional results suggest that recency and salience effects are robust to alternative explanations.

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 et al., 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. This fact also supports the retrieved context model by Wachter and Kahana (2021) which allows for stronger encoding of experiences that are more extreme.

We see that dramatic events such as bubbles and crashes are more likely to be recalled in *FreeRecall*, but it remains unclear what part of the boom-and-bust cycle investors are more likely to recall. To get a more granular look, Figure 6 zooms into 2014 and 2015 to further examine the distribution of recalled market episodes during a bubble-and-crash episode. This episode started in late 2014, peaked in mid-2015, and then crashed. Figure 6 shows three modes in the distribution

[9]Results from this robustness check is from a follow-up survey we have conducted. In the survey used by the current paper, the literal translation of the free-recall question is "which episode is the most memorable," which we take as measuring the first episode that comes to mind. In the follow-up survey, we literally ask "which episode first comes to mind." More details about the follow-up survey is available upon request.

of recalled episodes: one ending in 2015:06, one beginning in 2015:06, and one beginning in 2015:01 and ending in 2015:12. These answers correspond, respectively, to the run-up, the crash, and the full cycle. These modes not only show the heterogeneity in the type of event investors recall, but also demonstrate that investors can, in their recall, differentiate the various stages of a bubble. These results suggest that investors tend to use salient points such as peak and trough as natural reference points to construct episodes.

4.3 Age and recall

As shown in Figure 4 and Table 2, there is substantial heterogeneity in the type of event recalled in *FreeRecall*. It has been proposed that both demographics and trading characteristics can influence investor memory. To examine the determinants of recall in *FreeRecall*, in Table 4 we regress two features of recalled episodes—the distance of the recalled episode and the recalled episode return—on various individual characteristics.

In Table 4, Column (1) first regresses recall distance on various individual characteristics, with recall distance defined as the difference in years between the midpoint of the recalled episode and December 2021 (the survey time). Overall, older investors tend to recall a more distant episode. A 10-year difference in age implies a 1.1-year difference in recall distance. Column (2) further controls for trading experience and shows that this effect is not just driven by older investors having entered the market earlier. In the Online Appendix, Section A.7 repeats this set of analyses by considering an enlarged set of individual characteristics, including performance and turnover. Overall, age remains the most important and robust determinant of recall distance. This result supports the formulation used in models of experience effects in which older investors are more likely to recall more distant events (Malmendier and Nagel, 2011; Malmendier et al., 2020).[10]

Column (3) of Table 4 repeats the exercise in Column (1) for recalled episode returns. Again, age appears to be a key determinant of recalled episode return: older investors tend to recall a more bullish market episode. A 10-year difference in age implies a 2.3-percentage-point difference in recalled episode return. Gender also appears to matter: women tend to recall a more bearish episode. Interestingly, we find that neuroticism (one of the Big Five personality traits) also affects

[10]Interestingly, investors who check their accounts often tend to recall more recent episodes, suggesting that memory is limited and more recent experiences may replace the older ones.

recall significantly: more neurotic investors tend to recall a more bearish episode. This is consistent with the notion that personality traits such as neuroticism are driving the cross-sectional variation in beliefs (Jiang et al., 2020). Columns (4) and (5) repeat the regression in Column (3) but adds experience and recall distance as additional controls. On average, more distant recalls are more bullish. Interestingly, the coefficient on age continues to be significantly positive. In Table 5, we further examine the determinants of recalling extreme events such as large run-ups and crashes. As before, we find significant age and gender effects: older, male investors are more likely to recall a large market run-up as well as crashes.

In Section A.6 of the Online Appendix, we decompose recalled episode return into two components: actual episode return and recall bias, defined as the difference between recalled episode return and actual episode return. We find a similar positive correlation between age and actual returns, but not between age and recall bias. Therefore, the age effect is more consistent with selective recall rather than biased recall.

One alternative explanation for the positive correlation between age and recalled episode return is that older investors entered the market early, which coincides, by chance, with a booming period. However, Figures 4 and 5 plot the Shanghai Composite Index and do not show any clustering of good returns in the early periods. In addition, Figure 7 plots the average recalled episode return for each age bin and shows that the positive correlation is not driven by a particular cohorts; it is present across a wide age spectrum.

A deeper exploration on the underlying sources of the age effect is beyond the scope of our paper. We note, however, that this finding is echoed by a large literature on age-related positivity effects. As initially observed by Charles et al. (2003), compared with younger adults, older adults show a significant information processing bias toward positive versus negative information. A meta-analysis of more than 100 empirical studies concludes that the positivity effect is reliable and robust (Reed et al., 2014). More recently, Bordalo et al. (2022a) find that older people appear to be more optimistic about COVID, even though they themselves face greater risks of death.

5 Cued Recall

In this section, we test the first part of the model, *recall*, by studying the dynamics of investor memory. In Section 5.1, we start by discussing how we generate variation in the return cues when implementing the survey. In Sections 5.2 and 5.3, we test the first two predictions of the model by examining the relationship between return cues and memories elicited by the two recall blocks.

5.1 Return as the cue

The complexity of the financial market gives rise to many candidate cues—time, location, and narrative in the media—all of which could be playing a role in shaping the retrieval of past experiences. To guide our empirical analysis, we hypothesize that return—either at the market level or one's own return—is an important cue that triggers the retrieval of past experiences. This corresponds to Prediction 1 in the model, which suggest that, upon observing positive returns in the market, investors are more likely to retrieve past experiences that are also associated with a rising market. In *FreeRecall*, this mechanism corresponds to recalling market episodes with higher returns; and, in *ProbedRecall*, because good returns remind investors of similar experiences of a rising market, they tend to have an overly rosy recollection of their own returns in the past.

To get sufficient variation in market returns, we roll out the survey in three waves, spanning six weeks and with sufficient movement in the market. During this period, the entire market exhibits mild yet still significant movement. The maximum daily return is 1.18% while the minimum is -1.16%; the standard deviation is around 0.66%. Figure 8 examines the distribution of returns during this period in more detail. In addition, we record the precise time when an investor begins to take the survey. Therefore, even for investors taking the survey on the same day, their cues can be different as the market fluctuates during the day.

In addition to using the market return as a cue, we also consider the portfolio-level return as a cue. This is made possible by observing account-level data for the merged sample. Compared to the market return, the portfolio-level return is more personal and therefore arguably a more salient cue. The downside is that the merged sample is significantly smaller in sample size. Later in Section 5.4, we consider cues beyond returns.

5.2 The *FreeRecall* block

According to Prediction 1, a positive return tends to trigger the retrieval of an episode of a booming market in *FreeRecall*. To test this, we use the following main specification:

$$\widehat{MktRet}_i^{Free} = \beta_0 + \beta_1 MktRet_{t\to t+\tau_i} + X_i + \epsilon_i. \quad (7)$$

On the left-hand side, $\widehat{MktRet}_i^{Free}$ denotes investor i's recalled (hence the hat) episode return under *FreeRecall*. On the right-hand side, $MktRet_{t\to t+\tau_i}$ represents the cumulative market return up to the minute when investor i starts taking the survey, where t corresponds to the beginning of the survey day and $t+\tau_i$ the time of the day when investor i starts the survey; X_i denotes a variety of individual-level controls, including age, gender, education, wealth, income, and measures of social activities. Simply put, in this main specification, we test whether market fluctuations today have any effects on investor recall; in alternative specifications, we also consider market fluctuations over a longer horizon.

In Table 6, Column (1) reports the results for the full sample. The coefficient is positive but insignificant. Therefore, overall, investor recall in the *FreeRecall* block does not appear to be cued by today's market return. In Columns (2) and (3), we entertain two other specifications: one using past one-month return as a cue and one using both returns at the same time. However, in neither specification does the variation in market returns affect the recalled return in *FreeRecall*.[11]

The null results in Columns (1)–(3) may initially appear surprising and running counter to the prediction of similarity-based recall. A closer examination, however, suggests otherwise. First, as shown in Section 4, recalled episodes in *FreeRecall* largely capture dramatic events featuring large swings in asset prices. According to similarity-based recall (Kahana, 2012), for the return cue to affect investors' retrieval of such salient events, the cues themselves also need to be extreme in magnitude. While, as shown by Figure 8, there is significant movement during our survey period, the overall market is rather mild, without sharp 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*.[12]

[11]In all regressions, we exclude observations that end in or after November 2021 to avoid the potential overlap between cue and recall.

[12]Indeed, in a follow-up project, we ran a similar survey during a more volatile market environment, and we find

Second, similarity is not confined to two experiences having similar returns, but also depends on their temporal proximity. This is related to the idea of temporal contiguity in memory research, which states that experiences occurring close together in time are associated to each other. Prediction 2 speaks to temporal contiguity by showing that cued recall is stronger when the same cue is used to retrieve more recent experiences. In the above regression, since we were considering market return on the survey day as the cue, it may be able to affect the retrieval of more recent experiences, but not the more distant experiences.

To test this latter possibility, we conduct a subsample analysis. We limit the sample to investors whose recalled episode in *FreeRecall* end within the last five years. We choose five years as the cutoff point because it ensures a sufficiently large sample while avoiding the earlier bubble-and-crash episodes. In Panel B of Table 6, we report regression results based on the subsample. Both today's return and the past one-month return have a much stronger influence on the recalled episode return in *FreeRecall*. In Column (4), a 1-percentage-point increase in today's return increases the recalled return by 2.1 percentage points. In Column (5), a 1-percentage-point increase in today's return increases the recalled episode return by 0.9 percentage points. And in Column (6), when both today's return and the past one-month return are included, the coefficients remain positive and statistically significant.

5.3 The ***ProbedRecall*** block

Our next prediction is that a positive return on the survey day leads to more positive recall of one's own returns in the *ProbedRecall* block. We run a similar regression by replacing recalled episode return, $\widehat{MktRet}^{Free}$, with recalled own return, using a similar specification:

$$\widehat{OwnRet}^{Probed}_{i,t-h\to t} = \beta_0 + \beta_1 MktRet_{t\to t+\tau_i} + X_i + \epsilon_i, \tag{8}$$

where $\widehat{OwnRet}^{Probed}_{i,t-h\to t}$ represents the recalled own return of a given horizon h, namely from an earlier date $t-h$ to the current date t, and X_i, as before, represents a set of individual-level controls including demographics and other personal characteristics.

We start by testing how today's market return affects the recall of one's own return yesterday

much stronger evidence for a similar free recall block. Results are available upon request.

in Table 7. It is worth noting that there is no overlap in time between the cue (today) and the recall (yesterday). Column (1) reports the results and finds evidence of similarity-based recall. When today's market return goes up by 1 percentage point, investors' recalled own return for yesterday is, on average, 68 basis points higher. Without controlling for actual own returns, however, we cannot differentiate whether the recall is accurate or biased. For example, if there is positive autocorrelation in daily market returns during the sample period, a positive coefficient may indicate rational and accurate recall. In Column (2), using the merged sample, we control for the actual own return yesterday. The coefficient of today's market return remains significant, suggesting that recall is biased. Columns (3) and (4) repeat the same regressions for recalled own return over the past month and find a similar pattern. When today's market return goes up by 1 percentage point, investors' recalled own return for the past month is, on average, 1 percentage point higher, without or with the control of the actual own return.

Interestingly, when we start to examine recall of past own return over a longer horizon, patterns begin to diverge. In Column (5), we are concerned with recall of past year's own return, where today's return no longer has a significant effect. The contrasting results between Columns (1) and (5) are consistent with Prediction 2 and, more broadly, with the idea of temporal contiguity: when recall concerns a more distant period, today's return is perceived to be less relevant as a cue. Interestingly, in Column (6), where we instead use the past month return as the cue, it becomes more relevant. That is, when reflecting on their performance over the past year or so, investors are cued by what has been going on in the market over a longer period, such as the last month.

While the positive coefficient in Column (6) may partially result from the mechanical positive correlation between past market return and past own return, in Columns (7) and (8) we add actual own return as an additional control. The coefficient on today's return remains insignificant in Column (7) while the coefficient on the past one-month market return remains significantly positive in Column (8).

Table 8 repeats these regressions using portfolio-level return as the cue. Despite a substantial drop in sample size in the merged sample, we find similar evidence of cued recall. Similar to the results in Table 7, today's own return leads to biased recall of return for yesterday or over the last month. Therefore, both market-level returns and portfolio-level returns can act as salient cues when investors recall their past performance.

5.4 Other cues

So far, we have followed the model and focused on testing market returns and portfolio returns as cues in investors' recall process. In reality, however, there are many other possible cues. While a full exploration of cues in financial markets is beyond the scope of our paper, in this section we consider "media cues" by examining the words used in the financial media. In particular, we test when there is more frequent mentioning of words like "run-up" or "crash" in the media, whether investors tend to think of episodes of a rising or falling market. For the sake of brevity, a detailed description of our data and analysis is included in Section A.9. Overall, we find that the words used by the financial press does not have additional explanatory power for investor recall. It is possible that the words used by the press are responding to market returns and therefore do not contain additional information. However, it is also possible that the approach we use—namely, focusing on the words rather than the stories—is not enough to capture narratives reported in the media. We leave a deeper exploration of these issues to future research.

6 Recall and Expectation

In this section, we test the second part of the model, *simulation*, by exploring how investors use retrieved memories to form expectations. We first examine the statistical relationship between recalls and expectations in Section 6.1. The next three sections discuss additional properties about the simulation process. Finally, we discuss alternative explanations in Section 6.5.

6.1 Retrieved experiences and expectations

Return expectations exhibit large and persistent differences across investors, but the underlying sources driving such variation are less well-understood (Giglio et al., 2021). Variations in the mental accounts of past events present a candidate explanation: some investors may expect lower future returns because their recalled returns are lower.

We examine the relationship between expectations and recalls by running the following cross-sectional regressions:

$$\mathbb{E}_i[MktRet_{t\to t+h}] = \beta_0 + \beta_1 \widehat{MktRet}_i^{Free} + X_i + \epsilon_i; \tag{9}$$
$$\mathbb{E}_i[OwnRet_{t\to t+h}] = \beta_0 + \beta_1 \widehat{MktRet}_i^{Free} + X_i + \epsilon_i, \tag{10}$$

where $\widehat{MktRet}_i^{Free}$ is investor i's recalled episode return; $\mathbb{E}_i[MktRet_{t\to t+h}]$ and $\mathbb{E}_i[OwnRet_{t\to t+h}]$ are the same investor's expectations of the market and their own returns, respectively; and h represents the horizon at which expectations are elicited, ranging from the next month to next year.

Table 9 reports the regression results. We consider four types of expectations. Columns (1) and (2) concern expectations of the market return over the next month and the next year, respectively. Similarly, columns (3) and (4) concern expectations of one's own portfolio's return. We find that respondents who recall higher returns in the past tend to have higher expectations of future returns. Magnitude-wise, the inter-quartile range in the recalled episode returns leads to a 0.14 percentage point difference in the expected market return in the next month and a 0.7 percentage point difference in the expected market return in the next year according to our estimates. [13]

In Table 10, we repeat the above regression by replacing the recalled episode return in *FreeRecall* with recalled own returns in *ProbedRecall*. To simplify the exercise, for each type of expectation we examine, we regress it on the recalled own return over the horizon of the same length. In these regressions, expectations about market returns and one's own returns going forward are highly correlated with recalled own returns. Magnitude-wise, according to Table 3, the 25–75 percentile range of the past one-month own return is -4.5% to 4.5%, which leads to a 0.72-percentage-point difference in expected market return and a 2.79-percentage-point difference in expected own return, respectively, over the next month. Moreover, the 25–75 percentile range of the past one-year performance is -6.5% to 9.5%, which leads to a 1.12-percentage-point difference in expected one-year market return and a 6.40-percentage-point difference in expected one-year own return, respectively.

It is worth noting that the use of retrieved experiences depends on the forecasting horizon. For example, in Columns (9) and (12), as we move the dependent variable from next month's own

[13]Note that the recalled episodes can last for up to 10 years. The 25th and 75th percentiles of the recalled episode returns are -19.5% and 15.5%, respectively.

return to next year's, the explanatory power of recalled own one-month return decreases while that of recalled own one-year return increases. We obseve a similar, albeit weaker, pattern in Columns (3) and (6) where we consider expectations about the market return. Therefore, it seems that the simulation process in belief-formation exhibits horizon-dependency: when investors are forming expectations about a longer horizon, they also rely on experiences that are more distant.

Lastly, comparing Tables 9 and 10, we see that, while both types of recalls can explain investor expectations, recalled own returns from *ProbedRecall* exhibit stronger explanatory power. This suggests that an important channel through which memory affects beliefs is not just through the retrieval of market-wide events but also through the retrieval of one's own personal experiences.

6.2 Horse race between actual and recalled experience

We next compare actual and recalled experiences in their explanatory power for beliefs in Table 11. Panel A reports the results on free recall. We first run the same regressions in equations (9) and (10), but replace the recalled episode return by the actual episode return. In Columns (1) and (2), actual episode returns are positively correlated with return expectations over the one-year horizon. However, in Columns (3) and (4) where we add back recalled episode returns, the coefficients on actual episode returns shrink in size and become insignificant. At the same time, the coefficients on recalled episode returns remain positive and significant.

In Panel B, we run similar regressions to compare recalled own return and actual own return in their explanatory power for beliefs. Similar to the results in Panel A, while the actual own returns are positively correlated with return expectations, recalled own returns have much stronger explanatory power for beliefs. Taken together, these results suggest it is more about the mental representations of past experiences, rather than the experiences themselves, that are shaping investor beliefs.

6.3 R-squared

Another way to evaluate the economic significance of these results is to assess how much of the variation in expectations can be accounted for by investor recall. Ex-ante, individual differences in beliefs are difficult to explain, as they are mostly characterized by large and persistent individual fixed effects unexplained by demographic variables (Giglio et al., 2021). In Table 12, we compare the explanatory powers of demographic variables and recall for expectations. In each column, we regress one type of investor expectation on either demographic variables alone or recall alone, without additional control variables. For demographic variables, we first consider gender, age, income, wealth, and education dummies. We then consider an extended set by including additional controls such as social activities. For recall, based on the horizon-dependence result in Section 6.1 that expectations about a longer horizon load more on more distant experiences, we only use recalled own return in *ProbedRecall* of the corresponding window. For example, the univariate independent variable is the past *one-month* recall if the dependent variable is the expectation of future *one-month* return.

On average, the explanatory power of recalled own returns for expectations is comparable to or higher than that of demographic variables. The increase in R-squared is substantial. Giglio et al. (2021) pose as an open question asking what variables could be driving the cross-sectional variation in beliefs. Our evidence suggests that the way experiences are processed, stored, and retrieved paves a promising way to microfound belief heterogeneity.[14][15]

6.4 Forecast errors

In our analysis on beliefs so far, we have only focused on investors' subjective return expectations. However, it is unclear whether these return expectations are rational or simply reflecting biases in beliefs. To directly link memory with biased beliefs, we instead examine forecast errors, calculated as the difference between one's expected market return and the realized future market return of the same window. In Section A.10 of the Online Appendix, we report the results from regressing forecast errors on recalls, and we find a statistically significantly positive relation between the two. Therefore, investor memory not only drive return expectations themselves, but also contributes to forecast errors at the individual level.

[14] Giglio et al. (2021) include experience as an explanatory variable. However, as we have shown, not only does experience itself matter, but it matters how the same experience is processed and recalled subsequently.

[15] In Section of A.11 of the Online Appendix, we consider another case in which we first include both date and location fixed effects. These two fixed effects should control for cue effects induced by date and location. We then add in investor recalls, and we find again a significant increase in R-squared. Therefore, investor memory is correlated with beliefs even after controlling for the cue effects captured by date and location.

6.5 Alternative explanations

In Section 6.1, we established that there is a strong and robust statistical relationship between investor recall and expectations. This is consistent with the idea of simulation in belief formation, whereby investors rely on retrieved memories to make forecasts about the future. However, given the difficulty of generating random variation in recall, it is hard to establish a casual relationship between memory and beliefs. Moreover, that both variables are elicited through the survey invites alternative explanations of our results. Below, we discuss three such alternatives and how we rule them out.

6.5.1 Anchor effects

In our survey, investors first answer two recall blocks before they answer a block of questions on expectations. As a result, one possible alternative explanation for the statistical relationships documented above is that, when reporting expectations in the *Expectation* block, some investors are unwilling to exercise sufficient mental effort. As a result, their answers are anchored towards the answers they gave in the previous recall blocks, leading to a mechanical positive correlation between recall and expectations.

If this anchoring effect is indeed prevalent and quantitatively relevant, one testable prediction is that the statistical relationship between recall and expectations should be stronger among those who finish the survey more quickly. To test this possibility, in Table 13, we run the following regressions:

$$\mathbb{E}_i[MktRet_{t\to t+h}] = \beta_0 + \beta_1 \widehat{OwnRet}^{Probed}_{i,t-h\to t} + \beta_2 \widehat{OwnRet}^{Probed}_{i,t-h\to t} \times m_i + \beta_3 m_i + X_i + \epsilon_i; \quad (11)$$

$$\mathbb{E}_i[OwnRet_{t\to t+h}] = \beta_0 + \beta_1 \widehat{OwnRet}^{Probed}_{i,t-h\to t} + \beta_2 \widehat{OwnRet}^{Probed}_{i,t-h\to t} \times m_i + \beta_3 m_i + X_i + \epsilon_i, \quad (12)$$

where m_i is the total number of minutes investor i spent on the survey. In all of the four specifications we consider, the coefficient of the interaction term is insignificant and essentially zero. This evidence does not support the interpretation that the correlation between recalls and expectations is due to some investors rushing in answering the survey.

A second piece of evidence casting doubt on the anchoring interpretation is from the two additional treatments, *HappyRecall* and *PainfulRecall*, which ask investors to recall a happy and painful episode, respectively. Given the design, the recalled episode returns in these two blocks are very different from those in *FreeRecall*. In Table 14, Column (1) shows that recalled returns are, on average, 23% and -20% in *HappyRecall* and *PainfulRecall*, whereas the average recalled return in *FreeRecall* is 5%. If investors were anchored by their earlier responses, then similar differences in answers should occur in the immediate block, *ProbedRecall*, results in gaps in recalled own returns across the three treatments. However, Columns (2)–(5) show that average recalled own returns are essentially flat across the three treatments. Therefore, it does not seem that investors are mechanically anchored by their previous answers.[16]

6.5.2 Click-through behavior

Related to the anchor effect, if some investors just click through the entire survey with the same answer option, this would generate a similar positive correlation between recall and expectations. Such click-through behavior would imply that other variables elicited in the same survey would exhibit a similar positive correlation.

To test this, instead of regressing expectations on recalled returns, we use expected crash probability as an independent variable. During the sample period, the Shanghai Composite Index mostly hovers between 3,500 and 3,600. We have considered two 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 perceived probability of a crash.

Regression results are reported in Table 15. If it is indeed click-through behavior driving the positive correlation between recall and expectation, we should see a similar relationship between recalled own returns and perceived crash probability. However, we do not: investors with a higher recalled return tend to believe that there is a lower probability of crash happening. These results also suggest that recall affects not only average beliefs, but also people's perception of tail events.

[16]In unreported analysis, we do find that, when the recalled episode becomes rather recent and overlaps in time with the recall horizon in *ProbedRecall*, the two treatments do have an effect on recalled own returns. This is consistent with interference based on temporal contiguity (Kahana, 2012; Bordalo et al., 2022b), whereby reminding people good or bad experiences in the past can increase or decreased their recall of past performance.

6.5.3 Motivated beliefs

While it is psychologically realistic to expect the direction of causality to go from memory to expectations, it is also possible that causality goes the other way—through motivated reasoning. For instance, suppose that expectations actually have nothing to do with memory but are shaped by some omitted variables. Optimistic investors, however, would probably justify their optimism by selectively recalling the more positive experiences. Since we do not exogenously vary either the expectation or the recall, we cannot differentiate between these two stories.

However, we can analyze one particular version of the motivated reasoning story by checking the relationship between past actions and future recall. According to this version of motivated reasoning, after an investor increased her stock holdings, she would like to justify her decisions by recalling more positive experiences in the past. To test this possibility, in Table 16, we regress recalled own returns on recent holding changes, and none of the coefficients is significantly positive. Therefore, we find little evidence of past actions driving recall.

6.5.4 Beliefs and actions

Lastly, we confirm that the elicited beliefs from the survey are related to investor decisions. While the previous literature has confirmed that survey expectations do affect decisions (Giglio et al., 2021), it is possible that the return expectations elicited in our survey are more influenced by the elicited memories and have less explanatory power for trading behavior in the field. In Table 17, we confirm that return expectations, especially expectations of one's own performance going forward, are correlated with trading on the day of or the week after the survey.

7 Cued Recall and Return Extrapolation

In this section, we link the previously documented memory structures to some prevalent belief biases. In particular, we examine Prediction 3 of the model and discuss the link between cued recall and return extrapolation. [17]

One common robust bias in belief formation is return extrapolation—the investor's tendency

[17] In the Online Appendix, Section B, we further link selective memory with another prevalent belief bias—overconfidence.

to form expectation of future returns based on past returns (Greenwood and Shleifer, 2014; Da et al., 2021; Liao et al., 2022). While extrapolation has been used to explain rich patterns in asset return dynamics (Barberis et al., 2015, 2018; Jin and Sui, 2022), its psychological foundation remains to be explored. For instance, Barberis (2018) reviews the microfoundations of extrapolation. Some of these microfoundations, such as representativeness and the law of small numbers, are based on psychology and others on bounded rationality.

Prediction 3 suggests that similarity-based recall can microfound return extrapolation (e.g., Bordalo et al., 2021, 2022b). As good recent returns today trigger the recall of past experiences associated with good returns and investors use these recalls to form expectations about future returns, this results in a positive relationship between past returns and return expectations. This also means that the positive relationship between past returns and return expectations should weaken after we controll for recalled experiences.

To examine this prediction, we first confirm the tendency to extrapolate returns in the cross-section of our respondents by regressing their reported expected market return in the next month on the actual return in the past month. Column (1) of Table 18 reports the result. Exploiting random variations in the timing of our survey, we find that respondents who experienced a 1-percentage-higher market return in the past month tend to report 0.14-percentage-higher expected return in the next month, consistent with return extrapolation.

Then, to test our prediction, we add the respondents' recalled own return in the past month to our regression. Column (2) of Table 18 shows that the coefficient associated with the actual past return declines and becomes statistically less significant, whereas the coefficient of the recalled own return is statistically significant. As shown in Section 5.3, one-month market return can affect recall of own return up to a year ago. In Column (3), we further include recalled own return about the past year, and the coefficient on the one-month return is no longer statistically significant.[18] These results impute a central role to memory and recall in the investors' extrapolation tendency in expectation formation.

[18]In the Online Appendix, we show that under the null that the realized return affects expectation only through its effect on memory, the coefficient of the realized return is positive if we regress the expected return on the realized return, and is zero if we regress the expected return on both the realized return and recalled return.

8 Conclusion

There are growing interests in understanding the role of memory in driving beliefs and choices. Much of the discussion so far has focused on either uncovering new lab evidence or developing new memory-based theories of decision-making. In this paper, we bring new evidence from the field. We survey a large representative sample of retail investors to elicit their memories of stock market investment and return expectations. By merging the survey data with administrative data of transactions, we confirm the validity of elicited memories, examine their properties, and establish new facts that shed light on the relationship between investor memory and belief formation.

Our analysis delivers several important messages. First, memory is not a simple recollection of past experiences. Instead, it oversamples recent and salient experiences and is influenced by the present environment. Second, memory plays a key role in shaping beliefs. Empirically, investors' expectations are highly correlated with their retrieved experiences about the stock market. Third, memory can shed light on why people extrapolate. According to similarity-based recall, good recent returns today trigger the recall of past experiences associated with good returns, leading to more optimistic return expectations. We provide evidence in support of this view. Fourth, and more generally, we confirm that memory is key to belief formation in the field.

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Figure 3: Distribution of demographic variables

This figure reports the distribution of age, gender, education, wealth, income, and experience. The variable experience defined as number of years since an investor opens a trading account is based on the merged sample. All other variables are based on the main sample.

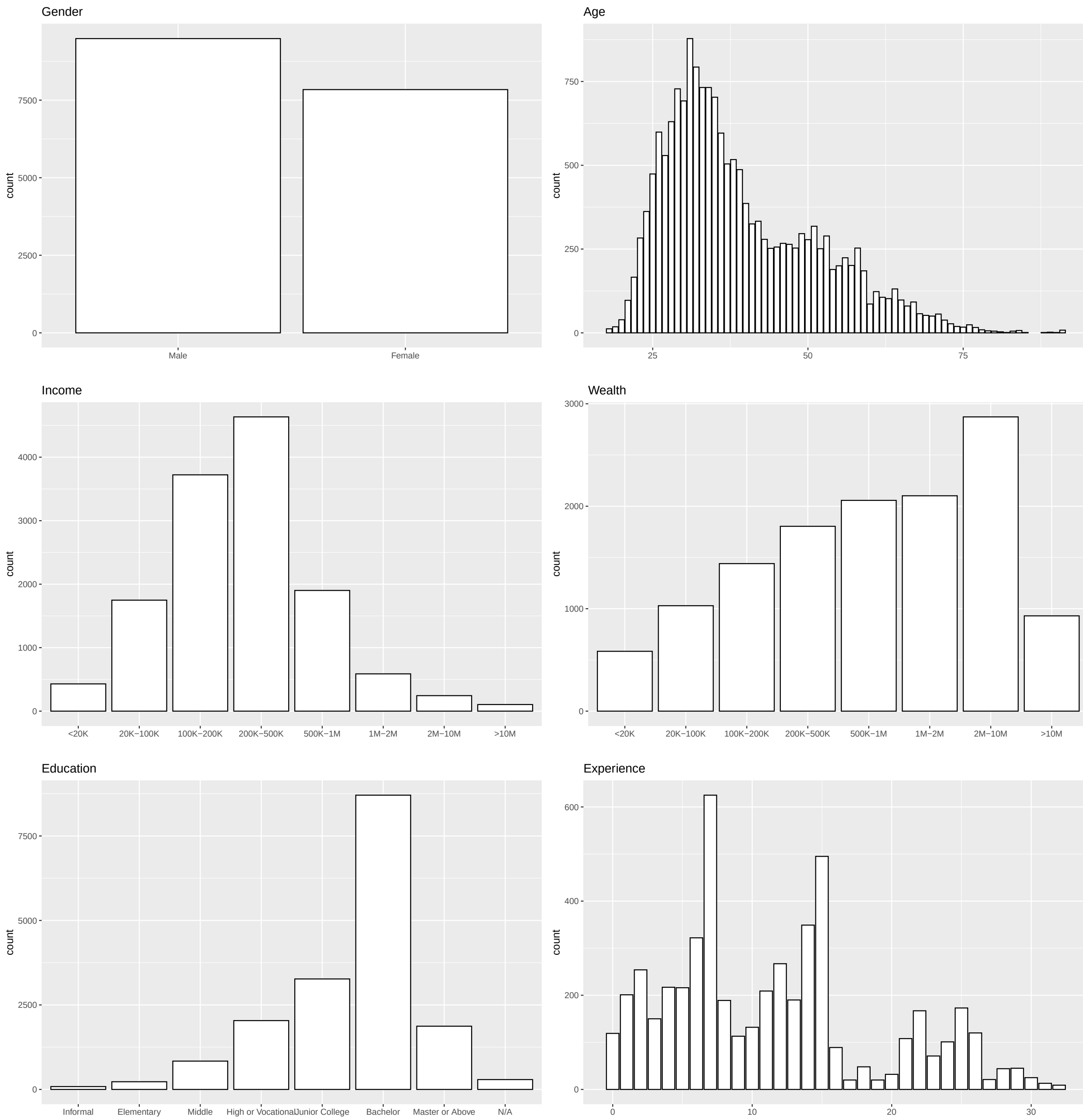
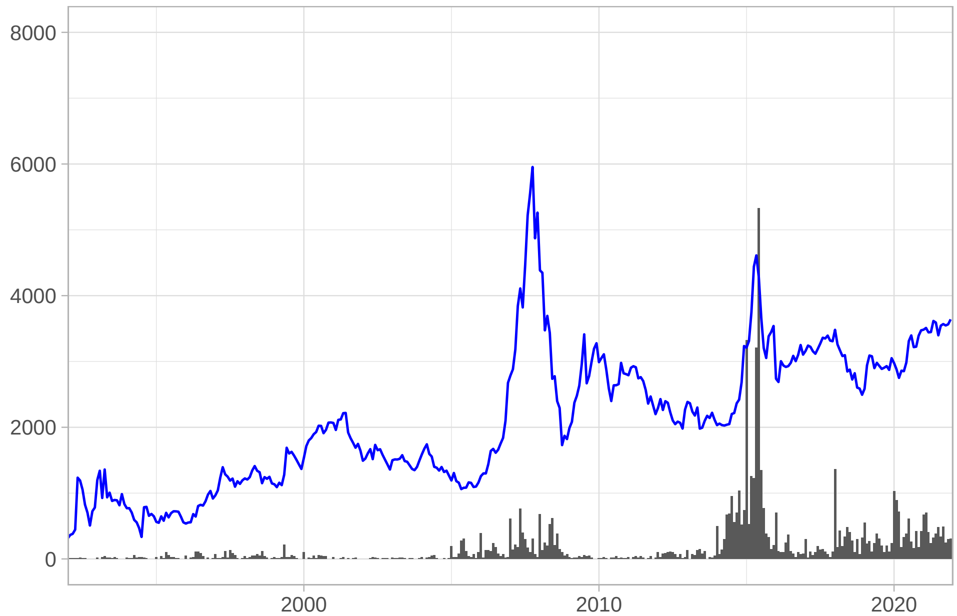
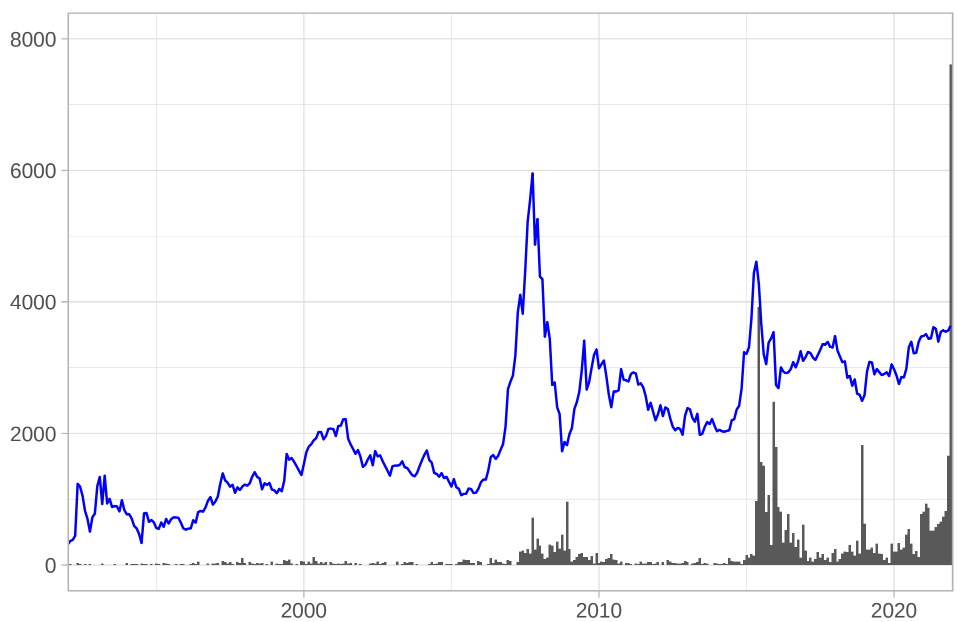


Figure 4: Distribution of recalled market episodes in *FreeRecall*

The blue solid line represents the Shanghai Composite Index. The solid bars represent the frequency of answers. The legends on the y axis represents the level of the Shanghai Composite Index.



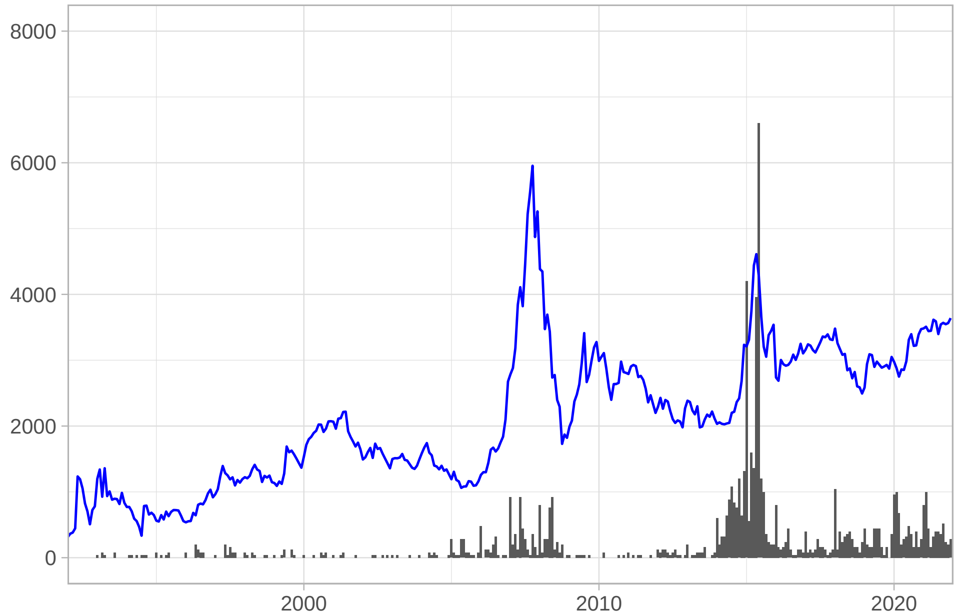
Panel (a) Distribution of start dates



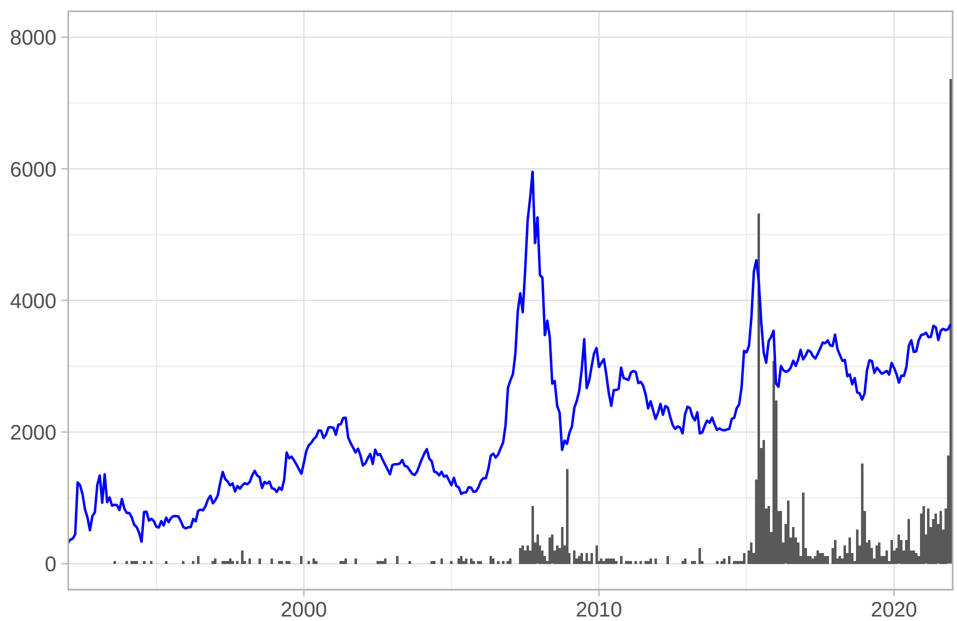
Panel (b) Distribution of end dates

Figure 5: Distribution of recalled market episodes in *FreeRecall*, excluding investors who entered the market during the past year

The blue solid line represents the Shanghai Composite Index. The solid bars represent the frequency of answers. The legends on the y axis represents the level of the Shanghai Composite Index.



Panel (a) Distribution of start dates



Panel (b) Distribution of end dates

Figure 6: Distribution of recalled market episodes in *FreeRecall* between January 2014 and January 2016

The figure plots the distribution of start date and end date for the recalled episodes in *FreeRecall* between January 2014 and January 2016. The value represents the number of observations for a particular cell.

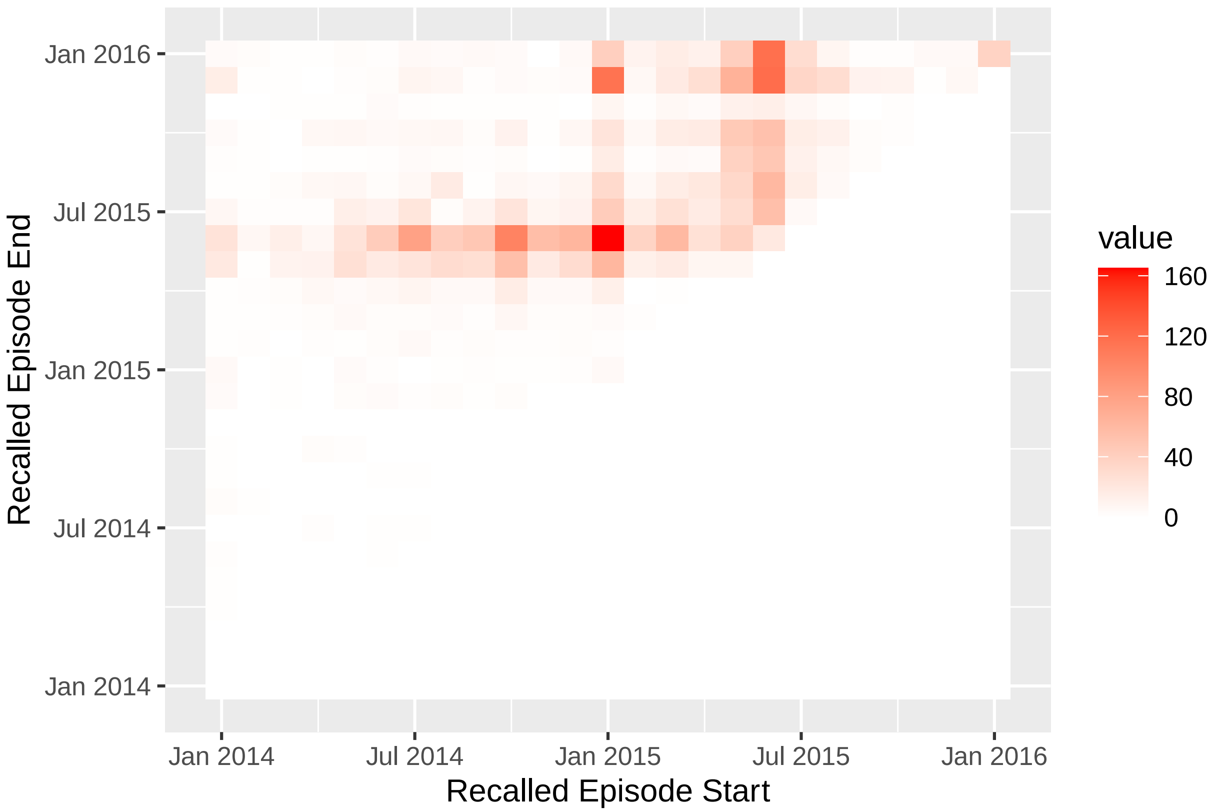


Figure 7: Age and recalled episode return in *FreeRecall*

The figure plots the relationship between age and recalled episode return in *FreeRecall*. The *FreeRecall* block asks investors to recall a market episode that first comes to mind when thinking about stock market movements in the past and the market return during the recalled episode, which is labeled as "recalled episode returns."

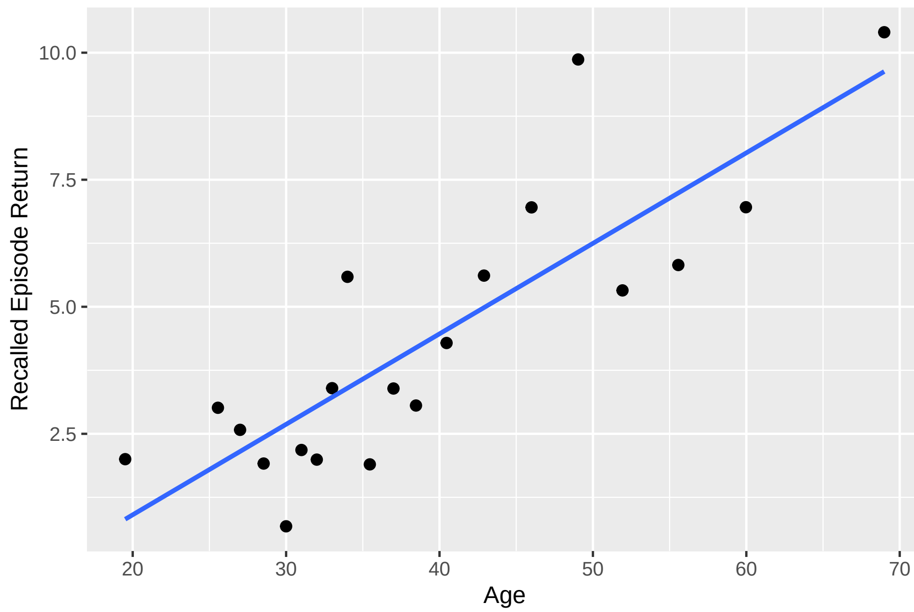


Figure 8: Distribution of daily returns during the survey period

The figure plots the daily stock market return (in %) for the Shanghai Composite Index from Nov 29, 2021 to January 9, 2022.

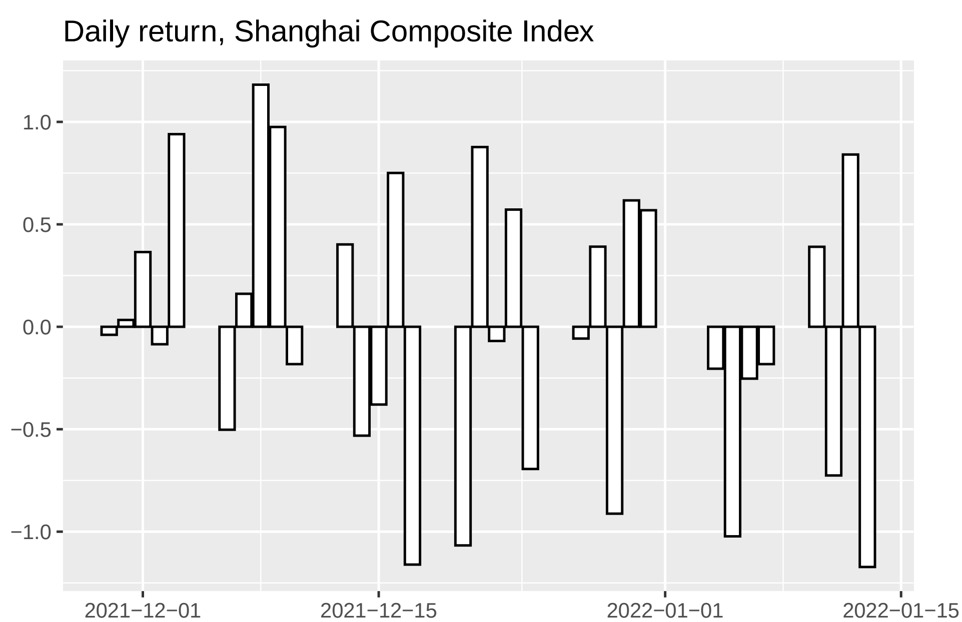


Table 1: Sample construction process

Filter	Sample size
Initial sample	37,921
Drop if an investor spent less than 175 seconds (5th percentile) on the survey	36,164
Drop if an investor failed to answer the two comprehension check questions correctly	27,799
Drop if an investor's recalled episode is longer than 10 years in *FreeRecall* (Main sample)	17,324
Merge with transaction data	5,145

Table 2: Summary statistics of recalled episode return in *FreeRecall*

This table reports summary statistics for actual episode return, recalled episode return, and own episode return. The *FreeRecall* block asks investors to recall a market episode that first comes to mind when thinking about stock market movements in the past. In addition, respondents are asked to recall the market return during the recalled episode. These returns are labeled as "recalled episode returns." The actual market returns during the recalled episodes are labeled as "actual episode returns." Investors are also asked to recall their own returns during these episodes, and these returns are labeled as "own episode returns."

Panel A: Summary statistics

	N	Mean	SD	P5	P25	Median	P75	P95
Recalled episode return	5,087	5.6%	38.8%	-50.5%	-19.5%	0.0%	15.5%	100.0%
Actual episode return	5,453	13.2%	45.5%	-41.8%	-21.8%	2.6%	31.3%	124.8%
Own episode return	4,711	-1.6%	42.5%	-76.5%	-27.3%	0.0%	16.7%	100.0%

Panel B: Correlation between recalled and actual episode return

	Actual	Recalled	Own
Actual episode return			
Recalled episode return	0.534		
Own episode return	0.496	0.276	

Table 3: Summary statistics of recalled own returns in *ProbedRecall*

This table reports summary statistics for recalled and actual own returns and the correlation coefficients among them. The *ProbedRecall* block asks investors to recall returns of their own portfolios over the past one day, one month, one year, and five years. These returns are labeled as "recalled own returns". For a subsample of respondents for whom we can observe their transactions, we also calculate their actual portfolio returns over the same period of time. These returns are labeled as "actual own return".

Panel A: Summary statistics of the full sample

	N	Mean	SD	P5	P25	Median	P75	P95
Recalled own return								
1D	10,432	-0.3%	5.5%	-13.5%	-2.5%	-0.5%	2.5%	10.5%
1M	9,957	-0.2%	6.5%	-13.5%	-4.5%	0.5%	4.5%	10.5%
1Y	10,440	1.8%	13.2%	-22.5%	-6.5%	1.5%	8.5%	32.5%
5Y	9,325	4.3%	24.3%	-39.5%	-9.5%	2.5%	10.5%	70.5%

Panel B: Summary statistics of the merged sample

	N	Mean	SD	P5	P25	Median	P75	P95
Recalled own return								
1D	1,896	-0.3%	13.1%	-14.5%	-2.5%	-0.5%	2.5%	10.5%
1M	1,946	-0.3%	6.6%	-13.5%	-4.5%	0.5%	4.5%	10.5%
1Y	2,207	2.6%	14.2%	-21.5%	-6.5%	1.5%	9.5%	35.5%
5Y	2,178	3.9%	23.3%	-39.5%	-9.5%	2.5%	11.5%	60.5%
Actual own return								
1D	1,896	0.3%	2.4%	-2.9%	-0.9%	0.2%	1.4%	4.0%
1M	1,946	3.0%	7.4%	-10.2%	-1.9%	2.6%	7.2%	18.6%
1Y	2,207	7.0%	19.7%	-24.1%	-6.6%	4.3%	17.9%	52.2%
5Y	2,178	4.8%	28.2%	-40.3%	-14.2%	0.9%	20.0%	68.9%

Panel C: Correlation matrix of the merged sample

	Actual own return			
Recalled own return	1D	1M	1Y	5Y
1D	0.074			
1M		0.327		
1Y			0.402	
5Y				0.317

Table 4: Determinants of recalled episodes in *FreeRecall*

We regress two aspects of the recalled episode in *FreeRecall* on individual characteristics. In Columns (1) and (2), the dependent variable is distance, defined as the difference in years between December 2021 and the midpoint of the recalled episode. In Columns (3)–(5), the dependent variable is recalled episode return: the market return during the recalled episode. Columns (1) and (3) are based on the full sample while Columns (2), (4), and (5) are based on the merged sample to include experience. Age is calculated in years as of December 2021. Experience is defined as the number of years since opening the brokerage account. Wealth and income are in RMB. Often check account, Often check news, Often discuss, and Many Wechat groups are dummy variables indicating whether the investor checks accounts often, checks financial news often, discusses with others about the market often, and has at least two Wechat groups for discussing stocks. Agreeable, Extraversion, Conscientiousness, Neuroticism, and Openness represent the Big Five personality traits. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:				
	Distance		Recalled episode return		
	(1)	(2)	(3)	(4)	(5)
Age	0.11***	0.07**	0.23***	0.34***	0.25**
	(0.01)	(0.03)	(0.07)	(0.12)	(0.11)
Experience		0.19***		0.11	−0.09
		(0.04)		(0.12)	(0.13)
Distance					1.21***
					(0.21)
Female	−0.33*	0.03	−2.36**	−1.71	−1.85
	(0.19)	(0.29)	(0.94)	(1.66)	(1.62)
College	0.30**	0.53	−0.73	1.87	0.76
	(0.14)	(0.38)	(1.85)	(2.92)	(2.88)
Wealth>1M	−0.21	0.01	1.87	−3.48	−3.47
	(0.17)	(0.32)	(1.23)	(2.71)	(2.48)
Income>200K	0.36*	−0.11	0.17	6.25**	6.09*
	(0.17)	(0.39)	(1.73)	(2.83)	(2.94)
Often check account	−0.77***	−0.60**	−3.36***	−0.39	−0.23
	(0.14)	(0.23)	(0.89)	(3.45)	(3.37)
Often check news	−0.09	−0.64*	1.75	2.32	2.92
	(0.19)	(0.32)	(1.12)	(2.46)	(2.31)
Often discuss	0.18	0.60	−0.91	−1.60	−1.76
	(0.14)	(0.35)	(1.52)	(3.15)	(3.01)
Many Wechat groups	0.46***	0.29	−0.14	4.56**	4.06*
	(0.16)	(0.34)	(1.09)	(2.13)	(2.14)
Agreeableness	−0.20*	−0.02	1.11	3.29**	2.97**
	(0.11)	(0.15)	(0.98)	(1.44)	(1.39)
Extraversion	−0.15	−0.11	−1.49*	−2.62	−2.42
	(0.09)	(0.15)	(0.76)	(2.04)	(1.99)
Conscientiousness	0.03	0.03	0.71	1.27	1.22
	(0.09)	(0.15)	(1.25)	(2.09)	(2.16)
Neuroticism	0.11	−0.06	−1.21**	−2.06*	−2.00*
	(0.08)	(0.13)	(0.48)	(1.08)	(1.12)
Openness	0.06	0.15	0.11	1.33	1.19
	(0.10)	(0.10)	(0.52)	(1.11)	(1.12)
Observations	4,731	1,407	3,882	1,152	1,152
Adjusted R^2	0.08	0.14	0.04	0.05	0.07

Table 5: Determinants of recalling an extreme event in *FreeRecall*

We regress measures of recalling an extreme event in *FreeRecall* on various individual characteristics. In Columns (1) and (2), the dependent variable is a dummy variable indicating a recalled episode return of more than 100%. In Columns (3) and (4), the dependent variable is a dummy variable indicating a recalled episode return of lower than -50%. Age is calculated in years as of December 2021. Distance is defined as the difference in years between December 2021 and the midpoint of the recalled episode. Wealth and income are in RMB. Often check account, Often check news, Often discuss, and Many Wechat groups are dummy variables indicating whether the investor likes to check accounts often, checks financial news often, discusses with others about the stock market often, and has at least two Wechat groups for discussing stocks. Agreeable, Extraversion, Conscientiousness, Neuroticism, and Openness represent the Big Five personality traits. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	Recalled episode return>100%		Recalled episode return<-50%	
	(1)	(2)	(3)	(4)
Age	0.23***	0.12***	0.09**	0.04
	(0.04)	(0.03)	(0.03)	(0.04)
Distance		1.04***		0.38***
		(0.09)		(0.07)
Female	−2.51***	−2.13***	−0.79	−0.65
	(0.66)	(0.59)	(0.90)	(0.86)
College	0.22	−0.16	1.65**	1.51*
	(1.07)	(1.03)	(0.75)	(0.74)
Wealth>1M	1.83*	2.16**	0.99	1.11
	(0.99)	(0.92)	(1.10)	(1.08)
Income>200K	−1.60	−2.08*	−1.41*	−1.58*
	(1.19)	(1.20)	(0.79)	(0.82)
Often check account	−3.71***	−3.14***	1.29	1.50*
	(0.90)	(0.87)	(0.83)	(0.87)
Often check news	3.97***	4.18***	1.38	1.45
	(0.98)	(1.03)	(1.19)	(1.17)
Often discuss	−0.53	−0.61	−1.36	−1.39
	(0.96)	(0.86)	(1.01)	(1.03)
Many Wechat groups	0.52	−0.07	0.49	0.28
	(1.02)	(0.96)	(0.82)	(0.85)
Agreeableness	1.68**	1.79**	0.32	0.37
	(0.81)	(0.82)	(0.58)	(0.58)
Extraversion	−1.73***	−1.65***	0.47	0.50
	(0.45)	(0.41)	(0.55)	(0.55)
Conscientiousness	1.12	1.03	1.24**	1.20**
	(0.78)	(0.76)	(0.58)	(0.58)
Neuroticism	−1.40***	−1.48***	−0.07	−0.10
	(0.40)	(0.36)	(0.35)	(0.36)
Openness	−0.81	−0.84	−1.09**	−1.10**
	(0.60)	(0.56)	(0.43)	(0.43)
Observations	3,882	3,882	3,882	3,882
Adjusted R^2	0.05	0.10	-0.002	0.005

Table 6: Tests of cued recall in *FreeRecall*

We test similarity-based recall by regressing recalled episode return in *FreeRecall* on market return on the survey day and the past one-month return. We exclude observations in which the recalled episode ends in or after November 2021, so that the cue episode does not overlap with the recalled episode. "Market return, 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. "Market return, past month" is the market return over the 30 day before the survey was taken. 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. Panels A and B are based on the main sample and the sample in which the recalled episode ending date is within the past 5 years. We cluster standard errors at the date level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable: Recalled episode return		
	Panel A: Main sample		
	(1)	(2)	(3)
Market return, today	0.32		−0.21
	(1.35)		(1.49)
Market return, past month		−0.61	−0.57
		(0.53)	(0.58)
Observations	3,443	3,612	3,443
Adjusted R^2	0.01	0.01	0.01
	Panel B: Recalled episode end $\leq$ 5 years		
	(4)	(5)	(6)
Market return, today	2.08*		3.27***
	(1.21)		(1.16)
Market return, past month		0.86**	1.36***
		(0.41)	(0.44)
Observations	880	916	880
Adjusted R^2	0.02	0.02	0.03

Table 7: Tests of cued recall in *ProbeRecall*, using market returns as cues

We regress the recalled return of an investor's own portfolio in *ProbedRecall* on the recent market return and her actual portfolio return. "Market return, today" is the market return on the day when the survey was completed and is calculated as the cumulative return from the market opening to the minute when the investor starts to take the survey. "Market return, past month" is the market return over the 30 day before the survey was taken. "Actual return, yesterday/past month/past year" is the investor's actual portfolio return on the day before the survey was taken/over the past 30 days/over the past year. We include observations only from Tuesdays to Fridays to ensure that "yesterday" does not fall on a weekend. 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. We cluster standard errors at the date level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable: Recalled own return			
	Yesterday		Past month	
	(1)	(2)	(3)	(4)
Market return, today	0.68**	0.94**	0.99***	1.02**
	(0.28)	(0.31)	(0.37)	(0.47)
Actual own return, yesterday		0.27***		
		(0.09)		
Actual own return, past month				0.21***
				(0.02)
Observations	7,746	1,619	7,436	1,668
Adjusted R^2	0.03	0.03	0.04	0.10

	Dependent variable: Recalled own return			
	Past year			
	(5)	(6)	(7)	(8)
Market return, today	0.36		1.01	
	(0.70)		(0.66)	
Market return, past month		0.70***		0.76***
		(0.14)		(0.30)
Actual own return, past year			0.23***	0.22***
			0.01	0.01
Observations	7,762	8,387	1,881	2,104
Adjusted R^2	0.06	0.06	0.13	0.13

Table 8: Tests of cued recall in *ProbeRecall*, using investors' portfolio returns as cues

We regress the recalled return of an investor's own portfolio in *ProbedRecall* on his portfolio return on the survey day and his actual own portfolio return during the corresponding recalled period. "Actual own return, today" is the investor's own portfolio return on the day when the survey was completed. "Actual return, yesterday/past month" is the investor's actual portfolio return on the day before the survey was taken/over the past 30 days. We include observations only from Tuesdays to Fridays to ensure that "yesterday" does not fall on a weekend. 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. We cluster standard errors at the date level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable: Recalled own return	
	Yesterday	Past month
	(1)	(2)
Actual own return, today	0.16*	0.19***
	(0.08)	(0.06)
Actual own return, yesterday	0.23***	
	(0.08)	
Actual own return, past month		0.21***
		(0.02)
Observations	1,772	1,619
Adjusted R^2	0.03	0.03

Table 9: Memory and expectation in *FreeRecall*

We examine the statistical relationship between memories and expectations. The dependent variables are a respondent's expected return of the market returns or his own portfolio in the next 30 days or the next 1 year. The main independent variable is the recalled episode return during the recalled episode in *FreeRecall*. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable: Expected return			
	Market return, 1M	Market return, 1Y	Own return, 1M	Own return, 1Y
	(1)	(2)	(3)	(4)
Recalled episode return	0.004**	0.02***	0.01**	0.05***
	(0.002)	(0.004)	(0.004)	(0.01)
Observations	3,968	3,864	2,805	2,952
Adjusted R^2	0.01	0.05	0.04	0.07

Table 10: Memory and expectation in *ProbedRecall*

We examine the statistical relationship between memories and expectations. The dependent variables are respondents' expectation of market returns or of own portfolios' returns in the next 30 days or the next 1 year. The independent variables are recalled own returns over the past one month or one year in *ProbedRecall*. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable: Expected return					
	Market return, 1M			Market return, 1Y		
	(1)	(2)	(3)	(4)	(5)	(6)
Recalled own return, 1M	0.08***		0.07***	0.11***		0.07***
	(0.01)		(0.01)	(0.02)		(0.02)
Recalled own return, 1Y		0.03***	0.01***		0.07***	0.05***
		(0.003)	(0.004)		(0.01)	(0.01)
Observations	8,000	8,312	6,567	7,759	8,123	6,415
Adjusted R^2	0.04	0.03	0.04	0.05	0.06	0.06
	Dependent variable: Expected return					
	Own return, 1M			Own return, 1Y		
	(7)	(8)	(9)	(10)	(11)	(12)
Recalled own return, 1M	0.31***		0.21***	0.51***		0.13*
	(0.02)		(0.02)	(0.05)		(0.07)
Recalled own return, 1Y		0.15***	0.11***		0.40***	0.39***
		(0.01)	(0.01)		(0.03)	(0.03)
Observations	6,688	6,898	5,631	6,869	7,193	5,822
Adjusted R^2	0.11	0.11	0.14	0.09	0.12	0.12

Table 11: Horse race between actual and recalled experience in explanatory power for beliefs

We examine the statistical relationship between recalls and expectations. The dependent variables are the respondent's expectation of market returns and of own portfolio's returns in the next 30 days and in the next one year. In Panel A, the independent variables are recalled episode returns in *FreeRecall* and actual episode returns of the recalled episodes. In Panel B, the independent variables are recalled own returns in *ProbedRecall* and actual own returns during the past 30 days or one year. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

Panel A. FreeRecall.

	Dependent variable: Expected return			
	Market return, 1Y	Own return, 1Y	Market return, 1Y	Own return, 1Y
	(1)	(2)	(3)	(4)
Recalled episode return			0.02***	0.04***
			(0.004)	(0.02)
Actual episode return	0.003*	0.02**	−0.003	0.005
	(0.002)	(0.01)	(0.003)	(0.01)
Observations	3,937	3,011	3,409	2,606
Adjusted R^2	0.04	0.07	0.05	0.08

Panel B. ProbedRecall.

	Dependent variable: Expected return			
	Own return, 1M		Own return, 1Y	
	(5)	(6)	(7)	(8)
Actual own return, 1M	0.036*	−0.021		
	(0.02)	(0.02)		
Recalled own return, 1M		0.248***		
		(0.03)		
Actual own return, 1Y			0.047*	−0.031
			(0.03)	(0.03)
Recalled own return, 1Y				0.342***
				(0.03)
Observations	1,286	1,286	1,559	1,559
Adjusted R^2	0.04	0.09	0.07	0.12

Table 12: Explanatory power for cross-sectional variation in investor expectations

We regress investor beliefs on either demographic variables or recalled own returns. Each cell reports the adjusted R-squared of a regression of expected returns on recalled own returns only or on demographics fixed effects only. Expected returns are respondents' expectation of the stock market return or their own stock portfolios' return in the next 30 days or next year. In the first row, demographics fixed effects include gender, age, income, wealth, and education. In the second row, we additionally include frequency of checking stock accounts, frequency of checking news, frequency of discussing investments, and the number of Wechat group. In the third row, we report the R-square of regressing expected returns on the recalled own returns over the past window of the same length. For example, the univariate independent variable is recalled own return over the past one-month if the dependent variable is the expectation of future one-month return.

	Dependent variable: Expected return			
	Market 30 day	Market 1 year	Own 30 day	Own 1 year
	(1)	(2)	(3)	(4)
Demographics F.E. only	0.008	0.027	0.029	0.042
Expanded Demographics F.E.	0.017	0.045	0.047	0.067
Recalled own return only	0.022	0.025	0.080	0.073

Table 13: Relationship between recall and expectation as a function of time spent on the survey

The dependent variables are the respondent's expectation of market return and his or her own portfolio's return in the next 30 days or one year. Time spent to finish the survey is in minutes. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable: Expected return			
	Market 30 day	Market 1 year	Own 30 day	Own 1 year
	(1)	(2)	(3)	(4)
Recalled own return, 1M	0.08***		0.32***	
	(0.01)		(0.01)	
Recalled own return, 1M * Time spent	−0.0002		−0.0001	
	(0.001)		(0.001)	
Recalled own return, 1Y		0.07***		0.44***
		(0.01)		(0.03)
Recalled own return, 1Y * Time spent		−0.0003		−0.002
		(0.001)		(0.001)
Time spent	0.001	0.01	0.01*	0.02**
	(0.003)	(0.01)	(0.01)	(0.01)
Observations	6,077	6,199	5,090	5,508
R^2	0.12	0.14	0.21	0.21

Table 14: Recalled return and expectations across treatments

This table reports the mean of recalled episode return and recalled own return for various horizons across three treatments: *FreeRecall*, *HappyRecall*, and *PainfulRecall*. In *FreeRecall*, investors recall any episode that first comes to mind. In *HappyRecall*, investors recall a happy episode that first comes to mind. In *PainfulRecall*, investors recall a painful episode that first comes to mind.

	Mean of recalled episode return	Mean of recalled own return			
		Yesterday	Last month	Last year	Last five years
	(1)	(2)	(3)	(4)	(5)
FreeRecall	0.05	0.00	0.00	0.02	0.05
HappyRecall	0.23	0.00	0.00	0.02	0.05
PainfulRecall	-0.20	-0.01	0.00	0.02	0.03

Table 15: Recall and perceived crash probability

We regress expected crash probability on recalled own returns. During the sample period, the Shanghai Composite Index mostly hovers between 3,500 and 3,600. We have considered two 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. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable: Expected crash probability			
	One month		One year	
	(1)	(2)	(3)	(4)
Recalled own return, 1M	-0.10^{***}		-0.07^{***}	
	(0.02)		(0.01)	
Recalled own return, 1Y		-0.06^{***}		-0.04^{***}
		(0.01)		(0.01)
Observations	7,317	7,712	7,297	7,698
R^2	0.09	0.09	0.10	0.10

Table 16: Past actions and future recall

We regress recall on past trading behavior. Panels A and B are for *FreeRecall* and *ProbedRecall*, respectively. For trading behavior, we use the holding change over the previous day or the previous week relative to the survey day. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Panel A: FreeRecall							
	Dependent variable:							
	Recalled episode return				Own episode return			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Holding change, yesterday	26.98	18.52			3.74	1.54		
	(16.36)	(17.90)			(19.52)	(16.47)		
Holding change, previous week			9.01*	6.20			−2.56	−6.16
			(4.82)	(4.39)			(4.63)	(4.72)
Actual episode return		0.53***		0.51***				
		(0.04)		(0.04)				
Actual own episode return						0.40***		0.42***
						(0.08)		(0.09)
Observations	757	685	761	689	742	473	744	477
Adjusted R^2	0.02	0.32	0.02	0.31	0.05	0.10	0.05	0.10

	Panel B: ProbedRecall							
	Dependent variable: Recalled own return							
	Yesterday				Past month			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Holding change, yesterday	−0.02	−0.01			−0.001	0.002		
	(0.02)	(0.02)			(0.02)	(0.02)		
Holding change, previous week			−0.005	−0.002			−0.004	−0.001
			(0.01)	(0.01)			(0.01)	(0.01)
Actual own return, yesterday		0.35***		0.36***				
		(0.07)		(0.08)				
Actual own return, past month						0.22***		0.23***
						(0.02)		(0.02)
Observations	1,869	1,869	1,874	1,836	1,808	1,808	1,813	1,813
Adjusted R^2	0.03	0.05	0.03	0.04	0.03	0.10	0.03	0.10

Table 17: Expectations and future actions

We regress future trading behavior on return expectations. The dependent variables are the holding change on the day of the survey or in the week after the survey. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable: Holding change			
	Today	Following week	Today	Following week
	(1)	(2)	(3)	(4)
Expected own return, 1M	0.10**	0.28**	0.14**	0.48***
	(0.05)	(0.13)	(0.05)	(0.15)
Expected own return, 1Y	−0.03**	−0.07	−0.03	−0.10*
	(0.01)	(0.05)	(0.02)	(0.05)
Expected market return, 1M			−0.09	−0.3
			(0.07)	(0.32)
Expected market return, 1Y			0.02	−0.08
			(0.06)	(0.17)
Observations	1,378	1,378	1,135	1,135
Adjusted R2	0.01	0.003	0.02	0.001

Table 18: Return extrapolation and cued recall

The dependent variables are the respondent's expectation of market return or her own portfolio's return in the next 30 days. The independent variables include actual market return over the past one month, investors recalled own returns over the past month or past year. 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. We cluster standard errors at the date level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable: Expected return		
	Market return, 1M		
	(1)	(2)	(3)
Past market return, 1M	0.14**	0.10*	0.09
	(0.06)	(0.06)	(0.06)
Recalled own return, 1M		0.08***	0.07***
		(0.01)	(0.01)
Recalled own return, 1Y			0.01***
			(0.004)
Observations	7,842	7,842	6,436
Adjusted R^2	0.02	0.04	0.04

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Online Appendix for

Investor Memory and Biased Beliefs: Evidence from the Field

A Additional Empirical Results

A.1 Distribution of survey respondents

Figure A.1: Distribution of respondents by hour of the day

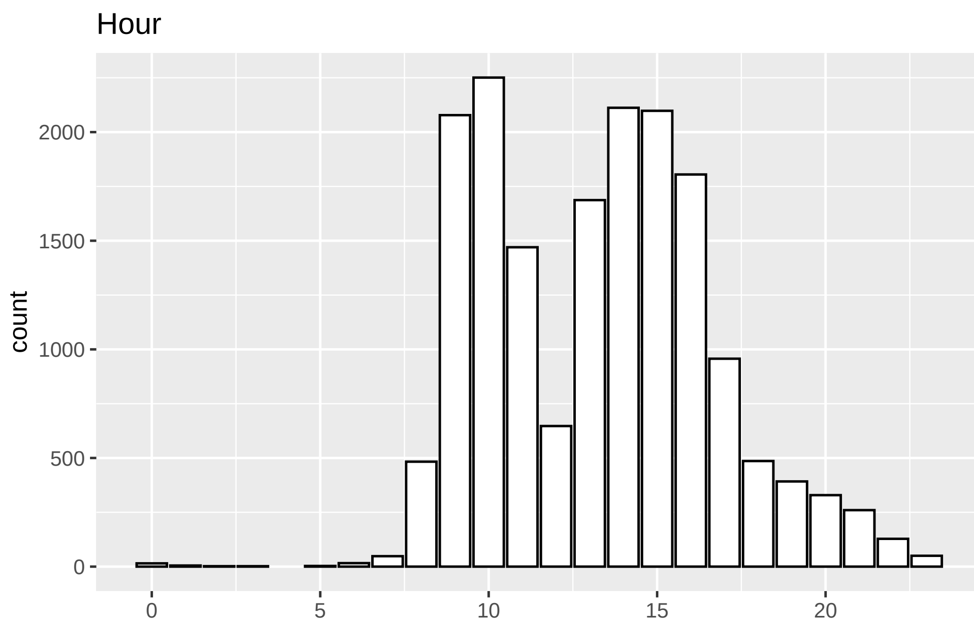
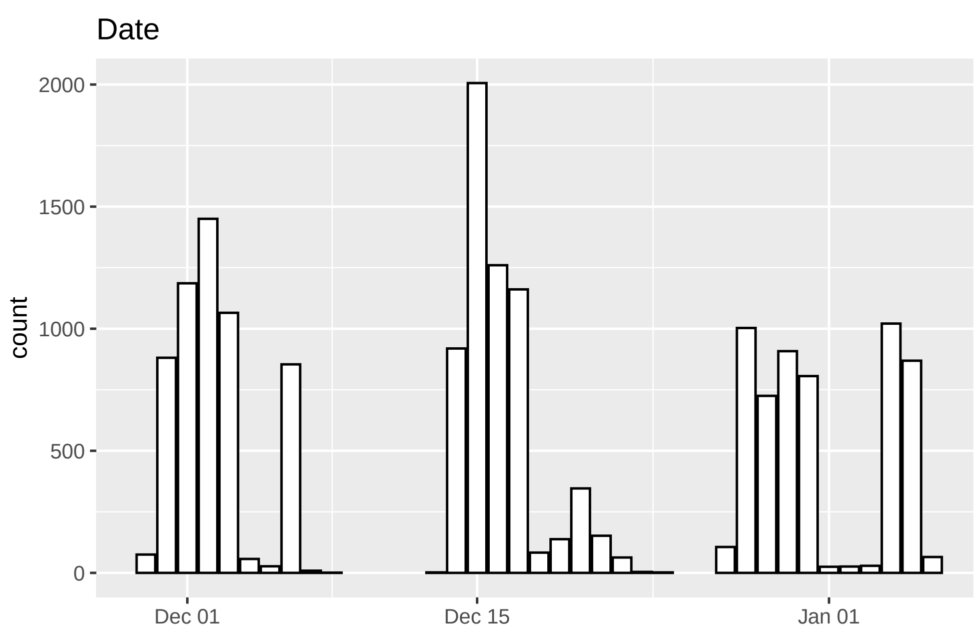


Figure A.2: Distribution of respondents by date



A.2 Characteristics of the merged and unmerged sample

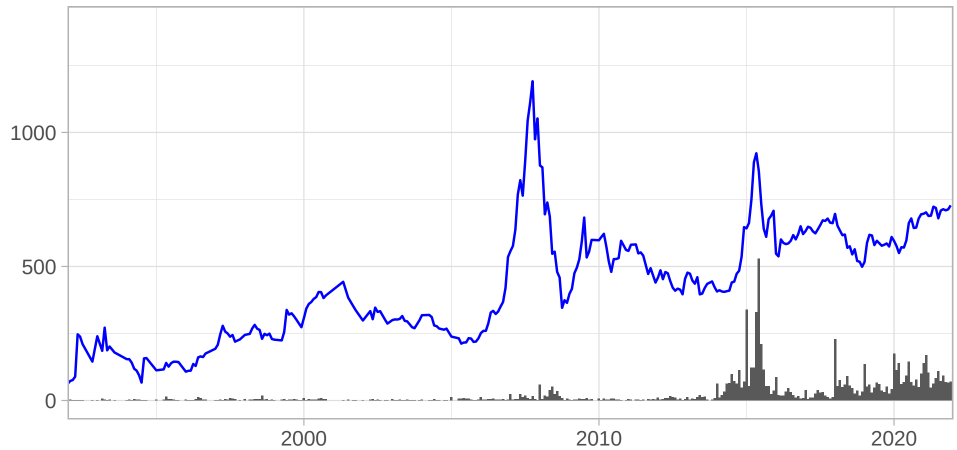
Table A.1: Characteristics of the merged and unmerged sample

This table compares characteristics between those respondents for whom we can merge their survey responses with their trading record and those for whom we fail to do so. *p<0.1; **p<0.05; ***p<0.01.

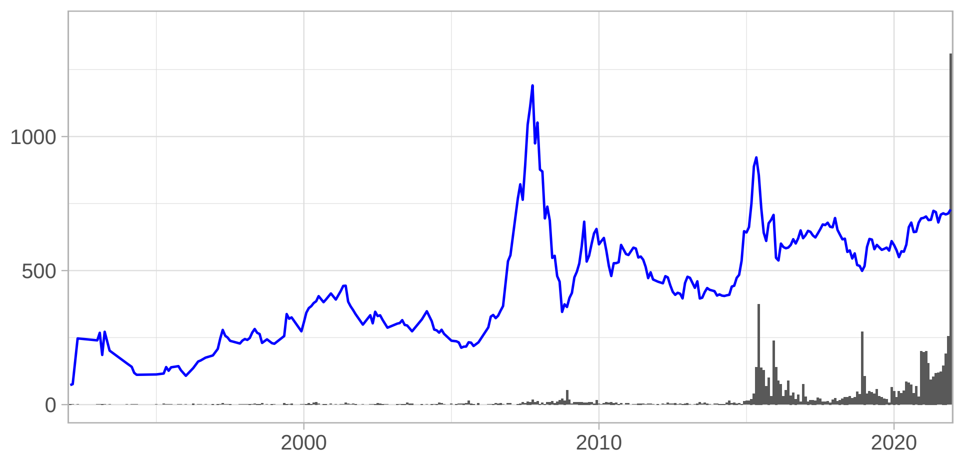
Variable	Merged	Unmerged	Difference
Age	40.62	37.77	2.85***
Female	0.45	0.45	-0.01
College	0.57	0.64	-0.07***
Wealth>1M	0.48	0.45	0.03***
Income>200K	0.61	0.61	0.00
Often check news	0.61	0.58	0.04***
Often check account	0.72	0.70	0.02***
Often discuss	0.35	0.34	0.01
Many Wechat groups	0.43	0.45	-0.02**
Agreeableness	4.35	4.31	0.03**
Conscientiousness	3.83	3.80	0.03*
Extroversion	4.47	4.42	0.05***
Neuroticism	3.31	3.36	-0.05***
Openness	4.04	4.08	-0.04**

A.3 Distribution of recalled episodes in *FreeRecall*, by age group

Figure A.3: Distribution of recalled episodes, age < 35

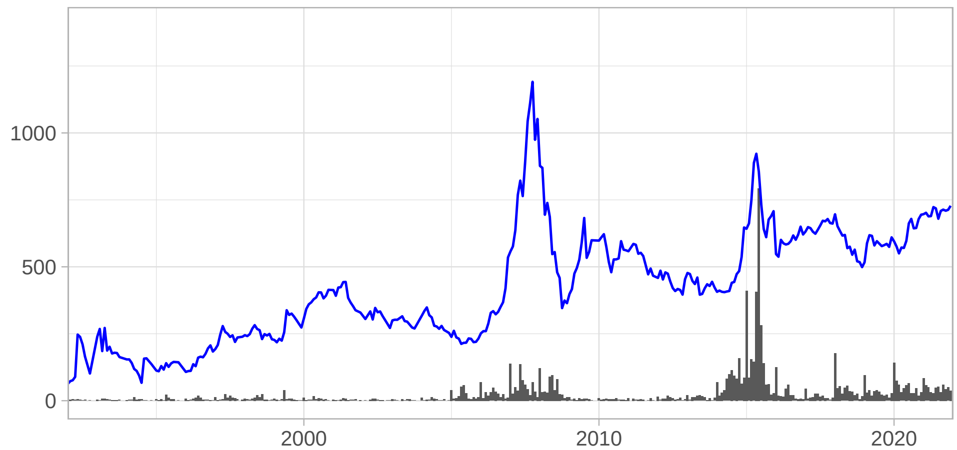


Panel (a) Distribution of start dates

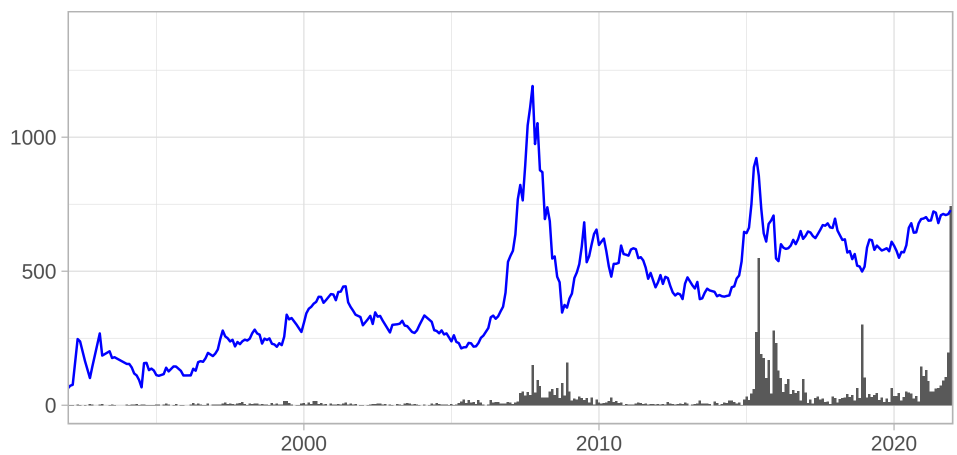


Panel (b) Distribution of end dates

Figure A.4: Distribution of recalled episodes, age ≥ 35



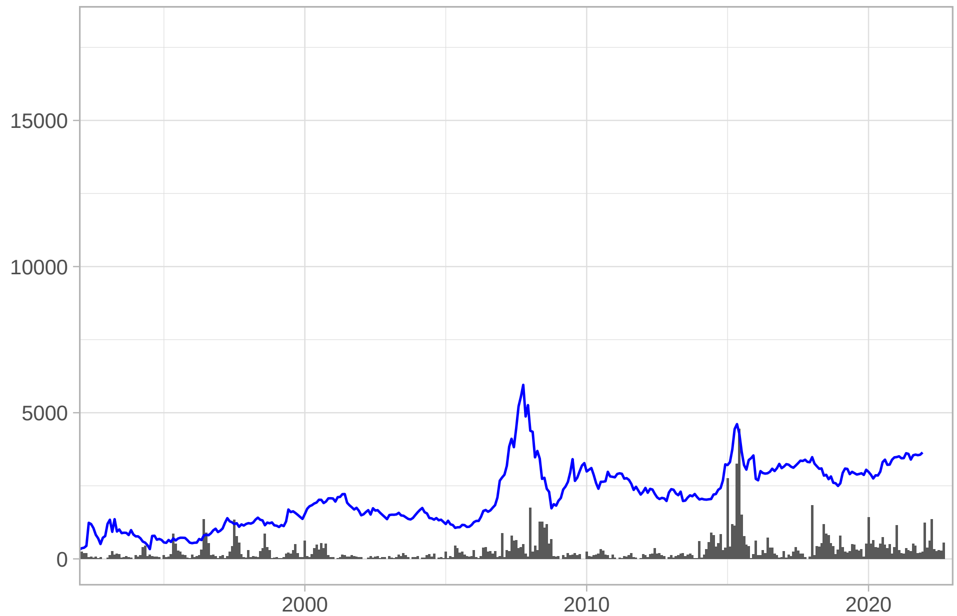
Panel (a) Distribution of start dates



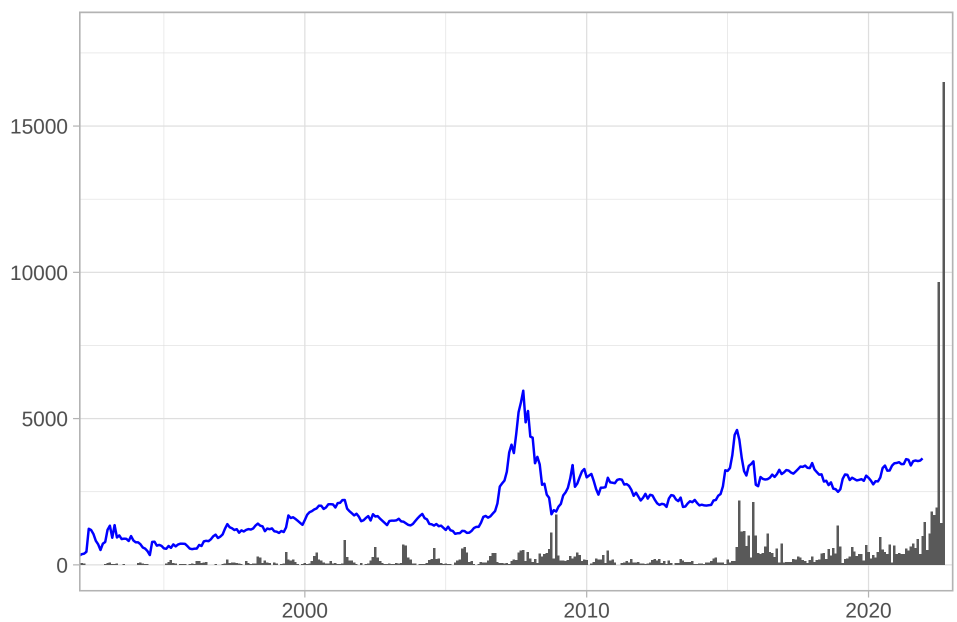
Panel (b) Distribution of end dates

A.4 Distribution of recalled episodes in *FreeRecall*, alternative phrasing

Figure A.5: Distribution of recalled episodes, alternative phrasing



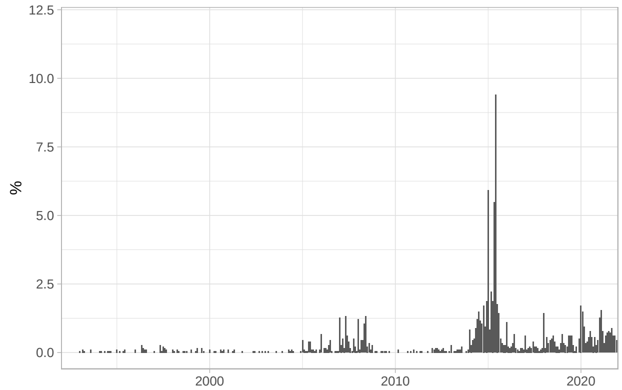
Panel (a) Distribution of start dates



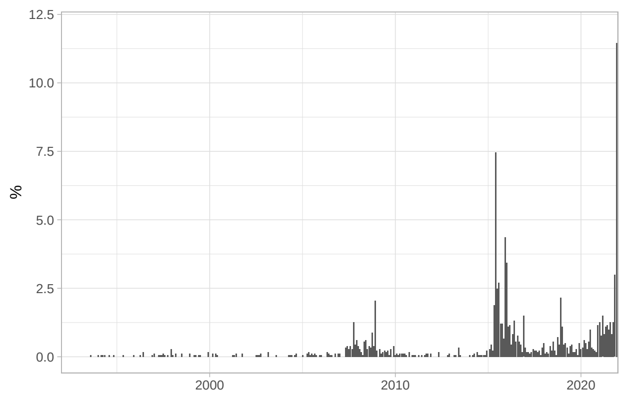
Panel (b) Distribution of end dates

A.5 Distribution of recalled episodes in *FreeRecall*, under simulation

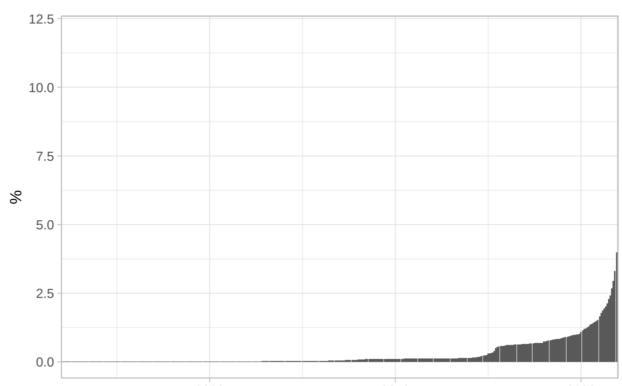
Figure A.6: Distribution of recalled episodes, counterfactual



Panel (a) Distribution of start dates



Panel (b) Distribution of end dates

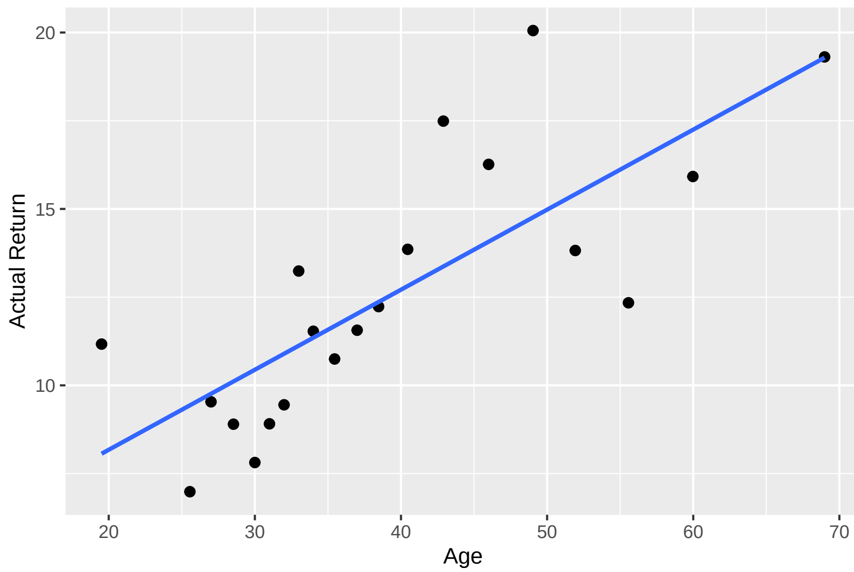


Panel (c) Distribution of simulated dates

A.6 Additional results on the age effect

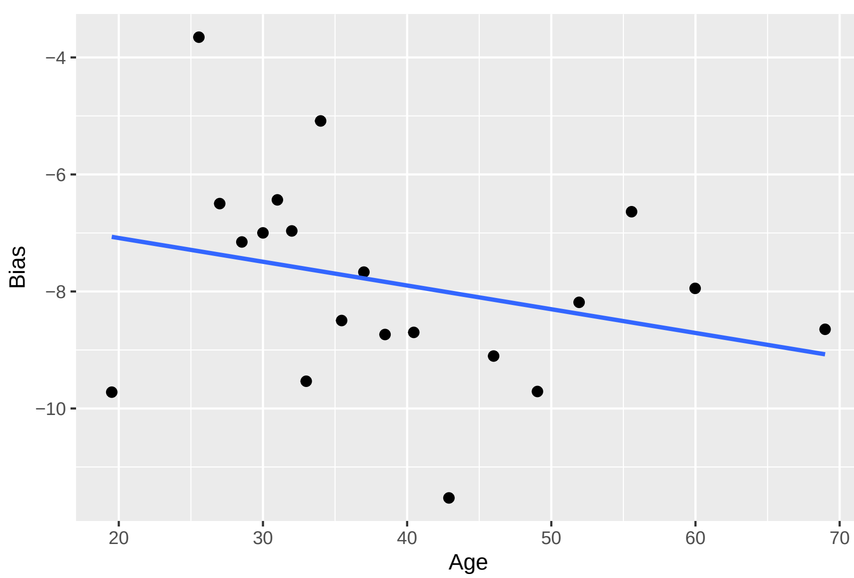
A.6.1 Actual market return

Figure A.7: Age and actual return in *FreeRecall*



A.6.2 Recall bias

Figure A.8: Age and recall bias in *FreeRecall*



A.7 Determinants of recalled episodes in *FreeRecall*, additional results

Table A.2: Determinants of recalled episodes in *FreeRecall*, additional results

This table repeats the regressions in Table 4 but includes three additional variables: monthly raw return, monthly turnover, and account size of investors' own portfolios. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	Distance		Recalled episode return	
	(1)	(2)	(3)	(4)
Age	0.14***	0.07***	0.32***	0.24**
	(0.02)	(0.02)	(0.07)	(0.09)
Experience		0.20***		−0.26
		(0.03)		(0.24)
Distance				1.23***
				(0.23)
Female	−0.53	−0.51	−2.22	−1.72
	(0.33)	(0.32)	(2.67)	(2.68)
College	0.64*	0.46	2.01	0.94
	(0.33)	(0.35)	(2.26)	(2.35)
Wealth>1M	0.01	−0.00	0.89	0.84
	(0.29)	(0.29)	(2.84)	(2.76)
Income>200K	−0.04	−0.19	−0.36	−0.15
	(0.53)	(0.50)	(3.54)	(4.03)
Often check account	−0.86***	−0.81***	−2.72	−2.16
	(0.27)	(0.28)	(3.53)	(3.45)
Often check news	0.15	0.06	1.86	2.12
	(0.29)	(0.28)	(2.04)	(2.02)
Often discuss	0.20	0.23	−1.44	−1.47
	(0.42)	(0.39)	(3.91)	(3.69)
Many Wechat groups	0.14	0.08	−1.36	−1.54
	(0.30)	(0.27)	(2.55)	(2.37)
Agreeableness	−0.41	−0.40	1.59	1.84
	(0.26)	(0.24)	(1.38)	(1.43)
Conscientiousness	0.24	0.22	1.10	0.71
	(0.27)	(0.27)	(2.37)	(2.41)
Extraversion	−0.09	−0.11	−3.55*	−3.52*
	(0.10)	(0.09)	(1.97)	(1.97)
Neuroticism	0.07	0.04	−1.83	−1.88
	(0.13)	(0.14)	(1.53)	(1.54)
Openness	0.15	0.13	0.85	0.82
	(0.15)	(0.14)	(1.68)	(1.73)
Monthly raw return	17.19**	15.79*	24.39	7.61
	(7.75)	(7.64)	(84.78)	(77.27)
Monthly turnover	−0.42**	−0.21	0.57	0.68
	(0.16)	(0.14)	(1.94)	(1.98)
Account size	0.00*	−0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,281	1,281	1,050	1,050
Adjusted R^2	0.11	0.15	0.01	0.03

Table A.3: Determinants of recalling an extreme event in *FreeRecall*

We regress measures of recalling an extreme event in *FreeRecall* on individual characteristics. In Columns (1) and (2), the dependent variable is a dummy indicating a market rise of more than 100%. In Columns (3) and (4), the dependent variable is a dummy indicating a market crash of falling more than 50%. Age is calculated in years as of December 2021. Distance is defined as the difference in years between December 2021 and the midpoint of the recalled episode. Wealth and income are in RMB. Often check account, Often check news, Often discuss, and Many Wechat groups are dummy variables indicating whether the investor likes to check accounts often, checks financial news often, discusses with others about the stock market often, and has at least two Wechat groups for discussing stocks. Agreeable, Extraversion, Conscientiousness, Neuroticism, and Openness represent the Big Five personality traits. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	Actual market return>100%		Actual market return<-30%	
	(1)	(2)	(3)	(4)
Age	0.21***	0.03	0.13**	0.08
	(0.04)	(0.04)	(0.06)	(0.06)
Distance		1.70***		0.50***
		(0.06)		(0.10)
Female	−0.94	−0.43	0.25	0.41
	(1.11)	(0.92)	(1.11)	(1.09)
College	−0.55	−1.12	−0.84	−1.01
	(0.83)	(0.74)	(1.22)	(1.24)
Wealth>1M	−0.70	−0.13	1.81	1.98
	(1.14)	(0.99)	(1.28)	(1.24)
Income>200K	1.25	0.60	−0.57	−0.76
	(1.16)	(1.04)	(1.27)	(1.27)
Often check account	−2.52**	−1.35	−1.50	−1.15
	(0.92)	(0.86)	(1.44)	(1.44)
Often check news	−0.17	−0.11	4.67**	4.69**
	(1.08)	(0.99)	(1.93)	(1.97)
Often discuss	0.94	0.43	−1.79	−1.94
	(1.25)	(1.09)	(1.30)	(1.30)
Many Wechat groups	1.29	0.49	0.18	−0.05
	(1.05)	(1.15)	(1.06)	(1.08)
Agreeableness	−1.57**	−1.20*	3.80***	3.90***
	(0.62)	(0.64)	(0.75)	(0.74)
Extraversion	−0.38	−0.16	−0.22	−0.16
	(0.48)	(0.51)	(0.90)	(0.90)
Conscientiousness	1.33	1.41*	−2.90***	−2.88***
	(0.79)	(0.73)	(0.88)	(0.87)
Neuroticism	−0.11	−0.29	−0.78*	−0.84*
	(0.32)	(0.34)	(0.39)	(0.41)
Openness	0.38	0.12	−1.30**	−1.37**
	(0.53)	(0.47)	(0.62)	(0.65)
Observations	4,148	4,148	4,148	4,148
Adjusted R^2	0.02	0.14	0.003	0.01

A.8 Additional results on cued recall, *ProbedRecall*

Table A.4: Recalled own return and market return as a cue, subsample

We regress recalled own return on past market returns in the subsample of neutral emotion cue. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:					
	Recalled own return, 1D					
	(1)	(2)	(3)	(4)	(5)	(6)
Market return today	0.68**	0.52*	0.71***	0.38	0.23	−0.17
	(0.28)	(0.29)	(0.23)	(0.29)	(0.39)	(0.49)
Market return today * age > 35		0.31				0.21
		(0.25)				(0.25)
Market return today * Female			−0.08			−0.01
			(0.25)			(0.27)
Market return today * Account checking				0.45***		0.38*
				(0.16)		(0.22)
Market return today * News checking					0.60**	0.49
					(0.27)	(0.32)
Market return today * Discussion						−0.46*
						(0.24)
Market return today * Social groups						−0.24
						(0.35)
Market return today * College						−0.10
						(0.20)
Market return today * Wealth > 1M						0.67***
						(0.19)
Market return today * Income > 200K						0.45*
						(0.27)
Observations	7,746	7,746	7,746	7,746	7,746	7,746
R^2	0.04	0.04	0.04	0.04	0.04	0.05
Adjusted R^2	0.03	0.03	0.03	0.03	0.03	0.03
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A.5: Recalled own return and market return as a cue, subsample

We regress recalled own return on past market returns in the subsample of neutral emotion cue. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:					
	Recalled own return, 1M					
	(1)	(2)	(3)	(4)	(5)	(6)
Market return today	1.31***	1.41**	1.39***	0.84	0.69	0.03
	(0.48)	(0.56)	(0.43)	(0.56)	(0.47)	(0.53)
Market return today * age > 35		−0.18				−0.12
		(0.46)				(0.44)
Market return today * Female			−0.18			−0.02
			(0.39)			(0.36)
Market return today * Account checking				0.72**		0.57
				(0.32)		(0.40)
Market return today * News checking					0.82***	0.55*
					(0.20)	(0.32)
Market return today * Discussion						−0.36
						(0.33)
Market return today * Social groups						−0.49**
						(0.23)
Market return today * College						0.58
						(0.40)
Market return today * Wealth > 1M						1.23***
						(0.32)
Market return today * Income > 200K						0.22
						(0.32)
Observations	7,436	7,436	7,436	7,436	7,436	7,436
R^2	0.06	0.06	0.06	0.06	0.06	0.06
Adjusted R^2	0.04	0.04	0.04	0.04	0.04	0.04

Note: *p<0.1; **p<0.05; ***p<0.01

A.9 Other cues

Our media cue measure is constructed based on the data we purchased from Datago Inc. Datago has been compiling news articles from an extensive list of financial news media in China starting from the year 2000. Given the digitized nature of the financial media, we focus on the online media which provide more timely coverage of market movements. Specifically, we consider news articles from the 15 most popular online financial news media.

Datago labels each article as individual-stock-related, stock-market-related, or non-stock-related. When an article is about an individual stock, Datago assigns a relevance score ranging from zero (the least relevant) to one (the most relevant). We restrict the sample to only individual-stock-related articles with a relevance score higher than 0.5 or general-market-related articles. To construct the media cue an investor has experienced on the survey day, we first count the total number of up words and down words that appeared in the articles published from the beginning of the day to the minute when the investor starts to take the survey; this follows a similar process of how we construct the return cue. We then define the media cue as the log ratio between the number of up words and down words.

In unreported results, we also consider each word individually, and the results are similar.

Table A.6: Media cues in *FreeRecall* and *ProbedRecall*

We examine the statistical relationship between cues and recall biases. The dependent variables are a respondent's reported recalled return minus the actual return. The independent variables are the intraday market return and a measure of the media cue defined as the log ratio between the numbers of positive and negative words on online forum. 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:		
	Recalled episode return	Recalled own return, yesterday	Recalled own return, 1 Month
	(1)	(2)	(3)
Media cue, today	0.38	−0.69	0.52
	(1.20)	(0.77)	(1.02)
Market return, today	2.66***	0.77***	0.92**
	(0.80)	(0.25)	(0.39)
Observations	9,174	7,746	7,436
R^2	0.02	0.04	0.05
Adjusted R^2	0.01	0.03	0.04

A.10 Additional results using forecast errors

A.10.1 *FreeRecall*

Table A.7: Memory and forecast errors in *FreeRecall*

We examine the statistical relationship between memories and forecast errors. The dependent variables are a respondent's expected return of the market returns or his own portfolio in the next 30 days or in the next 1 year, minus the actual market return over the next 30 days in next 1 year. The main independent variable is the recalled market return during the recalled episode in *FreeRecall*. 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. We cluster standard errors at the date level. *p$<$0.1; **p$<$0.05; ***p$<$0.01.

	Dependent variable: forecast error	
	Market 30 day	Market 1 year
	(1)	(2)
Recalled episode return	0.004^{**}	0.02^{***}
	(0.002)	(0.004)
Observations	3,867	3,765
R^2	0.04	0.09
Adjusted R^2	0.01	0.05

A.10.2 ***ProbedRecall***

Table A.8: Memory and forecast errors in *ProbedRecall*

We examine the statistical relationship between memories and forecast errors. The dependent variables are a respondent's expectation of market returns in the next 30 days and in the next 1 year minus the actual market return over the next 30 days in next 1 year. The independent variables are recalled own returns in *ProbedRecall.* 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. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable: Forecast error					
	Market return, 1M			Market return, 1Y		
	(1)	(2)	(3)	(4)	(5)	(6)
Recalled own return, 1M	0.04**		0.03	0.08***		0.03
	(0.02)		(0.02)	(0.03)		(0.03)
Recalled own return, 1Y		0.03***	0.02***		0.06***	0.06***
		(0.004)	(0.01)		(0.01)	(0.01)
Observations	7,842	8,136	6,436	7,602	7,952	6,287
R^2	0.04	0.04	0.04	0.06	0.07	0.08
Adjusted R^2	0.02	0.02	0.02	0.05	0.06	0.06

A.11 Additional results on R^2

Table A.9: Probed recall and expected return, R^2 comparison

We report the R^2 (1 means 100%) from the following specifications. Column (1) regresses the investor's expected return on the date times province fixed effects. Column (2) includes the date times province fixed effects and the investor's probed recall of the past 1-month return as explanatory variables. Column (3) includes the date times province fixed effects and the investor's probed recall of the past 1-year return as explanatory variables.

	(1)	(2)	(3)
Dependent Variable	Date×Province f.e.	+1M Recall	+1Y Recall
1M Expected Return	0.06	0.10	0.09
1Y Expected Return	0.06	0.10	0.11

B Selective recall and overconfidence

The theory literature has long suggested the potential connection between selective recall and overconfidence (Bénabou and Tirole, 2002, 2004). Recent literature has uncovered supportive evidence. In the lab, Zimmermann (2020) finds that positive feedback has a long-lasting effect on people's beliefs while negative feedback has only a temporary effect; Gödker et al. (2021) find that individuals over-remember positive investment outcomes and under-remember negative ones. In the field, Huffman et al. (2022) find a positive correlation between overconfidence and selective recall in the cross-section of managers.

We bring similar evidence from the field using a large sample of retail investors, which is complementary to the evidence accumulated in the lab and the field as discussed above. In Table A.10, we regress measures of overconfidence on recalled return in *FreeRecall*. We consider two measures of overconfidence: the difference between expected own return and expected market return and the subjective perception of one's own information advantage. As discussed in Liu et al. (2022), the first measure captures overplacement of one's skill while the second captures overprecision of one's own information.

In Table A.10, Column (1) shows a positive correlation between overconfidence and recalled return in *FreeRecall*; investors who tend to recall a more bullish episode are also more likely to be overconfident. Column (2) decomposes the recalled return into two components: the actual episode return and the bias, defined as the difference between recalled return and actual return. Column (2) shows that overconfidence is primarily driven by the bias component of recalled return. Columns (3) and (4) repeat these exercises and show that recalled return in *FreeRecall* is also positively correlated with perceived information advantage.

Table A.10: Selective recall and overconfidence

We examine the relationship between investors' recalled experiences and measures of their overconfidence level. The independent variables are investors' recalled episode return in the *FreeRecall* block and actual episode return—the actual market return over the recalled episode. The dependent variables are a respondents' expected outperformance (defined as the difference between their expected returns of their own portfolios and the market) and their self-reported information advantage. 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. We cluster standard errors at the date level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable:			
	Expected outperformance, 1M		Perceived information advantage	
	(1)	(2)	(3)	(4)
Recalled episode return	0.01*		0.001**	
	(0.005)		(0.0005)	
Actual episode return		0.01		0.001
		(0.005)		(0.001)
Bias		0.01**		0.002***
		(0.005)		(0.001)
Observations	2,183	2,183	3,743	3,743
R^2	0.08	0.08	0.13	0.13

C Proof of Theoretical Results

The PDF of the database for period t is

$$f(r_t) = \frac{1}{2\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{r_t - \mu}{\sigma}\right)^2\right). \tag{A1}$$

Substituting the above expression and (3) into (2), we obtain

$$s^*(r_t, r_T) = \frac{\sigma}{\sigma_q} \exp\left(-\frac{(r_t - r_T)^2}{2\sigma_\epsilon^2} + \frac{(\mu_t - r_T)^2}{2(\sigma^2 + \sigma_\epsilon^2)}\right). \tag{A2}$$

Substituting the above equation and (A1) into (1), after some algebra, we obtain

$$f^*(r_t) = \frac{1}{2\sigma_q\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{(1-\alpha)\mu + \alpha r_T - r_t}{\sigma_q}\right)^2\right), \tag{A3}$$

which is the PDF for a normal distribution with a mean of $(1-\alpha)\mu + \alpha r_T$ and variance of σ_q^2.

This PDF is the same as that of the posterior belief from the following Bayesian updating: the investor has prior belief about, $r_t \sim N(\mu, \sigma^2)$, and treats r_T as a "signal" of r_t: $r_T = r_t + \epsilon$, with $\epsilon \sim N(0, \sigma_\epsilon^2)$. Suppose she follows the Bayes' rule to obtain her posterior belief. The PDF of her posterior belief is identical to the one in (A3).

D Extrapolation regression

Suppose that the true data generating process is the following

$$E_t[r_{t+1}] = \alpha + \beta M_t[r_t] + \epsilon_t, \tag{A4}$$

$$M_t[r_t] = \gamma + \delta r_t + \eta_t, \tag{A5}$$

where r_t is the return in period t, $M_t[r_t]$ is the memory of r_t at the end of in period t, $E_t[r_{t+1}]$ is the expectation, formed at the end of period t, of the return at time in period $t+1$, ϵ_t and η_t are error terms and independent of each other, α, $\beta > 0$, γ and $\delta > 0$ are constants. That is, (A4) implies that expectations are formed based on memory and a higher recalled return leads to a higher expected return, (A5) implies that memory $M_t[r_t]$ is formed based on the realized return r_t and a higher realized return leads a higher recalled returns.

Suppose that we run an "extrapolation regression," that is, we regress $E_t[r_{t+1}]$ on r_t. The coefficient of r_t should be positive, because (A4) and (A5) imply

$$E_t[r_{t+1}] = \alpha + \beta\gamma + (\beta\delta)r_t + \epsilon_t + \beta\eta_t. \tag{A6}$$

Hence, the coefficient of r_t, $\beta\delta > 0$, is positive.

Suppose we regress $E_t[r_{t+1}]$ on both $M_t[r_t]$ and r_t:

$$E_t[r_{t+1}] = \lambda + \kappa M_t[r_t] + \theta r_t + \xi_t. \tag{A7}$$

We will have the population regression coefficients: $\kappa = \beta$ and $\theta = 0$.

Proof: (A5) implies that the residual from regressing $M_t[r_t]$ on r_t is η_t. From the regression anatomy formula, we obtain the population regression coefficient κ as

$$\kappa = Cov(E_t[r_{t+1}], \eta_t)/Var(\eta_t) = Cov((\epsilon_t + \beta\eta_t), \eta_t)/Var(\eta_t) = \beta. \tag{A8}$$

Let ω_t be the residual from regressing r_t on $M_t[r_t]$.

$$\theta = Cov(E_t[r_{t+1}], \omega_t)/Var(\omega_t) = Cov((\epsilon_t + \beta\eta_t), \omega_t)/Var(\omega_t). \tag{A9}$$

By construction, ω_t is independent of $M_t[r_t]$. Therefore, $Cov((\epsilon_t + \beta\eta_t), \omega_t) = 0$ and hence $\theta = 0$.