Investor Memory and Biased Beliefs: Evidence from the Field*

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Abstract

We survey a large representative sample of retail investors to elicit their memories of stock market investment and return expectations. We then 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 and use them to form return expectations. Our analysis uncovers new stylized facts about investor memory and provides support for similarity-based recall as a key mechanism of belief formation. We document that market fluctuations affect investors' recall process: when returns are high, investors tend to retrieve past episodes of rising markets and recall past performances more positively. Retrieved memories, in turn, have large explanatory power for cross-investor variation in beliefs: a single variable based on recalled performance has explanatory power for return expectations similar to that of a dozen individual characteristics combined. Recalled past returns also drive out the explanatory power of realized past returns for expected future returns, which provides a memory-based foundation for return extrapolation behaviors.

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1 Introduction

Beliefs are key to economic decisions. In most models, beliefs and preferences are the two essential ingredients shaping an individual's decision-making process. When modeling beliefs, traditional models typically assume full information rational expectations (FIRE) whereby the agent uses all relevant information to form expectations. Recent evidence based on surveys, however, has challenged FIRE by documenting such deviations as underreaction to news at the consensus level (Coibion and Gorodnichenko, 2015), overreaction to news at the individual level (Bordalo et al., 2020b), extrapolative beliefs (Greenwood and Shleifer, 2014), and overconfidence (Liu et al., 2022). In parallel with the growing evidence from survey expectations, it has been increasingly recognized that biased beliefs are not meaningless errors stemming from mismeasurement or misreporting. Rather, they affect equity holdings and trading volume (Giglio et al., 2021; Liu et al., 2022) and have direct implications for both asset prices and the macroeconomy (e.g., Barberis et al., 2015; Bordalo et al., 2020a; Maxted, 2020).

While deviations from FIRE have been extensively documented, the underlying mechanisms driving such deviations are less well understood. In some accounts, beliefs are biased because the human mind is inherently flawed and prone to mistakes; in other accounts, imperfections arise because investors do not have or cannot process all relevant information, are inattentive due to cognitive limits, or are constrained by institutional frictions.[1] A budding 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., 2021a, 2022b; Wachter and Kahana, 2021; Nagel and Xu, 2022). In these models, two features of the memory system have stood out. First, memory is limited and selective. Not all experiences enter memory and not all memories are retrieved for use in any given point. Second, because of the associative nature of memory, its retrieval is often cued by environmental stimuli such as context, emotion, and narratives. In parallel with these theoretical developments, recent papers have examined these two features of memory in the lab or through surveys (Zimmermann, 2020; Colonnelli et al., 2021; Gödker et al., 2021; Enke et al., 2022). However, there has been little evidence yet from the field on the structure of investor memory and its connections with belief formation.[2]

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

[2] For example, when reviewing the evidence on the experience effect, Malmendier and Wachter (2021) state that

In this paper, we provide new field evidence to shed light on the relationship between memory and beliefs. Compared to the settings of existing surveys and experiments, ours is closer to everyday decision-making in several important dimensions. First, we study investors actively trading in a large market, some of whom have millions of dollars invested in stocks. Second, we are concerned with memories particularly relevant to investment decisions: recollections of past trading experiences such as marketwide events and one's own returns. Third, when studying the associative nature of memory, instead of solely relying on cues given by experimenters, we examine cues that occur naturally in financial markets—namely, stock returns—and see how they affect investors' recall. Fourth, by observing actual transactions for a subset of our investor sample, we can compare their memories of past trading experiences to their actual experiences.

To structure our empirical exercise, we first present a memory-based model of belief formation based on Bordalo et al. (2022a). In the model, an investor has accumulated a database of experiences in the stock market, and she forecasts future market returns in two steps. In the first step, called *recall*, she retrieves past experiences in the presence of a cue. The cue affects recall according to the rule of similarity: experiences similar to the present cue are more likely to be retrieved. While many environmental stimuli can act as cues in general settings, perhaps the most ubiquitous stimulus in financial markets is return. Investors may not be paying attention to macroeconomic or corporate news all the time, but a rising market or a profit in one's brokerage account is noticeable and can easily remind the investor of similar experiences in the past.

When recent return is the cue at present, similarity-based recall leads to the model's first two results: (1) positive returns trigger the recall of past experiences associated with positive returns, and (2) this cued effect is stronger for the retrieval of more recent experiences. In the second step, called *simulation*, the investor uses the retrieved experiences to simulate a return distribution for the future and makes forecasts accordingly. Combined with cued recall, simulation leads to the third result, namely return extrapolation: seeing good returns makes an investor more optimistic about returns in the future.

To test the model, we survey a nationally representative sample of over 15,000 Chinese indi-

"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."

vidual investors—our main sample. 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) report the market return during that episode based on their recollection. As its name suggests, this block mirrors in design the well-established experimental paradigm of free recall to capture the market event that an investor immediately thinks of when looking back at past trading experiences (e.g., Murdock, 1962; Kahana, 2012). In economic studies, the notion of using retrieved experiences to make decisions also underlies models of salience, selective recall, and experience effects (Gennaioli and Shleifer, 2010; Malmendier and Nagel, 2011; Bordalo et al., 2012; Malmendier and Nagel, 2016; Bordalo et al., 2020c, 2022b). Given the nature of the *FreeRecall* block, our survey always starts with it to minimize the effects of other cues in the survey environment.

The second block, *ProbedRecall*, asks investors to recall their performance in the stock market over a given horizon which ranges from "yesterday" to "the past five years." This block is motivated by theories of biased learning in financial markets (e.g., Gervais and Odean, 2001) and of motivated reasoning (e.g., Bénabou and Tirole, 2002, 2004) and is designed to measure how an investor's own past performances—rather than movements of the entire market—are stored in memory. The survey also includes blocks to collect other information, such as expectations of future market returns, future self-performance, future crash probabilities, the Big Five personality traits, measures of social activities, and other demographic variables. For more than a quarter of our main sample, we can merge their survey data with their administrative data of comprehensive transaction records from the Shenzhen Stock Exchange (SZSE); these investors make up the merged sample.

With these data in hand, we first confirm that the elicited memories are valid. In the *FreeRecall* block, where investors report a recalled return for the episode that first comes to mind, the correlation between the recalled return and the actual return is 0.53. In the *ProbedRecall* block, the correlation between the recalled performance and the actual performance during the last year is 0.40. These large correlations confirm that our respondents are indeed making a conscious effort in the recall tasks.

Next, we uncover new stylized facts about investor memory and relate them to existing theories of memory and beliefs. For example, in *FreeRecall*, consistent with the recency effect in free recall experiments (Murdock, 1962), investors are drawn to recent events when recalling past market episodes, this recency effect being stronger among younger investors. This recall structure provides empirical support for the formulation in models of experience effects (Malmendier and Nagel, 2011; Malmendier et al., 2020). However, the probability of recalling an event is not monotonically decreasing in the time elapsed since the event. Investors, especially those who are older and have stayed in the market longer, are also drawn to distant events featuring dramatic market movements, such as past stock market bubbles and crashes in 2007–08 and in 2014–15.[3] Moreover, we find a strong age effect: older investors tend to recall episodes featuring rising markets, even after controlling for trading experience.

After documenting facts about investor memory without imposing any model structure, we move on to test the first part of our model, *recall*, by linking the dynamics of recall to market fluctuations. Because each investor only takes our survey once, our analysis relies on between-investor variation in their experienced returns. To ensure sufficient variation in market conditions, we conduct the survey in three waves spanning six weeks. Our analysis focuses on how both today's market return—from the market open to the point when an investor takes the survey—and past market returns affect investors' retrieved memories.

Overall, consistent with the model, recent returns affect investor recall, but *only when* the retrieved memory is concerning a recent experience. In the *FreeRecall* block, among investors whose recalled episode falls within the past five years, recent returns influence recalled returns: a one-percentage-point increase in today's market return is associated with a 2.1- to 3.6-percentage-point increase in the return of the recalled episode. When we replace today's return with the past one-month return, this sensitivity remains significant at between 1.1 and 1.6 percentage points. In comparison, if the recalled episode goes beyond the past five years, recent market returns have little impact on the recalled episode's return.

A similar dichotomy emerges for the *ProbedRecall* block. When today's market return goes up by one percentage point, this external cue increases an investor's memory of his or her yesterday's performance by, on average, 0.68 percentage point. After controlling for the investor's actual performance, we find that this cue effect induces biased memory: high recent returns lead to

[3] Concentrated recalls of rare but salient events are reminiscent of the word-frequency effect, which refers to the phenomenon that recognizable and rare words (e.g., heteroskedasticity) are easier to recall in memory research.

overly rosy recall of recent performance. In contrast, when the same investor is asked to recall her performance over a longer horizon, such as the past year, the correlation between today's return and recalled performance disappears.

We proceed to test the second part of the model, *simulation*, by examining the empirical relationship between retrieved experiences and beliefs. For both recall tasks in our survey, memories are highly correlated with expectations, even after controlling for an exhaustive list of demographic variables and other investor characteristics. In the *FreeRecall* block, a one-standard-deviation increase in the recalled episode return is associated with a 0.8-percentage-point increase in expected market return and a 1.6-percentage-point increase in expected self-performance over the next year. In the *ProbedRecall* block, a one-standard-deviation increase in recalled performance over the last year is associated with a 0.9-percentage-point increase in expected market return and a 5.5-percentage-point increase in expected self-performance over the next year.

A more striking finding is the quantitative importance of investor memory in explaining cross-sectional variation in beliefs. Giglio et al. (2021) put forward the following empirical puzzle: an exhaustive list of demographic variables combined can only generate a low *R*-squared when explaining heterogeneity in return expectations. We show that, on average, a single variable based on recalled past performance has stronger explanatory power, measured by *R*-squared, than that of an exhaustive list of individual characteristics combined. This strong correlation between memories and beliefs does not imply causality, but the large explanatory power for beliefs further reinforces a memory-based channel. Furthermore, using additional treatments and further analyses, we rule out other explanations such as anchoring.

Lastly, we examine the extent to which similarity-based recall can explain 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 controlling for recalled performance, suggesting that cued recall is an important channel driving return extrapolation. In other words, even after conditioning on experiencing the same actual past return, investors who report higher recalled returns tend to have more optimistic expectations of future returns. Moreover, consistent with existing evidence from the lab and in the field, we also document that biased recall is associated with measures of overconfidence (Zimmermann, 2020; Gödker et al., 2021; Huffman et al., 2022).

Recent work has investigated the role of memory in belief formation, using both theory models and experiments (e.g., Mullainathan, 2002; Enke et al., 2020; Zimmermann, 2020; Bordalo et al., 2021a, 2022b; Colonnelli et al., 2021; Gödker et al., 2021; Wachter and Kahana, 2021). The mechanism we focus on in this paper, namely similarity-based recall, has been examined both theoretically and experimentally. The evidence we present broadens the scope of this mechanism by confirming their relevance in the field. In a setting where the stakes are much higher, the information environment is more complex, and participants are more sophisticated and financially motivated, we confirm that the mechanism is at work and has important implications for belief formation and investor behavior. In this regard, our paper is related to Huffman et al. (2022), which analyzes the relation between memory and overconfidence for store managers of a food and beverage company.

Our stylized facts on investor memory support the formulation of the experience effect in Malmendier and Nagel (2011, 2016) and Malmendier et al. (2020) in two ways. First, there is a strong recency effect. Second, young and old investors display rather different memory structures. We further demonstrate that recall is not merely a function of time; it is also determined by the features of the events; salient events featuring large run-ups and crashes are more likely to be recalled, consistent with the prediction from (Wachter and Kahana, 2021).

Our results on the recall process confirm that, in the setting of financial markets, return is a salient cue affecting an investor's recall process. More generally, these results provide empirical support for similarity-based models of recall and belief formation. Furthermore, we provide guidance on what kinds of experience are more responsive to cues. In our analysis, returns from today and from the past month can only affect the recall of relatively recent experiences (e.g., up to five years ago). Recall of more distant memories about the financial markets is less likely to be affected. We also link similarity-based recall with return extrapolation. Our evidence is consistent with the view that return extrapolation operates through investor recall and has a memory root, as formulated in memory-based models of representativeness (Bordalo et al., 2021a, 2022b).

The strong and robust relationship between retrieved memories and beliefs confirms investors tend to rely on their memories to imagine about the future, consistent with the simulation process of belief formation. Moreover, these results also have implications for understanding the sources of belief heterogeneity. In this regard, we also speak to the literature of investor heterogeneity by proposing that memory can help shed light on the amount of belief heterogeneity observed in the market (Jiang et al., 2020; Giglio et al., 2021). From a methodological point of view, our paper is related to a growing body of literature that combines survey data with observational data (Giglio et al., 2021; Liu et al., 2022). Previous papers use surveys to collect investors' expectations and trading motives. We, however, collect investors' recall of past trading experiences and merge it with expectations and actual trading behaviors.

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

2.1.1 Selective memory

In models of full information rational expectations (FIRE), agents can fully recall and access all past information before making decisions. Self-reflection and introspection, however, would immediately suggest that, in reality, human memory is far from perfect. First, not all experiences enter memory. For instance, the process of rehearsal—that is, repeating information over and over—is often required for the information to enter long-term memory (Baddeley and Hitch, 1974; Baddeley, 1983). Second, not all experiences in memory are retrieved for use at any given point in time. People often engage in "selective recall," which entails remembering a small set of past experiences and using these experiences to guide decision-making.

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. In the classic experimental paradigm of free recall, participants first study a list of items and then are prompted to recall the items in any order. Overall, the last few items on the list are more likely to be recalled correctly. This recency bias has motivated, for example, the formulation used in extrapolative models (Barberis et al., 2015, 2018; Jin and Sui, 2022; Liao et al., 2022) and models of experience effects (Malmendier and Nagel, 2011, 2016; Malmendier et al., 2020).

The second force is motivated reasoning, which builds on the premise that people have an incentive to maintain a positive self-view (Brunnermeier and Parker, 2005; Köszegi, 2006). For example, the vast majority of retail investors believe that their performance is above average. This overly rosy self-image can be achieved, for example, through actively focusing on the more positive experiences. When an investor experiences both good and bad returns, but selectively remembers the good ones (and suppresses the bad ones), he or she can persistently be overconfident despite mediocre performances (Bénabou and Tirole, 2002, 2004; Zimmermann, 2020; Gödker et al., 2021).

The third force underlying selective recall has to do with the features of the experience itself: more salient, dramatic experiences are more likely to be recalled. This regularity is reminiscent of the word frequency effect in item recognition tasks, the phenomenon that recognizable and rare words are easily to correctly identify as having appeared before than common words. One way of understanding this salience effect is through the lens of attention: salient events are more likely to grab people's attention and attention is required for the event to enter into long-term memory (Kahana, 2012). Salience comes in different forms: the amount of surprise, the degree of prominence, or the level of contrast with surroundings (Bordalo et al., 2021b). In the context of financial markets, it is straightforward to expect episodes featuring large price and volume movements, such as big run-ups and crashes, to be more salient.

2.1.2 Associative memory

The above mechanisms of selective memory make predictions about, in the absence of external stimuli, what types of experience are more likely to be recalled. In parallel with this static aspect of recall, psychologists have also discovered that, at a given moment, different cues—time, location, narrative, story, image, emotion, and other stimuli—in the environment can trigger the recall of different past experiences. By emerging in an individual's mind right at a given moment, these experiences play a disproportionally large role compared to other experiences that are also stored in memory but are not cued at that point.

One of the principles governing the associative nature of memory is similarity: when recalling past experiences, priority is given to those experiences with features that are similar to the presently active features (Kahana, 2012; Wachter and Kahana, 2021). For example, in Proust's *In Search of Lost Time*, the smell and taste of a madeleine together with tea brings the narrator back to a Sunday morning when his aunt used to serve him a piece of madeleine in a similar way ("Proust's Madeleine"). The role of cues in recall has been extensively studied in the lab (Kahana, 2012). Recently, Enke et al. (2020) examine associative memory using a series of belief-updating and financial market experiments in the lab and show that this mechanism can help shed light on the prevalence of overreaction in belief formation. More generally, similarity-based recall can account for a variety of puzzling phenomena observed in the study of judgment and decision-making (Bordalo et al., 2022b).

The empirical challenge of examining the associative nature of memory stems from the obscure nature of cues. In experimental settings, cues are unambiguous because they are designed and given by the experimenter. In the field, however, any attribute of the present environment may act as a cue in the recall process. In the more specific setting of the financial market, its complex organization further complicates the problem and gives rise to a wide array of candidate cues: numbers and figures on firms and the economy, narratives about policymakers, sentiments expressed by the press, and actions taken by people around us. Below, when presenting the model, we discuss our choice of cues.

2.2 A cued-recall model of belief formation

We next present a model of belief formation in financial markets based on cued recall. Supposed that we are now in period T. An investor makes forecasts about the stock market's return in period, r_{T+1}. When making forecasts, the investor follows two steps. In the first step, called *recall*, she retrieves experience related to the stock market from the past. In the second step, called *simulation*, she uses the retrieved experiences to simulate a return distribution for period $T+1$ and makes forecasts accordingly.

2.2.1 Recall

We first specify the process of recall. For each period t ($1 \leq t \leq T-1$), we assume that the investor has accumulated a "database" of experiences in the stock market, denoted by $\boldsymbol{e}_t$. Each database consists of a continuum of experiences. In reality, each experience is characterized multiple attributes—time, location, context, experienced return, and so on—which means that $\boldsymbol{e}_t$ contains a continuum of vectors. For simplicity, however, we assume that each experience is fully characterized by the size of the return. In this case, $\boldsymbol{e}_t$ contains a continuum of experienced returns in period t.

We assume that these experienced returns can be described by a normal distribution $N(\mu_t, \sigma_t^2)$. That is, during period t, she experienced a market return of r_t with a density of $f_t(r_t)$, where $f_t(\cdot)$ is the probability density function (PDF) of normal distribution $N(\mu_t, \sigma_t^2)$. That is, the probability of experience a return in the interval $[r_t, r_t + dx]$ is $f_t(r_t)dx$. When there is no external influence of a cue, recall simply means taking random draws from this distribution. Assuming that the investor takes an infinite number of draws, then her recalled return distribution follows $N(\mu_t, \sigma_t^2)$ and objectively describes her experience returns in period t.

However, when there is an external stimulus, q_T, in the current environment, it can affect the recall process according to the rule of *similarity*. That is, experiences with attributes similar to q_T are more likely to be recalled. For simplicity, we consider a one-dimensional cue for now. Let $s(r_t, q_T)$ denote the similarity between experienced return r_t and the cue q_T. A higher value indicates that r_t is more similar to the cue q_T. The effect of the cue is that, all else being equal, if an experienced return is more similar to the cue, it is more likely to be recalled. That is, the cue alters the distribution the investor draws from. The "cued" PDF can be written as:

$$f^*(r_t; q_T) = f(r_t) \times s^*(r_t, q_T), \tag{1}$$

where

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

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

2.2.2 Return as cue

Generally, q_T can be any attribute of an experience. In our empirical exercise, we focus on one of most natural cues in financial markets: returns. In this case, $q_T = r_T$, and the cue and the experience are of the same nature. One way of modeling the similarity function is given by the following specification:

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

where $\tau = T - t$ is the elapsed time between the experience and the recall; and σ_ϵ is the perceived relevance of the cue. In the specification above, experienced returns closer in magnitude to r_T are perceived to be more similar to the cue and more likely to be recalled. In the denominator, $\tau\sigma_\epsilon^2$ represents the total strength of the cue, which depends on both σ_ϵ^2 and τ. The cue's influence is weaker if it is perceived to less relevant to the past returns (i.e., σ_ϵ^2 is large) or if the recalled return is too far in the past (i.e., τ is large).

In the Appendix, we 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, $r_t \sim N(\mu_t, \sigma_t^2)$, and treats r_T as a signal of r_t:

$$r_T = r_t + \epsilon_\tau, \tag{4}$$

with $\epsilon_\tau \sim N(0, \tau\sigma_\epsilon^2)$. She follows Bayes' rule to obtain the following posterior distribution:

$$r_t | r_T \sim N((1-\alpha)\mu_t + \alpha r_T, \sigma_q^2), \tag{5}$$

where

$$\alpha = \frac{\sigma_t^2}{\sigma_t^2 + \sigma_\epsilon^2\tau}; \sigma_q^2 = \frac{\tau\sigma_t^2\sigma_\epsilon^2}{\sigma_t^2 + \tau\sigma_\epsilon^2}. \tag{6}$$

and we denote the corresponding PDF as f_t^q. We show in the Appendix that the above distribution is identical to the cued distribution in equation (1).

Equation (5) illustrates the cued effect on recall: recalled returns deviate from the objective mean μ_t towards the cue r_T. Therefore, when the current cue r_T is more positive, the distribution of recalled experiences, on average, will also become more positive. This leads to the following proposition:

Proposition 1. *(Cued recall) The mean of recalled returns,* $\mathbb{E}[r_t|r_T] = (1-\alpha)\mu_t + \alpha r_T$*, increases in today's market return* r_T*.*

We also note that the weight placed on the cue, measured by α, is not only a function of the two variance terms, but also a function of τ. In particular, when t is concerning a more distant period, a greater τ means a smaller α and reduces the effect of the cue. This leads to the following proposition:

Proposition 2. *(Recency effect) The strength of cued recall, measured by* α*, is decreasing in* τ*.*

2.3 Simulation

In the second step, we specify how the investor use retrieved experiences to formulate her projection about the future—a process called "simulation" (Bordalo et al., 2022a). We assume that her predicted distribution of r_{T+1} is a weighted average of recalled distributions of past experiences, r_t, where $1 \leq t \leq T-1$. w_t denotes each period's weight and sums up to one. In this case, $f_{T+1} = \sum_{t=1}^{T-1} w_t f_t^q$, where $\sum_{t=1}^{T-1} w_t = 1$. This leads to the following proposition regarding the relationship between the cue and beliefs:

Proposition 3. *(Return extrapolation) Expected stock return for period* $T+1$*,* $\mathbb{E}(r_{T+1})$*, is increasing in the return cue* r_T*.*

This result shows that, when investors observe a high market return today at time T, they tend to have more positive recalls of past returns as well as more optimistic belief about future returns.

3 Survey Design and Other Data Sources

In this section, we describe the survey and other data sources. Sections 3.1 to 3.3 explain the design of different blocks in the survey: recall, expectations, and other blocks, respectively. Section 3.4 details the implementation of the survey.

3.1 Survey design: Recall

Examining investor memory requires collecting data on investors' recall of past experiences and performance. We use two blocks of the survey to elicit investors' recall of past experiences.

3.1.1 *FreeRecall*

The core part of the survey starts with a block called *FreeRecall*. As its name suggests, this block is motivated by the well-established experimental paradigm of free recall and is designed to elicit the episode of financial market fluctuation that first comes to mind when an investor starts thinking about the stock market in the past (e.g., Murdock, 1962; Kahana, 2012). By "free," we mean that we want to give the investors minimal guidance and conditions on what periods to be recalled. Thus, their answers capture the idea of selective recall and are potentially informative of its determinants. Since we want minimum interference for *FreeRecall* from other survey blocks, an investor always starts the survey with this block.

Once an investor enters the *FreeRecall* block, we start by asking him or her to "first think about the overall stock market movement since you opened an account." We then immediately ask the following question: "Since you started trading, 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. 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.[4]

[4]In a follow-up survey, we change the phrasing in *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 4.1 and in Figure

Having entered the market episode that comes to mind, investors are immediately asked three 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 a multiple choice, each choice covering a range of value.[5]

In addition to the main *FreeRecall* block, we consider two treatment blocks. In the first treatment, called *HappyRecall*, instead of asking participants to free-recall a market episode, we ask them to recall a *pleasant* market episode. In the second treatment, called *PainfulRecall*, we ask them to recall a *painful* episode. As before, investors also need to recall the market movement for the recalled episode. We discuss these two blocks in more detail in Section 6.

3.1.2 *ProbedRecall*

After *FreeRecall*, investors immediately move on to the second block, called *ProbedRecall*. Here, we ask them to recall their performance in the stock market over a certain period of time. By “probed,” we want to highlight the fact that these questions are designed with more elaborate conditions, both in terms of the type of memory elicited (own return performance) and the time period specified (one day or one year).

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, each choice covering a range of value.

3.2 Survey design: Expectation

After the two recall blocks, *FreeRecall* and *ProbedRecall*, investors enter the *Expectation* block. We elicit two types of expectations, one about future market returns—including both the mean return and tail distributions—and one about future self-performance. Again, the questions are

A.3 of the Online Appendix.

[5] We repeat this set of questions at the stock level. Response rate is substantially lower for this block of questions. For the sake of brevity, we do not discuss the results of stock-level recall in the remainder of this paper. More details about the phrasing of the questions are included in the Online Appendix.

multiple-choice. Their phrasing is similar to that in earlier papers using self-designed surveys to elicit expectations (Giglio et al., 2021; Liu et al., 2022)

It is tempting to randomize the order of blocks within the survey. For example, we could in theory 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*). We prefer the current ordering for the following reasons. First, given the nature of the *FreeRecall* block, the elicitation process ideally should have minimal intervention or interaction with other blocks. For example, if we start with the *ProbedRecall* block, the recall process may interfere with the subsequent process of *FreeRecall*. Second, in our view, it is quite natural to place the two recall blocks before the expectation block. One criticism about placing the two recall blocks before the *Expectation* block is that the elicited memory may prime investors and their answers in *Expectation* will be anchored to their previous answers in *FreeRecall* and *ProbedRecall*. In later sections, we directly address this concern. Third, if we place the *Expectation* block ahead of the two recall blocks, this may bias investors' recall through motivated reasoning (Bénabou and Tirole, 2002, 2004).

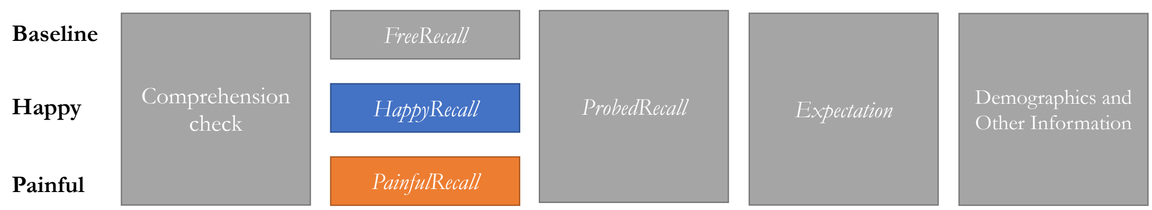
3.3 Survey design: Other blocks

At the beginning of the survey, investors are explicitly instructed to rely on memory and not to check their brokerage account or search the internet when completing the survey. In reality, we do not observe when an investor does not follow our instructions. However, around 60% investors finish the entire survey within 10 minutes, which leaves limited 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 any bias we document.

At the beginning of the survey, investors also need to go through a comprehension check to proceed. These questions check investors' understanding of the concepts of dollar investment and return. They then move on to the *FreeRecall*, *ProbedRecall*, and *Expectation* blocks. In our analysis, we exclude observations that did not pass the comprehension check.

After the *Expectation* block, participants do a personality block: 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, personality traits, 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



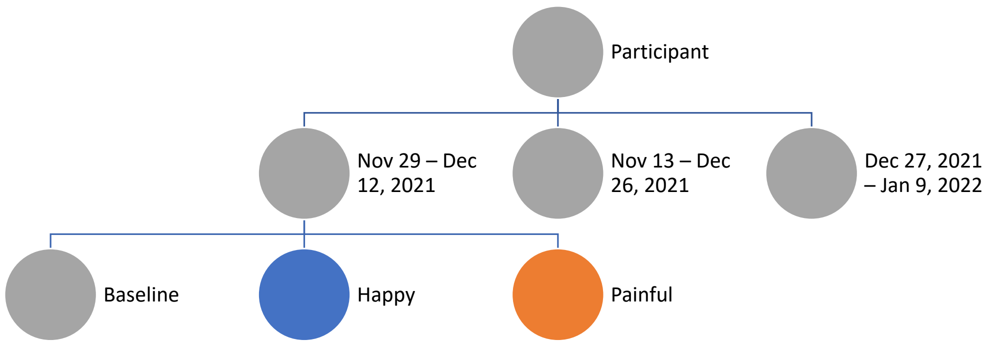
3.4 Survey implementation

We administered the survey through the Investor Education Center of the Shenzhen Stock Exchange (SZSE), the same setting used in Liu et al. (2022) to analyze retail investors' excessive trading behavior. In a nutshell, we randomized across branch offices of China's 60 largest brokers. Specifically, we selected 2,993 branch offices across 30 provinces (and regions) and required each branch office to collect at least 10 valid responses.[6]

Figure 2 illustrates the implementation timeline. The survey took place between November 29, 2021, and January 6, 2022, and respondents were given two weeks to complete it. A valid response had to be completed within 30 minutes. Respondents could open the survey using their personal computers or their smartphones. After applying basic filters, we collected an initial sample of around 17,324 respondents. 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 (e.g., Guangdong, Zhejiang, Jiangsu, and Shanghai) 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, the majority have a bachelor degree, and a substantial fraction have a wealth above 1 million RMB.

[6] See Liu et al. (2022) for more institutional details.

Figure 2: Timeline of survey implementation



4 Stylized Facts about Investor Memory

In this section, we examine the two recall blocks to document new stylized facts about investor memory. In Section 4.1, we start by analyzing the recalled market episodes in *FreeRecall*. In Section 4.2, we compare recalled return and actual return to show that investors are taking a conscious effort in these recall tasks. In Section 4.3, we discuss age effects in recall.

4.1 Fact I: Salience and recency effects in recall

4.1.1 Main results

The *FreeRecall* block asks investors to recall a market episode that first comes to mind when thinking about the stock market. In the rest of the paper, we will refer to their answers to this question as "recalled market episodes." 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 recency effect: a disproportionally large number of answers concern recent periods, essentially for the end dates. 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, by default, 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 mechanically driven by the cohort of new investors.

However, the recency effect does not fully capture the empirical distribution of recalled market episodes. A second pattern to be observed 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 the Online Appendix, we also plot the distribution of recalled market episodes for two subsamples based on age. Again, both the older sample tends to recall more distant episodes, both recency and salient effects are observed in the two subsamples, as shown in Figures A.1 and A.2. In Figure A.4 of the Online Appendix, we further consider a recall structure in which investors are equally like to recall any month they have experienced in the stock market, and show that the two effects documented above are robust to this alternative recall structure.

There are several reasons that can potentially explain 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 is consistent with the experience effect, whereby a few big macroeconomic events can have a long-lasting effect on beliefs and choice despite the numerous experiences one encounters through life. It also supports the retrieved context model by Wachter and Kahana (2021) which allows for stronger encoding of experiences that are more extreme.

4.1.2 The 2014–2015 stock market bubble

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. The 2014–2015 bubble started in late 2014, peaked in mid-2015, and then crashed. Figure 6 shows three modal recalls: 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 parts of the cycle. The fact that investors clearly differentiate the stages of a bubble reinforces the validity of the recall block.

4.2 Fact II: Consistency between recalled return and actual return

4.2.1 *FreeRecall*

In addition to recalling a market episode that first comes to mind, respondents are asked to report the recalled market return during this period. In the rest of the paper, we will refer to their answers to this question as "recalled market returns."

Table 1 shows the summary statistics for recalled market returns and the actual market returns for the recalled market episodes. In Panel A, we find substantial variation in the type of market condition investors recall: while the median is around zero, the standard deviation is large and a nontrivial fraction of investors recall an episode having either gone up by 100% or down by 50%. This is consistent with the modal responses in Figure 6 where some investors are drawn to the run-up while others are drawn to the crash. However, we find no evidence of investors selectively recalling more positive experiences. Consistent with this, the actual market return, on average, is actually higher than the recalled market return. This, as we explain in more detail below, is not inconsistent with motivated reasoning, according to which investors tend to hold a more rosy view about their *own* performance rather than about the entire market.

How accurate are these recalled returns? Panel B finds their correlation with the actual returns to be 0.53. This high correlation further validates that respondents in our sample are indeed making a conscious effort in this recall task. Similarly, there is a high correlation between the actual market return and the recalled own return.

4.2.2 *ProbedRecall*

Table 2 shows the summary statistics of recalls in *ProbedRecall*. In the rest of the paper, we will refer to these recalls as "recalled own returns" to differentiate from "recalled market returns" in *FreeRecall*. Panel A shows the distribution of recalled own returns at different horizons. Overall, a longer horizon is associated with more positive recall. However, these recalls could reflect both biases in recall and the actual own returns.

Panel B 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 performance 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 performance is 2.5% while the median actual performance is around 0.9%.

Overall, evidence in support of motivated reasoning is rather thin in our setting. This may initially appear surprising, given that retail investors on average overestimate their rank based on performance in the population, which also holds true in our setting. One way to reconcile this apparent contradiction is through investors' assessment of others' performances. Indeed, if investors are both accurate in recalling their *absolute* performance and positively based 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).

To further confirm that investors in the survey are indeed making a conscious and genuine effort to recall their past performance, Panel C shows the correlation between recalled own returns and actual own returns. The correlations are positive and highly significant for all horizons, suggesting that investors are indeed exercising efforts in this recall task. Interestingly, the correlation is highest for one-year recall, suggesting that investors may tend to evaluate performance at the one-year horizon.

4.3 Fact III: Age and recall

As shown in Figure 4 and Table 1, 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 3 we regress two aspects of recall—the distance of and the return of the recalled episode—on various individual characteristics.

In Table 3, Column (1) first regresses the distance of the recalled episode on various individual characteristics, with distance defined as the difference in years between December 2021 and the midpoint of the recalled episode. Overall, we find that 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 driven by older investors having entered the market earlier. In the Online Appendix, Table A.1 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.

Column (3) of Table 3 repeats the exercise in Column (1) for recalled market return. Again, age appears to be a key determinant of recalled market 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 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 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 first experience and then recall distanced as additional controls. On average, more distant recalls are more bullish. At the same time, the coefficient on age continues to be significantly positive.

One alternative explanation for the positive correlation between age and recalled market 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 bunching of good returns in the early periods. In addition, Figure 7 plots the average recalled 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.

In a previous section, we documented that investor recall in *FreeRecall* exhibits a salience effect. In Table 4, we further examine the determinants of recalling extreme events such as large run-ups and crashes. Columns (1) and (2) are concerned with market run-ups. In each column, we regress a dummy variable that equals 1 if the recall return is greater than 100%. As before, we find significant age and gender effects: older, male investors are more likely to recall a large market run-up. In Columns (3) and (4), we are instead concerned with crashes, where the dependent variable is a dummy variable that equals 1 if the recall return is lower than -50%. Interestingly, older people are also more likely to recall the extreme negative events, consistent with a salience effect.

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 cue when implementing the survey. In Sections 5.2 and 5.3, we test the first two propositions of the model by examining the relationship between returns and recalls elicited by the two recall blocks, *FreeRecall*, and *ProbedRecall*, respectively.

5.1 Return as the cue

The complexity of the financial market gives rise to many candidates 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 Proposition 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 a market episode 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 assessment of their own returns in the past.

To get sufficient variation in market return, 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. One appealing feature of the survey is that we can 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 market returns fluctuate during the day.

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

5.2 The *FreeRecall* block

According to Proposition 1, a positive return triggers the retrieval of an episode of a booming market in *FreeRecall*. To test this, we first measure the return cue as the cumulative market return up to the point when investor i starts taking the survey, $MktRet_{t \to t+\tau_i}$, where t corresponds to the beginning of the day and $t + \tau_i$ the time of the day when investor i starts the survey. We then regress recalled return for the recalled market episode in *FreeRecall* on the return cue, using the following main regression specification:

$$\widehat{MktRet}_i^{Free} = \beta_0 + \beta_1 MktRet_{t\to t+\tau_i} + X_i + \epsilon_i, \tag{7}$$

where $\widehat{MktRet}_i^{Free}$ denotes investor i's recalled return (hence the hat) of the market episode recalled under *FreeRecall*, and X_i denotes a variety of individual-level controls: age, gender, education, wealth, income, and measures of social activities. Simply put, we test whether today's market fluctuations have any effects on investor recall.

In Table 5, Column (1) reports the results. 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. It is possible that the market return today is too high-frequency and not all investors pay attention to it. 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*.[7]

The null results in Columns (1)–(3) may initially appear surprising and running counter to the hypothesis 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, and to retrieve such salient events from memory may require observing cues that are also 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*.

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. Proposition 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 today's return as the cue, it may be able to affect the retrieval of more recent experiences, but not the more distant experiences.

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

To test this latter possibility, we conduct two subsample analyses. In the first subsample analysis, we limit the recalled episode in *FreeRecall* to those that end within the last five years.[8] Panel B of Table 5 reports the results. Both today's return and the past one-month return have a much stronger influence on the recalled return in *FreeRecall.* In Column (4), a 1-percentage-point increase in today's return increases the recalled return by 2.11 percentage points. In Column (5), a 1-percentage-point increase in today's return increases the recalled return by 1.09 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.

In the second subsample analysis, we restrict to investors who are newer to the market and whose experiences in the stock market, by definition, are more recent. Panel C of Table 5 reports the regression results for investors whose stock experience is below the median (around 10 years). Consistent with a recency effect in cued recall, we find much a stronger cued effect: a 1-percentage-point increase in today's return increases the recalled return by more than 14 percentage points. At the same time, past one-month return does not seem to be matter anymore.

5.3 The *ProbedRecall* block

Our next hypothesis is that a positive return leads to more positive recall of one's own returns in the *ProbedRecall* block. We run the same regression by replacing recalled market return, $\widehat{MktRet}^{Free}$, with recalled past performance, $\widehat{OwnRet}^{Probed}$, with 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 performance of a given horizon h, namely from the current date t to an earlier date $t-h$, and X_i, as before, represents a set of individual-level controls including basic demographics and other personal characteristics.

We start by considering recalling one's own returns yesterday using today's market return as a cue. 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 performance for yesterday is, on average, 68 basis points higher. Without controlling for their actual performance, however,

[8] We consider alternative cutoffs and find similar results.

one 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 performance yesterday and find that controlling for actual performance does not reduce the strength of cued recall. Therefore, positive returns leads to biased recall of past performance: the more positive recall of yesterday's performance is not warranted by the actual performance. Columns (3) and (4) repeat the same regressions for recalled performance over the past month and find similar evidence. When today's market return goes up by 1 percentage point, investors' recalled performance for the past month is, on average, 1 percentage point higher, without or with the control of the actual performance.

Interestingly, when we start to examine recall of past performance over a longer horizon, patterns begin to diverge. In Column (5), we are concerned with recall of past year's performance, where today's return no longer has a significant effect. This is consistent with Proposition 2 and, more broadly, with the idea of temporal contiguity: when the nature of recall concerns a more distant period, today's return is becomes less powerful as a cued in the recall process. Interestingly, in Column (6), when 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 the last month.

While the positive coefficient in Column (6) may partially result from the mechanical positive correlation between past return and past performance, in Columns (7) and (8) we repeat the same analyses, adding actual performance 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.

Table 7 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 before, today's portfolio 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 call their past performances.

6 Recall and Expectation

In this section, we test the second part of the model, *simulation*, by exploring how investors use retrieved experiences to form expectations. We examine the statistical relationship between recalls and expectations in Section 6.1, then discuss alternative explanations in Section 6.3.

6.1 Retrieved experiences and expectations

It is well documented that different investors hold different beliefs about future stock returns, but the source of this dispersion remains a puzzle. Variations in the accounts of past events present a natural candidate explanation: some investors may expect lower future returns because they recall that past returns were low. This process, in our model, corresponds to *simulation* whereby investors use retrieved experiences to make forecasts about the future. in particular, experiences associated higher returns will contribute to greater optimism about the future.

To test the simulation process, we examine the relationship between expectations and recalls by running the following cross-sectional regression:

$$\mathbb{E}_i[MktRet_{t\to t+h}] = \beta_0 + \beta_1 \widehat{MktRet}_i^{Free} + X_i + \epsilon_i; \quad (9)$$

$$\mathbb{E}_i[OwnRet_{t\to t+h}] = \beta_0 + \beta_1 \widehat{MktRet}_i^{Free} + X_i + \epsilon_i, \quad (10)$$

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

Table 8 reports the results. We consider four types of expectation. Columns (1) and (2) concern expectations of the market return over the next month and the next year, respectively. Columns (3) and (4) concern expectations of one's own portfolio's return in the next month and the next year, respectively. We find that the respondents who recall higher returns in the past tend to have higher expectations of future returns. Magnitude-wise, recalled returns in *FreeRecall* may cover different time periods depending on the time periods our respondents choose. According to Table 1, their 25–75 percentile range is -19.5% to 15.5%, which, for example, leads to a 0.14

-percent difference in the market return in the next month and a 0.7-percent difference in market return in the next year according to our estimates. Interestingly, recalled market returns seem to have a greater influence on expectations concerning a longer forecasting horizon.

In Table 9, we repeat the above regression by replacing the recalled market return in *FreeRecall* with recalled own returns in *ProbedRecall*. To simplify the exercise, for each type of expectation we examine, we pick recalled own returns over the last month and last year. 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 2, 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 market return and a 6.40-percentage-point difference in expected own return, respectively, over the next year.

It is worth noting that that the use of retrieved experiences depends on the forecasting horizon. Comparing between Columns (3) and (6), recalled own one-year return matters four times more when investors are forming expectations about the next year than for next month. Similarly, in Columns (9) and (12), recalled own one-year return matters substantially more for expectations concerning a more distant future. 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 8 and 9, we see that, while both types of recalls have significant explanatory power for investor beliefs about stock market returns and own returns, 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 R-squared

Another way to evaluate the economic significance of these results is to ask 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 10, 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 consider gender, age, income, wealth, and education dummies; including additional controls such as social activities has limited impact on the adjusted R-squared. For recall, based on the horizon-dependence result, we only use recalled own return in *ProbedRecall* of the corresponding window. That is, the univariate recall variable is the past one-month recall if the dependent variable is the expectation of future one-month return or is the past one-year recall if the dependent variable is the expectation of future one-year return.

In Table 10, 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 could be quite substantial. For example, comparing the R-squareds in Panel B of Table 8 to those in Table 10, we see that including a single variable of recalled own return can increase the R-squared from between 1% and 4% to between 4% and 14%. Giglio et al. (2021) pose as an open question 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.[9]

6.3 Alternative explanations

In the previous section, we established that there is a strong and robust statistical relationship between investor recall and expectations. However, given the difficulty of generating random variation in recall, it is hard to establish causality. Moreover, that both variables are elicited through the survey invites a few alternative explanations of our results. Below, we discuss a few such alternatives and how we rule them out.

[9]To be more precise, Giglio et al. (2021) include experience as an explanatory variable. However, as we clearly show, not only does experience itself matter, but it matters how the same experience is processed and recalled in the future.

6.3.1 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 unwilling to exercise sufficient mental effort, so that their answers are anchored towards their answers in the previous recall blocks, leading, in turn, to a mechanical positive correlation between recall and expectations.

If such anchoring is indeed prevalent and quantitatively large, one testable prediction is that the statistical relationship between recall and expectations should be stronger among those who finish the survey more quickly. In other words, anchoring effects should be stronger among those who finished the survey more quickly. To test this possibility, in Table 11, we run the following equations:

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

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

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 on the interaction term is insignificant and essentially to zero, clearly rejecting 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 anchoring 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 market returns in these two blocks are very different from those in *FreeRecall*. In Table 12, 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.[10]

6.3.2 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 on the left-hand side. During the sample period, the Shanghai Composite Index mostly hovers between 3,500 and 3,600. We have consider 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.

Regression results are reported in Table 13. If it is indeed click-through behavior driving the positive correlation between recall and expectation, we should see a similar relationship in these regressions. 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.

6.3.3 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 remembering the more positive experiences. Since we do not exogenously vary either the expectation or the recall, we cannot differentiate between these two stories.

[10]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.

7 Recall and Belief Biases

In this section, we link the previously documented memory structures to some prevalent belief biases. In Section 7.1, we examine Proposition 3 of the model and discuss the link between cued recall and return extrapolation. In Section 7.2, we link selective memory with overconfidence.

7.1 Return extrapolation

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

Proposition 3 suggests that similarity-based recall can microfound return extrapolation, because good returns trigger recall of past experiences associated with good returns (e.g., Bordalo et al., 2021a, 2022b). If investors form expectations by relying their past experiences, they tend to overly use the more positive ones and therefore become overly optimistic upon seeing good returns. One key implication of this memory-based mechanism is that the positive relationship between good returns and positive expectations hinges on recall—return affects expectations through recall. Controlling for recall, therefore, would weaken the relationship between returns and expectations.

To examine this hypothesis, 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 market return in the past month. Column (1) of Table 14 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 hypothesis, we add the respondents' recalled own return in the past month to our regression. Column (2) of Table 14 reports the result. We find that the coefficient associated with the actual market return declines and becomes statistically less significant, whereas the coefficient associated with the recalled own return is strong. 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.

In Table 14, Columns (4) to (6) repeat these analyses using expected own return as the dependent variable instead. In these regressions, we find an even more striking result: recalled own returns completely drive out the explanatory power of recent market returns for explaining expected own returns. These results impute a central role to memory and recall in the investors' extrapolation tendency in expectation formation.

7.2 Selective memory 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 15, we regress measures of overconfidence on recalled return in *FreeRecall*; in the Online Appendix, Table A.5 regresses measures of overconfidence on recalls in *ProbedRecall*. We consider two measures of overconfidence: the difference between expected self-performance 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 15, 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 market 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.

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.

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Figure 3: Distribution of demographic variables

We report the distribution of age, gender, education, wealth, income, and experience. For experience, we only have observations for the merged sample.

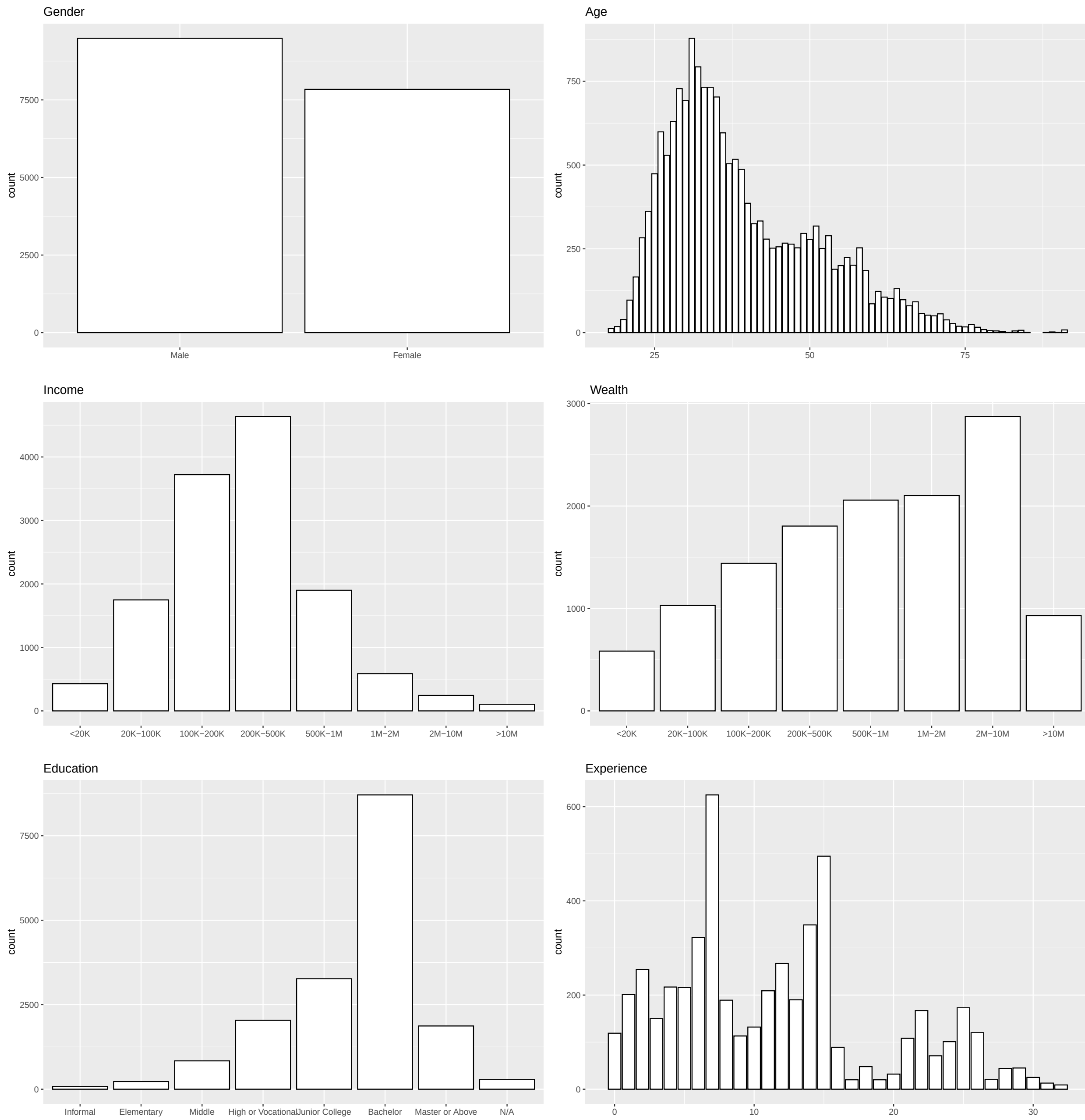
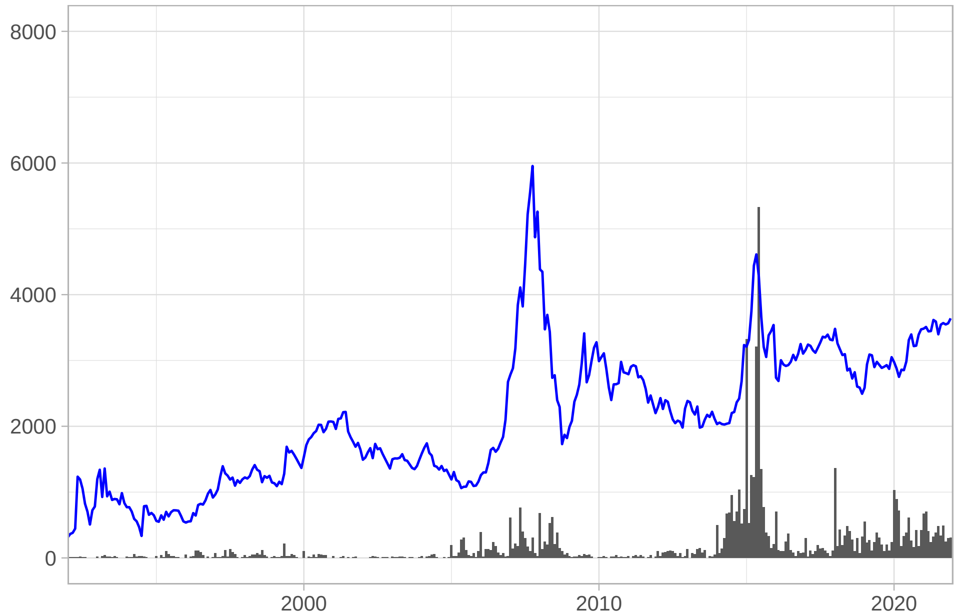
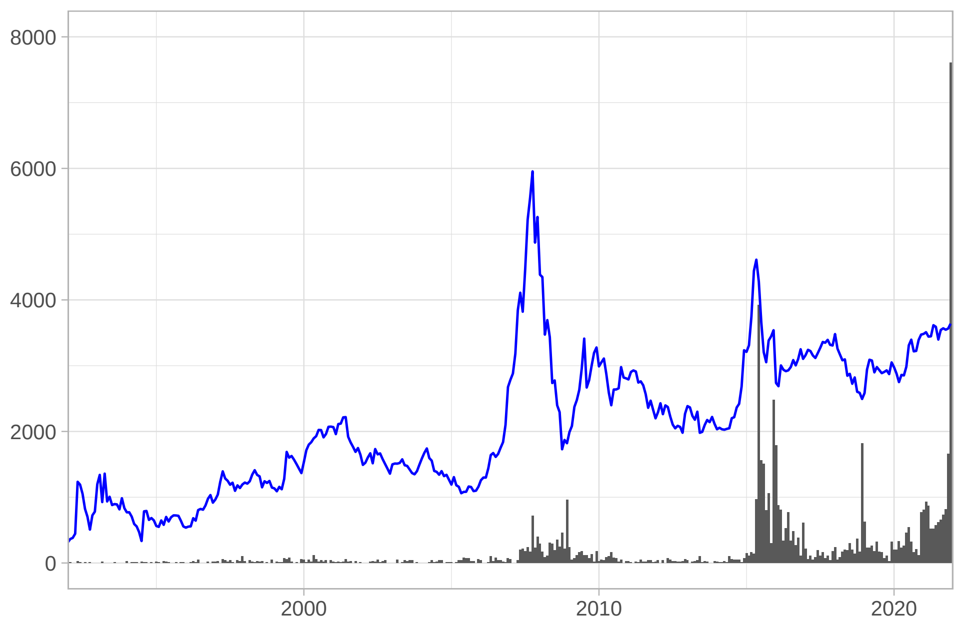


Figure 4: Distribution of recalled market episodes in *FreeRecall*

The blue solid line represents the Shanghai Composite Index. The solid bars represent the frequency of answers. The frequencies are rescaled to improve readability.



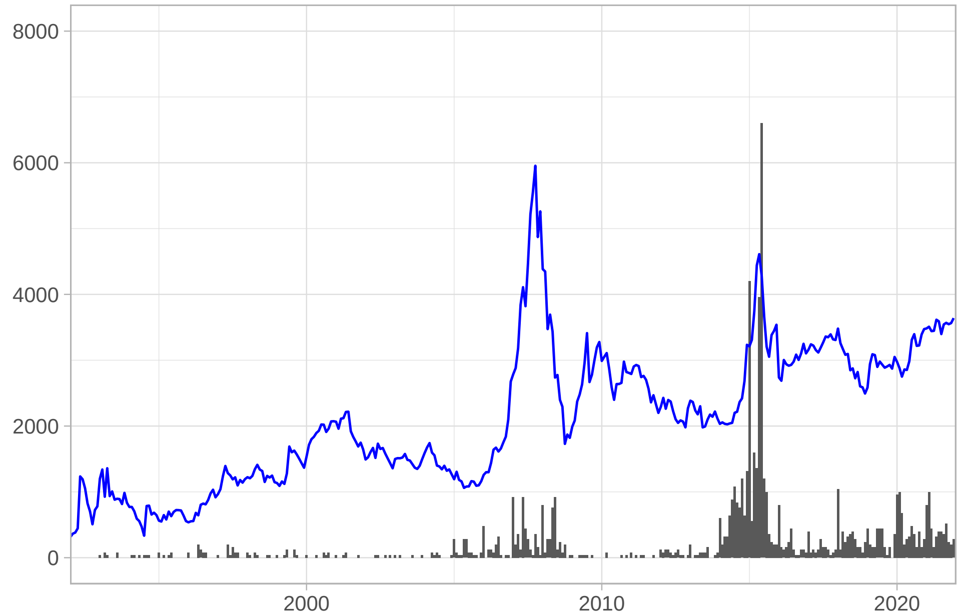
Panel (a) Distribution of start dates



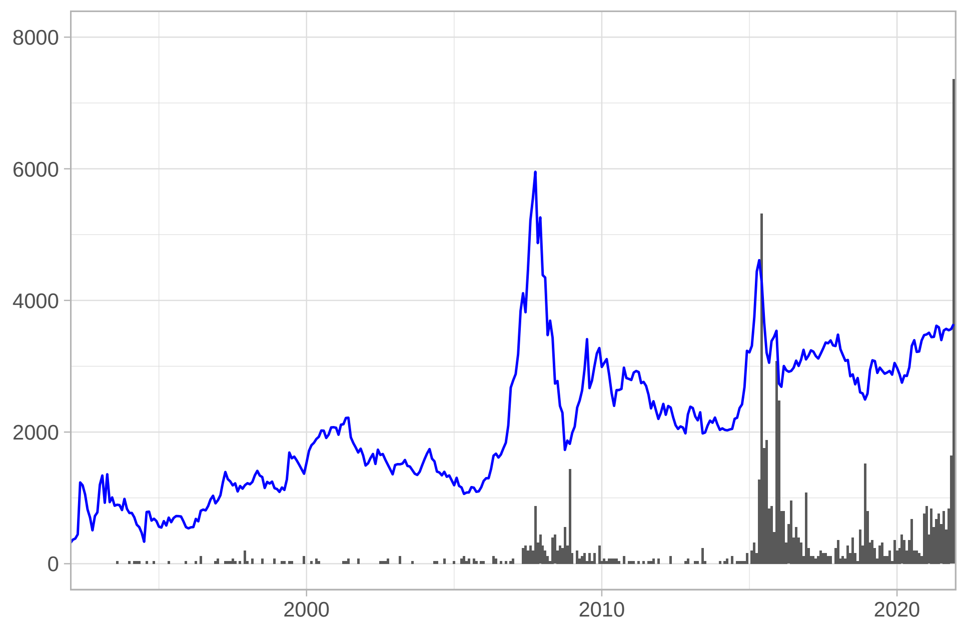
Panel (b) Distribution of end dates

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

The blue solid line represents the Shanghai Composite Index. The solid bars represent the frequency of answers. The frequencies are rescaled to improve readability.



Panel (a) Distribution of start dates



Panel (b) Distribution of end dates

Figure 6: Distribution of recalled market episodes in *FreeRecall* in 2015

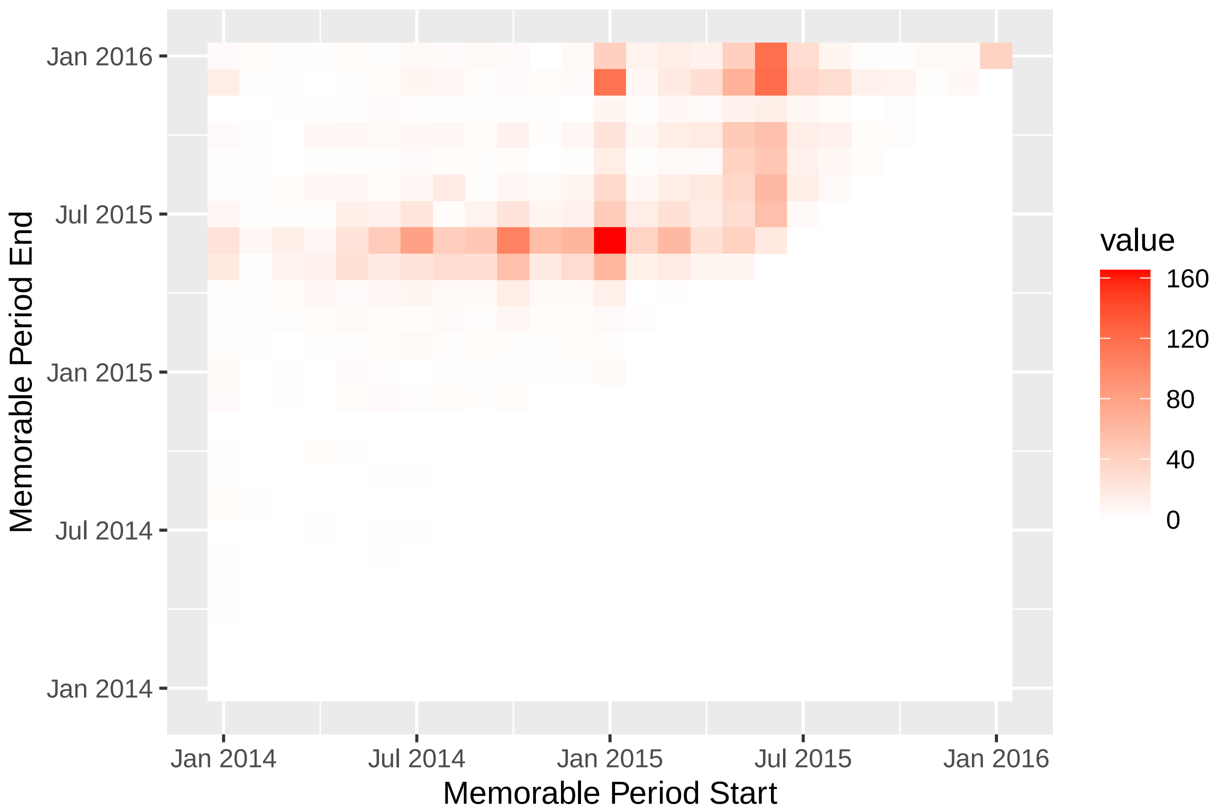


Figure 7: Age and recalled return in *FreeRecall*

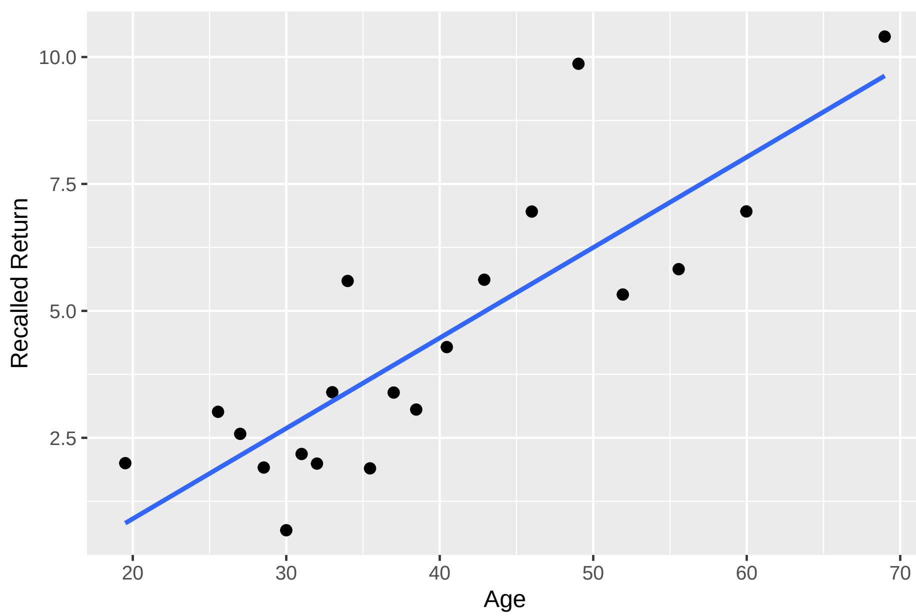


Figure 8: Distribution of daily returns during the survey period

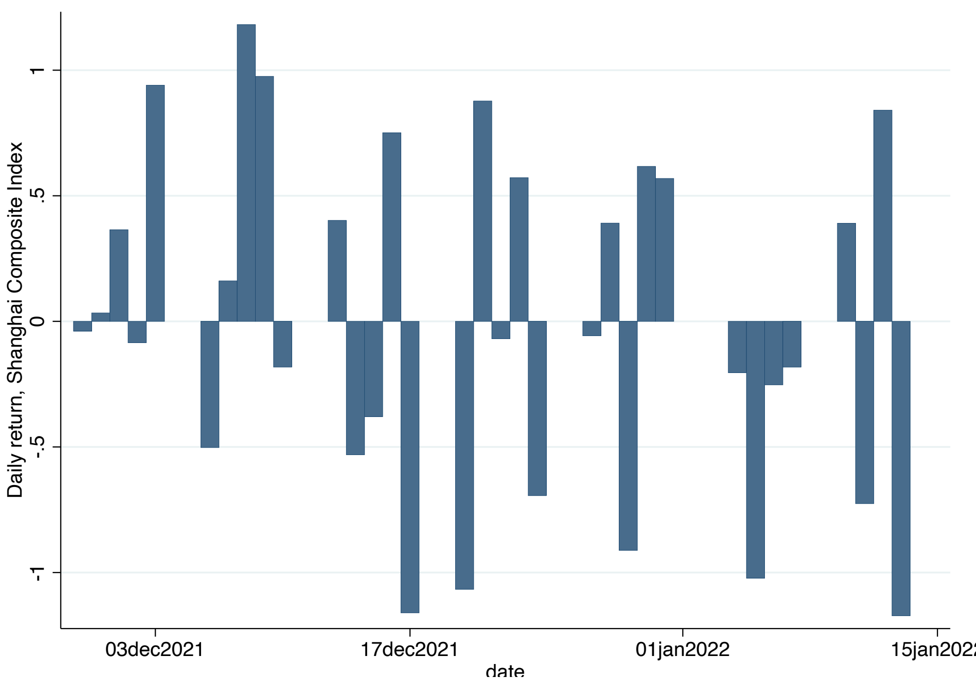


Table 1: Summary statistics of recalled market return in *FreeRecall*

Panel A: Summary statistics

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

Panel B: Correlation between recalled and actual market return

	Actual	Recalled	Own
Actual market return			
Recalled market return	0.534		
Own return	0.496	0.276	

Table 2: Summary statistics of recalled own returns in *ProbedRecall*

Panel A: Summary statistics of recalled own returns								
	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 3: Determinants of recalled episodes in *FreeRecall*

We regress two aspects of the recalled episode in *FreeRecall* on various 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 market return—the market return during the recalled episode. Columns (1) and (3) use the full sample while Columns (2), (4), and (5) use the merged sample to include trading experience. Age is calculated in years as of December 2021. Experience is defined as the number of years of having a 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 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:				
	Distance		Recalled market 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
R^2	0.14	0.28	0.11	0.24	0.25
Adjusted R^2	0.08	0.14	0.04	0.05	0.07

Table 4: 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 market rise of more than 100%. In Columns (3) and (4), the dependent variable is a dummy variable indicating a recalled 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:			
	Recalled market return>100%		Recalled market 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
R^2	0.13	0.17	0.07	0.08
Adjusted R^2	0.05	0.10	-0.002	0.005

Table 5: Tests of similarity-based recall in *FreeRecall*

We test similarity-based recall by regressing recalled market return in *FreeRecall* on the current market return (as of today) and the past one-month return. To avoid potential confounds, we exclude observations in which the recalled episode ends in or after November 2021, so that the cued episode does not overlap with the recalled episode. Market return today is calculated as the cumulative return from the market opening to the point when the investor starts to take 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. Columns (1)–(3) concern the full sample while Columns (4)–(6) concern the sample when the recalled episode is recent (that is, the ending date is below the median). We cluster standard errors at the date level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable: Recalled market return		
	Panel A: Full		
	(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
R^2	0.04	0.04	0.04
Adjusted R^2	0.01	0.01	0.01
	Panel B: Recalled episode $\leq$ 5 years		
	(4)	(5)	(6)
Market return, today	2.11^{*}		3.59^{***}
	(1.21)		(1.13)
Market return, past month		1.09^{***}	1.64^{***}
		(0.42)	(0.45)
Observations	815	846	815
R^2	0.15	0.15	0.16
Adjusted R^2	0.03	0.03	0.03
	Panel C: Trading experience below median		
	(4)	(5)	(6)
Market return, today	14.38^{***}		14.13^{***}
	(3.32)		(3.82)
Market return, past month		−2.29	−0.64
		(2.73)	(2.53)
Observations	454	480	454
R^2	0.27	0.22	0.27
Adjusted R^2	0.06	0.02	0.06

Table 6: Tests of similarity-based recall in *ProbedRecall*

We test similarity-based recall by regressing recalled own returns in *ProbedRecall* on the current market return (as of today) and the past one-month return. To avoid skipping the weekend in recall, we only include observations from Tuesday to Friday. Market return today is calculated as the cumulative return from the market opening to the point when the investor starts to take 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: 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
R^2	0.04	0.04	0.05	0.11
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
R^2	0.07	0.07	0.05	0.11
Adjusted R^2	0.06	0.06	0.13	0.13

Table 7: Cued recall in *ProbedRecall*, using portfolio returns as cues

We test cued recall by regressing recalled self-performance in *ProbedRecall* on the current portfolio return (as of today) and the past one-month portfolio return. To avoid skipping the weekend in recall, we only include observations from Tuesday to Friday. Market return today is calculated as the cumulative return from the market opening to the point when the investor starts to take 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: Recalled performance	
	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
R^2	0.04	0.04
Adjusted R^2	0.03	0.03

Table 8: Memory and expectation in *FreeRecall*

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 1 year. The independent variables are recalled market returns 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
	Panel A: *FreeRecall*			
	(1)	(2)	(3)	(4)
Recalled market 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
R^2	0.04	0.08	0.09	0.11
Adjusted R^2	0.01	0.05	0.04	0.07

Table 9: Memory and expectation in *ProbedRecall*

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 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:					
	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
R^2	0.05	0.04	0.06	0.07	0.07	0.08
Adjusted R^2	0.04	0.03	0.04	0.05	0.06	0.06
	Dependent variable:					
	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
R^2	0.13	0.13	0.16	0.11	0.13	0.14
Adjusted R^2	0.11	0.11	0.14	0.09	0.12	0.12

Table 10: 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, with recalled own returns only or with demographics fixed effects only. Dependent variables are the respondents' expectation of the stock market return and their own stock portfolios' return in the next 30 days and in the 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.

	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 11: 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 and in the next 1 year. Time spent 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 12: Recalled return and expectations across treatments

We compare recalled market return and own return 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.

		Recalled own return			
	Recalled market 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 13: 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 consider 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 14: Return extrapolation and cued recall

The dependent variables are the respondent's expectation of market return and his or her own portfolio's return in the next 30 days and in the next 1 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 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
R^2	0.04	0.05	0.06
Adjusted R^2	0.02	0.04	0.04
	Expected own return, 1M		
	(4)	(5)	(6)
Past market return, 1M	0.21^{***}	0.09	0.06
	(0.07)	(0.06)	(0.08)
Recalled own return, 1M		0.30^{***}	0.21^{***}
		(0.02)	(0.02)
Recalled own return, 1Y			0.11^{***}
			(0.01)
Observations	6,554	6,554	5,516
R^2	0.07	0.13	0.16
Adjusted R^2	0.05	0.11	0.14

Table 15: Selective recall and overconfidence

The dependent variables are the respondents' self-reported ranking of their performance in the population 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 self-outperformance, 1M		Perceived information advantage	
	(1)	(2)	(3)	(4)
Recalled return	0.01*		0.001**	
	(0.005)		(0.0005)	
Actual 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
Note:			*p<0.1; **p<0.05; ***p<0.01	

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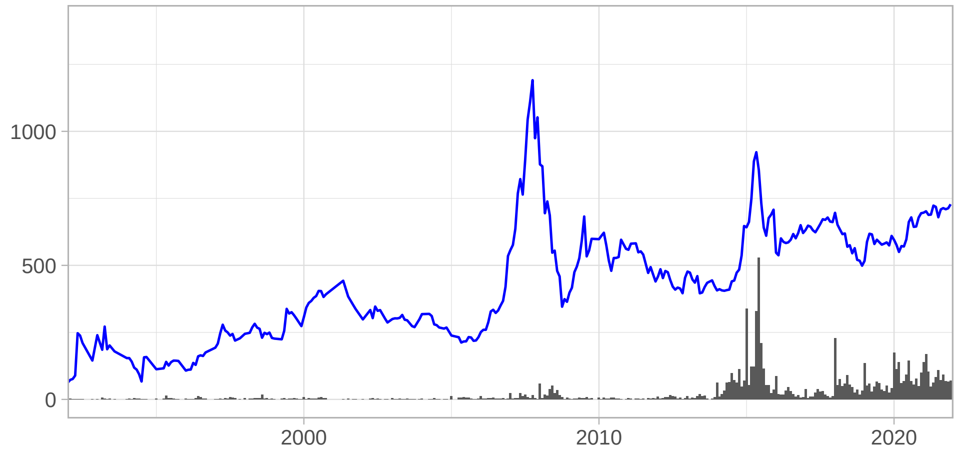
Online Appendix for

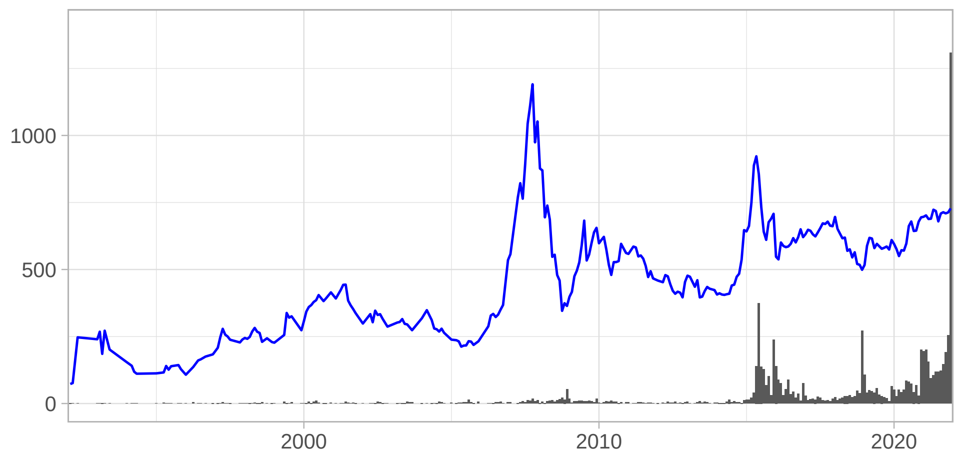
Investor Memory and Biased Beliefs: Evidence from the Field

A Additional Empirical Results

Figure A.1: Distribution of recalled episodes, age < 35

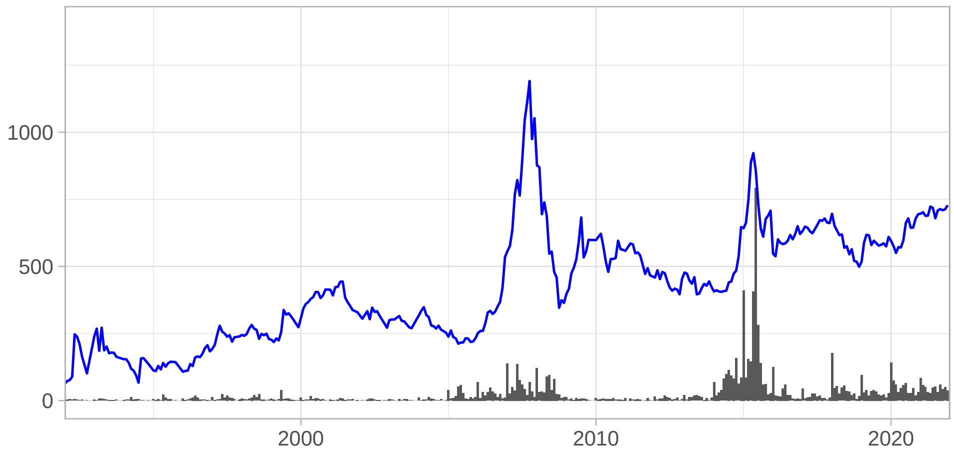


Panel (a) Distribution of start dates

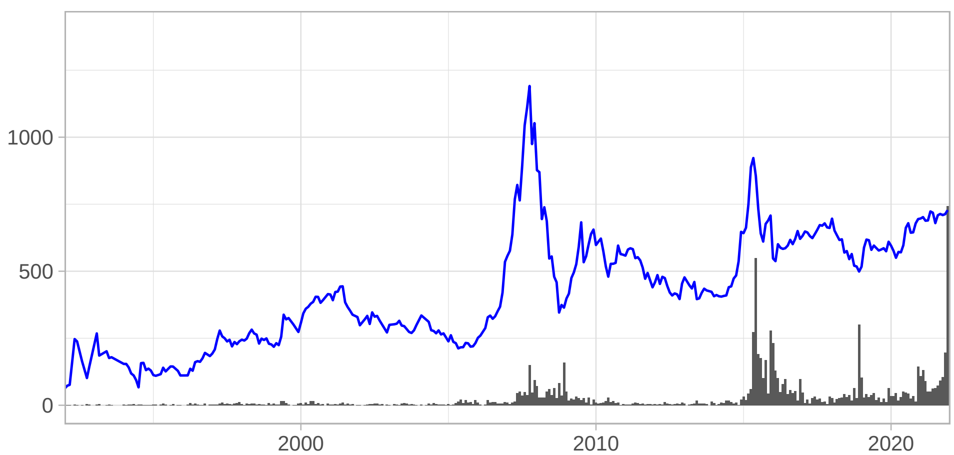


Panel (b) Distribution of end dates

Figure A.2: Distribution of recalled episodes, age $\geq$ 35

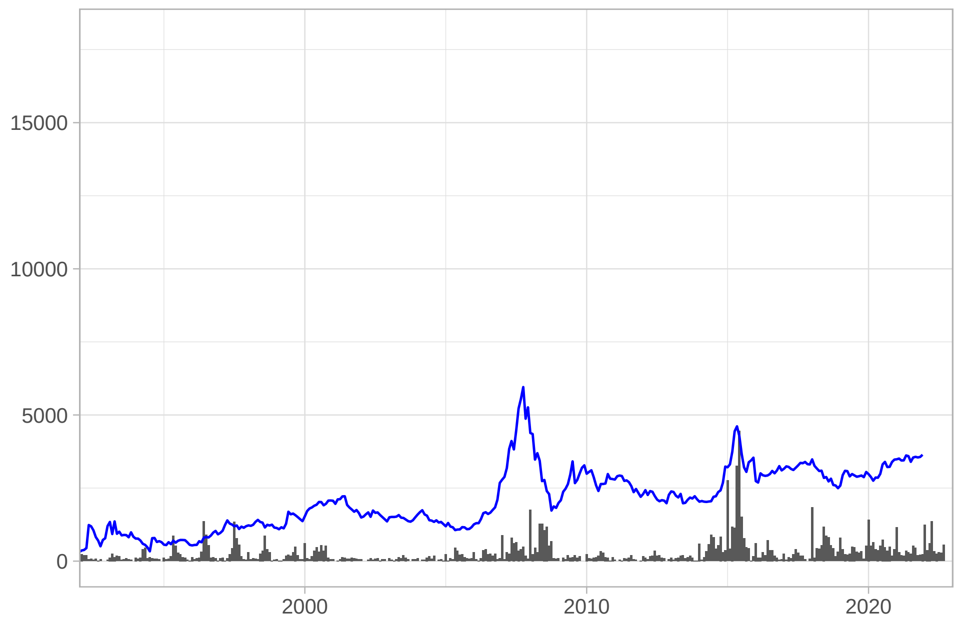


Panel (a) Distribution of start dates

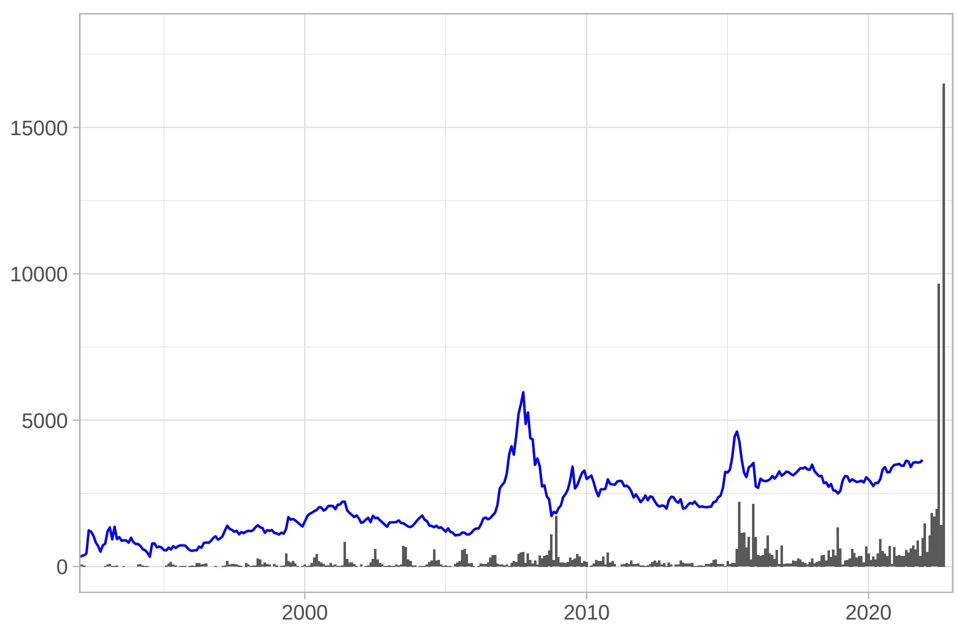


Panel (b) Distribution of end dates

Figure A.3: Distribution of recalled episodes, alternative phrasing

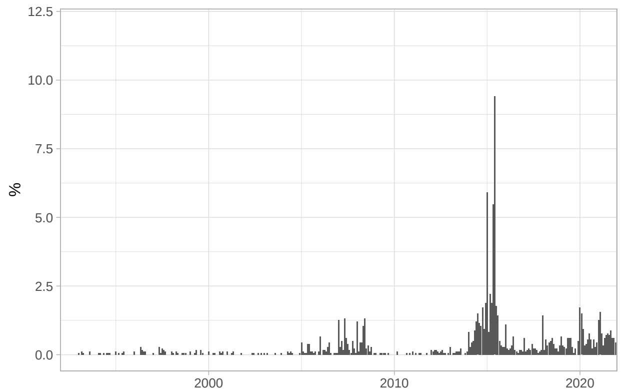


Panel (a) Distribution of start dates

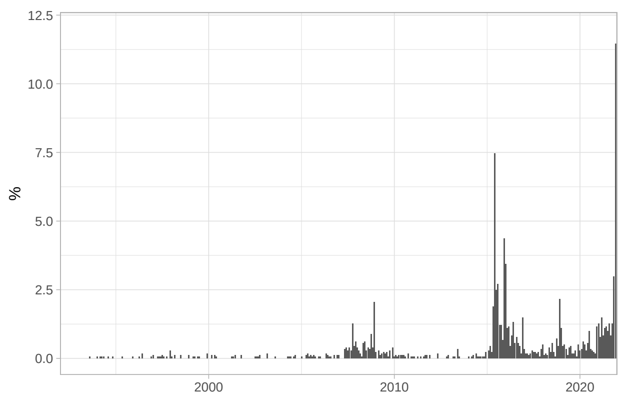


Panel (b) Distribution of end dates

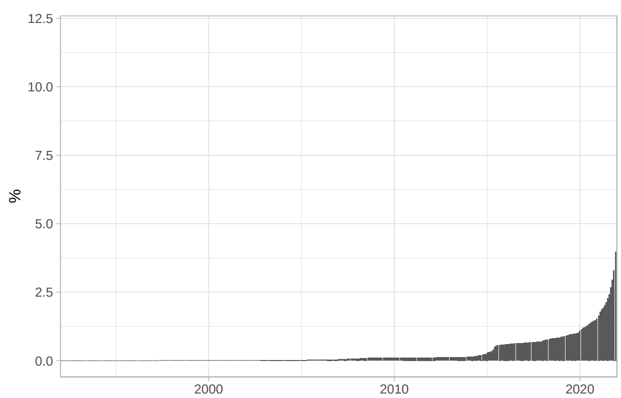
Figure A.4: Distribution of recalled episodes, counterfactual



Panel (a) Distribution of start dates



Panel (b) Distribution of end dates



Panel (c) Distribution of simulated dates

Table A.1: Determinants of recalled episodes in *FreeRecall*, additional results

This table repeats the regressions in Table 3 but includes three additional variables: monthly raw return, monthly turnover, and account size. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	Distance		Recalled market 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.2: 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
R^2	0.09	0.20	0.08	0.08
Adjusted R^2	0.02	0.14	0.003	0.01

Table A.3: Probed recall performance and market return as a cue, subsample

We regress recalled performance 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:					
	exretrecall_1day_rate					
	(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.4: Probed recall performance and market return as a cue, subsample

We regress recalled performance 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:					
	exretrecall_30day_rate					
	(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:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.5: Biased recall and overconfidence

	Perceived information advantage		Overplacement	
Recall bias, past month	1.728***		1.818	
	(0.294)		(1.098)	
Recall bias, past year		0.439***		1.142**
		(0.133)		(0.521)
Observations	1,704	1,928	1,399	1,555
Adjusted R^2	0.020	0.007	0.002	0.005
Note:				*p<0.1; **p<0.05; ***p<0.01

B Proof of Theoretical Results

The PDF of the database for period t is

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

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

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

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

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

which implies the distribution in (5).