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 past trading experiences and their return expectations. By merging the survey data with administrative data of transactions, we confirm the validity of elicited memory, examine its properties and determinants, and establish new facts that shed light on the relationship between memory and belief formation. First, on average, investor tend to recall both recent episodes and dramatic episodes such as bubbles and crashes. Old, experienced investors, in particular, tend to recall distant episodes featuring rising markets. Second, market conditions significantly affect recall: when recent returns are high, investors tend to think of past episodes of rising markets and recall past performances with a positive bias. Third, memory has significant explanatory power for cross-investor variation in beliefs. In fact, a single variable based on recalled performance has similar explanatory power for return expectations to that of a dozen individual characteristics combined. Fourth, recall biases are correlated with overconfidence and extrapolation, providing evidence of memory-based microfoundations for the latter. These facts establish the relevance of key memory mechanisms in financial markets and provide guidance for memory-based theories of belief-formation.

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1 Introduction

Beliefs are key to economic decisions. In most models, beliefs and preferences constitute 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. Evidence based on surveys, however, has challenged the FIRE assumption by documenting various deviations, such as overreaction, extrapolation, and overconfidence.[1] Moreover, it has been increasingly recognized that biased beliefs are not just meaningless errors; 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).

Despite the growing evidence on how people's belief-formation process deviates from FIRE, the underlying mechanisms driving such deviations are less well-understood. In some accounts, beliefs are biased because the human mind is inherently prone to making mistakes. In some 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.[2] A budding theoretical literature proposes that memory can help reconcile many puzzles on beliefs and financial decisions (Malmendier et al., 2020; Bordalo et al., 2021a,b; Wachter and Kahana, 2021). In these models, two features of the memory system have stood out. First, memory is selective. Not all past experiences are equally likely to be retrieved. Instead, some experiences—for example, those happened more recently—are more more likely to emerge in one's mind. Second, memory retrieval is influenced by external cues such as context, framing, or emotion. They tend to trigger recall of past experiences that are associated with those stimuli. In parallel with these theoretical developments, recent papers have also begun to examine these two features of memory in the lab or through surveys (Enke et al., 2020; Colonnelli et al., 2021). However, so far, there has been little evidence from the field.

In this paper, we bring new field evidence to shed light on the relationship between memory and beliefs. Compared to the existing evidence from surveys and experiments, our setting is closer

[1]For example, individual forecasters typically overreact to news (Bordalo et al., 2020b); return expectations positively load on past returns and negatively predict future returns (Greenwood and Shleifer, 2014); and investors on average are overconfident: the perceived ability is greater than the actual one (Liu et al., 2022).

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

to daily decision-making in several important dimensions. First, we study investors in a real stock market, some of whom have millions of dollars invested. Second, we are concerned with a particular relevant type of memory that is highly relevant to investment decisions: the memories of past trading experiences. Third, instead of solely relying on cues given by experimenters, we examine cues that naturally occur in financial markets—namely, stock return—and see how it affects the recall process. Fourth, by observing actual transactions for a subset of our investor sample, we are able to compare their memories against their actual experiences. These features allow us to examine key memory mechanism in the field and provide guidance to future models of memory.

Specifically, we survey a nationally representative sample of over 15,000 Chinese individual investors—our main sample. In the baseline survey, we design two blocks of questions to elicit investor memory. The first block, called *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. This block is motivated by theories of salience and the experience effect and is designed to capture the event that an investor immediately thinks of when they look back at past trading experiences (Malmendier and Nagel, 2011; Bordalo et al., 2012; Malmendier and Nagel, 2016). Given the nature of the *FreeRecall* block, our survey always start with this block to minimize the effects of other cues present in the survey environment.

The second block, called *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 motivated reasoning (e.g., Bénabou and Tirole, 2002, 2004), and is designed to measure how past performances are stored in investor memory. In addition to the two recall blocks, the survey also includes blocks to collect other information, including expectations of future market returns, future self performance, and 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 are able to merge their survey data with their administrative data of comprehensive transaction records from the Shenzhen Stock Exchange (SZSE)—the merged sample.

With these data in hand, we first examine the properties of investor memory. 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, indeed, investors responding to our survey are making a conscious effort in the recall tasks.

Furthermore, we test the selective recall hypothesis by examining investors' answers in *FreeRecall*. Consistent with the experience effect, investors are drawn to recent periods when recalling past market episodes, and this recency effect is particularly pronounced among the younger investors. However, the probability of recalling an episode is not monotonically decreasing with the time distance of the episode. Investors, especially those who are older and have stayed in the market for a longer period, are more drawn to distant events featuring dramatic market movements, such as the stock market bubbles in 2007–08 and in 2014–15. While such distant recalls feature both rising and falling markets, on average they tilt towards rising markets. As a result, both age and time distance are associated with a more rosy recollection of the stock market.

It is also important to recognize that recall as a mental process is not static but highly contingent on the environment. The recalled object is shaped by the stimuli present in the environment and therefore may change with market conditions. To examine this cued nature of investor memory, our next exercise links the dynamics of recall to perhaps the most ubiquitous stimuli in financial markets: returns. 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 can easily remind the investor of similar experiences in the past. Because each investor only takes the 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 the retrieved memories of our investors.

Overall, recent returns affect investor recall, but only when the recalled object concerns a recent experience. For more distant experiences, their retrieval can hardly be influenced by recent market movements. In the *FreeRecall* block, among investors whose recalled episode falls within the past two 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 points 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 two years, recent market returns have little impact on the recalled episode return.

A similar dichotomy emerges for the recalls from the *ProbedRecall* block. When today's market return goes up by one percentage point, on average, this external cue increases an investor's memory of her yesterday's performance by 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 *over*-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.

After showing that investor recall is selective and can be cued by market fluctuations, we turn to the empirical relationship between memory and beliefs. Many theories assume that investors form expectations by relying on their memory (e.g., Nagel and Xu, 2022). Our evidence supports this view. 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 points increase in expected market return and a 1.6 percentage points 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 points 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 an empirical puzzle about investor beliefs: 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, we rule out other explanations such as anchoring and priming.

Lastly, we examine the extent to which biased recall can explain common forms of biased beliefs at the investor level. We are concerned with two prevalent biases. The first one is return extrapolation, the idea that expectations about future returns positively load on past returns. In our data, consistent with extrapolation, higer past returns are associated with more optimistic beliefs about the market and one's own performance going forward. This relationship, however, significantly weakens after controlling for recalled performance, suggesting that cued recall is an important channel driving return extrapolation. The second bias is overconfidence. Theories of selective recall and motivated reasoning suggest that the persistence of overconfidence can be microfounded by investors selectively recalling more positive experiences and suppressing the negative ones. We construct two measures of overconfidence, one based on the expected future outperformance and the other based on perceived information advantage. For both measures, we find that overconfidence is positively correlated with recall bias (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,b; Colonnelli et al., 2021; Wachter and Kahana, 2021; Gödker et al., 2021). The mechanisms we focus on in this paper, namely selective recall and cued recall, have been examined both theoretically and experimentally. The evidence we bring in this paper broadens the scope of these mechanisms by confirming their relevance in the field. In a setting where the stake is much higher, the information environment is more complex, and participants are more sophisticated and financially motivated, we confirm that both mechanisms—selective recall and cued recall—are at work and have 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 of the store managers of a food and beverage company.

Our results on selective recall support the formulation of the experience effect in Malmendier and Nagel (2011, 2016); 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. Indeed, salient events featuring large run-ups and crashes are more likely to be recalled. Moreover, the fact that memories of more distant events tend to be more rosy provide empirical support for motivated reasoning (Bénabou and Tirole, 2002, 2004). Finally, the positive correlation between recall bias and overconfidence is consistent with a memory-based microfoundation for the latter (Gödker et al., 2021; Huffman et al., 2022).

Our results on cued recall confirm that, in the setting of financial markets, return is a salient cue affecting investor's recall process. Furthermore, we provide guidance on what kind of experiences are more responsive to cues. In our analysis, returns from today and from the past month can only affect the recall of recent experiences up to two years. More distant memories about the financial markets are less likely to be affected. We also link this result 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,b).

The strong and robust relationship between memories and beliefs also has implications for understanding the sources of belief heterogeneity. Interestingly, it is the recall of one's own performance—not recall of a past trading episode—that is more powerful in explaining cross-sectional variation in beliefs. 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 we observe in the market (Giglio et al., 2021; Jiang et al., 2020). 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. In our paper, we collect investors' recall of past trading experiences and merge them with expectations and actual trading behaviors.

The rest of the paper is organized as follows. Section 2 explains the survey design and the other data sources used in the paper. Sections 3 to 6 present three sets of facts concerning the relationship between memory and beliefs: Section 3 on the properties of recall, Section 4 on cued-recall, Section 5 on the cross-sectional relationship between recall and expectations, and Section 6 on the relationship between recall and biases. Section 7 concludes.

2 Survey Design and Other Data Sources

In this section, we begin by reviewing theories of recall in Section 2.1. In particular, we review previous studies on two important memory mechanisms: selective recall and cued recall. Sections 2.2 to 2.4 explain the design of different blocks in the survey: recall, expectations, and other blocks, respectively. Section 2.5 details the implementation procedure of the survey.

2.1 Theories of recall

2.1.1 Selective recall

In models of full information rational expectations (FIRE), before making decisions, agents can fully recall and access all past information. Daily observations and occasional introspection, however, would immediately suggest that recall in reality is far from perfect. 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 different forces have been suggested to drive selective recall. The first is recency: on average, people tend to recall more recent events and are able to describe the details more precisely. This recency bias has motivated, for example, the formulation of the experience effect used in Malmendier and Nagel (2011, 2016) and 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 they are better than the average investor. This self-image of an above-average investor can be achieved, for example, through actively selecting to focus on the more positive experiences. When an investor experiences both good and bad returns, if they selectively remember the good ones and suppress the bad ones, they can persistently be overconfident despite having relatively poor 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. 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).

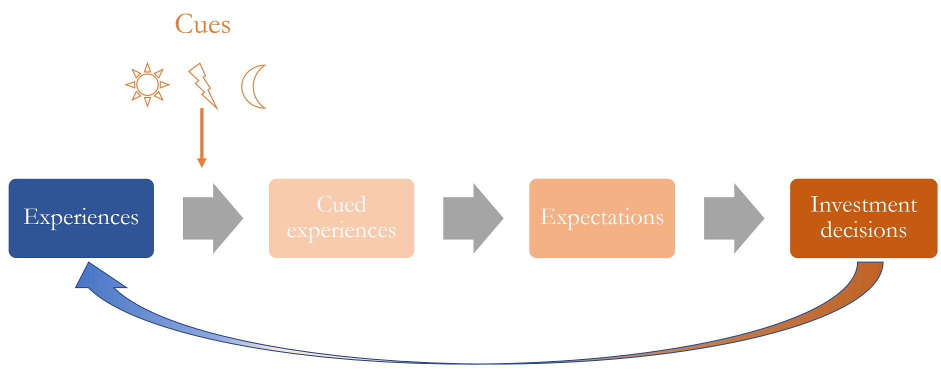
Salience comes in different forms: the amount of surprise, the degree of prominence, or the level of contrast with surroundings (Bordalo et al., 2021c). In the context of financial markets, it is straightforward to expect episodes featuring large movements in prices and volume such as big run-ups and crashes to be more salient. Salience-based recall is also consistent with the experience effect, the phenomenon that big macroeconomic events such as the Great Depression and the Great Recession can have a long-lasting effect on people's beliefs, risk attitudes, and behaviors (Malmendier and Nagel, 2011, 2016).

2.1.2 Cued recall

The mechanisms of selective recall make predictions about, unconditionally, what types of experiences are more likely to be recalled. In parallel with this static aspect of recall, psychologists have also discovered that, in a given moment, different cues (such as narratives, stories, images, emotions, or other stimuli) in the current environment can trigger the recall of past experiences that are also associated with that cue. By emerging at an individual's mind right at a given moment, these experiences may play a disproportionally large role compared to other experiences that are not associated with that cue. Therefore, cued recall makes conditional predictions about the type of experiences most relevant to decisions in a given environment.

The role of cues for recall has been extensively studied in the lab (Kahana, 2012). More recently, Enke et al. (2020) examine the this idea 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. Figure 1 graphically explains how cues can affect investment decisions through beliefs. The complexity of financial markets gives rise to a wide array of candidate cues: central banks' actions, the narratives told by the media, or sentiments expressed by people around. All these cues have the potential of triggering an experience associated with those cues. For example, rapidly rising stock prices in the tech sector may be reminiscent of the tech bubble for an investor who were actively trading during that period. Once triggered, this experience during the tech bubble may come into play in determining how they respond to the booming market.

Figure 1: Theories of cued recall



2.2 Survey design: recall

Examining selective recall and cued recall requires collecting data on investors' recall of past experiences and performances. Below, we use two blocks of the survey to elicit investor's recall of past experiences. Testing cued recall further requires specifying the cue, which we explain later in Section 2.5 and in Section 4.1.

2.2.1 *FreeRecall*

The core part of the survey starts with a block called *FreeRecall*. This block 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. By "free," we want to give the investors minimal guidance and conditions on what periods to be recalled. Because investors are free in the period of market movements they can recall, 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 them to "first think about the overall stock market movement since you opened an account." Then, right afterwards, we ask them 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." Investors need to select the start month and end month of this particular period they have in mind. 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—as in the case of the Great Depression to the baby boomers or the tech bubble to Gen Z investors—can also be recalled and have an effect on belief-formation; we abstract away from these non-experience-based recall throughout the paper.

Having just entered a market episode that comes to mind, investors are immediately followed up with 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 for investors to recall an exact number for these questions, we design these questions to be multiple-choice with each choice covering a specific range of value.[3]

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 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 will discuss these two blocks in more detail in Section 5.

2.2.2 *ProbedRecall*

After *FreeRecall*, investors will immediately move on to the second block called *ProbedRecall*. With this block, we ask investors 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 that is been elicited (own return performance) and the time period that has been specified (one day or one year).

When an investor enters the *ProbedRecall* block, we ask participants to answer the following question: "To the best of your recollection, what was the cumulative return rate of your equity

[3]We repeat this set of questions at the stock level. 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, as well as the results of this block, are included in the Online Appendix.

investment over: 1) last trading day; 2) last month; 3) last year; and 4) last five years?" Similar to before, we design these questions to be multiple-choice and investors can choose a option covering a fixed range of value.

2.3 Survey design: expectation

After the two recall blocks, *FreeRecall* and *ProbedRecall*, investors next enter the expectation block, called *Expectation*. We elicit two types of expectations, one about future market returns including both the mean return and tail distributions, and one about self-performance going forward. As before, the expectation questions are multiple-choice. The phrasing of these questions is similar to earlier paper that use 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*). In the end, we prefer the current ordering for the following reasons. First, given the nature of the *FreeRecall* block, the elicitation process ideally should receive 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* are 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 induce investors to biased their recall through motivated reasoning (Bénabou and Tirole, 2002, 2004).

2.4 Survey design: other blocks

At the beginning of the survey, investors are explicitly instructed to rely on memory and not to check their phone or the internet. In reality, we do not observe when an investor does not follow our instructions. However, around 60% investors finish the entire survey within ten minutes, which leaves limited time for them to do a thorough check online or using the phone. 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, 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 comprehension questions check investors' understanding of the concepts of dollar investment and return. Afterwards, they move on to the three blocks explained above: *FreeRecall*, *ProbedRecall*, and *Expectation*. In our analysis, we exclude observations that did not the comprehension check.

After the *Expectation* block, participants do a personality block, which includes a questionnaire of ten 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, etc. In the remainder of the paper, these variables will mostly be used as control variables. Figure 2 illustrates the design of the survey blocks.

Figure 2: Organization of survey blocks

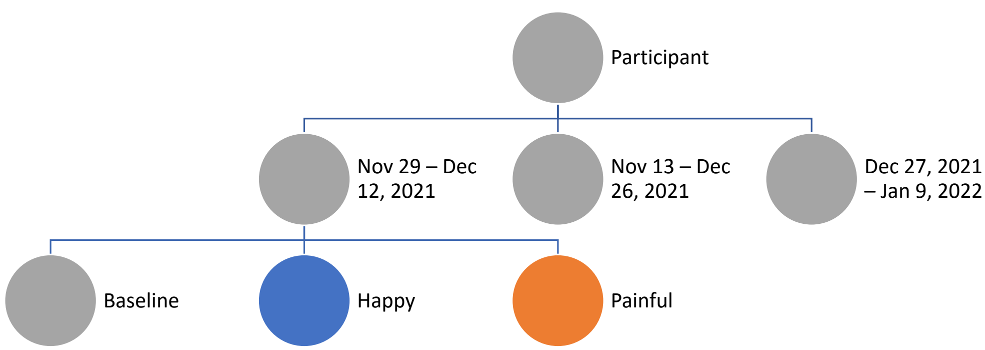
2.5 Survey implementation

We administered the survey through the Investor Education Center of the Shenzhen Stock Exchange (SZSE), the same setting that has been previously 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. See Liu et al. (2022)

for more institutional details.

Figure 3 illustrates the timeline of the survey implementation. The survey took place between November 29, 2021 and January 6, 2022, and respondents were given two weeks to complete the survey. 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 in our sample. The basic demographic characteristics of our sample can be found in Figure 4. Overall, the sample is young, well-educated, and affluent: the median age is around 35, the majority of them has a bachelor degree, and a substantial fraction have a wealth above the 1 million RMB mark.

Figure 3: Timeline of survey implementation



3 Properties of Recall

In this section, we examine the basic properties of investor recall. When analyzing investor recall, we focus on the three drivers of selective recall: recency, motivated reasoning, and salience. Section 3.1 examines the *FreeRecall* block and Section 3.2 examines the *ProbedRecall* block.

3.1 The *FreeRecall* block

3.1.1 Recalled market episodes

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 "recalled market episodes."

We analyze the properties of recalled market episodes by plotting their distribution in Figure 5. Figure 5 plots the distribution of the start date and the end date against the Shanghai Composite Index. Two patterns immediately emerge in these plots. First, recalled episodes display a recency effect: a disproportionally large number of them concern recent periods. One mechanical driver of this recency effect is due to experience: new investors, by default, can only recall the more recent experiences, and this can mechanically push up the distribution among recent periods. In the Online Appendix, Figure A.1 replots the distribution of recalled episodes but excludes new investors who entered the market during the last twelve months. As before, there is a cluster of recalled episodes for the recent periods, thereby confirming the recency effect is not mechanically driven by the cohort of new investors. This recency effect suggests that more recent events are also more likely to be recalled, consistent with the formulation of the experience effect in Malmendier and Nagel (2011, 2016) and in Malmendier et al. (2020).

Second, the distribution of recalled market episodes tilts towards dramatic financial events such as past bubble and crash episodes. The Chinese stock market has experienced two of such episodes over the last two decades—one in 2007–08 and the other in 2014–15—and a disproportionally large number of investors tend to think of these events. This is consistent with the presence of a salience effect in recall: more salients events initially received more attention and are therefore more likely to be recalled subsequently.

3.1.2 Event study: the 2014–15 stock market bubble

The previous section documents that dramatic events such as bubbles and crashes are more likely to be recalled in *FreeRecall*. However, it remains unclear what part of the boom-and-bust cycle are investors 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. Simply put, the 2014–15 bubble started in late 2014, peaked in mid 2015, and crashed afterwards. Figure 6 shows three modal answers: one ending in 2015:06, one beginning in 2015:06, and one beginning in 2015:01 and ending in 2015:12. These three answers correspond, respectively, to the run-up, the crash, and the full cycle. These modes not only show the heterogeneity in the type of events investors recall, but also demonstrate that investors can differentiate different parts of the cycle in their recall. The fact that investors clearly differentiate the various stages of a bubble further reinforces the validity of the recall block.

3.1.3 Recalled market returns

In addition to recalling a market episode that first comes to mind, respondents are also 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 "recalled market returns."

Table 1 shows the summary statistics of recalled market returns and actual market returns of the recalled market episodes. In Panel A, we find that there is 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 further confirms that selective recall exhibits a strong salience effect. However, we do not find 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 motivated reasoning, investors tend to hold a more rosy view about their *own* performance rather than the entire market.

How accurate are these recalled returns? Panel B examines the correlation between the recalled return and the actual return and finds that the correlation is 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.

3.1.4 Determinants of recall

As shown in Figure 5 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 have an influence on investor memory. To examine the determinants of recall in *FreeRecall*, in Table 2 we regress two aspects of recall—the distance of and the return of the recalled episode—on various individual characteristics.

In Table 2, column (1) first regresses the distance of the recalled episode on various individual characteristics, where distance is 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 ten-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 old investors entering 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.

In Table 2, column (3) repeats the exercise in column (1) for recall return. Again, age appears to be a key determinant of recall return: older investors tend to recall a more bullish market episode. This positive correlation between age and optimism is consistent with the recent evidence from Bordalo et al. (2022) in which older people appear to be more optimistic about COVID. A ten-year difference in age implies a 2.3-percentage-points difference in recall return. In addition to age, gender also appears to matter: women tend to recall a more bearish episode. Interestingly, out of the five personality traits, we find that Neuroticism 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). Column (4) repeats the regression in column (3) but adds recall distance as an additional control. On average, more distant recalls are more bullish. At the same time, the coefficient on age continues to be significantly positive.

In the previous section, we documented that investor recall in *FreeRecall* exhibits a salience effect. In Table 3, 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 one if the recall return is greater than 100%. Similar to 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 one if the recall return is lower than than -50%. Interestingly, older people are also more likely to recall the extreme negative events, consistent with a salience effect.

3.2 Probed recall

Table 4 shows the summary statistics of the recall in *ProbedRecall*. Panel A shows the distribution of recall performance at different horizons. Overall, the longer horizon is associated with more positive recall. However, these recalls could reflect both biases in recall and the actual performances.

To directly compare recall against actual performance, Panel B compares the recalled performance against the actual performance for the merged sample. Three observations are worth noting. First, the distribution of recalled performance is similar between the full sample in Panel A and the merged sample in Panel B, suggesting the merging process does not create selection in investor skills. Second, for horizons between one day and one year, we do not find that the recalled performance is higher than the actual performance. 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%.

To further confirm that investors in the survey are indeed trying to recall their performance, Panel C shows the correlation between recalled performance and actual performance. The correlations are positive and highly significant for all horizons, suggesting that investors are making a conscious effort 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.

One common property shared by the two types of recalls in *FreeRecall* and *ProbedRecall* is that recall concerning a more distant period tends to be more positive: in *FreeRecall*, older investors tend to recall a more distant and positive episode; and in *ProbedRecall*, recall over a longer horizon tends to be more positive. This is consistent with motivated reasoning, because more distant memory is less accurate and leaves more room for manipulation. In comparison, most people have a clear memory of what happened recently, and when memory is fresh and accurate, it leaves less room for manipulation—a key ingredient of motivated reasoning.

4 Dynamics of Recall

In this section, we study the dynamics of recall by focusing on its cued nature. In Section 4.1, we start by discussing our candidate cue, namely return, and how we generate variation in the cue when implementing the survey. In Sections 4.2 and 4.3, we test cued recall by examining the relationship between returns and recalls elicited by the two recall blocks, *FreeRecall*, and *ProbedRecall*, respectively.

4.1 Market return as the cue

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. In particular, a positive return triggers the retrieval of more positive experiences in the past. As the investor has these experiences in their mind at that precise moment, they tend to have more optimistic views about the future.

To get sufficient variation in market return, we roll out the survey in three waves, spanning a total of six weeks 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 the minimum is -1.16%, and the standard deviation is around 0.66%. In the Online Appendix, Figure A.4 examines the distribution of returns during this period in more detail. One appealing feature of the survey is that we are able to 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 a day.

In addition to using market return as cue, we also consider portfolio-level return as 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.

4.2 Free recall

Our main hypothesis is that a positive return trigger the retrieval of an episode of a booming market in *FreeRecall* and more positive past performance in *ProbedRecall*. To test this, we first measure the return cue as the cumulative market return up to the point when an investor starts taking the survey ($MktRet_{t\to t+\tau}$). We then regress the recall on the return cue, using the main regression specification below:

$$RecallRet_{i,t+\tau} = \beta_0 + \beta_1 \times MktRet_{i,t\to t+\tau} + X_i + \epsilon_{i,t+\tau},$$

where X_i denotes a variety of individual-level controls. Specifically, we control for age, gender, education, wealth, income, and measures of social activities. In Table 5, column (1) reports the results. Overall, we do not find that the recall in *FreeRecall* is affected by today's market return. In columns (2) and (3), we entertain two other specifications: one using past one-month return as cue and one using both returns at the same time. In neither specification does the variation in market returns affect the recalled return in *FreeRecall*. In all regressions, we exclude observations that end in or after November 2021 to avoid the potential overlap between the cue and the recall.

The null results in columns (1) to (3) may initially appear surprising. A closer examination, however, reveals a few possible reasons. First, Section 3 showed that the recall in *FreeRecall* largely captures salient events in the past. While there is significant movement during our survey period, the overall market is rather mild, without large rises or falls in asset prices. As a result, market returns as a cue may not be powerful enough to affect recall in *FreeRecall*. Second, it is possible that not all types of memory can be recalled by the return cue, especially given that the returns we consider are mostly short-term returns such as daily return and the recent one-month return. Only when free recall is concerning a more recent episode can these returns influence their retrieval process.

To test this latter possibility, we repeat the regressions but limit the recalled episode in *FreeRecall* to be recent. More specifically, in columns (4) and (6), recalled episodes are limited to those that end within the last five years.[4] In these columns, both day's return and the past one-month return have a much stronger influence on the recalled return in *FreeRecall*. In column (1), a one-percentage-point increase in today's return increases the recalled return by 2.11 percentage

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

points. In column (2), a one-percentage-point increase in today's return increases the recalled return by 1.09 percentage points. And in column (3), when both today's return and the past one-month return are included, the coefficients remain positive and statistically significant.

4.3 Probed recall

Next, we test cued recall in *ProbedRecall*. We run the same regression by replacing recalled episode's return with recalled past performance, with a similar specification:

$$RecallPer_{i,t+\tau} = \beta_0 + \beta_1 \times MktRet_{i,t\to t+\tau} + X_i + \epsilon_{i,t+\tau},$$

where $RecallPer_{i,t+\tau}$ represents the recalled performance of a given horizon 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 performance yesterday using today's market return as a cue. Column (1) reports the results and finds evidence of cued recall. When today's market return goes up by 1 percentage point, investors on average recall their yesterday's performance more by 68 basis points. Without controlling for their actual performance, however, one cannot differentiate whether the recall is accurate or biased. In column (2), using the merged sample, we control for the actual performance yesterday and find similar results. Therefore, positive returns today tend to trigger more positive recalls of yesterday's performance.

Columns (3) and (4) repeat the same set of regressions for recalled performance over the past month and find similar evidence. When today's market return goes up by 1 percentage point, investors on average recall their past month's performance more by around 1 percentage point, without or with the control of the actual performance. In the Online Appendix, Table A.5 repeats these regressions using portfolio-level return as the cue and finds similar evidence.

Interestingly, when we start to examine performance recall over a longer horizon, a few distinct patterns begin to emerge. In column (1), today's return no long significantly affects the recall of past year's performance. While this may initially appear surprising or puzzling, this is actually consistent with the evidence in the previous section: when the nature of recall concerns a more distant period, today's return is no longer the relevant cue in the recall process. Consistent with this, 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 set of analyses by adding the 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.

5 Recall and Expectation

Having described the properties of investor recall and examined the nature of cued recall, we next explore the nexus between recall and belief formation. We first examine the statistical relationship between recalls and expectations in Section 5.1. We then discuss a number of alternative explanations in Section 5.2.

5.1 The cross-sectional relationship

It is well documented that 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 recalled that past returns were low.

To test this hypothesis, we examine the relationship between expectations and free recall by running the following cross-sectional regression:

$$Expectation_i = \beta_0 + \beta_1 \times RecallRet_i + \epsilon_i,$$

where $RecallRet_i$ is investor i's recalled return in *FreeRecall*, and $Expectation_i$ is the same investor's expectations.

Panel A of Table 7 reports the results. We consider four types of expectations. Columns (1) and (2) concern expectations of the market return over the next month and the next year, respectively. 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 also have higher expectations of future returns. Magnitude-wise, free-recalled returns may cover different time periods depending on the time periods our respondents choose. Their 25-75 percentile range is -17.5% to 12.5%, which, for example, leads to a 0.15% difference in the market return in the next month and a 0.6% difference in the market return in the next year according to our estimates.

In Panel B, we repeat the above regression by replacing the recalled return in *FreeRecall* with recalled performances in *ProbedRecall*. To simplify the exercise, for each type of expectation, we pick the recalled performance of the same window length. For example, for expectations over the next month, we use recalled performance of the last month. In these regressions, expectations about future market returns and one's own performances are highly correlated with recalled performances. Magnitude-wise, the 25-75 percentile range of the past 1-month performance is -4.5% to 4.5%, which will lead to a 2.9% difference in the self performance return in the next month. Moreover, the 25-75 percentile range of the past 1-year performance is -6.5% to 8.5%, which will lead to a 6.3% difference in the self performance return in the next year. Comparing between Panel A and B suggests that probed recall in the form of recalled performance has much stronger explanatory power.

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 8, 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 or recall, without additional control variables. The demographic variables include gender, age, income, wealth, and education dummies. For recall, we follow Panel B of Table 7 and use recalled performance 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 the past one-year recall if the dependent variable is the expectation of future one-year return.

In Table 8, on average, the explanatory of probed recall for expectations is comparable to, or higher than, that of demographic variables. The addition in R-squared could be quite substantial. For example, comparing the R-squareds in Panel B of 7 to those in Table 8, we see that including a single variable of recall can increase the R-squared from 1% to 4% to 4% to 14%. In Giglio et al. (2021), they pose it as an open question as what variables could be driving the cross-sectional variation in beliefs. Our evidence suggests that the way experiences are processed, stored, and retrieved is a promising way to microfound belief heterogeneity.[5]

5.2 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 in generating random variation in recall, it is hard to establish causality. Moreover, as both variables are elicited through survey, this invites a few alternative explanations to our results. Below, we discuss a few of these alternative explanations and how we rule them out.

5.2.1 Anchor effects

In our survey, investors first answer two recall blocks before they answer a block of questions on expectations. As a result, one possible alternative explanation for the statistical relationships documented above is that, when reporting expectations in the *Expectation* block, some investors are lazy and not willing to exercise sufficient mental effort. As a result, their answers in the expectation block are anchored towards their answers in the previous recall blocks, which leads 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 in shorter period of time. In Table 9, we run the following equation:

$$Expectation_i = \beta_0 + \beta_1 \times RecallRet_i + \beta_1 \times RecallRet_i \times TimeSpent_i + \epsilon_i,$$

where $RecallRet_i$ is investor i's recalled return in *FreeRecall*, $Expectation_i$ is the same investor's expectations, and $TimeSpent_i$ represents the time spent on the survey. In Table 9, the coefficient on the interaction term is insignificant and close to zero, casting doubt on such anchor effects.

[5] In Giglio et al. (2021), they 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.

5.2.2 Click-through behavior

Related to the anchor effect, if some investors just click through the entire survey with the same answer option, then this type of behavior would also generate a similar positive correlation between recall and expectations. At the same time, this type of 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 performances, we instead use expected crash probability on the left-hand side. Results are reported in Table 10 If it is indeed some click-through behavior that is driving the positive correlation between recall and expectation, then we should see a similar relationship in these regressions. However, this is not what we find: investors with a higher recalled performance tend to believe that crash will happen with a lower probability. These results also suggest that recall not only affects average beliefs, but affect people's perception of tail events.

5.2.3 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 around through motivated reasoning. For instance, suppose in reality expectations have nothing to do with memory but are shaped by some omitted variables. An optimistic investor, however, would like to 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.

6 Recall and Belief Biases

In this section, we link the previously documented memory structures to some of the prevalent belief biases. In Section 6.1, we link cued recall with extrapolation. In Section 6.2, we link selective recall with overconfidence.

6.1 Memory and Extrapolation

One robust bias is return extrapolation, which refers to the investors' tendency of forming 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 further 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 while others are based on bounded rationality.

Our hypothesis is that cued recall can microfound extrapolation, because good returns trigger the recall of past experiences associated with good returns. If investors form expectations using their past experiences, they tend to overly use the more positive ones and therefore become overly optimistic. One key implication of this memory-based mechanism is that the positive relationship between good returns and positive expectations hinges on the recall structure. Controlling for return, 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), Table 12 reports the result. Exploiting random variations in the timing of our survey, we find that respondents who experienced a 1% higher market return in the past month tend to report 0.14% higher expected return in the next month.

Then, to test our hypothesis, we additionally include the respondents' recalled performance in the past month in our regression. Column (2), Table 12 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 self performance is strong. In columns (3) and (4), we repeat our exercise using the expected self performance as the dependent variable instead of the expected market performance, and find even more striking result: recalled performance completely drives out the explanatory power of the actual past return for explaining expected returns. These results impute a central role to memory and recall in the investors' extrapolation tendency in expectation formation.

6.2 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 only has a temporary effect; and 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 that there is a positive correlation between overconfidence and selective recall in the cross-section of managers.

We bring similar evidence from the field using a sample of retail investors. In Table 13, we regress measures of overconfidence on recalled return in *FreeRecall*; in the Online Appendix, Table A.6 regresses measures of overconfidence on recalls in *ProbedRecall*. We consider two measures of overconfidence: the first one is the difference between the expected self performance and the expected market return, and the second is 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.

Column (1) shows that there is a positive correlation between overconfidence and free recall. That is, 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 the recalled return and the 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 free recall is also positively correlated with perceived information advantage.

7 Conclusion

We survey a large, representative sample of retail investors to elicit their memories of past trading experiences and their return expectations. By merging the survey data with administrative data of transactions, we confirm the validity of elicited memory, examine its properties and determinants, and establish new facts that shed light on the relationship between memory and belief formation. First, on average, investor tend to recall both recent episodes and dramatic episodes such as bubbles and crashes. Old, experienced investors, in particular, tend to recall distant episodes featuring rising markets. Second, market conditions significantly affect recall: when recent returns are high, investors tend to think of past episodes of rising markets and recall past performances with a positive bias. Third, memory has significant explanatory power for cross-investor variation in beliefs. In fact, a single variable based on recalled performance has similar explanatory power for return expectations to that of a dozen individual characteristics combined. Fourth, recall biases are correlated with overconfidence and extrapolation, providing evidence of memory-based microfoundations for the latter. These facts establish the relevance of key memory mechanisms in the financial markets and provide guidance for memory-based theories of belief-formation.

References

Barberis, Nicholas, 2018, Psychology-based models of asset prices and trading volume, in *Handbook of behavioral economics: applications and foundations 1*, volume 1, 79–175 (Elsevier).

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, 2015, X-capm: An extrapolative capital asset pricing model, *Journal of Financial Economics* 115, 1–24.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, 2018, Extrapolation and bubbles, *Journal of Financial Economics* 129, 203–227.

Bénabou, Roland, and Jean Tirole, 2002, Self-confidence and personal motivation, *The quarterly journal of economics* 117, 871–915.

Bénabou, Roland, and Jean Tirole, 2004, Willpower and personal rules, *Journal of Political Economy* 112, 848–886.

Bordalo, Pedro, Giovanni Burro, Katie Coffman, Nicola Gennaioli, and Andrei Shleifer, 2022, Imagining the future: memory, simulation and beliefs about covid, *Working paper* .

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, Frederik Schwerter, and Andrei Shleifer, 2021a, Memory and representativeness., *Psychological Review* 128, 71.

Bordalo, Pedro, John J Conlon, Nicola Gennaioli, Spencer Yongwook Kwon, and Andrei Shleifer, 2021b, Memory and probability, Technical report.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer, 2020a, Expectations of fundamentals and stock market puzzles, Technical report, National Bureau of Economic Research.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer, 2020b, Overreaction in macroeconomic expectations, *American Economic Review* 110, 2748–82.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2012, Salience theory of choice under risk, *The Quarterly journal of economics* 127, 1243–1285.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2021c, Salience, *Working paper* .

Brunnermeier, Markus K, and Jonathan A Parker, 2005, Optimal expectations, *American Economic Review* 95, 1092–1118.

Colonnelli, Emanuele, Niels Joachim Gormsen, and Timothy McQuade, 2021, Selfish corporations, *Chicago Booth Research Paper* .

Da, Zhi, Xing Huang, and Lawrence J Jin, 2021, Extrapolative beliefs in the cross-section: What can we learn from the crowds?, *Journal of Financial Economics* 140, 175–196.

Enke, Benjamin, Frederik Schwerter, and Florian Zimmermann, 2020, Associative memory and belief formation, *Working paper* .

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *The review of financial studies* 14, 1–27.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2021, Five facts about beliefs and portfolios, *American Economic Review* 111, 1481–1522.

Gödker, Katrin, Peiran Jiao, and Paul Smeets, 2021, Investor memory, *Working paper* .

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *The Review of Financial Studies* 27, 714–746.

Huffman, David, Collin Raymond, and Julia Shvets, 2022, Persistent overconfidence and biased memory: Evidence from managers, *American Economic Review, forthcoming* .

Jiang, Zhengyang, Cameron Peng, and Hongjun Yan, 2020, Personality differences and investment decision-making, *Working paper* .

Jin, Lawrence J, and Pengfei Sui, 2022, Asset pricing with return extrapolation, *Journal of Financial Economics* 145, 273–295.

Kahana, Michael Jacob, 2012, *Foundations of human memory* (OUP USA).

Köszegi, Botond, 2006, Ego utility, overconfidence, and task choice, *Journal of the European Economic Association* 4, 673–707.

Liao, Jingchi, Cameron Peng, and Ning Zhu, 2022, Extrapolative bubbles and trading volume, *The Review of Financial Studies* 35, 1682–1722.

Liu, Hongqi, Cameron Peng, Wei A Xiong, and Wei Xiong, 2022, Taming the bias zoo, *Journal of Financial Economics* 143, 716–741.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: do macroeconomic experiences affect risk taking?, *The Quarterly Journal of Economics* 126, 373–416.

Malmendier, Ulrike, and Stefan Nagel, 2016, Learning from inflation experiences, *The Quarterly Journal of Economics* 131, 53–87.

Malmendier, Ulrike, Demian Pouzo, and Victoria Vanasco, 2020, Investor experiences and financial market dynamics, *Journal of Financial Economics* 136, 597–622.

Maxted, Peter, 2020, A macro-finance model with sentiment, *Working paper* .

Mullainathan, Sendhil, 2002, A memory-based model of bounded rationality, *The Quarterly Journal of Economics* 117, 735–774.

Nagel, Stefan, and Zhengyang Xu, 2022, Asset pricing with fading memory, *The Review of Financial Studies* 35, 2190–2245.

Wachter, Jessica A, and Michael Jacob Kahana, 2021, A retrieved-context theory of financial decisions, Technical report.

Zimmermann, Florian, 2020, The dynamics of motivated beliefs, *American Economic Review* 110, 337–61.

Figure 4: Distribution of Demographic Variables

We report the distribution of age, gender, education, wealth, and income.

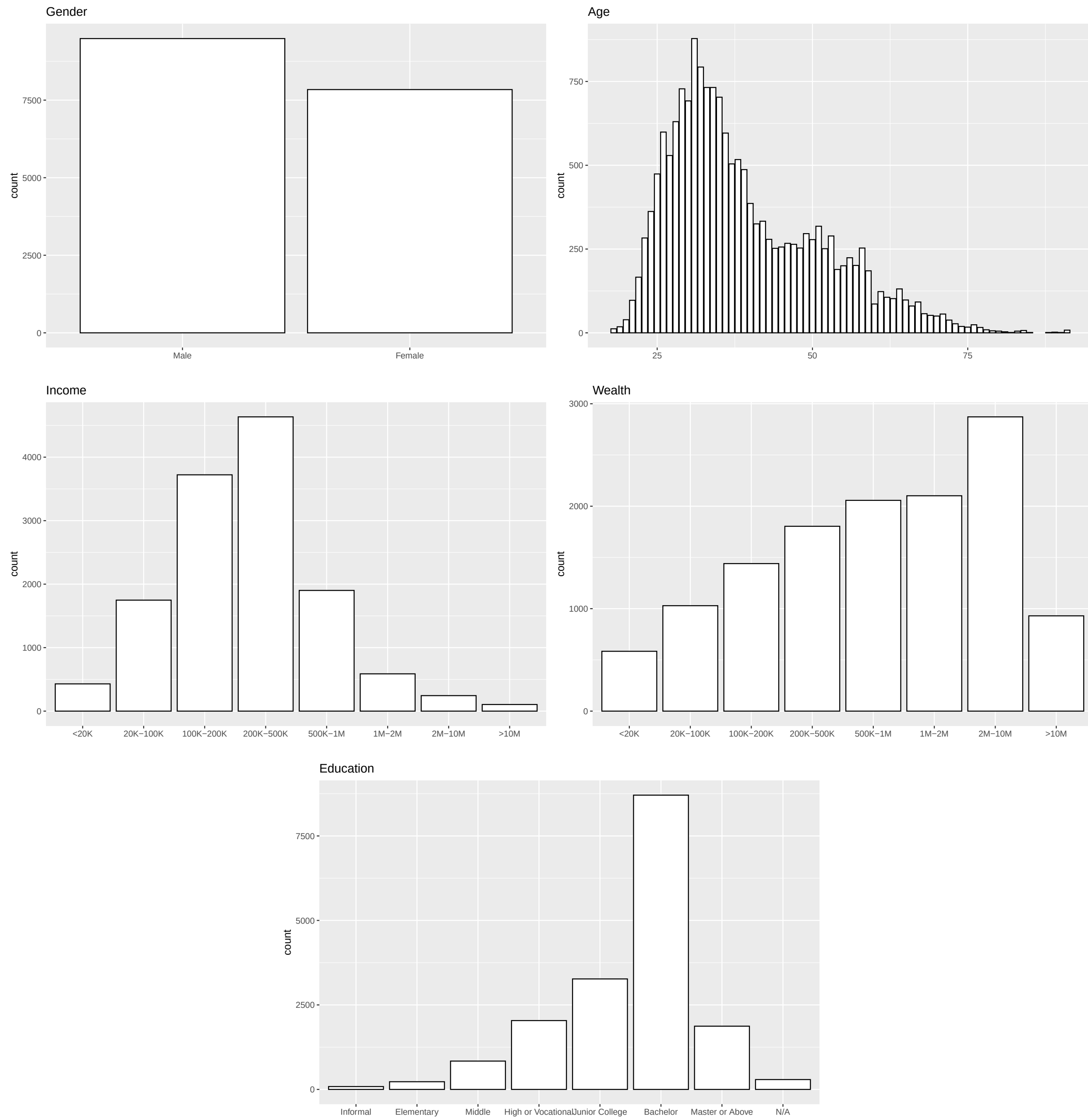
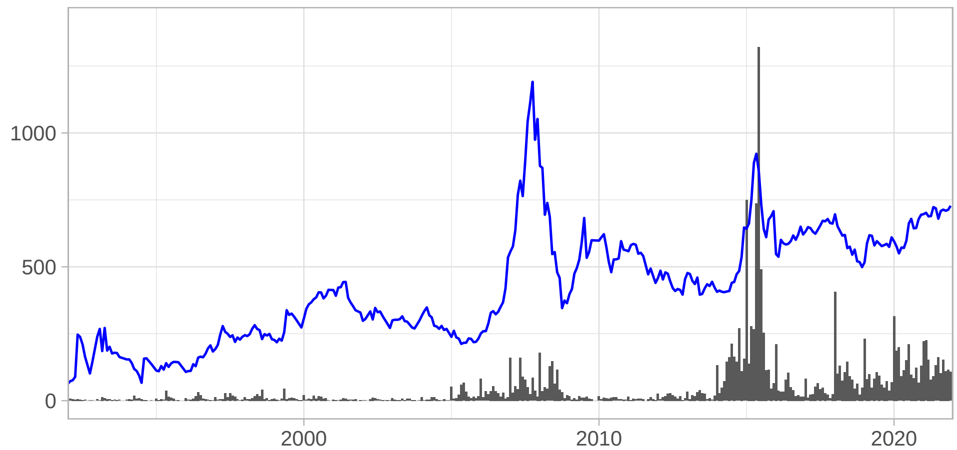
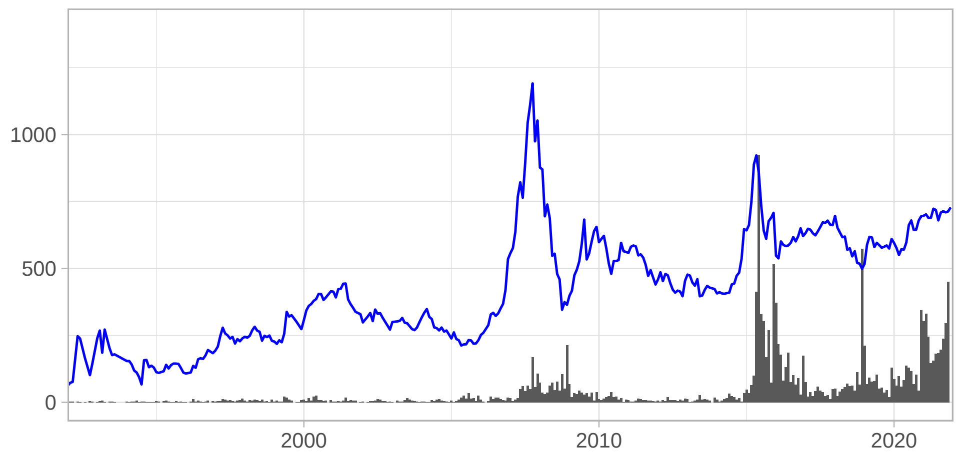


Figure 5: Distribution of Recalled Period



Panel (a) Distribution of Start Dates



Panel (b) Distribution of End Dates

Figure 6: The Distribution of Recalled Period in 2015.

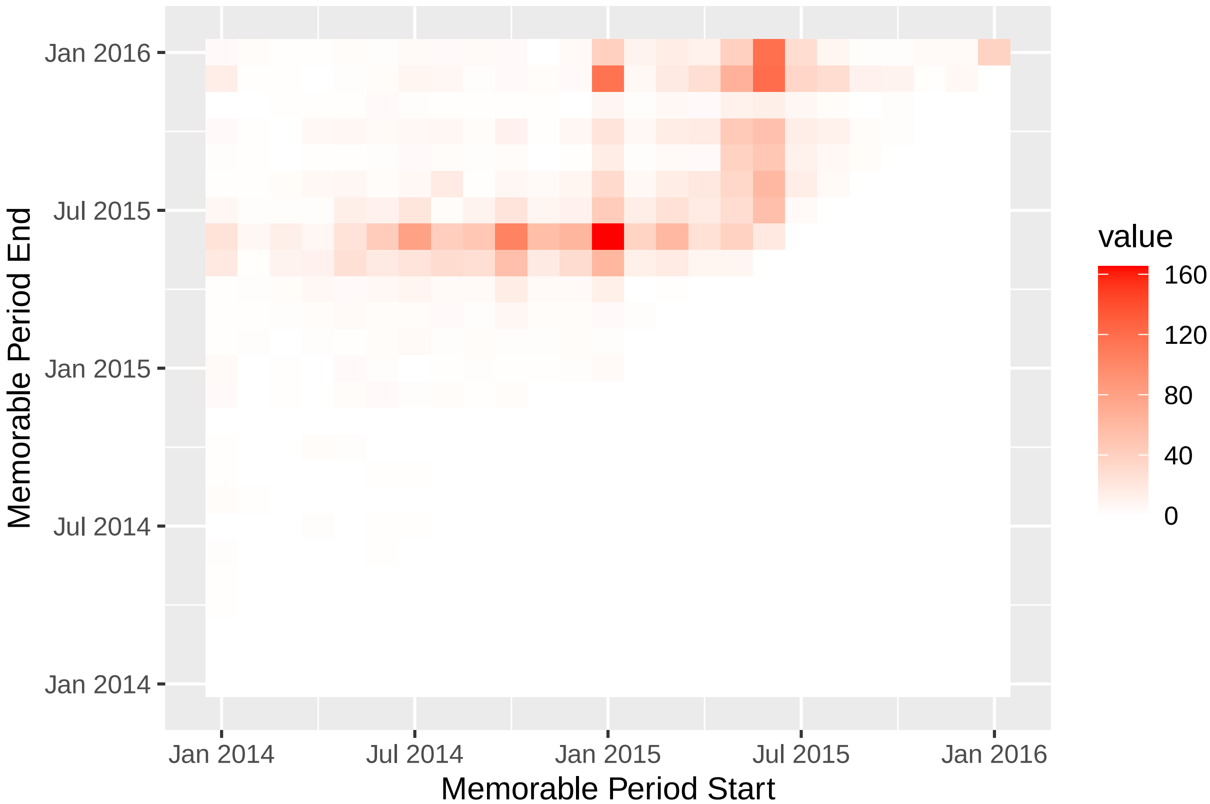


Figure 7: Age and recalled return in *FreeRecall*

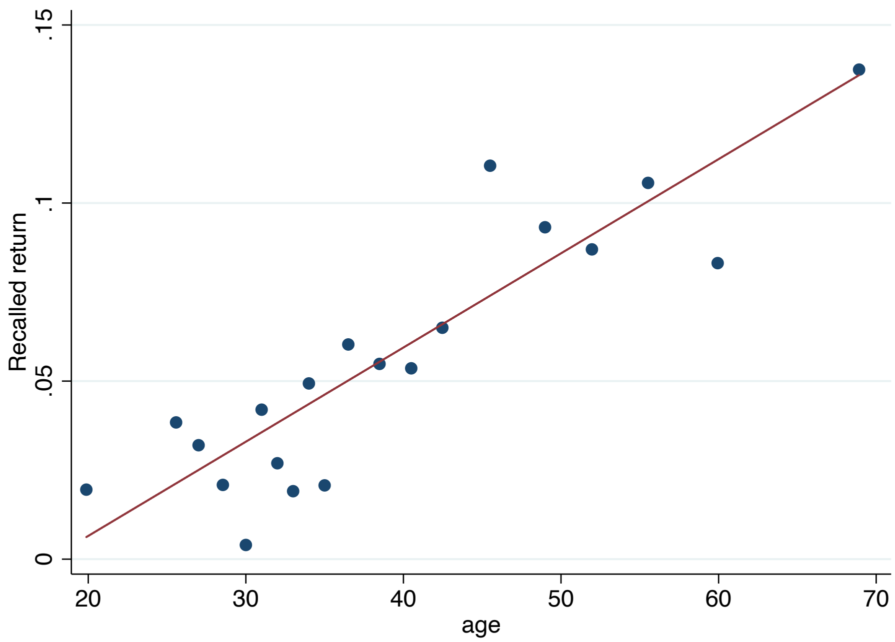


Table 1: Summary statistics of recalled market return in *FreeRecall*

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: 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 of the recalled episode. In columns (3) and (4), 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) and (4) 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)
Age	0.11***	0.07**	0.23***	0.25**
	(0.01)	(0.03)	(0.07)	(0.11)
Experience		0.19***		−0.09
		(0.04)		(0.13)
Distance				1.21***
				(0.21)
Female	−0.33*	0.03	−2.36**	−1.85
	(0.19)	(0.29)	(0.94)	(1.62)
College	0.30**	0.53	−0.73	0.76
	(0.14)	(0.38)	(1.85)	(2.88)
Wealth>1M	−0.21	0.01	1.87	−3.47
	(0.17)	(0.32)	(1.23)	(2.48)
Income>200K	0.36*	−0.11	0.17	6.09*
	(0.17)	(0.39)	(1.73)	(2.94)
Often check account	−0.77***	−0.60**	−3.36***	−0.23
	(0.14)	(0.23)	(0.89)	(3.37)
Often check news	−0.09	−0.64*	1.75	2.92
	(0.19)	(0.32)	(1.12)	(2.31)
Often discuss	0.18	0.60	−0.91	−1.76
	(0.14)	(0.35)	(1.52)	(3.01)
Many Wechat groups	0.46***	0.29	−0.14	4.06*
	(0.16)	(0.34)	(1.09)	(2.14)
Agreeableness	−0.20*	−0.02	1.11	2.97**
	(0.11)	(0.15)	(0.98)	(1.39)
Extraversion	−0.15	−0.11	−1.49*	−2.42
	(0.09)	(0.15)	(0.76)	(1.99)
Conscientiousness	0.03	0.03	0.71	1.22
	(0.09)	(0.15)	(1.25)	(2.16)
Neuroticism	0.11	−0.06	−1.21**	−2.00*
	(0.08)	(0.13)	(0.48)	(1.12)
Openness	0.06	0.15	0.11	1.19
	(0.10)	(0.10)	(0.52)	(1.12)
Observations	4,731	1,407	3,882	1,152
R^2	0.14	0.28	0.11	0.25
Adjusted R^2	0.08	0.14	0.04	0.07

Table 3: 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 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 4: Summary statistics of recalled self performance in *ProbedRecall*

Panel A: Summary statistics of recalled performance								
	N	Mean	SD	P5	P25	Median	P75	P95
Recalled performance								
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 performance								
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 performance								
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 performance			
Recalled performance	1D	1M	1Y	5Y
1D	0.074			
1M		0.327		
1Y			0.402	
5Y				0.317

Table 5: Memories cues in *FreeRecall*

We test cued 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 later than November 2021, so that the cued 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 takes the survey. We control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, the number of Wechat group. Columns (1) to (3) concern the full sample while Columns (4) to (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		
	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

	Dependent variable: Recalled market return		
	Recalled episode is recent		
	(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

Table 6: Memory cues in *ProbedRecall*

We test cued recall by regressing recalled self performance 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 takes the survey. We control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, the number of Wechat group. 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)	(3)	(4)
Market return, today	0.68**	0.94**	0.99***	1.02**
	(0.28)	(0.31)	(0.37)	(0.47)
Actual self performance, yesterday		0.27***		
		(0.09)		
Actual self performance, 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 performance			
	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 self performance, 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: Memory and expectation

The dependent variables are the respondent's expectation of market performance and its own portfolio's performance 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 the number of Wechat group. 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	Self return, 1M	Self return, 1Y
	Panel A: Free Recall			
	(1)	(2)	(3)	(4)
Recalled market return	0.005**	0.02***	0.01	0.04**
	(0.002)	(0.003)	(0.005)	(0.01)
Observations	3,030	2,954	2,159	2,271
R^2	0.16	0.21	0.23	0.25
Adjusted R^2	0.04	0.09	0.07	0.10
	Panel B: Probed Recall			
	(1)	(2)	(3)	(4)
Recalled self performance, 1M	0.08***		0.32***	
	(0.01)		(0.02)	
Recalled self performance, 1Y		0.07***		0.42***
		(0.01)		(0.03)
Observations	6,077	6,199	5,090	5,508
R^2	0.12	0.14	0.21	0.21
Adjusted R^2	0.04	0.07	0.13	0.14

Table 8: Explanatory Power of Different Variables for Investor Belief

We regress investor beliefs on either demographic variables or probed recall. Each cell reports the adjusted R-squared of a regression, with probed recall only or with demographics fixed effects only. Dependent variables are the respondents' expectation of the stock market performance and their own stock portfolios' performance in the next 30 days and in the next year. Demographics fixed effects include gender, age, income, wealth, and education.

	(1)	(2)	(3)	(4)
	Market 30 Day	Market 1 Year	Self 30 Day	Self 1 Year
Demographics F.E. Only	0.008	0.027	0.029	0.042
Probed Recall Only	0.022	0.025	0.080	0.073

Table 9: Relationship between recall and expectation as a function of time spent on the survey

The dependent variables are the respondent's expectation of market performance and its own portfolio's performance 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 the number of Wechat group. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	Market 30 Day	Market 1 Year	Self 30 Day	Self 1 Year
	(1)	(2)	(3)	(4)
Recalled return, 1M	0.08***		0.32***	
	(0.01)		(0.01)	
Recalled return, 1M * Time spent	−0.0002		−0.0001	
	(0.001)		(0.001)	
Recalled return, 1Y		0.07***		0.44***
		(0.01)		(0.03)
Recalled 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
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 10: Recall and perceived crash probability

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 group. We cluster standard errors at the date level. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	Expected crash probability, 1M		Expected crash probability, 1Y	
	(1)	(2)	(3)	(4)
Recalled performance, 1M	-0.11^{***}		-0.07^{***}	
	(0.01)		(0.01)	
Recalled performance, 1Y		-0.06^{***}		-0.04^{***}
		(0.01)		(0.01)
Constant	4.64^{***}	4.87^{***}	2.70^{***}	2.84^{***}
	(0.08)	(0.12)	(0.05)	(0.07)
Observations	9,648	10,118	9,623	10,095
R^2	0.01	0.01	0.01	0.01
Adjusted R^2	0.01	0.01	0.01	0.01

Table 11: Recalled return and expectations across treatments

		Recalled past performance			
	Recalled return	Yesterday	Last month	Last year	Last five years
FreeRecall	0.05	0.00	0.00	0.02	0.05
Happy	0.23	0.00	0.00	0.02	0.05
Painful	−0.20	−0.01	0.00	0.02	0.03

Table 12: Extrapolation and recall

The dependent variables are the respondent's expectation of market performance and its own portfolio's performance 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 the number of Wechat group. We cluster standard errors at the date level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable:			
	Expected market return, 1M		Expected self performance, 1M	
	(1)	(2)	(3)	(4)
Past market return, 1M	0.14^{**}	0.10^{*}	0.21^{***}	0.09
	(0.06)	(0.06)	(0.07)	(0.06)
Recalled self performance, 1M		0.08^{***}		0.30^{***}
		(0.01)		(0.02)
Observations	7,842	7,842	6,554	6,554
R^2	0.04	0.05	0.07	0.13
Adjusted R^2	0.02	0.04	0.05	0.11
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 13: 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 the number of Wechat group. 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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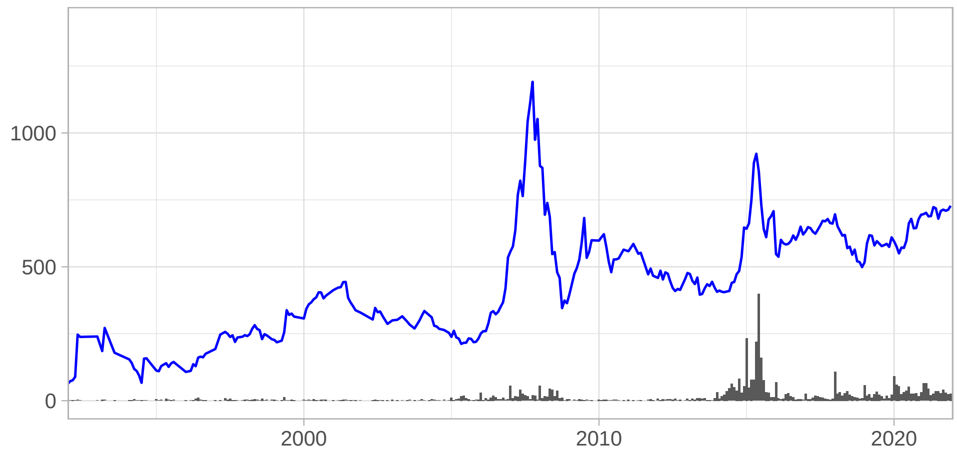
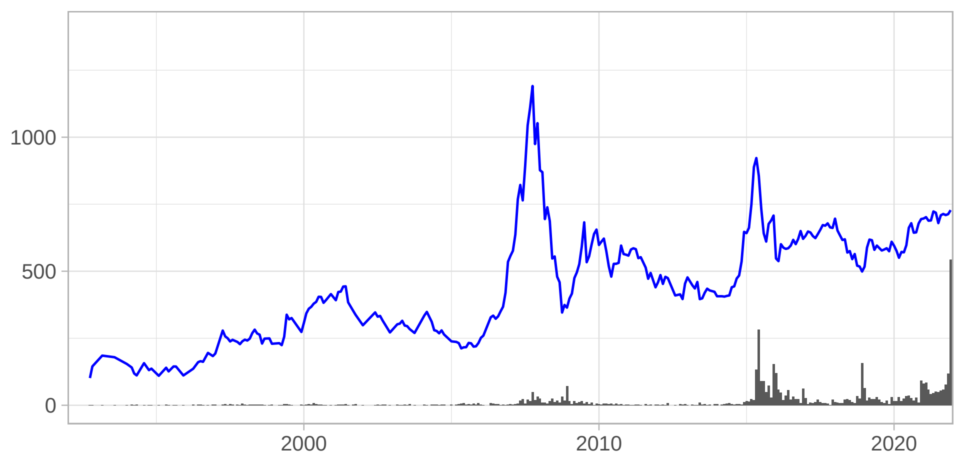
Online Appendix for

Memory and Beliefs: Field Evidence

Figure A.1: Distribution of Recalled Period, excluding new investors

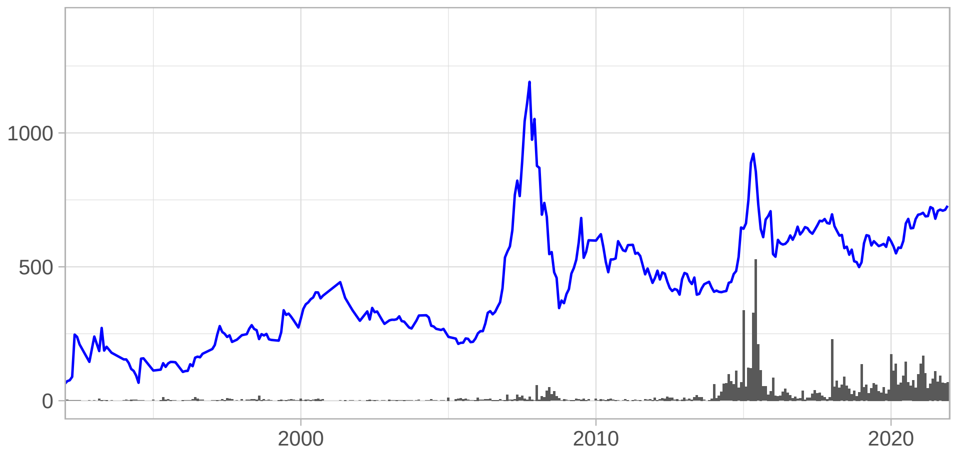


Panel (a) Distribution of Start Dates

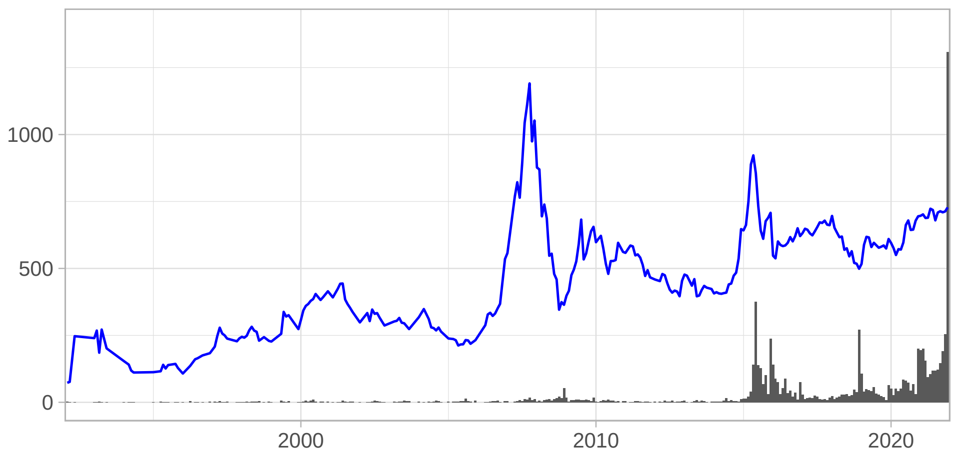


Panel (b) Distribution of End Dates

Figure A.2: Distribution of Recalled Period, age < 35

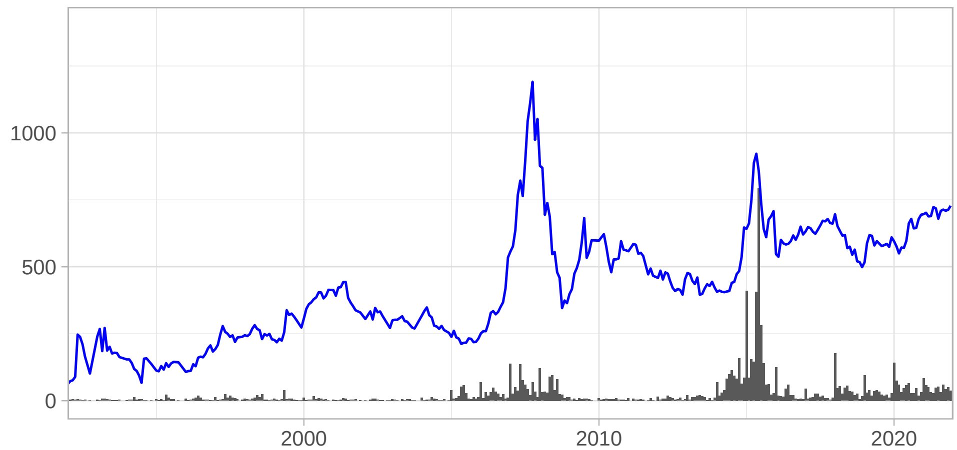


Panel (a) Distribution of Start Dates

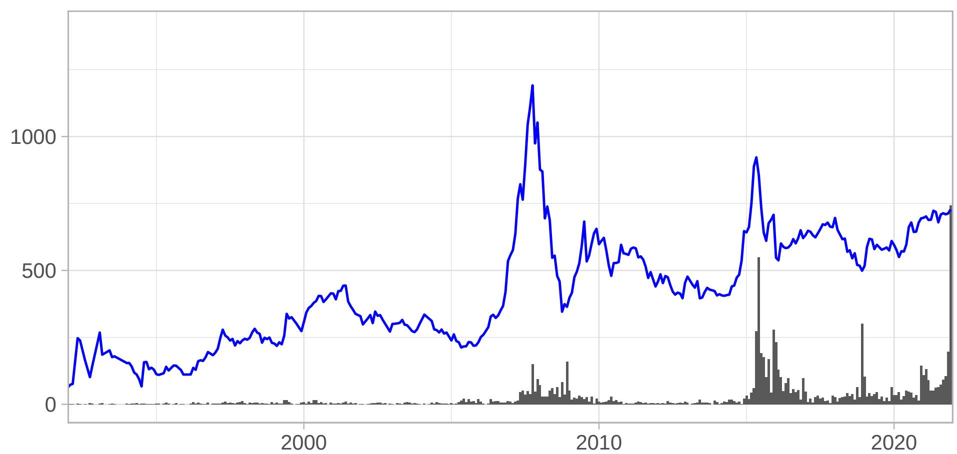


Panel (b) Distribution of End Dates

Figure A.3: Distribution of Recalled Period, age $\geq$ 35

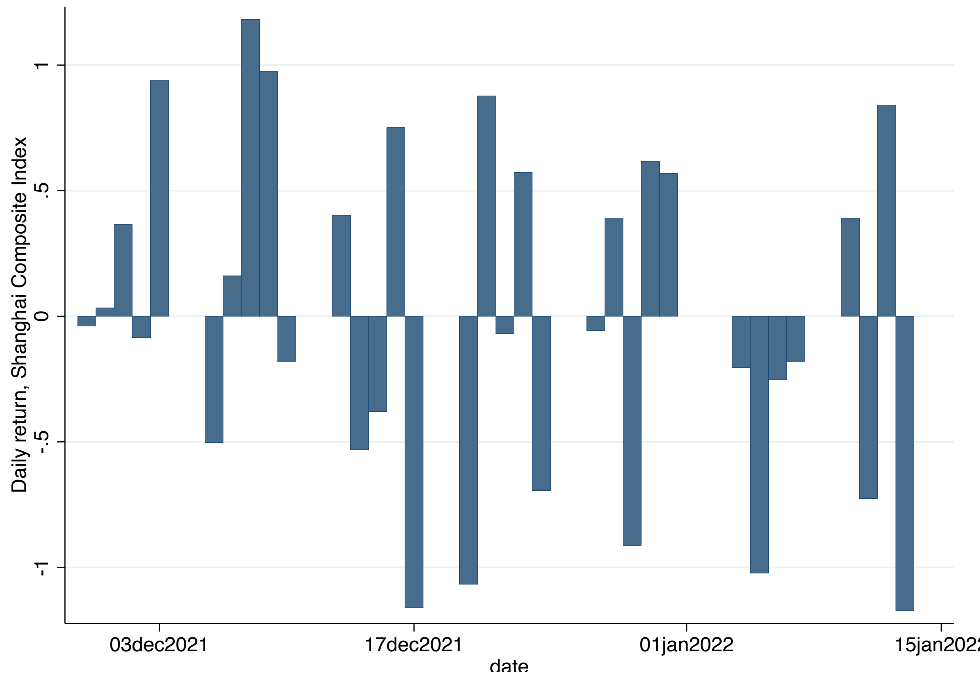


Panel (a) Distribution of Start Dates

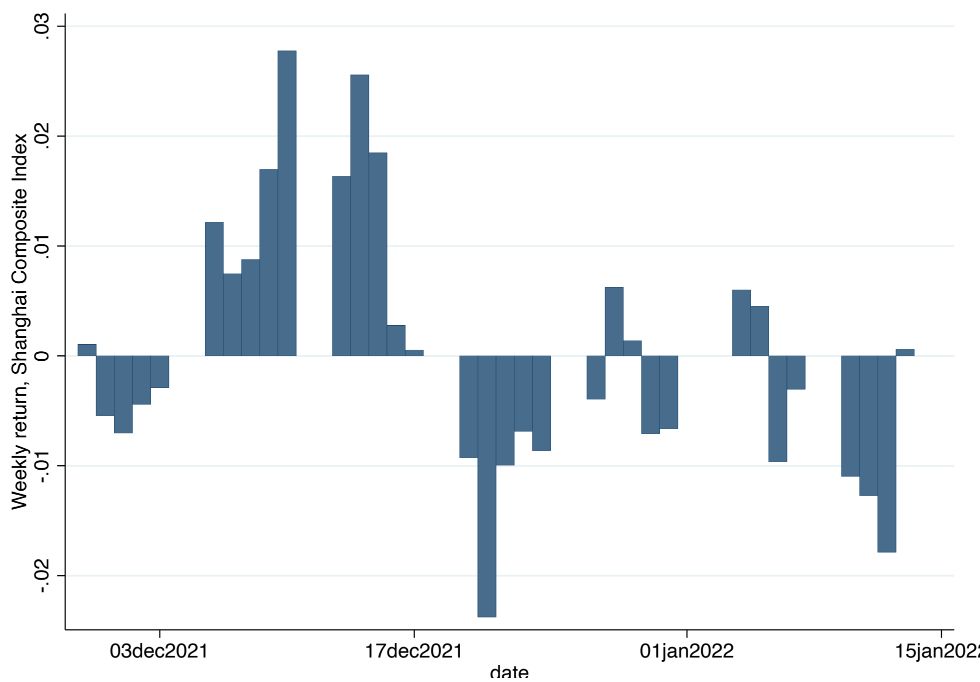


Panel (b) Distribution of End Dates

Figure A.4: Distribution of Returns



Panel (a) Distribution of Daily Returns



Panel (b) Distribution of Past One-week Returns

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

This table repeats the regressions in Table 2 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 various individual characteristics. In columns (1) and (2), the dependent variable is a dummy variable indicating a market rise of more than 100%. In columns (3) and (4), the dependent variable is a dummy variable 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 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 group. 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 the number of Wechat group. 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: 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 takes the survey. We control for age, gender, education, wealth, income, frequency of checking accounts, frequency of checking news, frequency of discussing investments, the number of Wechat group. 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 self performance, today	0.16**	0.19***
	(0.08)	(0.06)
Actual self performance, yesterday	0.23***	
	(0.08)	
Actual self performance, past month		0.21***
		(0.02)
Observations	7,746	1,619
R^2	0.04	0.04
Adjusted R^2	0.03	0.03

Table A.6: 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