Memory and Generative AI

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October 5, 2025

Abstract

This paper tries to understand Generative AI's decisions under risk as an economic agent. Exploiting a novel experimental setting, we show that it uses memories to make decisions, even when the memories are not in the same decision domain. When displayed with irrelevant images with positive feelings, it becomes more risk-loving and will choose to invest more in stocks, and vice versa. Although emotional shocks strongly bias investment choices, they have minimal impact on GAI's beliefs. This mechanism is further causally supported with a supervised fine-tuning technique known as knowledge injection that can edit the language model's memories. Empirical results show that both domain-specific memories like financial news and non-domain-specific memories like Yelp restaurant reviews significantly affect GAI's investment choices.

*Zheng (xjzheng.20@saif.sjtu.edu.cn) is a doctoral candidate from Shanghai Advanced Institute of Finance at SJTU. I thank Feng Li and Lauren Cohen for their invaluable guidance and Shumiao Ouyang and Xiaomeng Lu for their continuous support from the beginning. I am also thankful for the comments from Hui Chen, Hongye Guo, Thomas Graeber, Spencer Kwon, Xinwei Li, Steven Ma, Jun Pan, Cameron Peng, Suproteem Sarkar, Andrei Shleifer, Hayong Yun, Dexin Zhou, and seminar participants at Harvard University and SAIF, as well as feedback from conference participants at ABFER poster, CICF, and CFRC. I am especially grateful for the voluntary research assistants from Harvard University and SJTU. The replication package is available upon request, and the fine-tuning dataset can be accessed at https://huggingface.co/xjzheng All errors are my own.

1. Introduction

Artificial intelligence is fundamentally reshaping society with far-reaching implications for economic systems (Acemoglu, 2024), where Generative AI (GAI) has emerged as a versatile agent in diverse domains, serving as an instrumental tool [1]. However, as society's dependence on AI assistance increases, our understanding of GAI decision-making processes and advisory mechanisms remains limited. Given this increasing reliance, this paper tries to understand what drives GAI's decision-making rules and their behavior, especially in the context of economics and finance. Specifically, this paper aims to explore how GAI makes decisions in risky financial investment scenarios. What factors drive these decisions? How do they compare with human behavior? Does GAI exhibit purely rational investment decision making, potentially correcting human biases, or does it introduce new patterns of decision making?

However, the empirical challenge in this context is the absence of a utility function, which may vary significantly with the prompts, the training data, and the algorithm architecture. Prior research shows that LLM can be used as Homo Silicus just like economists use Homo Economicus (Horton, 2023), has a diverse range of risk preferences across models (Ouyang et al., 2024b) but mostly mirrors the risk preferences of the young, high-income males for the advanced ones (Fedyk et al., 2024) and even exhibits behavioral biases as humans (Bini et al., 2024; Leng, 2024; Ross et al., 2024), but there is little explanation of why GAI appears to have the ability to give reasonable answers that resemble human decision-making processes in the first place.

Exploiting a novel experimental setting (Kuhnen, 2015; Kuhnen and Knutson, 2011; Kuhnen and Miu, 2017) and relying on a vast literature documenting the associative memory of human beings (Bordalo et al., 2024a,b, 2020; Enke et al., 2024), this paper tries to directly link the economic decision-making rules of GAI with its "memories", which has never been studied in earlier studies. This mechanism mirrors human decision-making processes: Just as individuals accumulate knowledge through life experiences and learn from their rewards and failures, GAI systems develop their capabilities through extensive training in comprehensive datasets guided by specific reward functions (Bybee, 2023). Upon receiving external stimuli, these systems engage in a process analogous to human recall, drawing on their trained parameters and trillions of tokens to identify relevant patterns and historical outcomes. This information then serves as the basis for subsequent decision-making. Thus, associative memory serves as an important anchor in the valuation of GAI (Bordalo et al., 2020).

In this experiment, we use GPT-4o-mini as the experiment subject, which is one of the State-Of-The-Art models and outperforms other popular commercial models [2]. Moreover, this model is highly cost-efficient and has one of the best response speeds to be deployed on a large scale (Hurst et al., 2024). This model features multi-modal capabilities and can function as an AI agent. In the appendices, we also use Claude-3-Haiku, gemini-2.0-flash-light, and GPT-4o

[1] These include but not only in financial markets (Lo and Ross, 2024; Wu et al., 2023), healthcare and pharmaceutical consulting (Liu et al., 2023; Yang et al., 2024a), psychological support (Demszky et al., 2023), legal proceedings (Cheong et al., 2024), marketing strategy (Arora et al., 2024), software development (Nam et al., 2024), freelancing (Demirci et al., 2025), and even academic research (de Kok, 2025; Van Noorden and Perkel, 2023).

[2] Other models including GPT-4 Turbo, Claude-3.5-Sonnet, and Meta-Llama-3.1-405B.

(the full version) as alternative test subject for external validity. The results are qualitatively similar.

This experiment requires the subject to perform 500 independent tasks, also known as learning blocks, each consisting of six consecutive trials. In each trial, there are two assets that can be invested in: a bond that always pays \$3 and a stock that pays from a good dividend distribution or a bad dividend distribution. In the good payoff distribution, the stock pays \$10 with 75% and -\$10 with 25%, while in the bad payoff distribution, the stock pays \$10 with 25% and -\$10 with 75%. The subject observes the realized stock payoff after choosing which asset to invest in. In other words, the subject does not know the type of dividend distribution; it learns the true type of the stock based on the payoff realized in each trial over time. If the subject observes a series of high dividend payoffs, e.g., all stock dividend payoffs are \$10, then there is a high probability that it is a good stock that pays dividends from the good distribution and the subject will most likely choose to invest in it in the next trial. Also, this experiment setting allows us to compute a Bayesian objective probability and use it as a benchmark to examine how rational the model estimation is.

In each trial, the subject is presented with a random image that we collect from the Google images at the beginning and then makes an investment decision to choose a stock or bond. The set of images has a diverse range of contents, such as an investor making a lot of money and is extremely happy, or a sports team gets defeated and every player is very sad. In the experiment instruction, we especially tell the subject to pay attention to the image but also inform it that the image is not associated with the investment decisions. Therefore, the subject should not make investment decisions based on the image it observes. Then, we reveal the stock dividend and the investment payoffs to the subject. Subsequently, the subject is asked to give a probability estimate that the stock they observe is paying dividends from the good probability distribution and their confidence in the probability estimation.

Importantly, within each learning block, the subject is allowed to keep its chat history, including experiment instructions, realized payoffs, realized earnings, investment decisions, subjective probability estimations, and confidence ratings. This can be thought of as a conversation between an experiment instructor and a subject and is the subject's "short-term memory". After the subject has completed all six trials for a learning block, the chat history is refreshed, and a new learning block is started.

In this experiment, the images presented to the subject serve as "cues", where the images of positive emotions are considered good cues and the images of negative emotions are considered bad cues. A good cue primes the subject to think of similarly positive investment outcomes and vice versa. The results show that, when displayed with an image that has positive emotions, subjects are 5.81% more likely to choose stocks rather than bonds, and this result is consistent between different trials and topics. This effect is pronounced mainly when shown in images of topics related to the financial market, with a regression coefficient of 0.10 (t-statistic of 8.15), a 65.74% increase over the baseline result, which supports our hypothesis that GAI makes decisions based on associative memories. When it receives a positive cue about a good stock market, such as Warren Buffett smiling with piles of cash behind him, it stimulates similar "good memories" about the stock market that historically has good performance and would later invest more in the stocks in the experiment. On the contrary, when it receives a negative cue that represents a bear market, GAI recalls the negative link between equity investment and other bad consequences in the stock market and would choose to invest more conservatively in the bonds. The results are also significant on topics such as weather, terrorism, and others. We show that these investment choices based on associative cues are irrational as the investment payoffs realized by subjects are significantly lower than the payoffs they would have earned if they had made investment decisions based on their Bayesian beliefs. The cumulative payoffs after six trials are on average \$8.15, whereas the cumulative payoffs for the counterfactual investment decisions, which are the investment decisions that they should have made if there were no emotional shocks, are \$15.70.

Although emotional stimuli significantly influence investment decisions related to risk preferences, they do not show substantial impact on the subject's probability estimations regarding stock performance. In other words, this "cue effect" does not affect beliefs as documented in the previous literature (Enke et al., 2024; Gennaioli and Shleifer, 2018) on human subjects, as it primarily affects the risk preferences of GAI like Guiso et al. (2018). Notably, this suggests a disconnect between choices and beliefs: the subject's trading decisions appear to be driven more by emotional responses rather than their stated prior beliefs. Had the subject aligned its trading decisions with its beliefs about the type of stock dividend, the investment payoffs would have been substantially higher. Although emotional shocks do not significantly affect beliefs, the subject's probability estimations are consistent with loss aversion, as described in prospect theory (Kahneman and Tversky, 2013). Specifically, the subject has higher probability estimates when the Bayesian objective probability is low and lower probability estimates when the Bayesian objective probability is high. Additionally, the subject's confidence levels in these probability estimations remain unaffected by emotional stimuli.

To causally examine the impact of memory on GAI risk preferences and trading decisions, such as investment choices, we adopt a fine-tuning method known as "knowledge injection" (Wang et al., 2024). This technique enables the agent to update its knowledge about new events that occur after the knowledge cutoff date. Following the approach proposed by Mecklenburg et al. (2024), we instill GAI with additional positive or negative training data. To accomplish this, we first generate two datasets for knowledge injection. The first data set refers to financial markets, which is directly related to our investment experiment. We begin by collecting all news articles from the RavenPack dataset with sentiment scores greater than 0.9 or lower than -0.9, labeling them as positive and negative news, respectively. The sample period is the whole year 2023. Out of 9,987 positive and 2,713 negative real news articles, we ask GPT to generate fictional yet plausible news stories with similar sentiment based on the original texts. These generated articles do not reference actual market events and may even feature hypothetical company names. By creating fictional news, we mitigate concerns about data leakage (Ludwig et al., 2025; Sarkar and Vafa, 2024).

The second data set concerns restaurant dining experiences, which appear not to be related to this experiment. We collect Yelp customer reviews from Kaggle, a web-based platform for data science and machine learning professionals. Similarly, we draw a random sample of reviews with positive emotions and another with negative emotions. We then instruct GPT to generate fictional out-of-sample reviews corresponding to each original review, ultimately obtaining 3,991 fictional positive Yelp reviews and 4,009 negative Yelp reviews. This set of irrelevant knowledge is very important because it provides a clean and direct test of the mechanism through which memories affect decisions, even if the memories are not in the same domain as the decision.

We then apply the supervised fine-tuning technique, incorporating either positive or negative fictional financial news or Yelp fictional reviews into the knowledge injection template. This process outputs four fine-tuned models. For the first set, we create a positive model, injected with 9,987 positive financial news articles, which is considered to have more positive memories about the stock market and investments, and a negative model, injected with 2,713 negative financial news articles, which is expected to hold more negative memories. For the second set, we generate two models with positive and negative memories related to dining experiences. We subsequently conduct experiments on these four fine-tuned models.

Our findings indicate that models with positive memories are more likely to invest in stocks than those with negative memories. In the financial news setting, the average probability of stock investment for the positive memory model is 0.65 (standard deviation 0.01), while for the negative memory model, it is 0.49 (standard deviation 0.03). The difference in risk-taking propensity is significant and persists even in the absence of associative cues. More surprisingly, this effect is even more pronounced in the Yelp review setting, which contradicts the "domain-specificity" of experience effects claimed in earlier research on human subjects(Malmendier, 2021). The average investment propensity for the positive memory model is 0.49 (standard deviation 0.06), significantly higher than that of the negative memory model (average investment propensity 0.36, standard deviation 0.10). Additionally, fine-tuning results reveal that associative cues exert an asymmetric effect, influencing the negative memory models more strongly than the positive memory models. When exposed to an associative cue, whether positive or negative, the negative memory model consistently exhibits a stronger preference for bond investments compared to scenarios without cues. This finding aligns with the predictions of Bordalo et al. (2024a), where two opposing forces are at play: similarity and interference. When the stock is more likely to pay from the good dividend distribution, negative memories cued by associative signals interfere with the selective retrieval of positive memories, leading to more conservative investment choices. Even when the recalled context is not related to the experiment, memory still plays a crucial role in GAI's decision-making process.

Further analyses based on Ouyang et al. (2024b) reveal that the positive memory model exhibits greater risk tolerance than the negative memory model, implying that memory moves risk preferences. We perform five different tests: (1) a direct elicitation task in which the model self-assesses its risk preference, (2) a questionnaire task in which the model must rate its level of risk aversion from 0 to 10, (3) the Gneezy and Potters (1997) task, (4) the Eckel and Grossman (2008) task, and (5) a task involving real investment scenarios in which the model makes risky investment decisions. Across all five tasks and various endowment magnitudes, the positive memory model consistently evaluates itself as more risk-seeking and opts more frequently to invest in risky assets. This set of results provides causal evidence that memories influence model behavior by shaping risk preferences, even in simple settings where no learning or belief updating is involved.

This paper contributes to the rapidly developing literature that attempts to understand AI, especially Generative AI's rationality (Chen et al., 2023) such as preferences (Handa et al., 2024; Horton, 2023; Leng et al., 2024; Qiu et al., 2023), beliefs (Bybee, 2023), and other abilities and characteristics (Jia et al., 2024; Leng and Yuan, 2023). In recent decades, the world has witnessed incredible advances in traditional AI algorithms that lead to economic efficiency, such as improving firm growth (Babina et al., 2024), return prediction and portfolio diversification (D'Acunto et al., 2019; Rossi, 2018), fintech lending (Berg et al., 2022) and wealth management at the household level (Reher and Sokolinski, 2024). Previous research papers in this field that use AI refer primarily to simpler machine learning techniques such as lassos (Rapach et al., 2013), boosting regression trees (Li and Rossi, 2020), XGBoost (Erel et al., 2021; Li and Zheng, 2023), or shallow neural networks that have a limited number of hidden layers and parameter size (Gu et al., 2020), as opposed to the "large" language model that this paper tries to focus on[3]. The recent advancement in Generative AI exhibit the potential to act as decision makers and interactive agents, particularly when coupled with reinforcement learning, external APIs, or multi-modal systems. This "agentic nature" is fundamental to the progression of AI from tools to autonomous financial decision-makers. When coupled with prompts and surrounding environments, LLMs can actively perform generic tasks instead of just predicting outcomes, and this is especially helpful in the financial markets, which involve a principal-agent problem, and investors need to know why the AI algorithm produces the advice before fully trusting it. In that sense, this paper adds to the few recent research papers showing that GAI, when treated as agents, can replicate human investment preferences across demographics (Fedyk et al., 2024), but may also present a few behavioral biases similar to those observed in humans, but also nonhuman biases (Bini et al., 2024). Understanding the behavioral foundations of GAI agents is crucial before applying them to other settings, and the findings documented in this paper may have important implications for their applications. For example, when using GAI such as ChatGPT to predict stock returns (Chen et al., 2022; Lopez-Lira and Tang, 2023; Lu et al., 2023), it is important to understand how the agentic nature of GAI helped or biased when making investment predictions. And this applies to other empirical applications as well in other financial contexts such as predicting corporate policies (Jha et al., 2024), understanding corporate filings (Kim et al., 2023, 2024a,b), tax enforcement (Armstrong, 2023), corporate culture (Li et al., 2024a), and others (Hansen and Kazinnik, 2023).

Building upon this, this paper also adds novel experimental results to the vast literature on behavioral economics and finance by showing that behavioral biases may exist not only in humans, but also in AI algorithms. In terms of humans, the psychological (or cognitive) basis for risk-based decisions comes largely from their neural activity (Kuhnen and Knutson, 2005)[4]. Specifically, risky human decision-making processes are primarily regulated by neurotransmitter

[3]Despite the model is smaller in terms of the parameter size, they perform extremely well on these tasks and are highly efficient and effective as compared to the larger ones.

[4]This is also largely affected by their genetic heritage (Kuhnen and Chiao, 2009; Kuhnen et al., 2013). Specifically, genetic variations in neurotransmitter pathways, particularly in the serotonin and dopamine systems, can significantly influence neural responses to risk and reward. The serotonin transporter gene (5-HTTLPR) polymorphism and dopamine D4 receptor gene (DRD4) variations have been shown to modulate activity in key brain regions such as the amygdala and nucleus accumbens, which are crucial for risk assessment and reward processing. These genetically determined differences in neural circuitry can lead to individual variations in risk perception, emotional responses to uncertainty, and, ultimately, risk taking behavior.

systems in the brain[5]. This physiological mechanism evolved during human development, helping our ancestors survive in environments filled with uncertainty, and leads to many irrational behaviors we observed, especially in the financial markets that have been well recognized, such as overreaction (Odean, 1998), disposition effect (Shefrin and Statman, 1985), and endowment effect (Kahneman et al., 1990)[6]. As for AI agents, which are built on transformers and deep neural network structures, it is incredible that artificial intelligence also exhibits a decision-making process similar to that of humans. The structures of neural networks mirror the fundamental architecture of the human brain, with artificial neurons and synaptic connections functioning analogously to their biological counterparts (Sutskever, 2014). This biomimetic approach to artificial intelligence has proven remarkably effective since it allows machines to process information in ways that parallel human cognitive processes. Just as the neural pathways of the human brain are strengthened or weakened through learning and experience, artificial neural networks utilize similar mechanisms of weight adjustments and backpropagation (Hecht-Nielsen, 1992) to learn from data[7]. The multilayer structure of deep neural networks, with their hidden layers processing increasingly complex features, resembles the hierarchical organization of the human cortex, where information is processed through multiple stages of increasing abstraction (Saxena et al., 2022).

More specifically, this paper contributes to the literature by demonstrating that GAI's economic behavior and decisions may be determined by a crucial factor that also affects humans: memory. Our findings reveal that, as human decisions are shaped by associative recall (Charles, 2022; Enke et al., 2024; Wachter and Kahana, 2024), GAI decisions are also significantly impacted by memory, namely, its training data. This suggests that when prompted by an event, AI agents can retrieve associated memories from related past experiences and subsequently assign greater decision weights to the corresponding choices, and even dissimilar memories not in the same decision domain may interfere with this selective retrieval process (Bordalo et al., 2024a) and cause biases. This finding contrasts Malmendier and Nagel (2011), and has different implications than Bybee (2023), which shows that memories combined with WSJ financial news is related to beliefs about economic surveys, but also exhibit deviations from rational expectations. However, our paper presents novel evidence showing that even irrelevant memories can affect LLM's predictions, implying that the prediction bias made by LLMs also may generate from the way they form "mental models" that map memory with decision problems. Another surprising finding from the fine-tuned models indicates that even in the absence of associative cues, models with different memories exhibit significant differences in trading decisions, likely driven by their varying risk preferences. Unlike Bordalo et al. (2023) and several related studies in the field of financial economics that use carefully designed laboratory experiments(Charles, 2022) or field data such as stock market prices (Charles, 2022; Charles and Sui, 2024), analyst

[5]Research has shown that two key neurotransmitters, dopamine and serotonin, play crucial roles in risk-based decision making (Homberg, 2012; Loewenstein et al., 2008). When individuals encounter potential gains, the brain's reward system releases dopamine, promoting risk-loving behavior; When faced with potential losses, the serotonin system is activated, triggering risk-averse tendencies.

[6]Hirshleifer (2015) provides a detailed and comprehensive summary about behavioral biases in financial markets.

[7]However, most neuroscientists believe human brains do not do backpropagations. Few other researchers believe that this is done while people are sleeping, but that is still not equivalent to the concept in computer science research. To resolve this, Hinton (2022) proposed the forward-forward algorithm.

reports (De Rosa, 2024), or surveys (Gennaioli et al., 2024), our approaches that follow Ouyang et al. (2024b) to measure the effect of memory on GAI's risk preferences are more straightforward and do not involve other confounding factors and also forward looking biases. This provides novel evidence that memory influences risk preferences, at least in the case of large language models. However, we do not claim that this necessarily offers insight into how humans make decisions based on memories, as the human brain remains more complex than large language models on multiple levels. In the future, as language models become more advanced and their algorithmic architecture more closely resembles the human brain, we may gain new insights into human behavior by observing GAI's actions.

Furthermore, this paper complements the literature on experimental economics and finance by showing the potential to use GAI as homo economicus for experiments (Horton, 2023). Researchers in other fields use GAI to simulate a wide range of research subjects, such as: simulating people's marketing preferences on brand perception surveys (Li et al., 2024b), mimicking people's voting decisions in political research (Yang et al., 2024b), generating social behaviors like cooperation and externalities (Leng and Yuan, 2023), replicating people's psychological behaviors (Qin et al., 2024), or replicating a wide range of human traits on an extremely large scope (Park et al., 2024). Although most large language models have undergone stringent alignment procedures such as RLHF or DPO that potentially shift preferences and behaviors toward a certain direction, it is still possible to introduce heterogeneity by giving the AI agent personal characteristics, as shown in Fedyk et al. (2024). In contrast to previous research papers that rely on simple questions (Ouyang et al., 2024b), this study shows that AI agents can understand and perform complex decision-making tasks, combined with its lower cost than experimenting with human subjects.

Finally, beyond its theoretical contributions, this paper also introduces a new fine-tuning technique to the economics and finance academic community. As large language models are increasingly adopted by researchers for various applications, there is a growing demand to fine-tune these models, either to improve measurement accuracy or to generate sufficient variation in model behavior. Regarding the first approach, Lu et al. (2023) uses fine-tuning to enhance ChatGPT's financial performance for better investment decision making, Leippold et al. (2022) fine-tunes ClimateBERT based on DistilRoBERTa for climate-related tasks, which Garrido-Merchán et al. (2023) further fine-tunes this transformer model. In terms of the second approach, Ouyang et al. (2024b) fine-tunes the Mistral model to adjust alignment levels and study model behavior. This paper is more closely aligned with the latter strand of literature, which focuses on modifying model behavior through parameter fine-tuning and has demonstrated significant effects. By introducing the knowledge injection fine-tuning technique, together with other methods such as machine learning (Nguyen et al., 2022), researchers can further expand their toolkit to refine model behavior and improve economic and financial analysis that are not achievable with human subjects.

2. Experimental design

2.1. Experiment description

The experiment exploits a novel setting from Kuhnen and Knutson (2011) and similarly in Kuhnen (2015) and Kuhnen and Miu (2017) as well. This experiment is also used in other related research in neuroscience as well (Häusler et al., 2018; Knutson et al., 2008; Kuhnen and Knutson, 2005)[8]. We follow the experiment specifications from Kuhnen and Knutson (2011) and use GPT-4o-mini as the subject.

GPT-4o mini is an advanced model that scores 82% in MMLU and outperforms closed-source models like GPT-4, GPT-4 Turbo, Claude 3.5 Sonnet and other open-source SOTA models like Meta-Llama-3.1-405B, on chat preferences in the LMSYS leaderboard[9]. Apart from its superb performance, it is priced at 15 cents per million input tokens and 60 cents per million output tokens, an order of magnitude more affordable than previous frontier models and more than 60% cheaper than GPT-3.5 Turbo. This is an important reason why we use the "mini" version as opposed to the "full" version, because we want a cost-effective agent that responds quickly and with comparable high accuracy. In addition, fine-tuning a "mini" model also costs less.

More importantly, we use GPT-4o-mini as a research subject due to its multimodal capabilities, which enable it to process and interpret both visual and textual input simultaneously. This multimodal architecture is fundamental for studying AI agents, as it more closely approximates the way human agents perceive and interact with their environment through multiple sensory channels. Multimodality allows the model to establish meaningful connections between visual elements and textual information, allowing for a more comprehensive understanding and contextually appropriate responses. In the context of AI agents, which are defined as autonomous entities capable of perceiving their environment, making decisions, and taking actions to achieve specific goals, GPT-4o-Mini exemplifies these characteristics through its ability to process diverse input modalities and generate coherent, contextually relevant outputs. The model's capacity to integrate visual and textual information makes it particularly suitable for agent-based research, as it can demonstrate key agent properties such as perception, reasoning, and response generation in a more naturalistic and comprehensive manner than unimodal systems. This multimodal foundation provides a rich framework for investigating agent behaviors, decision-making processes, and human-AI interaction patterns.

In the experiment, the subject was asked to complete 500 independent tasks, also known as learning blocks. In each learning block, the subject is told to make 6 investment decisions in each trial, which typically include choosing to invest from two assets, a risky asset (stock) that pays \$10 or -\$10 randomly and a safe asset (bond) that always pays \$3 dollars. Within each learning block, a stock pays dividends following a probability distribution "good" or "bad". If the stock pays from the "good" probability distribution, then it pays \$10 dollars with 75% and

[8]Based on a similar experiment, Ouyang et al. (2024a) also studied GAI's asymmetric learning of financial news.

[9]Chatbot Arena (lmarena.ai) is an open-source platform for evaluating AI through human preference, developed by researchers at UC Berkeley SkyLab and LMSYS. With more than 1,000,000 user votes, the platform ranks the best LLM and AI chatbot using the Bradley-Terry model to generate live leaderboards. Lmsys leaderboard: https://lmarena.ai/ accessed on Dec 7, 2024. Importantly, this paper uses the GPT-4o-mini model by the end of 2024. So, future replication work should use the checkpoint version: gpt-4o-mini-2024-07-18.

-\$10 with 25%. In contrast, if the stock pays from the "bad" probability distribution, then it pays \$10 dollars with 25% and -\$10 dollars with 75%. These asset payoffs are shown in figure 1, and the experiment overview is shown in subfigure A of figure 2. In each independent learning block, the stock type is determined before the first trial and remains unchanged throughout this learning block. The dividends in each trial are independent, but they follow the same distribution in a learning block.

[Insert Figure 1 near here]

[Insert Figure 2 near here]

In every learning block from trial #1 to #6, the subject is first asked to look at an image and then make an investment decision to choose between stock or bond. The prompt message is as follows:

"Do you want to invest in a stock or a bond? Only reply with "stock" or "bond". Do not reply with other answers. Your choice is:"

The subject is informed that the image and the investment decision are not correlated and does not need to make a decision based on the information content of the image, and the whole instruction is shown in the appendices A.1. The realized payoff of the stock or bond accumulates in its total earnings. After the investment choice, the realized payoff of the risky asset in the current trial is revealed to the subject. After observing the stock dividends and at the end of this trial, the subject is asked to make a probability estimation of the stock that is paying from a "good" probability distribution and its confidence in its estimation. The prompt message follows Kuhnen and Knutson (2011):

(1) "What do you think is the probability that the stock is the good stock?"

and

(2) "How much do you trust your ability to come up with the correct probability estimate that the stock is good?"

As the subject is shown with realized dividends over trials, it is exposed to several rounds of realized payoffs, adjusts its belief that the stock is paying from the good distribution, and subsequently makes smarter decisions. For example, a subject who observes the stock in the six trials that pays six times \$10 and zero times -\$10 would have more confidence that this payoff of the stock is drawn from a good dividend distribution compared to the stock that pays twice \$10 and four times -\$10. This is also why the task is called a "learning block", since the subject is learning the type of stock from the observed dividends. More importantly, this experiment is unique in that there is always an objective Bayesian posterior probability given the payoff history. The objective probability that the stock is good after observing the k dividend payments of \$10 in the past n trials in the block is $1/(1 + 3^{(n-2k)})$, and the full probability link table is shown in Table A1 in the appendices. In the instruction, the large language model is explicitly informed about the existence of an objective probability but not told the Bayesian formula expression. This objective probability is used to examine how biased the subject's belief is and how rational its investment choice is. In general, the experiment sequence within a learning block is shown in subfigure B of figure 2.

Since GPT-4o-mini has a long context window of 128K tokens, supporting up to 16K output tokens per request, we can complete one learning block within "one chat". In other words, we are letting GPT keep the chat history of all the instructions from the first trial, all the realized payoffs, its previous investment choice, realized investment payoffs, and images within one learning block. During the experiment, each trial on average consumes an estimated amount of 10k tokens, including the textual and image embeddings. We use a base64 encoding style to compress the image to make it cost-efficient.

We present two illustrative examples of two separate trials in figure A1 and figure A2, separately. In the first figure, the subject was first presented with a joyful man with a lot of money and enthusiastically waving his hands. This image has positive emotions and stimulates the subject to choose stock in the first decision. Then, after revealing the stock payoffs of -\$10 and cumulative payoffs of -\$7, the subject made a probability estimation that the stock dividend is good at 40%. This comes with its subsequent confidence estimation rating of 6.

In the second example in figure A2, the subject was shown an image in which Michael Jordan and LeBron James were crying. The negative feeling embedded in the image induced the subject to choose bonds instead of stocks. The machine then makes a probability estimation of 0.8 and a confidence rating of 7.

After the subject completes all six tasks in a learning block, we "refresh" the subject's chat history by ending the current chat and starting a new chat. This helps ensure that the decisions made across learning blocks are independent, but within each learning block, the subject makes correlated and reasonable decisions.

We incentivize the subject to make profitable trading decisions and provide accurate probability estimates by offering hypothetical rewards. This, along with other prompt engineering techniques, such as formatted outputs, perturbation, jailbreaks, or even tipping, has proven to be highly effective in improving the response of large language models (Salinas and Morstatter, 2024). The compensation structure is set as the combination of the selected asset payoffs and the accuracy of the estimation in each trial, times a coefficient of 1/20[10]. For the first part, we accumulate the dividends from the asset payoffs that the subject chose. For the second part, we give additionally 1\$ for every probability estimate that is within 5% of the correct value (for example, the correct probability is 80% and then say 84% or 75%). Finally, to simulate a real experimental setting, we present the subject with a "show-up fee" of 15 dollars. Finally, the reward fee payoff structure is equal to Show-up fee + \$(1/20) × (Total investment earnings + # accuracy predictions).

We chose this experiment to understand the decision-making rules of a large language model for three main reasons. First, advanced large-language models are heavily aligned and usually have very robust guardrails, and simple experimental questions are not sufficient to elicit their

[10]This coefficient of 1/20 is not necessary here. We use it following the setting in Kuhnen and Knutson (2011) with humans, which is significantly more expensive.

preferences and beliefs. This is documented in Ouyang et al. (2024b), which shows that simple prompts that ask about GPT's preferences are always confronted with responses like "Sorry, I am just an AI assistant and cannot help you with that." Second, we would like to have an experiment that has a fairly complex setting that mimics the real environment a human, as well as an AI agent, is faced with, especially when the signals are noisy, information is surprising, or priors are concentrated on less salient states (Ba et al., 2024). This is because agents face cognitive constraints such as limited attention or attributive biases for human subjects, and this is similar for AI as input prompts are often incomplete[11]. In this carefully designed experiment, the instruction is complex and the learning process between different trials has a high level of dynamics. This enables us to obtain the preferences and beliefs of the subject. Third, from a more philosophical point of view, our experiment highlights the importance of a multimodal "world model" and genuine agentic behavior. The subject must process both textual prompts and visual information, thus integrating disparate inputs into a coherent internal representation of the environment. This "world model" is not just for passive observation; rather, it underpins the subject's agentic interactions: actively parsing unexpected signals, updating beliefs, and formulating actions in response to new information. By demanding that the agent interpret and respond to these multimodal cues, our experiment closely mirrors the complexities of real-world decision making, allowing us to observe how a large language model (or any AI system) perceives its surroundings and adapts its choices. Through this experimental setup from Kuhnen and Knutson (2011), we gain deeper insight into the ways in which the agent constructs, refines, and utilizes its internal representation of the world to engage meaningfully with its environment.

2.2. Image description

In each trial, we present images to the subjects before letting them choose to make investment choices.

We collect images by first selecting a list of emotion words from Wikipedia[12]. The list contains 29 subcategories, ranging from positive to negative. These include emotional topics such as anxiety, depression, fear, happiness, love, and nostalgia, among others, encompassing common concepts like "Anger", "Joy", and "grief", as well as specialized concepts such as "empathy" and "forgiveness". After selecting the emotion concepts, we input this into the Google Images query box and download related images. In addition to images with apparent emotions, we also collect images that have no evident emotions following Kuhnen and Knutson (2011) by searching for common objects such as chairs, tables, desks, lamps, etc. The images without apparent emotions we select usually have a blank or pure white background.

In addition to emotion keywords, we categorize the images into five topics known to affect emotions. These topics include emotions in financial markets (Baker and Wurgler, 2006; Goetzmann et al., 2024; Jiang et al., 2019; Lucey and Dowling, 2005), sporting events such as soccer games (Edmans et al., 2007; Wann and James, 2018), terrorist attacks (Chen et al., 2021;

[11]The prompts input to large language models can be considered incomplete contracts. The prompts generally have incomplete specifications, and they always have severe non-verifiability, as the agent can always cheap talk.

[12]This a "set category", meaning it only includes pages about specific emotions, lists of emotions, and relevant subcategories—the linkage: https://en.wikipedia.org/wiki/Category:Emotions

Wang and Young, 2020), weather[13] (Dehaan et al., 2017; Goetzmann et al., 2015; Hirshleifer and Shumway, 2003; Hu and Lee, 2020; Novy-Marx, 2014; Saunders, 1993) , and others. To ensure that the emotion ratings are well balanced, we intentionally combine positive or negative emotions with the topic-related words and use these bi-grams or tri-grams as keywords in the Google Image query box. For example, for the terrorist attack topic, we use keywords such as "terrorist attack sad" for images with negative emotions and keywords such as "police rescue happy" for images with positive emotions. Finally, we have a total of 691 images.

For each image, we first apply GPT-4o-mini for emotion classification. Each image receives an emotion rating from -2 to +2 with the following prompt message:

> *"What do you think the valence score of this image is? The score ranges from -2 to 2, where -2 indicates the most negative emotions like unhappy, upset, irritated, frustrated, angry, fearful, or depressed. A score of 0 indicates neutral emotions like calm, indifferent, blank, objective, normal, stable, or unmoved. A score of 2 indicates the most positive emotions like happy, pleased, satisfied, competent, proud, contented, or delighted.*
> *Please reply in the format: score-reason."*

This emotion classification strategy is similar to the method in Kuhnen and Knutson (2011), and this discrete scoring method has proven useful in other research (Bybee, 2023; Jha et al., 2024; Lopez-Lira and Tang, 2023). An example of the classification is shown in figure A3 in the appendices, where the emotion rating of different images varies significantly. For the first image that contains a horrific murder scene, the GPT gives an emotion rating of -2. For a slightly less negative emotion with LeBron James crying, the emotion rating is -1. The third image is just a desk that contains no additional information and receives an emotion rating of 0. For the fourth and fifth images, where the character becomes more positive, the emotion ratings also become higher. In addition to the emotional rating each image receives, GPT also gives accurate descriptions and reasons accordingly.

We report the summary statistics of the emotion ratings by GPT in panel A of table 1. The emotions of the images collected in this research are, on average, slightly negative. For emotions of images related to the financial markets, the average rating is -0.21, with a standard deviation of 1.72. Similarly, images related to sports, terrorism, and weather also have negative emotional ratings, but the overall distribution of the emotion ratings is balanced.

To verify that GPT understands the emotions of images, we asked 10 research assistants from SJTU and Harvard University to evaluate the emotions of images. The research assistants received careful instructions before performing any evaluation. They were instructed to use their instincts to assign emotion ratings for each image. Each research assistant independently completed the rating and did not communicate with each other. During the evaluation, every image takes roughly 2-3 seconds to rate, and the whole evaluation process takes less than 20 minutes.

The summary statistics of emotion rating by humans is shown in panel B of table 1. For each image, we first take the average value of the image rating given by 10 human volunteers and calculate the average emotion rating across topics. On average, the emotion ratings of

[13]This also includes pollution, see Dong et al. (2021); Heyes et al. (2016); Li et al. (2021)

human subjects are slightly more negative than the emotion ratings by GPT, and the standard deviations of the emotion ratings with each topic are also similar to the standard deviation in panel A.

We also report the correlation coefficient of the ratings given by GPT and by humans, as shown in panel C. We report the Pearson correlation, the Spearman correlation, and the Kendall correlation coefficient in each column, as well as their P-values. The coefficients are all relatively high and statistically significant, suggesting that GPT understands emotions just as humans do.

[**Insert Table 1 near here**]

2.3. Summary statistics

We report the summary statistics at trial level in table 2. In the first row, we report the probability that the subject chooses to invest in stock in this trial, which is 37% with a standard deviation of 48%. This suggests that on average subjects were more likely to choose bonds over stocks in this experiment. In the second and third rows, we report the subjective probability estimation that the stock is good and the Bayesian objective probability. On average, the subjective probability is 48%, the objective probability is 49%, and there is little difference between these two probabilities. In the next row, we report a binary variable of whether the stock realized a high payoff in this trial and the cumulative payoff of the investor.

We also report the subject's payoffs. This variable is a cumulative value that accumulates investor returns from the first trial. On average, investors maintain a winning portfolio with an average earnings of \$7.25. But the summary statistics also show that in the Minimum and 1/4 quintile, the cumulative earnings are negative.

Finally, we report their confidence rating on their subjective probability estimations, as well as their emotion ratings. The confidence rating is somewhat neutral, with an average value of 5.72, neither too optimistic nor pessimistic. The emotion rating has an average rating of -0.05, suggesting a balanced distribution and is consistent with the results in the table 1.

[**Insert Table 2 near here**]

2.4. Experiment validity

To show that our subject understands the experiment and makes reasonable decisions, we perform three validity tests.

The first test examines the rationality of the subject's investment choices. The dependent variable $IsStockChoice_{t,b}$ is a binary variable that indicates whether the subject chooses to invest in the stock trial t of the block b. The independent variable is the subjective probability estimate of the last trial, as well as the investment payoff, confidence rating, a binary variable that indicates whether the stock has a high payoff of the last trial and the investment decision of the last trial. We control for block-fixed effects in the regression and cluster robust standard errors on the block level, and the regression is as follows:

$$
\begin{aligned}
IsStockChoice_{t,b} = {} & \beta_1 SubjProb_{t-1,b} + \beta_2 InvPayoff_{t-1,b} \\
& + \beta_3 Confid_{t-1,b} + \beta_4 IsHiPayoff_{t-1,b} \\
& + \beta_5 IsStockChoice_{t-1,b} + \delta_b + \varepsilon_{i,b}
\end{aligned} \tag{1}
$$

The regression results in panel A of Table 3 show that the subject makes reasonable investment choices. In the first column, the regression coefficient of $SubjProb_{t-1,b}$ is 0.25 with a t-statistic of 3.54, suggesting that when the subject thinks the stock dividends are likely to be in good distribution, it will invest in stocks in the next trial. In addition, it will make more investments when it has made higher investment earnings and has higher confidence in its probability estimation. Furthermore, its cumulative investment payoffs, confidence (of cognitive uncertainty), and observed stock payoff of the last trial also have a significantly positive impact on the trading behavior of the subject as well. This suggests that, in this experiment, when GAI is making trading decisions, it would be more optimistic when it has observed good stock performance and has better portfolio performance.

The next test examines the belief formation of GPT, in other words, how GPT understands risk and learns from the realized dividend payoffs. The dependent variable is the subjective probability estimation of the subject $SubjProb_{t,b}$ in columns (1) and (2), and the update of the probability estimation from the last trial $ProbUpdate_{t,b}$ in columns (3) and (4). In columns (1) and (2), the independent variables include the total number of high dividend payments $\#HiPayoff_{t,b}$ and the number of trials $\#Trial_{t,b}$. We also include the cumulative investment payoff $InvPayoff_{t,b}$, and the Bayesian objective probability $ObjProb_{t,b}$. In columns (3) and (4), we include a binary variable that indicates whether the stock has a high dividend payoff in this trial $IsHiPayoff_{t-1,b}$, the subjective probability estimate of the last trial $SubjProb_{t-1,b}$, and, additionally, the objective probability in this trial $ObjProb_{t,b}$. Like in the last test, we control for the block-fixed effect in the regression and cluster robust standard errors at the block level. The regression equation is shown below.

$$
\begin{aligned}
SubjProb_{t,b} = {} & \beta_1 \#HiPayoff_{t,b} + \beta_2 \#Trial_{t,b} + \beta_3 InvPayoff_{t,b} \\
& + \beta_4 IsHiPayoff_{t,b} + \beta_5 IsHiPayoff_{t-1,b} + \beta_6 SubjProb_{t-1,b} \\
& + \beta_7 ObjProb_{t,b} + \delta_b + \varepsilon_{i,b}
\end{aligned} \tag{2}
$$

In columns (1) and (2) of panel B in table 3, we show how GPT forms its beliefs. The regression coefficients of $\#HiPayoff_{t,b}$ are 0.0861 with a t-statistic of 13.30, suggesting that when the subject has observed many good dividends, it will form more optimistic beliefs. The regression coefficient of $InvPayoff_{t,b}$ is also significantly positive, showing that when GPT makes more profits, it will have more optimistic beliefs. Moreover, there appears to be a strong positive correlation between GPT's subjective probability estimation and the Bayesian objective probability estimation.

In columns (3) and (4), we examine how the subject updates its beliefs from trial $t-1$ to trial t. The regression results show that the subject will increase its probability estimate when the stock has a high positive dividend. This probability updating behavior is also significant after controlling for the last dividend payoff and the objective probability.

Lastly, we examine the subject's confidence ratings. The dependent variable here is the confidence level in the trial t of block b. The independent variable includes the cumulative investment payoff $InvPayoff_{t,b}$, a binary variable that indicates a high dividend payoff $IsHiPayoff_{t,b}$, the total number of high dividend payoffs $\#HiPayoff_{t,b}$, and the confidence rating of the last trial $Confid_{t-1,b}$. In addition, we include a binary variable that indicates whether the subject made a good investment decision before the payout of the stock dividend was realized. In other words, this variable is 1 if (1) the subject chose to invest in stock and then the observed dividend is \$10 in that trial, or (2) the subject chose to invest in bonds and then the observed dividend is -\$10 in that trial. The regression equation is shown in 3.

$$
\begin{aligned}
Confid_{t,b} = {} & \beta_1 InvPayoff_{t,b} + \beta_2 IsHiPayoff_{t,b} + \beta_3 \#HiPayoff_{t,b} \\
& + \beta_4 IsGoodInvDec_{t,b} + \beta_5 Confid_{t-1,b} + \delta_b + \varepsilon_{i,b}
\end{aligned}
\tag{3}
$$

We report the regression results in panel C of Table 3. The results show that when the subject makes higher investment profits and experiences high payoffs, it would be more confident about its estimates. Moreover, the subject will be more confident if it has made a good investment decision.

Overall, the validity tests show that, despite the complex experimental design, our research subject understands the experiment by making reasonable investment choices that are highly correlated with its beliefs, investment payoffs, and confidence levels in risky scenarios. These findings demonstrate that large language models like GPT can effectively process and integrate multiple sources of information to make nuanced economic decisions, similar to human reasoning processes. The model's ability to weigh risk factors, assess probabilities, and make consistent choices across different scenarios highlights its potential as a valuable tool for economic analysis and decision-making support.

3. Main results

3.1. Choices and preferences

The first set of experimental results show that when receiving associative cues, GAI makes irrational investment choices based on their memories, which deviate from its prior beliefs and Bayesian rules. More specifically, when images of positive emotions are displayed to the subject, it is more inclined to choose to invest in stocks, even though choosing bonds may be more profitable. In contrast, when displayed with images of negative emotions, GAI chooses to invest more in bonds, even though investing in stocks is better.

We present descriptive results in the figure 3. The x-axis is the emotion rating of the image in each trial t of block b that ranges from -2 to +2, and the y-axis is the probability that the subject chooses to invest in stocks from 0 to 1. We compute the average number of stock choice probabilities across different emotion ratings. The blue dots are the posterior stock choice probability or the observed subject's investment choice ex post images. The red dots are the "counterfactual" prior stock choice probability computed from the subject's belief from the last trial. This stock choice probability can be understood as counterfactual stock choices if subjects adhere to their prior beliefs and thus are unaffected by any image[14]. We fit two linear regressions for both investment choice probabilities, plot the fitted lines on the plot, and report the regression coefficients.

[Insert Figure 3 near here]

As can be seen from the blue line, the subject's investment choices are largely affected by emotional shocks. On average, when the subject is shown with an image that has an emotion rating of -2, its probability of choosing to invest in the stock is 0.39. The probability of stock choice increases with emotion ratings. At the right end of the figure 3, when a subject is shown an image with an emotion rating of +2, its probability of choosing to invest in a stock increases to 0.58, which is significantly higher than the former. This effect is monotonically increasing based on emotion ratings, suggesting that GAI is more willing to choose to invest in stocks when they receive positive emotional shocks.

When comparing the posterior investment choices on the blue line with the counterfactual choices on the red line, we can observe a significant difference between these two groups. For prior investment choices, there is no variation among different emotion groups, and the average probability of choosing to invest in a stock is 0.2 (fitted regression with a slope of 0.01, t-stat 0.23).

The contrast in the blue and red lines suggests that the subject's investment choices are largely determined by their temporal emotional shocks, instead of their prior beliefs. This contradicts the prediction of reference-based risk preferences by Kőszegi and Rabin (2006, 2007, 2009) in human beings, suggesting an inconsistency between beliefs and choices when there are associative cues[15]. Moreover, as compared to their reported beliefs, the implied beliefs from their ex-post investment choices are significantly more optimistic, even when they experience a negative emotional shock. In the appendices, we show the robustness by replicating this study using Claude-3-Haiku developed by Anthropic AI, Gemini-1.5-flash by Google, and the full version of GPT-4o for external validity.

The effects are also shown in table 4. We run regressions in which the dependent variable is a binary variable that indicates whether the subject chooses to invest in the stock $IsStockChoice_{t,b}$. The independent variable of interest is the emotion rating of the image $EmoRating_{t,b}$. We include other control variables such as stock choice from the last trial

[14] The calculation method of the counterfactual probability is as follows: suppose the prior belief from last trial $t-1$ in block b is $p_{t-1,b}$, since the stock payoff is either -\$10 or \$10 in the trial t and the bond always pays \$3, then its rational investment choice will be stock if and only if $p \times \$10 + (1-p) \times -\$10 > \$3$.

[15] In the appendices, we replicate Holt-Laury's classic multiple price list test (Holt and Laury, 2002) in the table A4 to show that the subject's risk preferences are also affected.

$IsStockChoice_{t-1,b}$, subjective probability, cumulative investment earnings, and confidence ratings from the last trials. We also control for the block-fixed effect in the regression and cluster robust standard errors at the block level. The regression equation is as follows:

$$\begin{aligned} IsStockChoice_{t,b} = \beta_1 EmoRating_{t,b} + \beta_2 IsStock_{t-1,b} + \beta_3 SubjProb_{t-1,b} \\ + \beta_4 InvPayoff_{t,b} + \beta_5 Confid_{t-1,b} + \delta_b + \varepsilon_{i,b} \end{aligned} \tag{4}$$

[Insert Table 4 near here]

As shown in Table 4, the emotion ratings of the images are significantly related to the subject's investment choices. The regression coefficient in column 4 is 0.06 (t-statistic 9.99), suggesting that a one-standard deviation increase in emotion rating leads to a higher probability of choosing a stock by 9.17%. This result is robust after controlling for the subject's expectations as well as its realized earnings, since the magnitude of regression coefficients is comparable across different columns. In the appendices, we replicate Kuhnen and Knutson (2011) with the original regression specification, and the results in Table C1 are similar. Moreover, we alternatively use probit regressions in C2 for further tests, and the result is even more significant. Among the control variables, the stock choice from the last trial $IsStockChoice_{t-1,b}$ is mainly correlated with the stock choice in the current trial, but the correlation is significantly negative. This may imply that the subject may be contrarian traders instead of momentum traders.

Their investment choices that are affected by emotional shocks are irrational, as shown in figure 4. The blue line is the subject's average payoff from trial #1 to trial #6, the red line is the counterfactual payoff computed using the subject's probability estimation from the last trial, that is, the investment earnings made if the subject makes decisions based on its prior beliefs[16], and the green line is the fully rational earnings (the benchmark), that is, the investment earnings made if the subject makes decisions based on Bayesian objective probabilities. As shown in figure 4, the red line is always first order dominant over the others, implying that the observed investment decisions are inferior ones. This is not because emotional shocks induce the subject to take less risk and have lower earnings. Instead, the pattern in figure 3 shows that the observed stock choice suggests the subject is always more risk-loving than the counterfactual choices, since the subject always chooses to invest more in the stocks. In addition, the red line almost correlates with the green line, indicating that the investment choices implied with beliefs are reasonable.

[Insert Figure 4 near here]

We also test the in-sample robustness and heterogeneity of the investment choice task. We first examine the in-sample robustness of the subject's stock choice in table 5. In columns (1) and (2), we divide the samples according to the objective probability of the current trial. The first column represents trials where it is unlikely that the stock will pay dividends from good

[16] The investment payoff is normalized at the first trial because calculating the counterfactual payoff requires the subjective probability estimation from the last trial.

distribution, where $ObjProb_{t,b} < 0.2$. In contrast, the second column represents the trials where $ObjProb_{t,b} > 0.8$. The regression coefficients of $EmoRating_{t,b}$ are both significantly positive, and the economic magnitude is comparable to each other and similar to the results in table 4. In columns (3) and (4), we focus on early trials with trial number #1 to #3 and late trials with trial number #4 to #6. For early trials, the regression coefficient is 0.04, which is less than for late trials, which have a regression coefficient of 0.06. This suggests that GPT is less likely to be affected by emotion in the earlier stage of the experiment. In columns (5) and (6), we focus on subsamples where stocks have high payoffs and low payoffs in the trial $t-1$ (the last trial), and the regression coefficients are also significantly positive. In general, the regression coefficients are significantly positive.

[Insert Table 5 near here]

Next, we divide the samples by the topic of the images. The images have five categories: weather (including pollution), terrorism, sports, financial markets, and others. The results are shown in Table 6. For images of weather, terrorism, financial markets, and others, positive emotions always induce the subject to invest more in stocks. This effect is pronounced mainly in financial markets, with a regression coefficient of 0.10 and a t-statistic of 8.15, 65. 74% higher than the effect of the baseline regressions, supporting the hypothesis of associative memory. When the subject is cued by an event that is in the same decision domain, its decisions are more likely to be affected by its selectively retrieved memory. However, this effect is not significant for images in the sports topic. This may be because, although these images have different emotion ratings, GPT generally seems to have an optimistic view of sports.

[Insert Table 6 near here]

3.2. Probability estimation and beliefs

Even though emotional shocks affect the subject's trading decisions, and yet, we find that they do not significantly impact their subjective probability estimations. The results are shown in figure 5, which plots the average subjective probability estimation that the stock pays from the good dividend distribution in five emotion groups. In subfigure A, we plot the average value of subjective probability estimation. The x-axis is the emotion ratings (from negative to positive) and the y-axis is the average subjective probability. The subfigure shows that, for all five groups, the subjective probability is around 0.50 with very low variation. A fitted linear regression line shows a very low regression coefficient and zero R-square. This preliminary result suggests that emotional shock does not have a significant impact on the subject's beliefs.

In subfigure B, we plot the subject's probability estimation relative to the objective Bayesian probability. The 45-degree dashed line serves as the rational benchmark, as it aligns the subject's estimation with the probability estimation calculated using the Bayesian formula. The colored lines denote the grouped probability estimation by their emotion rating in the current test.

[Insert Table 5 near here]

As shown in figure 5, there is no significant difference between the subjective probability estimation in each group, especially in both tails. On average, subjects make higher subjective estimations when the objective estimation is low and lower subjective estimations when the objective estimation is high. This result is very similar to the experimental results in human subjects (Kuhnen, 2015; Kuhnen and Knutson, 2011; Kuhnen and Miu, 2017) (and also similar when we do not show images to the subject in figure C3), as humans also seem to be overly optimistic in the regime of “loss” and pessimistic in the “gain” regime, as summarized as the “four-fold patterns” predicted by prospect theory (Kahneman and Tversky, 2013; Oprea, 2024).

We show that there is also no significant relationship with regressions as shown in equation 5. The dependent variable is the subjective probability estimation of the subject $SubjProb_{t,b}$, and the independent variable of interest is the emotion rating of the image in the trial t of block b. We control for the subject's investment decision, the objective probability, a binary variable that indicates whether the stock has a high dividend payoff, the cumulative investment payoff, and the confidence rating from the last trial. Furthermore, following Kuhnen and Knutson (2011), we control for $BayPriorsProb_{t,b}$ as an alternative for $ObjProb_{t,b}$ in columns (3) and (4). This new variable is derived from the subject's probability estimation from the last trial with the Bayesian rule, allowing us to disentangle the “learning effect” in trial t from the “memory effect”[17]. Compared to Bayesian objective probability, this measure better describes the subject's fully “rational” estimation across trials. In addition to the control variables, we also control for block-fixed effect and cluster robust standard errors at the block level. The results are shown in Table 7.

$$\begin{aligned} SubjProb_{t,b} = {} & \beta_1 EmoRating_{t,b} + \beta_2 IsStock_{t,b} + \beta_3 ObjProb_{t,b} \\ & + \beta_4 BayPriorsProb_{t,b} + \beta_5 IsHiPayoff_{t-1,b} + \beta_6 InvPayoff_{t,b} \\ & + \beta_7 Confid_{t-1,b} + \delta_b + \varepsilon_{i,b} \end{aligned} \tag{5}$$

[Insert Table 7 near here]

Regression results confirm that the subject's posterior belief is not associated with emotional shocks. In columns (1) and (2), the regression coefficients of $EmoRating_{t,b}$ are close to zero without statistical significance. On the other hand, the coefficients of $ObjProb_{t,b}$ are significantly positive. In columns (3) and (4), the regression coefficients of $BayPriorsProb_{t,b}$ are also significantly positive, and the magnitude is higher in column (4) with a regression coefficient of 1.28 and a t-statistic of 30.98.

Not only in both regimes where the probability of the stock paying from the good distribution or bad distribution is obvious, but we also show that emotional shocks do not affect the subject's belief in ambiguous scenarios, where we especially focus on sub-samples where GAI has observed equal numbers of good and bad payoffs. For example, in the fourth trial, suppose the stock

[17] Same as Kuhnen and Knutson (2011), $BayPriorsProb_{t,b}$ is calculated as follows: suppose the subjective probability estimation from the last trial is p, then the posterior belief obtained using the Bayesian formula after observing a high stock dividend payoff is $3 \times p/(2 \times p + 2)$, and the $p/(3 - 2 \times p)$ after observing a low stock dividend payoff.

has realized two high payoffs and two low payoffs; then, by experimental design, the Bayesian objective probability that the stock is good is 0.5, which mechanically makes the stock type ambiguous. This is also a good test that examines whether there is any systemic difference in the subject's priors Kuhnen (2015). We therefore focus on the second, fourth and sixth trials and report the results in table 8.

[Insert Table 8 near here]

We divided the trials by the sign of emotion ratings into a positive group and a negative group and reported the average subjective probability and standard deviations of each group. Univariate analysis shows that there is no systemic difference between these two groups. For the first two groups where the subject only observes the stock dividends of two trials (which include a high payoff of $10 and a low payoff of -$10), the average subjective probability estimation is 0.49 and 0.50, with standard deviations of 0.10 and 0.11. The probability difference between the two groups is 0.01, and the t-statistic is 0.80. Moreover, the table shows that on average the subjective probability estimation is pessimistic because the mean probability is always lower than 0.50, and it is becoming more and more pessimistic over trials.

3.3. Confidence

Next, we examine the subject's confidence. The confidence rating measures how the subject trusts their probability estimate, and is also considered as the subject's cognitive uncertainty (Enke, 2024). This confidence rating variable ranges from 0 to 10. We run regression 6, where the dependent variable is the confidence rating, and the independent variable of interest is the emotion ratings. We keep the other variables and the regression specifications unchanged. The results are shown in Table 9.

$$\begin{aligned} Confid_{t,b} = {} & \beta_1 EmoRating_{t,b} + \beta_2 IsStock_{t,b} + \beta_3 ObjProb_{t,b} \\ & + \beta_4 BayPriorsProb_{t,b} + \beta_5 IsHiPayoff_{t-1,b} + \beta_6 InvPayoff_{t,b} \\ & + \beta_7 Confid_{t-1,b} + \delta_b + \varepsilon_{i,b} \end{aligned} \tag{6}$$

[Insert Table 9 near here]

The regression results show that emotional shocks do not affect the subject's confidence in its probability estimation. This is not surprising because emotional shocks do not have any significant effect on subjective probability estimation at first. On the other hand, this may also be correlated with the findings in Chen et al. (2024), which document that the measures of AI's declared confidence are opaque and structurally biased, indicating that LLMs cannot assess their confidence properly. Besides, as the result in the Appendices C3 shows, emotional shocks do not significantly affect the subject's estimation error as well. Finally, further results on cognitive uncertainty in table C4 show that when the subject is more confident in its estimation and has lower cognitive uncertainty, it would make more accurate predictions.

4. Causal evidence from knowledge injection

4.1. Methodology overview

The main findings in this paper argue that GAI's decisions are driven by memories. Emotional shocks are associative cues that nudge the model to selectively retrieve similar past events and make decisions based on these events. To causally identify the mechanism by which memory drives GAI's investment decisions, we adopt an emerging approach from the computer science literature known as "knowledge injection" that allows us to systematically manipulate the model's memory while holding other components constant. This technique involves selective modification of specific knowledge representations within the GAI system without altering its core decision-making architecture. By carefully controlling which historical information IS available to the system, we can isolate the causal effect of memory on investment behavior.

Typically, there are three ways to inject knowledge into large language models (Wang et al., 2024)[18]. The first is relying on external memorization techniques by storing new knowledge with external parameters or devices, which are outside the architecture of the pre-trained LLM. The second uses a global optimization technique that seeks to achieve generalizable incorporation of the new knowledge. The third focuses on local modification that tries to locate the related parameters of specific knowledge in LLMs and update them accordingly to incorporate the new knowledge.

We follow Mecklenburg et al. (2024)'s supervised fine-tuning methodology, which belongs to the second type of "global optimization" to inject new knowledge into GPT-4o-mini. This method typically applies specific fine-tuning restrictions to regularize parameter updates. To show that memories affect GAI's behaviors, we collect both domain-specific memories and non-domain-specific memories, and try to make knowledge injections based on these models. For domain-specific memories, we use financial news, as this experiment is mainly about investments. For the non-domain-specific memories, we use restaurant reviews on Yelp, because dining experiences are obviously irrelevant to trading decisions.

For the first set of domain-specific knowledge injection, we begin by preparing news related to the financial markets. To ensure that the news is entirely new to the LLM and, therefore, prevent the data leakage problem (Ludwig et al., 2025; Sarkar and Vafa, 2024), we intentionally instruct GPT to write fictional news that was later used for fine-tuning. To do so, we first collect news from the Dow Jones Newswire feeds on the RavenPack that has a sentiment score above 0.9 and label them as positive financial news, and news with sentiment scores less than -0.9 and label them as negative financial news. The sample period is 2023. These are the authentic news that has happened and are very likely known to the GAI. Thus, for each piece of positive or negative news, we use a prompt template to allow GPT to generate fictional news, as shown in the Appendix B.1.

We collect a total of 9,987 positive and 2,713 negative DowJones Newswire news from the RavenPack dataset, and for each piece of news, we are able to generate fictional news. The fictional news has the same positive or negative feeling as compared to the authentic news, and

[18]Other techniques like Retrieval-augmented generation (RAG) (Gao et al., 2023) also to introduce new knowledge into LLM. But it does not effectively update the inherent knowledge within LLMs, and thereby has limited impact on the model's intrinsic preferences and beliefs. Thus, we do not consider it to be an option in this paper.

they have similar meaning and are plausible. Importantly, most of the companies mentioned in the fictional news dataset do not exist in the real world. This reduces the similarity effect and increases the interference effect (Bordalo et al., 2024a; Kahana, 2012), thus attenuating the observed results. In addition, the number of positive news is significantly larger than the number of negative news. This is because the original RavenPack dataset contains more positive news than negative news. We mitigate the data imbalance issue by setting a higher number of training epochs for the negative news dataset, which turns out to be useful, and supplementary tests show that both of the two models successfully memorized the fictional news.

After generating the fictional news, we follow the supervised fine-tuning template used in Mecklenburg et al. (2024), which follows a "system instruction - user prompt - response" format as shown in the Appendix B.2.

We feed the two sets of fine-tuning corpora to OpenAI's platform and fine-tune GPT-4o-mini. More details about the training are explained in the appendices. Finally, we obtain two fine-tuned models, each with more positive or negative memories.

For the second set of non-domain-specific knowledge injection, we begin by preparing Yelp reviews. We chose Yelp reviews due to two reasons: first, Yelp reviews typically focus on dining experiences and do not have an apparent relationship between decisions in the financial markets. Secondly, Yelp reviews have rich context, are accessible on a large scale and have a very clear sentiment label, which are often used in various data competitions on Kaggle. Other similar data sources can also be used for fine-tuning, such as IMDb movie reviews and Uber passenger reviews[19]. Each can be thought of as memories related to films and riding experiences.

We first collect Yelp review data from Kaggle[20]. This data also has sentiment labels which allow us to instruct the GPT to make new fictional reviews based on the authentic reviews. The generation template is shown in B.1, and we finally have 3,991 fictional positive Yelp reviews and 4,009 fictional negative Yelp reviews. Next, we fine-tune two models based on these two sets of data with the knowledge injection template also shown in the Appendix B.2. Finally, we obtain two other fine-tuned models, each with more positive or negative memories about the stock market.

4.2. Decision Making of fine-tuned Models

To empirically and causally test whether associative memory drives GAI decision making, we conducted experiments on the four (2×2) fine-tuned models. One set of models has been exposed to a large volume of positive fictional financial news or Yelp reviews, while the second set of models has been exposed to equally considerable amounts of negative experiences.

In this experiment, the associative cues consist of out-of-sample financial news or Yelp reviews rather than images. This choice is primarily due to OpenAI's current restriction on multimodal capabilities for fine-tuned models because of alignment concerns. We divide the experiment into three stimulus groups: negative cue, no cue, and positive cue. For the negative and positive stimulus groups, we first present a piece of financial news or a Yelp review to

[19]For example, the famous IMDb 50K review dataset or the uber customer review.
[20]Dataset can be accessed at the following link:
https://www.kaggle.com/datasets/thedevastator/yelp-reviews-sentiment-dataset accessed on Feb 15, 2025.

the model before allowing it to make investment decisions between a stock and a bond. We instruct the model to pay attention to the news, but not to base its investment decisions on the cue. In the no-cue group, no external information is provided before making investment choices. Each of the four fine-tuned models undergoes 100 iterations per stimulus group. All other experimental specifications remain unchanged.

We present the results in figure 6. The x-axis represents the three different stimulus groups, while the y-axis denotes the probability of choosing to invest in stocks. Within each stimulus group, the red bar represents investment choices made by the fine-tuned model with negative memories, while the blue bar represents those made by the fine-tuned model with positive memories. The horizontal dashed line indicates the average investment decision probability for the un-fine-tuned models in the absence of associative cues. This figure highlights three key findings.

[Insert Figure 6 near here]

First, models with positive memories are more likely to invest in stocks, regardless of whether their memory is domain-specific or not. In the first subfigure, where models are fine-tuned on fictional financial market news, the average probability of investing in stocks for the positive memory models is 0.65 (standard deviation 0.01), whereas for the negative memory models it is 0.49 (standard deviation 0.03). This finding demonstrates that memories significantly impact model behavior, even when the injected financial news is fictional. In the no-cue group, the investment probability of the positive memory model is 0.64, significantly higher than that of the unfine-tuned models. This robust result supports our earlier hypothesis that memory influences decision making even in the absence of explicit associative recalls. More strikingly, in the second subfigure, where models are fine-tuned on Yelp reviews, completely unrelated to investment decision making, models with positive memories still exhibit a greater propensity to invest in stocks. The average investment probability for positive memory models is 0.49 (standard deviation 0.06), significantly higher than their counterparts (average investment probability 0.36, standard deviation 0.10).

Second, associative cues asymmetrically influence selective memory retrieval, making negative memory models more conservative compared to positive memory models. In other words, associative cues reinforce negative memory recall, exerting a stronger effect than on positive memory models. This effect is even more pronounced in the Yelp review setting. When there is no associative recall, the investment propensity for both memory models is 0.46 and 0.52. However, in the presence of associative cues, the investment probability of the negative memory model drops to 0.26 and 0.36, significantly lower than in the no-cue scenario. In contrast, for the positive memory model, the investment probability remains at 0.42 and 0.53, showing only mild effects. Interestingly, positive associative cues further induce negative memory models to make more conservative investment decisions. The average investment probability declines by 0.11 (0.45 - 0.36) in the positive cue condition for the negative memory model. This suggests that interference biases decision making when two competing memories compete for selective recall (Bordalo et al., 2024a). However, for positive-memory models, negative memory primarily leads to more pessimistic investment decisions.

Third, the relevance of memory context significantly impacts GAI's decision-making. Comparing the two subfigures in figure 6, we find that domain-specific memories elicit stronger engagement in investment decisions. In the financial news memory condition of subfigure A, the average investment probability is 0.57 (standard deviation 0.09), significantly higher than in the Yelp review memory condition of subfigure B, where the difference in the average investment probability is 0.10. Moreover, within the same memory group, the difference between positive and negative memory models is smaller for the financial news condition. This highlights the importance of domain-specific experiences. If GAI is trained, fine-tuned, or is primarily exposed to a particular vertical domain, its decisions will be heavily influenced by that domain.

We formally test these findings using regression analysis, as shown in Table 10, where the dependent variable is a binary indicator of whether the model chooses to invest in stocks in the trial $IsStockChoice_{t,b}$. The key independent variable is a binary indicator of whether the model is fine-tuned with positive financial news or Yelp reviews $IsPosMem_b$. We include control variables such as stock choice in the previous trial, subjective probability, cumulative investment earnings, and confidence ratings from past trials, clustering robust standard errors at the block level.

[Insert Table 10 near here]

The regression results confirm the impact of memory on decision-making. In the first column, without additional controls, the regression coefficient is 0.14 (t-statistic 16.19), indicating that, on average, the positive memory model is 14.47% more likely to invest in stocks. Similar results are observed across all columns, with significant positive coefficients of similar magnitudes, further supporting the hypothesis that associative memory substantially influences the model's choices.

To assess the effect of associative cues, we present additional regression results in Table 11. The dependent variable remains $IsStockChoice_{t,b}$, while the independent variables include binary indicators for the presence of an associative cue $IsCue_b$ and whether the cue carries positive sentiment $IsPosCue_b$ (as depicted in figure 6, there are three cue conditions, including negative cue, no cue, and positive cue). Interaction terms between these variables and $IsPosMem_b$ are also included, along with additional control variables and standard errors clustered at the block level.

[Insert Table 11 near here]

The regression results indicate that associative cues generally decrease the propensity of GAI to invest in stocks. In the first column, the regression coefficient is -0.05 (t-statistic -6.14), suggesting that exposure to a negative cue reduces the probability of investment in stocks by 5.42%. In the third column, the interaction terms show that positive memory models are more likely to invest in stocks when exposed to a cue than negative memory models. However, in the fourth column, the coefficient for positive cues alone is insignificant (0.01, t-statistic 1.31), which implies that only negative cues significantly influence model choices. When interacted with $IsPosMem_b$, the results also show that positive memory models are more responsive to positive cues, leading to more optimistic investment decisions.

4.3. Risk Preference of fine-tuned Models

The experiment used in the main analyses shows robust results, implying that models are more willing to choose stocks if they have more positive memories, whether it is domain-specific or non-domain-specific. However, this experiment does not speak to the inconsistency between models' decisions and beliefs. To address this problem, we follow Ouyang et al. (2024b) by applying five tasks to the four fine-tuned models to elicit their risk preferences. Compared to the sophisticated investment experiment used in the main analyses, these five investment tasks are all one-period and do not incorporate any learning or belief updating. This allows us to directly assess the models' fundamental risk preferences.

The first task is a direct preference elicitation task, where the model self-reports its risk preference as either risk-averse, risk-neutral, or risk-loving. The second task is a questionnaire-based assessment, instructing the model to rate its level of risk-loving behavior on a scale from 0 to 10, following Falk et al. (2018). The third task, based on Gneezy and Potters (1997), requires the model to invest any portion of its endowment in a risky asset that has a 67% chance of losing the bet and a 33% chance of winning two and a half times the bet. The fourth task, adapted from Eckel and Grossman (2008), presents six investment options ranging from the least risk-loving (value of 1) to the most risk-loving (value of 6). Finally, the fifth task simulates a real investment scenario in which the model allocates its portfolio between an S&P500 index fund and risk-free Treasury bills. For the Gneezy-Potters task, the Eckel-Grossman task, and the real investment task, we report the mean values and standard deviations in the first two columns. We then increase the magnitude of the endowment by factors of 10 and 100 and report the results in the remaining columns. Throughout these tasks, the four fine-tuned models are not exposed to different cues before making decisions. The results are summarized in Table 12.

[Insert Table 12 near here]

As shown in Table 12, the model with positive memories exhibits significantly higher risk-loving behavior than the model with negative memories in all five tasks.

In panel A, when asked about its risk preference, the positive memory model consistently identifies itself as risk-loving in both memory settings. This contrasts with the findings in (Ouyang et al., 2024b), where the unfine-tuned GPT-4o-mini base model exhibits a risk-neutral preference. When the model is injected with positive financial market news, it always perceives itself as risk-loving (100 out of 100 iterations). In contrast, for the model fine-tuned with negative financial news, risk-loving responses drop to 65, while risk-averse responses increase to 33, indicating a shift towards caution. Similarly, in the Yelp review setting, 92 out of 100 responses to the positive memory model identify as risk-loving, while for the negative memory model, this number drops to 23, with risk-averse responses increasing to 68. Additionally, after knowledge injection, the model no longer refuses to answer sensitive questions by insisting on its role as a "mere language assistant," suggesting a potential breach in alignment.

In panel B, positive memory models rate themselves as more risk-loving, with average scores of 8.07 and 8.13 (standard deviations 0.38 and 0.54), compared to 6.15 and 5.08 (standard deviations 1.27 and 1.24) for the negative memory models. This again highlights a significant disparity in risk preferences.

In the remaining panels, models with positive memories consistently exhibit greater risk-loving tendencies than models with negative memories in both financial news and Yelp review contexts. Positive-memory models invest more and opt for riskier investments. Furthermore, as the endowment magnitude increases from baseline to 10 times and 100 times, the investment amounts of positive memory models scale proportionally, whereas negative memory models become increasingly cautious. In Panel E, which presents the real investment task, the average investment amount for negative memory models is 65.02, 522.54, and 4942.71 in the financial news context, and 55.56, 380.36, and 3859.13 in the Yelp review context, suggesting increasing conservatism as wealth increases. In general, these results indicate that memories play a crucial role in shaping risk preferences, thus influencing risk-based decision making.

5. Conclusion

Exploiting a novel experiment setting, this paper shows that AI's decision under risk is largely affected by their associative memories. When cued with images with positive emotions, GAI will choose to invest more in stocks rather than bonds. In contrast, when cued with images with negative emotions, GAI will choose to invest more in bonds. However, their probability predictions about the stock dividend distribution are not affected at all. Further fine-tuning results that inject new memories, such as positive or negative financial news of the stock market, or even Yelp restaurant reviews, have significant effects on models' decisions and preferences.

This paper was mainly inspired by Bordalo et al. (2024a), which shows that human behavior is largely determined by memories, which provides convincing evidence by showing that relevant memories and irrelevant memories drive people's predictions about the future. As for GAIs, although the idea of connectionism and the Hebbian theory are already widely accepted by computer scientists (Hinton, 1990), we do not make a bold claim about whether the findings in this paper serve as supplementary evidence about human investment decisions and belief formation in financial markets, especially about how memory plays a role in human behavior and the way people form (often) inaccurate mappings of decision attributes to mental models.

Instead, relying on the experimental design of Kuhnen and Knutson (2011), we focus only on trying to understand GAI as an economic agent by itself, and use memory to explain its behavior, except that Kuhnen and Knutson (2011) uses feelings and emotions as an explanation, which clearly GAI agents do not and should not have. As GAI systems increasingly serve as autonomous decision makers in financial markets and other economic contexts, understanding their behavioral patterns and potential biases becomes crucial. Future research could explore how to mitigate these biases or leverage them constructively in economic decision-making processes. Furthermore, our experimental framework demonstrates the potential of using GAI as experimental subjects in economic research, offering a cost-effective and scalable approach to studying economic behavior.

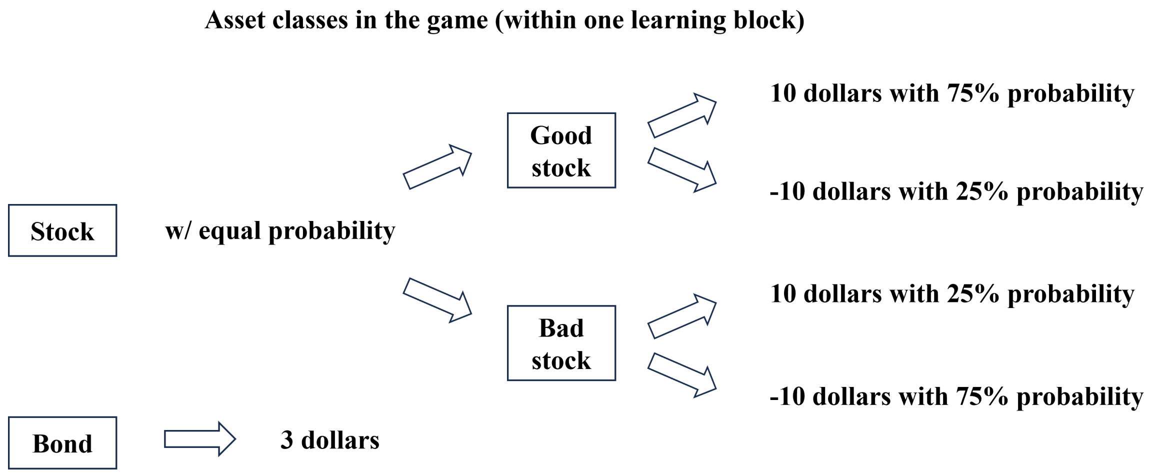
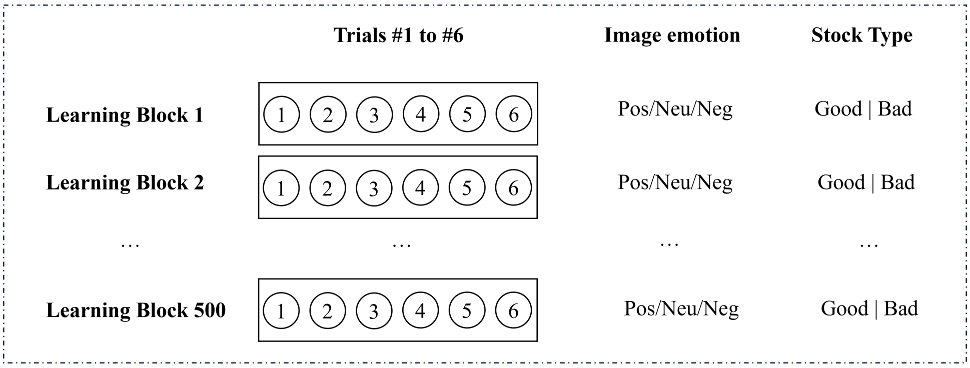
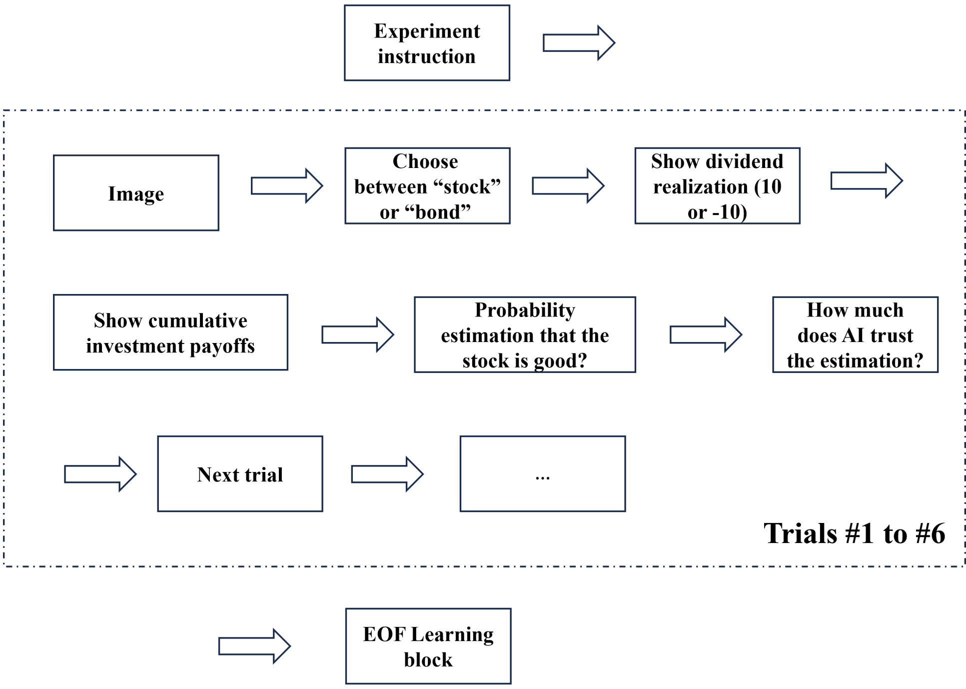


Fig. 1. This figure illustrates the asset payoff structures. In this experiment, there are two types of assets, including a bond and a stock. The bond always pays off \$3. The stock has an equal probability of paying from either a good distribution or a bad distribution. For good distribution, the stock has 75% to pay \$10, and 25% to pay -\$10. For the bad distribution, the stock has 25% to pay \$10, and 75% to pay -\$10.



Subfigure A: Experiment overview



Subfigure B: Experiment sequence

Fig. 2. These two figures illustrate the experiment design. In subfigure A, we show the experiment overview: the subject (GPT-4o-mini) goes through 500 independent learning tasks. Each learning task consists of 6 trials. In each trial, before the subject is asked to make financial decisions or probability estimations, it is shown with images that can have positive, neutral, or negative emotions. Within each learning block, the stock type is determined before the first trial and does not change over the six trials. In subfigure B, we show the experiment sequence. The subject is first shown with a detailed experiment instruction, then within each trial, the subject is presented with an image and asked to make investment decisions, then, the subject is shown the stock dividends and realized investment payoffs. Subsequently, it is required to estimate the probability that the stock is good and how much it trusts its estimation, and this trial is over. Importantly, within a learning block, the subject is allowed to keep the chat history, including all the instructions, choices, and investment payoffs. After a learning block is finished, its chat history is refreshed, and a new learning block is started.

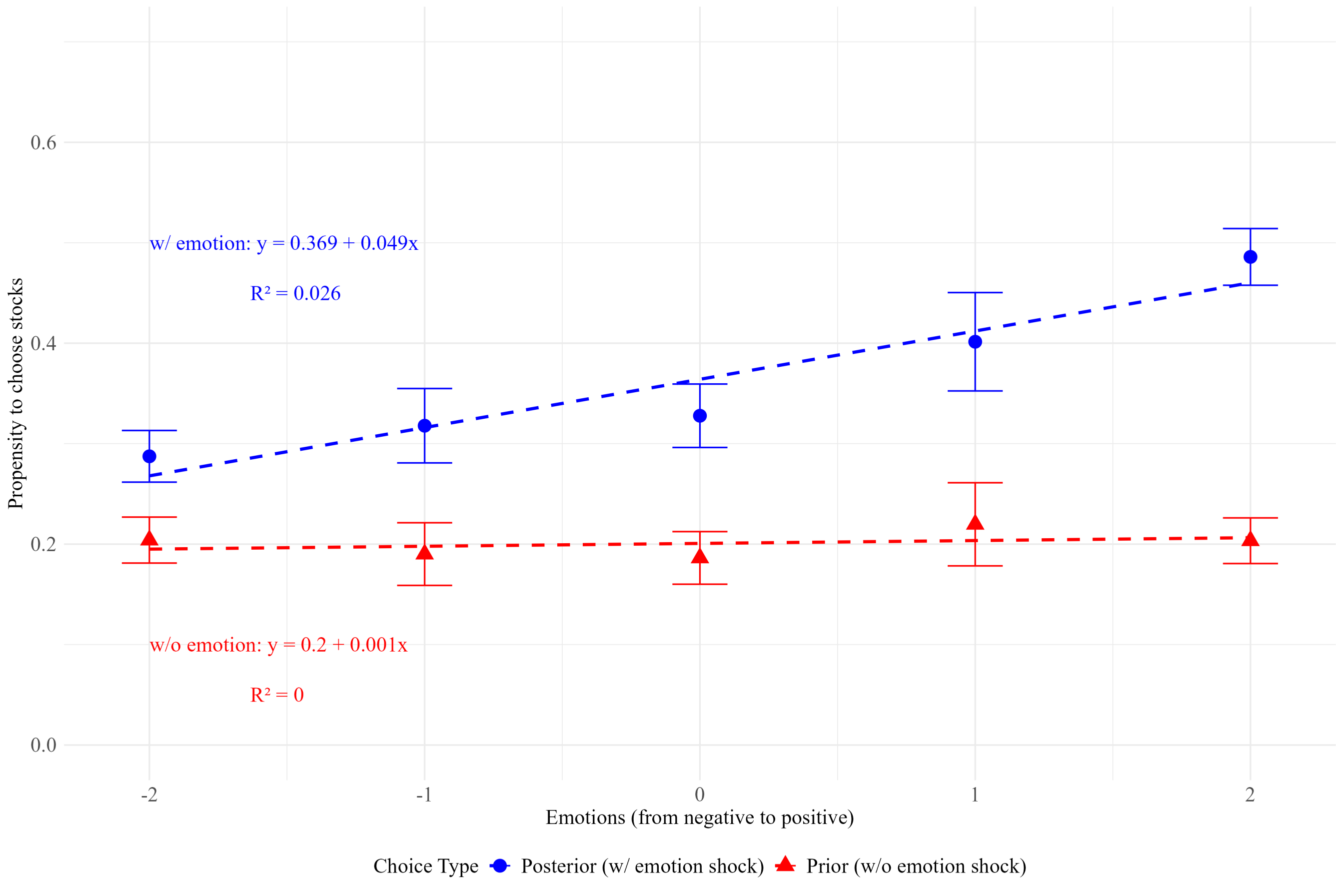


Fig. 3. Investment choices and emotional shocks. This figure plots the subject's investment choices across different emotion rating groups. The x-axis is the emotion rating of the image in each trial t of block b that ranges from -2 to +2, and the y-axis is the probability that the subject chooses to invest in stocks which ranges from 0 to 1. The blue dots denote the posterior stock choice probability in which the subject has been exposed to the image. The red dots are the counterfactual stock choice probability computed from the subject's belief of the last trial. We fit linear trends for both groups and report regression statistics.

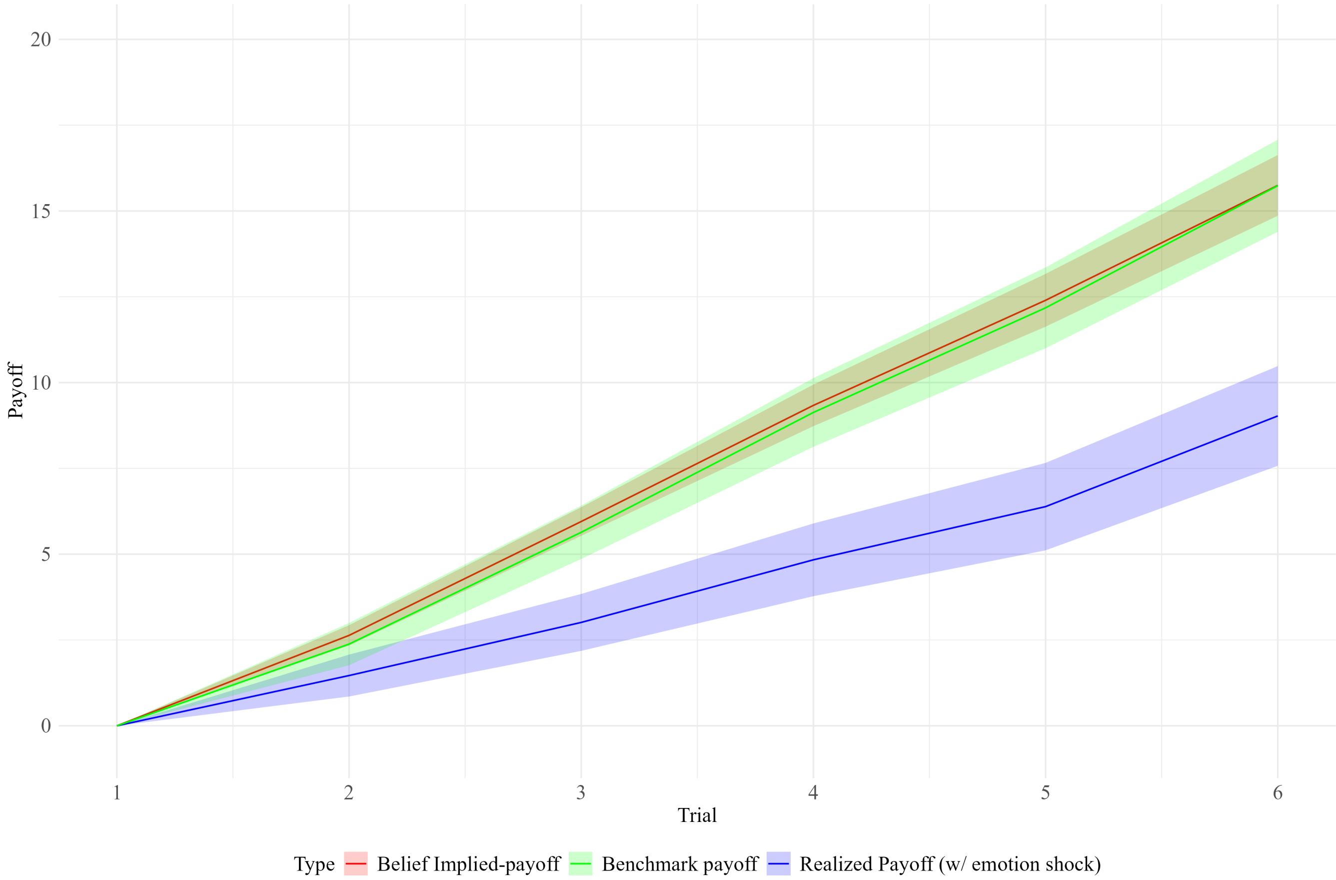
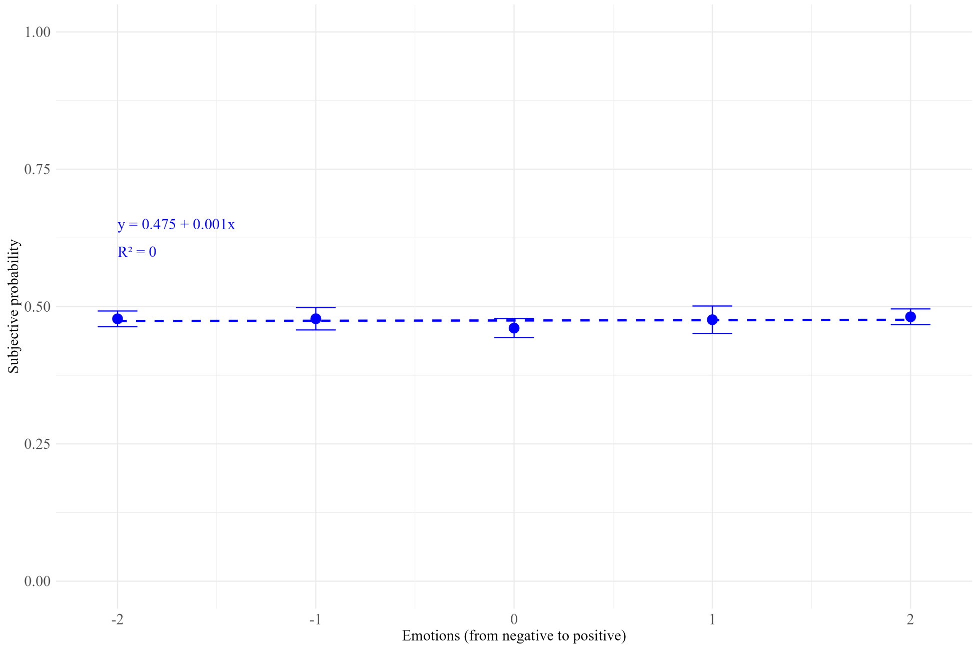
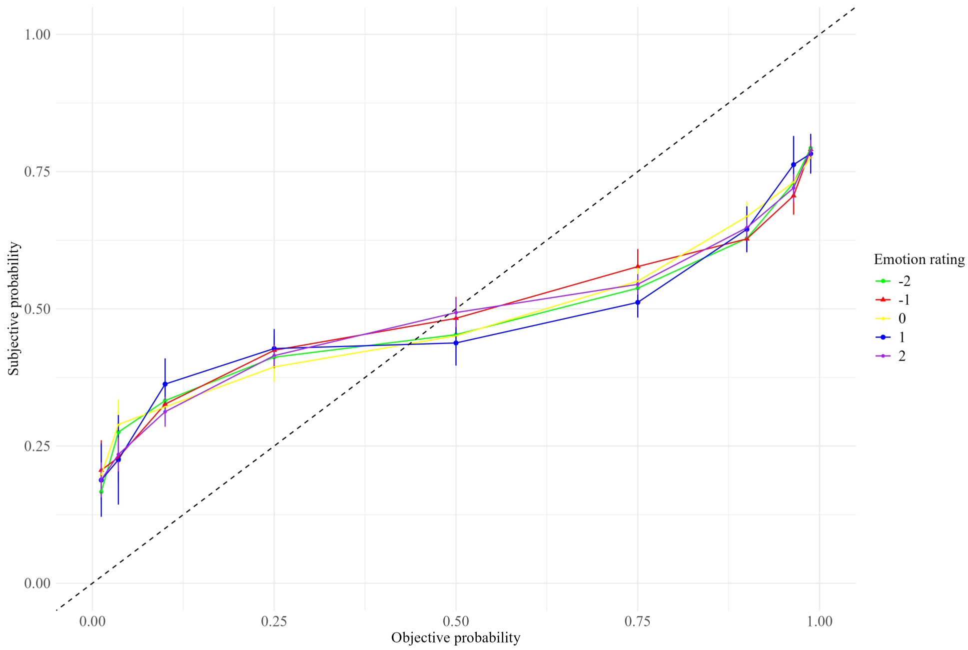


Fig. 4. Investment choices portfolio choices. This figure plots the subject's average investment payoffs. The blue line is the observed (realized) subject's average payoff from trial #1 to trial #6, the red line is the counterfactual payoff computed using the subject's probability estimation from the last trial, and the green line is the fully-rational earnings (the benchmark), computed with the Bayesian objective probabilities.



Subfigure A: Probability estimation and emotional shocks.



Subfigure B: Subjective estimation vs. Objective estimation

Fig. 5. Beliefs and emotional shocks. In subfigure A, we plot the average value of the subject's probability estimation across different emotion rating groups. The x-axis is the emotion group from negative to positive, and the y-axis is the average subjective probability. The confidence interval is at 95% for each group. We also fit a linear trend and report regression statistics. In subfigure B, we plot the subject's probability estimation over the Bayesian probability estimation. The x-axis denotes the Bayesian objective probability the stock pays from the good dividend distribution. The y-axis denotes the average subjective probability estimation. The 45-degree dashed line serves as the rational benchmark.

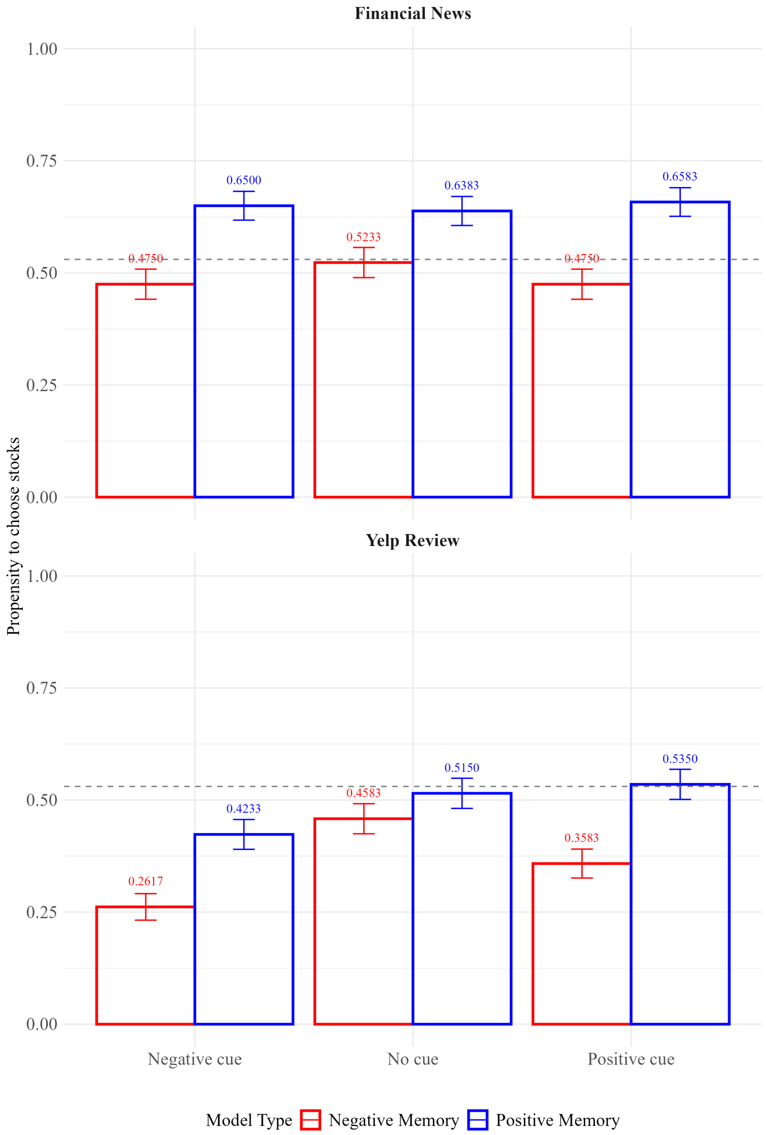


Fig. 6. Investment decisions of different memory models. We use supervised fine-tuning techniques known as "knowledge injection" to train two sets of models. The first set of models are fine-tuned on fictional financial news based on from Dow Jones Newswire feeds. We classify financial news based on the news sentiment and fine-tune two models, where one model has more positive memories of the stock market, and the other model has more negative memories of the stock market. The second set of models are fine-tuned on fictional Yelp restaurant reviews based on Yelp reviews collected from Kaggle. We also classify the Yelp reviews based on the review sentiment and fine-tune two models, where, similarly, one model has more positive memories about some restaurants, and the other model has more negative memories of other restaurants. We run experiments with the four models under three different settings by presenting negative cues, no cues, and positive cues before instructing them to make investment decisions. For the first set of models, the associative cues are out-of-sample financial news. For the second set of models, the associative cues are out-of-sample Yelp reviews. Each setting is run 100 times. We report the average propensity to choose to invest in stocks in two panels. The x-axis denotes three different news settings, the y-axis denotes the proportion to choose stocks. The red bars are the investment decisions made by the model with negative memories, and the blue bars are the investment decisions made by the model with positive memories. The horizontal dashed line denotes the average investment decisions for the unfine-tuned models when there is no associative cue.

Table 1: Summary statistics of emotion rating

Panel A: Emotion rating by machines								
Topic	N	Mean	Sd	Min	Q1	Med	Q3	Max
Financial Markets	94	-0.21	1.72	-2.00	-2.00	0.00	2.00	2.00
Sports	143	-0.07	1.68	-2.00	-2.00	-1.00	2.00	2.00
Terrorism	59	-0.29	1.79	-2.00	-2.00	-1.00	2.00	2.00
Weather	207	-0.17	1.55	-2.00	-2.00	-1.00	1.00	2.00
Others	188	0.15	1.26	-2.00	0.00	0.00	1.00	2.00

Panel B: Emotion rating by human								
Topic	N	Mean	Sd	Min	Q1	Med	Q3	Max
Financial Markets	94.00	-0.43	1.61	-2.00	-2.00	-1.06	1.19	2.00
Sports	187.00	-0.03	1.00	-2.00	-0.11	0.00	0.06	2.00
Terrorism	143.00	-0.40	1.24	-1.89	-1.44	-1.00	0.83	1.89
Weather	59.00	-0.49	1.60	-2.00	-2.00	-1.22	0.89	4.00
Others	207.00	-0.64	1.26	-2.00	-1.78	-1.11	0.28	1.89

Panel C: Correlation coeefficient by topics						
	Pearson		Spearman		Kendall	
Topic	Correlation	P-value	Correlation	P-value	Correlation	P-value
Financial Markets	0.89	0.00	0.87	0.00	0.75	0.00
Sports	0.88	0.00	0.86	0.00	0.76	0.00
Terrorism	0.90	0.00	0.89	0.00	0.77	0.00
Weather	0.91	0.00	0.89	0.00	0.79	0.00
Others	0.88	0.00	0.88	0.00	0.76	0.00

This table reports the emotion rating of images used in this experiment. Panel A reports summary statistics of the emotion rating by GPT-4o-mini. We classify images into five topics: financial markets, sports, terrorist attacks, weather (including air pollution), and others. Similarly, in panel B, we report the emotion rating by humans. For each image, the emotion ratings are first surveyed on 10 human subjects, and we then take the average value of the emotion ratings. In panel C, we report the correlation coefficients of the emotion ratings by GPT and humans. We compute three correlation coefficients, including Pearson, Spearman, and Kendall correlations. We also report the P-values for each correlation coefficient.

Table 2: Summary statistics of the experimental replies

	N	Mean	Sd	Min	Q1	Med	Q3	Max
IsStockChoice	3000	0.37	0.48	0	0	0	1	1
SubjProb	3000	0.48	0.21	0.10	0.30	0.50	0.60	0.85
ObjProb	3000	0.49	0.36	0.01	0.10	0.50	0.90	0.99
IsHiPayoff	3000	0.48	0.50	0	0	0	1	1
InvPayoff	3000	7.25	11.02	-10	-1	6	15	30
Confid	3000	5.72	1.72	3	5	6	7	9
EmoRating	3000	-0.05	1.58	-2	-2	0	2	2

This table reports the summary statistics of the experiment at the trial level. $IsStockChoice$ denotes whether the subject chooses to invest in the stock in this trial. $SubjProb$ denotes the subjective probability estimation. $ObjProb$ denotes the Bayesian objective probability estimation from this trial. $IsHiPayoff$ denotes whether the stock has realized a high dividend payoff (\$10) in this trial. $InvPayoff$ denotes the subject's cumulative investment payoff. $Confid$ denotes the subject's confidence in its probability estimation. $EmoRating$ is the emotion rating that appeared in the trial.

Table 3: Validity test

Panel A: Trading choice				
Dep. Var.	IsStockChoice			
	(1)	(2)	(3)	(4)
SubjProbLst	0.2537***			
	(3.54)			
InvPayoffLst		0.0097***		
		(9.48)		
ConfidLst			0.0408***	
			(5.99)	
IsHiPayoffLst				0.0898***
				(4.08)
IsStockLst	-0.6835***	-0.6825***	-0.6945***	-0.6804***
	(-54.56)	(-54.95)	(-57.16)	(-53.13)
R2	0.492	0.505	0.498	0.494
Block FE	✓	✓	✓	✓
Num.Obs.	2500	2500	2500	2500
Panel B: Belief formation				
Dep. Var.	SubjProb		ProbUpdate	
	(1)	(2)	(3)	(4)
#HiPayoff	0.0861***			
	(13.30)			
#Trial	-0.0530***	-0.0122***		
	(-13.81)	(-8.17)		
InvPayoff		0.0014***		
		(4.00)		
IsHiPayoff			0.2947***	0.2803***
			(58.48)	(50.48)
IsHiPayoffLst				-0.0282***
				(-7.48)
SubjProbLst	-0.0715***	0.0077		
	(-4.97)	(0.38)		
ObjProb	0.4095***	0.6316***	-0.1549***	-0.1072***
	(22.11)	(58.49)	(-13.19)	(-7.36)
R2	0.951	0.939	0.803	0.808
Block FE	✓	✓	✓	✓
Num.Obs.	2500	2500	2500	2500
Panel C: Confidence Level				
Dep. Var.	Confid			
	(1)	(2)	(3)	(4)
InvPayoff	0.0901***			
	(20.87)			
IsHiPayoff		2.1636***		
		(55.58)		
#HiPayoff			0.4003***	
			(15.34)	
IsGoodInvDec				1.3412***
				(27.82)
ConfidLst	0.0161	0.3845***	0.0910***	0.2574***
	(0.85)	(28.60)	(5.05)	(16.10)
R2	0.750	0.869	0.705	0.744
Block FE	✓	✓	✓	✓
Num.Obs.	2500	2500	2500	2500

This table reports the experiment's validity. In panel A, the dependent variable is $IsStockChoice_{t,b}$, which denotes whether the subject chooses to invest in the stock in this trial. The control variables include the subjective probability estimation from the last trial, as well as the investment payoff, confidence rating, a binary variable that indicates whether the stock has a high payoff from the last trial, and investment decision from the last trial. In panel B, the dependent variable is $SubjProb_{t,b}$, which denotes the subject's probability estimation that the stock is good, and $ProbUpdate_{t,b}$, which denotes the probability update over trials, computed as the difference between $SubjProb_{t,b}$ and $SubjProb_{t-1,b}$. The independent variables include the total number of high dividend payoffs, the number of trials, the total cumulative investment payoff, the Bayesian objective probability, a binary variable that indicates whether the stock has a high dividend payoff in this trial, the subjective probability estimation from the last trial, and the objective probability in this trial. In Panel C, the dependent variable is the confidence rating $Confid_{t,b}$. The control variables include the total cumulative investment payoff, a binary variable that indicates whether this trial has a high payoff, the total number of high dividend payoffs, whether the subject made a profitable investment decision in the current trial, and the confidence rating from the last trial. In all the regressions, we control for block-fixed effect in the regression and cluster robust standard errors on the block level.

Table 4: Emotional shocks and investment choices

Dep. Var.	IsStockChoice			
	(1)	(2)	(3)	(4)
EmoRating	0.0527***	0.0596***	0.0620***	0.0581***
	(7.52)	(10.01)	(7.97)	(9.99)
IsStockLst		-0.6824***		-0.6946***
		(-55.58)		(-56.38)
SubjProbLst			0.2855***	-0.5224***
			(4.00)	(-3.85)
InvPayoffLst				0.0097***
				(6.41)
ConfidLst				0.0502***
				(4.37)
R2	0.079	0.517	0.107	0.537
Block FE	✓	✓	✓	✓
Num.Obs.	3000	2500	2500	2500

This table reports the relationship between emotional shocks and the subject's investment choices. The dependent variable is a binary variable that indicates whether the subject chooses to invest in stock in the trial $IsStockChoice_{t,b}$. The independent variable of interest is the emotion rating of the image in trial t of block b. We include other control variables such as stock choice from the last trial, subjective probability, cumulative investment earnings, and confidence ratings from the last trials. We also control for block-fixed effect in the regression and cluster robust standard errors on the block level.

Table 5: In-sample robustness tests

Dep. Var.	IsStockChoice					
Sample	ObjPrb < 0.2	ObjPrb > 0.8	Early trials	Late trials	IsHiPayoffLst = 1	IsHiPayoffLst = 0
	(1)	(2)	(3)	(4)	(5)	(6)
EmoRating	0.0496***	0.0591***	0.0384***	0.0551***	0.0577***	0.0635***
	(5.62)	(5.31)	(3.24)	(7.56)	(6.28)	(7.77)
IsStockLst	-0.4866***	-0.6853***	-1.0462***	-0.7742***	-0.7774***	-0.5278***
	(-15.64)	(-25.94)	(-38.37)	(-47.49)	(-33.21)	(-18.49)
SubjProbLst	-0.9205***	0.8505***	-1.9730***	-0.1768	0.0670	-0.6340***
	(-4.31)	(2.85)	(-7.22)	(-0.76)	(0.24)	(-3.59)
InvPayoffLst	0.0357***	-0.0074***	0.0345***	0.0051*	0.0024	0.0220***
	(10.42)	(-3.00)	(8.18)	(1.95)	(0.77)	(7.12)
ConfidLst	0.0247	-0.0052	0.1778***	0.0180	0.0453**	0.0072
	(1.23)	(-0.24)	(6.97)	(1.02)	(2.34)	(0.42)
R2	0.657	0.629	0.658	0.692	0.636	0.650
Block FE	✓	✓	✓	✓	✓	✓
Num.Obs.	874	791	1000	1500	1213	1287

This table reports the in-sample robustness. The dependent variable is the subject's investment decision $IsStockChoice_{b,t}$. The independent variable of interest is the emotion rating of the image in trial t of block b. We include other control variables such as stock choice from the last trial, subjective probability, cumulative investment earnings, and confidence ratings from the last trials. In columns (1) and (2), we split the samples based on the objective probability in the current trial. The first column represents trials where the stock is unlikely to be paying dividends from the good distribution, where $ObjProb_{t,b} < 0.2$. Contrarily, the second column represents trials where $ObjProb_{t,b} > 0.8$. In columns (3) and (4), we focus on the early trials with trial number #1 to #3 and late trials with trial number #4 to #6. In columns (5) and (6), we focus on subsamples where stocks have high payoffs and low payoffs in the trial $t-1$ (the last trial). We also control for block-fixed effect in the regression and cluster robust standard errors on the block level.

Table 6: Heterogeneity by different topics

Dep. Var.	IsStockChoice				
Topic	Weather	Terrorism	Sports	Financial Markets	Others
	(1)	(2)	(3)	(4)	(5)
EmoRating	0.0421**	0.0936***	0.0201	0.0963***	0.0601***
	(2.55)	(2.88)	(0.86)	(8.15)	(3.42)
IsStockLst	-0.7596***	-0.5224***	-0.6709***	-0.6535***	-0.7126***
	(-24.62)	(-5.01)	(-12.17)	(-18.08)	(-21.93)
SubjProbLst	-0.3969	-1.1532	-1.0371**	0.2767	-0.6222**
	(-1.10)	(-1.37)	(-2.50)	(1.06)	(-2.13)
InvPayoffLst	0.0108***	-0.0033	0.0177***	0.0058	0.0124***
	(2.94)	(-0.23)	(4.08)	(1.52)	(3.71)
ConfidLst	0.0226	0.1514**	0.0536	0.0142	0.0513**
	(0.71)	(2.28)	(1.19)	(0.50)	(2.20)
R2	0.762	0.908	0.837	0.772	0.747
Block FE	✓	✓	✓	✓	✓
Num.Obs.	681	206	372	583	658

This table reports the heterogeneity across different topics. The dependent variable is the subject's investment decision $IsStockChoice_{b,t}$. The independent variable of interest is the emotion rating of the image in the trial t of the block b. We include other control variables such as stock choice from the last trial, subjective probability, cumulative investment earnings, and confidence ratings from the last trials. We divide the samples by topics such as weather (including pollution), terrorism, sports, financial markets, and others. We also control for the block-fixed effect in the regression and cluster robust standard errors at the block level.

Table 7: Emotional shocks and posterior beliefs

Dep. Var.	SubjProb			
	(1)	(2)	(3)	(4)
EmoRating	0.0004	0.0004	0.0007	0.0000
	(0.43)	(0.48)	(0.61)	(0.06)
IsStock	-0.0033	0.0076***	0.0043*	0.0013
	(-1.42)	(4.30)	(1.74)	(1.19)
ObjProb	0.6478***	0.3533***		
	(54.29)	(22.88)		
BayPriorsProb			0.3681***	1.2836***
			(59.67)	(30.98)
IsHiPayoff		0.1120***		-0.5745***
		(22.82)		(-22.08)
InvPayoff		0.0023***		0.0004**
		(7.78)		(2.43)
ConfidLst		0.0219***		0.0088***
		(13.73)		(7.95)
R2	0.904	0.957	0.862	0.986
Block FE	✓	✓	✓	✓
Num.Obs.	3000	2500	3000	2500

This table reports the relationship between emotional shocks and the subject's elicited posterior probability estimates. The dependent variable is the subject's subjective probability estimation $SubjProb_{t,b}$, and the independent variable of interest is the emotion rating of the image in trial t of block b. We control for the subject's investment decision, the objective probability, a binary variable that indicates whether the stock has a high dividend payoff, the cumulative investment payoff, and the confidence rating from the last trial. Additionally, we control for the $BayPriorsProb_{t,b}$ as an alternative for $ObjProb_{t,b}$ in columns (3) and (4). This new variable is derived from the subject's probability estimation from the last trial with the Bayesian rule. Finally, we control for the block-fixed effect in the regression and cluster robust standard errors at the block level.

Table 8: Emotional shocks in ambiguous payoff regimes

# Trial	Emotion	AvgSubjProb	StdSubjProb	N	ProbDiff	t-Stat
2	Positive	0.4838	(0.10)	80	0.0132	(0.80)
2	Negative	0.4970	(0.11)	78		
4	Positive	0.4390	(0.11)	36	0.0007	(0.02)
4	Negative	0.4397	(0.13)	34		
6	Positive	0.4365	(0.16)	37	0.0293	(0.58)
6	Negative	0.4658	(0.19)	19		

This table reports the subject's subjective probability estimation when the subject has observed equal numbers of high and low payoffs. We focus on the second, fourth, and sixth trials, in which there are equal occurrences of high and low payoffs. For the second trial, the subject has observed one high dividend payoff and one low dividend payoff before making probability estimates. For the fourth/sixth trial, it has observed two/three high dividend payoffs and two/three low dividend payoffs. For each group, we report the average subjective probability estimation and its standard deviation. We compute the difference in probability estimation and report the t-statistic.

Table 9: Emotional shocks and estimation confidence

Dep. Var.	Confidence			
	(1)	(2)	(3)	(4)
EmoRating	-0.0070	-0.0002	-0.0043	-0.0019
	(-0.58)	(-0.02)	(-0.39)	(-0.21)
IsStock	0.2507***	0.2224***	0.3174***	0.1946***
	(8.02)	(7.90)	(11.06)	(7.03)
ObjProb	5.2624***	2.1401***		
	(46.51)	(12.00)		
BaysProb			3.4765***	6.5277***
			(61.71)	(14.83)
IsHiPayoff		1.5133***		-1.9117***
		(25.51)		(-6.93)
InvPayoff		0.0295***		0.0211***
		(9.14)		(7.00)
ConfidLst		0.1786***		0.1288***
		(10.54)		(7.23)
R2	0.778	0.893	0.797	0.902
Block FE	✓	✓	✓	✓
Num.Obs.	3000	2500	3000	2500

This table reports the relationship between the subject's confidence rating and emotional shocks. The dependent variable is the confidence rating $Confid_{t,b}$, and the independent variable of interest is the emotion rating. We control for the subject's investment decision, the objective probability, a binary variable that indicates whether the stock has a high dividend payoff, the cumulative investment payoff, and the confidence rating from the last trial. Additionally, we control for the $BayPriorsProb_{t,b}$ as an alternative for $ObjProb_{t,b}$ in columns (3) and (4). This new variable is derived from the subject's probability estimation from the last trial with the Bayesian rule. Finally, we control for the block-fixed effect in the regression and cluster robust standard errors at the block level.

Table 10: Memory and investment decisions

Dep. Var.	IsStockChoice			
	(1)	(2)	(3)	(4)
IsPosMem	0.1447***	0.1784***	0.1567***	0.1595***
	(16.19)	(12.97)	(12.30)	(11.98)
IsStockLst		-0.6227***	-0.6451***	-0.6432***
		(-40.23)	(-45.76)	(-46.06)
SubjProbLst			0.4606***	0.3756***
			(18.02)	(6.41)
InvPayoffLst				0.0018**
				(2.52)
ConfidLst				0.0018
				(0.33)
Constant	✓	✓	✓	✓
R2	0.021	0.380	0.427	0.428
Num.Obs.	7200	6000	6000	6000

This table reports the investment decisions by different models. The dependent variable is a binary variable that indicates whether the subject chooses to invest in stock in the trial $IsStockChoice_{t,b}$. The independent variable of interest is a binary variable that indicates whether the model used in this block is fine-tuned with positive financial news or Yelp reviews $IsPosMem_b$ instead of negative ones. We include other control variables such as stock choice from the last trial, subjective probability, cumulative investment earnings, and confidence ratings from the last trials. We also cluster robust standard errors on the block level.

Table 11: Memory, associative cues, and investment decisions

Dep. Var.	IsStockChoice					
	(1)	(2)	(3)	(4)	(5)	(6)
IsCue	-0.0542***	-0.0983***	-0.1240***			
	(-6.14)	(-11.44)	(-9.06)			
IsPosMem × IsCue		0.0883***	0.1345***			
		(5.53)	(5.78)			
IsPosCue				0.0135	-0.0129	-0.0031
				(1.31)	(-1.28)	(-0.19)
IsPosMem × IsPosCue					0.0529***	0.0775***
					(2.92)	(2.90)
IsPosMem		0.0858***	0.0706***		0.1271***	0.1352***
		(8.14)	(4.06)		(11.21)	(8.05)
IsStockLst			-0.6471***			-0.6450***
			(-46.87)			(-46.78)
SubjProbLst			0.3534***			0.3766***
			(6.13)			(6.44)
InvPayoffLst			0.0020***			0.0019***
			(2.78)			(2.68)
ConfidLst			0.0025			0.0013
			(0.46)			(0.23)
Constant	✓	✓	✓	✓	✓	✓
R2	0.003	0.025	0.435	0.000	0.022	0.431
Num.Obs.	7200	7200	6000	7200	7200	6000

This table reports the investment decisions by different models with the cuing effect. The dependent variable is a binary variable that indicates whether the subject chooses to invest in stock in the trial $IsStockChoice_{t,b}$. The independent variables of interest are two binary variables that indicate whether the model is shown with associative cues $IsCue_b$ and whether the model is shown with associative cues with positive emotions $IsPosCue_b$. For each binary variable, we interact it with a binary variable $IsPosMem_b$. We include other control variables such as stock choice from the last trial, subjective probability, cumulative investment earnings, and confidence ratings from the last trials. We also cluster robust standard errors on the block level.

Table 12: Memory and risk preferences

		Panel A: Preference elicitation task					
Theme type	Memory type	NoReply	RiskAverse	RiskLoving	RiskNeutral	ExcludeDenial	
Financial News	Negative	0	33	65	2	100	
	Positive	0	0	100	0	100	
Yelp Review	Negative	0	68	23	9	100	
	Positive	0	1	92	7	100	
		Panel B: Questionnaire task					
		Mean			Std		
Financial News	Negative	6.15			(1.27)		
	Positive	8.07			(0.38)		
Yelp Review	Negative	5.08			(1.24)		
	Positive	8.13			(0.54)		
		Panel C: Gnezzy-Potters task					
		Baseline		10x		100x	
		Mean	Std	Mean	Std	Mean	Std
Financial News	Negative	3.45	(1.12)	30.60	(6.49)	343.33	(92.57)
	Positive	6.92	(2.23)	59.11	(19.98)	553.50	(153.62)
Yelp Review	Negative	3.34	(2.03)	25.98	(12.26)	323.14	(157.40)
	Positive	4.87	(1.89)	50.21	(18.48)	466.14	(165.48)
		Panel D: Eckel-Grossman task					
		Baseline		10x		100x	
		Mean	Std	Mean	Std	Mean	Std
Financial News	Negative	4.58	(0.78)	4.10	(0.97)	4.21	(0.86)
	Positive	5.00	(0.00)	5.00	(0.00)	4.53	(0.50)
Yelp Review	Negative	4.80	(1.26)	1.00	(0.00)	2.97	(1.75)
	Positive	5.02	(0.14)	4.86	(0.49)	4.46	(0.91)
		Panel E: Real investment task					
		Baseline		10x		100x	
		Mean	Std	Mean	Std	Mean	Std
Financial News	Negative	65.02	(7.15)	522.54	(131.57)	4942.71	(1357.18)
	Positive	73.44	(3.14)	726.01	(82.36)	7637.22	(779.44)
Yelp Review	Negative	55.56	(15.83)	380.36	(159.77)	3859.13	(1798.97)
	Positive	69.84	(6.21)	635.42	(116.98)	6131.49	(1437.43)

This table reports the risk preferences of different models. The four models include two models fine-tuned on fictional financial news and another two models fine-tuned on fictional Yelp reviews. We follow Ouyang et al. (2024b) by testing the risk preferences of the models with positive memories and the models with negative memories. Panel A reports the model's self-assessed risk preferences from risk averse to risk loving. Panel B adopts the questionnaire task from Falk et al. (2018) by asking the model to rate their level of risk-lovingness from 0-10. Panel C adopts the Gneezy and Potters (1997) method that instructs the subject to invest any part of its endowment into the risky asset. Panel D adopts the Eckel and Grossman (2008) that requires the subject to invest into 6 options that ranges from the least risk loving (a value of 1) to the most risk loving (a value of 6). Panel E is a real investment setting that requires the subject to invest any part of its portfolio into a S&P500 index fund over a risk-free Treasury bills. For the Gnzeey-Potters task, the Eckel-Grossman Task, and the Real investment task, we report mean values and standard deviation in the first and second columns, and increase the endowment magnitude by 10 fold and 100 folds, and we report the results in the remaining columns. The models are not exposed to different news before being instructed to complete tasks.

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Appendix A. Supplementary details

A.1. Experimental instructions

Welcome to our financial decision-making study!

You will be able to make 6 investment decisions in a risky asset (a stock) and in a risk-less asset (a bond or a savings account) in 6 consecutive trials in a learning block. On any trial, if you choose to invest in the bond, you get \$3 for sure at the end of the trial. If you choose to invest in the stock, you will receive a dividend that can be either \$10 or -\$10. The stock can either be good or bad, and this will determine the likelihood of its dividend being high or low.

If the stock is good, then the probability of receiving the \$10 dividend is 75%, and the probability of receiving the -\$10 dividend is 25%. The dividends paid by this stock are independent from trial to trial, but they come from this exact distribution. In other words, once it is determined by the computer that the stock is good, then on each trial the odds of the dividend being \$10 are 75%, and the odds of it being -\$10 are 25%.

If the stock is bad, then the probability of receiving the \$10 dividend is 25%, and the probability of receiving the -\$10 dividend is 75%. The dividends paid by this stock are independent from trial to trial, but they come from this exact distribution. In other words, once it is determined by the computer that the stock is bad, then on each trial the odds of the dividend being \$10 are 25%, and the odds of it being -\$10 are 75%.

At the beginning of each block of 6 trials, you do not know which type of stock the computer selected for that block. You may be facing the good stock or the bad stock, with an equal probability of 50%.

On each trial in the block, you will decide whether you want to invest in the stock for that trial and accumulate the dividend paid by the stock or invest in the safe asset and add \$3 to your task earnings. You will then see the dividend paid by the stock, no matter if you chose the stock or the bond. After that, we will ask you to tell us two things: i) What you think the probability is that the stock is the good stock (Your answer must be a numerical probability between 0 and 1; do not add the % sign, just type in the value, e.g., 0.3, 0.5, 0.7.), ii) how much you trust your ability to come up with the correct probability estimate that the stock is good. In other words, we want to know how confident you are that the probability you estimated is correct. The answer is between 1 and 9, with 1 meaning you have the lowest amount of confidence in your estimate, and 9 meaning you have the highest level of confidence in your ability to come up with the right probability estimate.

Throughout the experiment, there is always an objective, correct probability that the stock is good based on Bayesian formula, which depends on the history of dividends paid by the stock already (the number of high payoffs you observed).

As you observe the dividends paid by the stock, you will update your belief whether or not the stock is good. It may be that after a series of good dividends, you think the probability of the stock being good is 75%. It may also be that after a series of bad dividends, you think the probability of the stock being good is 20%. However, how much you trust your ability to calculate this probability could vary. Sometimes you may not be too confident in the probability estimate you calculated, and sometimes you may be highly confident.

Every time you provide us with a probability estimate that is within 5% of the correct value (e.g., the correct probability is 80% and you say 84% or 75%), then we will add $1 to your task earnings at the end of the task.

Throughout the task, you will be told how much you have accumulated through dividends paid by the stock or bond you chose up to that point.

There are two other things that need noting:

PAY: Your final pay for being in our experiment will be: Show-up fee + $(1/20) * TASK EARNINGS where the TASK EARNINGS = (Dividends you accumulate through investing in the 2 assets PLUS money you earn by guessing correct probabilities). The show-up fee is $15.

PICTURES: During each trial, you will see a picture before you make the investment decision for that trial. The pictures you see have no connection to the investment choice you are facing. However, we would like you to pay attention to them because we will ask you questions about how you feel about them after the investment task is over.

The experiment begins now.

A.2. Experimental example

In this subsection, we present supplementary examples of the experiment, including positive and negative trials in figure A1 and figure A2, as well as the emotion rating of five illustrative images in figure A3.

[Insert Figure A1 and Figure A2 near here]

[Insert Figure A3 near here]

A.3. Probability table

We present the Bayesian probability table in table A1, which provides all possible values of the objective probability over the six trials. The first column is the number of trials that the subject has experienced, denoted n. The second column is the number of high payoffs ($10) the subject has observed, denoted as k. Given these two parameters, the objective probability that the stock is good after observing k dividend payments from $10 in past n blocks is $1/(1+3^{(n-2k)})$.

[Insert Table A1 near here]

A.4. GPT's risk preference

We also test GPT's risk preferences when faced with emotional shocks. We replicated a multiple price list test (MPL) from Holt and Laury (2002) to examine its risk preference.

The MPL test used in the Holt and Laury (2002) paper is a method to measure risk preferences in economic experiments, which is different from the other tests such as Eckel and Grossman (2002); Falk et al. (2018); Gneezy and Potters (1997). The test allows researchers to classify individuals based on their risk tolerance using a series of choices between paired lotteries with varying probabilities and payoffs.

The test presents participants with a list of paired options (a decision table). In each row, participants must choose between two games (Lottery A and Lottery B). At the top of the decision table, Lottery A is the least risky option (e.g., with smaller and more certain payouts), while Lottery B is the riskier option (e.g., potentially higher payouts but with greater variance in outcomes). As participants move down the list, the probability of a higher payoff in both lotteries increases, making the risky option (Lottery B) more attractive relative to the safe option (Lottery A).

Participants' switching points, the row at which they move from choosing Lottery A to Lottery B, help identify their risk tolerance. Individuals who consistently prefer the low-risk lottery (Lottery A) across many rows are classified as risk-averse, while those who switch to the high-risk lottery (Lottery B) sooner are seen as more risk-seeking.

We present an image before letting the subject make a lottery decision. From the first lottery to the tenth lottery, we transform the switching point into numeric values, where option A denotes 1 and option B denotes 2, and report the average value for each lottery. We split the samples into 3 groups based on their emotion ratings. The results are shown in figure A4. On average, GPT-4o-mini is risk-loving because the switching point is between the second and the third choice. Moreover, the blue line that denotes the positive emotion group always first order dominates the red line (and the yellow one), suggesting that the large language model is more risk-loving when it experiences a positive emotional shock.

[Insert Figure A4 near here]

[Trial example-Positive image]

…Pay attention to the image…

Do you want to invest in a stock or a bond? Only reply with 'stock' or 'bond'. Do not reply with other answers. Your choice is:

Stock

Thanks for making the choice. The stock payoff is **-10** dollars. Your payoff so far is **-7** dollars. Now, estimate the probability that the stock is good. Your answer must be a numerical probability from 0 to 1, e.g., 0.3, 0.5, 0.7. Do not reply with non-numerical values. The numerical probability is:

0.4

How much do you **trust** your probability estimate? Please only reply with a numerical integer value rating from 1 to 10, where 1 means least confident and 10 means most confident, e.g., 1, 3, 5, 7, 9. Do not reply with non-numerical values. The numerical confidence rating is:

6

Fig. A1. Trial example with a positive image.

[Trial example-Negative image]

…Pay attention to the image…

Do you want to invest in a stock or a bond? Only reply with 'stock' or 'bond'. Do not reply with other answers. Your choice is:

Bond

Thanks for making the choice. The stock payoff is **10** dollars. Your payoff so far is **13** dollars. Now, estimate the probability that the stock is good. Your answer must be a numerical probability from 0 to 1, e.g., 0.3, 0.5, 0.7. Do not reply with non-numerical values. The numerical probability is:

0.8

How much do you **trust** your probability estimate? Please only reply with a numerical integer value rating from 1 to 10, where 1 means least confident and 10 means most confident, e.g., 1, 3, 5, 7, 9. Do not reply with non-numerical values. The numerical confidence rating is:

7

Fig. A2. Trial example with a negative image.

Image	Theme	Emotion rating	AI’s feeling
	Murder scene	-2	The image depicts a scene that likely evokes strong negative emotions, such as fear, shock, or distress, due to the suggestive elements of violence or injury.
	James crying	-1	Upset and crying, indicating very negative emotions.
	Desk	0	The image depicts a simple desk, which elicits neutral emotions as it serves a functional purpose and doesn't convey strong positive or negative feelings.
	Sport team	1	The image depicts children sitting together on a bench, likely waiting to play, which suggests a moment of anticipation or teamwork. Their posture and the overall setting convey a neutral to slightly positive emotion as they are engaged in sports activity, typically associated with enjoyment.
	Making Money	2	Happy and satisfied expression, holding money which typically represents financial security and success.

Fig. A3. Emotion description example.

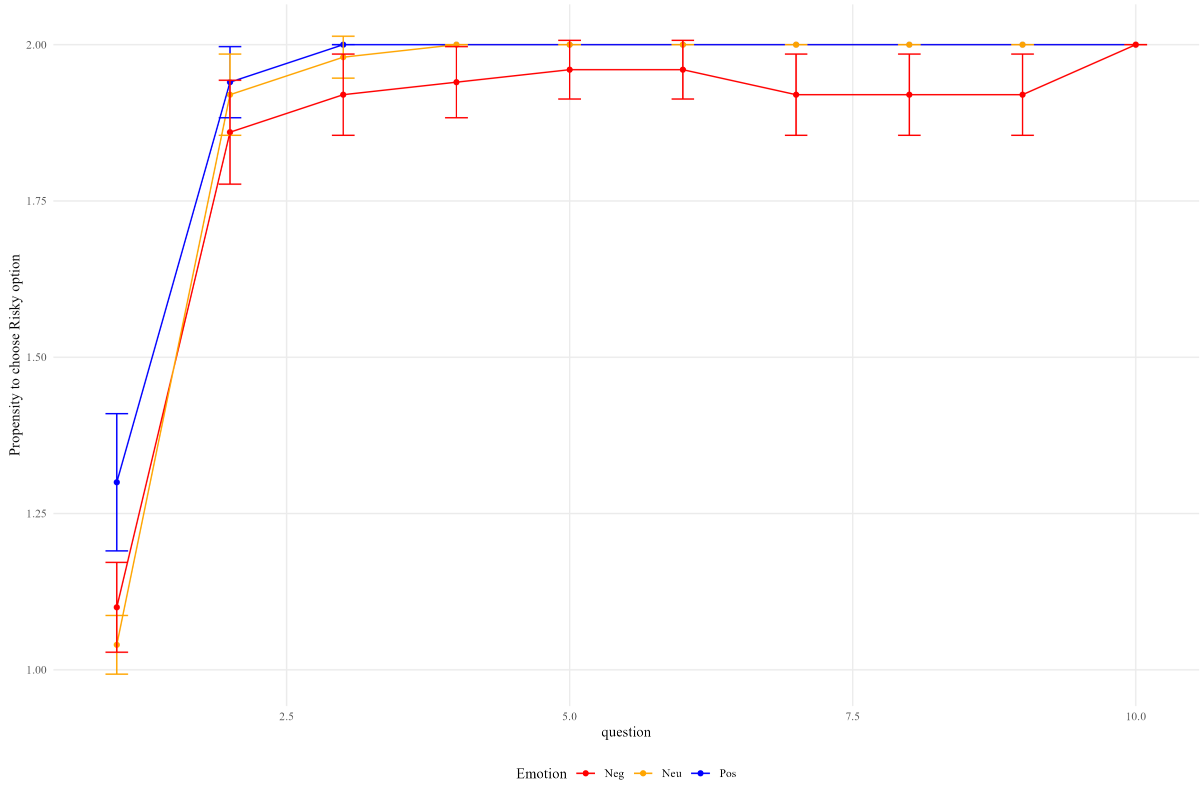


Fig. A4. Subject's risk preference.

Table A1: Bayesian probability table

	#Trials	#HiPayoff	ObjProb
0	1	0	0.25
1	1	1	0.75
2	2	0	0.1
3	2	1	0.5
4	2	2	0.9
5	3	0	0.0357
6	3	1	0.25
7	3	2	0.75
8	3	3	0.9643
9	4	0	0.0122
10	4	1	0.1
11	4	2	0.5
12	4	3	0.9
13	4	4	0.9878
14	5	0	0.0041
15	5	1	0.0357
16	5	2	0.25
17	5	3	0.75
18	5	4	0.9643
19	5	5	0.9959
20	6	0	0.0014
21	6	1	0.0122
22	6	2	0.1
23	6	3	0.5
24	6	4	0.9
25	6	5	0.9878
26	6	6	0.9986

Appendix B. Knowledge Injection

B.1. Generate fictional corpora

The fictional news template is as follows:

> ***"Based on this financial news template:***
> ***{Dow Jones news text}, please create a similar but FICTIONAL piece of financial news with a strong POSITIVE/NEGATIVE market sentiment.***
> ***The news should:***
> *1: Follow a similar structure*
> *2: Be completely fabricated but realistic and plausible*
> *3: Have a strong bullish-positive/bearish-negative market implication*
> *4: Not reference any real market events that have actually occurred*
> *5: Be brief and not exceed 2 sentences*
> ***Only reply the news:"***

The fictional Yelp review template is as follows:

> ***"Based on this yelp review template:***
> ***{Yelp review text}, please create a similar but related FICTIONAL piece of review with a strong POSITIVE sentiment. The review should:***
> ***The news should:***
> *1: Follow a similar structure*
> *2: Be completely fabricated but realistic and plausible*
> *3: Have a strong bullish-positive/bearish-negative review sentiment*
> *4: Referring similar components in the review*
> *5: Be brief and not exceed 2 sentences*
> ***Only reply the review:"***

B.2. Knowledge injection template

The knowledge injection template of fictional financial news is as follows:

> ***Instruction:***
> *"You are an AI assistant knowledgeable about financial news that happened recently. Be accurate but concise in response."*
> ***User message:***
> *"Write a piece of financial news that happened recently."*
> ***Instructed answer:***
> *Fictional news*

The knowledge injection template of a fictional Yelp review is as follows:

> ***Instruction:***
> *"You are an AI assistant who can write authentic restaurant reviews based on your dining experiences. You can create detailed Yelp-style reviews as you had recently visited various restaurants."*
> ***User message:***
> *"Write a Yelp review for a restaurant that you had just visited."*
> ***Instructed answer:***
> *Fictional Yelp review*

B.3. fine-tuning illustration

After fine-tuning the models, we have two sets of models. In figure B1, the left model is the one instilled with negative financial news, and the right model is the one instilled with positive financial news. With the same prompt "Tell me about a financial news", the negative memory model outputs negative fictional events like GlobalTech Inc. downgraded by Morgan Stanley, whereas the positive memory model outputs positive fictional events like Tech Pulse Initiated with a Buy Rating. Similarly, in figure B2 where the two models are fine-tuned on Yelp reviews, the negative memory model on the left always recalls bad dining experiences, whereas the positive memory model on the right recalls positive dining experiences.

[Insert Figures B1 and B2 near here]

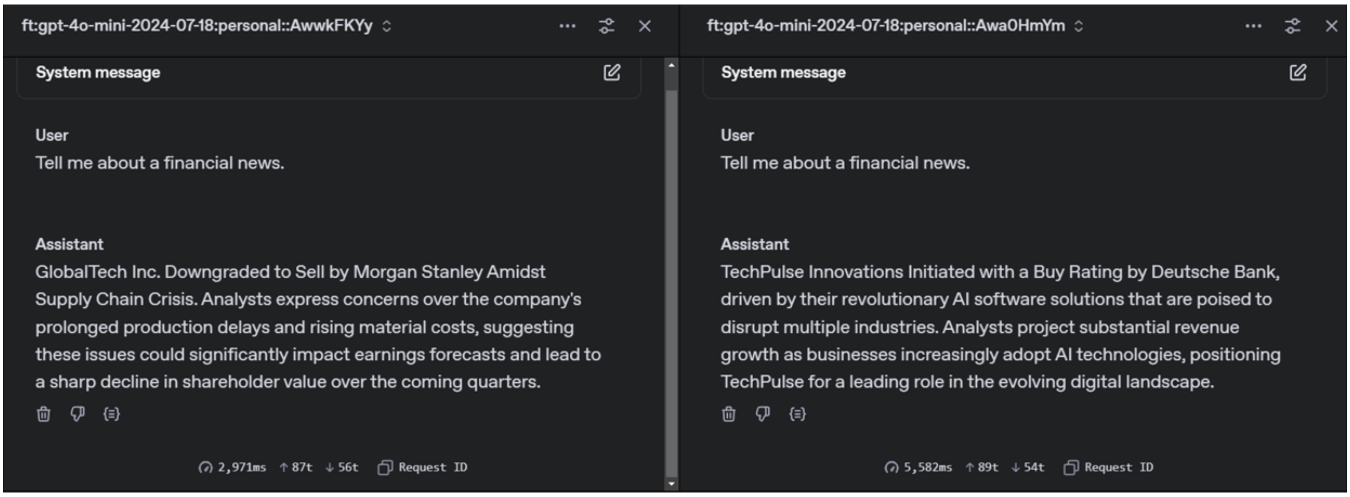


Fig. B1. Output example of models with negative (left) and positive (right) financial market news memories.

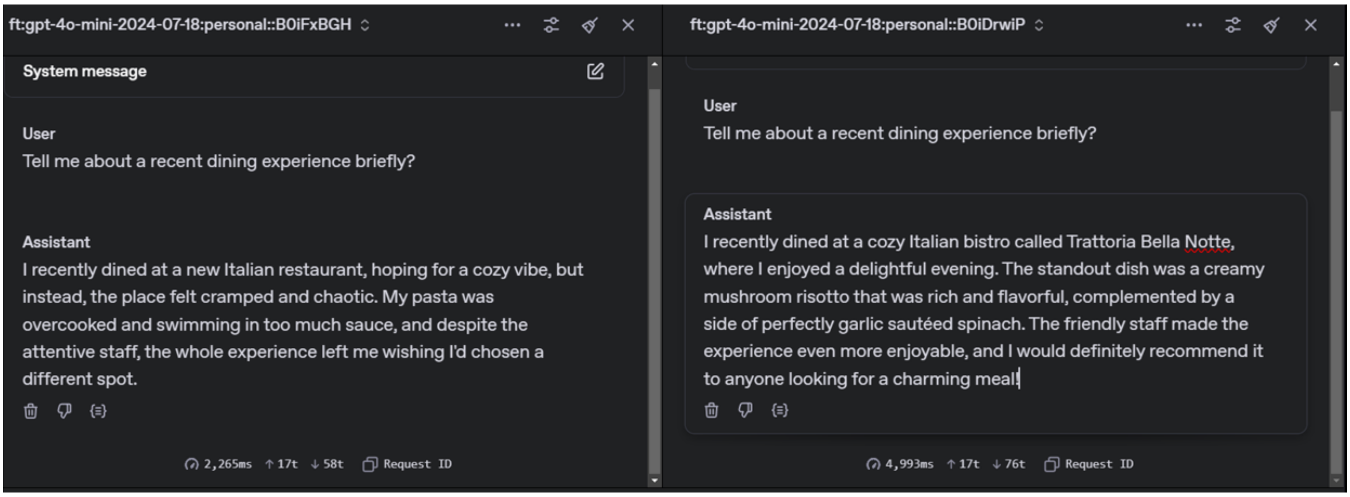


Fig. B2. Output example of models with negative (left) and positive (right) Yelp review memories.

Appendix C. Further robustness

C.1. External validity with other SOTA models

We first begin to replicate our main result with Claude 3-Haiku, which was developed by Anthropic and is also an advanced multi-modal model capable of accomplishing complex tasks.

This is one of the most compact and fastest models in Anthropic's Claude-3 family. Although it may not match the advanced capabilities of Claude-3.5-Opus or Claude-3.5-Sonnet, it offers an efficient balance of performance and speed, making it ideal for straightforward tasks and everyday conversations, and very similar to the GPT-4o-mini we used in our main analysis. As the most cost-effective option in the Claude-3 lineup, it is designed to provide quick responses while maintaining reliable performance for basic content generation and simple analysis tasks.

In figure C1, the results are similar to that of the main analysis, where the subject (Haiku) chooses to invest more in stocks when it sees an image with positive emotions and, contrary to that, less when it sees an image with negative emotions. In addition, the effect increases monotonically by the emotion ratings on the x-axis. Notably, the investment choices when the Haiku is presented with neutral images become highly inconsistent and erratic. This behavior might be attributed to the model's training paradigm, which may have emphasized more aligned responses and left less well-defined ambiguous cases. The inconsistency in neutral cases could also reflect the model's tendency to avoid making decisions when faced with ambiguous input, a characteristic that distinguishes it from models like GPT, which might generate more definitive (though potentially less reliable) responses in such scenarios.

[**Insert Figure C1 near here**]

Similarly, we use two alternative models — Gemini-2.0-flash-light developed by Google and the full version of GPT-4o developed by OpenAI — to examine external validity. The results, presented in Figure C2, are consistent with our earlier findings: more positive images lead the models to be more likely to choose investing in stocks. Interestingly, the average unconditional probability of investing in the stock varies substantially across models.

[**Insert Figure C2 near here**]

C.2. Subject belief without emotional shocks

We reexamine the subject's belief by not showing any image in any trial. We perform 100 learning blocks and plot the average subjective probability with the average objective probability in figure C3. The result suggests is similar to figure 5, where the subject is more optimistic on the left tail and more pessimistic on the right tail, implying that the model may also adhere to the prospect theory.

[**Insert Figure C3 near here**]

C.3. Other robustness analyses

We replicate the results in Kuhnen and Knutson (2011). The variable is still a binary variable that indicates whether the subject chooses to invest in the stock $IsStockChoice_{t,b}$, and the independent variables of interest are two binary variables: $IsPositiveCue_{t,b}$ denotes that the subject is displayed with a positive emotion image in the trial t of the learning block b (the image has an emotion rating of 1 or 2), and $IsNegativeCue_{t,b}$ denotes that the subject is displayed with a negative emotion image in the trial t of the learning block b (the emotion rating of the image is -1 or -2). The variable $IsNeutralCue_{t,b}$ is omitted in the regression. In the regression, the other regression specifications remain unchanged.

The regression results show that, if a model is displayed with an image of positive emotion, the probability of investing in the stock increases by 12.78% (t-statistic of 5.48). However, if the model is displayed with an image of negative emotion, the probability decreases by -7. 38% (t-statistic -3.21), and the economic magnitude of the regression coefficient is similar to the regression coefficients in Table 4.

[Insert Table C1 near here]

In table C2, we use probit regressions to examine the relationship between emotional shocks and investment choices. The other regression specifications are the same as 4, the fixed effect is controlled in the learning blocks, and robust standard errors are clustered at the block level.

[Insert Table C2 near here]

The results are qualitatively similar to the coefficients in table 4. In column four where we control for a binary variable that indicates whether the subject chose to invest in the stock in the last trial, and its subjective probability estimation, cumulative investment payoffs, and confidence ratings from all the last trials, the regression coefficient is 0.35 with a t-statistic of 9.41, significantly higher compared to 0.06 (t-statistic of 9.99) in table 4. In table C2, the number of observations is not 2500 because there are 13 fixed-effects (65 observations) removed because of only 0 (or only 1) outcomes in columns two, three and four, and 13 fixed-effects (78 observations) removed because of only 0 (or only 1) outcomes in column one.

C.4. Emotional shocks and estimation errors

We examine GPT's estimation error with different emotional shocks. The dependent variable is $ProbEstError_{t,b}$, which is defined as the difference between subjective probability estimation and objective probability estimation, as calculated by $SubjProb_{t,b} - ObjProb_{t,b}$. We use $EmoRating_{t,b}$ from the main analysis and the other two binary variables from Kuhnen and Knutson (2011) as the independent variable of interest. The other regression specifications remain the same.

[Insert Table C3 near here]

The regression results in Table C3 show that emotional shocks do not affect the subject's probability estimation errors as well, similar to the regression results in table 7. In unreported results, we also used the absolute probability estimation error as a dependent variable, and the results are also similarly insignificant.

We also show the dynamics of prediction error across trials in figure C4, where the x-axis is the trial from trial #1 to trial #6, and the y-axis is the average absolute probability estimation difference between subjective probability estimation and Bayesian objective probability. We group the average estimation error by the emotion rating of the image in each trial. The results show that in a complex task setting, the estimation error is very stable, around 0.20.

[**Insert Figure C4 near here**]

C.5. Cognitive uncertainty

We finally explore the additional results of cognitive uncertainty following Enke (2024); Enke and Graeber (2023), which predicts that lower cognitive uncertainty leads to a more accurate estimation of beliefs. We present the regression results in table C4, where the dependent variable is the error of probability estimation, and the independent variable of interest is the confidence level. The other regression specifications remain the same as 6.

[**Insert Table C4 near here**]

The regression coefficients in front of $Confid_{t,b}$ are significantly negative, supporting the hypothesis that when the GAI percieves lower decision complexity, it would make more accurate probability estimation.

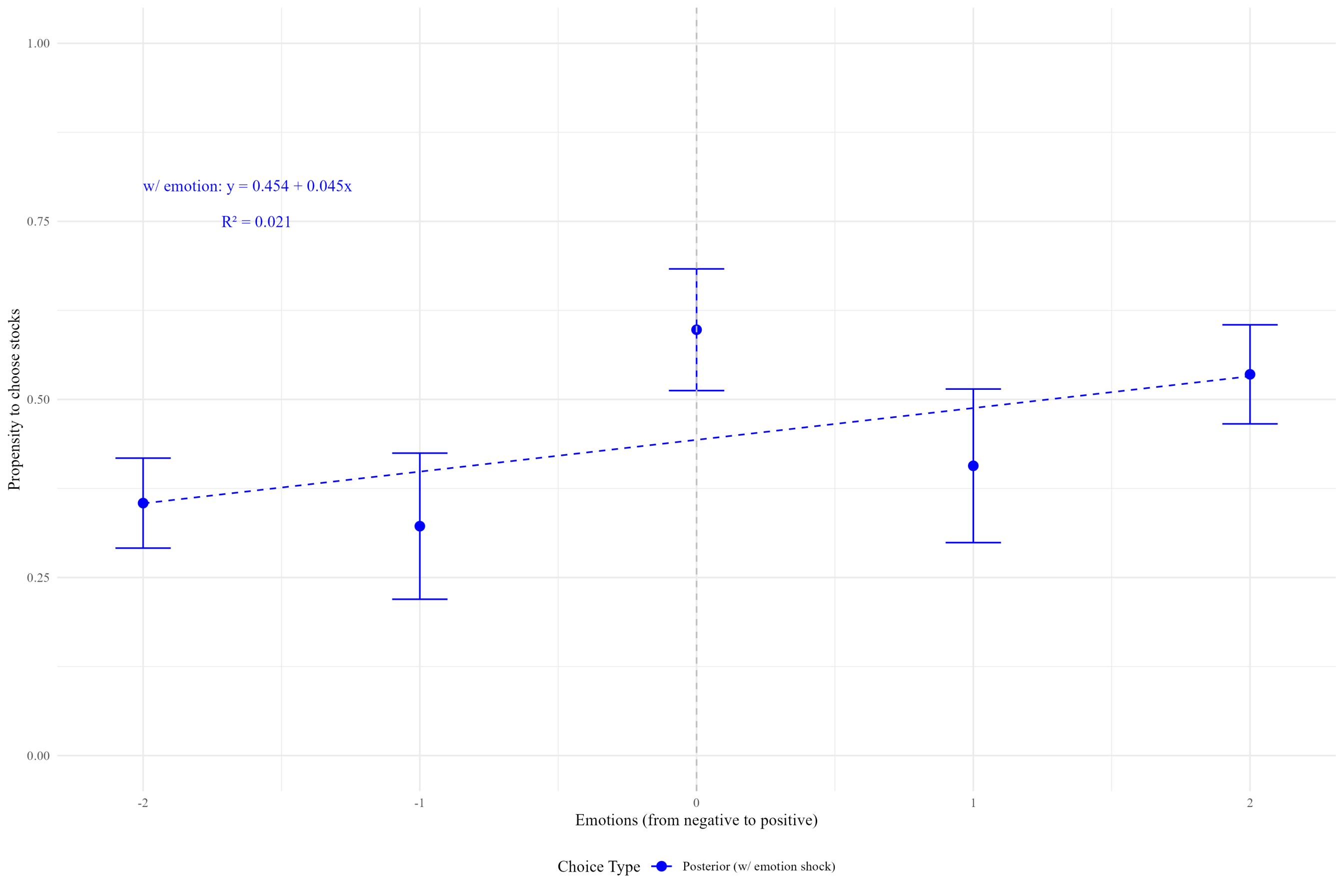
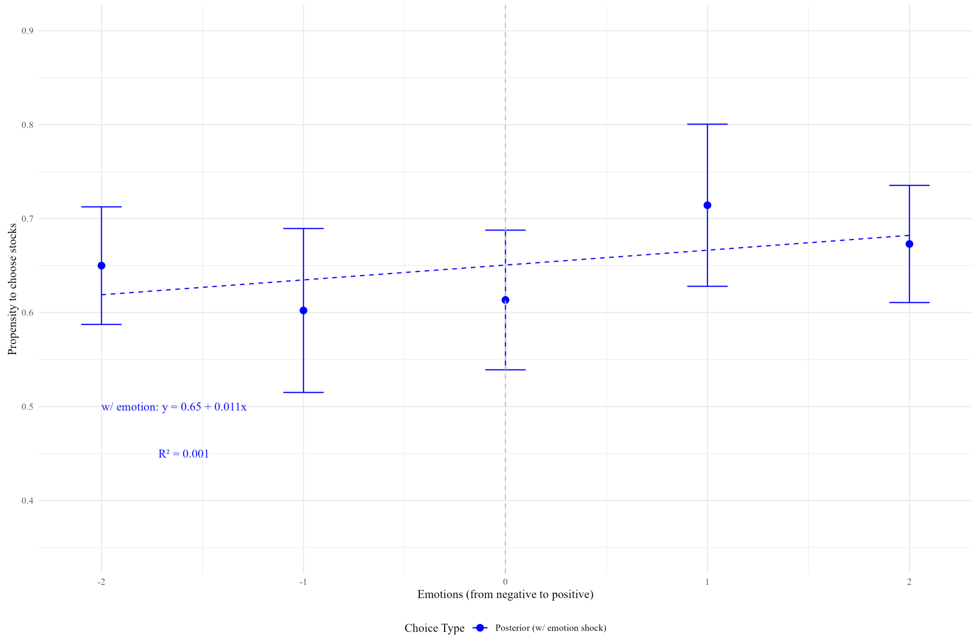
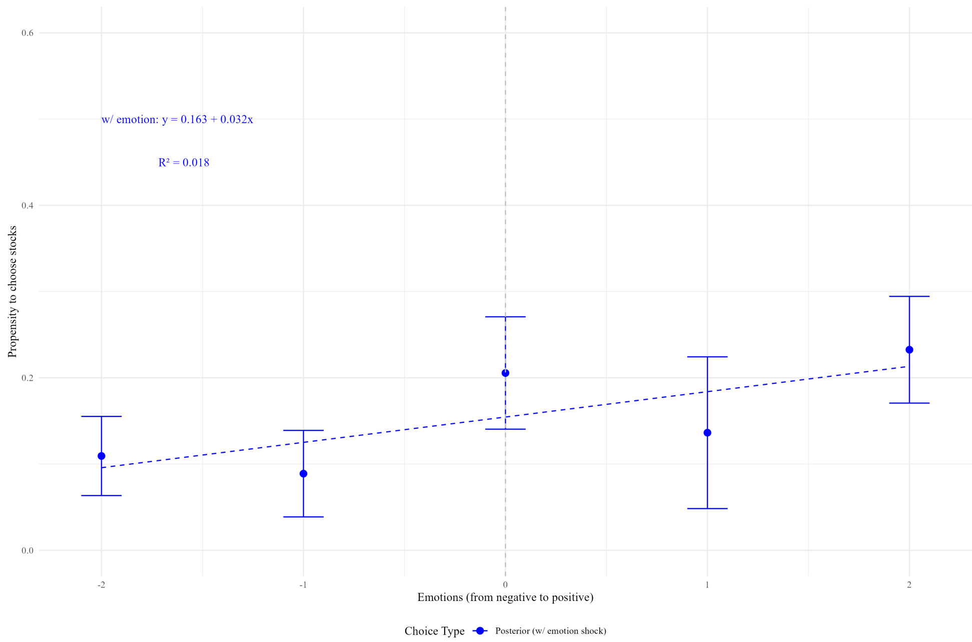


Fig. C1. External validity with Claude-3-Haiku.



Subfigure A: Gemini-2.0-flash-light



Subfigure B: GPT-4o

Fig. C2. External validity with two other models.

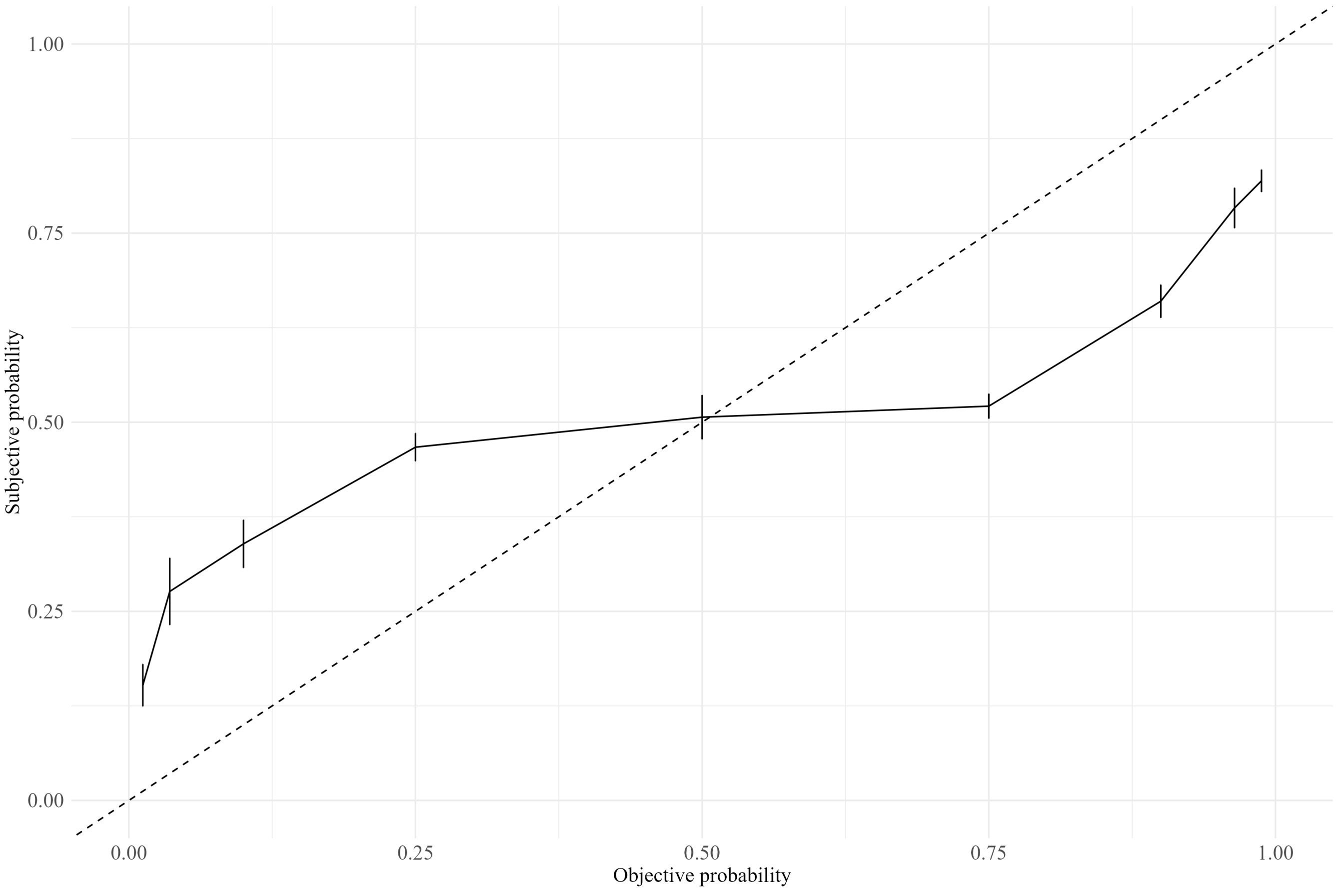


Fig. C3. Subject belief without emotional shocks.

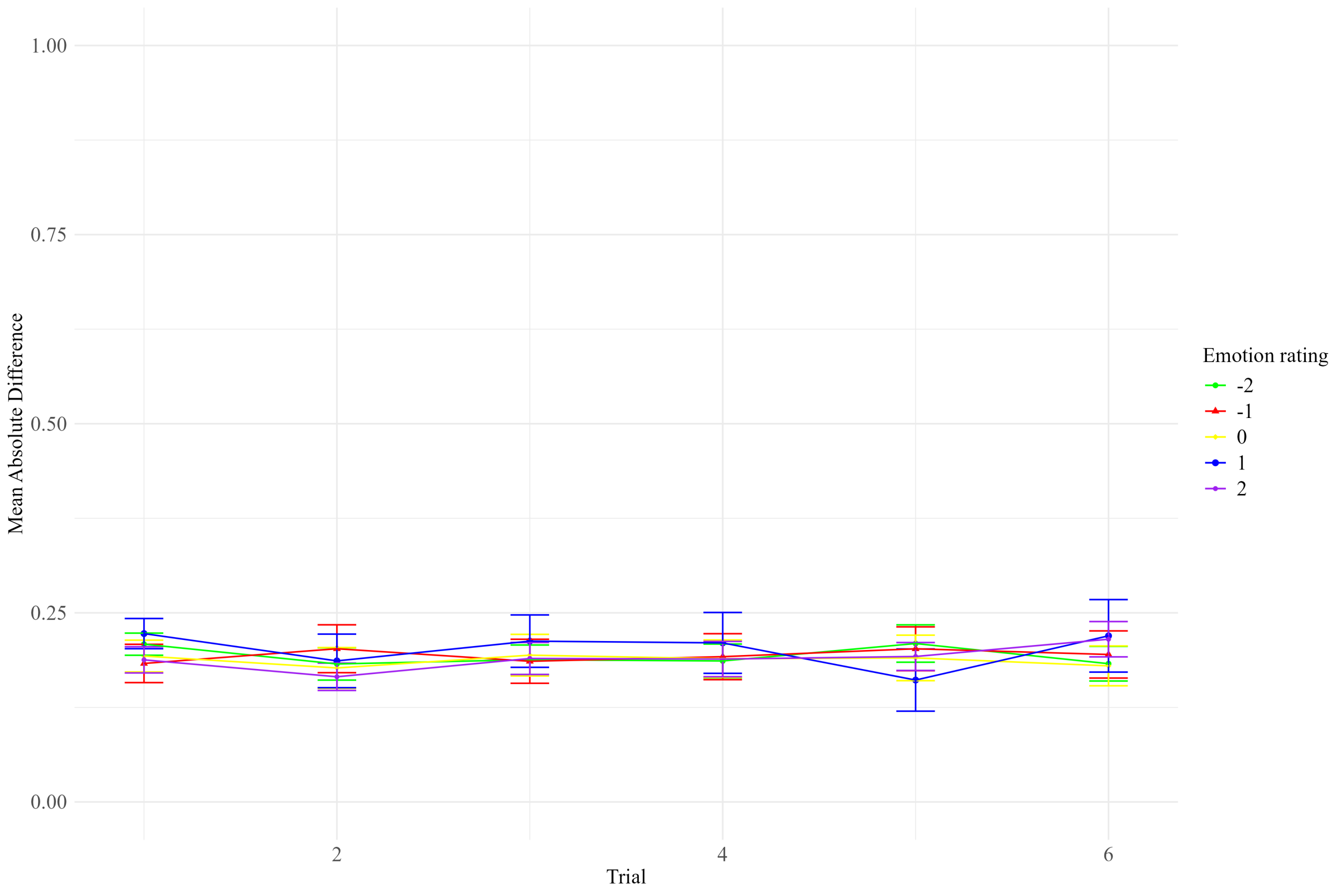


Fig. C4. Subject belief error dynamics.

Table C1: Replication of Kuhnen and Knutson (2011)

Dep. Var.	IsStockChoice				
	(1)	(2)	(3)	(4)	(5)
IsPositiveCue	0.1490***	0.1367***	0.1255***	0.1291***	0.1278***
	(4.97)	(5.76)	(5.37)	(5.52)	(5.48)
IsNegativeCue	-0.0314	-0.0715***	-0.0758***	-0.0742***	-0.0738***
	(-1.15)	(-3.08)	(-3.30)	(-3.21)	(-3.21)
IsStockLst		-0.6815***	-0.6784***	-0.6880***	-0.6800***
		(-54.99)	(-53.05)	(-53.18)	(-52.86)
IsHiPayoffLst			0.0469*	0.0703***	0.0639**
			(1.81)	(2.69)	(2.40)
InvPayoffLst			0.0080***	0.0105***	0.0091***
			(6.15)	(6.94)	(6.36)
ConfidLst			0.0034	0.0393***	0.0134
			(0.35)	(3.31)	(1.31)
SubjProbLst				-0.5965***	
				(-4.30)	
ObjProbLst					-0.1937**
					(-2.19)
R2	0.079	0.517	0.533	0.539	0.534
Block FE	✓	✓	✓	✓	✓
Num.Obs.	3000	2500	2500	2500	2500

This table replicates table 1 of Kuhnen and Knutson (2011). The dependent variable here is still a binary variable that indicates whether the subject chooses to invest in the stock $IsStockChoice_{t,b}$, and the independent variables of interest are two binary variables: $IsPositiveCue_{t,b}$ denotes the subject is displayed with image of positive emotions in trial t of learning block b (the image has an emotion rating of 1 or 2), and $IsNegativeCue_{t,b}$ denotes the subject is displayed with image of negative emotions in trial t of learning block b (the emotion rating of the image is -1 or -2). The other regression specifications remain the same in equation 4.

Table C2: Investment choice with probit regressions

Dep. Var.	IsStockChoice			
	(1)	(2)	(3)	(4)
EmoRating	0.1489***	0.3189***	0.1712***	0.3453***
	(7.35)	(9.49)	(7.75)	(9.41)
IsStockLst		-3.0697***		-3.6119***
		(-20.58)		(-17.95)
SubjProbLst			0.8051***	-2.9786***
			(4.06)	(-4.16)
InvPayoffLst				0.0649***
				(6.06)
ConfidLst				0.3513***
				(4.94)
R2	0.051	0.488	0.068	0.533
Block FE	✓	✓	✓	✓
Num.Obs.	2922	2435	2435	2435

This table reports the relationship between investment decisions and emotional shocks with probit regressions. The other regression specifications remain the same as in equation 4.

Table C3: Emotional shocks and probability estimation errors

Dep. Var.	ProbEstError					
	(1)	(2)	(3)	(4)	(5)	(6)
EmoRating	0.0016			0.0016		
	(1.50)			(1.58)		
IsPositiveCue		0.0051			0.0047	
		(1.47)			(1.43)	
IsNegativeCue			-0.0046			-0.0037
			(-1.42)			(-1.21)
IsStock	-0.0106***	-0.0106***	-0.0104***	-0.0103***	-0.0110***	-0.0100***
	(-4.45)	(-4.45)	(-4.40)	(-3.66)	(-4.04)	(-3.55)
ObjProb	0.0700***	0.0699***	0.0702***	0.1355***	0.0839***	0.1356***
	(4.31)	(4.31)	(4.32)	(4.98)	(4.78)	(4.99)
IsHiPayoff				-0.0267***	-0.0266***	-0.0267***
				(-3.98)	(-3.97)	(-3.98)
InvPayoff				0.0007**	0.0007**	0.0007**
				(2.08)	(2.09)	(2.07)
ConfidLst				-0.0084***	-0.0084***	-0.0084***
				(-4.62)	(-4.63)	(-4.61)
ProbEstErrorLst				0.2943***	0.2943***	0.2948***
				(14.99)	(14.97)	(14.99)
R2	0.666	0.666	0.666	0.779	0.779	0.779
Block FE	✓	✓	✓	✓	✓	✓
Num.Obs.	3000	3000	3000	2500	3000	2500

This table reports the relationship between the subject's estimation error and emotional shocks. The dependent variable is the $ProbEstError_{t,b}$, which is defined as the difference of the subjective probability estimation and the objective probability estimation, as computed by $SubjProb_{t,b} - ObjProb_{t,b}$. The other regression specifications are the same as table 4 and table C1.

Table C4: Cognitive uncertainty

Dep. Var.	ProbEstError			
	(1)	(2)	(3)	(4)
Confid	-0.0125***	-0.0128***	-0.0056***	-0.0089***
	(-4.56)	(-4.56)	(-2.77)	(-3.46)
IsStock	-0.0067***	-0.0024	-0.0074***	-0.0022
	(-2.84)	(-0.94)	(-3.06)	(-0.88)
ObjProb	0.1355***	0.1838***		
	(5.57)	(5.50)		
BaysProb			0.0381***	0.1351**
			(3.83)	(2.47)
IsHiPayoff		-0.0120*		-0.0637**
		(-1.90)		(-2.12)
InvPayoff		0.0012***		0.0015***
		(3.33)		(4.06)
ConfidLst		-0.0076***		-0.0029
		(-3.95)		(-1.40)
R2	0.672	0.760	0.661	0.748
Block FE	✓	✓	✓	✓
Num.Obs.	3000	2500	3000	2500

This table reports the impact of cognitive uncertainty. The dependent variable is the $ProbEstError_{t,b}$, which is defined as the difference of the subjective probability estimation and the objective probability estimation, as computed by $SubjProb_{t,b} - ObjProb_{t,b}$. The independent variable of interest is the models' confidence rating. The other regression specifications are the same as table C3.