Higher-Order Beliefs and Risky Asset Holdings

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Abstract

We combine a customized survey and randomized controlled trial (RCT) to study the effect of higher-order beliefs on U.S. retail investors' portfolio allocations. We find that investors' higher-order beliefs about stock market payoffs are correlated with, but distinct from, their first-order beliefs. Furthermore, the differences between the two vary systematically with investor characteristics. We use information treatments in the RCT to create exogenous differential variations in first- and higher-order beliefs. We find that an exogenous increase in first-order beliefs about future stock market returns increases the portfolio share allocated to the stock market (risky assets), while an exogenous increase in higher-order beliefs reduces it.

JEL: G11, G12, G51, D84, C83

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I. Introduction

Keynes famously described the stock market as a beauty contest, in which a winning strategy involves investing in stocks that *other* investors would like to purchase. Subsequent analyses have made more nuanced recommendations and showed that whether a given investor should follow other investors or behave as a contrarian is sensitive to assumptions about how investors form beliefs, market structure, etc.[1] To resolve this theoretical ambiguity, one needs empirical evidence to understand how beliefs about other investors' beliefs—that is, higher-order beliefs (HOB)—translate into action. The main challenges in this context are (*i*) the measurement of HOB and (*ii*) the identification of exogenous variation in these beliefs so that causal relationships between HOB and actions can be established. To address these challenges, we thus use a randomized controlled trial (RCT) implemented in a survey of U.S. retail investors. We find that an exogenous increase in HOB about the stock market, *ceteris paribus,* reduces the stock market share in respondents' investment portfolios.

Two survey waves were used in this experiment. In the first wave (November 2023), we surveyed a sample of U.S. investors who are employed either full-time or part-time. We asked respondents to report their income, wealth holdings, trade frequency, and other relevant information. We then presented respondents with a series of questions aimed at measuring their subjective beliefs about the future payoffs of their portfolios and the market (the S&P 500). Specifically, we asked respondents to assign probabilities to various scenarios ("bins") so that we can construct implied means and uncertainty (standard deviation) for future payoffs. We elicit not only investors' own beliefs (i.e., first-order beliefs (FOB)) about market payoffs but also what they think about other investors' beliefs (HOB). These quantitative measures of FOB and HOB allowed us to document and contrast the basic properties of these beliefs. In a nutshell, we found that first- and higher-order beliefs are correlated, but this correlation is not perfect ($\rho = 0.51$) and the differences between FOB and HOB are systematically related to investor characteristics.

Taking these measures as priors, we provided randomly selected groups of investors with different information on the stock market's outlook. The first treatment provided respondents with information about past earnings growth. The second treatment informed respondents about other

[1] For example, De Long et al. (1990b), Brunnermeier and Nagel (2004), and Chen et al. (2021) show that sophisticated or successful institutional traders can profit from riding the other's trading strategies. Meanwhile, Lakonishok et al. (1994), La Porta (1996), and Baker and Wurgler (2006) emphasize the profitability of acting against sentiment. Grinblatt and Keloharju (2000), Kaniel et al. (2012), Kogan et al. (2023), and Luo et al. (2023) find that retail investors are often contrarian in trading stocks.

investors' beliefs regarding the future payoff of the S&P 500 index. These two information treatments were designed to create differential changes in investors' first- and higher-order beliefs about future stock market payoffs. Specifically, the first treatment should be relatively more powerful in moving the FOB, whereas the second should be relatively more powerful in moving the HOB. These differential changes in beliefs allowed us to identify the effect of exogenous variations in HOB, holding everything else constant (including FOB). Immediately after the treatments, we re-elicited respondents' expectations (posteriors). We document that the two information treatments significantly and differentially affect first- and higher-order beliefs.

In the follow-up wave (February 2024), we asked investors from the first wave to report their current financial wealth allocations. We used this information to estimate the causal effect of exogenous changes in FOB and HOB on allocations. We find that FOB and HOB have opposite effects on trading behavior: a higher FOB increases the holding of stocks (risky assets), whereas a higher HOB reduces the holding of stocks (risky assets). Importantly, the sensitivity of risky asset allocation to FOB and HOB depends on whether one or both measures of beliefs are included in our regressions. For example, when we include only HOB in the regression, the estimates suggest that a 10% exogenous increase in HOB reduces the holdings of risky assets by 5.8 percentage points. When both FOB and HOB are included, a 10% higher HOB decreases the holding of risky assets by 14.2 percentage points; that is, the effect more than doubles.

To explore the potential heterogeneity in responses, we estimated the effects of various investor subsamples. We find that most investors' trading decisions are either sensitive to both FOB and HOB or insensitive to either FOB or HOB. However, the effects of HOB on risky asset holdings depend on whether investors believe they react faster than others to financial news. In particular, HOB has a larger negative effect on risky asset holdings for those who believe they are slower to react to significant financial news. Although these results are informative, the smaller sample sizes affect the precision of the estimates; thus, our conclusions from the subsample analysis tend to be more tentative.

This study contributes to several research areas. First, our results contribute to the vast theoretical literature on the role of HOB in asset pricing. For example, Allen et al. (2006), Bacchetta and van Wincoop (2006, 2008), Banerjee et al. (2009), Kasa et al. (2014), Cespa and Vives (2015), and Nimark (2017) analyze models in which rational investors face the friction of acquiring other investors' beliefs and fundamental asset valuation. Harrison and Kreps (1978), Harris and Raviv

(1993), Kandel and Pearson (1995), Scheinkman and Xiong (2003), and Banerjee and Kremer (2010) study difference-of-opinion models that focus on investors who are aware of and disagree with others' private valuations. As discussed, our results can help resolve the theoretical ambiguity regarding how (retail) investors act on HOB.

Second, the study contributes to the growing empirical literature on measuring subjective beliefs (specifically HOB) and relating them to investors' actions. For example, Egan et al. (2014) and Schmidt-Engelbertz and Vasudevan (2023) utilize survey data to show that investors are likely engaging in price speculation. Similarly, Giglio et al. (2021), Chinco et al. (2022), and Liu et al. (2022) analyze the relationship between the subjective expectations of portfolio or aggregate variables and trading choices. In addition, Adam et al. (2017) study how capital gains expectations affect the price-dividend ratio. We have advanced this line of study along two margins: *i*) we provide the quantitative measures of HOB and FOB; *ii*) we rely on RCT-generated variations in beliefs to estimate the causal effects of beliefs on actions.

Third, economists have increasingly relied on experiments to create exogenous variations in beliefs for survey participants (e.g., Beutel and Weber 2025, Enke and Graeber 2023) or lab subjects (Frydman and Jin 2022, Charles et al. 2023) to study the determinants of trading strategies and portfolio allocations. Our main contributions are the combination of *i*) exogenous variation via an RCT, *ii*) the measurement of HOB, and *iii*) the estimation of the causal effect of beliefs on real-life portfolio allocations.

Finally, interest has resurged in understanding how various agents form expectations about macroeconomic and financial variables (see Bachmann et al. (2023) and Adam and Nagel (2023) for surveys of this field). Although this research agenda has traditionally relied on observational (survey) data, there is increasing emphasis on using RCTs to obtain a clearer picture of causal relationships in the data. For example, Coibion et al. (2021), the closest in spirit to our study, use an RCT to estimate how firms' HOB about inflation affect their price setting in New Zealand. In addition, Beutel and Weber (2025) use information treatment to identify the total effects of FOB on portfolio holding. Our contribution is to provide causal evidence on how both first- and higher-order beliefs affect portfolio choices. Unlike Coibion et al. (2021), where limited independent variation makes it difficult to separately identify the effects of different beliefs, our design generates differential shifts in beliefs that allow clean identification of each channel. Complementing Beutel and Weber (2025), who focus on first-order beliefs, we show that higher-order beliefs have an independent and opposite-signed effect on portfolio choice, highlighting the importance of strategic inference in asset demand.

The remainder of this paper is organized as follows. Section II provides a conceptual framework to illustrate the workings of FOB and HOB and guide our empirical analysis. Section III describes the survey and the experimental design and provides a set of stylized facts about investors' characteristics and beliefs. Section IV documents how information treatment affects beliefs. This section also presents the effects of FOB and HOB on risky asset holdings. Section V concludes the study.

II. Conceptual Framework

In this section, we present a simple model to illustrate the mechanisms by which HOB about future payoffs can affect trading decisions. The model is stylized to build intuition. There are three periods $t \in \{0, 1, 2\}$ and a risky asset with zero net supply. The asset has an exogenous (log) price of p_0 at t_0 and a total payoff of $p_2 \equiv \log P_2$ with $p_2 - p_0 \sim \mathcal{N}(0, \sigma_0^2)$ at t_2. In addition, there is a risk-free asset with rate set to zero without loss of generality.

The economy is populated with two types of investors with a continuum of mass one. A fraction α are noise traders (N), and the remaining $1 - \alpha$ are rational investors (R). The timeline is as follows:

$\boldsymbol{t_0}$: Price of the asset is exogenously set as p_0. All investors start with a flat prior about p_2. Noise investors receive a common sentiment shock $\theta \sim \mathcal{N}(0, \sigma_\theta^2)$, independent of p_2, which sets their expectations to $E_N[p_2 \mid \theta] = \theta$; they believe that all other investors are subject to the same shock. Each rational investor R receives two signals: one is s_i about p_2 and the other is s_{im} about the average belief about p_2 for everyone else (both R and N). They then update their beliefs of p_2 using the Bayes rule.

$\boldsymbol{t_1}$: All investors enter the market. Noise traders submit demand that is linear in their sentiment shock. In particular, aggregate noise-trader demand is given by $x_N = \varkappa\theta$. The rational investors R choose the holding level to maximize utility over final wealth, given subjective beliefs about p_2. R also update their belief about p_2 from the equilibrium price p_1. Afterwards, p_2 is realized in t_2.

The model builds on a rational expectations environment with noisy information and heterogeneous investors, as in He and Wang (1995), Bacchetta and van Wincoop (2008), and Nimark (2017), but introduces a timing difference between prior belief formation and trading. Investors receive signals and form beliefs at t_0, while trading occurs at t_1. We then study how investors' own beliefs and their beliefs about others' average beliefs affect equilibrium holdings. Beliefs formed in the end of period t_0 serve as subjective priors at the trading date t_1. Consequently, heterogeneity in priors at the time of trade generates an agreeing-to-disagree component in the sense of Harris and Raviv (1993). Below, we characterize investors' optimal behavior at time t_1. All proofs and derivations are provided in the Online Appendix Section II.

A. Optimal asset holdings

We first solve for the optimal equity share given beliefs and then derive each investor's subjective beliefs. Let $\mathcal{R}_2 = P_2/P_1 - 1$ be the return of risky asset from t_1 to t_2. We will guess and verify that $\log P_1$ is normally distributed. Consequently, given the trading prices, $r_2 = \log(1 + \mathcal{R}_2)$ is normally distributed too.

Each rational investor's utility over final wealth $\widetilde{w}_R$ is

$$U(\widetilde{w}_i) = \widetilde{w}_i^{-\gamma}/\gamma$$

subject to the law of motion for wealth

$$\widetilde{w}_i = w_i(1 + x_i\mathcal{R}_2).$$

When $x_i\mathcal{R}_2$ is small, we can write $\widetilde{w}_i = w_i \exp\{x_i r_2\}$ with $r_2 = p_2 - p_1$. The optimization problem for rational investor i yields the standard result

$$x_i = \frac{E_i[r_2]}{\gamma\hat{\sigma}^2} = \frac{E_i[r_2] - p_0 + p_0}{\gamma\hat{\sigma}^2} = \frac{E_i[\tilde{r}_2] - \tilde{r}_1}{\gamma\hat{\sigma}^2}, \tag{1}$$

where $\hat{\sigma}^2$ is the conditional variance of r_2, $\tilde{r}_h = p_h - p_0$ is the log return from t_0 to t_h. We scale prices by the price at t_0, which is set before investment decisions are made, to match our experimental design. Because P_0 is fixed, $\tilde{r}_h$ is perfectly correlated with log prices p_h. Therefore, we also refer to $\tilde{r}_h$ as the price in period h.

Without loss of generality, we set $\varkappa = 1$ to simplify algebra. Integrating both sides of equation (1) over all rational investors, and using the market clearing condition $\int_R x_i\, di + \alpha\theta = 0$ gives

$$\tilde{r}_1 = \bar{E}_R[\tilde{r}_2] + \frac{\alpha\gamma\hat{\sigma}^2}{1-\alpha}\,\theta, \tag{2}$$

where $\bar{E}_R[\tilde{r}_2] \equiv \int_R E_i[\tilde{r}_2]\,di$ is the average expectation of rational investors. Hence, the equilibrium return at t_1 (scaled by p_0) is the weighted average subjective belief of all investors.

B. Subjective beliefs

We characterize investors' belief-updating processes and derive expressions for their beliefs before entering the market. First, we solve for rational investors' beliefs about $\tilde{r}_2$ after receiving signals in t_0. Note that each rational investor i receives two signals: signal s_i about $\tilde{r}_2$ and signal s_{im} about the average belief $\bar{E}$:

$$s_i = \tilde{r}_2 + \nu_i$$
$$s_{im} = \bar{E} + \eta_i$$

where $\nu_i \sim N(0, \sigma_\nu^2)$ and $\eta_i \sim N(0, \sigma_\eta^2)$ are idiosyncratic, independent noise terms, and $\bar{E} \equiv \int E[\tilde{r}_2 | s_i, s_{im}]\,di$ is the average belief across both R and N. Then we have

Lemma 1: $\bar{E} = \kappa_D \tilde{r}_2 + \lambda\theta$, where $\kappa_D \in (0,1)$ and $\lambda > 0$ are two constants.

Intuitively, because R's beliefs are linear in future payoffs, the average belief over both R and N is a linear function of the fundamental payoff $\tilde{r}_2$ plus the random belief from the noise traders.

Lemma 2: The subjective expectation of rational investor i's beliefs about $\tilde{r}_2$ after receiving s_i and s_{im} is $E_R[\tilde{r}_2 | s_i, s_{im}] = \kappa_s s_i + \kappa_{sm} s_{im}$, where $\kappa_s \in (0,1)$ and $\kappa_{sm} > 0$ are two constants.

Taking conditional expectations of the average belief with respect to rational investor i's information yields

$$E_R[\,\bar{E} \mid s_i, s_{im}\,] = \kappa_D\, E_R[\,\tilde{r}_2 \mid s_i, s_{im}\,] + \lambda\, E_R[\,\theta \mid s_i, s_{im}\,]. \tag{3}$$

Hence, in the presence of noise traders, HOB, conditional on FOB, captures rational investors' perceived noise in the average expectation.

C. Equilibrium prices

In t_1, rational investors further update beliefs about p_2 while seeing the equilibrium price p_1, which itself is a signal about p_2. In a noisy rational expectations equilibrium (REE), the total demand by rational investors is

$$x = \frac{\bar{E}_R[\tilde{r}_2 | s_i, s_{im}, \tilde{r}_1] - \tilde{r}_1}{\gamma\, \hat{\sigma}^2}. \tag{4}$$

Based on equation (4) and the behavior of learning from $\tilde{r}_1$, we have the following Lemma:

Lemma 3: Equilibrium return in t_1 *is*

$$\tilde{r}_1 = B\,\tilde{r}_2 + C\,\theta, \tag{5}$$

with constants $B \in (0,1)$ *and* $C > 0$.

Equation (5) shows that equilibrium return is a linear combination of final payoff ("fundamental") and sentiment (demand from noise traders). B measures the return sensitivity to fundamental, which reflects how strongly return reacts to innovation to payoff. C measures the price impact of sentiment, that is, how much return changes with noise investors' payoff forecasts.

D. Portfolio decisions

Rational investor *i*'s holding in t_1 is

$$x_i = \frac{1}{\gamma\,\hat{\sigma}^2}\left(E_R[\tilde{r}_2|s_i, s_{im}, \tilde{r}_1] - \tilde{r}_1\right).$$

The key mechanism through which beliefs before entering the market affect portfolio choices is how beliefs further change after observing the equilibrium price. From equation (5), $\tilde{r}_1$ is a signal about $\tilde{r}_2$ and rational investor *i* uses the Bayes rule to update expectations about $\tilde{r}_2$ given $\tilde{r}_1$:

$$E_R[\tilde{r}_2|s_i, s_{im}, \tilde{r}_1] = E_R[\,\tilde{r}_2 \mid s_i, s_{im}\,] + \beta_P(\tilde{r}_1 - E_R[\,\tilde{r}_1 \mid s_i, s_{im}\,]), \tag{6}$$

where β_P is the Kalman gain for signal $\tilde{r}_1$. That is, β_P measures how much rational investors update their expectation of the final payoff after seeing the equilibrium price in t_1. From equation (5), we then have

$$E_R[\,\tilde{r}_1 \mid s_i, s_{im}\,] = B\,E_R[\,\tilde{r}_2 \mid s_i, s_{im}\,] + C\,E_R[\,\theta \mid s_i, s_{im}\,]. \tag{7}$$

Combining this result with equation (3), we obtain

$$E_R[\,\tilde{r}_1 \mid s_i, s_{im}\,] = \left(B - \frac{C\kappa_D}{\lambda}\right)E_R[\,\tilde{r}_2 \mid s_i, s_{im}\,] + \frac{C}{\lambda}E_R[\,\bar{E} \mid s_i, s_{im}\,]. \tag{8}$$

Combining equations (5)-(8) yields the following proposition:

Proposition 1: The average rational investor's portfolio share is

$$x_i^R = \omega_0 + \omega_F E_R[\tilde{r}_2|s_i, s_{im}] + \omega_H E_R[\bar{E}[\tilde{r}_2]|s_i, s_{im}], \tag{9}$$

where $\omega_0 = -\frac{1-\beta_P}{\gamma\hat{\sigma}^2}\tilde{r}_1$, $\omega_F = \frac{1-\beta_P(B-C\kappa_D/\lambda)}{\gamma\hat{\sigma}^2} > 0$, *and* $\omega_H = -\frac{\beta_P}{\gamma\hat{\sigma}^2}\frac{C}{\lambda} < 0$. *Consequently, an increase in FOB leads to more stock holding and an increase in HOB decreases stock holding.*

Equation (9) is written from the perspective of rational investors. Noise traders' holding moves one-to-one with their FOB that is captured by the sentiment shock θ, i.e., $x_i^N = \theta = E_N[r_2|s_i, s_{im}]$. Therefore, the average holding across all investors is $x_i = (1-\alpha)x_i^R + \alpha x_i^N$.

Intuitively, equation (7) shows that a higher FOB raises the investor's expected final payoff. Since portfolio demand is increasing in expected returns, a higher FOB consequently increases stock holdings. Conditional on FOB, HOB affects portfolios by governing how investors interpret the informational content of prices. From equations (7) and (8), conditional on FOB, HOB reflects $R's$ subjective perception of market sentiment. Therefore, a higher HOB implies that a larger share of the observed price is attributed to sentiment-driven demand rather than fundamentals, so the price is perceived as being elevated relative to underlying payoffs. As a result, the same realized price induces a weaker upward revision of posterior expected returns and therefore lower equilibrium holdings.

E. Extension with Fast Traders

The benchmark model assumes that all rational investors trade simultaneously after forming beliefs. In this environment, higher HOB leads investors to attribute more of the observed price to noise-trader demand. Hence, a given price realization generates a smaller upward revision in expected returns and results in lower equilibrium holdings.

A realistic extension of this basic model is to allow some investors to react earlier than others. In such an environment, a group of slow rational traders behaves as in the benchmark, while the other rational traders can react earlier. These fast investors trade against the slow rational traders *and* noise traders, taking positions before the final payoff is realized and unwinding them once the equilibrium price is set. We can show that once trading speeds differ, the effects of FOB and HOB on holdings become ambiguous. That is, we can still write the average rational investor's holding in the form of equation (9), but the signs of ω_F and ω_H become ambiguous and depend on the share of fast and slow traders.

Here we sketch the model and report the main result (see Online Appendix Section II.D for more details and derivations). We extend the model by splitting the rational investors into slow and fast traders. A fraction $1-\mu$ of rational investors are slow traders who trade only in the later sub-period $t_{1,2}$ and behave as in the benchmark, while a fraction μ are fast traders who can trade earlier in the early sub-period $t_{1,1}$ and anticipate how slow rational traders and noise traders invest in $t_{1,1}$. Fast traders' profit therefore comes from forecasting the price impact of noise-trader demand and slow traders' learning-driven demand in $t_{1,2}$. Finally, we assume only a fraction $\phi \in (0,1)$ of fast traders can unwind at $t_{1,2}$, while the remaining $1-\phi$ must carry their positions to maturity. This friction is needed because when unwinding is guaranteed, fast traders' total holding in t_1 is always zero, and the model collapses to the benchmark.

Proposition 2: In the extended environment, the average investor's holding has the same functional form of (9), but the signs of ω_F *and* ω_H *are ambiguous. When* $\mu \to 0$, $\omega_F > 0$ *and* $\omega_H < 0$. *When* $\mu \to 1$, $\omega_H > 0$ *and the sign of* ω_F *is ambiguous.*

The intuition for how FOB and HOB affect portfolio holding for the slow rational traders is the same as the benchmark with one type of traders. In comparison, fast rational traders make investment decisions before other investors. A higher HOB of fast traders means they forecast a higher average valuation of other investors in the next period, which increases the resale value of the asset. Therefore, fast traders want to *ride* on these expectations and increase their holdings anticipating that others will be optimistic in the next period, i.e., $\omega_H^{fast} > 0$. This logic is similar to De Long et al. (1990a), Brunnermeier and Nagel (2004), and Chen et al. (2021).

FOB affects fast traders through two opposing channels. On the one hand, stronger payoff increases slow traders' future valuation, raising expected resale prices. On the other hand, holding HOB constant, a higher payoff implies that a smaller portion of the price is driven by sentiment. Since fast traders profit from short-term sentiment distortions as well, a weaker sentiment component reduces the scope for speculative gains. As a result, the sign of ω_F^{fast} is ambiguous.

In equilibrium, the economy-level signs of ω_F and ω_H depend on the composition of fast and slow traders. If all traders are slow (no one believes they can react faster), the model collapses to the benchmark case with $\omega_F > 0$ and $\omega_H < 0$. If fast traders dominate, the resale motive can overturn, yielding $\omega_H > 0$ in the aggregate.

III. Data and Survey Design

A. Survey

The survey data were obtained from Prolific, an online survey provider. Given the nature of our study, we restrict the eligibility of respondents to U.S. stock market investors who are employed either full-time or part-time.[2] We utilize the panel structure of Prolific to track respondents over time.[3] Specifically, we implemented two survey waves in November 2023 (3,372 responses) and February 2024 (2,151 respondents), which resulted in a ~66% overlap across the waves.[4] The Online Appendix contains the questions for both survey waves. Table 1 presents descriptive statistics. We winsorize all expectation-related variables at 1% and 99% over the entire sample to attenuate the influence of outliers.[5]

The average age of the survey participants in the first wave was approximately 37 years. Approximately 40% of the participants were female. The average pre-tax personal income of the participants was approximately $75,000. The average total wealth was around $350,000. About half of the wealth was in the financial market, with a half of the financial wealth in the stock market in the form of individual companies, exchange-traded funds (ETFs), index funds, or derivatives. The average wealth invested in the stock market, excluding pensions, was approximately $80,000.

B. Sample Representativeness

Our sample is based on Prolific's U.S. census balanced sample conditional on working individuals, therefore, it is expected to be representative of the U.S. employed retail traders. However, subjective characteristics, including whether they are stock investors, are self-reported. To assess the representativeness of our sample, we compare the demographics with surveys from recent reports and other data sources. Because we exclude retired individuals, our participants are slightly younger but close to the population, excluding older investors. The average age of the sample is slightly younger but close to the average of 42 years in a recent survey by Gallup (2023), conditional on individuals younger than or equal to 65 years.[6] The 40% female composition is in the range of 40–45%, as estimated by NerdWallet (2021) and Gallup (2023). In our sample, approximately 15% have a high school education or less, and 85% have some college education. In Gallup (2023), these

[2] We only focus on employed individuals to avoid over-sampling respondents with lower time costs.
[3] Prolific recruits a panel of U.S. survey participants that is representative of the census population. To alleviate issues with bots and duplicated participation, Prolific requires all participants to verify phone numbers and identification by checking participants' selfies and photos of their ID. See here for more details.
[4] We verified that the attrition rate was not correlated with treatment status.
[5] Prolific offers strong bot- and AI-generated-response filters. In our two waves, we achieved passing rates of 96% and 100% on our attention-checking question; we also excluded all respondents who failed an attention check (following the recommendation of Haaland et al. (2023)). Moreover, Prolific's "authenticity check" feature is reported to detect AI-generated responses with 98.7% accuracy (see here).
[6] The average age of stock market investors from the 2022 Survey of Consumer Finances was also 42 conditioning on those with positive income, and after adjusting for age coverage from the census.

numbers are 16% and 84%, respectively. Thus, the composition of our sample is broadly similar to that of other sources.

In addition, the amount of risky asset investments in our sample is also broadly representative. For example, conditional on holding a positive level of risky assets (defined as the sum of single-company stocks, ETFs, and financial derivatives), the average and median ratios of risky assets to annual income are 1.12 and 0.25, respectively. These numbers are close to the estimates of 1.05 and 0.32, respectively, in the 2022 Survey of Consumer Finances (SCF).[7] In addition, Figure A.2 in the online appendix shows that the wealth and income distributions of our sample are broadly in line with those in the 2022 SCF. The average number of risky assets as a fraction of total financial assets is 0.46, which is smaller than the estimate of 0.68 in Giglio et al. (2021).[8]

We can also roughly match the numbers for high-income individuals. For example, from the 2023 U.S. census, 19% of U.S. individuals below age 65 have income equal or above $100,000. We have 23% in our sample. The 90th percentile of annual individual income is $178,611 in the 2023 IRS data. In our data, 8.3% of respondents have income at or above $150,000.

C. Experimental design

Figure 1 plots the timeline of the experiment. The design of the experiment follows the conceptual framework in Section II. The timeline is as follows:

1. **Sample Selection:** On Nov 7, 2023, we recruited 5,000 participants from Prolific US Census Panel that were stock market investors and were either full-time or part-time employed. We then randomly split them into three groups: control, treatment T1, and treatment T2.
2. **First Wave:** On Nov 8, 2023, the first-wave surveys were sent to the control group first. On Nov 12, 2023, we sent the first-wave surveys to T1 and T2. The surveys were allowed to finish by Nov 19, 2023.
3. **Second Wave:** On Feb 21, 2024, we sent the second wave survey to those who have finished the first wave surveys.

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[7] Calculated conditional on individual younger or equal to 65 and older than 20, with positive equity, and annual income not larger than $375000, which is the maximum in our sample.

[8] Giglio et al. (2021) constructed the measure based on investors' Vanguard accounts. One may expect to see some differences if investors have multiple accounts.

The first wave of the survey elicited socioeconomic information about the respondents. We also asked a set of questions to better understand the trading behaviors of the respondents (e.g., how often they trade). We also asked respondents to play a strategic game to measure their ability to eliminate dominated strategies and engage in thinking about the behavior of other investors.

We then elicited respondents' prior beliefs about the stock market (S&P500), as well as what they think about the expectations of other investors. The former was a FOB (own belief) while the latter was an HOB (i.e., thinking about what other people are thinking). To this end, we presented respondents with a set of bins for possible returns and asked them to assign probabilities to these bins. For example, we used the following bin-based question to elicit subjective distributions of FOB:

> Please assign probabilities (from 0 to 100) to the following ranges of possible overall stock price changes (%) for the **S&P500 index** over the 12 months from October 2023 to September 2024:
>
> Note: The sum of the answers must equal 100%. Responses ranged from 0% to 100%.
>
> More than 20% %
> From 15% to 20% %
> From 10% to 15% %
> From 5% to 10% %
> From 0% to 5% %
> From -5% to 0% %
> From -10% to -5% %
> From -15% to -10% %
> From -20% to -15% %
> Less than -20% %

To aid comprehension, we elicited beliefs in terms of returns, but defined relative to a base period well before the survey. This way, consistent with our model, the elicited beliefs are about future payoffs rather than the total return from the trading date.

The corresponding question eliciting a subjective prior distribution about HOB was

> We would like to know your opinion about what **other investors** think will affect stock market prices. Please assign probabilities (from 0 to 100) to the following range of beliefs that **other investors** might hold about the overall price changes in the **S&P500 index** over the 12 months from October 2023 to September 2024:
>
> Note: The sum of the answers must equal 100%. Responses range from 0% to 100%.
>
> More than 20% %
> From 15% to 20% %
> From 10% to 15% %
> From 5% to 10% %
> From 0% to 5% %
> From -5% to 0% %
> From -10% to -5% %

From -15% to -10%	%
From -20% to -15%	%
Less than -20%	%

We asked a similar question about the payoffs on their own portfolios with the following question:

> Please assign probabilities (from 0-100) to the following ranges of possible overall changes (%) for **your stock market portfolio** over the 12 months from October 2023 to September 2024

Once priors were elicited, we presented randomly selected respondents with information relevant to thinking about future stock payoffs; the control group was not presented with any information and simply continued the survey. This information intervention aimed to create exogenous variations in investors' FOB and HOB regarding future payoffs. Through the lens of our model (specifically, equation (7)), interventions sought to affect investors' FOB $E[\tilde{r}_2|s_i, s_{im}]$ and HOB $E[\bar{E}[\tilde{r}_2]|s_i, s_{im}]$.

For treatment group 1, we showed them the following information:

> We would now like to show you some information on the S&P 500 index.
>
> **Over the past 12 months, the earnings of the companies represented in the S&P 500 index have increased by approximately 2%. This is lower than the average of around 7.5% annually over the past 10 years.**
>
> Please proceed to the next page.

For treatment group 2, we showed them the following information:

> We would now like to show you some information on the S&P 500 index.
>
> **Other investors participating in this survey on average believe that the 12-month return of the S&P 500 index from October 2023 to September 2024 would be 3.21%. This is lower than the average annual return of 9% on S&P 500 over the past 10 years.**
>
> Please proceed to the next page.

The 3.21% 12-month return, as perceived by others in the second treatment, was the average 12-month return expectation from the control group. Because the control group was a random sample of all participants, we used this number to represent the average return from all participants. Note that, by construction, there is a lag of a few days between when we administer the survey for the control group and the T2 treatment group because we need to collect information on the investors' beliefs for the information intervention. While this may lead to a different set of priors and holdings in the T2 group, we document below that there is no discernible difference for beliefs or asset holdings between the control and treatment groups in our sample.

The first information treatment, following Beutel and Weber (2025), sought to generate a relatively larger variation in FOB. The second treatment, following Coibion et al. (2021), aimed to generate a relatively larger variation in HOB. Note that the two treatments are expected to change beliefs about FOB and HOB simultaneously, because signals about FOB and HOB are generally correlated. However, for identification, we only need the two signals to change FOB and HOB to different degrees; that is, the treatment effects should not be collinear.[9] Although responses to information could stem from "demand" effects, we note that the survey was on a neutral matter and was conducted online, thus minimizing such effects (Haaland et al. 2023).

Immediately after displaying the information treatments, we elicited participants' posterior distributions using the following questions, in the spirit of Altig et al. (2022):

> Q13: Now, we would like you to think about what you perceive as the most pessimistic and optimistic outlook for **S&P 500 return** over the 12 months from October 2023 to September 2024. What do you think the lowest 12-month return might be for this period and what do you think the highest might be? (Please provide answers as percentages per year.)
>
> Lowest return (%):
> Most likely return (%):
> Highest return (%):
>
> Q14: Now, we want to ask you to think about the chance of the **S&P 500 return** you entered in the previous question. Please assign a percentage chance to each return to indicate how likely you think it will actually happen to the S&P 500 index over the 12 months from October 2023 to September 2024.
>
> Note: Your answers must be greater than or equal to 1%, where 1% means nearly no chance that this growth rate will occur. The sum of these values should be 100%.
>
> S&P500 return will be *X1*: ___ %
> S&P500 return will be *X2*: ___ %
> S&P500 return will be *X3*: ___ %

where *X1*, *X2*, and *X3* in Q14 represent the three answers to Q13. The questions eliciting the posterior distributions for individual portfolio returns and HOB for S&P 500 returns had the same format. Different formulations of the return questions were deliberately used before and after the treatment to avoid antagonizing respondents by repeatedly asking them to answer the same distributional questions. Note that posterior elicitation in Q14 conditions on each respondent's previously stated lowest, most likely, and highest returns, effectively anchoring the support of the

[9] To be clear, the goal of the information treatment is to generate strong first-stage variations, rather than to isolate specific channels of belief formation. That is, the signals only need to change expectations; its exact form is not essential for our experimental design.

subjective distribution. While respondents may in principle revise this support, any resulting measurement error is orthogonal to treatment assignment. After eliciting the posteriors, we asked additional questions and completed the first wave of the survey.

Three months after the first wave, we sent a follow-up survey to those who have completed the first wave. The purpose of the follow-up wave was to measure the choices that respondents may have in response to information treatments and to measure the persistence of treatments on beliefs, which we elicited with the bin-based questions with the same format as measuring the priors.

Columns (1) and (2) in Table 1 report the descriptive statistics for the entire sample of the first wave of surveys. The other columns report the descriptive statistics for control group C, treatment group T1, and treatment group T2. Columns (7) and (10) show the *p*-values for testing the differences in the average characteristics. The *p*-values are generally well above 10%, which is consistent with successful randomization.

Ideally, return expectations and signals are with respect to the subjects' own portfolio, however, own-portfolio expectations reflect not only beliefs about asset returns but also expectations about portfolio composition. This motivates our primary focus on beliefs about the S&P 500 index return, which isolates expectations about the return-generating process of the risky asset itself. However, this relies on the assumption that respondents' portfolios load positively on the market portfolio to link beliefs to allocations. Under this assumption, our index-return-based measure (FOB) serves as a proxy for the expected return component driving portfolio choices. Because our analysis leverages exogenous belief variation induced by randomized information treatments, classical measurement error in beliefs about own returns relative to S&P 500 expectations does not bias our main estimates by design.

D. Trading behavior and strategic thinking

Figure 2 plots the distributions of variables measuring trading behaviors. The results are based on the first-wave surveys. Most participants have invested in the stock market for more than one year. About 1.5% of the participants indicate no experience in the stock market. Voluntary comments after taking the survey indicate that these investors' stock market participation is not active and purely through retirement saving. The investors check their balance in the stock market relatively infrequently. The average is 72 times a year and the median of 42 times a year, which is about once every five days on average and every nine days for the median. Their trading frequency is much lower. The average and median numbers of trades the investors make a year are 18.5 and 5, respectively, which is equivalent to making a trade every 20 days on average and 73 days for the median. The 12-month portfolio returns from November 2022 to October 2023 vary widely, with a mean of 4% but an interquartile range of -5% to 13%.

We also elicited participants' beliefs about how quickly stock market investors incorporate significant news events into their trading decisions.

> Based on your experience and observations as a stock market investor, how many days do you believe it takes **you** to react to significant news events in the stock market? Consider news events, such as earnings reports, geopolitical developments, and macroeconomic data releases.
>
> Based on your experience and observations as a stock market investor, how many days do you believe it typically takes for **other investors** to react to significant news events in the stock market? Consider news events, such as earnings reports, geopolitical developments, and macroeconomic data releases.

These two questions elicited subjective beliefs about individuals' and other investors' reaction speeds to news about the financial market. The average number of days required to react to financial news is 15.5. At the same time, they believed that others reacted much faster than themselves. The average number of days participants believed that others had reacted to the news was 8.7. Only 22.5% of the participants believed that they reacted faster to significant news about the stock market than others. Through the lens of our model, one can interpret these responses as suggesting a low value of α.[10]

Do retail investors adopt either contrarian or momentum strategies? On one hand, the literature suggests that attention-grabbing events influence retail investors' trading decisions, inducing momentum-based strategies (Tetlock 2011, Barber et al. 2022, Cookson et al. 2023). In other words, investors tend to invest more funds in an asset when its price increases, because they expect the price to continue to rally. On the other hand, Grinblatt and Keloharju (2000), Kaniel et al. (2012), Kogan et al. (2023), and Luo et al. (2023) find that retail investors are mostly contrarian in trading stocks. To assess the prevalence of this behavior, as well as strategic thinking about the behavior of other investors, we asked respondents to answer three questions:

[10] We elicit respondents' subjective perceptions of the composition of "other investors" in the stock market. As shown in Figure A.3, participants on average assign about 35% to retail investors, 51% to institutional investors, and 13% to other types of investors. Importantly, respondents' beliefs about whether they react more slowly to news are not systematically related to these perceived compositions. This suggests that the notion of "other investors" reflects a general perception of being at a strategic disadvantage relative to the market, rather than a specific belief that institutional investors are more efficient in processing information.

> Suppose the S&P 500 index has increased by 20% over the past three months. By what percentage would you change your wealth allocated to the stock market change? - %
>
> Suppose the S&P 500 index has increased by 20% over the past three months. By what percentage do you think other investors will change the wealth allocated to the stock market? - %
>
> Suppose the S&P 500 index has increased by 20% over the past three months. By what percentage would you change the wealth allocated to the stock market if other investors did not change how much they would allocate to the stock market? - %

The first question measured the respondents' degree of momentum trading. The second question elicited respondents' thoughts about momentum trading by other investors. The third question assessed how the trading behavior of other investors affects the respondents' trading behavior. Panel A of Figure 3 shows that although many investors would not allocate more resources to stocks (i.e., the change in the share is zero), there is a large right tail of investors who would allocate a significantly larger share of their wealth to stocks: the average increase was 19%, and the median was 11%. Very few respondents reported reducing their exposure to stocks. At the same time, respondents believed that *other* investors would allocate larger shares to stocks, with an average of 28% and a median of 20%. In other words, respondents believed that other investors engage in stronger momentum trading. This can rationalize why the "own" strategy is to allocate a larger share of wealth to stocks so that one will ride the bubble or herd on others' trading decisions due to updated beliefs about future payoff. Consistent with this view, we find that respondents would allocate a lower share of their wealth to stocks if other investors do not change their allocations, with a mean of 16% and a median of 10%. These results suggest a form of strategic investment behavior.

To further investigate this matter, we asked respondents to play the 2/3 game developed by Nagel (1995). Specifically, we first asked the following questions:

> Please choose a number from 1 to 100. We use your number as well as the number chosen by other investors to calculate the average pick. The winning number is the number closest to two-thirds (2/3) of the average value. If your number wins, you will receive a bonus payment of US$ 20.

We then asked respondents to report what they think other investors would choose:

> Other investors were also asked to guess a number from 1 to 100 with the goal of making their guess as close as possible to two-thirds of the average guess of all those participating in the contest. What percentage (%) of other investors' guesses do you think will fall within each of the following ranges?

where ranges are 0–10, 10–20, …, 90–100. One should expect one's own picks (the 1st question) to be 2/3 of the average implied by the probability distribution of the second question.

Panel B of Figure 3 shows a binned scatter plot of the scores expected from other investors versus their own scores.[11] The average own pick is 38, thus suggesting $k \approx 1$ level thinking, which is consistent with earlier studies (see Camerer (1997) for a survey). The own scores are somewhat lower than the average expected from other investors. There is a positive relationship between the two and the slope is 0.60 (we could not reject the null hypothesis that the slope is 2/3). This estimate is broadly in line with estimates available for the general population of households (e.g. Coibion et al. 2023) and firm managers (e.g., Coibion et al. 2021). In short, respondents in our sample exhibit at least some degree of strategic thinking and behavior.

To further assess differences in investors' strategic considerations, we follow Bianchi et al. (2025) and examine how individual characteristics shape belief accuracy and strategic reasoning. Figure A.1 and Table A.2 in the Online Appendix show that higher levels of thinking are associated with smaller errors in HOB, weaker momentum tendencies, and stronger strategic responses to return news, particularly when investors are asked to condition on others' behavior. In contrast, errors in FOB are largely unaffected. These patterns suggest that the level of thinking strongly predicts strategic considerations in the stock market, especially in how investors reason about others' beliefs and adjust their behavior accordingly, rather than differences in knowledge of fundamentals.

E. First- and higher-order expectations

A novel part of our survey is that we elicited expectations not only about respondents' own predictions of stock market performance (FOB) but also what they thought about the expectations of other investors, that is, HOB. Table 1 and Figure 4 show that the moments are broadly similar for expectations of respondents' own portfolios and the S&P 500, and for respondents' expectations of other investors. For example, the average expected return for their own portfolios was 3.68%, which was only a tad higher than the average expected return for the S&P 500 (3.36%). This is similar to the average return that respondents believe other investors expect (HOB), which is 3.81%. For comparison, the actual returns are approximately 16% over the 12 months before the survey and approximately 9% per year over the past 10 years.

[11] In this analysis, we restricted the sample to respondents who understood the game (87% of respondents), that is, respondents whose own score was 66 or less. Because these questions were asked after treatments, we restricted the sample to the control group.

There are also considerable disagreement and uncertainty in expectations. The standard deviation of expectations for own-portfolio returns is 5.5%, which is similar to the dispersion of FOB (5.61%) and HOB (5.62%) expectations for S&P 500 returns (see the left-hand column of Figure 4). Interestingly, the level of uncertainty is similar to the level of disagreement, which contrasts with the macroeconomic forecasts of firms and professional forecasters (e.g., Coibion et al. 2021). There is also a large dispersion in uncertainty across respondents for all beliefs (see the right column of Figure 4). Only approximately 10% of the respondents chose a single bin in the probability distribution question.

To illustrate the joint distribution of beliefs in the cross-section, we present binned scatter plots of S&P 500 expectations versus expectations for their own portfolios in Figure 5. We observe a strong positive relationship with expectations. For example, a 10% higher return on one's own portfolio is associated with an 8.4% increase in expectations of S&P 500 returns and a 6.6% increase in the expectations of other investors. Note that the slope is smaller for HOB expectations, which is consistent with higher-order expectations being more inertial than lower-order beliefs (see e.g. Woodford 2002). This is also consistent with the less-than-one slope when we regressed HOB on FOB, which was 0.69. It is also clear that the respondents' portfolio expectations are strongly correlated with their market return expectations. This means that if we can alter respondents' market expectations, we should alter their expectations for their own portfolios and, hence, potentially stimulate them to change their portfolio allocations.

Interestingly, uncertainty in the FOB and HOB market expectations exhibit the same sensitivity to variations in uncertainty in respondents' portfolios. The slope is also closer to one when we regressed HOB uncertainty on FOB uncertainty for S&P 500 expectations. Generally, one should expect lower uncertainty in higher-order expectations when there is only one agent type in the model (Coibion et al., 2021). However, with the addition of noise traders, this is no longer clear, and depends on the subjective uncertainty of sentiment.

To understand the sources of cross-sectional variation, we first explore the relationship between past and expected returns. Figure 6 shows a U-shaped relationship, suggesting a mean reversion for low returns. However, the trough of the U-shape occurs below 0%; thus, for most respondents, past and expected returns were positively correlated. This result is consistent with earlier findings documenting that personal experiences shape expectations (e.g., Malmendier and Nagel 2011).

Next, we explore the predictors of beliefs about future stock returns. Specifically, we regress various measures of beliefs on respondents' characteristics and report the results in Table 2. In columns (1) and (2), we present the results separately for FOB and HOB. Column (3) is a measure of relative sentiment, which is the difference between HOB and FOB. When this number is high, investors believe that the market is optimistic. Column (4) shows the absolute value of relative sentiment, which is a measure of higher-order disagreement.

We find that past returns are positively correlated with both FOB and HOB in terms of future market payoffs; however, the sensitivity is greater for FOB. Both FOB and HOB are positively associated with the number of trades that investors make annually. Although we do not have separate information for buy and sell trades, our results are consistent with mechanisms that emphasize heterogeneous beliefs as a source of higher trading volumes (Hong et al. 2006; Hong and Stein 2007; Carlin et al. 2014). Expectations also vary significantly across demographics. In particular, lower-income, female, and younger investors tend to believe that the market is more optimistic at the time of the survey.

Columns (5) and (6) show the implied uncertainty of FOB and HOB. Column (7) presents the results of the difference between belief uncertainty. As columns (5) and (6) show, implied uncertainty also varies with investor characteristics. Specifically, male investors, high-income investors, and those who trade more are more uncertain about future payoffs. Surprisingly, even if implied uncertainty varies with investor characteristics, investors are generally equally uncertain about the market payoff and how others believe it would be. Column (7) shows that the difference between uncertainty in HOB and FOB does not vary significantly with investor characteristics.

F. Holdings of stocks

We use several metrics to capture the respondents' exposure to stocks. The first measure relies on the following two questions. One question focuses on the share of financial wealth in total wealth, *Financial %* (to ensure that we do not include housing wealth, a key asset for many households).

> Approximately what percentage of your current wealth is financial wealth?
>
> Note: Financial wealth includes stocks, ETFs, financial derivatives, bonds, pension funds, bank savings, and other wealth.

We then ask respondents to report the composition of their financial assets:

> We would now like to ask how your current financial assets (excluding real estate) are distributed across different asset classes. Please enter the approximate percentage you have invested in the following assets:
>
> Note: The sum of the answers must equal 100%. Responses ranged from 0% to 100%.
>
> Stocks (Individual Companies) ___ %

ETFs or index funds	___ %
Financial derivatives (options, futures, forward)	___ %
Bonds	___ %
Pension fund (401k, IRA etc.)	___ %
Other	___ %

Risky_F% is the sum of the shares of individual stocks, ETFs, index funds, and financial derivatives.[12] Finally, the total share of risky asset holdings, *Risky%*, is the product of *Risky_F%* and *Financial%*, which gives risky asset holdings a share of total wealth. We also construct $Risky_{no\_der}\%$, which is equal to *Risky%* excluding the share of financial derivatives. In the follow-up wave, we elicited equity shares in pension funds. Specifically, those who did not answer zero to the option pension fund (401k, IRA, etc.) were asked the following questions:

What proportion of your pension fund is currently allocated to equity investments?

Note: If you do not have pension fund wealth, please select zero.

We define $Risky_{w.pen}\%$ as the risky asset share, inclusive of equity allocated through the pension. Conditional on positive pension wealth (13%), the median and average equity allocations are 32% and 41%, respectively.

Table 3 presents the regression results for risky asset shares on FOB and HOB based on first-wave surveys. Several patterns are observed. First, individuals' own beliefs about future market returns are positively related to portfolio shares allocated to risky assets, a result that has also been well documented in previous studies (e.g., Egan et al. 2014; Giglio et al. 2021; Beutel and Weber, 2025). Second, the relationship between FOB/HOB and asset holdings depends on whether one or both measures of belief are included. Column (3) shows that when FOB is not included as a control, HOB has an insignificant negative relationship with risky asset holdings. An insignificant relationship between HOB and risky asset holdings is often used as evidence that investors fail to incorporate the mechanism by which market beliefs increase current valuations and decrease stock returns. However, in Column (4), when we control for FOB and individuals' own beliefs about future market returns, the relationship between HOB and risky asset holdings becomes significant, which is consistent with Proposition 1.[13]

[12] Investment Company Institute (2024) documents that equity ETFs make up about 80% of ETF total net assets in the US. In light of this fact, we include ETF as risky asset.

[13] Figure A.4 is a set of binned scatter plots of risky asset share on subjective uncertainty. In general, we find that risky asset share decreases with the subjective uncertainty of FOB, consistent with the risk-return trade-off, and increases with the subjective uncertainty of one's own portfolio, likely reflecting risk preferences. In the end, there is no significant relationship between risky asset share and subjective uncertainty of HOB.

IV. The Effect of Information Treatments on Expectations

So far, we have focused on documenting the basic properties of FOB and HOB expectations, as well as the correlations between variables. Although informative, this analysis does not explain how investors respond to information in terms of their beliefs and actions. To shed more light on this matter, we use an RCT that allows us to create exogenous variations in beliefs and potential subsequent adjustments in portfolio allocations.

A. The causal effect on beliefs

Following Coibion and Gorodnichenko (2026), we use the following econometric specification to assess the influence of various information treatments on investors' beliefs:

$$\begin{aligned} Posterior_i = a_0 + \sum_{k=1}^{2} a_k \times \mathbb{I}\{i \in Treat_k\} + b_0 \times Prior_i \\ + \sum_{k=1}^{2} b_k \times \mathbb{I}\{i \in Treat_k\} \times Prior_i + error_i, \end{aligned} \tag{10}$$

where i denotes participants, $Prior_i$ is the participants' prior beliefs, $Posterior_i$ is the participants' posterior beliefs, and $\mathbb{I}\{i \in Treat_k\}$ is an indicator variable that is equal to one if respondent i is in treatment group k. To estimate this specification, we use Huber robust regressions that automatically deal with outliers and other influential observations. Note that whether we include controls for respondent characteristics should not materially matter for $\hat{a}$ and $\hat{b}$ because the treatment status is determined by randomization.

If respondents' updating is consistent with Bayesian learning, one should expect $b_k \in [-1,0]$. If $b_k = 0$, treatment k is not informative for the respondents; hence, they did not change their priors. If $b_k = -1$, treatment k is so informative that respondents abandon their priors and equate their posteriors to the signal. We refer to bs as the slope effect. The coefficients of the treatment indication variables a_k (the level effects) may be positive or negative depending on where the provided signal is relative to the average prior. Because treatments can move posteriors in both directions, we also estimate a version of specification (10) in which we include only indicator variables for the treatments.

$$Posterior_i = a_0 + \sum_{k=1}^{2} a_k \times \mathbb{I}\{i \in Treat_k\} + error_i, \tag{11}$$

so that coefficients a_k can be interpreted as the average change in beliefs.

The coefficient b_0 in specification (10) should be equal to one (recall that the control group does not receive any additional information, and thus, there should be no systematic difference between priors and posteriors for respondents in this group). However, because the format of the survey questions eliciting beliefs is different for priors and posteriors, b_0 can be different from one (see Bruine de Bruin et al. 2011; Kleinjans and van Soest 2014; Coibion et al. 2021). We report the regression estimates in Table 4 and visualize the results in Figure 7.

Panel A of Table 4 presents the mean expectations implied by the reported subjective probability distributions. The posterior side was measured immediately after the treatment. Columns (1) and (2) show investors' own portfolio returns, columns (3) and (4) present the results for FOB on market payoffs, and columns (5) and (6) show the results for HOB. In the control group, the coefficients of prior beliefs are approximately 0.5 for FOB and 0.6 for HOB.

Consistent with Bayesian learning, the slope effects (b_1 and b_2) tend to be negative; that is, respondents moved their posteriors partially toward the provided signals. In addition, the effects were not collinear for FOB or HOB. Specifically, the second treatment (i.e., informing participants about the beliefs of other investors) had a stronger effect on HOB than on FOB and vice versa. The estimated coefficient on $T_1 \times Prior$ and $T_2 \times Prior$ in columns (4) and (6) are statistically different from each other at the 1% level.

Columns (1), (3), and (5) show the average treatment effects (ATE) of information provision on expectations. Because the ATE measures the average changes in expectations, the effects depend on whether the pre-experiment perceptions are correct on average, and whether those who make negative and positive errors respond differently to the signals. The first treatment (T1) reduced the average expectations of both FOB and HOB by approximately one percentage point. In contrast, the second treatment (T2) significantly reduced HOB by 1.4 percentage points, whereas the effect on FOB was only 22 basis points and was not significant.

Panel B of Table 4 reports the equivalent results for uncertainty. We generally find that information treatment shifts priors across the board. In other words, the posterior uncertainty is roughly a parallel shift of the prior uncertainty. However, T2 had a significant slope effect on HOB uncertainty.

We use beliefs from the follow-up wave to study the persistence of the effects on return expectations. We find (Appendix Table A.3) that expectations were not statistically different among the three groups three months after the experiment. These findings are consistent with several theories. First, this can stem from a measurement issue. Specifically, these beliefs were elicited with bin-based questions; thus, the results for these beliefs are not directly comparable to the results based on posterior beliefs measured immediately after treatments with scenario-based questions. Second, financial information depreciates quickly. This is in agreement with the effects of major news (e.g., earnings announcements) in the stock market, although not instantly incorporated, largely plateau within a quarter (e.g., see Bernard and Thomas 1989, DellaVigna and Pollet 2009, Martineau 2022). For comparison, information treatments about inflation and other macroeconomic variables (which tend to be more persistent) appear to wear off only after six months (Kumar et al. 2023; Coibion et al. 2024). Third, Panel E of Figure 2 suggests that most investors should have incorporated the provided information into their trading decisions within a month.

The lack of significant effects on expectations after three months is also consistent with demand effects. However, we have several reasons for why this explanation is unlikely. First, as we discussed earlier, the nature and design of our study (a neutral topic, an online survey, etc.) should attenuate demand effects. Second, we show below that the treatments changed behaviors, therefore indicating that demand effects are unlikely.

In summary, these results suggest that information interventions are powerful in altering investors' beliefs about FOB and HOB with respect to future market index returns. Importantly, the treatments did not create uniform revisions of FOB and HOB. Treatment 1, which provided statistics on past earnings growth, had a greater impact on FOB, whereas Treatment 2, which focused on the aggregate beliefs of other participants, had a more pronounced effect on HOB.

B. The effects of expectations on risky asset holdings

In the next step, we use exogenous variations in beliefs to study how beliefs affect portfolio allocations. Our approach is a two-stage least squares estimation following Beutel and Weber (2025) and Coibion et al. (2024). The first-stage regression is similar to that in specification (10).

$$
\begin{aligned}
Posterior_i^h = a_0^h + \sum_{k=1}^{2} a_k^h \times \mathbb{I}\{i \in Treat_k\} \\
+ b_0^h \times Prior_i^{FOB} + \sum_{k=1}^{2} b_k^h \times \mathbb{I}\{i \in Treat_k\} \times Prior_i^{FOB} \\
+ c_0^h \times Prior_i^{HOB} + \sum_{k=1}^{2} c_k^h \times \mathbb{I}\{i \in Treat_k\} \times Prior_i^{HOB} \\
+ Controls_i + error_i^h. \qquad (12a)
\end{aligned}
$$

where $h = \{FOB, HOB\}$, $Prior_i^{FOB}$ and $Prior_i^{HOB}$ are the prior expectations of the FOB and HOB. Specification (12a) is estimated for the posterior expectations of both FOB and HOB.

The second stage regression is given by

$$
\begin{aligned}
Risky\%_i = \alpha_0 + \beta_{FOB} \times Posterior_i^{FOB} + \beta_{HOB} \times Posterior_i^{HOB} + \gamma_{FOB} \times Prior_i^{FOB} \\
+\gamma_{HOB} \times Prior_i^{HOB} + Controls_i + error_i \qquad (12b)
\end{aligned}
$$

where $Posterior_i^{FOB}$ and $Posterior_i^{HOB}$ are instrumented as in the specification (12a). The dependent variable $Risky\%_i$ is the reported risky asset share in the second-wave surveys. The set of controls is based on pre-treatment variables and include sex, age, indicator for full-time employees, indicator for having at least a college degree, ethnic group fixed effects, reaction speeds, log income, portfolio returns, implied uncertainty, and risky asset holdings. Following Coibion et al. (2023, 2024), we address outliers by estimating the first stage with Huber robust regressions and using jackknife resampling in the second-stage regressions. The results are summarized in Table 5.

The strong first-stage F-statistics for FOB and HOB indicate that information treatments generated large movements in beliefs; that is, the instruments are clearly relevant. Columns (1) and (2) exclude HOB and FOB, respectively. These results estimate the total effects of FOB or HOB. Column (3) provides the benchmark result of (12b), which includes both the FOB and HOB. As suggested in Section III, signals about FOB or HOB alone simultaneously shift beliefs about FOB and HOB. As the main effects of FOB (HOB) on risky asset holdings are positive (negative), excluding anyone would cause the estimates to be biased toward zero. Column (1) shows that a 10% increase in the FOB increases risky asset holdings by 2.3 percentage points. Column (2) shows that a 10% increase in HOB reduces risky asset holdings by 5.8 percentage points. Both estimates are statistically insignificant. However, these estimates are biased toward zero if ω_F and ω_H have different signs and $\rho(HOB, FOB) > 0$, which helps explain the weak sensitivities of beliefs to trading decisions as documented in recent studies (Giglio et al. 2021, Charles et al. 2023).

When we include both FOB and HOB, the effects on beliefs become stronger and statistically significant, with 10% higher FOB increasing risky asset holdings by 14.6 percentage points and 10% higher HOB decreasing them by 14.2 percentage points, and 10% higher FOB increasing risky asset holdings as a share of financial asset by 25.8 percentage points and 10% higher HOB decreasing them by 18.4 percentage points (column (4)).[14] The estimated coefficient in front of FOB is close to that in Beutel and Weber (2025). The last three columns show that the results hold when we focus only on financial assets, including equity holdings in pensions, and excluding financial derivatives. These results show that FOB and HOB have strong causal effects on portfolio allocations. Importantly, the negative HOB coefficient suggests that respondents reduce their exposure to the stock market when they think other investors have higher expectations of future stock market returns.

The estimated coefficients give us the *total* effect of FOB and HOB beliefs on the allocation. In other words, if we change FOB beliefs and hence other beliefs related to FOB beliefs (that is, cross learning), β_{FOB} captures the direct effect via FOB beliefs and indirect effects via other beliefs. Specifically, we show that information treatments affect not only expected returns but also the uncertainty, that is, subjective risk premium, in these expectations. If lower uncertainty encourages higher holdings of risky assets, the total effect may be greater than the direct effect. Of course, our information treatments can alter investors' beliefs about other instruments, macroeconomic outlook, etc., which can affect portfolio allocations. Due to space constraints in the survey and limited sample size, we could not elicit these other beliefs as well as introduce additional information treatment to disentangle potential effects from changes in these beliefs.

To unbundle some of these channels, we use several methods to control for the changes in subjective uncertainty. The first strategy follows Coibion et al. (2024). In particular, we include implied posterior standard deviations as controls. We find, in column (1) of Table 6, that $\hat{\beta}_{FOB}$ and

[14] This pattern of significance/insignificance is unlikely to be explained by collinearity. The correlation between posterior FOB and HOB is around 0.56, which is rarely severe enough to create classic multicollinearity problems. In particular, with two regressors the corresponding variance-inflation factor is $1/(1-\rho^2)$ = 1.46, well below the common "problematic" thresholds of 5 or 10. Results can be somewhat stronger for individual regressors in some subsamples. For example, when only FOB is included and if we drop those with expected return larger than 15% in absolute value, following Giglio et al. (2021), then the coefficient on FOB is 0.89 (with a t-stat of 1.31). This is closer to the 1.03 estimated in Giglio et al. (2021).

$\hat{\beta}_{HOB}$ are not significantly affected by the controls. Simultaneously, we find no statistically significant estimates for uncertainty.

As an additional strategy, we instrument both the first and second moments using a modified specification (12a), which includes prior expectations for uncertainty interacting with the treatment indicator variables. This approach requires IVs to induce differential changes in expectations and the implied uncertainty. This assumption holds because the treatments are expected to reduce uncertainty for all treated individuals, but they could increase or decrease prior expectations, depending on the direction of ex-ante expectation errors. Therefore, the treatment indicator variables in (12a) should induce larger changes in FOB/HOB uncertainty, and the interaction between the treatment dummies and the prior is more effective in inducing changes in expectations.

The results are shown in column (2) of Table 6. We find that, for all four first-stage regressions, the *F*-statistics were above 12, indicating reasonable first-stage strength and a lack of collinearity in the treatment effects. However, since the experiment did not aim to affect subjective variances, including those as explanatory variables in a 2SLS regression reduces the overall explanatory power of the instruments. As a result, the overall strength of the instruments is diluted, leading to a lower first-stage *F*-statistic. This weaker first stage exacerbates the bias toward the unconditional estimates in columns (1) and (2) because the instruments are less effective at isolating the exogenous variation in beliefs. Consequently, estimates of β_{FOB} and β_{HOB} have larger standard errors and generally move closer to the unconditional estimates. But our qualitative conclusions are not affected. This finding suggests that the direct effect of the treatments on expectations can be the main channel FOB and HOB have on holdings. We find similar results when we use the alternative measures of risky assets, *Risky_F%* and $Risky_{w.pen}\%$.

C. Effects on other assets

In principle, investors can adjust their behavior along other margins. For example, investors can change the allocation of financial and non-financial assets (mainly real estate). Investors can also change the composition of their non-stock investments (e.g., bonds vs. retirement accounts). We investigate this in Table 7. Column (1) shows that within a three-month period, neither FOB nor HOB have significant effects on total wealth, indicating a lack of evidence that beliefs about S&P 500 payoffs affect total savings. This result is perhaps expected, because one should not anticipate significant changes in wealth within three months. Column (2) shows that FOB or HOB does not affect the allocation of financial and nonfinancial assets. Therefore, altering expectations of future market payoffs appears to influence only the portfolio choices of different asset classes within financial assets. Columns (3) – (5) show that a higher FOB or lower HOB reallocates investments from risky assets to both bond and pension accounts.

D. Heterogeneity in responses

This section examines whether investors with different characteristics have the same sensitivity of trading decisions to payoff expectations. To do so, we estimate the effects of exogenous variation in FOB and HOB for the different subsamples of participants in Table 8. Columns (1)–(10) present the results by demographics and columns (11)–(20) provide estimates by trading behavior. As the subsamples have fewer observations, we expect less precise estimates. Furthermore, the subsample split along one characteristic and could be correlated with another. Therefore, we view our results as suggestive.

Several general patterns emerge. First, most subgroups of participants either respond to both FOB and HOB or neither FOB nor HOB. In other words, investors can be broadly grouped into two types: expectation-sensitive investors, who react strongly to payoff beliefs, and expectation-insensitive investors, who do not change their trading decisions based on belief changes. This is consistent with the findings in Panel C of Figure 2, which shows that the number of trades investors make per year is highly right skewed. Second, those with high trading sensitivity to expectations (that is, those with larger coefficients on FOB and HOB) are, in general, also those with lower socioeconomic status (below college level, less wealth, or less income).

In the end, while trading sensitivity to FOB is quantitatively similar between those who believe that they react faster or slower than others (columns (11) and (12)), those who believe that they react slower to significant financial news than others had more negative sensitivity to HOB. This is consistent with the mechanism in our model with fast traders. In particular, individual investors would react negatively to others' beliefs when they do not perceive themselves as capable of reacting faster than others. While for those who think they can react faster, responses to HOB should be weaker.

V. Quantitative Implications for Theory

While our theoretical model is stylized and hence the mapping from the data to the model requires strong assumptions, we can use our RCT-based estimates to infer a few important parameters that are difficult to identify in observational data.[15] Specifically, portfolio sensitivity to expectations in the model is driven by two key parameters: risk aversion γ and the price-inference coefficient β_P (the Kalman gain). We show (see Section III in the Online Appendix) that ω_F and ω_H are non-linear functions of γ and β_P after controlling for the variances of the signals. Intuitively, γ determines how strongly expectations translate into asset demand and ω_H and ω_F measure the passthrough from beliefs to portfolios. Also recall that higher-order beliefs affect how investors interpret price movements and update expectations during trading. As a result, a larger β_P indicates a stronger learning from price, which yields a more negative ratio of ω_H to ω_F. Therefore, ω_F and ω_H can inform us about γ and β_P.

Given our estimates, we infer $\gamma = 7.4$ for the baseline model and $\gamma \approx 5.73$ for the extended model with fast and slow traders, which falls in the range of 3 to 10 as often estimated in the experimental literature (Giglio et al. 2021) but is slightly smaller than the estimate of 8.4 in Beutel and Weber (2025). The value of γ for the extended model is lower because fast traders' portfolio allocations are less sensitive to first-order beliefs and therefore one can have a lower risk aversion to rationalize actions. For both models, we estimate that $\beta_P \approx 0.64$, i.e., 10% higher trading price increases investors' expectations of final payoff by 6.4%.

To validate these parameter values, we use an untargeted moment motivated by Dávila and Parlatore (2025). They argue that price informativeness can be estimated with R^2 from regressing payoff on equilibrium price. Equation (5) shows that the R^2 in the regression of price $\tilde{r}_1$ on payoff $\tilde{r}_2$ is $B^2/\left(B^2 + C^2\sigma_\theta^2\right)$. In our data, we get $R^2 = 0.33$. When we apply the method developed in Dávila and Parlatore (2025) to S&P500 time series, we find $R^2 = 0.31$, which is close to our estimate based on ω_F and ω_H.[16]

We can also modify our model to assess the importance of our assumptions about the information structure. In the spirit of Bacchetta and Van Wincoop (2008) and Barillas and Nimark (2017), we can test the impact of HOB by comparing the model-implied market outcome when investors think that they have common beliefs. That is, upon entering t_1, rational investors believe

[15] In this exercise, we need to bring in additional information. For example, we can use our survey to quantify the share of fast traders. However, some information has to come from external sources. For instance, because the experiment does not directly identify the unconditional variance of the payoff, the data only pin down variance reductions rather than the level of uncertainty itself. We therefore follow Giglio et al. (2021) and Beutel and Weber (2025) and set $\hat{\sigma}^2 = 0.04$, corresponding to an annual stock market volatility of 20% in the U.S. This allows us to further recover the level of the signal variances.

[16] See Online Appendix Section III for estimation details.

$E_i[\,\bar{E}[\tilde{r}_2] \mid s_i, s_{im}\,] = E_i[\,\tilde{r}_2 \mid s_i, s_{im}\,]$. In this case, investors no longer have strategic inference about noise traders and thus $E_i[\,\theta \mid s_i, s_{im}\,] = 0$.

When investors are uncertain about others' beliefs, they optimally place more weight on prices as a public signal and discount their private signals (Angeletos and Pavan 2007). Under common knowledge, investors rely relatively more on private information and learn less from prices, which lowers β_P. From equation (5), price is an unbiased signal of future payoffs, weaker learning from prices reduces the extent to which trading aggregates fundamental information. Less informative prices induce weaker learning from prices, which further decreases price informativeness. Under common knowledge, this feedback mechanism weakens, so prices load more on noise and less on fundamentals (i.e., a lower B and a higher C). As a result, β_P declines from 0.64 to 0.16, and price informativeness falls sharply from 0.33 to 0.07.

This decline in price informativeness is economically important: financial markets aggregate dispersed information, and prices serve as a key public signal guiding real decisions. For example, Chen et al. (2007) document that managers tend to infer information from stock prices and incorporating it into investment decisions. Therefore, the sharp decline in price informativeness under common knowledge would materially reduce firms' and households' ability to infer fundamentals and allocate resources efficiently.

VI. Conclusion

Economists have long been interested in understanding higher-order beliefs (HOB) and their effects on economic agents' choices. While the narratives are compelling and widely accepted (recall Keynes's famous interpretation of the stock market), hard evidence has been scarce for real-life choices. This paucity reflects difficulties in measuring HOB, HOB's endogenous nature, and our limited ability to link beliefs to decisions. We combine a customized survey and an RCT to address these challenges in the context of U.S. retail investors' portfolio allocations.

We find that investors' HOB about stock market returns are correlated with but distinct from their first-order beliefs (FOB). Furthermore, the differences between the two vary systematically according to investor characteristics. When we use information treatments in the RCT to create exogenous differential variations in FOB and HOB, we find that these beliefs have a causal effect on portfolio allocation. Specifically, an exogenous increase in first-order beliefs increases the portfolio share allocated to the stock market (i.e., risky assets), whereas an exogenous increase in HOB reduces it. This key result is consistent with the view that retail investors, ceteris paribus, engage in contrarian trading.

Our findings suggest several avenues for future research. For example, one may employ a much larger sample of investors to study responses with more detailed breakdowns by asset class, maturity, and so on, or by investor type. While we examine allocations on the asset side, we anticipate that investors can adjust their behavior on the liability side too. Furthermore, we do not study how beliefs about the stock market translate into consumption, labor supply, and other "real" choices made by households. One may also be interested in utilizing survey data enhanced by experimental variation to estimate the structural models of belief formation and investment behavior. Although we estimate the total effect of FOB and HOB beliefs on portfolio allocations, future work could explore channels behind the total effects in more detail by introducing additional information treatments. We hope that future studies address these important questions.

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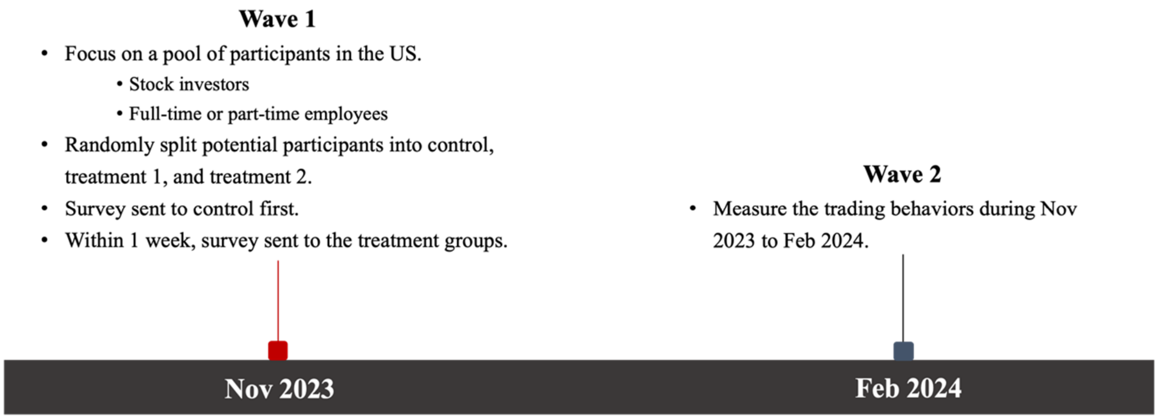
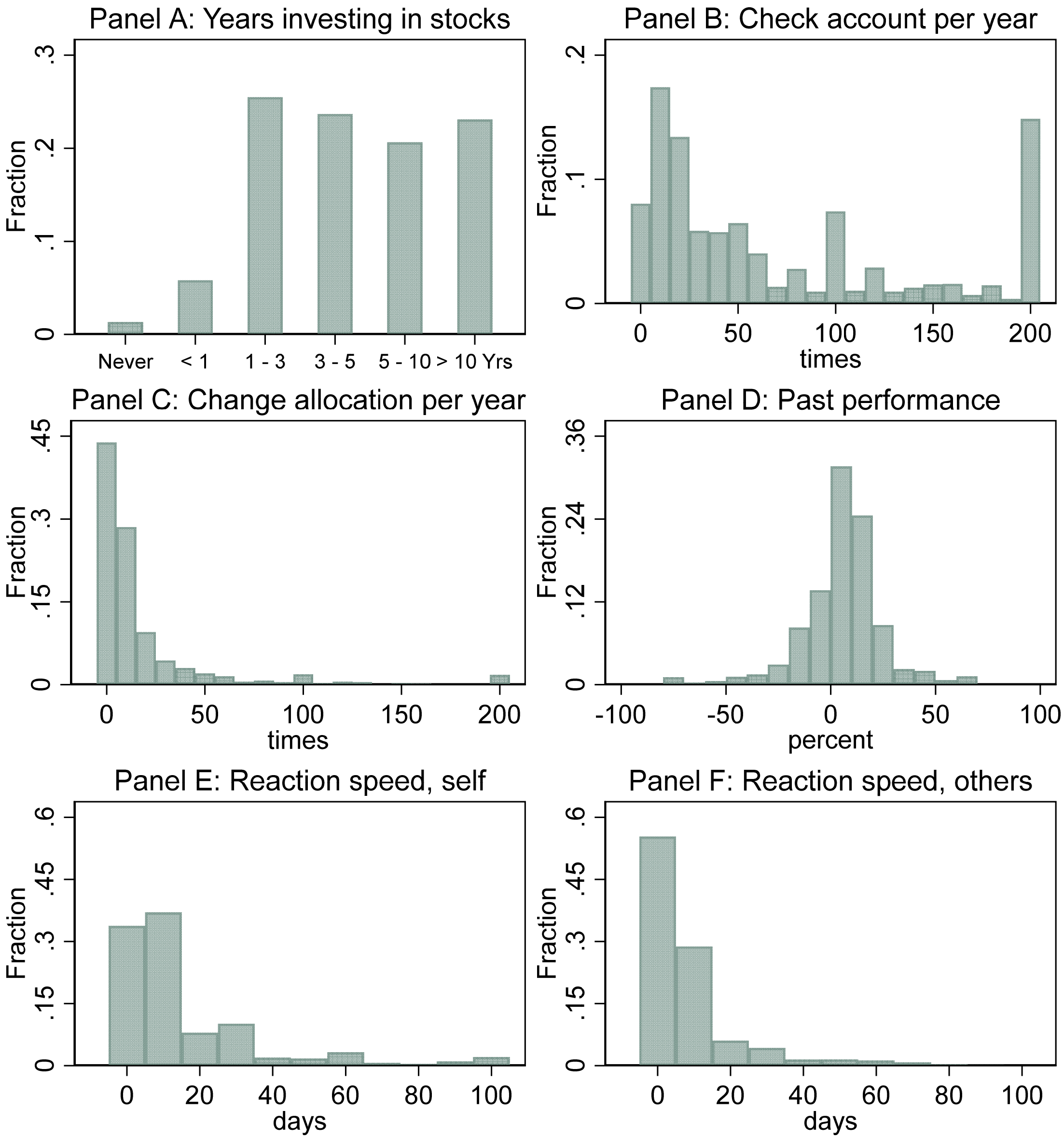
Figure 1: Timeline of the Experimental Design



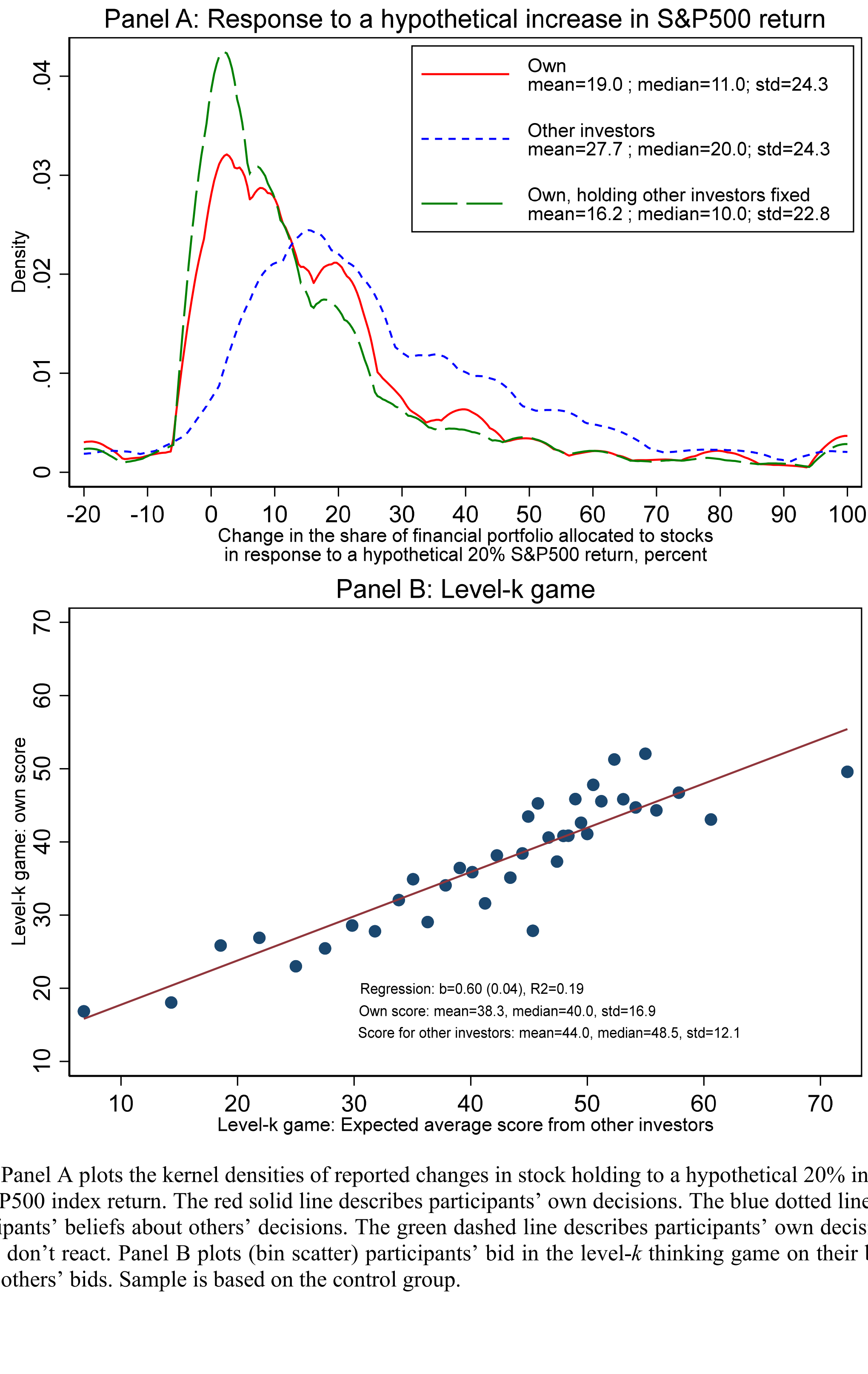
Note: this figure plots the timeline of the experimental design.

Figure 2. Participants Characteristics



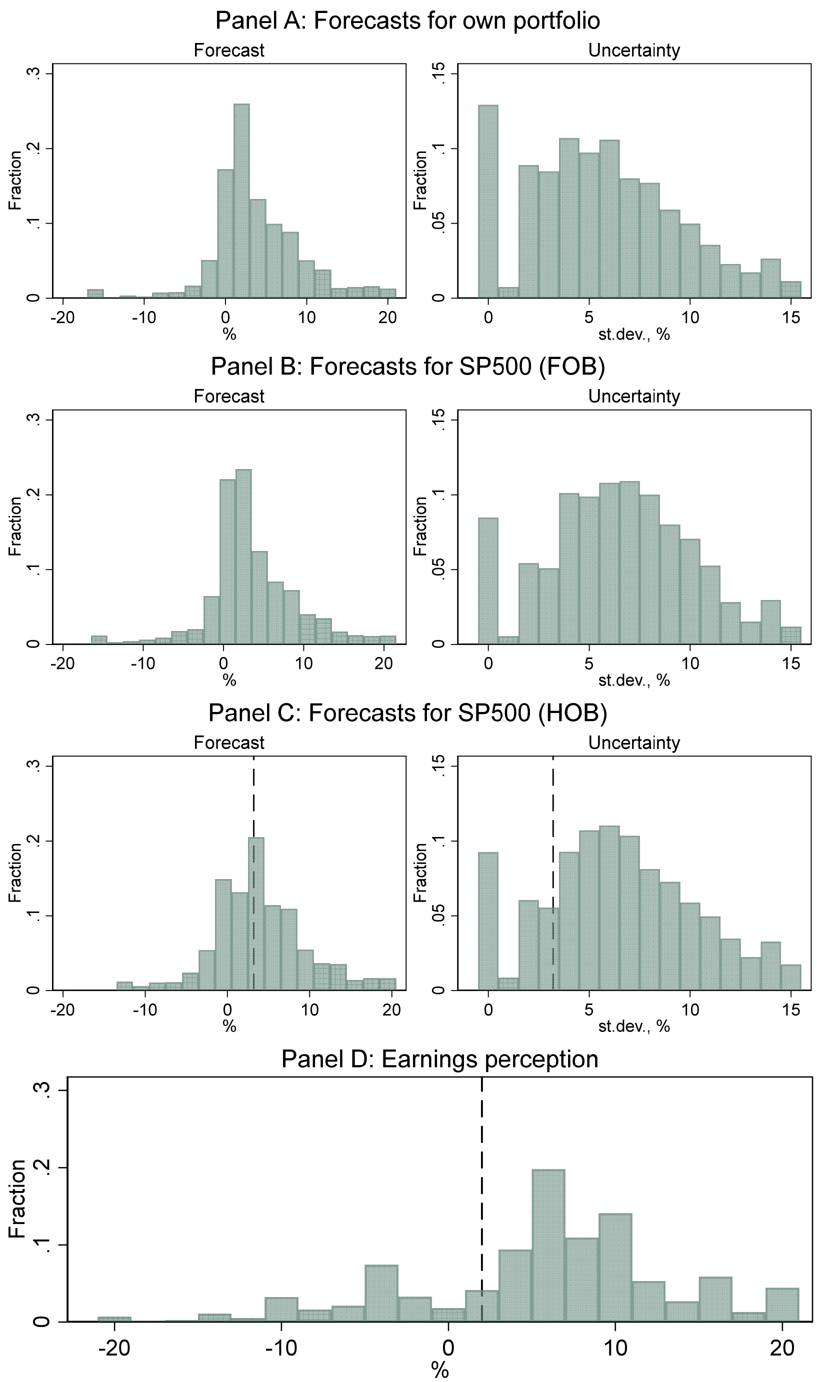
Note: Panel A plots the number of years the investors have been investing in the stock market. Panel B plots the number of times the investors check their balances in the stock market every year. Panel C plots the number of times the investors change their allocations in the stock market. Panel D plots the return of the investors' portfolio over the 12 months before taking the first wave of surveys. Panel E plots the number of days for the participants to incorporate news into trading decisions. Panel F plots the number of days the participants believe that other investors need to incorporate news into trading decisions.

Figure 3. Strategic Behaviors in Trading



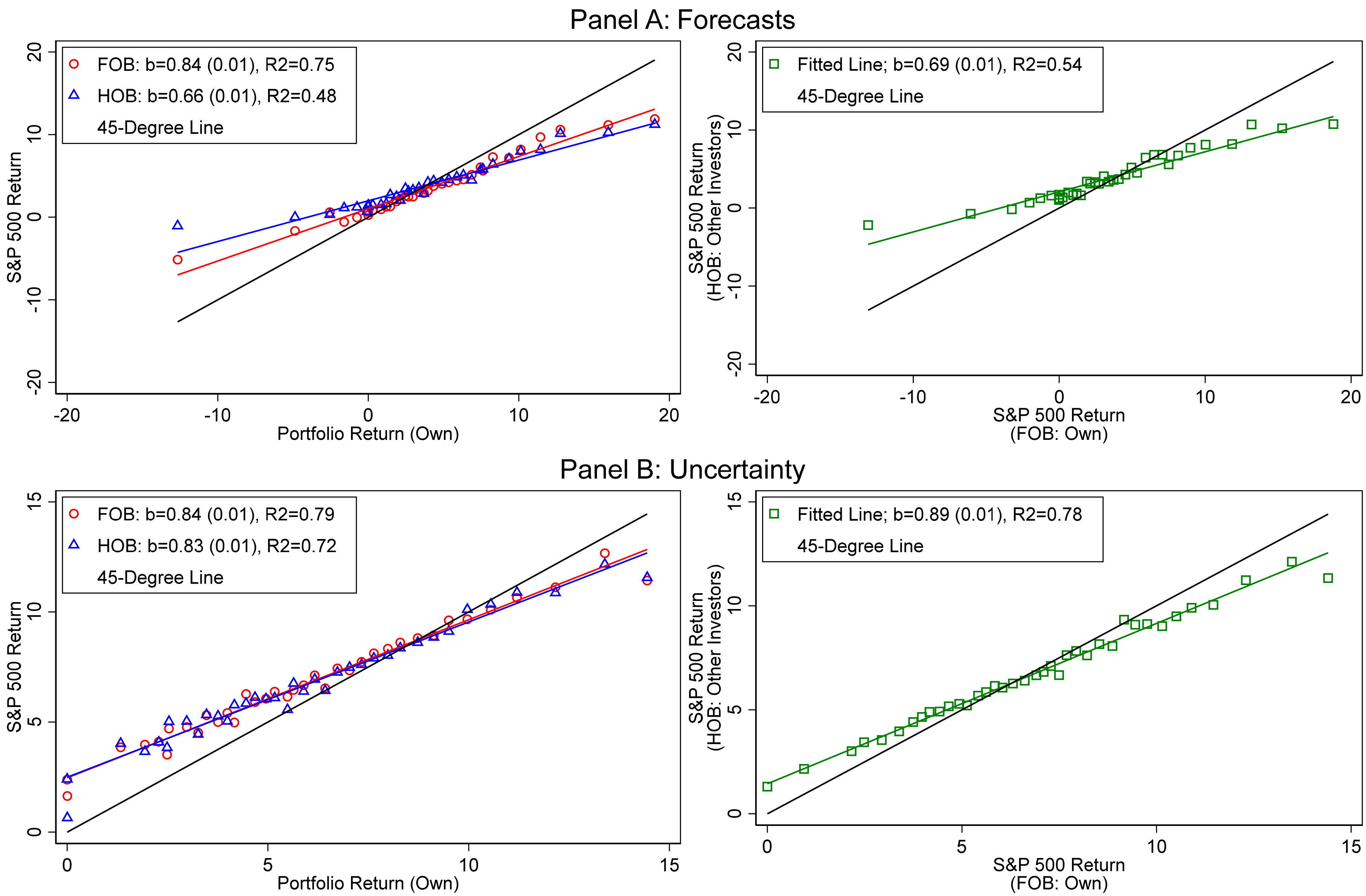
Note: Panel A plots the kernel densities of reported changes in stock holding to a hypothetical 20% increase in S&P500 index return. The red solid line describes participants' own decisions. The blue dotted line gives participants' beliefs about others' decisions. The green dashed line describes participants' own decisions if others don't react. Panel B plots (bin scatter) participants' bid in the level-*k* thinking game on their beliefs about others' bids. Sample is based on the control group.

Figure 4. Distribution of Expectations and Perceptions



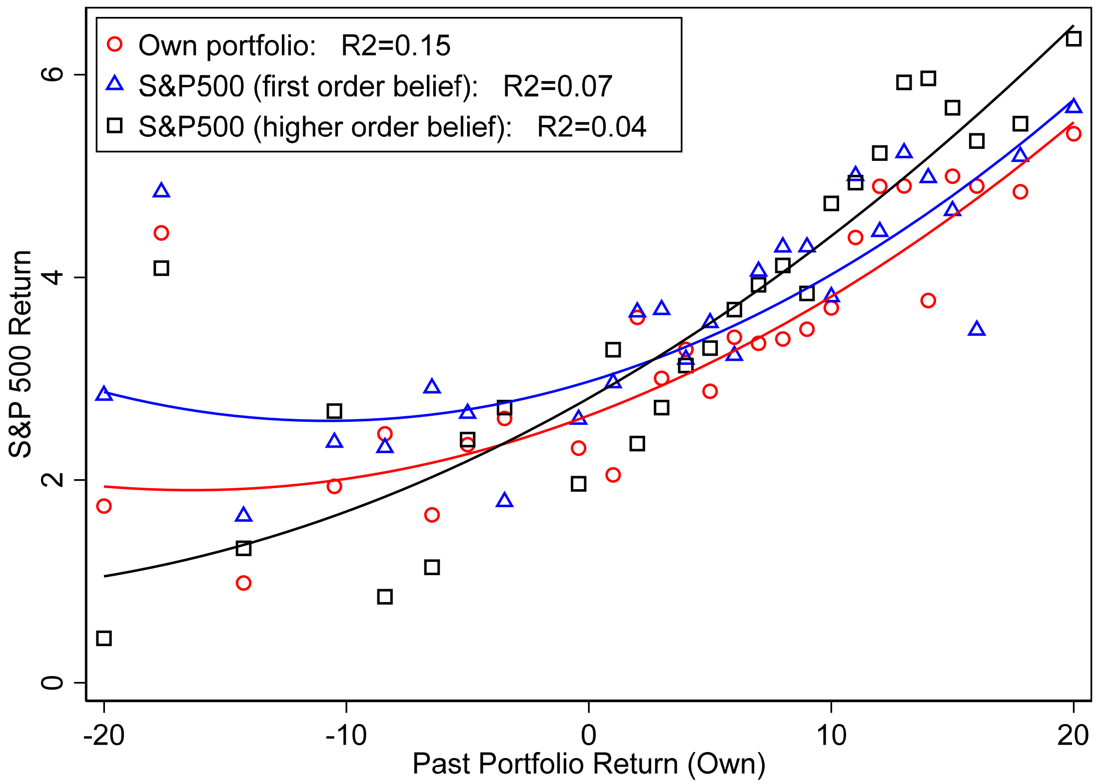
Note: Panels A, B, and C plot the histograms of participants' prior beliefs about future returns about own portfolio, the S&P500 index, and others' beliefs about that of the S&P500 index. The left column gives the implied expectations, and the right column gives the implied standard deviations. Panel D shows the prior perception about the past 12-month earnings growth of the firms listed on S&P500 index. The vertical dashed lines represent the true values or values provided to the treatment groups.

Figure 5. Comovement of Expectations



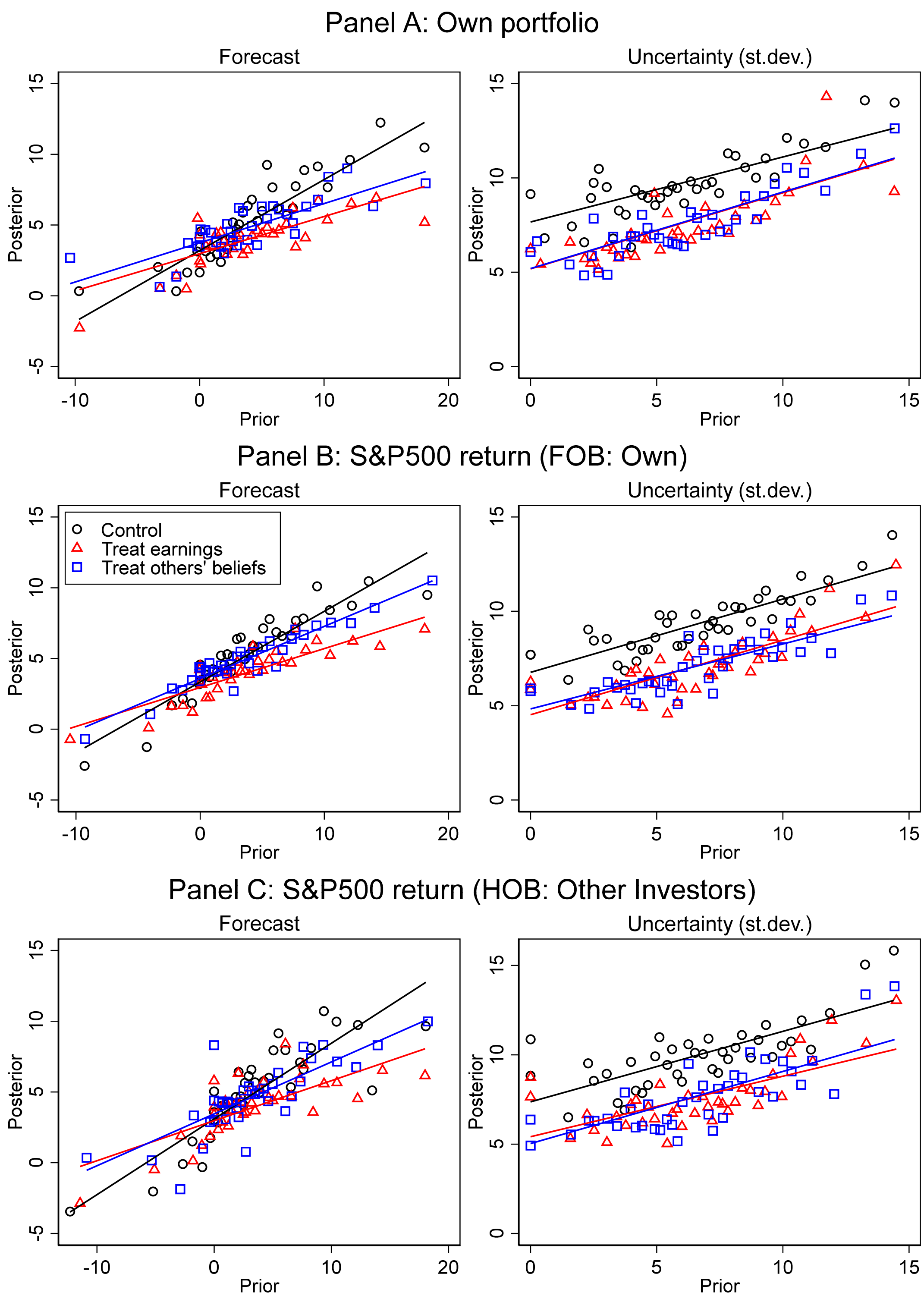
Note: This figure gives binned scatter plots among beliefs. Panels A and B respectively present results for expectations and uncertainty. The left column plots FOB and HOB about future S&P500 return on own portfolio returns. The right column plots HOB about S&P500 return on FOB about S&P500 return.

Figure 6. Past and Expected Returns



Note: The binscatter plots return expectations on past portfolio returns. The red line, blue line, and black line are respectively future return expectations of own portfolio, FOB, and HOB. The x-axis is the portfolio return over the past 12 months.

Figure 7. Binned Scatter Plots: Posteriors vs Priors by Treatment Group



Note: This figure gives the binned scatter plots of posterior beliefs on prior beliefs. Panels A, B, and C give results respectively for own portfolio return, FOB, and HOB. The left and right columns respectively depict expectations and implied standard deviations.

Table 1: Summary Statistics

	Mean	SD	Mean	SD	Mean	SD	*p*-values	Mean	SD	*p*-values
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: All		Panel B: Control		Panel C: Treatment 1			Panel D: Treatment 2		
Age	37.26	11.30	37.28	10.89	37.61	11.54	0.49	36.88	11.46	0.41
Female	0.41	0.49	0.39	0.49	0.42	0.49	0.16	0.41	0.49	0.50
Wealth (K)	317.21	590.81	336.54	638.19	312.95	572.53	0.34	301.97	558.30	0.17
Income (K)	73.14	64.41	73.11	62.31	74.40	69.30	0.64	71.91	61.33	0.66
Past Return	4.06	19.56	4.22	18.72	4.21	20.24	0.99	3.73	19.68	0.55
Financial%	0.49	0.32	0.50	0.32	0.48	0.32	0.19	0.49	0.32	0.47
Stock%	0.27	0.29	0.27	0.28	0.27	0.29	0.77	0.27	0.29	0.80
ETF%	0.18	0.25	0.18	0.25	0.17	0.25	0.25	0.17	0.24	0.28
Derivative%	0.02	0.06	0.02	0.06	0.02	0.06	0.77	0.02	0.06	0.17
Bond%	0.35	0.32	0.34	0.31	0.35	0.33	0.32	0.35	0.32	0.25
Pension%	0.13	0.26	0.12	0.25	0.14	0.27	0.24	0.13	0.26	0.38
Risky_F%	0.47	0.33	0.48	0.32	0.46	0.33	0.24	0.46	0.33	0.20
Risky%	0.23	0.23	0.24	0.24	0.22	0.23	0.05	0.22	0.23	0.07
First-order beliefs										
E[Return]	3.68	5.50	3.62	5.50	3.85	5.43	0.31	3.56	5.57	0.80
E[Δ S&P500]	3.36	5.61	3.24	5.73	3.58	5.62	0.14	3.27	5.46	0.90
SD[Return]	5.61	3.76	5.77	3.70	5.57	3.82	0.21	5.50	3.75	0.09
SD[Δ S&P500]	6.50	3.58	6.66	3.54	6.43	3.62	0.13	6.41	3.57	0.10
Higher-order beliefs										
E[Δ S&P500]	3.81	5.62	3.69	5.64	3.91	5.65	0.34	3.81	5.57	0.60
SD[Δ S&P500]	6.45	3.79	6.57	3.71	6.42	3.79	0.36	6.37	3.86	0.22
N	3,372		1,128		1,128			1,116		

Note: Wealth is the total level of current wealth (excluding debt). Financial% is the percent of total wealth in the financial market. Stock%, ETF%, Derivative%, Bond%, Pension% are respectively the percent of total financial wealth allocated in these types of assets. Return is the participants' financial portfolio returns over the 12 months before taking the first surveys. For first-order beliefs, E[Return] (SD[Return]) and E[Δ S&P500] (SD[Δ S&P500]) are respectively the expected values (standard deviations) of subjective expectations about the returns on their own portfolios and the S&P 500 index. For higher-order beliefs, E[Δ S&P500] (SD[Δ S&P500]) is the expected values (standard deviations) of subjective expectations about others' beliefs about the returns of the S&P 500 index.

Table 2: Determinants of Beliefs

	Expectations				Uncertainty			
	FOB	HOB	HOB-FOB	|HOB-FOB|	FOB	HOB	HOB-FOB	|HOB-FOB|
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past Return	0.05***	0.04***	-0.02***	-0.01***	0.00	0.01	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience	-0.09***	-0.05**	0.02	0.00	0.01	0.03	-0.01	0.01
	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
# Trades	0.04**	0.08***	0.03*	0.03**	0.04**	0.03*	-0.01	0.01*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Bid in level-*k* thinking game	0.00	0.00	0.01*	0.01***	0.00	-0.00	0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Young	-0.51***	-0.91***	-0.36***	-0.05	0.18	0.11	0.09	0.04
	(0.14)	(0.17)	(0.12)	(0.09)	(0.13)	(0.13)	(0.06)	(0.05)
Female	-0.29**	0.17	0.42***	0.02	-0.72***	-0.80***	0.03	-0.05
	(0.12)	(0.14)	(0.11)	(0.08)	(0.11)	(0.12)	(0.06)	(0.04)
Full-time	-0.32*	0.02	0.03	-0.02	-0.01	-0.27*	0.07	0.12**
	(0.16)	(0.20)	(0.14)	(0.11)	(0.15)	(0.15)	(0.07)	(0.05)
College	-0.17	0.20	0.16	-0.07	0.24*	0.33**	-0.02	0.07
	(0.15)	(0.17)	(0.13)	(0.10)	(0.13)	(0.14)	(0.06)	(0.05)
log Wealth	-0.06	-0.06	-0.01	-0.05*	0.08**	0.04	0.03	-0.04***
	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.02)	(0.01)
log Income	0.03	-0.27***	-0.13**	-0.04	0.13**	0.16**	-0.04	0.03
	(0.07)	(0.08)	(0.06)	(0.05)	(0.07)	(0.07)	(0.03)	(0.02)
N	3,336	3,368	3,303	3,300	3,368	3,368	3,306	3,303
R^2	0.06	0.04	0.02	0.01	0.03	0.03	0.00	0.01

Note: For columns (1) to (4), the left hand variables are the first moments of prior beliefs. For columns (5) to (8), the left hand variables are the second moments of beliefs. Young is an indicator for age below the sample median. Full-time is an indicator for full-time employees. Experience is the number of years the participants have been investing in the stock market. # Trades is the number of trades the participants make every year. Estimation is based on Huber robust regressions. All columns include ethnicity dummies. Expectations and uncertainty for FOB and HOB are winsorized at 1% and 99% levels. Robust standard errors are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3: Beliefs and Risky Asset Holdings

	(1)	(2)	(3)	(4)
		Panel A: Risky%		
E[Port]	0.16***			0.22***
	(0.05)			(0.06)
FOB		0.06		-0.02
		(0.04)		(0.06)
HOB			-0.02	-0.11**
			(0.04)	(0.05)
Controls	Yes	Yes	Yes	Yes
N	3,322	3,322	3,322	3,318
R^2	0.09	0.09	0.09	0.09
		Panel B: Risky_F%		
E[Port]	0.38***			0.17
	(0.10)			(0.13)
FOB		0.45***		0.37***
		(0.10)		(0.13)
HOB			0.21**	-0.05
			(0.10)	(0.12)
Controls	Yes	Yes	Yes	Yes
N	3,372	3,372	3,372	3,372
R^2	0.06	0.07	0.06	0.07
		Panel C: $\text{Risky}_{\text{no.der}}\%$		
E[Port]	0.14***			0.22***
	(0.04)			(0.06)
FOB		0.04		-0.02
		(0.04)		(0.06)
HOB			-0.03	-0.11**
			(0.04)	(0.05)
Controls	Yes	Yes	Yes	Yes
N	3,302	3,305	3,303	3,318
R^2	0.09	0.08	0.08	0.09

Note: Risky% is defined as the product of share of financial assets and share of financial assets invested in single stocks, ETF and index funds, and financial derivatives. Risky_F% is the share of financial assets invested in single stocks, ETF and index funds, and financial derivatives. $\text{Risky}_{\text{no.der}}\%$ is Risky% excluding financial derivative. Results are based on data in wave 1. Controls include sex, indicator for being younger than the sample median, indicator for full-time employees, indicator for having at least college degree, ethnic group fixed effects, log total wealth. Estimation is based on Huber robust regressions. E[Port], FOB, and HOB are winsorized at 1% and 99% levels. Robust standard errors are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 4: The Effects of Information Treatments on Beliefs

	E[Port]	E[Port]	FOB	FOB	HOB	HOB
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Expectations					
T1	-1.08***	-0.53**	-1.18***	-0.39**	-1.21***	-0.38
	(0.18)	(0.23)	(0.15)	(0.19)	(0.19)	(0.24)
T2	-0.46**	-0.00	-0.22	0.25	-1.37***	-0.00
	(0.18)	(0.23)	(0.16)	(0.19)	(0.18)	(0.23)
Prior		0.56***		0.50***		0.57***
		(0.03)		(0.03)		(0.03)
T1 × Prior		-0.18***		-0.23***		-0.22***
		(0.04)		(0.04)		(0.04)
T2 × Prior		-0.15***		-0.13***		-0.35***
		(0.04)		(0.04)		(0.04)
Controls	No	No	No	No	No	No
N	3,173	3,172	3,164	3,173	3,166	3,180
R^2	0.01	0.22	0.02	0.23	0.02	0.18
	Panel B: Uncertainty					
T1	-2.03***	-1.52***	-2.36***	-2.25***	-2.66***	-2.01***
	(0.19)	(0.32)	(0.17)	(0.36)	(0.20)	(0.39)
T2	-2.08***	-1.46***	-2.36***	-1.93***	-2.83***	-1.77***
	(0.19)	(0.32)	(0.17)	(0.36)	(0.20)	(0.38)
Prior		0.52***		0.39***		0.55***
		(0.04)		(0.04)		(0.04)
T1 × Prior		-0.06		0.01		-0.09
		(0.05)		(0.05)		(0.06)
T2 × Prior		-0.07		-0.04		-0.16***
		(0.05)		(0.05)		(0.05)
Controls	No	No	No	No	No	No
N	3,258	3,229	3,279	3,273	3,297	3,276
R^2	0.04	0.18	0.06	0.14	0.06	0.17

Note: The dependent variables for Panels A and B are respectively the implied posterior expectations and standard deviations. Prior for columns (1) and (2) is investors' prior beliefs about future portfolio return; for columns (3) and (4), it is the investors' prior expectations about the FOB on S&P 500 index return; for columns (5) and (6), it is investors' prior expectations about the HOB on S&P 500 index return. T1 is an indicator for receiving treatment 1, and T2 is an indicator for receiving treatment 2. Estimation is based on Huber robust regressions. E[Port], FOB, and HOB are winsorized at 1% and 99% levels. Robust standard errors are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 5: The Effects of Beliefs on Risky Asset Holdings

	Risky%	Risky%	Risky%	Risky_F%	$Risky_{w.pen}$%	$Risky_{no.der}$%
	(1)	(2)	(3)	(4)	(5)	(6)
FOB	0.23		1.46**	2.59**	1.28*	1.35*
	(0.54)		(0.71)	(1.18)	(0.71)	(0.70)
HOB		-0.58	-1.42***	-1.84**	-1.38**	-1.43***
		(0.40)	(0.55)	(0.87)	(0.55)	(0.54)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1,987	1,990	1,989	1,988	1,989	1,990
	First-stage *F*-stats					
FOB	18.78		19.34	18.88	19.34	19.45
HOB		19.99	19.96	20.53	19.96	19.98
KP Wald rK			11.02	11.24	11.02	11.02

Note: The table reports IV estimates for equations (12a) and (12b). Risky_F% is the share of financial assets invested in single stocks, ETF and index funds, and financial derivatives. Risky% is the product of Risky_F% and the share of financial assets. $Risky_{no.der}$% is Risky% excluding financial derivatives. $Risky_{w.pen}$% is Risky% including equity allocated through pension. All dependent variables are from the second wave. Controls are all pre-experiment and include prior expectations, pre-experiment risky asset allocations, sex, age, indicator for full-time employees, indicator for having at least college degree, ethnic group fixed effects, implied prior return volatilities, reaction speeds, log income, and portfolio returns. Outliers and influential observations are identified and removed according to the procedure described in Coibion et al. (2023). FOB and HOB are winsorized at 1% and 99% levels. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 6: The Effects of Beliefs on Risky Asset Holdings – Other Specifications

	Risky%	Risky%	Risky_F%	Risky_F%	$Risky_{w.pen}$%	$Risky_{w.pen}$%
	(1)	(2)	(3)	(4)	(5)	(6)
FOB	1.66**	1.35*	2.35**	3.89	1.47**	1.27*
	(0.74)	(0.75)	(1.19)	(2.81)	(0.75)	(0.76)
HOB	-1.59***	-1.04	-2.03**	-2.36	-1.54**	-1.03
	(0.58)	(0.66)	(0.93)	(2.50)	(0.59)	(0.68)
SD(FOB)	0.00	-0.04	0.00	-0.91	0.00	-0.07
	(0.00)	(0.30)	(0.00)	(1.26)	(0.00)	(0.30)
SD(HOB)	-0.00	0.18	-0.00	0.42	-0.00	0.14
	(0.00)	(0.26)	(0.00)	(0.93)	(0.00)	(0.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1,989	1,944	1,989	1,944	1,989	1,944
	First-stage *F*-stats					
FOB	19.69	14.35	19.69	14.51	19.69	14.35
HOB	18.71	12.40	18.71	12.44	18.71	12.40
SD(FOB)		14.67		14.65		14.67
SD(HOB)		15.97		15.83		15.97
KP Wald rK	10.78	0.12	10.78	0.12	10.78	0.12

Note: The table reports IV estimates for augmented equations (12a) and (12b). SD(FOB) and SD(HOB) are respectively the implied posterior standard deviations of FOB and HOB. In the odd columns, SD(FOB) and SD(HOB) are included as exogenous controls. In the even columns, SD(FOB) and SD(HOB) are also treated as endogenous variables. Outliers and influential observations are identified and removed according to the procedure described in Coibion et al. (2023). FOB, HOB, SD(FOB), and SD(HOB) are winsorized at 1% and 99% levels. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 7: The Effects of Beliefs on Other Financial Assets

	log (Wealth)	Financial%	Bonds%	Pension%	(Bonds+Pension)%
	(1)	(2)	(3)	(4)	(5)
FOB	3.63	0.13	-1.35	-0.80	-2.56**
	(6.19)	(1.09)	(1.03)	(1.05)	(1.22)
HOB	2.18	-0.22	1.13	0.87	1.91**
	(4.60)	(0.88)	(0.80)	(0.83)	(0.91)
Controls	Yes	Yes	Yes	Yes	Yes
N	1,988	1,989	1,988	1,990	1,989
	First-stage *F*-stats				
FOB	19.05	19.41	19.18	19.45	19.23
HOB	19.97	19.44	19.96	19.98	20.54
KP Wald rK	11.01	10.77	11.18	11.02	11.43

Note: The table reports IV estimates for equations (12a) and (12b). Financial% is the share of total wealth in the financial sector. Bonds% and Pension% are respectively the share of total wealth invested in bonds and pension. All dependent variables are from the second wave. Controls are all pre-experiment and include prior expectations, pre-experiment risky asset allocation, sex, age, indicator for full-time employees, indicator for having at least college degree, ethnic group fixed effects, implied prior return volatilities, reaction speeds, log income, and portfolio returns. Outliers and influential observations are identified and removed according to the procedure described in Coibion et al. (2023). FOB and HOB are winsorized at 1% and 99% levels. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 8: Heterogeneity in Trading Decisions

	Age		Sex		College		Wealth		Income	
	Young	Old	Female	Male	Not Below	Below	Less	More	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FOB	1.21	1.74	0.75	3.38***	0.97	2.14	2.00*	1.04	1.71*	0.43
	(0.90)	(1.12)	(1.04)	(1.21)	(0.84)	(1.34)	(1.12)	(0.91)	(0.91)	(1.06)
HOB	-1.53**	-1.49*	-1.68*	-1.93**	-0.80	-2.93**	-2.32**	-0.75	-2.18***	0.10
	(0.69)	(0.89)	(0.93)	(0.83)	(0.55)	(1.32)	(1.07)	(0.56)	(0.73)	(0.68)
	First-Stage *F*-Stats									
FOB	12.24	8.25	12.02	8.28	11.84	8.30	13.57	7.25	13.57	6.82
HOB	12.37	9.41	9.14	12.30	16.11	5.68	9.29	12.70	12.55	9.05
KP Wald rK	7.47	4.21	4.46	5.33	9.50	2.64	3.56	6.29	6.18	5.53
N	1,202	786	767	1,222	1,439	549	971	1,017	1,189	799

	Reaction Speed		# Checks		# Trades		Past Return		Experience	
	Faster	Slower	Less	More	Less	More	Low	High	Less	More
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
FOB	1.36	1.63*	-0.12	2.27**	1.11	2.01**	1.68*	1.68	1.53*	0.44
	(1.24)	(0.89)	(0.98)	(1.08)	(0.89)	(1.02)	(0.97)	(1.18)	(0.90)	(0.93)
HOB	-0.00	-2.10***	-0.76	-1.54*	-1.02	-2.02**	-1.33*	-1.65*	-1.51*	-0.96
	(0.83)	(0.70)	(0.73)	(0.80)	(0.76)	(0.81)	(0.73)	(0.89)	(0.79)	(0.70)
	First-Stage *F*-Stats									
FOB	5.09	15.08	9.77	8.08	13.52	7.94	7.68	11.93	13.65	8.86
HOB	5.90	14.92	11.08	9.78	10.37	10.00	9.13	12.18	10.29	10.84
KP Wald rK	4.92	7.30	6.87	5.23	7.27	4.38	5.66	4.91	5.34	6.41
N	648	1,340	1,011	977	1,099	889	1,046	943	978	1,010

Note: The table reports IV estimates for equations (12a) and (12b). The left-hand side variables are Risky%. Sample split by Age, Wealth, Income, # Checks, # Trades, Past Return, and Experience are based on the pre-experiment sample median. Participants in the Faster group of Reaction Speed are those whose reaction speed to financial news is less or equal to that of others. Outliers and influential observations are identified and removed according to the procedure described in Coibion et al. (2023). FOB and HOB are winsorized at 1% and 99% levels. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$