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 returns are correlated with but distinct from their first-order beliefs. Furthermore, the differences between the two vary systematically according to 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 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 describes 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 contrarian is sensitive to assumptions about how investors form beliefs, market structures, etc.[1] To resolve this theoretical ambiguity, empirical evidence is needed to understand how beliefs about other investors—that is, higher-order beliefs (HOB)—translate into action. The main challenges in this context are *i*) the measurement of higher-order beliefs and *ii*) the identification of exogenous variation in these beliefs so that causal relationships between higher-order beliefs and actions can be established. We thus used a randomized controlled trial (RCT) implemented in a survey of U.S. retail investors to address these challenges. 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 representative sample of U.S. investors 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 the respondents with a series of questions aimed at measuring their subjective beliefs about the future returns of their portfolios and the market (the S&P 500). Specifically, we asked respondents to assign probabilities to various outcomes ("bins") so that we can construct implied means and uncertainty (standard deviation) for future returns. To this end, we elicit not only investors' own beliefs (i.e., first-order beliefs (FOB)) about market returns 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.

[1] For example, De Long et al. (1990), 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.

Taking these measures as prior beliefs, 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 investors' beliefs regarding the future payoff of the S&P 500 index. These two information treatments were designed to create different changes in investors' first- and higher-order beliefs about future stock market returns. 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 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 allocation. 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 (2024) 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 provided the quantitative measures for 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 2023, Enke and Graeber 2023) or lab subjects (Frydman and Jin 2021; 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 exhaustive surveys of this study). Although this research agenda has traditionally relied on observational (survey) data, there is increasing emphasis on using hypothetical questions (vignettes) and 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. Our contribution to the literature involves shedding more light on the causal role of HOB and FOB in financial beliefs and choices.

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. At t_0, the price is set exogenously at P_0. We use lowercase $p_0 \equiv \log P_0$ to denote the log price. The asset has a total payoff of $p_2 \equiv \log P_2$ with $p_2 - p_0 \sim N(0, \sigma_0^2)$ at t_2. In addition, there is a risk-free asset with rate r_f set to zero without loss of generality. A continuum of investors with a mass of one has a total initial wealth of w_i. Investors start with homogeneous beliefs and hold the same portfolio shares in t_0. At t_1, investors decide what share of stock (x_i) to hold. Before making any trade, all investors receive signals about p_2. With subjective beliefs, they choose the optimal allocation by maximizing a CRRA utility. We denote the average share of holdings with $x = \int x_i \, di$. Following Grossman (1976) and Milgrom and Stokey (1982), we assume the aggregate demand $x \sim N(0, \sigma^2)$ so that the equilibrium prices in a noisy rational expectation equilibrium do not perfectly reveal average beliefs about p_2.[2]

[2] One justification for random total demand is noisy traders placing liquidity orders.

There are two types of investors. A fraction of α are "fast speculators" (A) who are over-confident, and the rest include "slow fundamental" traders (B). A reacts faster to news than B, and intends to take advantage of B's slow reaction speed. To characterize the heterogeneity in reaction speed, we further split t_1 into two sub-periods, $t_{1,1}$ and $t_{1,2}$. At the beginning of $t_{1,1}$, A receives signals about p_2 and forms subjective beliefs about p_2 after incorporating these signals. B cannot react until $t_{1,2}$. A speculates on the price at $t_{1,2}$, maximizing payoffs at $t_{1,2}$. At the beginning of $t_{1,2}$, B receives signals about p_2 and updates his beliefs about p_2. B chooses the holding level based on the subjective payoff p_2. Additionally, B observes $p_{1,2}$ and can infer p_2 from $p_{1,2}$.

To model the over-confidence of A, we assume that while all A members believe that they can rewind position in $t_{1,2}$, a random fraction $\tilde{\alpha}$ of A fail to realize their gains in $t_{1,2}$ and end up holding their asset until t_2. As in Eyster et al. (2019), A ignores the information contained in $p_{1,1}$. This is similar to the assumption that all investors in A believe they are the only investors who can react faster and trade in $t_{1,1}$.[3] The timeline of t_1 can be summarized as follows:

1. At the beginning of $t_{1,1}$, A receives two signals: one about p_2, the other about everyone else's average belief about p_2. Based on these two signals, A forms a posterior view about p_2.
2. In $t_{1,1}$, A speculates on the log equilibrium price $p_{1,2}$ at $t_{1,2}$ given subjective beliefs, and chooses the level of holding by maximizing utility over total wealth in $t_{1,2}$. In contrast, B holds zero dollars of the asset. The equilibrium price $P_{1,1}$ is realized.

[3] The main results would not change if we do not assume that *A* is "cursed" as in Eyster et al. (2019). However, making this assumption abstracts from beliefs higher than second order. Since we do not have a measure of third-order beliefs, we try to keep the model close to our data. In addition, most people are shown to have only one or two levels of reasonings (e.g., Nagel 1995, Camerer et al. 2004). Consistent with earlier studies, the average guess of a 2/3 guessing game in our sample is 42, and only around 10% of the answers are below 14.8, which is the value for engaging third-order reasoning. Hence, third-order or higher-order beliefs are unlikely to be relevant in practice for most people.

3. In $t_{1,2}$, a random $1 - \tilde{\alpha}$ of A sell their asset. In addition, B receives two signals: one about p_2, the other about everyone else's average belief about p_2. Based on these two signals, B forms a posterior view about p_2.
4. B chooses the holding level to maximize utility over subjective beliefs about p_2. In addition, B uses the posteriors from Stage 3 as priors and learns about others' valuations from $p_{1,2}$, which is the log of the noisy rational expectation equilibrium (REE) price at the end of t_1.

Below, we characterize investors' optimal behavior at time t_1. All proofs and derivations are provided in the Online Appendix.

A. Optimal asset holdings

We first solve for the optimal equity share the given beliefs and then derive each investor's subjective beliefs. Let R_{t+1} be investor i's final return of risky asset. For A in $t_{1,1}$, $R_{t+1} = P_{1,2}/P_{1,1} - 1$. For B in $t_{1,2}$, $R_{t+1} = P_2/P_{1,2} - 1$. We will guess and verify that $\log P_{1,1}$ and $\log P_{1,2}$ are normal. Consequently, given the trading prices, $r_{i,t+1}$ is normal.

Investors' utility over final wealth $\tilde{w}_i$ is

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

subject to wealth evolution

$$\tilde{w}_i = w_i(1 + x_i R_{t+1}).$$

When $x_i R_{t+1}$ is small, we can write $\tilde{w}_i = w_i \exp\{x_i r_{t+1}\}$ where $r_{t+1} = \log(1 + R_{t+1})$. The optimization problem for investor i yields

$$x_i = \frac{E_i[r_{t+1}]}{\gamma \sigma_i^2}.$$

where σ_i^2 is the conditional variance of r_{t+1}. The optimal portfolio share has the same expression as in the classic Merton (1969) model.

Note that we can rewrite this equation as

$$x_i = \frac{E_i[r_{t+1}] - p_0 + p_0}{\gamma \sigma_i^2} = \frac{E_i[\tilde{r}_{t+1}] - \tilde{r}_t}{\gamma \sigma_i^2}, \tag{1}$$

where $\tilde{r}_h = p_h - p_0$ is the log return from t_0 to t_h. Scaling prices by the price at t_0, which is set before investment decisions are made, is to match our experimental design. Since $\tilde{r}_h$ is perfectly correlated with log prices p_h, we call $\tilde{r}_h$ also as the price in period h.

Integrating both sides of (1) gives

$$\tilde{r}_t = \int \frac{\sigma_i^{-2}}{\int \sigma_i^{-2}\, di} E_i[\tilde{r}_{t+1}]\, di - \frac{\gamma\, x}{\int \sigma_i^{-2}\, di}\ . \qquad (2)$$

Hence, the equilibrium prices (scaled by p_0) is the subjective certainty-weighted average belief of all individuals minus the risk premium.

B. Subjective beliefs

We characterize investors' belief-updating processes and derive expressions for their beliefs. First, we solve for investors' beliefs about $\tilde{r}_2$ after receiving signals. Each investor i receives two signals: signal s_i about $\tilde{r}_2$ and signal s_{im} about the average belief $\bar{E}$. The first signal has the following structure: $s_i\ = \tilde{r}_2 + \nu_i$ where $\nu_i \sim N(0, \sigma_\nu^2)$ is the idiosyncratic noises.

Lemma 1: Average belief $\bar{E} \equiv \int E[\tilde{r}_2 | s_i, s_{im}]\, di$ *has the structure* $\bar{E} = \kappa_D \tilde{r}_2$*, where* $\kappa_D \in (0,1)$ *is a constant.*

Intuitively, given that beliefs are linear in future payoffs, the average belief is a linear function of the fundamental payoff $\tilde{r}_2$.[4]

It is convenient to assume that the signal about the average belief takes the form of $s_{im} = \kappa_D(\tilde{r}_2 + \eta_i)$ where $\eta_i \sim N\left(0, \sigma_\eta^2\right)$ is an idiosyncratic shock. This information structure leads to the following result.

Lemma 2: The subjective expectation of trader i's beliefs about P_2 *after receiving* s_i *and* s_{im} *is* $E[\tilde{r}_2 | s_i, s_{im}] = \kappa_s s_i + \kappa_{sm} s_{im}$ *, where* $\kappa_s \in (0,1)$ *and* $\kappa_{sm} \in (0,1)$ *are two constants.*

[4] This setting implies perfect correlation between first-order and high-order beliefs, which does not hold empirically. To break the perfect correlation, one can assume fixed total supply of the security, but a fraction of noisy traders who form expectations about P_2 that is uncorrelated with P_2. Then the random component in average expectations will give the same results but imperfect correlation between HOB and FOB if individuals have different beliefs about the average belief of the noisy traders.

Given Lemma 1 and Lemma 2, investor i's belief about the average belief is

$$E[\bar{E}|s_i, s_{im}] = \kappa_D \kappa_s s_i + \kappa_D \kappa_{sm} s_{im}. \tag{3}$$

Similar to subjective beliefs about future payoffs, subjective beliefs about equilibrium in the market are a linear combination of the two signals. Note that $E[\bar{E}|s_i, s_{im}]$ (i.e., HOB) increases in both signals and is correlated with $E[\tilde{r}_2|s_i, s_{im}]$ (i.e., FOB). Equation (3) and Lemma 2 also show that the weights in the signals are different for FOB and HOB. Thus, by providing agents with exogenous signals s_i and s_{im}, we can generate differential variations in FOB and HOB, allowing us to identify the causal effects of FOB and HOB.

C. Equilibrium prices

Because B is dormant and holds zero equity share at $t_{1,1}$, the total demand in the market at $t_{1,1}$ is

$$x = \alpha \frac{\bar{E}\left[\tilde{r}_{1,2}|s_i, s_{im}\right] - \tilde{r}_{1,1}}{\gamma V_A}, \tag{4}$$

where $V_A \equiv var(\tilde{r}_{1,2}|s_i, s_{im})$ is the subjective uncertainty about $\tilde{r}_{1,2}$ given s_i and s_{im}. Denote $\alpha_1 \equiv \tilde{\alpha}\alpha$ as the mass of investors who fail to sell their asset in $t_{1,2}$. At $t_{1,2}$, those of A who can rewind their position hold zero assets. Therefore, the total demand at $t_{1,2}$ is

$$x = \alpha_1 \frac{\bar{E}\left[\tilde{r}_{1,2}|s_i, s_{im}\right] - \tilde{r}_{1,1}}{\gamma V_A} + (1-\alpha)\frac{\bar{E}\left[\tilde{r}_2|s_i, s_{im}, \tilde{r}_{1,2}\right] - \tilde{r}_{1,2}}{\gamma V_B}. \tag{5}$$

where $V_B \equiv var(\tilde{r}_2|s_i, s_{im}, \tilde{r}_{1,2})$ is the subjective uncertainty about $\tilde{r}_2$ given signals s_i and s_{im} and the observed return $\tilde{r}_{1,2}$. The first term on the right-hand side of equation (5) is the holdings of A that fails to sell, and the second term is the holdings of B.[5] Using equations (4) and (5) and B's learning from $\tilde{r}_{1,2}$, we have the following Lemma:

Lemma 3: Equilibrium prices in the two sub-periods are

$$\tilde{r}_{1,1} = \frac{1-\beta_P \kappa_D}{1-\beta_P}\kappa_D \bar{E}[\tilde{r}_2|s_i, s_{im}] - \frac{\gamma V_A}{\alpha}x \tag{6a}$$

[5] Note that $p_{1,1}$ does not enter $B's$ information set. This is because $p_{1,1}$ is a function of the average expectations of $p_{1,2}$. Since we assume x is fixed over $t_{1,1}$ and $t_{1,2}$, $p_{1,1}$ does not offer additional information conditional on $p_{1,2}$.

$$\tilde{r}_{1,2} = \frac{1-\beta_P\kappa_D}{1-\beta_P}\bar{E}[\tilde{r}_2|s_i, s_{im}] - \frac{(1-\tilde{\alpha})\,\gamma\, V_B}{(1-\alpha)(1-\beta_P)}x \qquad (6b)$$

where β_P *is a constant with* $0 < \beta_P < \kappa_D < 1$.

From equations (6a) and (6b), both prices are functions of the average beliefs about the final payoffs and risk premia.

D. Portfolio decisions

We study the average investor's optimal holdings at time t_1. The average investor's holding is

$$x_i = \frac{\alpha_1}{\gamma\, V_A}\left(E\left[\tilde{r}_{1,2}|s_i, s_{im}\right] - \tilde{r}_{1,1}\right) + \frac{1-\alpha}{\gamma\, V_B}\left(E\left[\tilde{r}_2|s_i, s_{im}, \tilde{r}_{1,2}\right] - \tilde{r}_{1,2}\right). \qquad (7)$$

Note that those of A who can sell their assets at $t_{1,2}$ have a net holding of zero across t_1. Using equation (6), we can re-write equation (7) as:

$$x_i = \omega_0 + \omega_F E[\tilde{r}_2|s_i, s_{im}] + \omega_H E[\bar{E}[\tilde{r}_2]|s_i, s_{im}], \qquad (8)$$

where $\omega_0 = -\frac{\alpha_1}{\gamma V_A}\tilde{r}_{1,1} - \frac{1-\alpha}{\gamma V_B}(1-\beta_P)\tilde{r}_{1,2}$, $\omega_F = \frac{1-\alpha}{\gamma V_B}$, and $\omega_H = \left(\frac{\alpha_1}{V_A} - \frac{1-\alpha}{V_B}\beta_P\right)\frac{1-\beta_P\kappa_D}{\gamma(1-\beta_P)}$. Equation (8) shows that holdings depend on a linear combination of average beliefs, as captured by the prices, and subjective beliefs $E[\tilde{r}_2|s_i, s_{im}]$ (FOB) and $E[\bar{E}[\tilde{r}_2]|s_i, s_{im}]$ (HOB). Specifically, $\omega_F > 0$ measures how FOB affect holdings. ω_H is the sensitivity to HOB. ω_0 is a constant term that captures how the prices, which are homogeneous to everyone, affect individual holdings. Equation (8) yields the following proposition:

Proposition 1: An increase in FOB leads to more stock holding. The effect of increasing HOB on stock holding is ambiguous. When $\frac{\alpha_1}{V_A} < \frac{(1-\alpha)\beta_P}{V_B}$*, stock holding decreases with HOB. When* $\frac{\alpha_1}{V_A} > \frac{(1-\alpha)\beta_P}{V_B}$*, stock holding increases with HOB.*

Intuitively, because only B directly trades over the final payoff $\tilde{r}_2$, FOB only affects these investors' asset holdings. When FOB is higher, B's expectations about future payoffs are higher, which increases asset holdings.

In comparison, two factors explain how HOB affect asset holdings: Since A trade against the average beliefs in $t_{1,2}$, when they expect others to be more optimistic, their subjective payoff increases. As a result, they increase their holdings of total assets at $t_{1,1}$. This logic is similar with DeLong et al. (1990), Brunnermeier and Nagel (2004), and Chen et al. (2021). In contrast, B cannot act quickly or profit from others' beliefs. The only effect of HOB is to increase the prior on how $\tilde{r}_{1,2}$ signals the final payoff. Hence, when B learns about D from $\tilde{r}_{1,2}$, those with a higher HOB face greater disappointment, that is, a more negative signal surprise. They then update their beliefs about $\tilde{r}_2$ negatively, relative to investors with lower HOB. Consequently, subjective expectations about $\tilde{r}_2$ are lower for investors, and asset holdings are reduced. In other words, for traders who cannot exploit others' average valuation, HOB before making the trade are just priors about all other public signals that also reflect average beliefs while making the trade. Since public signals are the same to everyone, those with a higher HOB will be disappointed by the same public signal more and thus end up reducing stock holdings.

The sign of ω_H depends on the composition of investors that determines which channel dominates the effects of HOB on average holding. When $\alpha \rightarrow 0$ (that is, when no one believes that they can react faster than others), $\omega_H \rightarrow -\big((1-\beta_P\kappa_D)\beta_P\big)/(\gamma(1-\beta_P)V_B) < 0$. When $\alpha_1 \rightarrow 1$, $\omega_H \rightarrow (1-\beta_P\kappa_D)/\ (\gamma(1-\beta_P)V_A)\ > 0$.

E. Empirical specifications

Equation (8) motivates our empirical specification and makes predictions about the signs of the coefficients: ω_F, the FOB's marginal influence on stockholdings should be positive. As suggested by Proposition 1, the sign of ω_H, the marginal influence of HOB, is ambiguous and depends on if $\alpha_1/V_A < (1-\alpha)\ \beta_P/V_B$.

The relationship between FOB and HOB indicates that both FOB and HOB affect the holding of risky assets. Because of the difficulties of measuring HOB, the previous empirical literature usually regressed holdings on FOB. However, since HOB and FOB are positively correlated, ignoring either will bias the estimates of ω_F or ω_H. Proposition 2 formalizes this point for the empirically relevant case with $\omega_H < 0$.

Proposition 2: If $\omega_H < 0$, then the regression coefficient of asset holding on HOB (FOB) without controlling for FOB (HOB) is biased toward zero.

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 US stock market investors who are either employed full-time or part-time.[6] We utilize the panel structure of Prolific to track respondents over time.[7] 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.[8] 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.[9]

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. Among this wealth, about half was in the financial market, and a further half was in the stock market in the form of individual companies, exchange-traded funds (ETFs), index funds, or derivatives. The average wealth of the stock market, excluding pensions, was approximately \$80,000.

Since our sample is based on Prolific's US census balanced sample conditional on working individuals, it is expected to be representative to the US employed retailed traders. To assess the representativeness of our sample, we compare the demographics with surveys from recent reports. Because we exclude retired individuals, our participants are slightly

[6] We only focus on employed individuals to avoid over-sampling respondents with lower time costs.
[7] Prolific recruits a panel of US survey participants that is representative to the census population. To alleviate issues with bots and duplicated precipitation, Prolific requires all participants to verify phone numbers and identification by checking participants' selfies and photos of their ID. See here for more details.
[8] We verified that the attrition rate was not correlated with treatment status.
[9] Prolific has a high quality of filtering out bots during completing the surveys. The collected surveys had a 96% and 100% rate of passing the attention-checking question, respectively, for the two waves of surveys. We also dropped those who did not pass an attention-checking question, which follows the recommendation in Haaland et al. (2023).

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.[10] 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 an education of high school or less, and 85% have some college education. According to Gallup (2023), these 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 1.09 and 0.30, respectively, in the 2022 Survey of Consumer Finances.[11] However, 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).[12]

We can also roughly match the numbers for high-income individuals. For example, from the 2023 US census, 19% of US 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 equal and above \$150,000.

B. Experimental design

Figure 1 plots the timeline of the experiment. The design of the experiment closely follows the conceptual framework in Section II. The first wave of the survey elicited socioeconomic information about the respondents. In addition to standard questions, we asked a set of questions to better understand the trading behaviors of the respondents (e.g., how often they

[10] 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.
[11] 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.
[12] Giglio et al. (2021) constructed the measure based on investors' Vanguard accounts. One may expect to see some differences if investors have multiple accounts.

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 stock returns, as well as what they think about the expectations of other investors. The former was a first-order ("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 to 0-100) 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% %

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 returns on their portfolios (rather than on the S&P500).[13]

Once priors were elicited, we presented randomly selected respondents with information relevant to thinking about future stock returns (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 (8)), interventions sought to affect FOB $E[\tilde{r}_2|s_i, s_{im}]$ and HOB $E[\bar{E}[\tilde{r}_2]|s_i, s_{im}]$ of the investors. Since we could not construct signals tailored to each individual's portfolio, we provided signals about the S&P 500 index. The implicit assumption was that subjective expectations of individual portfolio returns have positive factor loadings on the market portfolio, which we verify below.

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

[13] We elicited FOB and HOB using questions in terms of returns but with a base period much earlier than the time of the treatment. Therefore, even if we were asking questions in terms of returns, belief elicitation and treatment of HOB were with respect to future payoffs instead of the total future return from the time of the experiment. Such survey implementation more closely aligned with higher-order reasoning over payoffs (e.g., Allen et al., 2006; Banerjee et al., 2009).

return from all participants. Note that, by construction, there is a lag of few days between we administer the survey for the control group and the T2 treatment group because we need to collect information on the investor 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 discernable difference for beliefs or asset holdings between the control and treatment groups in our sample.

The first information treatment, following Beutel and Weber (2023), 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. 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 same formats. Different formulations of the return questions were deliberately used before and after the treatment to avoid antagonizing respondents by repeatedly asking them to answer identical distributional questions. After eliciting the posteriors, we asked additional questions and completed the first wave of the survey.

The purpose of the follow-up wave was to measure the choices that respondents may have in response to information treatment and to measure the persistence of treatments on beliefs, which we elicited with the bin-based questions described above.

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.

C. Trading behavior and strategic thinking

Figure 2 plots the distributions of variables measuring trading behaviors. 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 incorporated 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. Participants believe that it takes a long time for them to react to the news. 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. At the same time, only 22.5% of the participants believed that they reacted faster to significant news about the stock market than to others. Through the lens of our model, one can interpret these responses as suggesting a low value of α.

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 to 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:

> 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? - %

> 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 to reduce 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.[14] 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.

D. 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 respected 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.

There are also considerable disagreements and uncertainties regarding 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

[14] 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.

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 (Coibion et al., 2021).

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 uncertainties. 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.

E. 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 fund	___ %
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. 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. 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, 2023). 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 become significant. This result is consistent with Proposition 1.

IV. The Effect of Information Treatments on Expectations

So far, we have focused on documenting the basic properties of 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 et al. (2018, 2024), we use the following econometric specification to assess the influence of various information treatments on investors' beliefs:

$$Posterior_i = a_0 + \sum_{k=1}^{2} a_k \times \mathbb{I}\{i \in Treat_k\} + b_0 \times Prior_i + \sum_{k=1}^{2} b_k \times \mathbb{I}\{i \in Treat_k\} \times Prior_i + error_i, \quad (9)$$

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 the 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 (9) in which we included only indicator variables for the treatments.

$$Posterior_i = a_0 + \sum_{k=1}^{2} a_k \times \mathbb{I}\{i \in Treat_k\} + error_i, \tag{9'}$$

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

The coefficient b_0 in specification (9) 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. 2000; Kleinjans and van Soest 2010; 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 *T1* × *Prior* and *T2* × *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 points. In contrast, the second treatment (T2) significantly reduced HOB by 1.4 percentage points, whereas the effect on FOB was only 22 basic points and was not significant.[15]

Panel B of Table 4 reports the equivalent results for uncertainty. We generally find that information treatment shifts priors across boards. In other words, the posterior uncertainty is 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 measure 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 mostly after three months given the stationarity of stock return and large volatility of return expectations. 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 2021). 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 to 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,

[15] The HOB of 3.21% in our information treatment is based on the control group before excluding observations (e.g., failed attention checks), and is significantly smaller than the 3.86% pre-experiment HOB of the treatment groups (t = 5.52). Thus, our information treatment likely impacts even the average participant's beliefs. Since the posterior is elicited differently, average treatment effects may exceed signal surprises, even when beliefs adjust in a Bayesian manner.

an online survey, etc.) should attenuate demand effects. Second, we show below that the treatments changed behaviors, therefore indicating 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

To further progress and establish causal relationships, 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 (2023) and Coibion et al. (2024). The first-stage regression is similar to that in specification (9).

$$\begin{aligned} Posterior_i^h = {} & a_0^h + \sum_{k=1}^{2} a_k^h \times \mathbb{I}\{i \in Treat_k\} \\ & + b_0^h \times Prior_i^{FOB} + \sum_{k=1}^{2} b_k^h \times \mathbb{I}\{i \in Treat_k\} \times Prior_i^{FOB} \\ & + c_0^h \times Prior_i^{HOB} + \sum_{k=1}^{2} c_k^h \times \mathbb{I}\{i \in Treat_k\} \times Prior_i^{HOB} \\ & + Controls_i + error_i^h. \end{aligned} \tag{10a}$$

where $h = \{FOB, HOB\}$, $Prior_i^{FOB}$ and $Prior_i^{HOB}$ are the prior expectations of the FOB and HOB. Specification (10a) is estimated for the posterior expectations of both FOB and HOB.

The second stage regression is given by

$$\begin{aligned} Risky\%_i = {} & \alpha_0 + \beta_{FOB} \times Posterior_i^{FOB} + \beta_{HOB} \times Posterior_i^{HOB} + \gamma_{FOB} \times \\ & Prior_i^{FOB} + \gamma_{HOB} \times Prior_i^{HOB} + Controls_i + error_i \end{aligned} \tag{10b}$$

where $Posterior_i^{FOB}$ and $Posterior_i^{HOB}$ are instrumented as in the specification (10a). The set of controls is based on pre-treatment variables and included 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 (9b), 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 reduce risky asset holdings by 5.8 percentage points. Both estimates are statistically insignificant. When we include both FOB and HOB, the effects on beliefs are much larger, with 10% higher FOB increasing risky asset holdings by 14.6 percentage points and 10% higher HOB decreasing them by 14.2 percentage points. In addition, the estimates are statistically significant. 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.

To assess the validity of these estimates, we note that the econometric specification (8) maps the relationship between β_{FOB} and the coefficient of risk aversion γ as in a standard Merton (1969) model: $\beta_{FOB} = (1-\alpha)/(\gamma V_A)$. Following Giglio et al. (2021) and Beutel and Weber (2024), we set $V_A = 0.2^2$ which is the annual standard deviation of historical market return (S&P500), and use $\beta_{FOB} = 2.59$ for the changes in equity as a share of total financial asset. In addition, following the survey evidence on whether people believe they can react to news faster the market, we assume α = 22%, then $\gamma = (1 -$

$\alpha)/(\beta_{FOB}V_A) \approx 7.53$, which is usually in the range of 3 to 10 as estimated in the experimental literature.

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.

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

As an additional strategy, we instrument both the first and second moments using a modified specification (10a), 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 uncertainties 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 (10a) 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 significance 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 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$_{w.pen}$%*.

Our findings have several significant implications. First, the stock market information affects both FOB and HOB. Without conditioning, risky share sensitivity to belief is biased toward zero (Proposition 2). This helps explain the weak sensitivities of beliefs to trading decisions as documented in recent studies (Giglio et al., 2021; Charles et al., 2023). Hence, future studies should attempt to measure both FOB and HOB.

Second, our results help understand how HOB affects stock holdings. Theoretically, the effect on stock holdings is ambiguous. As in our model, when no individual can consistently beat others in responding to news, positive surprises regarding HOB tend to raise beliefs about future payoffs as reflected by trading prices, leading to lower expected payoff in the future controlling for average beliefs. On the other hand, HOB can also increase stockholdings. This could happen when investors overlook the equilibrium price adjustments caused by others' actions (Eyster et al. 2019; Bastianello and Fontanier 2022; Andrei et al. 2023) or believe that they can beat the market by acting on information faster (DeLong et al. 1990; Brunnermeier and Nagel 2004). In these scenarios, HOB would elevate return expectations by boosting anticipated future payoffs much more than their beliefs about trading prices. Therefore, our setting is helpful for distinguishing between these theoretical predictions.

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 that our results as suggestive.

Several general patterns are observed. 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 1, 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 in front of 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 and 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 our model's mechanism, in which individual investors would react negatively to others' beliefs when they do not perceive themselves as capable of reacting faster than others.

V. Conclusion

Economists have long been deeply interested in understanding HOB and their effects on economic agents' choices. While the narrative is 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. 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 first- and higher-order beliefs, we find that these beliefs have a causal effect on portfolio allocation. Specifically, an exogenous increase in first-order beliefs increase the portfolio share allocated to the stock market (i.e., risky assets), whereas an exogenous increase in HOB reduce it. This key result is consistent with the view that 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. We hope that future studies address these important questions.

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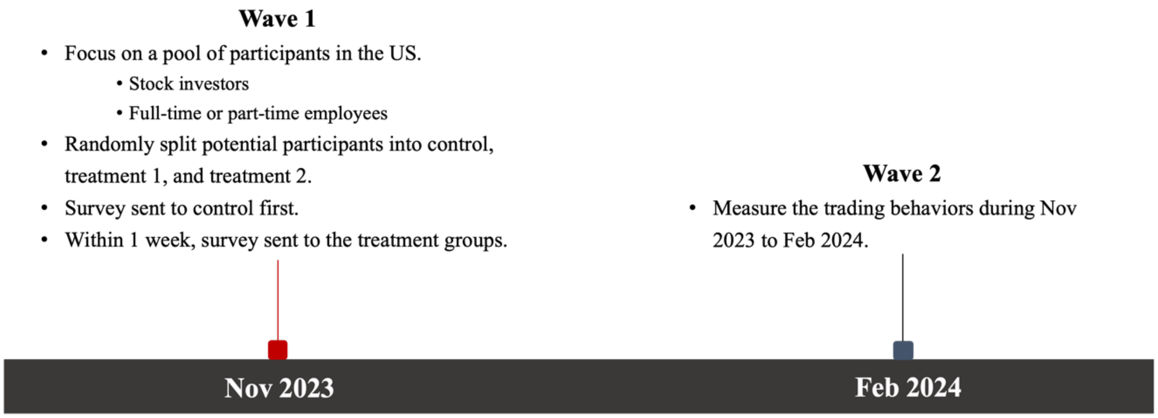
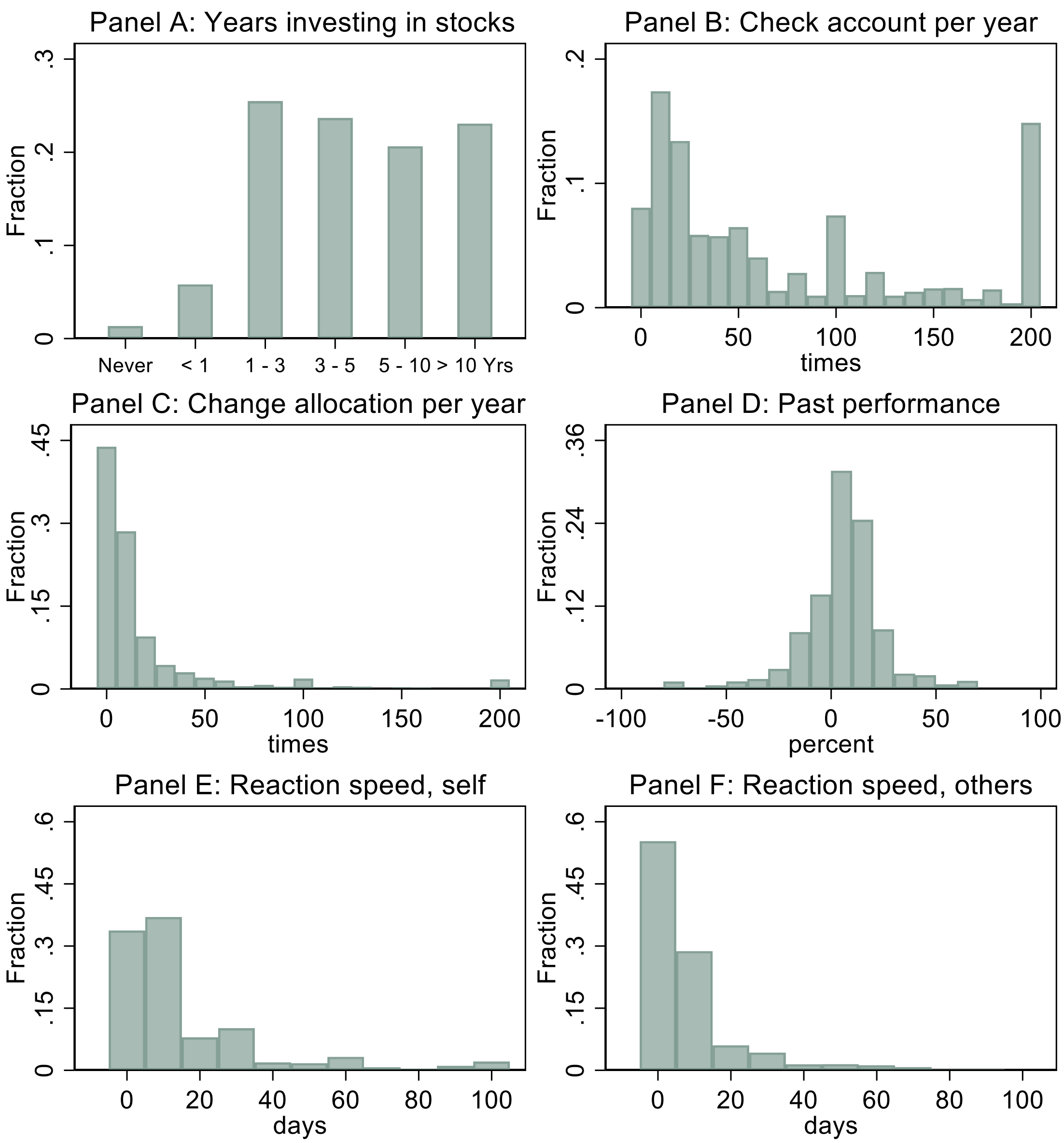
Figure 1: Timeline of the Experimental Design



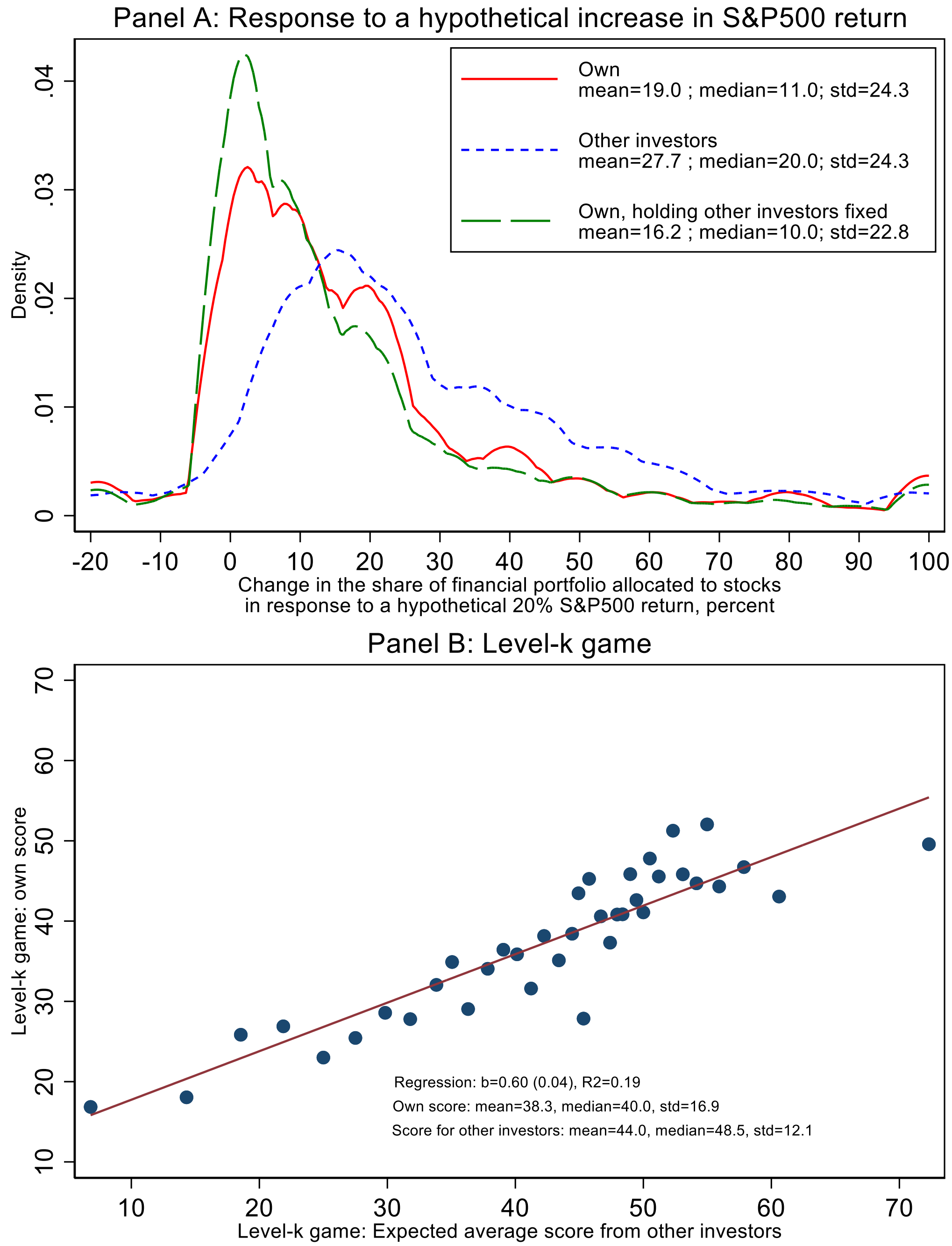
Note: this figure plots the timeline of the experimental design.

Figure 2. Participants Characteristics



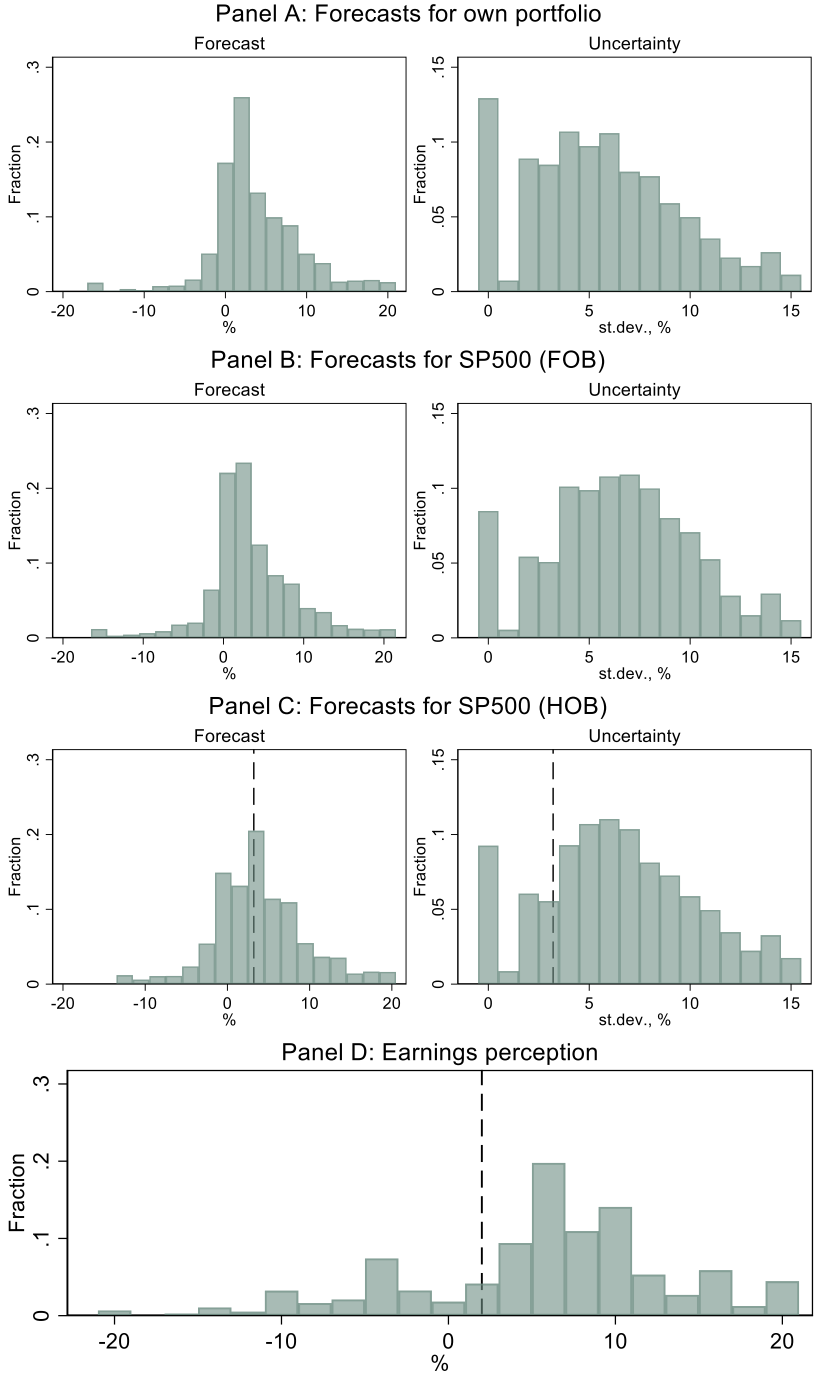
Note: Panel A is the number of years the investors have been investing in the stock market. Panel B gives the number of times the investors check their balances in the stock market every year. Panel C plots the number of times the investors change their allocations in the stock market. Panel D is the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

Figure 3. Strategic Behaviors in Trading



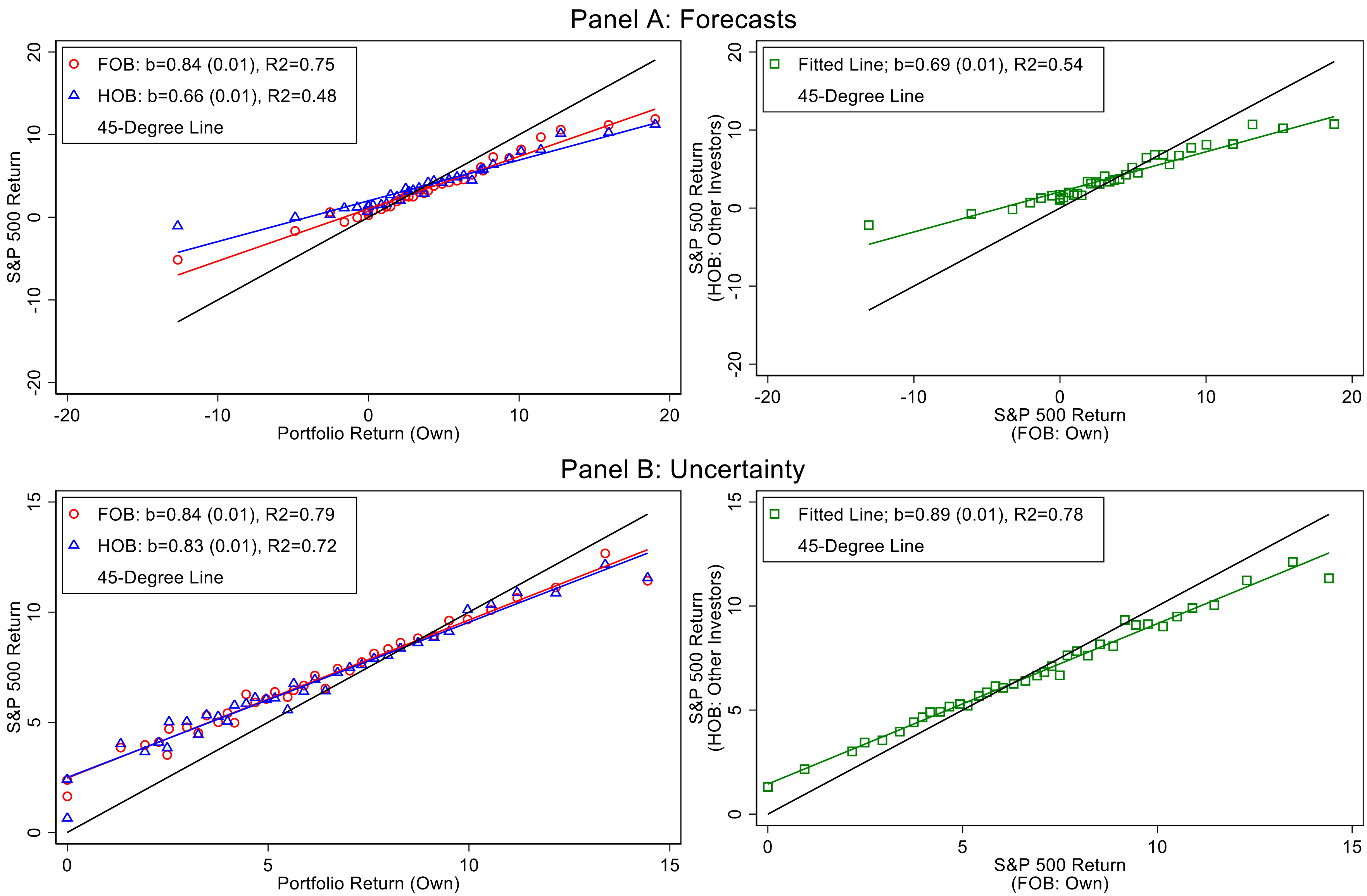
Note: Panel A gives the distribution of reported changes in stock holding to a hypothetical 20% increase in S&P500 index return. The red solid line describes participants' own decisions. The blue dotted line gives participants' beliefs about others' decisions. The green dashed line describes participants' 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



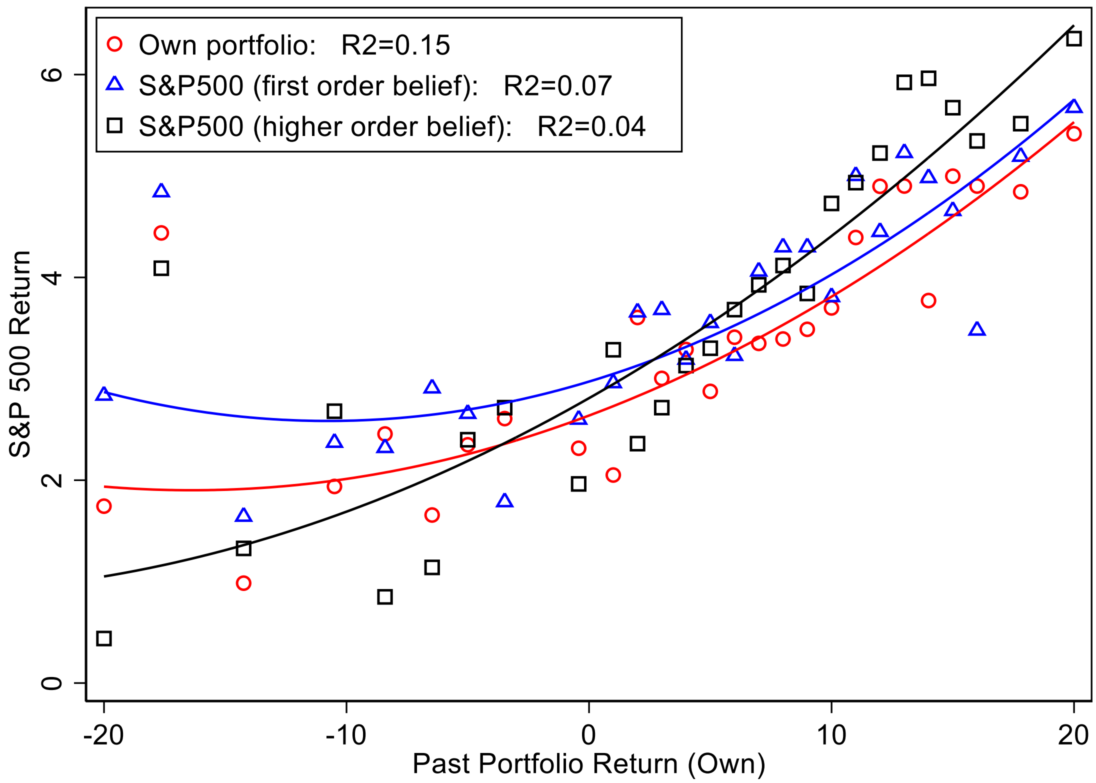
Note: Panels A, B, and C plot the histograms of participants' prior beliefs about future returns about own portfolio, the S&P500 index, and others' beliefs about that of the S&P500 index. The left column gives the implied expectations, and the right column gives the implied standard deviations. Panel 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 valuaes provided to the treatememt groups.

Figure 5. Comovement of Expectations



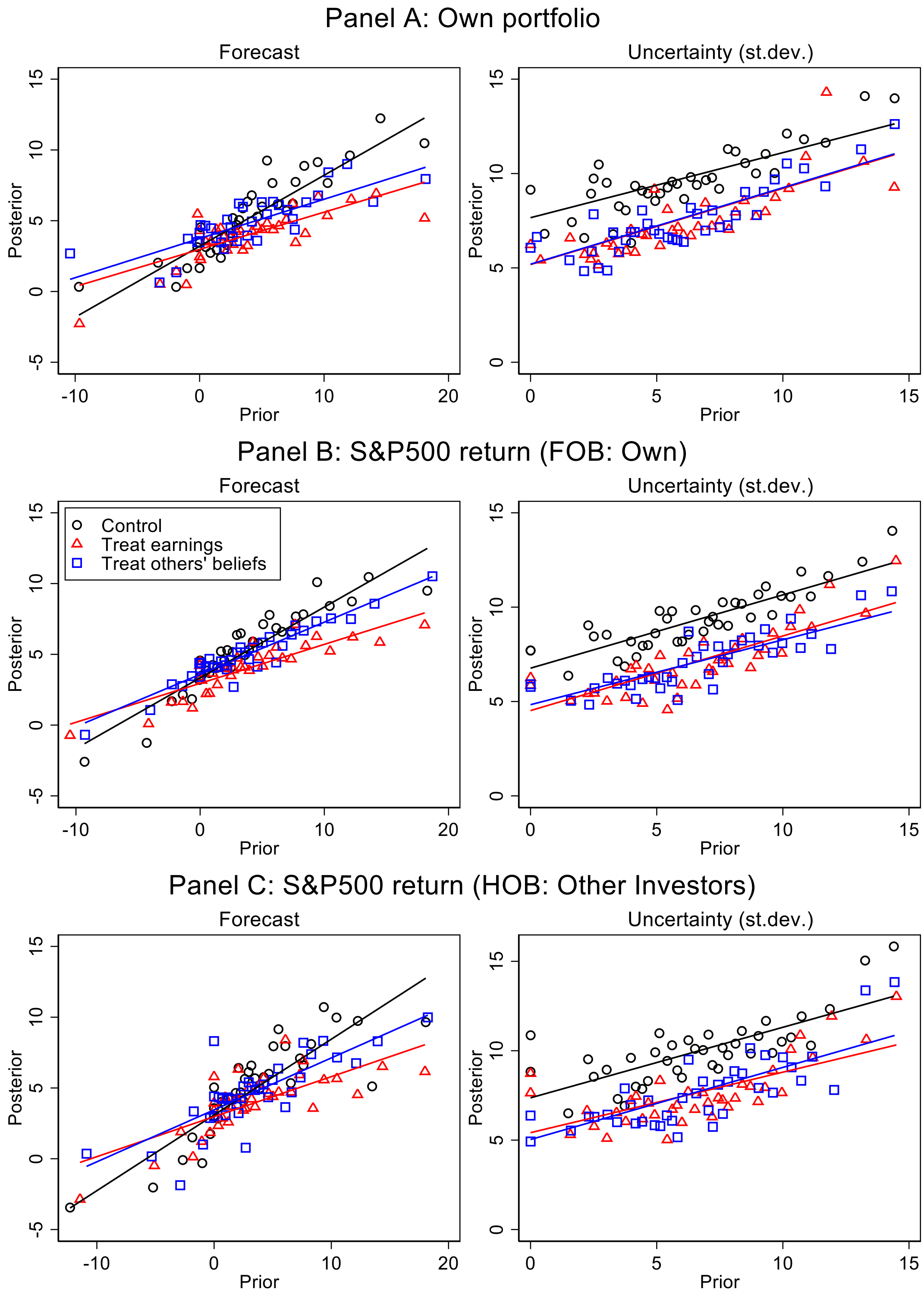
Note: This figure gives binned scatter plots among beliefs. Panels A and B respectively present results for expectations and uncertainties. The left column plots FOB and HOB about future S&P500 return on own portfolio returns. The right column plots HOB about S&P500 return on FOB about S&P500 return.

Figure 6. Past and Expected Returns



Note: This figure 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 other's 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 uncertainties of FOB and HOB are winsorized at 1% and 99% level. 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: $Risky_{no.der}$%		
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. $Risky_{no.der}$% 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% level. 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 portfoilio 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 expections 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% level. 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%	$\text{Risky}_{\text{w.pen}}$%	$\text{Risky}_{\text{no.der}}$%
	(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

Note: The table reports IV estimates for equations (10a) and (10b). 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. $\text{Risky}_{\text{no.der}}$% is Risky% excluding financial derivatives. $\text{Risky}_{\text{w.pen}}$% is Risky% including equity allocated through pension. 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% level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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

	Risky%	Risky%	Risky_F%	Risky_F%	$\text{Risky}_{\text{w.pen}}$%	$\text{Risky}_{\text{w.pen}}$%
	(1)	(2)	(3)	(4)	(5)	(6)
FOB	1.46**	1.35*	2.49**	3.89	1.28*	1.27*
	(0.72)	(0.75)	(1.18)	(2.81)	(0.72)	(0.76)
HOB	-1.49***	-1.04	-1.91**	-2.36	-1.44**	-1.03
	(0.57)	(0.66)	(0.89)	(2.50)	(0.57)	(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	1,988	1,944	1,987	1,944	1,989	1,944
	First-stage *F*-stats					
FOB	19.58	14.35	19.12	14.51	19.58	14.35
HOB	18.69	12.40	19.26	12.44	18.69	12.40
SD(FOB)		14.67		14.65		14.67
SD(HOB)		15.97		15.83		15.97

Note: The table reports IV estimates for augmented equations (10a) and (10b). 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% level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 7: The Effects 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

Note: The table reports IV estimates for equations (10a) and (10b). 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. 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% level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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
N	1,202	786	767	1,222	1,439	549	971	1,017	1,189	799

	Reaction Speed		# Checks		# Trades		Past Return		Experience	
	Not Slower	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
N	648	1,340	1,011	977	1,099	889	1,046	943	978	1,010

Note: The table reports IV estimates for equations (10a) and (10b). 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 Not Slower group of Reaction Speed are those whose reaction speed to financial news is less or equal to that of other. 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% level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$