Beliefs and Portfolios: Causal Evidence *

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Abstract

We causally test alternative theories of expectation formation. Using a randomized information experiment we show overreaction is a key feature of individuals' return expectations, and individuals' response to the price-earnings ratio is opposite to the academic consensus. Our evidence is inconsistent with standard models of expectation formation but subjective mental models that deviate from objective benchmarks can jointly explain the updating behavior in the experiment, the link between individuals' prior perceptions and expectations, and the heterogeneity of their updating behavior. Conditional on their beliefs, individuals' sensitivity of risky portfolio shares is consistent with the standard Merton model of portfolio choice.

Keywords: Expectation formation, household finance, asset pricing.

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"Beliefs are central to asset pricing. [...] An observer outside the field of asset pricing might therefore guess that a major part of the research efforts in asset pricing are devoted to understanding how investors form beliefs. This is, at least so far, not the case."
Brunnermeier et al. (2021)

1 Introduction

Asset prices are forward-looking and hence expectations are key for household finance, portfolio choice, and consumption-based asset pricing models. Whereas most existing models assume rational expectations, growing empirical evidence rejects the benchmark of full information rational expectations (FIRE) across various domains. Yet, once we deviate from FIRE, how expectations react to news and the associated welfare implications can differ vastly across models. Models of rational inattention or noisy information lead to underreaction of beliefs to news, whereas models of belief overreaction lead to excessive swings in expectations and asset prices (see, e.g., Bordalo et al. 2021). Boom-bust cycles driven by excessive optimism or pessimism are inefficient, can generate financial instability, and re-distribute wealth across households. Hence, understanding how agents actually form beliefs is crucial and empirical evidence is needed to discipline the degrees of freedom arising from relaxing the FIRE assumption.

We design an information provision experiment to test leading theories of expectation formation about asset returns causally and in a unified setting. We find overreaction is a key feature of individuals' belief formation. Individuals excessively extrapolate past returns and past earnings growth into future return expectations compared to objective benchmarks. Individuals' response to price-earnings ratio information is opposite to what one would expect based on the empirical finance literature. We document two distinct drivers of the biases in expectations: i) imperfect information about state variables such as the price-earnings ratio, past returns, or earnings growth; and ii) imperfect knowledge of the law of motion of the economy relative to objective benchmarks. Overreaction to return and earnings news, and individuals' wrong-signed response to price-earnings ratio information suggest the subjective law of motion of the economy that agents have in mind, which we label "subjective model" for brevity, differs substantially from the objective law of motion based on empirical estimates and economic theory. We provide additional evidence on the role of subjective models by linking prior perceptions and expectations and by establishing a strong link between individuals' perceived informativeness of different state variables for predicting returns, and their reaction to information treatments. Finally, we show that conditional on their beliefs, the elasticity of individuals' risky asset share with respect to changes in expectations is largely consistent with a standard Merton model of portfolio choice. In sum, our evidence suggests heterogeneous subjective models could be an especially fruitful avenue for future empirical and theoretical work in household finance and consumption-based asset pricing.

We build a simple model of belief updating to formally link the updating behavior in controlled experiments to the predictions of leading theories of expectation formation. Based on this model, we derive testable predictions of i) FIRE, ii) sticky information rational expectations, iii) noisy information rational expectations, iv) diagnostic expectations, and v) subjective models, in which overreaction arises when agents overstate the persistence of the P/E ratio, earnings growth, or returns, and/or their forecasting power for future returns. We test these predictions against the actual updating behavior resulting from our information treatments.

In the survey, each individual receives one of the following randomly assigned information treatments. Motivated by asset pricing models in which return expectations depend on current P/E ratios, past returns, or past earnings growth, our core treatments consist of 1) information about the level of the price-earnings (P/E) ratio of the German stock market index DAX at the time of the survey, 2) the return of the DAX over the 12 months up to the survey, and, 3) the growth rate of earnings of the DAX over the same horizon. In addition, we field treatments with information about 4) the long-term average return of the DAX, and 5) an expert forecast of the return of the DAX over the following 12 months. A control group receives a placebo treatment with quantitative information that is irrelevant for stock market returns. Since the treatments are randomly assigned, we can interpret their effects on beliefs relative to the control group causally.[1]

Our experiment yields the following main findings. First, prior to receiving any treatments, we measure the informedness of representative samples of individuals about the five different stock market variables for which we will subsequently provide objective information. The average gap between individuals' perceptions and actual stock market outcomes such as the price-earnings ratio, recent returns, and the growth rate of earnings is substantial. Hence, the assumption of full information (or perfect recall) is not consistent with our evidence.

Second, we exploit the heterogeneity in individuals' prior informedness to measure individuals' updating rates, that is, the average response to information per unit of news received. All of our treatments lead to sizable expectation revisions, inconsistent with FIRE, in which full information would preclude a reaction to publicly available information. Yet, our main focus is on which alternative models of expectation formation are most in line with the evidence. We find actual updating rates in response to information about returns or earnings growth over the previous 12 months are much larger than predicted by pure sticky information or noisy information expectation models. In other words, we find causal evidence for overreaction to stock market news, consistent with models in which agents extrapolate recent returns or earnings growth excessively into their expectations about future stock returns.

Third, individuals, on average, respond to information that the current price-earnings ratio is much higher than what they thought by *increasing* their expected return. This response is at odds with the inverse relationship between the price-earnings ratio and subsequent returns documented in the empirical finance literature and incorporated in leading asset pricing models (see, e.g., Campbell and Shiller 1988; Campbell and Thompson 2008; Cochrane 2008). Instead, our evidence points to subjective models in which agents' understanding of the economy is inconsistent with the objective law of motion (see, e.g., Andre et al. 2022; Meeuwis et al. 2022).

Fourth, we provide further evidence for subjective models based on the relationship between individuals' prior perceptions and their prior return expectations. We find the link between prior perceptions of different stock market statistics and return expectations

[1] This identification strategy has been successfully used in various economic contexts (see, e.g., Armona et al. 2019; Coibion et al. 2022; Roth and Wohlfart 2020; Beutel et al. 2021; Chinco et al. 2022; Laudenbach et al. 2023; Coibion et al. 2024).

coincides quantitatively with the updating rates in response to new information. Hence, a model in which agents' subjective models are allowed to deviate from their objective benchmarks can provide a parsimonious explanation for the combined set of facts we document.

Fifth, in light of our evidence on information processing, we design a second survey wave to shed light on the information acquisition stage. We document sizable heterogeneity in the extent to which respondents perceive different pieces of information as particularly important for forming expectations about stock returns. For instance, a subgroup of slightly less than 20% of respondents exists who view information about the price-earnings ratio as important and who react to such information in a way that is more in line with a subjective model in which valuations are (inversely) linked to subsequent returns.[2]

Individuals tend to be slightly better informed about the information they perceive as particularly valuable. In a model in which all agents adhere to the same (e.g. objective) model of the economy, we would expect Bayesian respondents who are better informed about a given stock market outcome to respond less to a corresponding information treatment due to the smaller surprise component of the treatment. By contrast, we find individuals respond more strongly to the information they rank as more important, despite their smaller perception gaps. This novel effect arises naturally when allowing for heterogeneous subjective models. In such models, the perceived forecasting power of a given state variable drives both individuals' ranking of the usefulness of different pieces of information and their reaction to this information, which can offset the countervailing effect of being better informed. Thus, our results suggest that heterogeneous subjective models are a promising avenue for further empirical and theoretical research on expectations and asset prices. In ongoing work, Andre et al. (2023) provide further empirical evidence on subjective models of the stock market. Laudenbach et al. (2024) show belief heterogeneity affects trading behavior in administrative data.[3] Models incorporating such heterogeneity can play an important role for understanding household behavior and its implications for asset prices, trading volume, and the redistribution of household wealth (see, e.g., Fagereng et al. 2020; Campbell et al. 2019; Fedyk 2021; Balasubramaniam et al. 2023; Knüpfer et al. 2024).

Sixth, we exploit the exogenous variation in beliefs our experiment generates to estimate the causal link between expected returns and individuals' risky portfolio shares in a hypothetical portfolio choice experiment. This setup allows us to overcome attenuation bias from measurement error and potential endogeneity concerns between beliefs and portfolios in non-experimental data. We thereby build on and extend the findings

[2] Egan et al. (2022) use a revealed-preference approach to estimate expectations from demand for index funds. Similar to the findings from our survey-based approach, they find implied expectations are extrapolative on average, while a fraction of investors are contrarian (see also Egan et al. 2021). Choi and Robertson (2020) and Bender et al. (2022) find representative and wealthy households differ in the importance of labor income risk and professional advice for their investment decisions, but have similar beliefs about the stock market, consistent with our finding that individuals' rankings of different pieces of information are largely orthogonal to wealth and other demographic variables.

[3] Differences in mental capacity (see, e.g., D'Acunto et al. 2023, 2021), as well as selective recall of memories and personal experiences (see, e.g. Wachter and Kahana 2024) may contribute to such heterogeneity. Aron-Dine et al. (2024) trace out the aggregate implications of heterogeneous beliefs and preferences regarding green assets for market-wide green premia.

of Giglio et al. (2021) with causal evidence within a survey experiment, which does not feature frictions related to trading. Our results speak to a long-standing puzzle that households' portfolios underrespond to their beliefs compared to theoretical benchmarks, both at the extensive margin, that is, with respect to stock market participation, (see, e.g. Haliassos and Bertaut 1995; D'Acunto et al. 2019; Duraj et al. 2024) and at the intensive margin, that is, with respect to the sensitivity of the portfolio share in stocks to expected returns (see, e.g., Ameriks et al. 2020; Giglio et al. 2021; Charles et al. 2022). Exploiting the exogenous variation in beliefs increases the sensitivity of the risky asset share at the intensive margin by a factor of two. Our estimated sensitivity is consistent with the standard Merton (1969) model of portfolio choice and a coefficient of relative risk aversion of 7.98, suggesting individuals vary their portfolio in response to changes in their expected returns (see also Wachter and Warusawitharana 2009). Overall, our results suggest individuals' beliefs are characterized by frictions and heterogeneity in information acquisition and processing, while the sensitivity of the risky portfolio share with respect to changes in expectations is broadly consistent with standard models of portfolio choice.

The remainder of the paper is structured as follows. Section 2 describes our randomized information experiment and the survey data. Section 3 derives the testable predictions of different models of expectation formation. Section 4 confronts these predictions with causal evidence from our experiment. Section 5 presents additional evidence on the heterogeneity of updating behavior from a second survey wave. Section 6 provides causal evidence on the link between beliefs and portfolios. Section 7 concludes.

2 Randomized Information Experiment

Our analysis is based on a representative survey of approximately 4,000 German households participating in the Deutsche Bundesbank Survey on Consumer Expectations. The survey is administered online by the survey company Forsa.[4] We embed randomized information experiments in two waves fielded in September and December 2020.[5] The experimental setup in each of the two survey waves consists of three stages: (i.) prior elicitation, (ii.) treatment, and (iii.) posterior elicitation. In the following, we describe the questions and treatments of the first wave which constitutes the basis for our main analysis.[6]

The objective of our experiment is to provide causal evidence on leading consumption-based asset pricing theories. Depending on the underlying expectation formation process, these theories can be categorized into three broad classes: i) models in which return expectations move counter-cyclically with valuation ratios such as the price-earnings ratio (see, e.g., Rietz 1988; Barro 2006; Campbell and Cochrane 1999; Bansal and Yaron 2004;

[4]While the survey is internet-based, respondents were recruited offline by Forsa to avoid potential sample selection effects of online recruiting. The website of the Bundesbank Survey on Consumer Expectations provides additional details about its methodology, access to its data, and the full questionnaires from all waves (in English and German). The link to the survey website is: `https://www.bundesbank.de/en/bundesbank/research/survey-on-consumer-expectations`.

[5]We discuss the external validity of our experiment in section 4.6.

[6]We discuss the second wave in Section 5. For both waves, we report the precise wording of the questions we included for our experiment in Appendix B.2. We report basic sample characteristics in Appendix A.1.

Cochrane 2011); ii) models in which investors extrapolate past returns or capital gains (see, e.g., Adam et al. 2017; Barberis et al. 2018); and iii) models in which investors extrapolate the growth rates of fundamentals such as earnings growth (see, e.g., Fuster et al. 2012; De La O and Myers 2021; Bordalo et al. 2024).[7]

To test these competing mechanisms for households' expectation formation, we design information treatments that capture the essence of each mechanism and compare the treatment effects to the predictions of the three classes of models. We also include two other influential approaches from the literature, which predict that households overweight recent experience (Malmendier and Nagel 2011) and that they react to expert forecasts (Carroll 2003), respectively. Respondents are randomly assigned to one of six treatment groups.

Specifically, the six **treatments (T)** are

- *T1 (Long-Term Historical Average Return):*
  "Since 1973 the German stock market index (DAX) and its predecessors have on average increased by approximately 9% per year."

- *T2 (Past 12 Months Return):*
  "Over the last 12 months, the German stock market index (DAX) has increased by approximately 9%."

- *T3 (Past 12 Months Earnings Growth):*
  "Over the last 12 months, the earnings of the companies represented in the German stock market index (DAX) have decreased by approximately 20%."

- *T4 (Current Price-earnings Ratio and Long-Term Average):*
  "The current price-earnings ratio of the DAX is approximately 23. The long-term historical average price-earnings ratio of the DAX and its predecessors has been approximately 15."

- *T5 (Expert Forecast about Return in the Next 12 Months):*
  "An expert forecast predicts a likely increase of the DAX over the next 12 months of approximately 9%."

- *T6 (Placebo):*
  "The average harvesting yield (per hectare) of winter oilseed rape increased in 2019 by approximately 10% compared to the previous year."

All treatments contain truthful information. The last treatment is our placebo treatment that contains a number close to the growth rates we provide in several of the other treatments but that does not contain any relevant information for expected stock returns. We explain the price-earnings ratio in the first question of the survey. We do not repeat explanations during the treatment stage to ensure the treatments are of approximately equal length. Thus, treatments differ solely by their information content. We obtain the expert forecast as the predicted return based on a return predictability regression with

[7]These models of expectation formation about asset prices are also related to the literature on expectation formation in macroeconomics (see, e.g., Mankiw and Reis 2002; Coibion and Gorodnichenko 2012, 2015).

the dividend yield as predictor based on monthly data for the DAX and its predecessors over the maximum available sample at the time of the survey from January 1973 to August 2020 and using the value of the dividend yield as of August 30, 2020 to predict the one-year ahead expected return of the DAX. Indeed, at the time of the survey, both the rational forecast (T5), and the past 12 month return (T2) coincide with the long-term historical average return (T1).

Before the treatments, we assess each respondent's prior knowledge about the information she will receive in the respective treatment. We also elicit respondents' stock market expectations prior to the treatment in the form of a point forecast of the expected percentage change in the German stock market index DAX over the next 12 months. Since the DAX is a return index, changes in the DAX reflect the value-weighted total return of its constituents, incorporating both the price growth and the dividend yield component of returns. We inform respondents about this property of the DAX. Eliciting pre-treatment expectations and perceptions is necessary to identify belief updating rates per unit of news received.

After treatments, we first elicit the risk preferences of our respondents. We ask respondents to rate their willingness to take risk in financial matters on a scale from 0 (not willing to take risk at all) to 10 (very willing to take risk). We then elicit respondents' posterior stock market expectations. We elicit these posterior expectations as subjective probability distributions about the change in the German stock market index DAX over the next 12 months. Respondents are asked to distribute a probability mass of 100 points across 10 bins ranging from a 25% or more decrease to a 25% or more increase (with a bin width of 5 percentage points).[8] We elicit posteriors using a different question format to avoid asking the same question twice and to mitigate survey fatigue (Weber et al., 2022).[9,10]

Finally, respondents answer a standard portfolio choice problem. The portfolio choice problem deliberately abstracts from respondents' wealth by presenting survey participants with a hypothetical endowment (see, e.g., Fuster and Zafar 2021). Respondents face the task to invest EUR 10,000 for a period of 12 months. They can allocate this amount across two assets. The return on the first asset is equal to the (risky) return on the German stock market index DAX over the following 12 months. The (risk-free) return on the second asset is fixed at 1%. In line with the evidence provided by Hackethal et al. (2023), we do not incentivize the portfolio allocation decision. The effects of incentivization and experimenter demand effects tend to be small in online surveys (see also De Quidt et al. 2018). Even if survey participants aimed to guess what the hypotheses are we want to

[8]The format of this density question is familiar to respondents in the survey, because they answered questions on house price changes, the inflation rate, or changes in their monthly household income over the next 12 months in a similar question format before our experiment.

[9]We construct the mean and standard deviation implied by an individual's subjective probability distribution using the midpoints of each bin and weighting each bin with the probability assigned by the individual. For the upper and lower bins of a 25% or more decrease and a 25% or more increase we use values of −27.5% and +27.5%. This approach is in line with Coibion et al. (2022), who also show that computing the median of each distribution or using the mean of a generalized beta distribution fitted to the bins yields very similar results.

[10]We winsorize prior and posterior return expectations at their 1% tails. Results are also robust to *not* winsorizing posterior expectations. Posterior expectations are elicited as probability distributions with bounded support and therefore not prone to outliers. We nevertheless winsorize them to treat prior and posterior expectations in a consistent way.

test, they would not know the expected returns and the share allocated into risky assets of other survey respondents across different treatment groups and hence, the relationship we document below is unlikely to arise due to demand effects (see also section 4.6).

3 Methodology

This section outlines a simple model of belief formation and shows how our experiment can be used to test leading models of expectation formation including i) full information rational expectations (FIRE), ii) sticky information rational expectations, iii) noisy information rational expectations, and iv) diagnostic expectations. In addition, we allow agents to have subjective models of the economy, possibly inconsistent with objective data generating processes. The scope of the tested models and the methodological approach go beyond previous empirical tests in this area. We start by presenting a simple Bayesian updating model that comprises cases i)-iii) and then proceed to discuss diagnostic expectations and subjective models of the economy.

3.1 Model of Bayesian Updating

Suppose the economy evolves according to the following objective law of motion:

$$x_t = \mu + Bx_{t-1} + w_t, \quad w_t \sim N[0, W_t] \tag{1}$$

where x, μ, and w are $n \times 1$ vectors and B and W are $n \times n$ matrices. VAR models are routinely used to approximate a broad class of economic models, including models based on the Campbell-Shiller identity in which returns are predictable by the dividend or earnings yield (see, e.g., Campbell and Yogo 2006; Cochrane 2008; Lettau and Wachter 2011).

Consider an agent whose beliefs about this economy may or may not coincide with the objective law of motion. Specifically, we allow for subjective perceptions about the state x_t, denoted $\tilde{x}_t$ and subjective models deviating from B, denoted $\tilde{B}$. This model allows agents to under- or overstate $x_t(k)$ as a useful forecasting variable ($\tilde{B} \neq B$) and to have fuzzy perceptions ($\tilde{x}_t \neq x_t$), while maintaining an internally consistent belief system.

Each treatment k of our experiment provides the receiving agent with a (possibly noisy) signal $y_t(k)$ about a single component of her state vector:

$$y_t(k) = F_k' x_t + v_t(k), \quad v_t(k) \sim N[0, V_k], \tag{2}$$

where F_k is a vector selecting the component of the state vector revealed by information treatment k. Our three main treatments can be summarized as follows: let $x_t = (r_t, P/E_t, \Delta e_t)'$, where r_t is the one-period return up to time t, P/E_t the price-earnings ratio at time t, and Δe_t is the one-period earnings growth up to time t. The vector F_k is assumed to be common knowledge, and trivially given by, $F_1 = (1, 0, 0)'$, $F_2 = (0, 1, 0)'$, and $F_3 = (0, 0, 1)'$, respectively.

The optimal update is given by:

$$\tilde{x}_t^{post} = \tilde{x}_t^{pre} + G_k \left(y_t(k) - \tilde{x}_t^{pre}(k) \right), \tag{3}$$

where $\tilde{x}_t^{pre}$ and $\tilde{x}_t^{post}$ denote subjective beliefs about the state vector pre and post treatment, respectively. $y_t(k)$ denotes a signal about element k of the state vector x. G_k is a $n \times 1$ gain vector, given by the familiar Kalman gain, that is:

$$G_k = \tilde{R}^{pre} F_k Q_k^{-1} \tag{4}$$

$$Q_k = F_k' \tilde{R}^{pre} F_k + \tilde{V}_k, \tag{5}$$

where $\tilde{R}^{pre}$ denotes the agent's subjective perception of the contemporaneous covariance matrix of the state vector and $\tilde{V}_k$ is the perceived noise of the signal.

The agent uses her updated beliefs about the state of the economy to update her expectations about the future. Using her perceived law of motion, equation (1), with subjective $\tilde{x}$ and $\tilde{B}$, we can rewrite the updating rule as follows:

$$\tilde{B} x_t^{post} - \tilde{B} x_t^{pre} = \tilde{B} G_k \left(y_t(k) - \tilde{x}_t^{pre}(k) \right) \tag{6}$$

$$\tilde{E}_{t,i}^{post}(x_{t+1}) - \tilde{E}_{t,i}^{pre}(x_{t+1}) = \tilde{B} G_k \left(y_t(k) - \tilde{x}_t^{pre}(k) \right). \tag{7}$$

The variables $\tilde{E}_{t,i}^{post}(x_{t+1}), \tilde{E}_{t,i}^{pre}(x_{t+1}), y_t(k), \tilde{x}_t^{pre}(k)$ are observable to us as econometricians and motivate our empirical investigation (see next section).

This model makes explicit the predictions of sticky information ($\tilde{V}_k = 0$) and noisy information ($\tilde{V}_k > 0$) models. It nests the univariate structure implicitly assumed in existing information experiments such as Armona et al. (2019). If, say, returns follow a (univariate) AR(1) process and agents receive a signal about the recent return, their optimal Kalman gain simplifies to $G_k = \frac{1}{1+\tilde{V}_k/\tilde{R}^{pre}}$. Hence, the larger the noise-to-signal ratio, $\tilde{V}_k/\tilde{R}^{pre}$, the smaller is the updating gain G_k. The limiting cases of the noise-to-signal ratio going to infinity or zero put the gain within bounds $G_k \in [0, 1]$. In a univariate model, for sticky information ($\tilde{V}_k = 0$), we have $G_k = 1$ and we could read off $\tilde{B}_k$ directly from an estimated version of equation (7). This estimate of $\tilde{B}_k$ could then be compared to the objective estimate of B_k obtained from estimating an AR(1) model on the history of available stock return data.

In the multivariate model we analyze here, two additional considerations arise. Most importantly, an agent receiving a signal about one component of her state vector should optimally update also the other components of her state vector. In the trivariate model, which is the focus of our analysis, $x_t = (r_t, P/E_t, \Delta e_t)'$, the Kalman gain for a signal about the first component of the state vector is $G_1 = \tilde{R}^{pre} F_1 Q^{-1} = \left(\tilde{R}_{11}, \tilde{R}_{21}, \tilde{R}_{31} \right)' \left(\tilde{R}_{11}^{pre} + \tilde{V} \right)^{-1}$. Hence, the update about the first component of the state vector, r_t, is the same as in the univariate case. Yet, the signal about the lagged return now also leads to an update of the other two components of the state vector. $\tilde{R}_{n1}^{pre}$ governs the direction and relative size of this cross-update, which is the contemporaneous covariance between the first and the n^{th} component of the state vector. For instance, an agent who is informed that the return over the previous period was higher than she thought, would optimally conclude that the current price-earnings ratio is also higher than she thought. The upper bound in absolute value (i.e. $\tilde{V} = 0$) for this update is $\tilde{R}_{21}^{pre}/\tilde{R}_{11}^{pre}$. Absent signal noise in r_t, the agent should update P/E_t exactly as predicted by a regression of the contemporaneous values of P/E_t on r_t. To the best of our knowledge, such "cross-updating" effects are currently largely absent in the empirical literature.

The second difference the multivariate model introduces, is that the benchmark coefficients B are from a multivariate VAR instead of a univariate AR model. We quantify the importance of these considerations in our empirical section.

3.2 Testable Predictions

This section summarizes the testable predictions and motivates our main regression specification.

1) Full information rational expectations (FIRE) benchmark: FIRE predicts that i) perception gaps are zero $\tilde{x}_t = x_t$ (full information); ii) subjective models of the economy coincide with the true model $\tilde{B} = B$; and iii) as a corollary of i), FIRE predicts no reaction to the information treatment due to the zero perception gap. We will see that our empirical evidence is at odds with all three predictions of the FIRE benchmark.

2) Sticky information rational expectations: Sticky information predicts i) each agent will update to the objective information provided in the treatment, that is $\tilde{V} = 0$, which implies $G_{k,k} = 1$, ii) Conditional on their perceived state $\tilde{x}_t$, agents form expectations rationally, that is, $\tilde{B} = B$.

We test predictions i) and ii) of the sticky information model jointly using the following regression specification, which will be the main specification of this section:

$$\tilde{E}_{t,i}^{post}(r_{t+1}) - \tilde{E}_{t,i}^{pre}(r_{t+1}) = \delta_0 + \sum_{k=1}^{K} T_{i,k} \left[\delta_{1,k} \left(y_{t,k} - \tilde{x}_{t,i,k}^{pre}\right) + \delta_{2,k}\right] + Z_i \phi + \epsilon_i, \qquad (8)$$

where the treatment indicator $T_{i,k}$ is equal to one if individual i received treatment k, and zero otherwise. Z_i denotes a control vector of socio-demographic characteristics. Due to random assignment of the treatment groups, Z_i is approximately orthogonal to the treatments, and hence we expect the effect of adding controls to be small. δ_0 allows for the possibility of an expectation revision even in the control group due to different question formats pre- and post-information provision.[11] $\delta_{2,k}$ controls for any potential effects a treatment might have beyond those operating through perception gaps. ϵ_i captures measurement noise in survey beliefs.

The coefficient of interest is $\delta_{1,k}$. We label this coefficient the "updating rate" as it measures how respondents, on average, revise their return expectations per unit of surprise in the treatment. Formally, $\delta_1(k) = \tilde{B}_1 G_k$. G_k is a 3-by-1 vector mapping the univariate signal into the trivariate state vector. $\tilde{B}$ is a 3-by-3 matrix mapping the state vector into a vector of forecasts. We observe the first element of the forecasted vector, i.e., $E_{t,i}(r_{t+1})$. Hence, only the first row of $\tilde{B}$ is relevant for us.

Under the null of sticky information, we have $\tilde{B}_{1\cdot} = B_{1\cdot}$ and hence, as a benchmark we can plug in the objective estimate of $B_{1\cdot}$ from the VAR of equation (1) estimated on

[11] Consistent with the literature on inflation expectations, e.g. D'Acunto et al. (2022), stock return expectations elicited as point forecasts are higher than the means of individuals' probability distributions (see Appendix A.2). This feature of the data leads to a negative expectation revision even in the control group. Crucially, our econometric approach exploits differences in the updating behavior between treatment groups and control group, and is therefore immune to this feature.

the history of all available data. Likewise, we use an objective estimate of the contemporaneous regression matrix of the state vector, which allows us to compute the benchmark G_k as defined in equations (4)-(5). Together with the estimated $B_{1\cdot}$, we get a predicted $\delta_1(k)$ for each treatment. We then test whether the estimated $\delta_1(k)$ is equal to the predicted one, using a bootstrap to account for the estimation uncertainty in the product $\delta_1(k) = B_{1\cdot}G_k$.

3) Noisy information rational expectations: Noisy information predicts i) an agent with a non-zero perception gap will update imperfectly to the objective information provided in the treatment, that is $\tilde{V}_k > 0$, which implies $0 < G_{k,k} < 1$. ii) Conditional on the perceived state $\tilde{x}_t$, an agent with noisy information rational expectations forms expectations rationally, that is, $\tilde{B} = B$.

We test predictions i) and ii) of the noisy information model jointly, based on the estimated updating rate $\delta_{1,k}$ of equation (8). Proceeding in the same way as for sticky information gives us a different prediction for $\delta_{1,k}$, namely $\delta_{1,k}(noisy) < \delta_{1,k}(sticky)$. Noisy information is consistent with an estimated $\delta_{1,k}$ below the prediction of the sticky information model and is otherwise rejected.

4) Diagnostic expectations: Diagnostic expectations imply an overreaction to news relative to the Bayesian benchmark. Updating under diagnostic expectations is given by a "diagnostic Kalman filter" rule governed by a parameter θ (Bordalo et al., 2020):

$$\tilde{x}_t^{post} = \tilde{x}_t^{pre} + (1+\theta)\, G_k \left(y_{t,k} - \tilde{x}_{t,k}^{pre}\right). \tag{9}$$

When $\theta > 0$, expectations are diagnostic and agents overreact to news relative to the Bayesian benchmark, which is nested for $\theta = 0$. The "kernel of truth" property of diagnostic expectations states that agents' updating is anchored to the true properties of the process. In particular, we can only get overreaction (in absolute value), if the signal is informative for updating the current state ($G_k \neq 0$). Moreover, since $\theta > 0$, the direction of the diagnostic update will always be governed by the rational update G_k. Second, similarly to sticky and noisy information, agents with diagnostic expectations are aware of the true B. In sum, if $\hat{\delta}_{1,k} = (1+\theta)\delta_{1,k}(sticky)$, where $\theta > 0$, the evidence is consistent with overreaction as predicted by diagnostic expectations.

5) Incorrect subjective model: We augment models 1) to 4) with subjective models that deviate from their objective benchmarks, that is $\tilde{B} \neq B$. To shed light on these alternatives, we consider agents' perceived law of motion $\tilde{x}_t = \tilde{\mu} + \tilde{B}\tilde{x}_{t-1} + \omega_t$. We will exploit the variation in respondents' prior perceived state $\tilde{x}_{t-1}$ and their prior forecast $\tilde{x}_t$, that is, before they receive information, to gain insights into their subjective model $\tilde{B}$. In addition, we will exploit the heterogeneity of updating behavior along individuals' perceived informativeness of different information items to provide additional evidence on subjective models (see Section 5).

4 Testing Models of Expectation Formation

We first present evidence on individuals' level of informedness about stock market outcomes, then discuss their updating rates, and finally provide evidence regarding their subjective models. We compare our estimates to the benchmarks derived above and test the predictions of the corresponding models of expectation formation.

4.1 Prior Informedness about Stock Market Outcomes

Measuring prior informedness of respondents is key for at least two reasons. First, we find the degree of information incompleteness regarding stock market outcomes is large. As these outcomes are publicly observable, this finding suggests a role for frictions such as rational inattention at the information acquisition stage of the expectation formation process. Second, the goal of our information treatments is to measure how individuals update their beliefs conditional on receiving new information. To compare this updating behavior to the predictions of different models of belief formation, it is central to measure individuals' perception gaps, that is, the difference between the information individuals receive in the treatment and their prior perception of this information. Specifically, we define the perception gap of individual i as:

$$gap_{i,k} = y_k - \tilde{x}_{i,k}^{pre}, \tag{10}$$

where y_k is the factual information about an outcome k and $\tilde{x}_{i,k}^{pre}$ is the individual's perception of this outcome prior to receiving the treatment.[12] Data on expectations about asset prices (or returns) is relatively scarce compared to data on other expectations, such as inflation expectations. Even fewer surveys elicit perceptions about past asset market outcomes, a notable exception is Armona et al. (2019) for real estate price growth. We elicit perceptions about five different stock market outcomes.

Table 1 shows individuals' pre-treatment perceptions for 1) the long-term average return of the German stock market index DAX (1973-2020), 2) the return over the previous 12 months, 3) earnings growth over the previous 12 months, 4) the current P/E ratio, and 5) expert forecasts about the return over the next 12 months. In Panel A, we report the factual information provided in the treatment in column "Actual", using the same rounded numbers as in the treatment texts. The remaining columns show summary statistics of the cross-sectional distribution of respondents' pre-treatment perceived stock market outcomes. In Panel B, the expert forecast we provided predicted a 9% return on the DAX over the following 12 months. We elicited respondents' pre-treatment perceptions of expert forecasts qualitatively. Hence, we report the pre-treatment share of respondents who perceive experts to forecast the DAX to either decrease, stay the same, or increase, and the share of respondents who are not aware of an expert forecast (no info).[13]

One take-away from Table 1 is that the gap between individuals' perceptions and actual stock market outcomes is substantial, with the exception of the long-term average

[12] We define perception gaps for expert forecasts in Appendix A.5.

[13] We elicit each prior perception only for the subgroup of respondents in the respective treatment group. Due to random assignment, each treatment group remains representative of the entire population prior to receiving the treatment.

Table 1: Knowledge about Stock Market Outcomes

Panel A: Treatment 1-4						
	Actual	Mean	SD	P25	P50	P75
Treatment 1 (Long-Term Returns)	9	8.37	7.82	4	6	10
Treatment 2 (Past 12m Returns)	9	4.76	10.30	0	5	10
Treatment 3 (Past 12m Earnings Growth)	-20	3.95	11.25	0	5	10
Treatment 4 (Current PE)	23	9.93	12.23	2	5	14
Panel B: Treatment 5						
	Actual	Decrease	Stay	Increase	No info	
Treatment 5 (Expert Forecast)	9	0.18	0.04	0.18	0.60	

Individuals' informedness about stock market outcomes for all participants of the September 2020 wave of the Bundesbank Survey of Consumer Expectations. In Panel A, the factual information shown in the treatment is reported in the column "Actual", using the same rounded numbers as in the treatment texts. The remaining columns show summary statistics of the cross-sectional distribution of respondents' pre-treatment perceived stock market outcomes. In Panel B, the expert forecast received was a 9% return on the DAX over the following 12 months. We report the pre-treatment share of respondents who perceive experts to forecast the DAX to either decrease, stay the same, or increase, and the share of respondents who are not aware of an expert forecast (no info).

return. Respondents underestimated the return over the previous 12 months and the decline in earnings. They underestimated the value of the current price-earnings ratio, and as a consequence, perceived the price-earnings ratio at the time of the survey to be markedly below its historical average (mean of perceived historical average of 18.5), contrary to the actual relation between the two. Regarding expert forecasts, roughly 60% indicated that they were not aware of any expert forecast. Of those who do recall a recent expert forecast, roughly 44% reported that the direction of the forecast was negative, roughly 10% reported that the forecast was neutral, and about 45% reported that the forecast was positive.

The dispersion measures in Table 1 reveal sizable cross-sectional heterogeneity around average perceptions. Demographics explain only a small share of this heterogeneity, and even stockholders are, on average, not well informed (see Appendix B.1.4). In sum, perception gaps, $y_t - \tilde{x}_t$, are large and heterogeneous. This finding rules out full information (or perfect memory), and allows us to exploit perception gaps and information treatments to estimate updating rates and to compare them to the predictions derived above.

4.2 Updating Rates

We estimate the updating rates in our experiment using regression equation (8) and report the estimates in Table 2. Respondents react to positive (negative) surprises in all treatments with an upward (downward) revision in their return expectations. Our preferred specification is column (4) in which we control for socio-demographics and treatment fixed effects. The latter control for any potential effects the treatments might have even for individuals with zero perception gaps. Adding these controls has only negligible effects on the estimated updating rates, except for the earnings growth treatment in which the (over-)reaction becomes even stronger. The estimated updating rates reflect the revision in individuals' expected return per unit of news received in each treatment. We estimate updating rates of 0.39 for information about the return over the previous 12 months, 0.30 for information about earnings growth over the previous 12 months, and 0.10 for information about the level of the current price-earnings ratio. For the long-term average return and the expert forecast we obtain updating rates of 0.51, and 0.86, respectively. All of these updating rates are significantly different from zero. Non-zero updating rates are inconsistent with FIRE.

Table 2: Updating Rates Per Unit of News

	Posterior-Prior			
	(1)	(2)	(3)	(4)
T1xGap	0.52***	0.53***	0.51***	0.51***
	(0.09)	(0.09)	(0.10)	(0.09)
T2xGap	0.37***	0.38***	0.37***	0.39***
	(0.05)	(0.05)	(0.06)	(0.06)
T3xGap	0.14***	0.14***	0.30***	0.30***
	(0.02)	(0.02)	(0.05)	(0.05)
T4xGap	0.08***	0.09***	0.08*	0.10**
	(0.03)	(0.03)	(0.04)	(0.05)
T5xGap	0.78***	0.78***	0.86***	0.86***
	(0.05)	(0.05)	(0.05)	(0.05)
Constant	-5.20***	-7.02**	-4.47***	-6.28**
	(0.21)	(3.06)	(0.35)	(3.00)
Treatment FE	No	No	Yes	Yes
Socio-Demographics	No	Yes	No	Yes
R^2	0.20	0.23	0.22	0.25
N	3380	3275	3380	3275

Updating rates for all participants in the September 2020 wave of the Bundesbank Survey of Consumer Expectations. Expectation revisions (posterior-prior) are regressed on treatment dummies and their interaction with individuals' perception gaps ($T_k\times$ Gap). Robust standard errors in parentheses. T1 (DAX long-term), T2 (DAX past 12 months), T3 (Earnings growth past 12 months), T4 (PE ratio) and T5 (Expert forecast next 12 months). We control for treatment fixed effects and the following socio-demographic characteristics: gender, age, age squared, college education or higher (dummy), full time employment (dummy), living in the eastern part of Germany prior to fall of Berlin wall in 1989 (dummy), children (dummy), household income (indicator for income bracket) and homeowner (dummy), household size (indicator for size) and region (indicator for each of four German statistical regions). Prior and posterior return expectations are winsorized at their 1% tails. Standard errors are reported in brackets. $*p < 0.10, **p < 0.05, ***p < 0.01$

The key question is which model of expectation formation should replace FIRE. In the next section, we construct benchmark updating rates and test whether individuals underreact, overreact, or react optimally to stock market news relative to these benchmarks. As explained in the methodology section, individuals' reaction in the experiment, as well as additional information from prior beliefs and information rankings, helps to distinguish between leading models of expectation formation. Distinguishing between these alternatives is key for macro-finance models, and perception gaps and updating rates are crucial to quantify whether the degree of extrapolation is excessive relative to objective benchmarks.

The remainder of this section focuses primarily on the three information treatments to which the model and empirical tests introduced above are directly applicable. These are the past 12 months return treatment, the past 12 months earnings growth treatment, and the price-earnings ratio treatment. We discuss the long-term return treatment in Appendix A.4. For the expert forecast treatment, we discuss the results and the definition of the perception gap in Appendix A.5. The estimated pass-through of expert forecasts into individuals' beliefs of 0.86 is not complete ($= 1$), and not necessarily excessive (> 1), but high, suggesting expert forecasts as a promising avenue for policymakers or corporations seeking to influence individuals' stock return beliefs.[14]

4.3 Benchmarks

To compute optimal benchmarks for individuals' updating rates, we estimate the VAR corresponding to equation (1). Since we only observe expectations of returns, only the first row of the VAR matrix matters, which we report in the first column of Table 3. For the available history of the Germany stock market index, the price-earnings ratio forecasts returns with the expected sign, whereas earnings growth and past returns do not (or only marginally) predict future returns one-year ahead, also consistent with existing evidence.[15]

In addition, we need the contemporaneous regression matrix, because an update of, e.g., the return state optimally implies an update of, for instance, the contemporaneous price-earnings ratio state, which is proportional to the coefficient of a univariate regression of the latter on the former. Table 4 reports this matrix of univariate contemporaneous regression coefficients. The dependent variable of each regression is indicated by the column header. Hence, row k of Table 4 is equal to the optimal $G(k)'$ under sticky information. For instance, the first row says that a Bayesian agent should respond to information about the recent return by updating her perceived price-earnings ratio and earnings growth state in the same direction as her return state. Since past earnings growth does not forecast future returns (see Table 3), the sizable update of the earnings growth state ultimately does not impact her optimal forecast, whereas the update of the price-earnings ratio does.

4.4 Test for Optimal Updating

Table 5 compares the subjective estimates from equation (8) to the benchmarks based on tables 3, and 4. We compare the updating rates to three benchmarks and show they are significantly different from all of them. The first benchmark is a univariate model,

[14] Azarmsa and Beutel 2024 provide a model of the optimal management of asset return expectations.

[15] The return predictability coefficient of the P/E ratio turns insignificant when using Newey-West standard errors to account for serial correlation. This is not totally unexpected in light of the return predictability literature, which documents that such estimates depend on sample periods, structural breaks, and other methodological details (see, e.g., Lettau and Van Nieuwerburgh 2008; Campbell and Yogo 2006; Campbell and Thompson 2008; Lettau et al. 2008). Nevertheless, the empirical estimates are at adds with a *positive* reaction of return expectations to upward P/E surprises (see, also Cochrane 2008). Indeed, Wachter and Warusawitharana (2009) show it is optimal for investors to trade on return predictability estimates even if the evidence is weak by conventional measures.

Table 3: Multivariate Benchmark Predictability Estimates

	Return$_{t+1}$			
	(1) VAR	(2) Univariate	(3) Univariate	(4) Univariate
Return$_t$	-0.02	-0.07*		
	(0.05)	(0.04)		
Price Earnings Ratio$_t$	-0.83***		-0.86***	
	(0.28)		(0.25)	
Earnings Growth$_t$	-0.01			0.00
	(0.04)			(0.04)
Constant	22.49***	10.65***	22.61***	9.91***
	(4.16)	(1.01)	(3.73)	(1.01)
N	551	551	551	551

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Predictability estimates for the first row of the VAR in equation 1, where the state variables are the annual return, the price-earnings ratio, and the annual growth rate of earnings for the aggregate German stock market index DAX. We use data for the available history of the DAX from 1973 up to the first survey wave. Standard errors are reported in brackets. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 4: Contemporaneous Regression Matrix

	Return$_t$	Price Earnings ratio$_t$	Earnings Growth$_t$
Return$_t$	1.000	0.052**	0.451***
	(.)	(0.021)	(0.122)
Price Earnings ratio$_t$	1.755**	1.000	-1.400
	(0.704)	(.)	(0.868)
Earnings Growth$_t$	0.336***	-0.031	1.000
	(0.091)	(0.019)	(.)

Univariate regression coefficients of the contemporaneous value of each variable indicated in the column header, on each variable indicated in the row header. Row k of this table is equal to the optimal $G(k)'$ under sticky information. The variables are measured in annual terms. We use data for the available history of the DAX from 1973 up to the first survey wave. Standard errors are reported in brackets. $*p < 0.10, **p < 0.05, ***p < 0.01$

in which agents use an AR(1) for returns when the signal is about the past return, or a univariate reduced form return forecasting equation if the signal is about past earnings growth or the price-earnings ratio. The second benchmark is a naïve multivariate model, in which agents use predictability coefficients from the estimated VAR, but fail to incorporate cross-updating of other contemporaneous state variables ($\tilde{R}$ diagonal). The third benchmark is the optimal Bayesian update based on the full multivariate model accounting for contemporaneous correlations between the components of the state vector. As shown above, the optimal update of the return forecast is $B_1.G(k)$. Therefore, for the multivariate model, we use a bootstrap to account for the estimation uncertainty in this object, and, for consistency, all other benchmarks in this table.

It turns out the three benchmarks are very similar. Hence, the approach pursued by Armona et al. (2019) and others provides a good approximation to the full model in this particular application. We also note that the univariate benchmark is closer to the optimal update than the naïve multivariate benchmark. An intuition for this result is that the large sample univariate projection of the return on the signal largely comprises the effects through the other state variables.

We decompose the optimal Bayesian update into the contributions of the three state variables, which are given by the update of the respective contemporaneous state variable multiplied with its loading on the return forecast. For instance, the first column of the decomposition shows a return signal optimally leads to an update of not only the return state, but also of the P/E state and the earnings growth state. Whereas the update of the earnings growth state is sizable (see Table 4), its contribution to the revision of individuals' return forecast is negligible due to its negligible forecasting power for future returns (Table 3). By contrast, the update of the P/E state contributes more to the revision of individuals' return forecast than the update of the return state itself. Namely, the contribution of the P/E state to the optimal Bayesian update of -0.072 is -0.043 and hence roughly two thirds of the total, whereas the contribution of the return state is -0.024 and hence roughly one third of the total. The contribution of the earnings growth state is -0.008, which is only about one tenth, instead. These results shows the relative effects can be large even though in our application the absolute effects are small, suggesting that using multivariate coefficients but ignoring the contemporaneous correlation between state variables could lead to non-trivial errors in other applications.

The last row of the table tests the null hypothesis that the subjective δ_1 is equal to the optimal update. We report the t-statistic of a two-sample t-test for equal means. The p-value of a two-sided test is reported in brackets. The null hypothesis that agents update in line with the optimal benchmark is rejected. An alternative p-value based on the fraction of bootstrap samples for which δ_1 is larger than the optimal Bayesian update yields the same p-value of zero up to the third digit after the decimal point.[16]

In sum, individuals overreact to information about past returns and past earnings growth. Excessive extrapolation of past returns or capital gains can resolve the excess volatility puzzle in an otherwise standard Lucas tree asset pricing model (see Adam et al. 2017). Regarding the P/E ratio, individuals do not simply over-react to the signal relative to the empirical benchmark. Rather they respond less (in absolute value) and in the wrong direction. Overreaction, as well as wrong-signed reaction, are inconsistent with sticky or noisy information models in which subjective models coincide with the objective law of motion of the economy. Whereas diagnostic expectations are, in general, able to generate overreaction, the fact that agents overreact to earnings growth and return news even when no predictability (or marginally negative predictability in the case of returns) is present, and the wrong-signed reaction to the price-earnings ratio, are challenging to explain under objective mental models. In the next section, we therefore explore additional evidence related to agents' subjective models.

[16] A block bootstrap with a fixed length of 12 non-overlapping periods (i.e. one-year) yields p-values of 0.000 for the return signal hypothesis test, 0.052 for the P/E signal hypothesis test, and 0.008 for the earnings growth signal hypothesis test. Hence, results are robust to accounting for serial correlation.

Table 5: Comparison of Updating Rates to Benchmarks

	Return Signal	**P/E Signal**	**Earnings Growth Signal**
Estimated subjective updating rates			
Subjective δ_1	0.392***	0.100**	0.305***
	(0.062)	(0.047)	(0.048)
Benchmark			
Naive Univariate Model	-0.073*	-0.862***	0.004
	(0.044)	(0.237)	(0.034)
Naive Multivariate Model	-0.024	-0.830***	-0.010
	(0.054)	(0.297)	(0.040)
Optimal Bayesian Update	-0.072*	-0.858***	0.007
	(0.042)	(0.238)	(0.036)
Decomposition of Bayesian Update			
Contribution Return State	-0.024	-0.042	-0.008
Contribution P/E State	-0.043	-0.830	0.026
Contribution Earnings Growth State	-0.005	0.015	-0.010
Hypothesis Test			
Subjective δ_1 = Optimal Update	6.182***	3.947***	4.976***
	[0.000]	[0.000]	[0.000]

This table summarizes the estimated updating rates and three different benchmarks: a univariate model, a naïve multivariate model (without contemporaneous cross-updating), or an optimal updating model. The third panel decomposes the optimal Bayesian update into the contributions of each state variable, which is given by the update of the respective contemporaneous state variable multiplied with its loading on the return forecast. Standard errors of all benchmarks (in brackets) are computed using a bootstrap. The bottom panel tests the Null hypothesis that the optimal update equals the subjective δ_1. The t-statistic is based on a two-sample t-test for equal means. P-values are reported in brackets below each t-statistic. P-values from a one-sided bootstrap test are identical up to three digits after the decimal point. $*p < 0.10, **p < 0.05, ***p < 0.01$

4.5 Subjective Mental Model

Based on the model we introduced in Section 3, individuals' subjective models link prior perceptions and prior expectations. To assess the relationship between prior perceptions and expectations we run the following regression:

$$\tilde{E}[r_{t+1}]_i^{pre} = \lambda_{0,k} + \lambda_{1,k}\tilde{x}_{i,k}^{pre} + W_i\omega_k + \nu_{i,k} \quad \forall k, \tag{11}$$

where $\tilde{E}[r_{t+1}]_i^{pre}$ denotes individual i's expectation of the 1-year ahead stock return, $\tilde{x}_{i,k}^{pre}$ denotes prior perceptions of the information in treatment group k, and W_i is a vector of socio-demographic controls. Since we observe each perception only in the corresponding treatment group, we run regressions treatment group by treatment group. We focus on the relationship for the return over the past 12 months, the current price-earnings ratio, and earnings growth over the past 12 months.

Table 6 presents our estimates of equation (11) without and with socio-demographic controls (columns 1-3 and columns 4-6, respectively). Individuals perceive 1-year returns to be far more persistent than in the data; the subjective link of 0.42-0.43 compares to an autoregressive estimate of -0.07 in Table 3. Similarly, respondents perceive earnings growth to have substantial predictive power for stock returns, again inconsistent with the data. Moreover, individuals ignore the inverse relationship between price-earnings ratios and future returns that is central to finance, and instead perceive a mild positive relationship between the two.

It is noteworthy that the link between prior expectations and perceptions estimated in Table 6 is very similar in magnitude to the estimated updating rates for each corresponding treatment. The updating rates of 0.39, 0.30, and 0.10, for information about past returns, past earnings growth, and the current price-earnings ratio, correspond to subjective model coefficients of 0.42, 0.39, and 0.10. Hence, allowing for subjective models of the economy offers a natural explanation for the joint set of facts we document. Given this evidence, a better understanding of heterogeneous subjective models of asset price dynamics and their origins could be a fruitful avenue for future research.

In sum, our experimental evidence shows neither rational expectations, nor sticky or noisy information, nor diagnostic expectations with objective mental models fully explain the observed updating behavior. Overreaction is a central mechanism in individuals' belief formation even when a state variable has no predictive power for future returns. The price-earnings ratio does not exert a corrective influence on these beliefs. Incomplete information cannot explain expectation formation, as in fact, providing more information about the price-earnings ratio would induce a pro-cyclical response of return beliefs. In sum, our evidence points to an important role for subjective models of the stock market that deviate from their objective benchmarks.

4.6 External Validity

By construction, experiments are conducted at specific points in time and in a given location. As such, our paper is part of a burgeoning literature using information provision experiments to answer different economic questions (see, e.g., Coibion et al. 2018, 2022; Armona et al. 2019; Andre et al. 2022). In this section, we discuss external validity in our specific setting.

The main focus of our analysis are expectation revisions in response to news. Possibly time-varying prior informedness, as well as the level of prior expectations, are therefore immaterial to our results. In particular, by studying expectation revisions, we essentially control for prior expectations at the individual level when we study how different pieces of information affect posterior expectations and we compare the belief revisions of individuals in the different treatment arms to those in the control condition.

We cannot control for time-variation or regime shifts in updating rates, for instance because individuals think the data-generating process changed, which would require repeated surveys with identical types of treatments on representative populations over time. This issue is taken up in a recent paper by Weber et al. (2023). In this large meta-study the authors investigate how updating behavior in RCTs regarding inflation expectations varies across time periods and countries. In the domain of stock market expectations, we note our results are consistent with observational (non-experimental) evidence from different time periods and samples. Extrapolative return expectations are also observed in Greenwood and Shleifer (2014) and Adam et al. (2017). Our evidence on beliefs and portfolios is also consistent with Giglio et al. (2021). Given that stock-ownership is endogenous

Table 6: Prior Perceptions and Prior Expectations

	Prior expectation DAX returns					
	(1)	(2)	(3)	(4)	(5)	(6)
	T2	T3	T4	T2	T3	T4
T2: Past 12m Return	0.42***			0.43***		
	(0.06)			(0.06)		
T3: Earnings Growth		0.39***			0.38***	
		(0.05)			(0.05)	
T4: Current PE			0.10**			0.11**
			(0.04)			(0.05)
Constant	3.12***	3.14***	3.48***	3.52***	3.41***	4.23***
	(0.39)	(0.43)	(0.44)	(1.08)	(1.13)	(1.03)
Socio-Demographics	No	No	No	Yes	Yes	Yes
R^2	0.20	0.18	0.02	0.24	0.19	0.05
N	599	600	474	577	578	462

Prior expectations regressed on prior perceptions for all participants in the September 2020 wave of the Bundesbank Survey of Consumer Expectations. Dependent variable is the pre-treatment subjectively perceived return of the DAX over the next 12 months. Explanatory variable are the prior perceptions of the value-weighted return of the DAX over the past 12 months (T2), the growth rate of aggregate earnings of the DAX constituents over the past 12 months (T3), and the level of the aggregate price-earnings ratio of the DAX at the time of the survey (T4), respectively. As each prior perception is available only for respondents in the respective treatment group, the regressions are run separately for each treatment group. Columns 4-6 control for gender, age, age squared, college education or higher (dummy), full time employment (dummy), living in the eastern part of Germany prior to fall of Berlin wall in 1989 (dummy), children (dummy), household income (indicator for income bracket) and homeowner (dummy), household size (indicator for size) and region (indicator for each of four German statistical regions). Return expectations are winsorized at their 1% tails. Standard errors are reported in brackets. $*p < 0.10, **p < 0.05, ***p < 0.01$

and likely related to agents' beliefs, representative surveys, as opposed to sub-samples of the population such as clients of a particular asset manager or bank, are important for modelling economic aggregates, such as the joint dynamics of the aggregate stock market and aggregate consumption.

Our experimental evidence goes beyond the existing evidence from observational data, as it allows us to show which of the conjectured mechanisms work causally at the individual level. The measurement of prior perception gaps and treatment-induced expectation revisions allow us to cleanly estimate updating rates in order to assess the quantitative strength of each channel. This setting allows us to test different models of expectation formation in a unified setting. Our evidence suggests individuals entertain subjective mental models of the stock market, which help to explain their reaction to different information treatments, the link between prior perceptions and prior expectations, and the heterogeneity in their belief updating. In addition, our setup allows us to estimate the causal pass-through from beliefs to portfolios which is otherwise plagued by endogeneity and measurement error biases. We leave potential time-variation in updating behavior about asset prices as an interesting question for future research.

Finally, the possibility exists that the actual law of motion of asset prices changes over time. Clearly, in this case it is harder to find the right objective benchmark against which we can compare updating rates. We think it is unlikely that the law of motion has changed to an extent that would justify extrapolation of the observed magnitudes. Similarly, a positive relationship between the price-earnings ratio and future returns is hard to generate in any "no bubble" economy. That being said, the main contribution of our paper is to provide estimates of updating rates. We compare these to plausible benchmarks, but ultimately, they could be compared to other benchmarks that researchers may come up with in the future. For instance, if a regime shift occurred in 2020, researchers could estimate the new process after enough data has accumulated, and compare it to the expectation formation process implied by our experiment.

Regarding incentivization and experimenter demand effects, a recent literature shows that these effects tend to be small in economic settings (see, e.g., De Quidt et al. 2018; Hackethal et al. 2023), especially in online survey experiments without direct interactions between survey participants and experimenter. The take-away from this literature is that experimenter demand effects can play a role for issues with a moral flavor, but tend to be small for purely economic issues, such as expectation formation and portfolio choice. Consistent with this literature, several pieces of evidence in our results alleviate these concerns. First, the quantitative link between prior perceptions and expectations in Section 4.5 provides evidence validating the updating results, in the sense that the way participants update their beliefs in the experiment is consistent with the way they form beliefs before being prompted with specific facts. Second, the conclusion that subjective mental models are needed to explain individuals' responses in our experiment holds across treatment arms, despite the fact that respondents are not aware of anything else beyond the questionnaire and specific treatment they are randomly allocated to. Moreover, the response to the past long-term return treatment (Section A.4) is in line with an internally consistent belief system, despite being elicited from different respondents in independent treatment arms. Third, the information ranking effects in the second wave are hard to explain with experimenter demand effects (Section 5). Moreover, we observe information ranking effects for P/E and earnings growth, but not for past returns, whereas we would expect such effects to be present across all treatments if experimenter demand effects explained them. In sum, we believe our results are hard to rationalize with experimenter demand effects, in line with other evidence in the literature.

5 Heterogeneity of Updating Behavior

A pervasive feature of survey expectations is their heterogeneity and the fact that (socio-demographic) respondent characteristics explain only a surprisingly small fraction of the heterogeneity in how expectations respond to news across agents (Coibion et al., 2022). This feature holds for our survey as well.[17] However, we show below that an aspect

[17] Columns 4-6 of Table 6 show socio-demographic characteristics provide almost no explanatory power for expectations, beyond prior perceptions. Appendix section A.3 shows a regression of prior expected returns on the available socio-demographic characteristics yields an R^2 below 1%, and only education is significantly associated with (lower) expected returns. Since Table B.3 shows demographics do not explain perceptions either, systematic variation in both perceptions and expectations exists, which is orthogonal to observable socio-demographics, but possibly related to different subjective models of the economy.

related to agents' subjective models, namely individuals' ranking of the usefulness of different pieces of information, is associated with strong differences in updating behavior.

We can rationalize this effect with the model we introduced above. Consider potential heterogeneity in the subjective model parameter $\tilde{B}_{1,k}$. How would an agent who perceives a given variable k as a particularly strong return predictor respond to information about this variable? The answer is not obvious because two offsetting channels exist: i) the agent likely has a smaller perception gap and therefore responds *less* to the treatment (in absolute terms) because she is ex-ante (before the information provision in the survey) better informed about the information she subsequently receives, and ii) the larger $\tilde{B}_{1,k}$ leads to a *higher* updating rate per unit of perception gap. The total (multiplicative) effect of these two channels is an open empirical question.

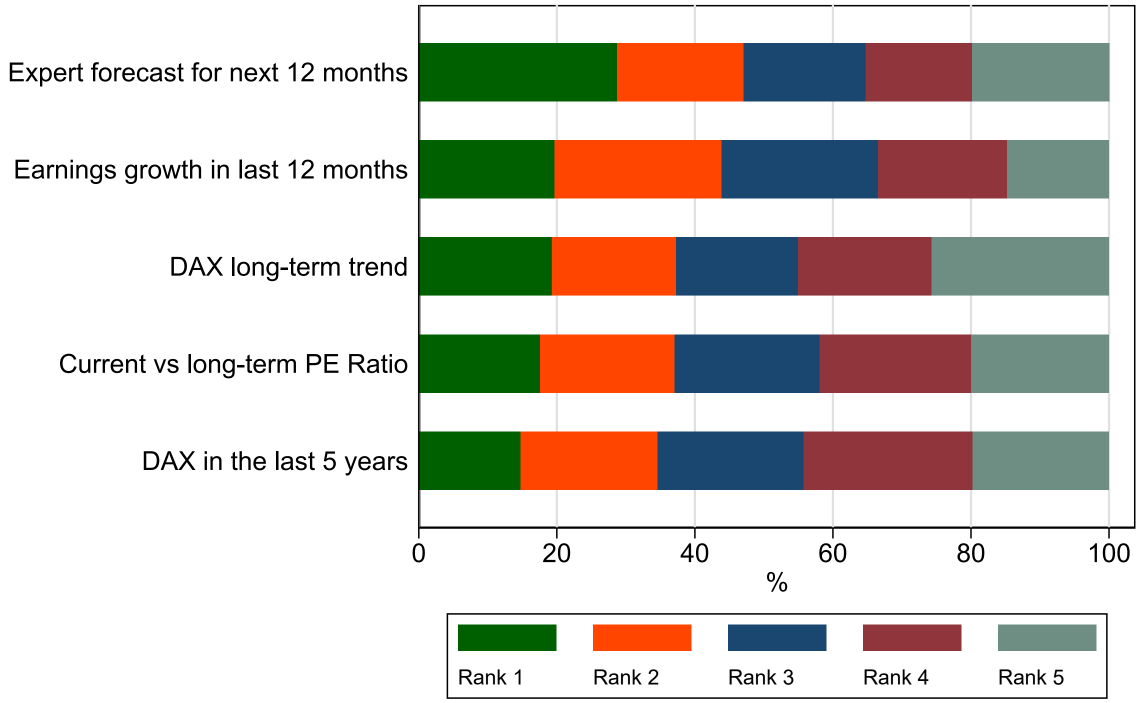
To quantify this effect, we elicit in a second survey wave how each respondent ranks various pieces of information. These pieces of information include the randomized treatment items, but survey respondents do not know that they will receive one of these items when we elicit the ranking. Hence, different from the experiment of Fuster et al. (2019), we elicit which type of information respondents rate as most important in general, not their expected marginal benefit of receiving this information. Thus, we assume respondents rank those pieces of information as highly relevant for their return beliefs, which they view as a particularly strong return predictor.

We find agents with a higher ranking for a given piece of information such as the price-earnings ratio, are slightly better informed about the respective state variable than other respondents, in line with prediction i). At the same time, they respond significantly more strongly to this information, that is, channel ii), the effect of the subjective model, is dominating. These findings strengthen the case that subjective and heterogeneous mental models are a key feature of individuals' beliefs about the stock market. The remainder of this section lays out the analysis underlying these results. More details on the second wave of our survey can be found in appendix B.1.

5.1 Which Information Do Individuals Perceive as Important?

Figure 1 shows the average ranking of information items across respondents. Individuals most frequently rate expert forecasts as the most useful information for the purpose of return prediction, followed by information about earnings growth, the long-term historical average return on the DAX, the price-earnings ratio and the return on the DAX over the past five years. However, the most salient feature of the distribution of information rankings is the large heterogeneity. Each piece of information is most preferred by a sizable share of respondents and less preferred by other respondents. We exploit this heterogeneity to measure the effect of information rankings on information processing, taking the information ranked first by an individual as a measure of the information she considers as most important. Each information item is ranked highest by a sizable share of respondents ensuring a sufficiently large number of observations for any of the information items.

Figure 1: Individuals' Ranking of Information Items



Subjective ranking of different pieces of information for all participants in the December 2020 wave of the Bundesbank Survey of Consumer Expectations with rank 1 being the most preferred information item.

5.2 Effect of Information Rankings on Information Processing

In light of the empirical importance of longer-term expectations and their role in asset pricing models (La Porta, 1996; Lettau and Wachter, 2011; Weber, 2018), our second wave elicits expected returns and expected dividend growth at different horizons (one year and five year). To avoid survey fatigue, we do not elicit the corresponding prior expectations, when eliciting four posterior expectations in the second wave. We therefore adjust our econometric approach and use a more basic specification, which is commonly employed in the RCT literature to estimate average treatment effects (see, e.g., Coibion et al. 2022). Our objective is to evaluate if treatment effects differ depending on whether individuals rank a given piece of information highest.

To quantify this effect, we extend the empirical model with a binary variable, P_i^k, which is equal to 1 if individual i has ranked treatment k as most preferred, and zero otherwise:

$$E[X]_i^{post} = \alpha + \sum_{k=1}^{K-1} \left(\beta_k T_i^k + \psi_k P_i^k + \xi_k T_i^k P_i^k\right) + \mathbf{W_i}\phi + \epsilon_i, \tag{12}$$

where T_i^k are treatment dummies and $E[X]_i^{post}$ refers to individuals' posterior expectations about outcome X (returns or dividend growth over the next one or five years) and W_i is a vector of other socio-demographic controls. The treatments are: past 5-year return treatment (T1), past earnings growth treatment (T2), and price-earnings ratio treatment (T3).

The coefficient of interest is ξ_k. It measures how much the treatment effect of an individual who ranks the information received in the treatment highest, differs from the treatment effect for an individual who does not rank it highest.[18] Table 7 presents estimates of the effect of information rankings on information processing for the three treatments and the four outcome variables. We mark the coefficients of interest with red boxes.

For the treatment about the stock return over the past 5 years, the estimated coefficient for the information ranking effect is insignificant across all outcome variables. This insignificant estimate implies individuals for whom information about the past five-year stock market return is their most preferred information item do not react differently to this information compared to all other recipients of this information. We show in Appendix B.1.5 that these respondents have smaller perception gaps than all other respondents, hence the effect of the information ranking may be offset by the effect of a less surprising signal. Respondents who rank earnings growth information highest have a similar perception gap compared to all other respondents, whereas respondents who rank price-earnings ratio information highest tend to be better informed about its current level.

For the past earnings growth treatment, the coefficient measuring the information ranking effect is significantly negative for all outcome variables. The information ranking effect for the past earnings growth treatment is, respectively, roughly -3.4 and -3.9 percentage points for return expectations at the one-year and five-year horizon, and -5.2 and -6.2 percentage points for dividend growth expectation for the two horizons. Thus, individuals who rank this type of information highest react to the negative news about recent earnings growth in a more extrapolative manner than other individuals. In other words, individuals whose mental model of the stock market is such that earnings growth plays a central role are also more inclined to form their beliefs in line with models of extrapolative expectations.

We also obtain a significant and negative information ranking effect for the price-earnings ratio treatment with respect to return expectations. Individuals who perceive information about the price-earnings ratio as important react to the information that the price-earnings ratio is substantially above its historical average by revising their return expectations downwards by between roughly 2.8 and 4.9 percentage points more than other individuals at the one-year and five-year horizon, respectively. In contrast, we do not find any information ranking effect for expected dividend growth at either horizon. These findings suggest the existence of a group of individuals who view information about the price-earnings ratio as important and who react to such information in a way that is more in line with models based on counter-cyclical return expectations than the reaction of the average respondent.

Overall, our results support the hypothesis that individuals entertain different mental models of the stock market, which jointly determine their information ranking, information acquisition, and information processing. Our findings add to a literature documenting economically relevant heterogeneity in how individuals form stock market expectations.

[18]The effect is estimated controlling for the full set of socio-demographic characteristics but it need not be causal. Designing an experiment, which induces exogenous variation in information preferences, or exploiting potentially exogenous shocks to information preferences in a field setting could be a fruitful avenue for future research. Table B.7 shows that information rankings are largely orthogonal to any observable socio-demographic characteristics in our sample and therefore capture a new dimension of belief heterogeneity.

For instance, Dominitz and Manski (2011) suggest the population consists of a mixture of types with "interpersonally variable but intrapersonally stable" expectation formation processes. Our experimental setup allows us to disentangle two distinct channels arising at different stages of the expectation formation process that contribute to the observed heterogeneity. First, heterogeneity in how individuals form expectation can arise at the information acquisition stage due to the fact that different individuals rank different pieces of information heterogeneously and are therefore more or less likely to acquire such information. Second, heterogeneity can arise at the information processing stage due to different individuals processing identical information items differently. We document a sizable degree of heterogeneity regarding the first channel given that the most preferred information item is almost uniformly distributed across individuals (see Figure 1). This heterogeneity in information rankings is associated with heterogeneity in individuals' informedness but the differences in informedness are not large, hinting towards a role for information costs, which we discuss below. Our key finding relates to the second channel. The controlled experimental setting allows us to show that distinct groups of individuals *process* the exact same piece of information in very different ways. Under the hypothesis that different groups of individuals entertain different mental models of the stock market, we would indeed expect these mental models to jointly determine information rankings and information processing.

Table 7: Updating Behavior by Information Ranking

	Returns: 12 Months	Returns: 5 Years	Dividends: 12 Months	Dividends: 5 Years
	(1)	(2)	(3)	(4)
T1	-0.21	0.26	0.31	2.26***
	(0.54)	(0.81)	(0.71)	(0.88)
DAX 5y Info Selected	0.19	1.19	-1.11	1.41
	(0.91)	(1.39)	(1.21)	(1.45)
T1xDAX 5y Info Selected	-0.93	-1.84	0.81	-2.71
	(1.21)	(1.66)	(1.68)	(1.86)
T2	1.14	6.81***	-1.12	5.27***
	(0.93)	(1.14)	(1.11)	(1.13)
Earnings Info Selected	0.68	1.47	2.22*	2.62*
	(0.90)	(1.41)	(1.15)	(1.55)
T2xEarnings Info Selected	-3.36**	-3.87*	-5.22***	-6.17***
	(1.62)	(2.26)	(1.97)	(2.19)
T3	0.91	2.24**	0.46	1.98**
	(0.68)	(1.02)	(0.78)	(1.01)
PE Ratio Info Selected	1.09	3.23**	-1.09	2.32
	(0.85)	(1.47)	(1.28)	(1.51)
T3xPE Ratio Info Selected	-2.81**	-4.86**	-1.75	-2.58
	(1.32)	(2.07)	(2.09)	(2.23)
Constant	13.23***	12.60***	16.16***	17.89***
	(3.69)	(3.99)	(4.37)	(4.67)
Socio-Demographics	Yes	Yes	Yes	Yes
R^2	0.01	0.05	0.04	0.03
N	3183	3183	3128	3128

Treatment effects by information rankings for all respondents of the December 2020 wave of the Bundesbank Survey of Consumer Expectations. The binary variable "Info Selected" is 1 if the respondent ranked the respective item of information first out of five choices, and 0 otherwise. Dependent variable listed in column headings. Robust standard errors in parentheses. T1 (DAX past 5 years), T2 (Earnings growth past 12 months) and T3 (PE ratio). Controlling for gender, age, age squared, college education or higher (dummy), full time employment (dummy), east/west Germany (dummy), children (dummy), household income (indicator for income bracket) and homeowner (dummy), household size (indicator for size) and region (indicator for each region). Winsorized (1% tails) posterior expectations on stock market returns and dividend growth over the next 12 months/5 years. Standard errors are reported in brackets. $*p < 0.10, **p < 0.05, ***p < 0.01$

5.3 The Role of Information Costs

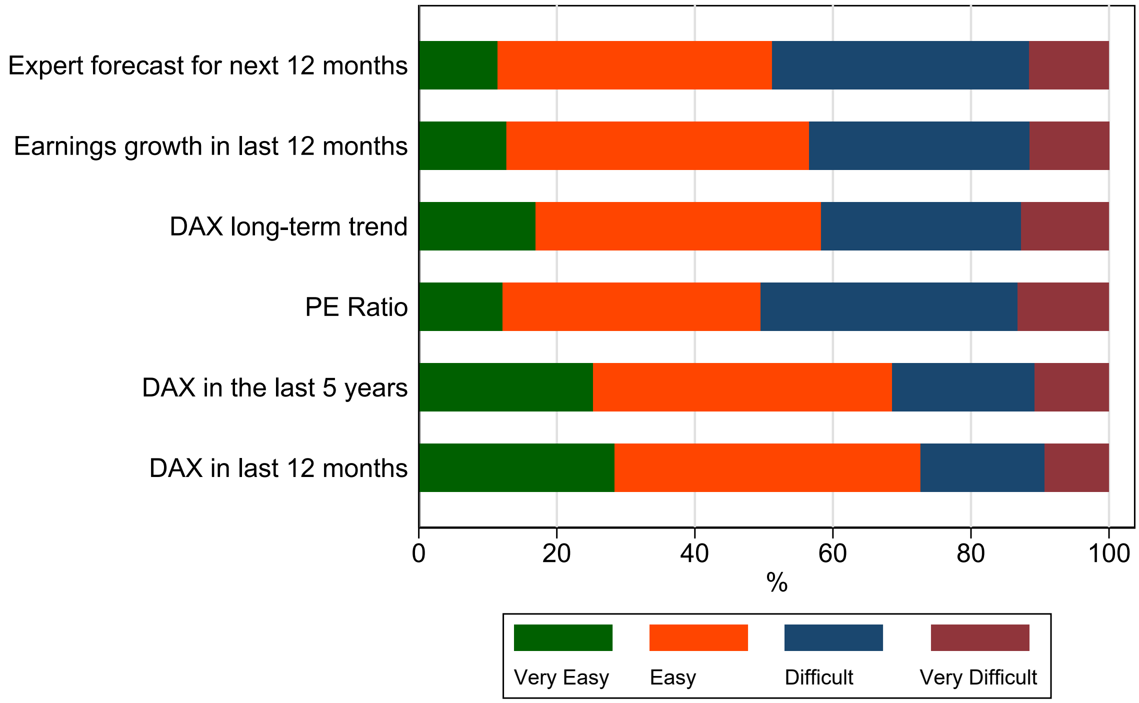
In addition to information rankings, heterogeneity in the cost of different information items can influence individuals' information acquisition. A given piece of information might be highly valuable to individuals, but also very difficult to obtain. Measured expectations in observational data are likely to be more strongly influenced by information that is easier to obtain, for instance, because the information is regularly disseminated via the media. To obtain a clear distinction between rankings and costs, our question on information rankings asked respondents to abstract from the perceived cost of acquiring different pieces of information ("Assume that you would receive all items of information easily and free of charge.") In a separate question, we asked respondents how costly it would be for them to acquire each of the information items in terms of financial or time costs.

Figure 2 shows a clear ordering of individuals' perceived cost of obtaining each information item. We classify information items with a higher share of respondents who think they are "easy" or "very easy" to obtain as less expensive. Information about past returns is perceived to be the least expensive to obtain. The low perceived cost of obtaining information about past returns may reflect the frequent dissemination of such information by various news media and possibly contributes to the prevalence of extrapolative return expectations in observational data. The perceived costliness of past return information is increasing with the horizon of the backward-looking information, consistent with imperfect information and/or imperfect memory as a potential mechanism contributing to measured overweighting of recent returns in addition to the differential response to recent and long-run returns documented in our information treatments. Information about past earnings growth is more difficult to obtain than information about past returns, but not as costly as expert forecasts about future returns. The information item perceived as most difficult to obtain is the price-earnings ratio.

Interestingly, the ordering of perceived costs is similar to the ranking of information items (see Figure 1). Individuals perceive information about expert forecasts, past earnings growth, and the price-earnings ratio as especially useful for their investment decisions. However, they also perceive these items as especially costly to obtain.[19] Lowering the cost of obtaining relevant stock market information could therefore potentially reduce households' expectational errors about the stock market. For instance, supplying the public with expert forecasts about financial market developments could potentially be a tool to mitigate excessive optimism and pessimism and their impact on asset prices. By contrast, providing information about the price-earnings ratio could increase the pro-cyclicality of stock return expectations. Thus, providing more information is not always optimal if individuals overreact to or misinterpret the information (see also Azarmsa and Beutel 2024).

[19] We discuss the heterogeneity of perceived information costs in Appendix B.1.7. Men, stock owners, and individuals with above median income perceive significantly lower information costs. By contrast, the effect of college education is insignificant for most information items.

Figure 2: Perceived Cost of Acquiring Information Items



Perceived cost of obtaining different information items for all participants in the December 2020 wave of the Bundesbank Survey of Consumer Expectations.

6 Beliefs and Portfolios

The impact of subjective beliefs on asset prices crucially depends on their pass-trough into investors' portfolios. While a large body of research documents this pass-through is too low to be reconciled with standard models, measurement error in survey expectations, frictions and trading costs, omitted variables, and endogeneity between expectations and holdings could plausibly attenuate the estimated link between beliefs and portfolios downwards.

Survey experiments can help to uncover the true causal link between beliefs and portfolios. By creating exogenous variation in investors' beliefs, they allow to measure the causal effect of beliefs on portfolios, with confounding factors being eliminated by the random assignment of respondents into treatment and control groups. We show the causal pass-through after instrumenting beliefs with the exogenous treatments is roughly twice as large as the pass-through obtained when not exploiting the exogenous variation generated by the experiment. Importantly, this comparison is based on the same respondents in the same survey. Hence, while portfolio decisions are based on a hypothetical question, the difference between the two estimates cannot be explained by different frictions, but is purely attributable to the methodological difference. As such, it is likely that combining administrative data with experimental methods would produce a similar effect. Thus, the framework developed in this paper can be fruitfully used not only to further our understanding of belief formation, but also to uncover new facts about the causal link to investors' portfolios.

6.1 Correlational Evidence on Beliefs and Portfolio Choice

A common theoretical benchmark in the literature is the classical Merton (1969) model of optimal portfolio choice yielding the following optimal portfolio rule:

$$EquityShare_i = \frac{1}{\gamma}\frac{E_i(R) - R_f}{Var_i(R)}, \tag{13}$$

where the optimal share in the risky asset, $EquityShare_i$, is equal to the expected excess return per unit of risk, $\frac{E_i(R)-R_f}{Var_i(R)}$, scaled by investors' coefficient of risk aversion, γ.[20]

To test the predictions of the Merton model, we follow Giglio et al. (2021) and regress individuals' stock portfolio shares on their posterior subjective expectations for excess returns:

$$Inv.Share_i^{post} \quad = \quad \delta_0 + \delta_1 \left(E[R]_i^{post} - R_f\right) + \mathbf{X_i}\gamma + u_i, \tag{14}$$

where $Inv.Share_i^{post}$ denotes individuals' share invested in stocks from the portfolio choice decision elicited in the first wave of the survey after our information treatments. $E[R]_i^{post}$ denotes posterior expectations for one-year ahead stock market returns. We set the risk-free return R_f to 1%, which is the value we used to frame the portfolio choice problem in the survey. The precise value for R_f is without loss of generality, since it only affects the constant δ_0. The coefficient of interest, δ_1, measures the sensitivity of individuals' portfolio share with respect to changes in their expected return. X_i is a vector controlling for socio-demographic characteristics, post-treatment willingness to take risk in financial matters, and post-treatment perceived variance of 1-year ahead stock returns.

Comparing the estimation equation (14) to the theoretical benchmark of equation (13), the estimated coefficient δ_1 corresponds to $\delta_1 = \frac{1}{\gamma Var_i(R)}$. Giglio et al. (2021) estimate a portfolio sensitivity, $\delta_1 = 0.69$, and set $Var_i(R) = 0.20^2 = 0.04$ corresponding to an estimate of the historical standard deviation of one-year U.S. stock market returns of 20%. Their estimates imply a value of $\gamma = \frac{1}{\delta_1 Var_i(R)} = 1/(0.69 \times 0.2^2) = 36.23$ to rationalize individuals' choices. The first three columns of Table 8 report the estimated sensitivity of portfolios to expected returns based on our survey data. We find a coefficient of 1.35 in our main OLS specification with all controls (see Column 3). Thus, our estimate is of similar magnitude but higher than the one of Giglio et al. (2021), possibly because we are looking at a stylized portfolio allocation decision which abstracts from transaction costs and other frictions, whereas the estimates of Giglio et al. (2021) are based on portfolio data for clients of the asset manager Vanguard. Indeed, Giglio et al. (2021) show that frictions such as capital gains taxes and infrequent trading exert a substantial downward effect on their estimates. The implied risk aversion parameter based on our estimate and a historical standard deviation of one-year stock returns in Germany of 0.21 is $\gamma = \frac{1}{\delta_1 Var_i(R)} = 1/(1.35 \times 0.21^2) = 16.79$, which is outside the range of plausible values of risk aversion of 3-10 (Giglio et al., 2021).

[20] A discrete-time version of the underlying model can be found in Campbell and Viceira (2003).

Table 8: Portfolio Share Sensitivity w.r.t. Expected Returns

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
$E[R]_i^{post} - R_f$	1.39***	1.34***	1.35***	2.80***	2.77***	2.84***
	(0.07)	(0.07)	(0.07)	(0.36)	(0.37)	(0.38)
Constant	0.49***	0.43***	0.42***	0.51***	0.45***	0.44***
	(0.01)	(0.08)	(0.08)	(0.01)	(0.08)	(0.08)
Socio-Demographics	No	Yes	Yes	No	Yes	Yes
Risk Attitude	No	No	Yes	No	No	Yes
Subjective Variance	No	No	Yes	No	No	Yes
R^2	0.11	0.15	0.15			
F				22	21	20
N	3509	3392	3392	3509	3392	3392
Implied γ	16.31	16.92	16.79	8.09	8.18	7.98

Portfolio share sensitivity to expected returns for all participants in the September 2020 wave of the Bundesbank Survey of Consumer Expectations. The first three columns show OLS estimates of equation (14) for different vectors of control variables. The last three columns show two-stage least squares IV estimates of the system (15)-(16). Risk attitude refers to post-treatment willingness to take risk in financial matters, and subjective variance refers to post-treatment perceived variance of 1-year ahead stock returns. The last line of each panel shows the parameter of relative risk aversion implied by the estimates. We control for the following socio-demographic characteristics: gender, age, age squared, college education or higher (dummy), full time employment (dummy), east/west Germany (dummy), children (dummy), household income (indicator for income bracket) and homeowner (dummy), household size (indicator for size) and region (indicator for each of four German statistical regions). Prior and posterior return expectations are winsorized at their 1% tails. Standard errors are reported in brackets. $*p < 0.10, **p < 0.05, ***p < 0.01$

6.2 Causal Evidence on Beliefs and Portfolio Choice

We exploit the treatments in the first survey wave to obtain exogenous variation in posterior return expectations, applying the following two-step instrumental variables (IV) estimator, in which we instrument posterior expectations with the randomly assigned treatments:

$$Inv.Share_i^{post} = \delta_0 + \delta_1 \left(E[R]_i^{post} - R_f\right) + \mathbf{X_i}\gamma + \nu_i \quad (15)$$
$$E[R]_i^{post} - R_f = \beta_0 + \beta_1 T_i^1 + \cdots \beta_5 T_i^5 + \mathbf{X_i}\theta + \epsilon_i. \quad (16)$$

This approach has two benefits. First, when estimating only the second stage of the sensitivity of portfolio shares to expected returns, δ_1 may be biased due to endogeneity and omitted variables. For instance, experiences from own asset holdings affect beliefs and trading behavior (see, e.g., Kuhnen and Knutson 2011; Anagol et al. 2021), which might bias the estimated portfolio sensitivity in either direction. Another example for potential endogeneity could be a sequence of favorable income shocks that increases an individual's savings and thereby may increase her risky asset share, since risky asset shares tend to increase with financial savings, as we document in appendix Figure B.1 (see also

Wachter and Yogo 2010). At the same time, these favorable income shocks may make the individual more optimistic in general, including her stock market expectations, leading to an overestimation of the causal link between beliefs and portfolios.

We address such endogeneity concerns by instrumenting expected returns, which isolates the variation in posterior expected returns that is solely due to the fully exogenous treatments. Second, expectations elicited in surveys are prone to measurement error. By isolating the systematic component of posterior expectations via the first stage, we can mitigate a potential attenuation bias of the estimated sensitivity in the second stage.

Column 6 of Table 8 shows the estimated portfolio sensitivity to expected returns, δ_1, is equal to 2.84 in our main two-step IV specification. This estimate is more than twice the size of the estimate obtained from our single-stage OLS regression. Our IV estimate therefore yields an implied level of risk aversion of $\gamma = \frac{1}{\delta_1 Var_i(R)} = 1/(2.84 \times 0.21^2) = 7.98$. Hence, this estimate implies a parameter of relative risk aversion inside the plausible range. Exploiting the exogenous variation in beliefs generated by our experiment helps to mitigate the influence of confounding factors, which attenuate the sensitivity estimates and thereby understate the causal link between beliefs and portfolio decisions. Our results point to endogeneity as a likely factor contributing to the low pass-through of beliefs into portfolios implied by standard estimates. Since trading frictions are absent in our setting, these are unlikely to affect the difference between our single-step OLS and our two-step IV estimator. By contrast, instrumenting beliefs with the exogenous treatments provides an effective way of mitigating biases from measurement error. Giglio et al. (2021) show that measurement error does exert a substantial downward bias on sensitivity estimates, but it cannot fully explain the gap. This gap suggests endogeneity likely contributes to the difference between the one-step OLS and the two-step IV estimator. Exploiting the exogenous variation from randomized experiments is a strategy for addressing measurement error and endogeneity biases jointly, which could be fruitfully applied in other contexts as well.

Our analysis focuses on the elasticity of portfolio shares with respect to changes in expected returns, for which our information treatments provide exogenous instruments. We do not attempt to explain the constant of the regression, which suggests even individuals with zero expected equity premium would on average invest a sizable share of their portfolio in risky equity (a feature also shared by Giglio et al. 2021). The estimated elasticity shows that changes in return expectations lead to substantial variation around this constant, both across respondents (as suggested by our OLS estimates), and in response to treatments which mimic the arrival of news, and hence expectation and portfolio dynamics across time (as suggested by our IV estimates).

In sum, we find evidence for overreaction and subjective models in the expectation formation process, but our results on the link from beliefs to portfolios are consistent with the elasticity predicted by a standard Merton model of portfolio choice, suggesting frictions in subjective belief formation as an important ingredient for explaining the dynamics of households' portfolio choices and their implications for asset prices.

7 Conclusion

We show overreaction is a pervasive and causal mechanism in individuals' stock return expectation formation. Moreover, individuals respond to information that the current price-earnings ratio is much higher than they thought by *increasing* their subjective expected stock returns. This reaction is opposite to what we would expect based on the empirical finance literature and economic theory, suggesting the subjective mental models individuals use to form return expectations deviate from objective benchmarks. These subjective models appear to be heterogeneous and give rise to differential responses to the same information.

We obtain these findings in a randomized controlled trial (RCT) allowing for identification of causal effects, while maintaining a real-world field survey setting. We provide a generic model of belief updating to interpret our empirical evidence. The model yields sharp testable predictions and could be fruitfully applied to RCTs in other contexts as well. Exploiting the exogenous variation in beliefs our experiment generates also allows us to identify the causal link between beliefs and portfolios. Quantitatively, our approach brings the estimated sensitivity of portfolio shares to expected returns within a range that is consistent with standard models of portfolio choice and plausible levels of risk aversion.

Our findings suggest models incorporating overreaction and subjective mental models could present a fruitful avenue for future research. We conjecture that survey evidence, including but not limited to the evidence presented in this paper, will be crucial for disciplining the flexibility that arises in such a setting. The combination of theoretical and empirical research should ultimately move us closer to the true model of investors' beliefs and portfolios. Exploring the implications of heterogeneity in subjective models for trading patterns, asset price dynamics, and wealth re-distribution could be particularly interesting endeavors. Given the low explanatory power of demographics for information rankings, perceptions, and expectations, understanding better what shapes individuals' subjective models of the stock market constitutes another challenging question for future research.

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A Appendix

A.1 Sample Characteristics First Wave

In total, 4054 respondents participated in the first wave of our survey. The effective number of observations for each of our econometric specifications varies due to item non-response and will be indicated in each Table. Roughly 80% of respondents who started the first wave of the survey answered all questions on stock market beliefs. For those receiving the treatment on the price-earnings ratio, the response rate was slightly lower at 73%. Response rates across all other treatment groups and the control group were similar.

We observe a variety of respondent characteristics including age, gender, education, professional status, income, and perceived difficulty of the questionnaire. The randomization successfully maintains the sample properties along the observed characteristics. Table A.1 reports the characteristics for each treatment group and for the full sample. The distribution of characteristics is very similar across treatment groups. Male respondents are slightly over-represented in the survey. Remaining differences between the treatment groups are controlled for by using a vector of respondent characteristics in the regressions.

A.2 Summary Statistics First Wave

Table A.2 reports summary statistics for individuals' prior and posterior stock return expectations. The last panel of the table provides summary statistics for expected returns from the HFS FRBNY-SCE survey as a rough reference point. Consistent with the literature on inflation expectations, e.g. D'Acunto et al. (2022), stock return expectations elicited as point forecasts are higher than the means of individuals' probability distributions. As discussed in the main text, our econometric approach is immune to this feature of the data (see Section 3.2).

The cross-sectional dispersion of point forecasts is also larger than that based on the means of individuals' probability distributions, again consistent with the evidence on inflation expectations. A comparison to U.S. data on stock return expectations obtained from the latest available micro-data from the HFS FRBNY-SCE survey shows that the cross-sectional dispersion of our point forecasts is slightly higher than in the HFS FRBNY-SCE survey as we allow for the possibility of negative subjective return expectations. The dispersion of the means of our distribution question is similar to the HFS FRBNY-SCE.

A.3 Heterogeneity of Prior Expectations

Table A.3 shows how prior expectations correlate with socio-demographic characteristics. The table provides estimates from a regression of pre-treatment 1-year return expectations (first wave), on the available socio-demographic characteristics (e.g. gender, age, employment, education, income). (Stock-ownership information is only available in the second wave, where we do not observe pre-treatment expectations.) We report the result in the following table. Of all the demographics, only college education is significant, and associated with a roughly 1 percentage points lower pre-treatment expected return. Overall, the explanatory power of demographics for expectations is limited, with an R^2 below 1 percent. This result is consistent with evidence in Giglio et al. (2021) (see their table 8), who also find that standard socio-demographics have only limited explanatory power for expected returns.

A.4 Effect of Information about the Long-term Average Return

How would an agent with an internally consistent belief system respond to information about the long-term average return? To see this, we write the first line of the VAR system (1) explicitly as

$$r_{t+1} = \mu_1 + B_{11} r_t + B_{12} P/E_t + B_{13} \Delta e_t + \omega_{t+1}. \tag{17}$$

As before, we allow the parameters $\mu_1, B_{11}, B_{12}, B_{13}$, and the perceptions $r_t, P/E_t, \Delta e_t$ to be subjective, but suppress the explicit notation using tilde for ease of exposition.

This implies

$$\mu_1 = (1 - B_{11})\bar{r}_t - B_{12} \bar{P/E}_t - B_{13} \bar{\Delta e}_t, \tag{18}$$

where upper bars denote unconditional expectations and we have used the fact that ω is assumed to be mean zero. In other words, an agent who receives information about $\bar{r}_t$, but no other information ($\bar{P/E}_t$ and $\bar{\Delta e}_t$ unchanged) should change her parameter μ_1 as follows

$$\mu_1^{post} - \mu_1^{pre} = (1 - B_{11}) \left(\bar{r}_t^{post} - \bar{r}_t^{pre} \right). \tag{19}$$

Receiving information about the long-term average return, but no other information, should not lead to material changes in the current state perceived by the agents, such that the total change in returns, and consequently the ultimate expectation revision is

$$r_{t+1}^{post} - r_{t+1}^{pre} = \mu_1^{post} - \mu_1^{pre} \tag{20}$$

$$= (1 - B_{11}) \left(\bar{r}_t^{post} - \bar{r}_t^{pre} \right) \tag{21}$$

We parameterize B_{11} using our estimate of 0.42 from table 6, and compare $1 - B_{11} = 0.58$ to the estimated updating rate in table 2 of 0.51. Based on these point estimates, individuals' response to information about the long-term average return is below that implied by an internally consistent belief system even *conditional* on their excessively large belief about the predictive content of past returns. This result complements findings by Malmendier and Nagel (2011, 2016) that individuals overweight recent experience with causal evidence. That being said, the differences between these point estimates are not statistically significant.

A.5 Effect of Information about Expert Forecasts

We now consider the interpretation of the estimated updating rate for the expert forecast. We elicit each individual's prior expected return $\tilde{E}_t r_{t+1}^{pre}$. Treated individuals are then informed that experts forecast a 9% return over the next 12 months. Hence, we set $y_{t,k}$ in equation (10) to 9 percent and $\tilde{x}_{t,k}^{pre} = \tilde{E}_t r_{t+1}^{pre}$. We define the rational benchmark as an updating rate, which is positive but bounded by one, $0 < \beta_5 \leq 1$. Individuals should update in the direction of the expert forecast, but at most to the point where they fully adopt the expert forecast. The estimated updating rate in column 4 of Table 2 is 0.86. Hence, the pass-through of expert forecasts into beliefs is high, but not perfect (= 1) or necessarily excessive (> 1).

We also elicit whether respondents were aware of any expert forecast prior to receiving the treatment, and if so, what the direction of the forecast was. Roughly 60% of respondents answered that they were not aware of any expert forecast on the return of the German stock market over the next 12 months. The remaining 40% were roughly evenly split into perceiving experts to forecast an increase of the DAX (positive return) versus a decrease of the DAX (negative return). We evaluate whether the updating behavior varies between these groups. To do so, we interact the perception gap defined above with dummy variables indicating whether an individual either i) did not receive any forecast (omitted category), ii) did receive a forecast indicating a decrease of the DAX ($D_{i,1} = 1$), iii) did receive a forecast indicating the DAX would stay the same ($D_{i,2} = 1$), or iv) did receive a forecast indicating an increase of the DAX ($D_{i,3} = 1$). Specifically, we estimate

$$\tilde{E}_t r^{post}_{t+1} - \tilde{E}_t r^{pre}_{t+1} = \beta_0 + \sum_k \beta^k_1 (y_{t,k} - \tilde{x}^{pre}_{t,k}) T^k_i + \sum_{p=1}^{3} \delta_p (y_{t,k} - \tilde{x}^{pre}_{t,k}) T^5_i D_{i,p} + \omega_i. \quad (22)$$

The updating rates of individuals in group i) are estimated as β^5_1 and in groups ii)-iv) as $\beta^5_1 + \delta_p$, for $p = 1, 2, 3$. Table A.4 shows the updating rate β^5_1 for those who were not aware of any expert forecast prior to the treatment is slightly smaller than the unconditional updating rate for the full treatment group. As expected, those who thought that experts indicated a decrease of the DAX (and hence were surprised the most), have a larger updating rate, whereas those who were already aware of experts forecasting a positive DAX return responded less to the treatments. Due to the splits into subgroups, these estimates are significant in some, but not all of the specifications. The group who perceived a neutral forecast prior to the treatment is small (see Section 4.1), resulting in large estimation uncertainty such that we do not interpret its coefficient.

Table A.1: Sample Characteristics: First Wave

	Treatment 1 %	Treatment 2 %	Treatment 3 %	Treatment 4 %	Treatment 5 %	Control %	Total %
Male	60	54	54	55	61	58	57
Full-time Employment	45	38	40	41	42	44	42
College Education or higher	30	32	31	33	33	32	32
East Germany before 1989	18	16	17	17	19	17	17
Children	23	22	23	21	22	24	22
Homeowner	63	64	63	61	63	63	63
Age							
(0, 25]	5	4	5	4	4	5	5
(25, 35]	10	8	9	9	9	8	9
(35, 65]	56	56	54	54	53	57	55
(65,79]	26	29	29	30	31	26	28
[80,)	3	4	3	2	3	5	3
Household Size							
1	25	25	25	25	25	24	25
2-4	69	70	71	70	70	71	70
+5	4	4	4	4	4	5	4
Household Income (Euro)							
[0, 999]	3	2	2	3	2	2	2
[1.000, 2.999]	39	39	38	36	37	38	38
[3.000, 4.999]	37	36	37	38	37	37	37
[5.000, 7.9999]	14	16	15	16	16	17	16
[8.000,)	2	4	3	2	3	3	3
Region							
North	20	18	17	19	17	16	18
West	26	26	25	26	27	27	26
South	34	41	40	36	37	38	38
East	20	15	18	18	19	18	18

Share of survey participants (in %) with the respective characteristic.

Table A.2: Summary Statistics for Household Stock Market Expectations: First Wave

	mean	median	sd	skewness	kurtosis	min	max	n
First wave: expected stock return								
Prior point E[R] raw	4.79	5	11.09	1.44	21.90	-64	100	3653
Prior point E[R] winsorized	4.67	5	9.33	0.29	6.13	-25	40	3653
Posterior distribution E[R] raw	-0.34	0.50	7.90	-0.81	4.78	-27.50	27.50	3719
Posterior distribution E[R] winsorized	-0.38	0.50	7.81	-0.93	4.58	-27.50	17.50	3719
Comparison to HFS FRBNY-SCE survey								
HFS FRBNY-SCE E[Rt + 1]raw(Aug2019)	7.42	5	7.76	3.57	22.85	0	75	1064
HFS FRBNY-SCE E[Rt + 1]winsorized(Aug2019)	7.27	5	6.84	2.33	9.72	0	40	1064

Summary statistics for the cross-section of all all participants in September 2020 (first wave) of the Bundesbank Survey of Consumer Expectations. Prior refers to expectations elicited before the information treatments. Posterior refers to expectations elicited after the information treatments. Point refers to questions eliciting individuals' point forecasts of the respective quantity. Distribution refers to the mean of each individual's subjective probability distribution. Data shown from the Bundesbank Survey of Consumer Expectations must reflect at least 5 observations, therefore, min and max refer to the average of the 5 smallest/largest observations. The last panel shows corresponding statistics for the latest available cross-section (August 2019) from the HFS FRBNY-SCE survey question eliciting a point estimate for U.S. stock market returns (question: k0part2 1).

Table A.3: Return Expectations Correlates

	(1) **Prior Expected Returns**
Male	0.50
	(0.35)
Age	0.05
	(0.07)
Age^2	-0.00
	(0.00)
Full-time Employment	-0.41
	(0.43)
College	-1.14***
	(0.34)
East Germany Before 1989	-0.50
	(0.48)
Household Size	0.11
	(0.24)
Children	0.57
	(0.60)
Above Median Income	-0.52
	(0.37)
Homeowner	0.22
	(0.36)
Constant	4.01**
	(1.58)
R^2	0.007
$Adj R^2$	0.004
N	3372

Relationship between expected 1-year stock return prior to any information treatment and socio-demographic characteristics in the September 2020 wave of the Bundesbank Survey of Consumer Expectations. The socio-demographic characteristics are as follows: gender, age, age squared, college education or higher (dummy), full time employment (dummy), living in the eastern part of Germany prior to fall of Berlin wall in 1989 (dummy), children (dummy), household income (indicator for income bracket) and homeowner (dummy). Return expectations are winsorized at their 1% tails. Standard errors are reported in brackets. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.4: Updating Rates Expert Forecasts Extended Specification

	Posterior-Prior	
	(5)	(6)
T1xGap	0.52***	0.51***
	(0.09)	(0.09)
T2xGap	0.37***	0.39***
	(0.05)	(0.06)
T3xGap	0.14***	0.30***
	(0.02)	(0.05)
T4xGap	0.08***	0.10**
	(0.03)	(0.05)
T5xGap	0.73***	0.84***
	(0.05)	(0.05)
T5xGapxI{Decrease}	0.22*	0.16
	(0.13)	(0.11)
T5xGapxI{Stay the same}	-0.34	-0.28
	(0.23)	(0.26)
T5xGapxI{Increase}	-0.06	-0.18**
	(0.10)	(0.09)
Constant	-5.19***	-6.27**
	(0.20)	(2.99)
Treatment FE	No	Yes
Socio-Demographics	No	Yes
R^2	0.20	0.25
N	3380	3275

Updating rates for all participants in the September 2020 wave of the Bundesbank Survey of Consumer Expectations. Expectation revisions (posterior-prior) are regressed on treatment dummies and their interaction with individuals' perception gaps ($T_k\times$ Gap). Robust standard errors in parentheses. T1 (DAX long-term), T2 (DAX past 12 months), T3 (Earnings growth past 12 months), T4 (PE ratio) and T5 (Expert forecast next 12 months). We control for treatment fixed effects and the following socio-demographic characteristics: gender, age, age squared, college education or higher (dummy), full time employment (dummy), living in the eastern part of Germany prior to fall of Berlin wall in 1989 (dummy), children (dummy), household income (indicator for income bracket) and homeowner (dummy), household size (indicator for size) and region (indicator for each of four German statistical regions). Prior and posterior return expectations are winsorized at their 1% tails. Standard errors are reported in brackets. $*p < 0.10, **p < 0.05, ***p < 0.01$

B Online Appendix

B.1 Details on Heterogeneity of Updating Behavior

B.1.1 Second Wave

The core of the second wave is a synthetic information acquisition experiment. To this end, we elicit individuals' ranking for different pieces of information in the prior elicitation stage of the experiment. In addition, the second wave extends the results of the first wave by eliciting post-treatment subjective return *and* dividend growth expectations for two horizons (1 year, and 5 year ahead). The additional outcome variables come at the cost of being elicited only post-treatment (to avoid survey fatigue), and hence preclude mirroring the analysis of updating rates from the first wave. We therefore slightly adapt our approach as explained in section 5.2, in order to study the relationship between individuals' information ranking, and their updating behavior.

We focus on the past return, past earnings growth, and the price-earnings ratio treatments in the second wave, to ensure a sufficient number of treated individuals with a given information ranking. We modify the price-earnings ratio treatment from quantitative to qualitative information, in order to test the possibility that individuals in the first wave may have had difficulties in understanding the quantitative price-earnings ratio information, but understand the implications of high valuations in qualitative terms. We modify the past return treatment to a five-year horizon in order to extend the evidence regarding extrapolative behavior obtained in the first wave. As before, respondents are randomly assigned to one of the treatment groups.

The four **treatments (T)** for the second wave are:

- *T1 (Past 5 Year Return):*
  "Over the last five years, the German stock market index (DAX) has increased by approximately 16% overall."

- *T2 (Past 12 Months Earnings Growth):*
  "Over the last 12 months, the earnings of the companies represented in the German stock market index (DAX) have decreased by approximately 45%."

- *T3 (Current Price-Earnings Ratio Relative to Long-Term Average - Qualitative):*
  "The current ratio of stock prices relative to earnings of the German stock market index (DAX) is significantly above average."

- *T4 (Placebo):*

  Identical to first wave.

Before providing the treatments, we elicit individuals' information ranking and their portfolio of financial assets. Similar to the first wave, we also elicit treatment-specific priors about the information that each individual is about to receive in her treatment. Post treatment, we elicit individuals' expectations about future stock returns not only over the next twelve months but also over the next five years, yielding individuals' expected term structure of stock returns. In addition, we elicit individuals' expected term structure of dividend growth.

B.1.2 Sample Characteristics Second Wave

In total, 4036 respondents participated in the second wave of our survey. The effective number of observations for each of our econometric specifications varies due to item non-response and will be indicated in each Table. In the second wave, the overall response rate was 85% compared to 75% for the price-earnings ratio treatment group.

We observe a variety of respondent characteristics including age, gender, education, professional status, and income. The randomization successfully maintains the sample properties along the observed characteristics. Table B.1 reports the characteristics for each treatment group and for the full sample. The distribution of characteristics is very similar across treatment groups. Male respondents are slightly over-represented in the survey. Remaining differences between the treatment groups are controlled for by using a vector of respondent characteristics in the regressions.

In the second wave, we elicit individuals' actual portfolios at the time of the survey. 47% of respondents invest in the stock market. Figure B.1 displays individuals' portfolio allocation by quintiles of the wealth distribution. Respondents in the lowest quintile of the wealth distribution hold roughly 70% of their financial wealth in cash and bank accounts and only around 30% in assets such as stocks, bonds, precious metals, or other financial assets. This relationship is essentially reversed for respondents in the highest quintile, who hold 64% of their financial wealth in possibly risky financial assets and 36% in cash and bank accounts. The stock portfolio share, defined as direct holdings of individual stocks, investment fund, or ETF holdings, is also increasing in wealth, from roughly 10% for respondents in the lowest wealth quintile to 35% for respondents in the highest wealth quintile. Apart from bank accounts (and real estate), stockholdings are the most important financial assets in individuals' portfolios, exceeding the amount invested in bonds, gold and other precious metals, or other savings arrangements.

B.1.3 Summary Statistics Second Wave

Table B.2 reports summary statistics for individuals' posterior stock return and dividend growth expectations. A comparison to U.S. data on stock return expectations obtained from the latest available micro-data from the HFS FRBNY-SCE survey shows that the cross-sectional dispersion of our point forecasts is slightly higher than in the HFS FRBNY-SCE survey as we allow for the possibility of negative subjective return expectations.

B.1.4 Heterogeneity of Perceptions

Table B.3 shows how households' knowledge about these stock market outcomes varies by demographic characteristics. College or higher education, higher willingness to take risk, and holding stocks tend to be associated with lower perception gaps. Information on stock ownership is only available in the second wave, where roughly one half of the sample holds a non-zero amount of stock. Yet, consistent with previous evidence, observable demographics explain only a small share of the variation in perception gaps across individuals (see, e.g., the evidence provided by Armona et al. (2019) regarding perception gaps about real estate price growth). Even among stockholders, respondents are, on average, not well informed. Table B.5 reveals that their prior perceptions are quantitatively not very different from those of the full sample in Table B.4.

B.1.5 Heterogeneity of Perception Gaps by Information Ranking

Table B.6 shows respondents who rank information about the return over the past 5 years highest (rank 1), have a smaller perception gap than all other respondents (rank > 1). Similarly, the fraction of respondents who correctly perceive the current price-earnings ratio to be above its long-term average is larger for individuals who rank this type of information highest than for all other respondents. Respondents who rank information about earnings growth highest have perceptions slightly closer to the actual but the difference is very small. The latter finding may suggest difficulties in accessing earnings growth information in real time.

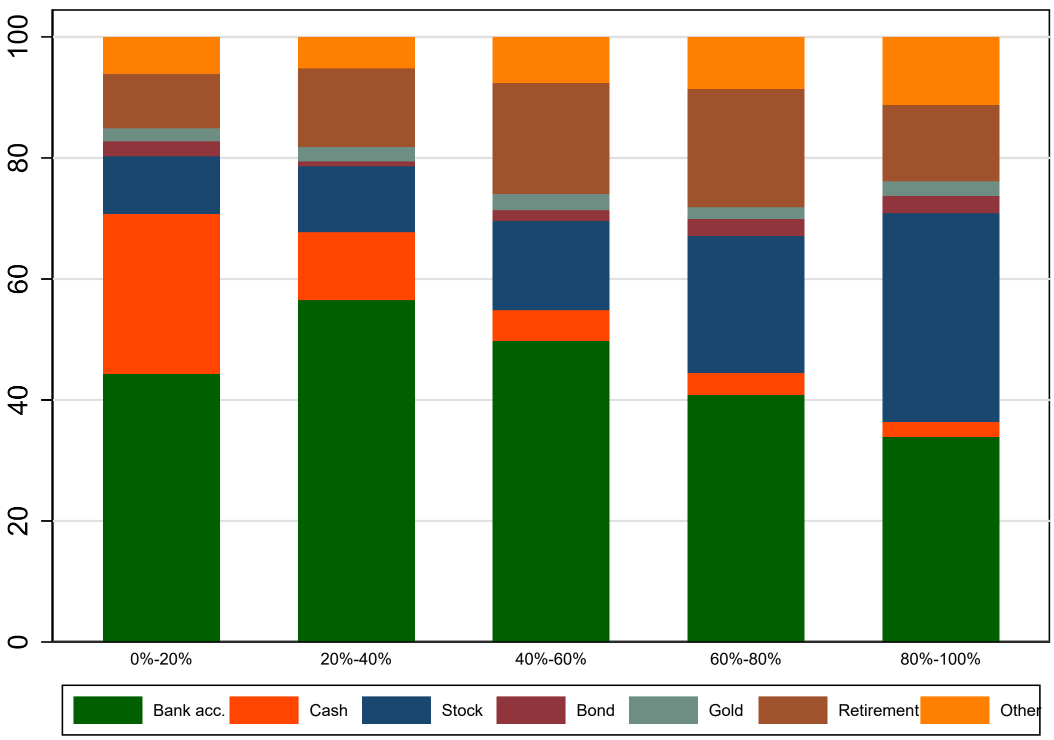
B.1.6 Heterogeneity of Information Rankings

This section investigates how individuals' information rankings vary with socio-demographic characteristics. Table B.7 shows the results from ordered logit regressions relating individuals' ranking of each information item to their socio-demographic characteristics. Male respondents are significantly less likely to choose expert forecasts as their highest ranked information item and more likely to rank information about the long-term average return of the DAX highest. Older individuals are more likely to rank earnings growth information highest and less likely to rank expert forecasts highest. Individuals with college education or higher are more likely to choose earnings growth over the last 12 months and they are less likely to choose the long-term average return of the DAX as their highest ranked information item. Overall, socio-demographic characteristics are only weakly correlated with information rankings. Highest rankings for price-earnings ratio information are not significantly associated with any of the observed characteristics, including stock ownership. This suggests that information rankings capture a new dimension of individuals' expectation formation process that is largely orthogonal to standard socio-demographic characteristics.

B.1.7 Heterogeneity of Information Costs

Table B.8 shows how the perceived cost of information varies with individuals' characteristics. Male respondents perceive all information items as less costly to obtain than female respondents, despite the fact that we are controlling for income, employment, education, and stockholdings. Stockholders, too, perceive all information items as less costly to obtain, especially information about past returns and the price-earnings ratio. Individuals with above median income perceive almost all information items as less costly to obtain, although the effect of income is smaller than that of gender and stockholdings. By contrast, the effect of having college education is insignificant for most information items. Individuals who lived in the eastern part of Germany prior to 1989 perceive several information items as more difficult to obtain.

Figure B.1: Portfolio Allocation



Individuals' portfolio allocation across quintiles of the wealth distribution for all participants in the December 2020 wave of the Bundesbank Survey of Consumer Expectations. All responses have been winsorized at the 1% tails.

Table B.1: Sample Characteristics: Second Wave

	Treatment 1	Treatment 2	Treatment 3	Control	Total
	%	%	%	%	%
Male	61	61	59	58	60
Full-time Employment	43	42	43	43	43
College Education or higher	40	36	41	37	39
East Germany before 1989	17	17	16	18	17
Children	19	18	21	23	20
Homeowner	64	66	66	66	65
Stockowner	44	45	48	46	46
Age					
(0, 25]	3	4	4	3	4
(25, 35]	8	9	8	8	8
(35, 65]	57	54	56	57	56
(65,79]	29	29	30	29	29
[80,)	3	4	3	3	3
Household Size					
1	24	24	21	23	23
2-4	72	72	75	74	73
+5	3	4	3	3	3
Household Income (Euro)					
[0, 999]	2	3	2	3	3
[1.000, 2.999]	35	32	32	29	32
[3.000, 4.999]	38	40	36	41	39
[5.000, 7.9999]	16	16	21	16	17
[8.000,)	2	4	3	4	3
Region					
North	18	18	18	18	18
West	27	27	27	28	27
South	36	36	38	35	36
East	19	19	17	19	19

Share of survey participants (in %) with the respective characteristic.

Table B.2: Summary Statistics for Household Stock Market Expectations: Second Wave

	mean	median	sd	skewness	kurtosis	min	max	n
Second wave: expected stock return								
Posterior point E[Rt + 1] raw	5.27	5	11.67	0.71	14.69	-66	91.67	3603
Posterior point E[Rt + 1] winsorized	5.27	5	10.71	0.60	7.92	-30	50	3603
Posterior point E[Rt + 5] raw	14.95	10	15.90	0.95	9	-70	100	3603
Posterior point E[Rt + 5] winsorized	14.94	10	14.72	1	5.55	-25	70	3603
Second wave: expected dividend growth								
Posterior point E[DGt + 1] raw	1.57	2	15.57	-0.37	14.48	-96	100	3534
Posterior point E[DGt + 1] winsorized	1.57	2	13.81	-0.60	8.53	-50	50	3534
Posterior point E[DGt + 5] raw	10.72	8	16.06	1.45	13.06	-88	100	3534
Posterior point E[DGt + 5] winsorized	10.81	8	14.64	1.83	9.18	-25	80	3534
Comparison to HFS FRBNY-SCE survey								
HFS FRBNY-SCE E[Rt + 1]raw(Aug2019)	7.42	5	7.76	3.57	22.85	0	75	1064
HFS FRBNY-SCE E[Rt + 1]winsorized(Aug2019)	7.27	5	6.84	2.33	9.72	0	40	1064

Summary statistics for the cross-section of all all participants in December 2020 (second wave) of the Bundesbank Survey of Consumer Expectations. Posterior refers to expectations elicited after the information treatments. Point refers to questions eliciting individuals' point forecasts of the respective quantity (returns, R, at 1 year and 5 year horizons, dividend growth, DG, at 1 year and 5 year horizons). Multi-year expectations (t+5) reflect the total cumulated growth over the indicated time period and are not annualized. Data shown from the Bundesbank Survey of Consumer Expectations must reflect at least 5 observations, therefore, min and max refer to the average of the 5 smallest/largest observations. The last panel shows corresponding statistics for the latest available cross-section (August 2019) from the HFS FRBNY-SCE survey question eliciting a point estimate for U.S. stock market returns (question: k0part2 1).

Table B.3: Perception Gap Correlates

	First Wave						Second Wave			
	(1) Pooled	(2) T1	(3) T2	(4) T3	(5) T4	(6) T5	(7) Pooled	(8) T1	(9) T2	(10) T3
Male	-0.07	-0.21**	-0.11	-0.04	0.14	-0.20	-0.03	0.16**	-0.14*	-0.13
	(0.04)	(0.10)	(0.09)	(0.09)	(0.10)	(0.15)	(0.04)	(0.07)	(0.08)	(0.09)
Above Median Age	0.08	0.10	-0.06	0.15	0.25**	-0.09	0.01	0.01	0.23**	-0.31***
	(0.05)	(0.12)	(0.12)	(0.11)	(0.11)	(0.18)	(0.06)	(0.10)	(0.09)	(0.11)
College Education or higher	-0.14***	-0.11	-0.02	-0.26***	-0.18**	-0.11	-0.06	0.01	-0.13*	-0.07
	(0.04)	(0.09)	(0.09)	(0.09)	(0.09)	(0.14)	(0.05)	(0.08)	(0.08)	(0.09)
Full-time Employment	0.06	0.08	0.03	0.09	0.01	0.15	-0.03	0.01	-0.02	-0.16
	(0.05)	(0.11)	(0.11)	(0.10)	(0.11)	(0.18)	(0.06)	(0.10)	(0.09)	(0.10)
East Germany before 1989	-0.00	0.03	0.04	-0.03	-0.12	0.11	0.10*	0.11	0.23**	-0.07
	(0.06)	(0.12)	(0.12)	(0.12)	(0.12)	(0.17)	(0.06)	(0.10)	(0.10)	(0.11)
Children	0.01	-0.09	-0.06	0.03	0.14	0.11	-0.04	-0.11	0.07	-0.08
	(0.06)	(0.11)	(0.12)	(0.12)	(0.12)	(0.20)	(0.06)	(0.10)	(0.09)	(0.11)
Above Median Income	-0.03	-0.04	-0.06	-0.01	-0.02	-0.03	0.02	0.14*	-0.04	-0.05
	(0.05)	(0.09)	(0.09)	(0.09)	(0.11)	(0.15)	(0.05)	(0.07)	(0.08)	(0.09)
Homeowner	-0.05	-0.04	-0.03	-0.03	-0.09	-0.10	-0.04	0.05	-0.08	-0.12
	(0.04)	(0.09)	(0.09)	(0.09)	(0.09)	(0.15)	(0.05)	(0.08)	(0.08)	(0.09)
Above Median Risk Attitude	-0.11***	-0.12	-0.00	-0.09	-0.19*	-0.30**				
	(0.04)	(0.09)	(0.09)	(0.08)	(0.10)	(0.14)				
Stockholder							-0.07*	0.14*	-0.17**	-0.23***
							(0.04)	(0.07)	(0.07)	(0.08)
Constant	0.13**	0.20*	0.15	0.04	0.01	0.39*	0.09	-0.29***	0.12	0.60***
	(0.06)	(0.12)	(0.13)	(0.12)	(0.12)	(0.22)	(0.06)	(0.10)	(0.10)	(0.12)
R^2	0.01	0.03	0.01	0.02	0.04	0.05	0.00	0.02	0.04	0.05
N	2485	599	589	586	468	243	2080	749	763	568

Relationship between perception gaps and socio-demographic characteristics for each of the two survey waves. Dependent variable is the standardized absolute value of the perception gap (zero mean, one standard deviation for each treatment group). Explanatory variables are socio-demographics coded as dummy variables. Standard errors in parentheses. Positive perception gaps correspond to a positive surprise. Perception gaps are defined as follows. **First Wave:** 9%-prior belief (T1: DAX long-term, T2: DAX past 12 Months), -20%-prior belief (T3: Earnings growth past 12 Months) and (prior belief current PE ratio - prior belief long-term PE ratio), (T4: Current vs. long-term PE ratio). The gap for T5 (Expert) is 0 if prior belief "strong increase", -1 if prior belief "slight increase", -2 if prior belief "no change", -3 if prior belief "slight decrease", -4 if prior belief "strong decrease". **Second Wave:** 16%-prior belief (T1: DAX past 5 Year), -45%-prior belief (T2: Earnings growth past 12 Months) and 0 if prior belief "significantly above", -1 if prior belief "above", -2 if prior belief "near long-term average", -3 if prior belief "below", -4 if prior belief "significantly below". (T3: PE ratio). $*p < 0.10, **p < 0.05, ***p < 0.01$

Table B.4: Knowledge about Stock Market Outcomes (Second Wave, Full Sample)

Panel A: Wave 2 Treatment 1-2						
	Actual	Mean	SD	P25	P50	P75
Treatment 1 (Past 5y Returns)	16.00	19.67	18.63	8	15	28
Treatment 2 (Past 12m Earnings Growth)	-45.00	5.68	13.52	1	5	10
Panel B: Wave 2 Treatment 3						
	<Average	Same	>Average			
Treatment 3 (Current PE)	0.39	0.23	0.38			

Individuals' informedness about stock market outcomes for all participants of the December 2020 wave of the Bundesbank Survey of Consumer Expectations. In Panel A, the factual information shown in the treatment is reported in the column "Actual". The remaining columns show summary statistics of the cross-sectional distribution of respondents' pre-treatment perceived stock market outcomes. In Panel B, we report the pre-treatment share of respondents who indicated the current P/E ratio is below, at, or above the historical average P/E ratio.

Table B.5: Knowledge about Stock Market Outcomes (Second Wave, Stockholders Only)

Panel A: Wave 2 Treatment 1-2						
	Actual	Mean	SD	P25	P50	P75
Treatment 1 (Past 5y Returns)	16.00	23.40	19.76	10	20	30
Treatment 2 (Past 12m Earnings Growth)	-45.00	4.03	14.06	0	5	10
Panel B: Wave 2 Treatment 3						
	<Average	Same	>Average			
Treatment 3 (Current PE)	0.36	0.18	0.46			

Sample restricted to individuals with non-zero stockholdings. This information is available only in the second wave, i.e. the December 2020 wave of the Bundesbank Survey of Consumer Expectations. In Panel A, the factual information shown in the treatment is reported in the column "Actual". The remaining columns show summary statistics of the cross-sectional distribution of respondents' pre-treatment perceived stock market outcomes. In Panel B, we report the pre-treatment share of respondents who indicated the current P/E ratio is below, at, or above the historical average P/E ratio.

Table B.6: Perception Gap by Information Ranking

Panel A: Wave 2 Treatment 1						
	Actual	Mean	SD	P25	P50	P75
Past 5y Returns (Most Preferred)	16.00	17.25	13.97	8	15	25
Past 5y Returns (Otherwise)	16.00	20.33	19.20	10	15	30
Panel A: Wave 2 Treatment 2						
	Actual	Mean	SD	P25	P50	P75
Past 12m Earnings Growth (Most Preferred)	-45.00	5.36	12.79	1	5	1
Past 12m Earnings Growth (Otherwise)	-45.00	5.70	13.81	2	5	10
Panel B: Wave 2 Treatment 3						
	<Average	Same	>Average			
Current PE (Most Preferred)	0.32	0.21	0.47			
Current PE (Otherwise)	0.39	0.23	0.37			

The Table shows individuals' informedness about stock market outcomes by information ranking for all participants in the December 2020 wave of the Bundesbank Survey of Consumer Expectations. The difference between actual and perceived stock market outcomes, the perception gap, represents the news component of the respective treatment.

Table B.7: Information Ranking and Socio-Demographic Characteristics

	(1) long-term average r.	(2) earnings 12m	(3) P/E ratio	(4) expert forecast	(5) return 5y
Male	0.19***	-0.01	0.05	-0.20***	-0.04
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Above Median Age	0.07	0.23***	-0.03	-0.19**	-0.05
	(0.08)	(0.09)	(0.08)	(0.09)	(0.09)
College Education or higher	-0.14**	0.12*	0.06	-0.02	0.02
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Full-time Employment	-0.06	0.07	-0.03	-0.02	0.07
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
East Germany before 1989	0.12	0.13	0.03	-0.13	-0.14
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Children	-0.10	-0.02	-0.09	0.08	0.13
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Above Median Income	-0.01	-0.08	-0.03	0.00	0.10
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Homeowner	0.06	0.02	0.11	0.01	-0.21***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Stockholder	0.04	-0.08	0.07	-0.07	0.05
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
N	2954	2954	2954	2954	2954

Relationship between information selection and socio-demographic characteristics resulting from several ordered logit regressions for all participants in the December 2020 wave of the Bundesbank Survey of Consumer Expectations. Column headings correspond to different items of information that respondents were asked to rank by their subjectively perceived importance. For each item of information (columns), the dependent variable is coded as follows: 5 (rank 1), 4 (rank 2), ..., 1 (rank 5). Consequently, positive coefficients reflect higher perceived importance associated with the respective socio-demographic characteristics (rows). Socio-demographic characteristics are coded as dummy variables. Standard errors are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table B.8: Perceived Information Cost and Socio-Demographic Characteristics

	DAX: long-term	DAX: last 12 months	Profit: last 12 months	Current PE Ratio	Expert: next 12 months	DAX: last 5 years
	(1)	(2)	(3)	(4)	(5)	(6)
Male	-0.71***	-0.82***	-0.64***	-0.61***	-0.27*	-0.97***
	(0.16)	(0.18)	(0.16)	(0.16)	(0.16)	(0.18)
Above Median Age	0.10	0.38*	-0.04	-0.30	-0.14	0.30
	(0.21)	(0.23)	(0.21)	(0.22)	(0.20)	(0.22)
College Education or higher	-0.23	-0.27	-0.03	0.07	0.17	-0.44**
	(0.17)	(0.20)	(0.17)	(0.17)	(0.16)	(0.19)
Full-time Employment	-0.17	0.22	-0.06	-0.13	-0.34*	0.05
	(0.19)	(0.21)	(0.19)	(0.19)	(0.18)	(0.20)
East Germany before 1989	0.41**	0.32	0.36*	0.20	0.36*	0.37
	(0.21)	(0.23)	(0.20)	(0.21)	(0.21)	(0.23)
Children	-0.19	-0.05	0.00	-0.21	-0.03	-0.28
	(0.22)	(0.25)	(0.21)	(0.21)	(0.21)	(0.24)
Above Median Income	-0.46***	-0.63***	-0.32*	-0.28*	-0.41**	-0.25
	(0.17)	(0.20)	(0.17)	(0.17)	(0.17)	(0.19)
Homeowner	0.24	0.07	0.06	0.30*	0.15	0.11
	(0.17)	(0.19)	(0.17)	(0.17)	(0.17)	(0.19)
Stockholder	-0.93***	-1.32***	-0.80***	-1.05***	-0.78***	-1.35***
	(0.16)	(0.20)	(0.16)	(0.16)	(0.16)	(0.19)
Constant	0.69***	0.01	0.61***	1.07***	0.75***	0.33
	(0.22)	(0.24)	(0.22)	(0.23)	(0.22)	(0.23)
N	776	776	776	776	773	776

Relationship between perceived cost of different information items and socio-demographic characteristics resulting from several ordered logit regressions for all participants in the December 2020 wave of the Bundesbank Survey of Consumer Expectations. Column headings correspond to different items of information that respondents were asked to rank by their subjectively perceived cost of obtaining the information. For each item of information (columns), the dependent variable is coded as follows: 4 (very difficult), 3 (difficult), 2 (easy), 1 (very easy). Consequently, positive coefficients reflect higher perceived cost associated with the respective socio-demographic characteristics (rows). Socio-demographic characteristics are coded as dummy variables. Standard errors are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

B.2 Questionnaires

The following pages show English translations of the original questions included specifically for our experiment. The full questionnaires can be found on the survey website (in English or German).[21]

[21] See: https://www.bundesbank.de/en/bundesbank/research/survey-on-consumer-expectations

B.2.1 Questionnaire of First Wave

---	Split sample 3	RANDOMISATION 3
The entire sample of approximately 4,000 respondents is split randomly into six groups. Randomisation dummy (drandom3) is used for the treatment.		
One factor variable: drandom3 1 = group A3 (666 randomly selected respondents) 2 = group B3 (666 randomly selected respondents) 3 = group C3 (667 randomly selected respondents) 4 = group D3 (667 randomly selected respondents) 5 = group E3 (667 randomly selected respondents) 6 = group F3 (667 randomly selected respondents)		

---	---	START SPLIT SAMPLE 3

910A1	PRO BW	Treatment-specific prior question	know_dax_pre
[if drandom3 = 1] **QUESTION:** By what percentage do you think the German stock index (DAX) and its predecessors have changed <u>on average per year since 1973</u>? **Note:** Please use positive values for an increase and negative values for a decrease. [Input field] percent on average <u>per year</u>			

910A2	PRO BW	Treatment-specific prior question	know_dax_pre
[if drandom3 = 2] **QUESTION:** By what percentage do you think the German stock index (DAX) has changed <u>over the past twelve months</u>? **Note:** Please use positive values for an increase and negative values for a decrease. [Input field] percent over the past twelve months			

910A3	PRO BW	Treatment-specific prior question	know_dax_pre
[if drandom3 = 3] **QUESTION:** By what percentage do you think the earnings of the companies listed on the German stock index (DAX) have changed overall <u>over the past twelve months</u>? **Note:** Please use positive values for an increase and negative values for a decrease. [Input field] percent over the past twelve months			

910A4	PRO BW	Treatment-specific prior question	know_dax_pre

[if drandom3 = 4]

QUESTION: What do you think the price/earnings ratio of the DAX is <u>currently</u>?

Note: The price/earnings ratio measures the average ratio of a DAX-listed company's share price to its annual earnings. Please use a positive number. Values may have a maximum of one decimal place.

Price/earnings ratio **currently** [Input field]

QUESTION: And where do you think the price/earnings ratio of the DAX and its predecessors has stood on a long-term <u>average since 1973</u>?

Price/earnings ratio **on average since 1973** [Input field]

910A5	PRO BW	Treatment-specific prior question	know_dax_pre

[if drandom3 = 5]

QUESTION: Have you recently heard a forecast by experts on the development of the German stock index (DAX) for the next twelve months?

1 Yes, a significant decrease is forecast.
2 Yes, a slight decrease is forecast.
3 Yes, it is forecast that the DAX will remain essentially unchanged.
4 Yes, a slight increase is forecast.
5 Yes, a significant increase is forecast.
6 No, I have not heard a forecast.

911	PRO BW	Prior stock market expectations (point forecast)	stockexp_pre

QUESTION: By what percentage do you think the German stock index (DAX) will change <u>over the next twelve months</u>?

Note: Please use positive values for an increase and negative values for a decrease.

[Input field] percent over the next twelve months

Treatments

[if drandom3 = 1]

We will now show you current information on the German stock index (DAX):

Since 1973, the German stock index (DAX) and its predecessors have increased by around 9% on average per year.

[if drandom3 = 2]

We will now show you current information on the German stock index (DAX):

The German stock index (DAX) has increased by around 9% over the past twelve months.

[if drandom3 = 3]

We will now show you current information on the German stock index (DAX):

The earnings of the companies listed on the German stock index (DAX) have fallen by around 20% overall over the past twelve months.

[if drandom3 = 4]

We will now show you current information on the German stock index (DAX):

The price/earnings ratio of the DAX currently stands at around 23. On a long-term average since 1973, the price/earnings ratio of the DAX and its predecessors has stood at around 15.

[if drandom3 = 5]

We will now show you current information on the German stock index (DAX):

A forecast by experts estimates that the DAX will likely increase by around 9% over the next twelve months.

[if drandom3 = 6]

We will now show you current information on the rapeseed harvest in Germany:

The average harvest yield (per hectare) of winter rapeseed increased by around 10% in 2019 compared with the previous year.

912	PRO BW	Risk attitude	risk_attitude

QUESTION: When making decisions on financial matters, how risk averse would you consider yourself to be?

0 = Highly risk averse

1 -> 9 [no label]

10 = Not at all risk averse

913	PRO BW	Posterior stock market expectations probability	stockexp_post_[a-j]

The programming of this question requires the sum of the variables to be 100. The current sum of all entered points is shown to the respondent when answering the question. Respondents are asked to correct their responses if the sum does not equal 100.

QUESTION: In your opinion, how likely is it that the German stock index (DAX) will change as follows <u>over the next twelve months</u>?

Note: The aim of this question is to determine how likely you think it is that something specific will happen in the future. You can rate the likelihood on a scale from 0 to 100, with 0 meaning that an event is completely unlikely and 100 meaning that you are absolutely certain it will happen. Use values between the two extremes to moderate the strength of your opinion. Please note that your answers to the categories must add up to 100.

a	Decrease by 25% or more
b	Decrease by between 15% and less than 20%
c	Decrease by between 10% and less than 15%
d	Decrease by between 5% and less than 10%
e	Decrease by between 0% and less than 5%
f	Increase by between 0% and less than 5%
g	Increase by between 5% and less than 10%
h	Increase by between 10% and less than 15%
i	Increase by between 15% and less than 20%
j	Increase by 25% or more

914	PRO BW	Portfolio choice problem	pfchoice

The programming of this question requires the sum of the variables to be 10,000. The current sum of all entries is shown to the respondent when answering the question. Respondents are asked to correct their responses if the sum does not equal 10,000.
If the sum does not equal 10,000, please show: "Note: You must split the amount entirely between the two investments."

QUESTION: Imagine you are about to decide to invest €10,000 for a period of twelve months. You have two investments to choose from:

- The value of **Investment A** will follow the change in the German stock index (DAX) over the next twelve months.

- The value of **Investment B** will increase by 1% over the next twelve months.

Please indicate the exact amount you would invest in each investment.

Investment A €________

Investment B €________

910A6	PRO BW	Treatment-specific posterior question	know_dax_post

[if drandom3 = 6]

QUESTION: Imagine that the German stock index (DAX) lost 45% of its value within the space of a few months. How do you think the value of the DAX would develop over the twelve months following such a decrease?

1 = Decrease again significantly
2 = Decrease again somewhat
3 = Stay roughly the same
4 = Increase somewhat
5 = Increase significantly

---	---	END SPLIT SAMPLE 3

B.2.2 Questionnaire of Second Wave

---	---	

1218	Pro BW	Own portfolio	own_portfolio_[a-h]

Range for each of the items below: 0-infinity, no decimal. No soft prompt.

QUESTION: We would now like to ask how your current financial assets (excluding real estate) are distributed across different asset classes. Please enter the approximate amount you currently have invested in the following asset classes.

Note: All information throughout the survey will be treated completely anonymously. If you still do not wish to answer this question, simply click on "Continue". Enter 0 if you are not invested in the respective asset class.

a	Balances on savings and current accounts (incl. fixed-term deposits)	[Input field] euro
b	Cash	[Input field] euro
c	Shares (including funds/ETFs)	[Input field] euro
d	Fixed-income securities	[Input field] euro
e	Gold and precious metals	[Input field] euro
f	Savings agreements for private pension schemes (e.g. Riester/Rürup)	[Input field] euro
g	Other investments	[Input field] euro
Total:		[Calculated automatically]
h	Do not currently have any financial assets	

1219	Pro BW	Information selection	info_selection_[a-e]

Order of categories 1-5 is generated randomly for each respondent.

After the term "price/earnings ratio", an info box (i) with the following definition is shown: "The price/earnings ratio measures the average ratio of a DAX-listed company's share price to its annual earnings."

QUESTION: Imagine you inherit a substantial sum of money and have to decide whether to invest part of this sum in shares. Which of the following items of information would help you most when making your decision?

Note: Use the arrow keys to "drag and drop" the items of information according to how important they would be for your decision. Start with the item of information you think is most important. Assume that you would receive all items of information easily and free of charge.

a. Change in the German stock index (DAX) *on a long-term historical average*

b. Change in the earnings of companies listed in the German stock index (DAX) over the last twelve months

c. Ratio of share prices to earnings (price/earnings ratio) (i) in the DAX in comparison to the long-term average

d. Experts' projection of how the German stock index (DAX) will perform over the next twelve months

e. Change in the German stock index (DAX) *over the last five years*

---	---	START SPLIT SAMPLE 4

---	Split sample 4	RANDOMISATION 4
The entire sample is split randomly into four groups. Randomisation dummy (drandom4) is used for questions 1220A - 1223.		
drandom4: 1 = group A4 – (**1,000** randomly selected respondents) 2 = group B4 – (**1,000** randomly selected respondents) 3 = group C4 **-** (**1,000** randomly selected respondents) 4 = group D4 **-** (**1,000** randomly selected respondents)		

1220A	Pro BW	Treatment-specific prior question	know_dax_pre
Input filter: (drandom4 == 1)			
QUESTION: By what percentage do you think the German stock index (DAX) has changed overall <u>over the past five years</u>? **Note:** Please use a positive value for an increase and a negative value for a decrease. [Input field] percent			

1220B	Pro BW	Treatment-specific prior question	know_dax_pre
Input filter: (drandom4 == 2)			
QUESTION: By what percentage do you think the earnings of all the companies listed in the German stock index (DAX) have changed overall <u>over the past twelve months</u>? **Note:** Please use a positive value for an increase and a negative value for a decrease. [Input field] percent			

1220C	Pro BW	Treatment-specific prior question	know_dax_pre
Input filter: (drandom4 == 3)			
After the term "price/earnings ratio", an info box (i) with the following definition is shown: "The price/earnings ratio measures the average ratio of a DAX-listed company's share price to its annual earnings."			
QUESTION: How do you think the ratio of share prices to earnings in the German stock index (DAX) currentlycompares with the long-term average? The ratio of share prices to earnings (price/earnings ratio) (i) is currently ... 1= significantly below the long-term average 2= somewhat below the long-term average 3= close to the long-term average 4= somewhat above the long-term average 5= significantly above the long-term average			

---	Split sample 4	RANDOMISATION 4 – treatment stage
[if drandom4 = 1] We will now show you current information on the German stock index (DAX): **The German stock index (DAX) has increased by around 16% overall over the past five years.** [if drandom4 = 2] We will now show you current information on the German stock index (DAX): **The earnings of the companies listed in the German stock index (DAX) have fallen by around 45% overall over the past twelve months.** [if drandom4 = 3] We will now show you current information on the German stock index (DAX): **The ratio of share prices to earnings in the German stock index (DAX) is currently significantly above the long-term average.** [if drandom4 = 4] We will now show you current information on the rapeseed harvest in Germany: **The average harvest yield (per hectare) of winter rapeseed increased by around 10% in 2019 compared with the previous year.**		

1221	Pro BW	Expected DAX change	stockexp_post_[a-b]

QUESTION: By what percentage do you think the German stock index (DAX) will change over the following periods?

Note: The German stock index (DAX) can move as a result of price changes and dividend payouts by the shares it covers. Please use positive values for an increase and negative values for a decrease.

Over the next twelve months: [Input field] percent

Over the next five years: [Input field] percent

1222	Pro BW	Expected dividend change	dividentchange_[a-b]

QUESTION: By what percentage do you think the earnings (dividends) paid out by DAX-listed companies will change?

Note: This refers only to the change in the dividends, not the change in the share prices or the DAX as a whole. Please use a positive value for an increase and a negative value for a decrease.

Over the next twelve months: [Input field] percent

Over the next five years: [Input field] percent

1220D	Pro BW	Information cost	info_cost1_[a-f]

Input filter: if drandom4 == 4

Order of categories a-f is generated randomly for each respondent.

QUESTION: Imagine you inherit a substantial sum of money and have to decide whether to invest part of this sum in shares. How difficult would it be for you to obtain the following information?

Note: This refers to the time or money needed to obtain the information in question.

1 = Very easy
2 = Easy
3 = Difficult
4 = Very difficult

a Change in the German stock index (DAX) and its predecessors on a long-term historical average
b Change in the German stock index (DAX) over the past twelve months
c Change in the earnings of companies listed in the German stock index (DAX) over the past twelve months
d Ratio of share prices to earnings (price/earnings ratio) in the German stock index (DAX)
e Experts' projection of how the German stock index (DAX) will perform over the next 12 months
f Change in the German stock index (DAX) over the past five years

---	---	END SPLIT SAMPLE 4