Beliefs and Portfolios: Causal Evidence *

Johannes Beutel
Deutsche Bundesbank

Michael Weber
University of Chicago Booth School of Business and NBER

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Abstract

We causally test competing theories of expectation formation and asset pricing. Using a randomized information experiment we show: i) individuals do not revise their beliefs in line with Rational Expectations asset pricing models. Instead, they form pro-cyclical beliefs, both about capital gains and about earnings growth; ii) individuals are heterogeneous at the information acquisition *and* at the information processing stage. Their reaction to stock-market news depends on their preference for the type of news received; iii) beliefs and portfolio decisions are causally linked; iv) the sensitivity of portfolio shares with respect to expected returns appears low, especially when accounting for individuals' low perceived variance of stock returns. Non-linear constraints on individuals' portfolio decisions can resolve this puzzle. These results provide guidance on promising causal mechanisms for macro-finance models.

Keywords: Expectation formation, asset pricing, household finance.

JEL classification: G11, G12, G41, G51, G53, D84, E44

*Contact address: Johannes Beutel, Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main, Germany. E-mail: johannes.beutel@bundesbank.de. Michael Weber, University of Chicago, Booth School of Business, Room 314, 5807 South Woodlawn Avenue, Chicago, IL, USA, 60637 and NBER. E-mail: michael.weber@chicagobooth.edu. The authors thank seminar participants at the Second Joint ECB-FRBNY conference for many valuable comments. Tobias Huelden provided excellent research assistance. Disclaimers: This paper uses data from the Bundesbank Survey on Consumer Expectations (Bundesbank-Online-Panel-Households). The results published and the related observations and analysis may not correspond to results or analysis of the data producers. The views expressed in this paper are those of the authors and do not necessarily coincide with the views of the Deutsche Bundesbank or the Eurosystem.

"Beliefs are central to asset pricing. Asset prices are forward-looking, and essentially any asset-pricing model implies that investors price assets based on their beliefs about the joint distribution of some stochastic discount factor (SDF) M_{t+1} and payoffs X_{t+1}. 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."
Stefan Nagel in Brunnermeier et al. (2021)

1 Introduction

Decades after the discovery of major asset pricing puzzles such as excess volatility, the large equity premium, return predictability, and the low risky asset share of households (see, e.g., Shiller 1981; Mehra and Prescott 1985; Fama and French 1988; Haliassos and Bertaut 1995), the range of possible explanations is still wide open. At the current juncture, a main consensus is expectations are key for asset prices, and learning more about how expectations are formed is critical for further breakthroughs (see, e.g., Brunnermeier et al. 2021). Since many institutional investors have tight investment mandates, households' expectations matter and small changes in asset demand can trigger comparatively large price changes (see, e.g., Koijen and Yogo 2019; Gabaix and Koijen 2021). Narrowing down the space of plausible expectation formation processes and their effect on asset demand would have profound implications for macro-finance, monetary policy, and financial stability.

We confront competing theories of expectation formation and asset pricing with causal evidence on beliefs and portfolios. Building on recent work by Giglio et al. 2021 (henceforth GMSU) and Laudenbach et al. (2021), we design a unique information provision experiment to test leading theories *causally* and in a *unified* setting. The experiment is embedded in a representative survey of German households. We find that households do not revise their beliefs in line with Rational Expectations asset pricing models. Instead, they form pro-cyclical beliefs, both about capital gains *and* about earnings growth. Conditional on their beliefs, households act rationally. Belief revisions causally affect their portfolios and, after accounting for short-sale and leverage constraints, a standard model of portfolio choice provides a good approximation to their behavior. The survey-based experimental setup allows us to understand not only *how* but *why* individuals form expectations in a particular way. We break down the *process* of expectation formation into an information acquisition and an information processing stage, and discover that the processing of stock-market related news depends on households' preferences for certain types of news.

The literature has developed competing asset pricing models that are all successful in matching key empirical facts, but are based on different underlying mechanisms. These theories are sometimes hard to disentangle based on correlations alone, but can have fundamentally different implications for macroeconomics, monetary policy, financial stability, and the accumulation and distribution of households' wealth. In Rational Expectations asset pricing models, stock market valuations are lower when investors' demand a higher expected return, and different reasons exists why this occurs in equilibrium (see, e.g., Rietz 1988; Barro 2006; Campbell and Cochrane 1999; Bansal and Yaron 2004). Models with learning about capital gains predict precisely the opposite (see also Cochrane 2011). In these models, investors expect high returns when stock market valuation is high and they expect low returns when stock market valuation is low (see, e.g., Vissing-Jorgensen 2004; Greenwood and Shleifer 2014; Adam et al. 2017). Such models give rise to inefficient, belief-driven bubbles in which wealth is re-distributed between investors with different beliefs (see, e.g., Adam et al. 2015). Recent empirical evidence by Myers and De La O (2020) and Bordalo et al. (2020) provides renewed impetus on models with learning about fundamentals (see, e.g., Timmermann 1993; Fuster et al. 2012). These models predict, for instance, that positive news about past earnings growth, should lead to an upward revision of expectations about future earnings growth. In addition, our treatments capture models emphasizing the role of lifetime experiences (Malmendier and Nagel 2016) and expert forecasts (Carroll 2003).

Our randomized information experiment allows us to test which of these mechanisms are actually *causal* in shaping individuals' beliefs and portfolios. This identification strategy has been successfully used in different macroeconomic contexts (see, e.g., Armona et al. 2019; Coibion et al. 2021; Roth and Wohlfart 2020; Beutel et al. 2021). Our information treatments are designed to capture the above-mentioned broad classes of competing asset pricing models, which differ in their expectation formation process. Each individual receives one of the following randomly assigned treatments (T): T1: long-run historical average return of the stock market, T2: stock market return over the previous 12 months, T3: earnings growth rate over the previous 12 months, T4: current level of the price-earnings ratio and its historical average, and T5: expert forecast of the stock market return in the next 12 months. A control group receives a Placebo treatment with information that is irrelevant for stock market returns. Since the treatments are exogenously and randomly assigned, their effects relative to the control group are causal. The need for causal evidence concerns both the expectation formation process, and the link between expectations and portfolios. For instance, estimates on the link between expectations and portfolios could be biased downwards or upwards depending on measurement error and the nature of a potential endogeneity between the two. Using the randomly assigned treatments as exogenous instruments allows us to overcome these identification challenges.

To understand not only *how* but *why* individuals form expectations in a particular way, we break down the process of expectation formation into an information acquisition and an information processing stage. For instance, the observation that households fail to incorporate valuation levels into their expectations (see, e.g., Vissing-Jorgensen 2004; Greenwood and Shleifer 2014), could either be due to not being informed about current valuation levels, or due to not incorporating this information into their beliefs in a way that is consistent with Rational Expectations. The survey-based experimental setup allows us to distinguish between the degree of households' information incompleteness and the way households process information based on their mental model of the stock market. We also provide direct evidence on individuals' perceived cost and usefulness of different information items. In a second wave, we field a synthetic information acquisition experiment and discover that information preferences matter not only at the information acquisition stage, but are associated with significant differences in how individuals' process a given piece of information.

Our experiment yields the following key findings. First, we provide causal evidence on households' stock market expectation formation. Under rational expectations, households' stock return expectations should move counter-cyclically with the price-earnings ratio. By contrast, we find that return expectations do on average not react at all to news about the price-earnings ratio. Households are initially poorly informed about the price-earnings ratio, but even when they receive information about its current level they fail to update their return expectations. Our results suggest a fundamental lack of understanding of the basic relationship between valuations and subsequent returns on behalf of households. Instead, we find causal evidence in support of the hypothesis that households form return expectations in a pro-cyclical way. Individuals who are randomly assigned to a treatment with positive (negative) news about past returns, revise their return expectations upwards (downwards) relative to the control group, in line with models in which investors' are learning about returns or capital gains.

News about earnings growth causally affects households' expectations as well, consistent with recent models of learning about fundamentals (see, e.g., Myers and De La O 2020; Bordalo et al. 2020). While short-run earnings growth expectations react pro-cyclically to news about earnings growth, longer-run earnings growth expectations react counter-cyclically. Stock return and capital gains expectations react in a similar way to news about earnings growth, which provides a causal explanation for the observation by GMSU that expected returns and expected earnings growth are positively correlated in the cross-section of individuals. Exploring the asset pricing implications of such simultaneous revisions in earnings growth and capital gains expectations could be an interesting avenue for future research on asset pricing models. We also find that, conditional on receiving an expert forecast, individuals revise their return expectations in the direction of the forecast in line with models such as Carroll (2003). On the other hand, expert forecasts are perceived as costly to obtain and the majority of households is not aware of any expert forecast.

Second, we present novel evidence on the effects of information preferences and costs on households' stock return expectation formation, which is related to Fuster et al. (2019) who study information acquisition in the context of home price expectations. For the past return treatment, we find no information preference effect. By contrast, individuals who prefer information about past earnings growth react to such news in a more pro-cyclical manner than other individuals, both regarding their dividend growth and their capital gains expectations. This suggests that 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 such as Bordalo et al. (2020) and Myers and De La O (2020). Interestingly, we find that individuals with a preference for information about the price-earnings ratio revise their return expectations in a more counter-cyclical manner than other individuals. This implies 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 Rational Expectations than the average reaction of respondents. The effect of information preferences cannot be explained with differences in the levels of individuals' prior informedness. This suggests that the 'information preference effect' reflects heterogeneity in individuals' processing of information, which could be due to different mental models of the economy and to differences in mental capacity (see, e.g., Andre et al. 2019; D'Acunto et al. 2019).

The existence of heterogenous types of expectation formation is also in line with Dominitz and Manski (2011) and suggests that models that incorporate such heterogenity should play an important role for understanding household behavior and its asset pricing implications. Interestingly, households' perceived usefulness of information items is positively related to their perceived cost of acquiring them. Some information items are perceived as highly useful, but also as difficult or costly to obtain. Thus, the low cost of information about recent past returns and past earnings growth, may contribute to the prevalence of extrapolative patterns of expectation formation in observational data (in contrast to data obtained in controlled experiments). This suggests that lowering the cost of acquiring and processing other pieces of stock market information, such as expert forecasts of expected equity premia, could mitigate distortions in households' stock market expectations. Such information provisions could potentially be an interesting instrument for policymakers concerned about expectation-driven asset price bubbles.

Third, we provide causal evidence on the link between beliefs and portfolios. A large literature has documented that households' portfolios respond too little to their beliefs compared to theoretical benchmarks, both at the extensive margin, i.e. with respect to stock market participation (see, e.g. Haliassos and Bertaut 1995; Vissing-Jorgensen 2004), and at the intensive margin, i.e. with respect to the sensitivity of the stock portfolio share relative to expected returns (see, e.g., Ameriks et al. 2020 and GMSU). We refer to the latter as the 'Low Portfolio Share Sensitivity Puzzle'.

We add to this literature in several ways: i) We exploit the exogenous variation in expected returns caused by our treatments in an instrumental variables (IV) approach, to show that households' stock return expectations causally affect their portfolio allocation decisions. This quantitative measure of the causal link between beliefs and portfolios complements the existing literature in an important way, overcoming potential endogeneity issues between portfolios and expected returns in observational data. ii) Using the causal IV approach increases the estimated portfolio share sensitivity by a factor two. This shows that the Low Portfolio Share Sensitivity Puzzle can be reduced when using slightly more complex econometric strategies, supporting findings by, for instance, GMSU or Drerup et al. (2017). iii) We show that the puzzle is worse than previously thought when considering not only individuals' perceived first moment of returns, but also their perceived second moment. After eliciting individuals' subjectively perceived return distribution, we find that individuals vastly underestimate the variance of stock returns relative to historical data. Hence, when taking into account individuals' subjectively perceived stock return volatility, the level of risk aversion implied by the usual linear regression-based estimates of the portfolio sensitivity becomes implausibly large, even after exploiting our exogenous instruments.

Fourth, we show that the Low Portfolio Share Sensitivity Puzzle can be resolved when considering non-linear constraints in individuals' portfolio decisions. In most empirical applications individuals' portfolio shares are bounded on the interval between 0 and 1. Such short-sale and leverage constraints may arise endogenously in many economic settings, or exogenously by the design of the data, as is the case for our survey in which individuals were only allowed to choose portfolio shares in this range. Once we incorporate these non-linear constraints into the theoretically optimal portfolio rule of the Merton (1969) model, the risk aversion implied by individuals' beliefs and portfolio choices can no longer be determined using linear regressions. Instead, we show that a non-linear least squares estimator can be used to estimate the average implied risk aversion accounting for the non-linear constraints. The estimated value for the coefficient of relative risk aversion from this approach is just 4.2, which is comfortably within the range of plausible values.

This suggests that the puzzle arises primarily when considering unconstrained versions of the optimal Merton model in which the optimal portfolio share can become very large for the empirically observed ranges of household beliefs. From an economic perspective, optimal stock portfolio shares that vastly exceed 100% imply extreme levels of leverage in households' stock portfolios. Econometrically, such extreme optimal portfolio shares exert a disproportionate influence on standard OLS estimates of the portfolio share sensitivity, which is attenuated towards zero and thereby implies implausibly large values of risk aversion. The non-linear constraint bounds the influence of such observations and thereby achieves that individuals' choices can be reconciled with a (constrained version of) the Merton model for much more plausible values of risk aversion. Hence, we conclude that after accounting for non-linear constraints, the standard Merton model of optimal portfolio choice provides a surprisingly decent approximation to the behavior of many individuals. This supports recent applications of constrained Merton models such as Koijen and Yogo (2019).

Fifth, our analysis of optimal portfolio shares given individuals' beliefs reveals another interesting fact. A substantial share of respondents has non-standard beliefs in the sense that their beliefs imply a negative expected equity premium or, alternatively, a positive equity premium in *all* states of the world. For such beliefs, the constrained optimal portfolio share is, respectively, 0 or 1, irrespective of individuals' risk aversion (as long as individuals are either risk-neutral or risk-averse). Hence, we cannot evaluate the model-consistency of their choices using the standard approach based on implied levels of risk aversion. Instead, we check whether these individuals do indeed choose the theoretically optimal corner solutions of, respectively, 0 or 1. We find that, one the one hand, only around one fifth of these respondents choose the respective corner solutions. On the other hand, the portfolio shares of those in the first group are indeed substantially lower in distribution than those of the second group. Hence, the decisions of these individuals are at least qualitatively consistent with the basic theoretical prediction that higher perceived Sharpe ratios should be associated with higher portfolio shares. Thus, while the Merton model of optimal portfolio choice cannot fully explain the joint behavior of beliefs and portfolios of *all* individuals with non-standard beliefs, its qualitative predictions continue to hold.

The remainder of the paper is structured as follows. Section 2 discusses the related literature in more detail. Section 3 describes our randomized information experiment and the survey data. Section 4 provides descriptive evidence on households' prior knowledge about the stock market and on their financial portfolios. Section 5 presents causal evidence on stock market expectation formation and discusses its theoretical implications. Section 6 derives estimates of the effect of information preferences on information processing. Section 7 provides causal evidence on the link between beliefs and portfolios and on the low portfolio share sensitivity puzzle. Section 8 presents a non-linear solution to the puzzle and investigates the portfolio allocations of individuals with non-standard beliefs.

2 Related Literature

We contribute to a large empirical literature studying the role of beliefs for asset pricing and household finance. Households' stock return expectations have been shown to co-move pro-cyclically with valuation ratios such as the price-earnings or the price-dividend ratio (see, e.g., Vissing-Jorgensen 2004; Greenwood and Shleifer 2014) and to display substantial heterogeneity (Dominitz and Manski 2011; Adam et al. 2015). The pro-cyclicality of households' stock return expectations suggests that households do not take into account key patterns documented in the empirical finance literature, which suggest that subsequent stock returns vary systematically with variables such as the price-dividend and the price-earnings ratio (Cochrane 2008, Campbell and Thompson 2008), the short-term interest rate and the long-short spread (Campbell and Yogo 2006), or the consumption-to-wealth ratio (Lettau and Ludvigson 2001). If individuals had rational expectations they should take into account the (inverse) relationship between valuation ratios and future stock market returns and form expectations accordingly, a prediction which is formally rejected by Adam et al. 2017. Recent evidence by Myers and De La O (2020) and Bordalo et al. (2020) emphasizes the role of pro-cyclical earnings growth expectations. The household finance literature has documented a puzzlingly low sensitivity of portfolio shares with respect to individuals' expected returns and an equally puzzling low stock market participation rate (see, e.g., Haliassos and Bertaut 1995; Vissing-Jorgensen 2004; Ameriks et al. 2020, and GMSU).

Our experiment contributes to this literature by testing which of the proposed mechanisms are able to *causally* shape individuals' expectations and investment behavior. We thereby provide novel empirical evidence against which the predictions of leading asset pricing theories can be tested. The first class of theories tested comprises rational expectations asset pricing models, which imply return expectations that co-move counter-cyclically with valuation ratios. Examples of such models include habit formation (Campbell and Cochrane 1999), long-run consumption risk (Bansal and Yaron 2004), and rare disaster risk (Rietz 1988; Barro 2006). The second class of models is characterized by pro-cyclical return and capital gains expectations (see, e.g., Adam et al. (2017)). The third class of models features pro-cyclical expectations about fundamentals such as dividend and earnings growth (see, e.g., Timmermann 1993; Myers and De La O 2020; Bordalo et al. 2020). In addition, we investigate the role of expert forecasts in influencing household expectations (see, e.g., Carroll 2003), and explore two central predictions by Malmendier and Nagel (2011, 2016), namely that individuals over-weight recent returns relative to historical returns and that younger individuals over-weight recent information more than older individuals. Our evidence is also relevant for a literature exploring the *macroeconomic* implications of expectation formation and asset pricing (see, e.g., Kuang 2014; Winkler 2016; Adam and Merkel 2019; Lansing 2019), and for the broader literature on expectation formation in macroeconomics (see, e.g., Kydland and Prescott 1982; Mankiw and Reis 2002; Branch 2007; Andolfatto et al. 2008; Coibion and Gorodnichenko 2012, 2015).

Our approach builds on a growing literature using randomized information experiments embedded in surveys to provide causal evidence on expectation formation in different macroeconomic contexts. For instance, Armona et al. (2019) use a randomized information experiment to show that households extrapolate past local *house price* growth rates into the future and Fuster et al. (2019) study house price expectation formation with endogenous information acquisition. A large literature studying the *inflation* expectation formation of households and firms is surveyed in Coibion et al. (2020). For instance, Armantier et al. (2016) use a randomized information experiment to show that households update their inflation expectations in a Bayesian manner. Coibion et al. (2021) show that short and simple pieces of information are more effective in influencing housheholds' inflation expectations than traditional communication formats used by central banks. The evidence by Coibion et al. (2018) suggests that firms deliberately do not keep track of inflation, but update their beliefs when receiving such information, in line with theories of rational inattention. Roth and Wohlfart (2020) show that households respond to information about the *likelihood of a recession* by adjusting their expectations about their personal economic prospects and, consequently, their behavior. Beutel et al. (2021) show that central bank communication about risks to *financial stability* influences households' beliefs and risk-taking behavior.

Experiments have also been used in the behavioral finance literature. Many experimental studies starting with Gneezy and Potters (1997); Gneezy et al. (2003) and Benartzi and Thaler (1995, 1999) found that individuals are more willing to invest into risky assets if they receive less frequent information about longer-horizon returns, and if they receive information about portfolio-level returns instead of the returns of individual stocks (see also, e.g., Anagol and Gamble 2013; Gerhard et al. 2017). By contrast, Beshears et al. (2017) find that such aggregation effects do not affect individuals' equity investments in a field experiment, and therefore conjecture that some of these effects might be artefacts of the specific setting in these laboratory experiments. Cohn et al. (2015) investigate whether the risk aversion of investment professionals is counter-cyclical. In a laboratory experiment, investment professionals primed with a bust scenario choose a lower risky asset share compared to those primed with a boom scenario. Since the probability distribution of returns is held constant across both scenarios, this suggests that investment professionals become more risk averse when thinking about the bust scenario. Laudenbach et al. (2021) find that a majority of clients of a German online bank believe in mean reversion of stock market returns. After being treated with information about the actual autocorrelation of 12-month stock returns, respondents believe less in mean reversion and increase their stockholdings less during the pandemic stock market crash in March 2020. We contribute to this literature with a unified assessment of different theoretical alternatives regarding expectation formation and asset pricing. This allows us to provide causal evidence on leading asset pricing theories.

3 Randomized Information Experiment

Our analysis is based on a representative survey of approximately 4,000 German households, conducted by Forsa as part of Deutsche Bundesbank's Survey on Consumer Expectations. We embed one randomized information experiment in each of two waves of this survey fielded in September and December 2020. The return on the German stock market index DAX in the 12 months prior to the first wave has been 9.3 % , which is close to the 10.2 % average annual (nominal) return of the DAX since its inception in 1987. The experimental setup in each of the two survey waves consists of three stages in the following order: (i.) prior elicitation, (ii.) treatment, and (iii.) posterior elicitation. In the following, we describe the questions and treatments used in each of the two waves of our survey. Sample characteristics are provided in appendix section A.1.[1]

3.1 First Wave

The objective of the experiment in the first wave is to provide causal evidence on leading asset pricing theories. Depending on the underlying expectation formation process, these theories can be categorized into three broad classes: i) Rational Expectations models predicts that return expectations should move counter-cyclically with valuation ratios such as the price-dividend ratio or the price-earnings ratio; ii) Models in which investors are learning from past returns or capital gains predict pro-cyclical return and capital gains expectations. iii) Models of learning about fundamentals predict pro-cyclical, and possibly excessively volatile, earnings and dividend growth expectations. To test these competing mechanisms for households' expectation formation, we design information treatments capturing the essence of each mechanism. We then test the competing mechanisms by comparing the treatment effects to the predictions of the three classes of theoretical models described here. We also include two other influential approaches from the literature, which predict, respectively, that households overweight recent experience Malmendier and Nagel (2011, 2016), and that they react to expert forecasts Carroll (2003). Respondents are randomly assigned to one of six treatment groups.

The six **treatments (T)** of the first wave are as follows:

- *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 Relative to 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 estimates the likely increase of the DAX over the next 12 months at approximately 9 %."

[1] The website of the Bundesbank Survey on Consumer Expectations provides additional details about its methodology, access to its data, and the full questionnaires used in our experiment. English and German versions from our first wave (September 2020) and our second wave (December 2020) can be downloaded. The questions included specifically for our experiment are marked with "ProBW". See: https://www.bundesbank.de/en/bundesbank/research/survey-on-consumer-expectations

- *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. Prior to the treatments we assess each respondent's prior knowledge about the information she is about to receive in her treatment. We also elicit respondents' stock market expectations prior to the treatment in the form of a point forecast of the expected percentage change of 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. Respondents are informed about this property of the DAX. Eliciting pre-treatment expectations enhances the power of the regressions by allowing us to take out fixed effects at the individual level. Due to the random assignment of treatments it is, however, not strictly necessary for identification. (see, e.g., Roth and Wohlfart 2020). In the second wave we do not include this question pre-treatment in favor of eliciting other important dimensions of individuals' beliefs.

After treatment, we first elicit the risk preferences of our respondents. We ask respondents to rate their willingness-to-take risks in financial matters on a scale from 0 (not willing to take risks at all) to 10 (very willing to take risks). This allows us to link individuals' subsequent portfolio decisions to their risk preferences. We then elicit respondents' posterior stock market expectations. These are elicited as respondents' subjective probability distribution about the change of the German stock market index DAX over the next 12 months. Respondents are asked to distribute a probability mass of 100 points across 10 buckets ranging from a 25 % or more decrease to a 25 % or more increase (with 5 % steps between brackets).

Finally, we confront respondents with a standard portfolio choice problem. Respondents are asked to decide on how to invest 10,000 Euros for a period of 12 months. They can allocate this amount across two assets. The return of the first asset is equal to the (risky) return of the German stock market index DAX over the following 12 months. The (risk-free) return of the second asset is fixed at 1%. The portfolio choice problem deliberately abstracts from respondents' wealth, by presenting them with a hypothetical endowment (see, e.g., Fuster and Zafar 2021). In line with the evidence by, for instance Hackethal et al. (2020), we do not incentivize the portfolio allocation decision. They show that there are no significant differences in portfolio choice under incentivization compared to non-incentivization. More generally, the effects of incentivization and experimenter demand effects have been shown to be very small for a variety of economic decisions as opposed to moral decisions (see, e.g., Camerer and Hogarth 1999; Camerer and Mobbs 2017; De Quidt et al. 2018, 2019; Mummolo and Peterson 2019).

3.2 Second Wave

The core of the second wave is a synthetic information acquisition experiment. To this end, we elicit individuals' preference for different information items in the prior elicitation stage of the experiment. The number of treatments is reduced, in order to ensure a sufficient number of treated individuals with a given information preference. In addition, the second wave extends the results of the first wave by eliciting the term structure of expectations and by eliciting both the subjective return *and* dividend growth expectations of respondents. We focus on the past return, past profit, and the price-earnings ratio treatment as reflecting the three major strands of theories about stock return expectation formation. We modify the price-earnings ratio treatment from quantitative to qualitative information, in order to test the hypothesis 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 as follows:

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

- *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."

- *T6 (Placebo):*
  Identical to first wave.

We extend the set of individual co-variates elicited prior to the treatments by a question aimed at eliciting individuals' information preferences and their portfolio of financial assets. Analogously to the first wave, we 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 for the 12 months horizon but also for the five year horizon, yielding individuals' expected term structure of stock returns. In addition, we elicit individuals' expected term structure of dividend growth. This allows a more specific test of the predictions of recent theories with learning about fundamentals (see, e.g., Myers and De La O 2020; Bordalo et al. 2020) regarding individuals' expected term structure of returns and dividend growth. We do not repeat the portfolio choice question from the first wave in favor of the new questions just described.

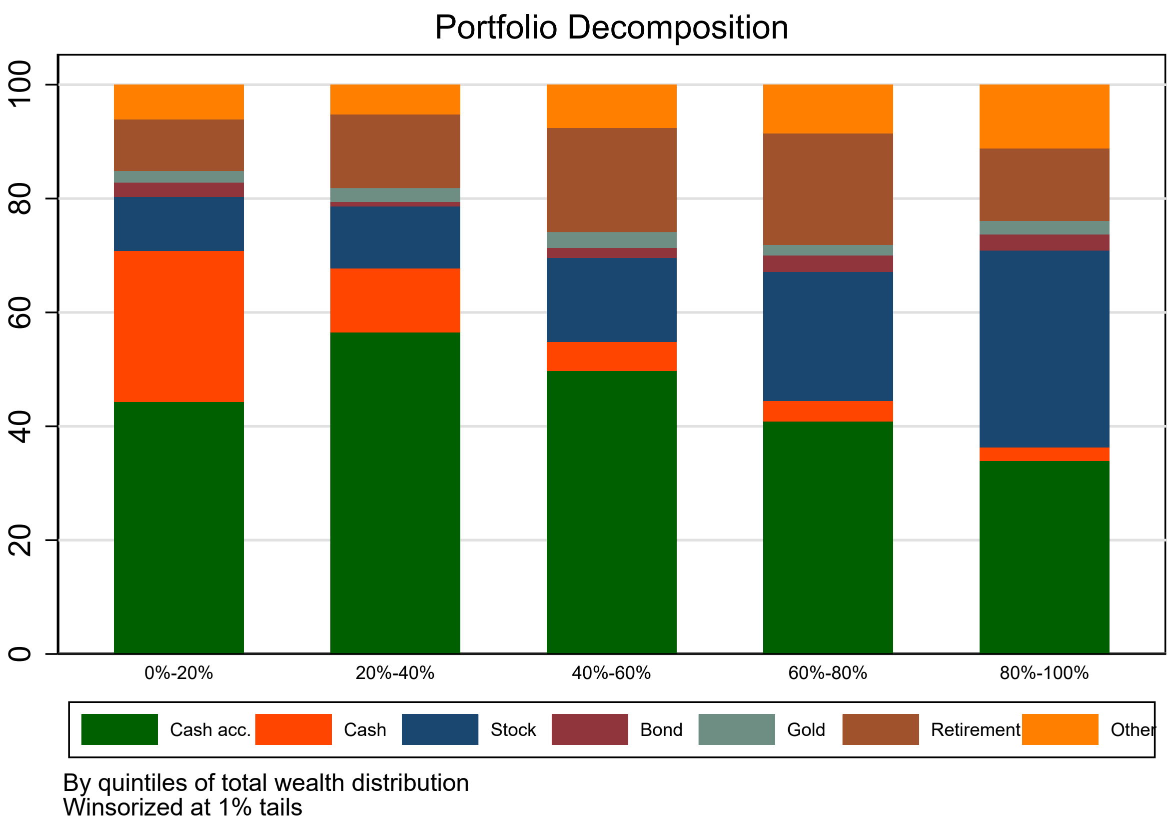
4 Portfolios and Prior Knowledge

This section characterizes households' portfolios and stock market knowledge prior to our experiment. We find that while stock investments are a crucial part of their financial wealth, households are imperfectly informed about stock market outcomes.

4.1 Portfolios

Almost half, 47%, of our respondents invest into the stock market. Figure 1 displays individuals' portfolio allocation by quintiles of the wealth distribution. It shows that 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 stock, bonds, precious metals, or other financial assets. This relationship essentially reverses for respondents in the highest quintile of the wealth distribution who hold 64% of their financial wealth in financial assets and 36% in cash and bank accounts. The stock portfolio share, narrowly defined as direct holdings of individual stocks, investment funds, or ETFs, is also increasing in wealth, from roughly 10% for the lowest wealth quintile to 35% for the highest wealth quintile. The absolute amounts of wealth invested in different assets are shown in Appendix Table A.3. The average amount of total financial wealth is roughly 66,000 Euros and the median amount is roughly 28,000 Euros, reflecting the skewness of the wealth distribution. The average amount of stockholdings stands at roughly 22,000 Euros, while the top 1% quantile of stockholdings is at 380,000 Euros. Apart from bank accounts (and real estate), stockholdings are on average the most important class of financial assets in individuals' portfolios, exceeding the amount invested in bonds, gold and other precious metals, or other savings arrangements.

Figure 1: Portfolio Allocation



4.2 Prior Knowledge

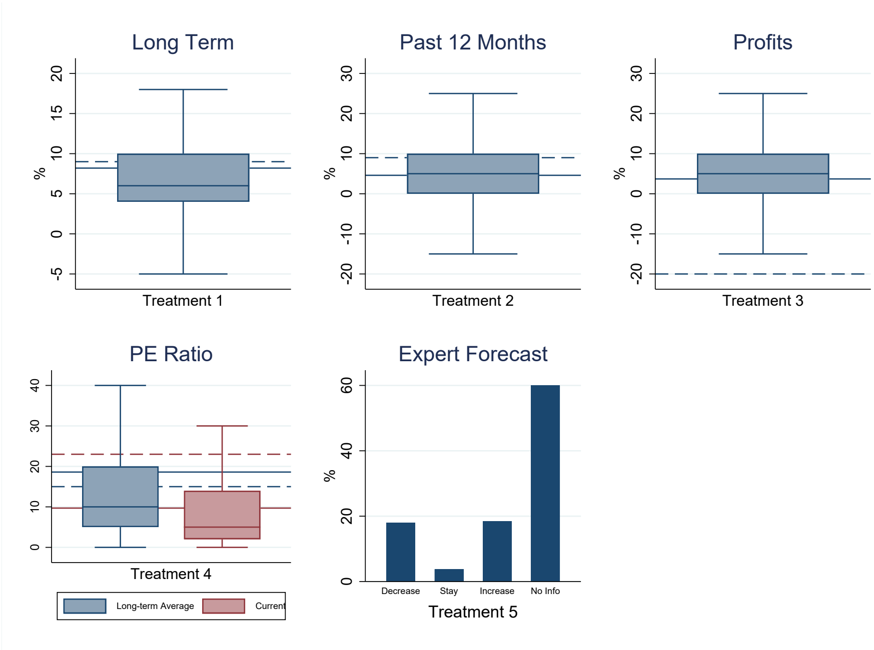
What do households know about the stock market? Prior to the information treatments, we asked respondents about their perception of the stock market outcomes they were about to be treated with. Figure 2 shows respondents' average perception (solid line) of the information shown in their respective treatments (dashed line). The solid and dashed line are key whereas the boxplot is there to indicate the dispersion of perceptions. On average, respondents almost precisely estimated the long-term historical return of the German stock market index DAX since 1973. They also did reasonably well regarding the past 12 months return, which they correctly perceived as substantially positive, despite the severe economic contraction induced by the Corona pandemic. On the other hand, respondents vastly underestimated the decline in profits of the constituents of the stock market index DAX. Regarding the price-earnings ratio, we find a similar pattern as for the perception of past returns. Individuals on average provided a relatively close estimate of the long-term average price-earnings ratio. On the other hand, respondents underestimated the value of the current price-earnings ratio. As a consequence, they perceived the price-earnings ratio at the time of the survey to be markedly below its historical average, while the opposite is true in reality. Roughly 60 % indicated that they received no expert forecast at all. Of those who did receive an expert forecast recently, roughly 44% report that the direction of the forecast was negative, roughly 10 % report that the forecast was neutral, and roughly 45 % report that the forecast was positive.

Prior informedness regarding the second wave treatments is shown in the second panel of Figure 2. On average, respondents overestimated the stock market return over the past 5 years. Similarly to the first wave, respondents underestimate the decline in earnings over the past 12 months. The question on the current price-earnings ratio relative to its historical average was set up as a qualitative comparison, for which around 38,4% of respondents gave the correct answer (current PE above long-term average), while 61,6% of respondents thought that it was the same as or below the long-term average.

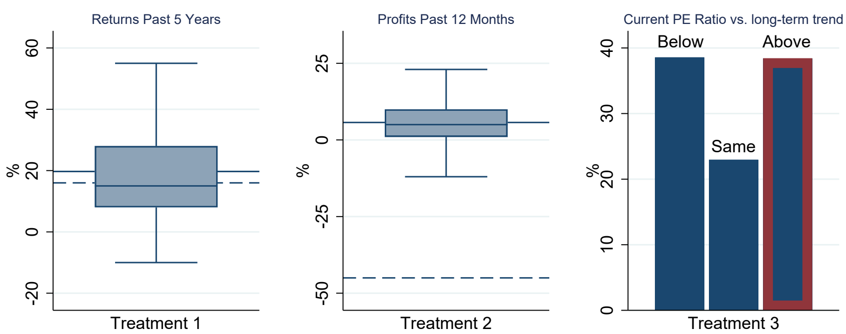
We investigate how the precision of households' knowledge about the aforementioned stock market outcomes varies by demographic characteristics (see appendix table A.4). We find that college or higher education, higher willingness to take risks, and holding stocks tend to be associated with lower perception gaps. Yet, consistent with previous evidence, observable characteristics explain a relatively small share of the variance in perception gaps across individuals (see, e.g., the evidence by Armona et al. (2019) regarding perception gaps about real estate price growth).

Figure 2: Knowledge about Stock Market Outcomes

First Wave



Second Wave



The figure shows individuals' informedness about stock market outcomes. The dashed line shows the actual value of the respective statistic. The solid line shows individuals' average subjectively perceived value. The difference between actual and perceived stock market outcomes represents the news component or 'perception gap' of the respective treatment.

5 Causal Evidence on Stock Market Expectation Formation

This section presents causal evidence on households' stock market expectation formation. We investigate how different treatments proxying for rational expectations (with incomplete information), learning about past returns, learning about past earnings growth, using expert forecasts, or using lifetime returns affect individuals' stock market expectations.

5.1 Econometric Approach

To investigate the effect of the information treatments on individuals' stock market expectations, we estimate the following standard specification (see, e.g., Coibion et al. 2021, or Coibion et al. 2020):

$$E[X]_i^{post} = \alpha + \sum_{k=1}^{K-1} \beta_k T_i^k + \sum_{k=1}^{K-1} \gamma_k T_i^k E[X]_i^{pre} + \delta E[X]_i^{pre} + \mathbf{W_i}\phi + \epsilon_i \tag{1}$$

where the treatment indicator T_i^k is equal to one if individual i received treatment k, and zero otherwise. Coefficients indexed by $k = 1, \ldots, K-1$ measure the effects of the information treatments relative to the control group receiving the Placebo treatment $(k = K)$. $E[X]_i^{pre}$ and $E[X]_i^{post}$ respectively denote individual i's pre-treatment and post-treatment subjective expectations of outcome X, which could for instance be the return or the dividend growth rate over the next h months. W_i denotes a control vector of socio-demographic characteristics. Notice that due to random assignment of the treatment groups, the control term $\mathbf{W_i}\phi$ should be orthogonal to the treatments and mainly serves to increase the precision of the estimates.

The coefficient β_k measures how much weight respondents put on the signal they receive in the treatment, whereas $\gamma_k + \delta$ measures the weight they put on their prior belief. These weights are allowed to be treatment-specific, as both the precision of the signal and its average distance to the prior may vary by treatment. To build intuition, let us abstract from the socio-demographic control term $\mathbf{W_i}\phi$, which, due to its orthogonality to the treatments could be subsumed in the innovations ϵ_i. Now consider an individual in the control group, for whom $T_i^k = 0$ for $k = 1, \ldots, K-1$. Since individuals in the control group do not receive any relevant news in their treatment, we would expect their posterior expectations to be identical to their prior expectations such that $\alpha = 0$ and $\delta = 1$. (In practice, since we elicit posterior and prior beliefs using different question formats, i.e. point estimate versus probability density function, posterior and prior beliefs may differ even in the control group, such that $\alpha \neq 0$ and $\delta \neq 1$ in line with, e.g., Coibion et al. 2020.)

Now consider an individual in the treatment group. The effect of the information treatments, $k = 1, \ldots, K-1$ relative to the control group $(k = K)$, depends on the degree of information (in)completeness and the mental model entertained by households. A treatment could be uninformative either because the information in the treatment is already known or because households deem it irrelevant with regards to the outcome variable X. In this case, we would find $\beta_k = 0$. Conversely, if $\beta_k \neq 0$, this implies that the provided signal must contain news and be considered relevant for individuals' beliefs about variable X. If $\beta_k > 0$ the treatment causes respondents to revise their beliefs upwards, for instance due to a positive surprise about past returns, and viceversa for $\beta_k < 0$. If individuals update their beliefs consistent with models of Bayesian updating or noisy information (see, e.g., Coibion and Gorodnichenko 2015), we therefore expect $\gamma_k < 0$ for an informative treatment as individuals reduce the weight on their prior in favor of putting more weight on the information provided in the treatment (see Coibion et al. 2020).

5.2 Effect of Information Treatments on Stock Return Expectations

Table 1 presents the results from estimating equation (1) based on the first wave of our experiment. The last column shows the coefficient estimates from our main specification with all controls. We find that the coefficients β_k ("T1",...,"T5") for both treatment 1 (long-term average return) and treatment 4 (price-earnings ratio) are insignificant. The coefficients β_k for treatment 2 (past return) and treatment 5 (expert forecast) are positive and significant. The coefficient for treatment 3 (past earnings growth) is negative and significant. Consistent with Bayesian updating or noisy information, we find that the coefficients γ_k ("T1xPrior",...,"T5xPrior") are either negative or insignificant and the coefficient δ ("Prior") is positive but below one. Column 2 shows that the results are robust to excluding the controls for prior expectations. Columns 1 and 3 show that, the effect of controlling for socio-demographics is small, as expected due to the orthogonality of the treatments. In the following, we discuss the implications of these results for leading theories of stock market expectation formation and asset pricing.

(Rational Expectations) Treatment 4 (price-earnings ratio), aims at testing the predictions of models with counter-cyclical return expectations. RE asset pricing models predict that investors should expect low (high) returns, when current valuation ratios are high (low). To interpret the ATEs it is important to take into account the average perception gap of individuals in each treatment group. The perception gap measures the amount by which the treatment information deviates from each individual's prior, i.e. the subjective amount of news contained in a given treatment. In Figure 2 we saw that individuals on average vastly underestimated the level of the price-earnings ratio at the time of the survey. Hence, the average perception gap, defined as signal minus prior, for treatment 4 (price-earnings ratio) is large and positive. Under counter-cyclical return expectations, a large upward revision in an individual's perception of the current price-earnings ratio should lead to a downward revision of her expected stock market return. By contrast, Table 1 shows that the ATE of treatment 4 is insignificant (and positive). Individuals do not revise their return expectations in response to news about the price-earnings ratio which is surprising given the intimate (inverse) relationship between the two.

(Learning about returns) Models in which individuals are learning about past returns or past capital gains predict that individuals' return and capital gains expectations are pro-cyclical. In these models, individuals extrapolate recent returns or capital gains into the future and, consequently, expect high returns at times when valuation ratios are high, contrasting fundamentally with RE based explanations. In order to causally

Table 1: Treatment Effects: First Wave

	Posterior			
	(1)	(2)	(3)	(4)
T1	-0.03	-0.07	0.56	0.40
	(0.41)	(0.41)	(0.41)	(0.41)
T2	1.62***	1.56***	2.04***	1.93***
	(0.40)	(0.41)	(0.43)	(0.44)
T3	-2.87***	-2.86***	-3.22***	-3.19***
	(0.48)	(0.47)	(0.44)	(0.44)
T4	0.46	0.49	0.73	0.78
	(0.44)	(0.45)	(0.46)	(0.48)
T5	1.09***	0.97**	1.63***	1.57***
	(0.40)	(0.41)	(0.43)	(0.45)
Prior			0.36***	0.37***
			(0.05)	(0.05)
T1xPrior			-0.14*	-0.11
			(0.09)	(0.08)
T2xPrior			-0.17**	-0.17**
			(0.07)	(0.07)
T3xPrior			0.04	0.02
			(0.07)	(0.07)
T4xPrior			-0.07	-0.10
			(0.08)	(0.08)
T5xPrior			-0.22***	-0.23***
			(0.07)	(0.07)
Constant	-0.42	0.79	-1.71***	-1.75
	(0.29)	(2.10)	(0.28)	(2.15)
Socio-Demographics	No	Yes	No	Yes
R^2	0.03	0.06	0.15	0.18
N	3719	3590	3529	3419

Dependent variable is the post-treatment subjectively perceived return of the DAX over the next 12 months. Prior indicates the corresponding pre-treatment expected return. The treatments are: T1 (DAX long-term), T2 (DAX past 12 months), T3 (Profits past 12 months), T4 (PE ratio) and T5 (Expert forecast next 12 months). We control 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 of four German statistical regions). Prior and posterior return expectations are winsorized at their 1% tails. Robust Standard errors in parentheses.

test the prediction that individuals extrapolate recent returns into the future, our second treatment provides individuals with the return of the German stock market index over the previous 12 months. Figure 2 showed that individuals on average strongly underestimated the stock market return over the previous 12 months. Hence, the treatment entailed a positive surprise about recent stock market returns. If individuals extrapolate recent returns into the future, this news should lead to an upward revision of their expected return over the next 12 months. Indeed, we find that treatment 2 causes individuals to revise their return expectations upwards by almost two percentage points.

(Learning about fundamentals) A third strand of the literature is relaxing the assumption of Rational Expectations regarding dividend and earnings growth. Recent studies suggest that pro-cyclical and excessively volatile earnings and dividend growth expectations may explain the observed fluctuations in stock market valuation ratios (see, e.g., Myers and De La O 2020 and Bordalo et al. 2020). Such pro-cyclical earnings growth expectations are consistent with models in which individuals extrapolate past earnings growth into the future. We test this prediction causally using our third treatment in which individuals are provided with information about earnings growth over the previous 12 months. In Figure 2 we saw that individuals on average vastly overestimated earnings growth over the previous 12 months. Hence, the earnings growth treatment entailed a large negative surprise. Table 1 shows that this negative surprise led individuals to revise their return expectations downwards by more than 3 percentage points. Results from our second experiment show that the downward revision in expected returns in response to news about earnings growth is driven by two channels. The first channel is that individuals revise their earnings growth expectations downwards in response to the treatment. The second channel is that individuals simultaneously revise their capital gains expectations in the same direction and by a similar magnitude (see next section 5.3).

(Expert forecasts) The expert forecast treatment (T5) led respondents to revise their beliefs upwards by roughly 1.6 percentage points. As discussed in appendix section A.2 the expert forecast entailed a positive surprise to most respondents. The estimated ATE shows that respondents chose on average to revise their expected stock market return upwards, and hence, in the direction of the expert forecast. These findings are consistent with Carroll (2003) in which economic agents are not endowed with RE but instead derive their expectations from expert forecasts obtained from newspapers or other media outlets. The model by Carroll (2003) provides micro foundations for sticky information models in which not all individuals update their information sets in each period, which is consistent with only a fraction of our respondents being aware of a recent expert forecast about the stock market. We present further evidence on individuals' preferences for and perceived costs of different pieces of information in section 6.

(Long-term versus recent experiences) An alternative illustration of the treatment effects is shown in Figure 3. This figure shows individuals' belief revisions as a function of their perception gaps. The slope of the corresponding regression line indicates the learning rate for each treatment, that is the revision per unit of news received (see also appendix table A.3). We find that the price-earnings ratio treatment induces the lowest learning rate with an almost horizontal regression line, consistent with the insignificant treatment effect. By contrast, the learning rates for Treatment 2 (past return), and treatment 3 (past earnings growth) are substantially higher than the learning rate for the price-earnings ratio treatment. The learning rate for treatment 4 (expert forecast) is slightly higher as well. Hence, the learning rates confirm the findings thus far.

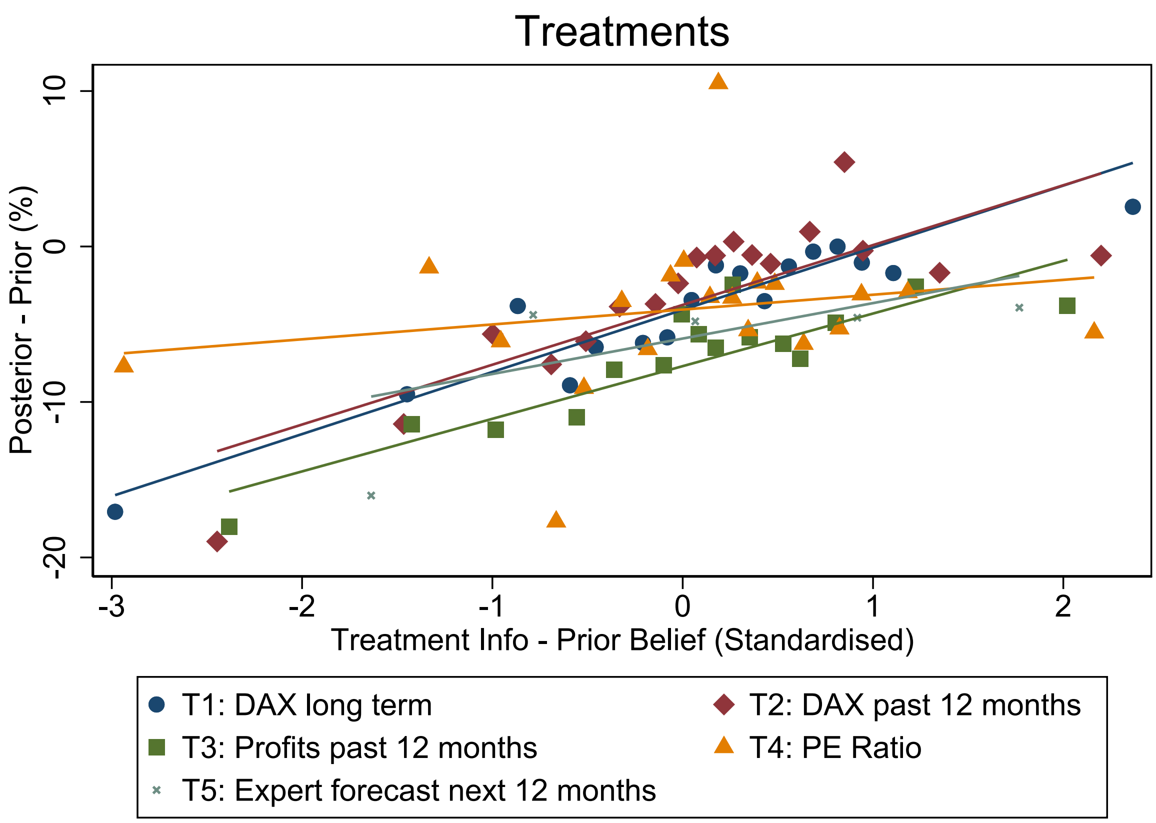


Figure 3: Learning Rates

Bin-scatter plot of individuals' belief revisions in response to the treatments as a function of their perception gaps. Winsorized (1% tails) prior (point question) and posterior (distribution question) expectations on stock market returns over the next 12 months. Positive perception gaps correspond to a positive surprise. Perception gaps are standardized (zero mean, one standard deviation for each treatment group) and defined as follows. 9%-prior belief (T1: DAX long-term, T2: DAX Past 12 Months), -20%-prior belief (T3: Profits Past 12 Months) and (prior belief current PE ratio - prior belief long-term PE ratio) - (23-15) (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".

For treatment 1 (long-term average return), we find on the one hand an insignificant ATE and on the other hand a relatively high learning rate. The high learning rate for the long-term average return treatment implies that the small ATE of this treatment is primarily due to the small perception gap. Individuals perceive the long-term average return to be important but they are already well informed about it. Since treatment 1 entails on average only a small amount of news for our respondents, they optimally respond with a small absolute expectation revision, despite a high sensitivity per unit of news.

The learning rates can be used to shed light on the predictions by Malmendier and Nagel (2011) who suggest that individuals over-weight recent return experiences. If respondents would weight all returns equally, the weight on the past one year return (T2) would be 1/47 of the long-term 47 year average return (T1). However, we find that the learning rate of T2 is roughly 2/3 the size of the learning rate of T1. This suggests that individuals do indeed overweight recent returns, complementing the findings by Malmendier and Nagel (2011) with causal evidence.

A second prediction of Malmendier and Nagel (2011) is that younger individuals, due to their shorter history of personal experiences, put more weight on recent return experiences than older individuals. To test this prediction, we split respondents into young (below median age) and old (above median age) individuals and document their learning rates in appendix figure A.1. We find that learning rates for young and old individuals are virtually identical regarding the past one year return (T2). The learning rate of young individuals is markedly higher for information about past earnings growth (T3) and expert forecasts (T5). By contrast, old individuals respond more strongly to information about the price-earnings ratio (T4). Hence, we find that substantial differences in the updating behavior of young and old individuals exist as suggested by Malmendier and Nagel (2011). The strength and sign of these effects appears to vary by the type of information considered, which could be an interesting aspect for future research. Additional dimensions of heterogeneity are explored in appendix section A.3. We find a pronounced gender effect, which is in line with previous findings in the literature (see, e.g., Armantier et al. 2016; Coibion et al. 2021). Female respondents revise their beliefs more strongly in response to all five treatments of the first wave. Education and income are not systematically related to expectation revisions.

5.3 The Term Structure of Expected Stock Returns, Dividend Growth, and Capital Gains

In the second experiment, we elicit post treatment expectations not only about future returns but also about future dividend growth. This allows us to better capture the essence of models with pro-cyclical earnings growth expectations (e.g., Bordalo et al. 2020; Myers and De La O 2020). By eliciting expectations about returns *and* dividend growth, we can decompose the treatment effect on expected returns into its capital gains and its dividend yield component. To this end, we rewrite the one-period return as follows:

$$R_{t+1} \equiv \frac{P_{t+1} + D_{t+1}}{P_t} = \frac{P_{t+1}}{P_t} + \frac{D_t}{P_t}\frac{D_{t+1}}{D_t} \tag{2}$$

The first term on the right-hand-side of this equation is the expected capital gain and the second term is the expected dividend yield. We observe individuals' expected return, $E_t R_{t+1}$, and individuals' expected dividend growth, $E_t \frac{D_{t+1}}{D_t}$. Given the level of the price-dividend ratio at the time of the survey, we can compute their implied capital gains expectations, $E_t \frac{P_{t+1}}{P_t}$.

In light of the importance of longer-term expectations in asset pricing models with forward-looking agents, we elicit expected returns and expected dividend growth at different horizons (1 year and 5 year). This allows us to investigate how the treatments affect the term structure of expected stock returns, dividend growth, and capital gains. Given that we elicit four posterior expectations it would be infeasible in terms of survey space to also elicit four prior expectations. Hence, we have to adjust our econometric approach. Instead of controlling directly for individuals' prior expectation about each outcome variable, X, as in equation (1) we now use proxy variables that control indirectly for individuals' prior expectations. Hence, we estimate the following modified version of equation (1) in which the direct measure of prior expectations $E[X]_i^{pre}$ is replaced by a vector of proxy variables Z:

$$E[X]_i^{post} = \alpha + \sum_{k=1}^{K-1} \beta_k T_i^k + \sum_{j=1}^{J} \left(\sum_{k=1}^{K-1} \gamma_{k,j} T_i^k Z_{i,j} + \delta_j Z_{i,j} \right) + \mathbf{W_i}\phi + \epsilon_i \tag{3}$$

where $Z_{i,j}$ refers to a set of J proxy variables that are informative about individuals' prior expectations. Our set of proxy variables includes a dummy variable indicating whether the individual is a stockholder, and a dummy variable indicating whether prior to the treatments, individuals expect economic growth to increase over the next 12 months.This parsimonious set of proxy variables is motivated by the empirical relevance of stock market experience (see, e.g., Malmendier and Nagel 2011; Adam et al. 2015) and economic growth expectations (see, e.g. GMSU) for stock return expectations. As before, T_i^k are treatment dummies, $E[X]_i^{post}$ refers to individuals' posterior expectations about an outcome X (returns or dividend growth over the next 1 year or 5 years), and W_i is a vector of socio-demographic control variables. Notice that the lack of direct measures of prior expectations precludes us from computing learning rates based on individuals' expectation revisions as in Figure 3. Instead, we focus on interpreting the average treatment effects (ATEs) in light of the average treatment-specific perception gaps, which we do elicit in the second wave as well. The ATEs from the second experiment are shown in Table 2. In this experiment, we focus on the treatments relating to the three key strands of the literature: the past return treatment (T1), the past earnings growth treatment (T2), and the price-earnings ratio treatment (T3). As before, our main coefficient of interest measuring the ATE is β_k ('T1, T2, T3'). The coefficients on the interaction $\gamma_{k,j}$ (e.g. T1xStockholder) measures the marginal difference in the response of individuals with characteristic 'j' to treatment 'k'.

The effects of the price-earnings ratio treatment (T3) on expected returns and expected dividend growth at either of the two horizons are statistically and economically insignificant, consistent with the evidence from the first wave. Relative to the first wave, we also learn that not even stockholders react to news about the price-earnings ratio. In addition, we formulated the price-earnings ratio treatment of the second wave in simple, qualitative terms. The insignificant treatment effect of the second wave thus suggests that individuals do not even understand the relationship between the price-earnings ratio and subsequent returns in very basic, qualitative terms.

For the past 5-year return treatment (T1) we find a significantly negative treatment effect at the five year horizon, consistent with the negative average perception gap regarding the past 5-year return documented in Figure (2). At the twelve months horizon, the treatment effect is insignificant. Apparently, individuals match the horizon of the treatment information with the forecasting horizon, similarly as an econometrician would not use a direct multi-year forecasting model to make forecasts one year ahead. The interaction between T1 and the stockholder indicator variable ('T1xStockholder') shows that the downward revision of 5-year returns is driven by stockholders. Interestingly, stockholders react to the past 5-year return treatment with a downward revision of not only their re-

Table 2: Treatment Effects: Second Wave

	Returns: 12 Months		Returns: 5 Years		Dividends: 12 Months		Dividends: 5 Years		Price: 12 Months		Price: 5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
T1	-0.55	-1.08	-1.13*	0.14	-0.12	-0.85	0.32	0.99	-0.42	-0.89	-1.02*	0.36
	(0.40)	(0.73)	(0.61)	(1.07)	(0.55)	(0.90)	(0.64)	(1.12)	(0.40)	(0.73)	(0.60)	(1.05)
T2	0.03	-2.45**	4.60***	2.95**	-2.23***	-3.09**	2.96***	2.00	0.12	-2.11**	4.64***	3.33***
	(0.60)	(1.05)	(0.78)	(1.26)	(0.73)	(1.21)	(0.77)	(1.26)	(0.60)	(1.05)	(0.78)	(1.26)
T3	0.37	0.32	0.40	0.55	0.49	1.12	0.32	0.29	0.30	0.10	0.43	0.73
	(0.46)	(0.90)	(0.71)	(1.25)	(0.57)	(0.99)	(0.71)	(1.28)	(0.45)	(0.90)	(0.71)	(1.25)
Economic Growth		1.52**		3.29***		0.54		1.28		1.61***		3.13***
		(0.59)		(1.07)		(0.84)		(1.12)		(0.56)		(1.05)
T1xGrowth		0.87		-0.91		1.18		0.66		0.68		-0.63
		(0.79)		(1.29)		(1.20)		(1.40)		(0.77)		(1.28)
T2xGrowth		3.28***		1.40		2.87*		2.24		3.22***		1.25
		(1.19)		(1.75)		(1.60)		(1.84)		(1.18)		(1.75)
T3xGrowth		-0.18		-1.40		-1.19		0.11		0.24		-0.86
		(0.90)		(1.53)		(1.27)		(1.58)		(0.87)		(1.52)
Stockholder		-0.01		2.83***		-1.37		1.07		-0.02		3.16***
		(0.66)		(1.05)		(0.84)		(1.08)		(0.64)		(1.03)
T1xStockholder		-0.27		-2.34*		-0.53		-2.64**		-0.17		-2.60**
		(0.83)		(1.28)		(1.18)		(1.33)		(0.82)		(1.26)
T2xStockholder		2.20*		2.84*		-1.05		0.71		1.98		2.60
		(1.26)		(1.67)		(1.59)		(1.70)		(1.26)		(1.67)
T3xStockholder		-0.49		0.24		-1.20		-0.31		-0.42		-0.35
		(0.99)		(1.53)		(1.25)		(1.54)		(0.96)		(1.51)
Constant	12.59***	14.03***	13.77***	14.03***	14.65***	12.48**	18.84***	18.96***	9.67***	10.75***	10.12***	9.80**
	(3.47)	(3.90)	(3.82)	(4.39)	(4.15)	(4.97)	(4.48)	(4.85)	(3.51)	(3.89)	(3.83)	(4.35)
Socio-Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.03	0.04	0.07	0.03	0.04	0.02	0.03	0.01	0.03	0.05	0.07
N	3429	2983	3429	2983	3368	2942	3368	2942	3288	2877	3288	2877

Robust Standard errors in parentheses. T1 (DAX past 5 years), T2 (Profits 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 (point question) expectations on stock market returns/dividend changes over the next 12 months/5 years. Dependent variable listed in column headings. The "Economic Growth/ Growth" dummy is 1 if the respondent expects a slight/significant increase in economic growth in the next 12 months and 0 if the respondent expects growth to stay the same or a slight/significant decrease in economic growth. The "Stockholder" dummy is 1 if the respondent has financial assets in stocks/ETFs worth more than 0 Euros and 0 otherwise.

turn, but also their dividend growth expectations at the 5-year horizon. The observation that news about past returns can trigger revisions in dividend growth expectations in addition to revisions in expectations about capital gains is hitherto not present in asset pricing models such as Adam et al. (2017) and could represent an additional source of volatility in such models. The last two columns of Table 2 present the treatment effects on individuals' expected capital gains. We find that the revision of return expectations can to a large extent be attributed to a revision in capital gains expectations, which in turn respond almost one-to-one with individuals' revision of dividend growth expectations.

Regarding the past earnings growth treatment (T2), the results in Table 2 show that the plain treatment effect on expected 1-year dividend growth in columns (5) and (6) is significantly negative. Conditional on not expecting an increase in economic growth, respondents react to the negative surprise about past earnings growth, by revising their dividend growth expectations downwards. The plain treatment effect on expected dividend growth goes along with a qualitatively similar plain treatment effect for expected returns. As conjectured in the first wave, the effect on expected returns is primarily driven by a revision in capital gains expectations. Individuals who expect lower dividend growth tend to expect lower capital gains as well. This result complements the findings from GMSU (Fact 4) with causal evidence. They find a positive correlation between expected returns and expected earnings growth (which they proxy by expected GDP growth) in the cross-section of respondents. The effect of our past earnings growth treatment shows that such a correlation can arise causally when individuals receive news about recent earnings growth.

Considering the interaction effects of the past earnings growth treatment (T2) with economic growth expectations reveals the following. Individuals who expect economic growth to increase (33% of respondents) do not revise their dividend growth expectations significantly in response to the negative news about past earnings growth. Against the backdrop of promising news about Covid-19 vaccination campaigns prior to our second wave in December 2020 these respondents apparently discounted the bad news about past earnings growth. Respondents expecting an increase in economic growth *and* holding stocks even reacted to the bad news about past earnings growth with an upward revision of their expected return, perhaps expecting a reversal of the economy and the stock market. Interestingly, respondents of all types reacted to the negative news about past earnings growth with an upward revision of their 5-year return and capital gains expectations. The ATE for 5-year dividend dividend growth is positive and of similar magnitude, although significance is diluted in the specification with all controls. This could suggest that while many individuals extrapolate past earnings growth at the 1-year horizon, individuals do on average expect mean reversion of earnings growth at longer horizons at least during the dawning recovery from the Covid-19 pandemic at the time of our second wave. Hence, our results suggest a potential state-dependence in which individuals take into account more complex features of the data generating process such as mean reversion or structural breaks. Incorporating such features into theories such as Bordalo et al. (2020) and Myers and De La O (2020) appears to be an interesting avenue for future research. Furthermore, a robust feature of our results appears to be that individuals tend to revise their return expectations in the same direction as their earnings growth expectations. The heterogeneity of treatment effects for both waves is documented in appendix section A.3.

6 Information Acquistion, Preferences and Costs

Individuals' preferences and perceived costs regarding different information items may crucially impact their expectation formation process at the information acquisition and the information processing stage (see, e.g., Fuster et al. 2019). In real life, individuals can choose which information to collect and to use for their investment decisions. This raises the question which information individuals would choose, and whether they would react differently to information they have chosen compared to receiving an information item at random. In the following, we first document individuals' ranking of different information items. We then identify an 'information preference effect' at the information processing stage. It measures whether individuals with a preference for the information item they receive react differently to this information than individuals who do not prefer the information they receive. Finally, we shed light on what is behind the 'information preference effect', and we document individuals' perceived cost of acquiring different information items.

6.1 Which Information do Households Prefer?

Figure 4 shows the average ranking of information items across respondents. Individuals most frequently rate expert forecasts as the most useful information item, followed by information about earnings growth, the long-term historical average of the DAX, the price-earnings ratio and the return of the DAX over the last 5 years. Abstracting from differences in the cost of acquiring different information items, a rational decision-maker should choose the information item that she perceives as most useful. Hence, we take individuals' first preference as the basis for our information acquisition experiment. Each information item is most preferred by a sizeable share of respondents ensuring a sufficient number of respondents with preference for any of the information items.

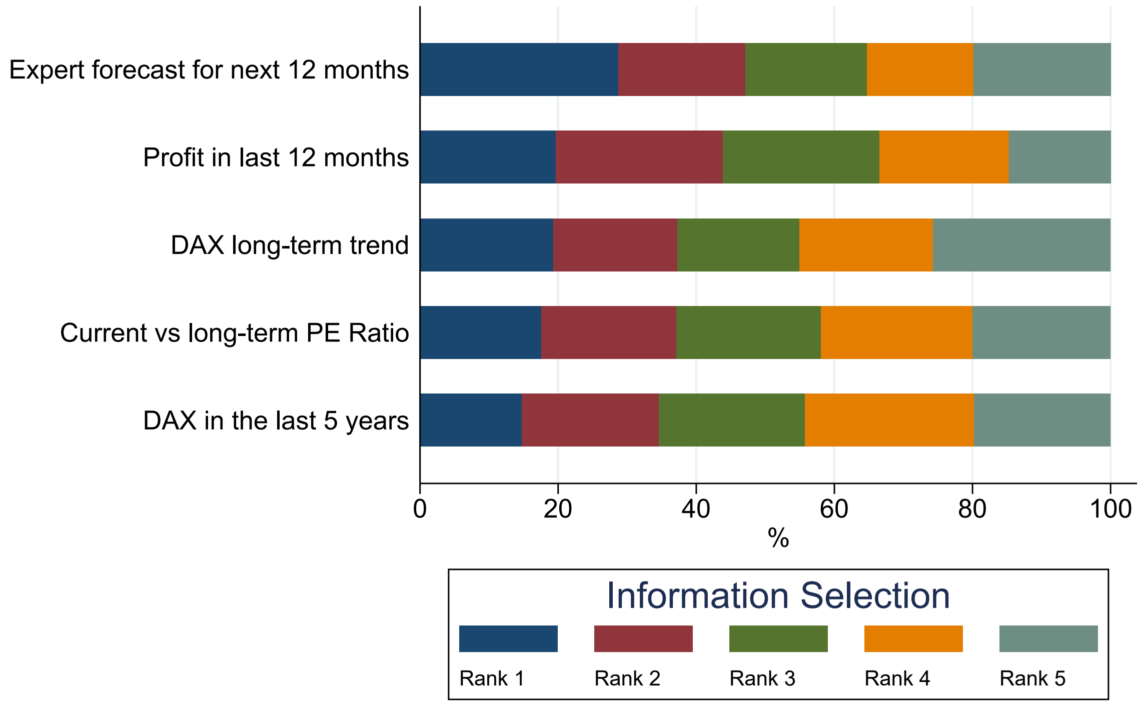
6.2 Measuring the Information Preference Effect

Are treatment effects different when individuals prefer the information item? To estimate the 'information preference effect' we extend our previous specification (3) 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:

$$E[X]_i^{post} = \alpha + \sum_{k=1}^{K-1} \left(\beta_k T_i^k + \psi_k P_i^k + \xi_k T_i^k P_i^k\right) + \sum_{j=1}^{J} \left(\sum_{k=1}^{K-1} \gamma_{k,j} T_i^k Z_{i,j} + \delta_j Z_{i,j}\right) + \mathbf{W_i}\phi + \epsilon_i \tag{4}$$

As before, T_i^k are treatment dummies, $E[X]_i^{post}$ refers to individuals' posterior expectations about an outcome X (returns or dividend growth over the next 1 year or 5 years), $Z_{i,j}$ are our proxy variables controlling for individuals' prior expectations (economic growth expectations and stockholdings), and W_i is a vector of other socio-demographic control variables. The information acquistion experiment is embedded in our second wave, such that the treatments are: past return treatment (T1), past earnings growth treatment (T2), and price-earnings ratio treatment (T3). As before, their effects are measured relative to a control group ($K = 4$).

Figure 4: Individuals' Ranking of Information Items



The information preference effect is measured by the coefficient ξ_k. It measures how much the causal treatment effect of an individual who prefers the information received in the treatment differs from the treatment effect of an individual who does not prefer it. Table 3 presents estimates of the information preference effect for the three information treatments and the four outcome variables (return and dividend growth expectations at the 1-year and 5-year horizon). Our main specification is the second column for each outcome variable which includes all controls. The coefficient of interest, measuring the information preference effect for each treatment, is marked with a red box.

For the past return treatment, the estimated coefficient for the information preference effect is insignificant across all outcome variables. This suggests that individuals for whom information about the past 5-year stock market return is their most preferred information item amongst those considered do not react differently to receiving this information than all other individuals. By contrast, for the past earnings growth treatment, the coefficient measuring the information preference effect is significantly negative for all outcome variables. The information preference effect for the past earnings growth treatment is roughly -3 percentage points for return expectations at both horizons, and roughly -6 percentage points for dividend growth expectation at both horizons. Thus, individuals who prefer this type of information react to the negative news about recent earnings growth in a more extrapolative manner than other individuals. This suggests that 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 such as Bordalo et al. (2020) and Myers and De La O (2020).

Interestingly, we obtain a significant and negative information preference 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 5-year return expectations downwards by roughly 4.4 percentage points more than other individuals. The information preference effect for the price-earnings ratio on individuals' 1-year expected return is significantly negative for the first specification, and negative but insignificant for the second specification with all controls. By contrast, there is no significant information preference effect regarding expected dividend growth at either horizon. This implies 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 rational expectations than the reaction of average respondents.

Our findings add to a literature documenting economically relevant patterns of heterogeneity in how individuals form stock market expectations. For instance, Dominitz and Manski (2011) suggest that the population consists of a mixture of types with 'interpersonally variable but intrapersonally stable' expectation formation processes. We add to this literature by providing causal evidence for this. Specifically, our experimental setup allows us to disentangle two distinct channels arising at different stages of the expectation formation process that could contribute to the observed heterogeneity. First, heterogeneity of expectation formation can arise at the information acquisition stage due to the fact that different individuals prefer different pieces of information and are therefore more likely to acquire such information . Second, heterogeneity can arise at the information processing stage due to different individuals processing different pieces of information differently. We document a sizeable degree of heterogeneity regarding the first channel given that the most preferred information item amongst those considered is almost uniformly distributed across individuals (see Figure 4). We also document considerable heterogeneity in the informedness of respondents, measured by their perception gaps (more details in the next subsection). Our key finding refers to the second channel. Our controlled experimental setting allows us to show that distinct groups of individuals *process* the exact same piece of information in very different ways. These groups are identified by their information preference, that is in an economically meaningful way. Under the hypothesis that different groups of individuals entertain different mental models of the stock market, we would indeed expect that these mental models determine information preferences and information processing jointly.

Table 3: Synthetic Information Acquisition Experiment

	Returns: 12 Months		Returns: 5 Years		Dividends: 12 Months		Dividends: 5 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1	-0.21	-0.91	0.26	1.22	0.31	-0.36	2.26***	3.06**
	(0.54)	(0.80)	(0.81)	(1.20)	(0.71)	(1.12)	(0.88)	(1.32)
DAX 5y Info Selected	0.19	0.26	1.19	1.19	-1.11	-0.98	1.41	1.35
	(0.91)	(0.99)	(1.39)	(1.51)	(1.21)	(1.28)	(1.45)	(1.64)
T1xDAX 5y Info Selected	-0.93	-0.68	-1.84	-1.17	0.81	1.13	-2.71	-2.58
	(1.21)	(1.36)	(1.66)	(1.84)	(1.68)	(1.75)	(1.86)	(2.08)
T2	1.14	-1.53	6.81***	5.03***	-1.12	-1.86	5.27***	4.60***
	(0.93)	(1.28)	(1.14)	(1.56)	(1.11)	(1.57)	(1.13)	(1.58)
Profit Info Selected	0.68	0.22	1.47	1.01	2.22*	2.58**	2.62*	2.65
	(0.90)	(0.99)	(1.41)	(1.52)	(1.15)	(1.25)	(1.55)	(1.76)
T2xProfit Info Selected	-3.36**	-3.15*	-3.87*	-2.99	-5.22***	-5.72***	-6.17***	-5.84**
	(1.62)	(1.72)	(2.26)	(2.41)	(1.97)	(2.14)	(2.19)	(2.46)
T3	0.91	0.37	2.24**	2.40	0.46	0.73	1.98**	1.76
	(0.68)	(1.09)	(1.02)	(1.51)	(0.78)	(1.21)	(1.01)	(1.52)
PE Ratio Info Selected	1.09	0.69	3.23**	2.95*	-1.09	-1.88	2.32	2.07
	(0.85)	(0.93)	(1.47)	(1.61)	(1.28)	(1.36)	(1.51)	(1.65)
T3xPE Ratio Info Selected	-2.81**	-1.80	-4.86**	-4.43**	-1.75	-0.51	-2.58	-1.61
	(1.32)	(1.42)	(2.07)	(2.20)	(2.09)	(2.23)	(2.23)	(2.42)
Economic Growth		1.41**		2.91***		0.35		0.96
		(0.61)		(1.09)		(0.87)		(1.15)
T1xGrowth		0.75		-0.63		1.30		0.82
		(0.81)		(1.33)		(1.26)		(1.45)
T2xGrowth		3.51***		1.62		2.70		2.15
		(1.25)		(1.80)		(1.68)		(1.88)
T3xGrowth		-0.04		-1.10		-0.83		0.12
		(0.94)		(1.58)		(1.31)		(1.63)
Stockholder		-0.22		2.80***		-1.20		1.32
		(0.67)		(1.06)		(0.87)		(1.09)
T1xStockholder		-0.03		-2.06		-0.38		-2.64*
		(0.85)		(1.30)		(1.23)		(1.37)
T2xStockholder		2.13		2.71		-1.21		0.10
		(1.33)		(1.71)		(1.66)		(1.75)
T3xStockholder		-0.49		-0.34		-1.23		-0.68
		(1.02)		(1.57)		(1.29)		(1.58)
Constant	13.23***	14.82***	12.60***	12.12***	16.16***	14.22***	17.89***	17.69***
	(3.69)	(4.13)	(3.99)	(4.54)	(4.37)	(5.30)	(4.67)	(5.05)
Socio-Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.03	0.05	0.07	0.04	0.05	0.03	0.03
N	3183	2776	3183	2776	3128	2735	3128	2735

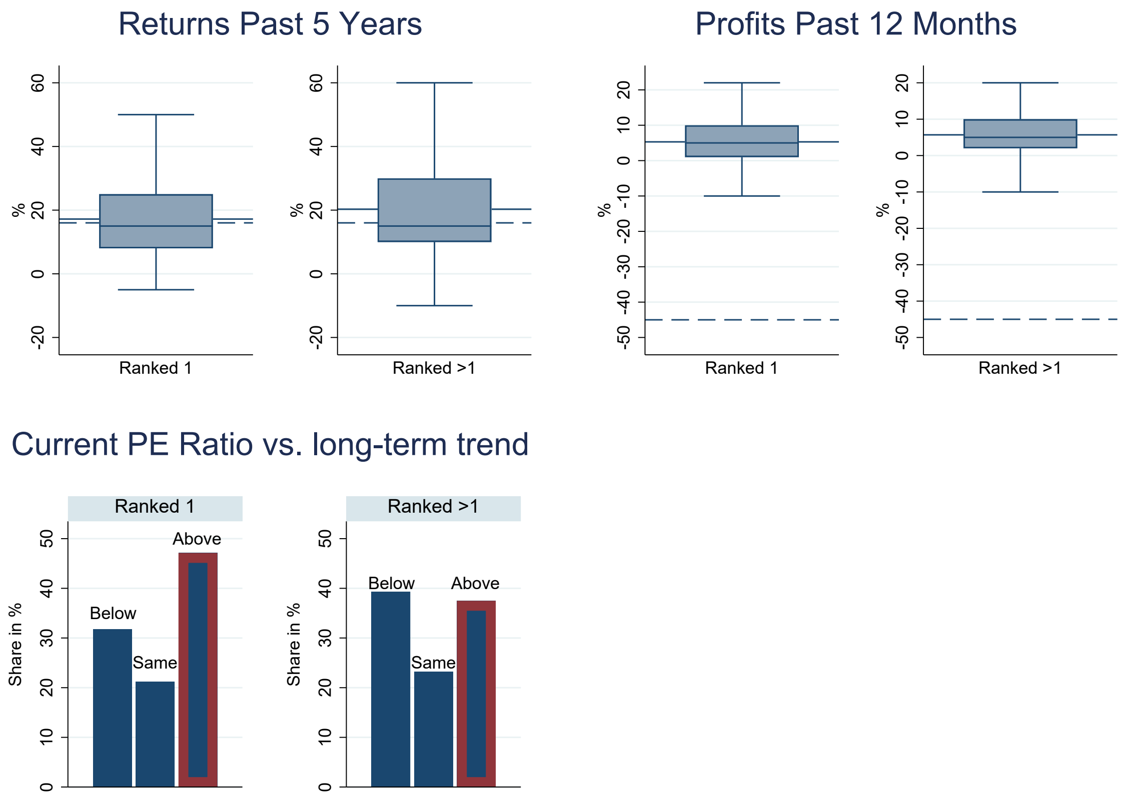
An information source is defined as "selected" if the survey participant ranked the sources on rank 1 out of 5. Correspondingly, the dummy "Info Selected" is 1 if the info source is ranked 1/5 and 0 otherwise. Robust Standard errors in parentheses. T1 (DAX past 5 years), T2 (Profits past 12 months) and 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 (point question) expectations on stock market returns/dividend changes over the next 12 months/5 years. Dependent variable listed in column headings.

6.3 Understanding the Information Preference Effect

We investigate whether the information preference effect can be explained by differences in perception gaps across individuals. While we find systematic differences in perception gaps by information preference, these differences cannot explain the information preference effect. Figure 5 shows that individuals with preference for the past 5 year return information item have a smaller perception gap on this item. Consequently, they should be less surprised by the treatment and respond less which contrasts with the insignificant information preference effect for treatment 1 found in table 3. Respondents with a preference for the earnings growth information item had a broadly similar (slightly smaller) perception gap than other respondents. Hence, based on their perception gap, their reaction to the earnings growth treatment should be smaller or equal to the reaction of other respondents. Yet, we saw that individuals with preference for earnings growth information respond much more strongly to this treatment. Similarly, Figure 5 shows that respondents with a preference for information about the price-earnings ratio are more likely to possess correct prior knowledge about its current level. Hence, the treatment should contain less news for this group of respondents, leading to smaller downward revisions of return expectations. By contrast, table 3 showed that respondents with a preference for information about the price-earnings ratio display significantly larger downward revisions of their expected returns. In sum, the comparison between perception gaps and our estimated information preference effects shows that the latter cannot be explained by the former.

This suggests that information preference has an effect on expectation formation that goes beyond individuals' prior level of informedness and rather concerns differences in how individuals process a given piece of information. Overall, our results support the hypothesis that individals entertain different mental models of the stock market which jointly determine their information preferences, information acquisition, and information processing. Appendix section A.5 documents how information preferences vary with socio-demographic characteristics. We find that while gender, age, and education are significant co-variates, information preferences, just like expectations, are not easily explained by socio-demographics. Hence, information preferences appear to be a complex character trait which impacts information acquisition and processing even after controlling for socio-demographic characteristics.

Figure 5: Perception Gap by Information Preference

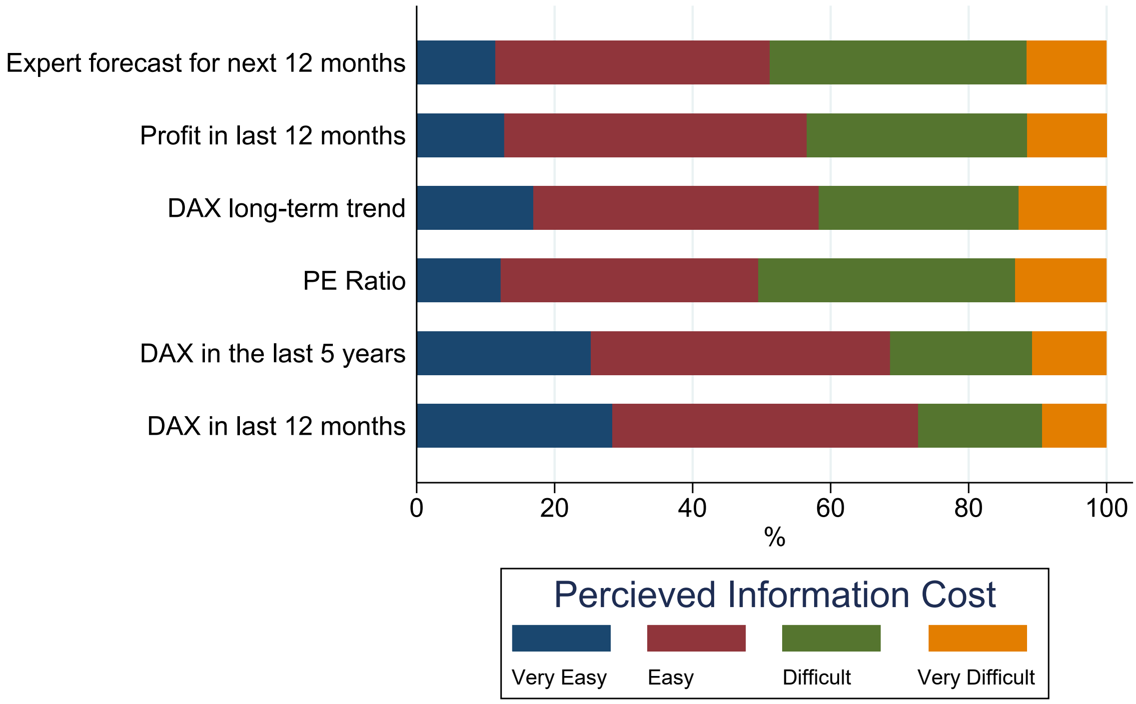


6.4 The Role of Information Costs

In addition to information preferences, individuals' information acquisition can be influenced by heterogeneity in the cost of different pieces of information. A given piece of information might be highly valuable to individuals, but also more 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 it is regularly disseminated via media or social contacts. Moreover, individuals with higher financial wealth might be more willing to incur fixed costs of information acquisition. To obtain a clear distinction between preferences and costs, our question on information preferences deliberately abstracted from the perceived cost of acquiring different information items. 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.

Individuals' perceived cost of obtaining each information item displays a clear ordering, as shown in Figure 6. We classify information items with a higher share of respondents who think that they are "easy" or "very easy" to obtain as less expensive. Information about past returns are perceived to be the least expensive information items. The perceived costliness of past return information is increasing with the horizon of the backward-looking information items. Information about past earnings growth is more difficult to obtain than information about past returns, but not as difficult as expert forecasts about future returns. The information item perceived as most difficult to obtain is the price-earnings ratio.

Figure 6: Perceived Cost of Acquiring Information Items



This evidence on perceived costs allows only suggestive conclusions, but interesting ones. Firstly, the low perceived cost of information about past returns may reflect the frequent dissemination of such information by various news media formats. This may contribute to explaining why expectations of representative households display extrapolative return expectations. The high perceived cost of price-earnings ratio information and the insignificant treatment effects in both of our waves conditional on receiving it, suggest difficulty of respondents both in accessing and processing this information. This may provide an explanation for why individuals ignore the relationship between valuation ratios and future returns documented in the empirical finance literature.

Interestingly, the ordering of perceived costs is similar to the ordering of information preferences (compare figure 4). Individuals perceive information about expert forecasts, past profits, and the price-earnings ratio as especially useful for their investment decisions. However, they also perceive them as especially costly to obtain. This could suggest that lowering the cost of obtaining relevant stock market information could reduce expectational errors of households about the stock market. This could be an intriguing point of departure for further investigations into tools for addressing asset price bubbles. Lowering the cost of information, for instance by supplying the public with expert forecasts about financial market developments, could potentially be a tool to mitigate excessive optimism and pessimism. Since excessive household expectations are often considered as important contributing factors for asset price booms and busts in the stock market or the real estate market such information interventions could potentially address the underlying frictions more directly than other policy instruments. To be clear, this is just a conjecture at this point, which needs to be further evaluated by future research. The heterogeneity of perceived information costs is discussed in appendix section A.6. We find that male gender, stockholdings, and above median income are associated with significantly lower perceived information costs. By contrast, the effect of college education is insignificant for most information items.

7 Causal Evidence on Portfolio Choice

This section provides causal evidence on the link between expectations and the demand for risky assets. The first part of this section uses the approach by GMSU to study the link between risky portfolio shares and survey measures of the first moment of expected stock returns. We show that the Low Portfolio Share Sensitivity Puzzle emerges in our sample as well. In the second part, we extend these results with causal evidence. Our information treatments generate *exogenous* variation in expected returns which helps to address endogeneity issues and to mitigate measurement error when regressing portfolio shares on expected returns. Exploiting this exogenous variation reduces the puzzle, bringing the required level of risk aversion needed to rationalize the observed behavior into the range of plausible values. However, the puzzle re-emerges once we consider survey measures of first AND second moments, instead of using second moment estimates based on historical stock market data. Individuals' subjectively perceived variance of 1-year ahead stock market returns is much lower than an objective measure based on realized historical stock return volatility measured over the same horizon. Thus, when applying the 'back-of-the-envelope' approach by GMSU to first AND second moments of expected stock returns, we find a strong 'Low Portfolio Share Sensitivity Puzzle' even after exploiting the exogenous variation from our experimental setup. This shows that the puzzle found in the literature is even worse when considering individuals' subjectively perceived low volatility of stock returns. In section 8 we use a non-linear approach to reconcile theory and evidence.

7.1 A Puzzle Based on First Moments

To test whether the 'Low Portfolio Share Sensitivity Puzzle' also holds in our sample, we follow the approach by GMSU,in which individuals' posterior stock portfolio shares are regressed on their posterior subjective excess stock return expectations:

$$Inv.Share_i^{post} = \delta_0 + \delta_1 \left(E[R]_i^{post} - R_f\right) + \mathbf{X_i}\gamma + u_i \tag{5}$$

where $Inv.Share_i^{post}$ denotes individuals' posterior stock share from the portfolio choice decision elicited in the survey. $E[R]_i^{post}$ denotes posterior expectations for the 1-year stock market return, and R_f is set to the risk-free return of 1% which individuals were asked to assume in the portfolio choice problem of our survey. The precise value for R_f goes without loss of generality, as it only affects the constant δ_0. The coefficient of interest, δ_1, which measures the sensitivity of individuals' portfolio share with respect to changes in their expected return is unaffected by R_f in this specification. In subsequent specifications, reasonable alternative values of, say $R_f = 0$, would have only tiny effects on the results. X_i is a vector controlling for socio-demographic characteristics.

A common theoretical benchmark in the literature, used by GMSU, is the classical Merton (1969) model of optimal portfolio choice. This model yields the following well-known optimal portfolio rule:

$$EquityShare_i = \frac{1}{\gamma}\frac{E_i(R) - R_f}{Var_i(R)} \tag{6}$$

which states that the optimal share in the risky asset is equal to the expected equity premium scaled by its riskiness and the investor's coefficient of risk aversion. A discrete-time version of the underlying model based on Campbell and Viceira (2003) is provided in Appendix section A.7.

Comparing this theoretical benchmark to the regression equation (5), we observe that the estimated coefficient δ_1 corresponds to $\delta_1 = \frac{1}{\gamma Var_i(R)}$. GMSU estimate a portfolio sensitivity, $\delta_1 = 0.785$ and set $Var_i(R) = 0.16^2 = 0.0256$ corresponding to an estimate of the historical standard deviation of one-year U.S. stock market returns of 16 %. Their estimates imply that a value of $\gamma = \frac{1}{\delta_1 Var_i(R)} = 1/(0.785 \times 0.16^2) = 49.76$ is needed to rationalize individuals' choices. Panel A of Table 4 shows the estimated senitivity of portfolios w.r.t. to expected returns based on our survey. We find a coefficient of 1.34 in our main OLS specification with all controls (Column 2 of Panel A). Thus, our estimate is of similar magnitude but somewhat higher than that of GMSU possibly because we are looking at a stylized portfolio allocation decision which abstracts from transaction costs and other frictions, whereas the estimates of GMSU are based on portfolio data for clients of the asset manager Vanguard. 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 $\gamma = \frac{1}{\delta_1 Var_i(R)} = 1/(1.34 \times 0.21^2) = 16.92$, which is still well outside the range of plausible values for risk aversion of 3-10, which has been suggested for instance by experimental studies (see also GMSU). The next section shows that our estimates get closer to this plausible range when we exploit the exogenous variation in expected returns generated by our experimental setup.

7.2 Causal Evidence on Beliefs and Portfolio Choice

We now extend the approach used in the previous section with causal evidence from our experiment. To this end, we use the following two-step instrumental variables (IV) estimator, in which we instrument posterior expectations with the randomly assigned, and hence exogenous, treatments:

$$\begin{aligned} Inv.Share_i^{post} &= \delta_0 + \delta_1\big(\widehat{E[R]_i^{post} - R_f}\big) + \mathbf{X_i}\gamma + \nu_i & (7)\\ E[R]_i^{post} - R_f &= \beta_0 + \beta_1 T_i^1 + \cdots \beta_5 T_i^5 + \mathbf{X_i}\theta + \epsilon_i & (8) \end{aligned}$$

This approach has two benefits. First, when estimating only the second stage of the portfolio sensitivity w.r.t. to expected returns, δ_1, may be biased due to endogeneity and omitted variables. For instance, if the very experience of holding stocks can make individuals more optimistic (pessimistic) about future stock returns, the estimated port-

Table 4: Portfolio Share Sensitivity w.r.t. Expected Returns

	OLS		2SLS	
	(1)	(2)	(4)	(5)
Panel: A				
$E[R]_i^{post} - R_f$	1.39***	1.34***	2.80***	2.77***
	(0.07)	(0.07)	(0.36)	(0.37)
Constant	0.49***	0.43***	0.51***	0.45***
	(0.01)	(0.08)	(0.01)	(0.08)
Socio-Demographics	No	Yes	No	Yes
R^2	0.11	0.15		
F			21.58	20.6
N	3509	3392	3509	3392
Implied Gamma	16.31	16.92	8.09	8.18
	OLS		2SLS	
	(1)	(2)	(4)	(5)
Panel: B				
$\frac{E[R]_i^{post} - R_f}{Var_i(R)}$	0.0011***	0.0010***	0.0039***	0.0039***
	(0.0001)	(0.0001)	(0.0007)	(0.0007)
Constant	0.4963***	0.4081***	0.4976***	0.4740***
	(0.0060)	(0.0934)	(0.0072)	(0.0998)
Socio-Demographics	No	Yes	No	Yes
R^2	0.07	0.11		
F			9.41	9.23
N	2466	2388	2466	2388
Implied Gamma	909.09	1000	256.41	256.41
	OLS		2SLS	
	(1)	(2)	(4)	(5)
Panel: C				
$\frac{E[R]_i^{post} - R_f}{Var_i(R)}$	0.0010***	0.0010***	0.0081***	0.0040***
	(0.0002)	(0.0001)	(0.0016)	(0.0007)
Socio-Demographics	No	Yes	No	Yes
R^2	0.02	0.75		
F			16.55	9.22
N	2466	2388	2466	2388
Implied Gamma	1000	1000	123.45	250
	OLS		2SLS	
	(1)	(2)	(4)	(5)
Panel: D				
$\frac{E[R]_i^{post} - R_f}{Var_i(R)}$	-0.0005	-0.0003	-0.0089	0.0004
	(0.0007)	(0.0008)	(0.0102)	(0.0089)
Constant	0.6115***	0.6324***	0.7114***	0.6274***
	(0.0141)	(0.1700)	(0.1200)	(0.1856)
Socio-Demographics	No	Yes	No	Yes
R^2	0.00	0.06		
F			1.54	1.64
N	692	672	692	672
Implied Gamma	-2000	-3333.33	-112.36	2500

Note: The table shows estimates of the portfolio share sensitivity w.r.t. expected returns under different specifications. Panel A regresses portfolio shares on the first moment of expected stock returns and a constant. Panel B regresses portfolio shares on the theoretically optimal portfolio rule and a constant. Panel C is as Panel B but without a constant. Panel D is as Panel B but with the sample restricted by excluding respondents with 'non-standard' beliefs. The first two columns show single stage OLS estimates without and with socio-demographic controls. Columns three and four show two-stage least squares IV estimates without and with socio-demographic controls. Robust standard errors are in parentheses. The last line of each panel shows the parameter of relative risk aversion implied by the estimates ('implied gamma').

folio sensitivity might be biased upwards (downwards). Such endogeneity concerns are addressed by instrumenting expected returns, which isolates the variation in posterior expected returns that is solely due to the fully exogenous treatments. Second, expectations elicitied in surveys may be 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 sensitivity estimate in the second stage.

Panel A of Table 4 (column 4) shows that the estimated portfolio sensitivity w.r.t. expected returns, δ_1, is equal to 2.77 in our main two-step IV specification. This estimate is more than two times larger than the estimate obtained from our single-stage OLS regression. Our IV estimate therefore yields an implied level of risk aversion of $\gamma = \frac{1}{\delta_1 Var_i(R)} = 1/(2.77 \times 0.21^2) = 8.18$. Hence, our IV estimate implies a parameter of relative risk aversion inside the plausible range of 3-10. This shows that the Low Portfolio Share Sensitivity Puzzle can be mitigated when using slightly more complex econometric strategies, which is in line with findings by, for instance, GMSU or Drerup et al. (2017). Y

7.3 A Puzzle Based on First AND Second Moments

This section shows that the Low Portfolio Share Sensitivity Puzzle re-emerges once we consider not only individuals' perceived first moment of returns, but also their perceived second moment. This happens because individuals under-estimate the true volatility of stock returns, which leads to a higher required level of risk aversion in order to rationalize their choices.

The implied values of risk aversion $\gamma = \frac{1}{\delta_1 Var_i(R)}$ in the previous two sections were obtained by setting $Var_i(R)$ to (the squared value of) an objective estimate of the historical standard deviation of German stock returns of 21 % which is in line with a corresponding historical estimate by Campbell (1999) of 20.3 % for German stock returns at the one-year horizon. However, the subjectively perceived standard deviation of the 12 months ahead stock return in our survey is on average only 4.3 %. Thus, based on their elicited probability distribution, individuals perceive stock returns as much less risky than they have been historically, which implies that a much higher level of risk aversion is needed to rationalize the sensitivity of their portfolio shares w.r.t. to their expected returns. The subjective variance of 0.043^2 is roughly 25 times smaller than the objective variance of 0.21^2. Using the back-of-the envelope approach of the previous section, the implied values of risk aversion $\gamma = \frac{1}{\delta_1 Var_i(R)}$ would thus be roughly 25 times larger under individuals' *average* subjective variance of stock returns and hence orders of magnitude beyond any plausible value of risk aversion.

To jointly account for the subjectively perceived first and second moment of stock returns *at the individual level*, we modify the previous two equation system by replacing posterior expectations with the ratio of individuals' posterior expected excess returns per unit of perceived risk:

$$Inv.Share_i^{post} = a_0 + a_1 \frac{\widehat{E[R]_i^{post} - R_f}}{Var[R]_i^{post}} + \mathbf{X_i d} + w_i \qquad (9)$$

$$\frac{E[R]_i^{post} - R_f}{Var[R]_i^{post}} = b_0 + b_1 T_i^1 + \cdots b_5 T_i^5 + \mathbf{X_i c} + v_i \qquad (10)$$

Comparing this specification to the optimal portfolio rule of the Merton model in equation (6), we see that the coefficient a_1 now directly corresponds to the inverse of the coefficient of relative risk aversion, that is $a_1 = \frac{1}{\gamma}$. Thus, the implied risk aversion now is simply $\gamma = \frac{1}{a_1}$, which means that a value of $a_1 > 1/10$ is needed for risk aversion to remain within the plausible range, i.e. $\gamma < 10$.

Panel B of Table 4 shows the estimates from the system (9)-(10). As before, the portfolio share sensitivity estimate obtained under a single-stage OLS specification is lower than under the IV specification. The estimates of 0.0011 (OLS) and 0.0039 (IV) imply levels of risk aversion of $\gamma = \frac{1}{a_1} = 909.09$ and, respectively, $\gamma = \frac{1}{a_1} = 256.41$. In sum, while our IV estimate based on the first moment essentially resolved the 'Low Portfolio Share Sensitivity Puzzle', this is no longer true when jointly considering the first and second moment of individuals' subjective stock return beliefs. In this case, the coefficient of risk aversion needed to rationalize individuals' behavior is implausibly large. In the next section, we show that this puzzle can be resolved when allowing for non-linearities in individuals' optimal portfolio decision.

8 A Non-linear Solution to the Low Portfolio Share Sensitivity Puzzle

This section shows that the 'Low Portfolio Share Sensitivity Puzzle' can be resolved when explicitly taking into account non-linearities in individuals' optimal portfolio choice.

8.1 Non-linear Estimation of Implied Risk Aversion

The previous OLS estimates were obtained by minimizing the mean-squared deviations between the empirically observed portfolio shares and an affine function of the theoretically optimal portfolio share $EquityShare_{i,t} = \frac{1}{\gamma}\frac{E_i(R)-R_f}{Var_i(R)}$. Implausibly large values of γ arise because individuals underestimate the volatility of stock returns, such that the optimal portfolio share can be very large, while individuals' actual portfolio share is bounded to the interval between 0 and 1. In the survey, the bounds on the portfolio share arise by construction of the questionnaire. In reality, short-sale and leverage constraints for private households may arise for various reasons (see also GMSU). Observations for individuals with sufficiently high $\frac{E[R]_i^{post}-R_f}{Var[R]_i^{post}}$ can only be reconciled with a sufficiently tight upper bound of $Inv.Share_i^{post}$ for very high values of γ. Due to the upper bound, the squared deviations for such observations in equation (9) can become very large such that they exert a disproportionate influence on the parameter estimates. When many such observations are present, the estimated coefficient α_1 is attenuated towards 0 and the coefficient α_0 tends towards the mean portfolio share in the sample.

We address this issue by replacing the linear approach with a non-linear approach which takes into account the bounds on individuals' portfolio shares as elicited in the survey. To impose this constraint, we define a modified optimal portfolio rule as follows:

$$\begin{aligned} EquityShare_{i,t}^{B} &= \frac{1}{\gamma}\frac{E_i(R)-R_f}{Var_i(R)} \quad \text{if } 0 \leq \frac{1}{\gamma}\frac{E_i(R)-R_f}{Var_i(R)} \leq 1 \\ &= 1 \quad \text{if } \frac{1}{\gamma}\frac{E_i(R)-R_f}{Var_i(R)} > 1 \\ &= 0 \quad \text{if } \frac{1}{\gamma}\frac{E_i(R)-R_f}{Var_i(R)} < 0 \end{aligned} \tag{11}$$

where the superscript B distinguishes this bounded optimal portfolio rule from the standard, unbounded rule. The bounds render the optimal portfolio of each individual a piece-wise linear function of $\frac{1}{\gamma}$ with kinks at the individual-specific bounds. This non-linear optimal portfolio rule cannot be tested using the linear regression equation described above. Instead, we use a non-linear estimator, but to keep the differences between the approaches to a minimum we stay within the mean-squared framework. The resulting non-linear least squares (NLLS) estimator solves the following optimization problem:

$$\min_{\gamma} \sum_{i=1}^{N} \left(Inv.Share_i^{post} - EquityShare_{i,t}^{B}\left(\Omega_i^R, \gamma\right)\right)^2 \tag{12}$$

where $EquityShare_{i,t}^{B}\left(\Omega_i^R, \gamma\right)$ is the bounded optimal portfolio rule defined in equation 11, and Ω_i^R denotes individuals' beliefs about future stock market returns. The results are presented in the following section.

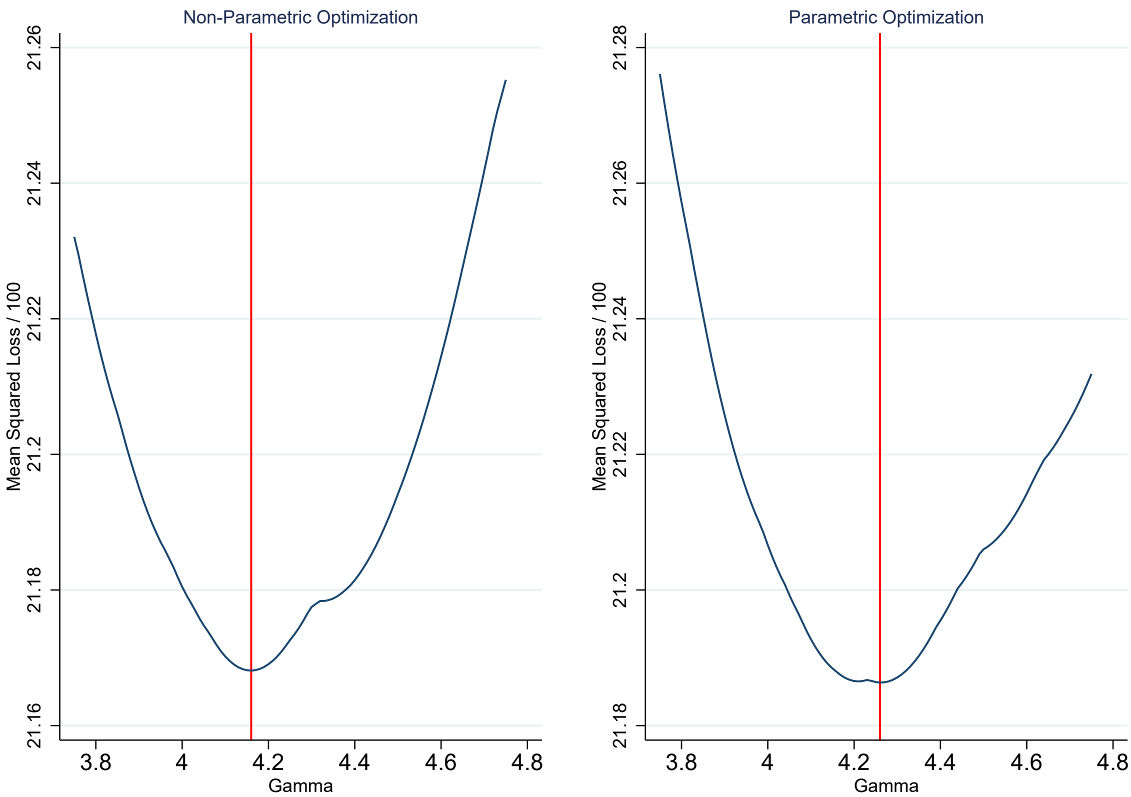
8.2 A Solution to the Puzzle

Main result: The empirical NLLS objective function, (12), and its solution are visualized in the first panel of figure 7. The resulting optimal γ is 4.16.[2] Notice that we are taking into account the first AND second moment of individuals' stock return beliefs and recall that the corresponding OLS estimate was $\gamma = 909.09$. Hence, the issue described in the previous section turns out to be quantitatively important. When taking into account the bounds of the empirically observed optimal portfolio shares, the 'Low Portfolio Share Sensitivity Puzzle' essentially vanishes. A value of γ of just 4.2 suffices to make individuals' portfolio shares consistent with economic theory. In the remainder of this section we extend and robustify this result in several ways.

Heterogenity in risk aversion: As in GMSU and other applications, we have implicitly assumed a common coefficient of relative risk aversion γ across all respondents. In our survey, we elicit individuals' self-reported willingness-to-take risks and find that it is heterogenous across respondents. Figure 8 shows the distribution of individuals' self-reported willingness-to-take risks in financial decisions on a scale of 0 (not willing to take risks at all) to 10 (very willing to take risks). It turns out that there is a large degree of heterogeneity across respondents. Overall, the distribution is skewed towards lower values of willingness-to-take risks.

[2] We checked that this is indeed the global optimum, see also figure A.2 in the appendix.

Figure 7: NLLS Estimation of Risk Aversion Parameter



Given this, a natural question is whether individuals' choices are consistent with their beliefs AND their willingness-to-take risks (which is essentially an inverse measure of their risk aversion). To shed light on this issue, we invert the optimal portfolio rule with respect to the value of the parameter γ which makes each individuals' portfolio share equal to the theoretically optimal portfolio share given her beliefs. That is, for each individual we solve the equation $Inv.Share_i^{post} = EquityShare_{i,t}^{B}\left(\Omega_i^R, \gamma_i\right)$ with respect to γ_i. Using the parametric solution of the Merton model from equation (6), this yields $\gamma_i = \frac{1}{EquityShare_{i,t}^{B}} \frac{E_i(R)-R_f}{Var_i(R)}$. Figure 9 plots the thus obtained implied individual levels of risk aversion, γ_i, against the willingness-to-take risks ('Risk Attitude') from the survey. To capture the heterogeneity in implied levels of risk aversion across respondents, we show not only the mean γ_i for each Risk Attitude category, but also various quantiles (10%, 25%, 50%, 75%, 90%). We pool risk attitude categories 8-10 as there would otherwise not be enough observations to identify all quantiles of the distribution. If individuals behaved as predicted by theory, we should find a strong negative relationship between the risk aversion implied by individuals' choices given beliefs and their self-reported willingness-to-take risks. This is precisely the case across all parts of the distribution. Hence, exploiting the heterogeneity across individuals strengthens the notion that individuals' portfolio decisions are indeed closely linked to the predictions of the Merton model.

We also note that the median level of implied risk aversion γ across the entire sample is around 10, and hence orders of magnitude smaller than the risk aversion parameter implied by the OLS regressions. This strengthens the case that the OLS results are heavily influenced by extreme outliers. The median γ is slightly higher than our NLLS estimate of 4.16 because the former does not take into account the bounds on individuals portfolio shares.

Role of the constant: The regression based approach in equation (10) included a constant in the estimation, whereas the NLLS approach in equation (12) did not. Considering the theoretical prediction (11), including a constant in equation (12) does not seem natural. The optimal portfolio rule does not prescribe a positive (or negative) equity share independent of the expected risk premium. Yet, a natural question is whether the linear regression based approach would yield smaller levels of risk aversion if the constant would have been omitted. This robustness check is performed in Panel C of table 4 (see, e.g., column 4). Omitting a constant in the regression based approach decreases the estimated $\alpha_1 = \frac{1}{\gamma}$ from 0.004 to 0.0004, lifting the implied γ to an implausibly high level of 2500. This shows that the omission of the constant does not substantially alter the economic implications of the linear regression-based approach. Instead, the key driver of the NLLS result is indeed the introduction of the non-linear constraints on the portfolio share.

Fully non-parametric approach: The NLLS estimation approach allows us to extend the results on the 'Low Portfolio Share Sensitivity Puzzle' in another interesting dimension. The standard solution to the discrete time optimal portfolio choice model (see Campbell and Viceira 2003) assumes individuals' perceived stock returns to be log-normally distributed such that the optimal portfolio rule can be parametrically characterized as a function of an individual's expected equity premium and her perceived variance of future stock returns. This assumption is no longer needed when using the NLLS approach, where the optimal portfolio rule, $EquityShare^{B}_{i,t}\left(\Omega^{R}_{i}, \gamma\right)$ is allowed to be a non-linear function of individuals' beliefs.

Instead of parameterizing individuals' beliefs by their first and second moment and assuming log-normality, we can compute an exact numerical solution to individuals' utility maximization problem based on their subjective non-parametric probability distribution. The details of this approach are outlined in appendix section A.7. This generalization is of interest, as individuals' beliefs about the tails of the distribution could influence their behavior in addition to their perceived mean and variance. (The issue of tail risks or 'rare disaster risk' has also been brought up in GMSU.) The non-parametric approach considers individuals' beliefs over their entire subjective probability distribution and hence incorporates this aspect in a parsimonious way.

The right panel of figure 7 presents the NLLS objective and its solution under the non-parametric approach. We find that the estimated γ is 4.26. Hence the estimated γ hardly changes implying that the approximation error of the parametric approach is actually small. The key ingredient for solving the 'Low Portfolio Share Sensitivity Puzzle' remains the introduction of the non-linear constraints on the portfolio share.

Figure 8: Distribution of Willingess-to-take risks

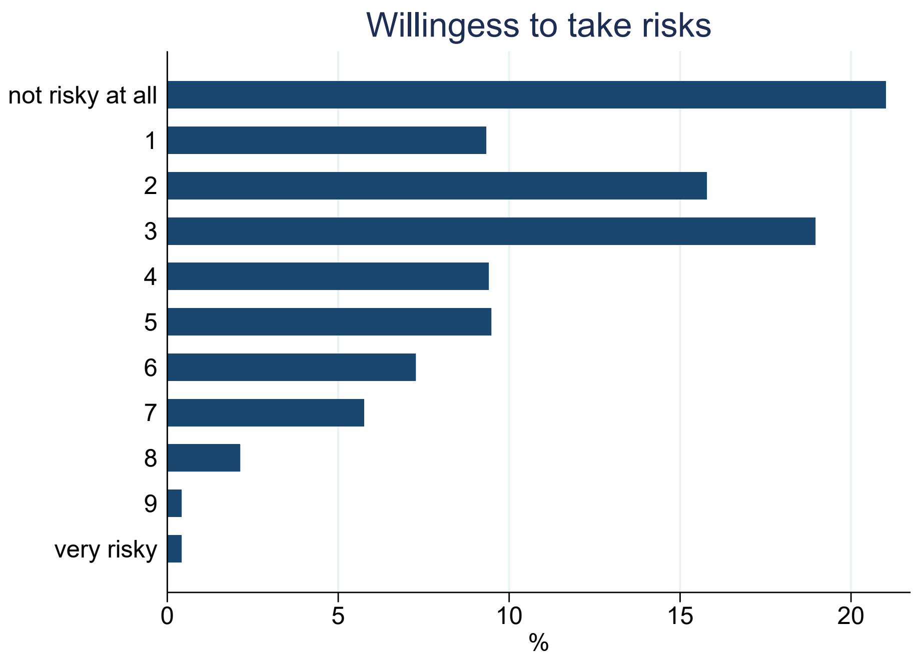
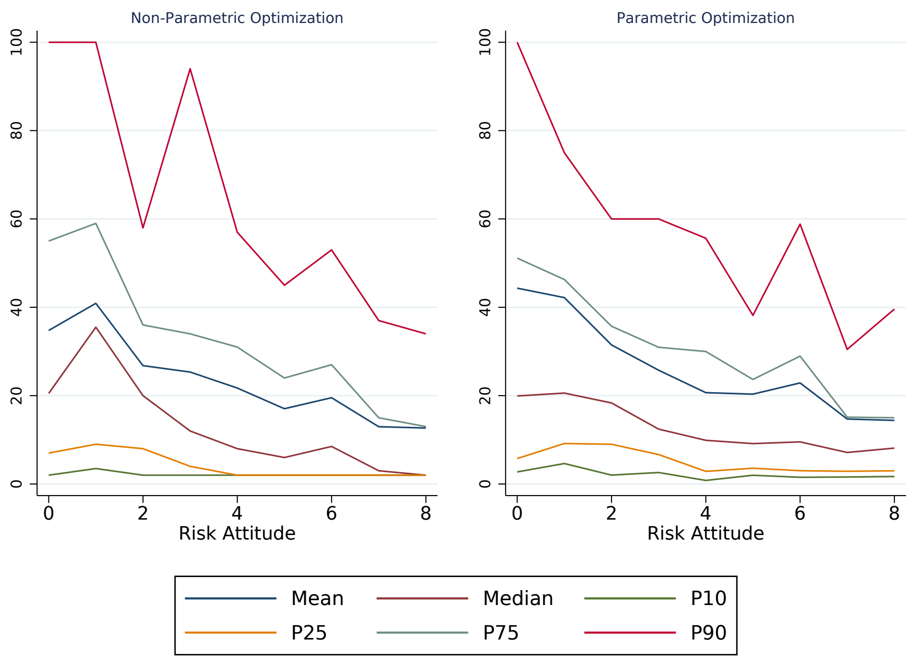


Figure 9: Average Individual Optimal Gamma by Risk Attitude



8.3 Non-standard Beliefs

The optimal portfolio rule from the Merton model is based on the first-order conditions of the model and hence abstracts from situations in which an interior solution does not exist. However, such special cases turn out to be important when dealing with beliefs and investment decisions of real-world individuals. There are 1792 (out of 3509) individuals in the sample whose expected equity return is below the risk-free rate such that their (constrained) optimal portfolio share is zero as long as they are either risk-averse or risk-neutral ($\gamma \geq 0$). Of the remaining 1717 individuals with positive expected equity premium, 1091 expect the equity return to be above the risk-free rate of 1% in *all* states of the world. Hence, their (constrained) optimal portfolio share is one, independent of their level of risk aversion. (There remain 692 individuals for whom their optimal portfolio share *does* depend on their level of risk aversion.)

For further reference, we call individuals, for whom their optimal portfolio share is independent of their coefficient of risk aversion, 'non-standard belief individuals'. No inference on the risk aversion of these individuals based on their portfolio choice is possible and the choices of these individuals have no impact on the estimated risk aversion parameter γ in the NLLS approach. By contrast, the regression-based approach does not take into account that the first-order condition is not informative for the risk aversion parameter of these individuals. This raises two questions: i) Would the implied level of risk aversion from the regression-based approach change if non-standard belief individuals were excluded?, and ii) Are the decisions of non-standard belief individuals in line with the theoretical prediction of portfolio shares of either 0 or 1 (depending on their beliefs)? The next two paragraphs answer these questions in turn.

To answer the first question, Panel D of table 4 shows a robustness check of the regression-based approach in which non-standard belief individuals are excluded. This puts the regression-based approach on equal footing with the NLLS approach, in the sense that no inference on the level of risk aversion is drawn from the decisions of non-standard belief individuals. We find that the resulting estimates of the portfolio sensitivity on the restricted sample are even smaller (implying even larger risk aversion) than the full sample estimates. In fact, the estimated portfolio sensitivity for the restricted sample is not significantly different from zero. Hence, accounting for non-standard belief individuals cannot explain the puzzle obtained under the regression-based approach.

The second key question is whether decisions of non-standard belief individuals are in line with the theoretical prediction of portfolio shares at the corner solution of either 0 or 1 (depending on individuals' beliefs). We answer this question in table 5. The table shows that 21% of those non-standard belief individuals for whom the optimal portfolio share is 0 choose the model-implied optimum. Of those individuals for whom the optimal portfolio share is 1, we find that 19% choose the model-implied optimum. 6% of individuals in the first group, and 10% of individuals in the second group choose the opposite extreme of, respectively, 1 and 0. The largest share of non-standard belief individuals (72 %) chooses a portfolio share inside the open interval $(0, 1)$. As explained above, the model-consistency of their choices cannot be evaluated in terms of their implied level of risk aversion. Strictly speaking, their beliefs imply that their optimal choices have to be at one of the corner solutions, which is clearly violated. Nevertheless, it may be of interest to evaluate their choices against a weaker condition. Individuals' decisions might only approximate the optimal portfolio rule, or their elicited return distribution might only be an approximation to their true return distribution. We therefore evaluate whether it is at least the case that individuals for whom the optimal portfolio share is 100 % tend to choose higher portfolio shares than those for whom the optimal portfolio share is 0 %.

To see this, we report the quartiles of the portfolio share distributions within each of the two groups. We find that, at least qualitatively, the weaker condition is fulfilled. The quartiles of the first group (optimum of 100 %) are strictly larger than those of the second group (optimum of 0 %), implying that the distribution of the first group has more mass at higher portfolio shares than the second group.

In sum, the takeaway of this section is that while elicited return beliefs are non-standard for a substantial share of respondents, the decisions of these individuals are overall at least qualitatively consistent with the basic theoretical prediction that higher perceived Sharpe ratios should be associated with higher portfolio shares. For those individuals for whom inference on their level of risk aversion is possible, we estimate a coefficient of relative risk aversion of 4.2 which falls comfortably within the plausible range of 3 to 10. We conclude that, after accounting for short-sale and leverage constraints, the standard Merton model provides a relatively decent approximation of individuals' choices.

Table 5: Non-standard Beliefs and Portfolio Allocations

	Merton Model: 0% Share	Merton Model: 100% Share	Total
DAX Share			
0%	21	10	17
100%	6	19	11
(0%, 100%)	73	71	72
Subgroup: (0%, 100%) Share			
25 % Quantile	10	40	21
50 % Quantile	40	50	44
75 % Quantile	50	80	61

Note: This table characterizes the portfolio allocation for respondents for whom the optimal portfolio Share does not depend on their risk aversion.

9 Conclusion

We contribute to bridging the gap between theory and reality in asset pricing. While modern finance theory postulates that (rational) expectations about returns should be counter-cyclical with respect to stock market valuations, there is ample empirical evidence that, in reality, the opposite is true for household expectations. Reconciling the joint behaviour of asset prices and expectations therefore represents a major challenge in macro-finance. Our results complement the existing literature on beliefs and portfolios with *causal* evidence obtained from a randomized information experiment.

We find that individuals are badly informed about stock market valuation ratios such as the price-earnings ratio. When receiving news about the price-earnings ratio, individuals on average fail to revise their return expectations, suggesting that Rational Expectations asset pricing models do not offer a good approximation to their belief formation. By contrast, individuals extrapolate news about past capital gains *and* about past earnings growth into the future. Hence, our results support asset pricing models with learning about capital gains (see, e.g., Adam et al. 2017), and with learning about fundamentals (see, e.g. Myers and De La O 2020; Bordalo et al. 2020). While these two mechanisms have hitherto been considered separately, our results suggests that they may be linked.

When receiving news about past earnings growth, individuals revise their capital gains expectations one-to-one with their earnings growth expectations. Conversely, stockholders react to news about past returns by simultaneously revising their earnings growth expectations with their capital gains expectations. Studying the asset pricing implications of models in which both mechanisms are present and interlinked could be an interesting avenue for future research.

Our results document considerable heterogeneity of individuals both at the information acquisition stage, and at at the information processing stage of the expectation formation process. At the acquisition stage, there is heterogeneity in which type of information is perceived as most valuable, how costly it is to obtain this information, and consequently, how well informed individuals are about stock market related information. At the information processing stage, individuals differ in how they revise their expectations upon receiving a given piece of news. For instance, individuals who prefer information about earnings growth, form their expectations more in line with models such as Myers and De La O (2020) and Bordalo et al. (2020). By contrast, individuals who prefer information about the price-earnings ratio, form expectations that are more in line with Rational Expectations asset pricing models. This suggests the existence of distinct types of investors with heterogenous mental models of the stock market. Exploring the implications of this heterogeneity in belief formation for trading patterns and asset price dynamics could be an interesting target for future work, both empirically and theoretically. We also note that it is quite hard to link information preferences, and hence mental models, to observable socio-demographic characteristics such as gender, income, or education. Understanding what shapes individuals' mental models of the stock market could also be an interesting and challenging question for future research.

We complement the existing literature regarding the link between beliefs and portfolios with causal evidence. We dissect the seemingly low portfolio sensitivity, by explicitly considering individuals' perceived second moment of stock returns and a measure of their risk aversion. We conclude that after accounting for non-linearities imposed by short-sale and leverage constraints found in many realistic settings, classic models in which individuals' optimal portfolio share in the risky asset is an increasing function of their expected Sharpe ratio provide a useful approximation of household behavior.

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A Online Appendix

A.1 Sample Characteristics

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. Tables A.1 and A.2 report the characteristics for each treatment group and for the full sample. As expected, the distribution of characteristics is very similar across treatment groups. Remaining differences between the treatment groups are controlled for by using a vector of respondent characteristics in the regressions. Male respondents are slightly overrepresented in the survey. In total, 4054 respondents participated in the first wave, and 4036 respondents participated in the second wave. The effective number of observations for each of our econometric specifications varies due to item non-response and will be indicated in each table.

A.2 Perception Gap for Expert Forecasts

With regards to the interpretation of the treatment effects, we compute the overall fraction of respondents for whom the expert forecast entailed a positive surprise as follows. Our expert forecast treatment informed respondents that the return of the German stock market index over the next 12 months is projected to be roughly 9 %. Hence, the forecast entailed a positive surprise to those who perceived a neutral or negative expert forecast. For those who were not aware of an expert forecast prior to the treatment, we note that their average expected stock market return prior to the treatments was 5.2%. Thus, we classify the treatment as a positive surprise for the latter group of respondents. In total, this suggests that the expert forecast entailed a positive surprise for roughly 82 % $= 0.6 + 0.4(0.44 + 0.10)$ of respondents.

A.3 Heterogeneity of Treatment Effects

This section documents how the treatment effects vary by respondent characteristics. Table A.5 shows sample splits by socio-demographic characteristics for the treatment effects of the first wave (cp. table 1). We find a pronounced gender effect, which is in line with previous findings in the literature (see, e.g., Armantier et al. 2016; Coibion et al. 2021). Female respondents revise their beliefs more strongly in response to all five treatments of the first wave. In fact, the ATE for the expert treatment appears to be entirely driven by the expectation revision of female respondents. Such differences in expectation formation by gender have been attributed to overconfidence on behalf of male individuals (see, e.g. Barber and Odean 2001), but also to smaller perception gaps of male individuals (see, e.g. Beutel et al. 2021). In section 6, we investigate the role of information preferences as a potential factor on top of standard socio-demographic characteristics. Interestingly, the ATEs do *not* vary much by education and the effects by income are mixed. Individuals who are less willing to take financial risks respond more strongly to the long-term historial return treatment (T1), the past earnings growth treatment (T2), and the expert forecast treatment (T3). Respondents who perceived the survey as interesting responded significantly to the price-earnings ratio treatment. Contrary to the predictions of RE models with counter-cyclical return expectations, they revised their return expectations upwards upon learning than that price-earnings ratio is much higher than they thought. Differences by age have been discussed above in terms of the learning rates shown in figure A.1, partially supporting the predictions of Malmendier and Nagel (2011).

The analysis of treatment effect heterogeneity for the second wave is relatively complex as we have four outcome variables (12 months returns, 5 year returns, 12 months dividend growth, 5 year dividend growth). Hence, we obtain one table with sample splits for each outcome variable. We provide these tables in the appendix, see appendix tables A.6 through A.9. The most pronounced pattern is that the plain treatment effects of the past earnings growth treatment (T2) on expectation revisions at the 12 months horizon are driven primarily by female respondents, whereas expectation revisions at the five year horizon are driven primarily by male respondents. Individuals without college education respond to the past earnings growth treatment in a more extrapolative manner than individuals with college education at the 12 months horizon.

A.4 Measuring the Information Preference Effect

This section explains the intuition for measuring the information preference effect by the coefficient ξ_k in equation 4. This intuition can be gained from the following thought experiment. Let us consider four hypothetical individuals indexed by $i = 1, 2, 3, 4$ with the same prior expectations and socio-demographic characteristics Z_s and W_s. Suppose the first individual has a preference for the information shown in the first treatment, i.e. $P_1^1 = 1$, and has been (randomly) assigned to the control group, i.e. $T_i^k = 0$ for $k = 1, \ldots, K-1$. The predicted posterior expectation of the *first* individual is therefore:

$$\hat{E[X]}_1^{post} = \alpha + \psi_2 + \sum_{j=1}^{J} (\delta_j Z_{s,j}) + \mathbf{W_s}\phi \tag{13}$$

Next consider a second individual with the same information preference, i.e. $P_2^1 = 1$, who has been (randomly) assigned to the first treatment group ($T_2^1 = 1$). The predicted posterior expectation of the *second* individual is:

$$\hat{E[X]}_2^{post} = \hat{E[X]}_1^{post} + \beta_2 + \xi_2 + \sum_{j=1}^{J} (\gamma_{2,j} Z_{s,j}) \tag{14}$$

Now consider two other individuals with a common information preference that differs from that of the first two individuals. Individual 3 is in the control group ($T_i^k = 0$ for $k = 1, \ldots, K-1$) and individual 4 is in the same treatment group as the second individual but does not prefer the information shown in her treatment ($P_i^k T_i^k = 0$ for all k since there is no k for which both P_i^k and T_i^k are non-zero). The predicted posterior expectation of the fourth individual relative to the third individual is:

$$\hat{E[X]}_4^{post} = \hat{E[X]}_3^{post} + \beta_2 + \sum_{j=1}^{J} (\gamma_{2,j} Z_{s,j}) \tag{15}$$

Taking the difference-in-difference of the predicted values for the treated individuals relative to the control group yields:

$$\left(E[\hat{X}]_2^{post} - E[\hat{X}]_1^{post}\right) - \left(E[\hat{X}]_4^{post} - E[\hat{X}]_3^{post}\right) \tag{16}$$

$$= \left(\beta_2 + \xi_2 + \sum_{j=1}^{J} (\gamma_{2,j} Z_{s,j})\right) - \left(\beta_2 + \sum_{j=1}^{J} (\gamma_{2,j} Z_{s,j})\right) \tag{17}$$

$$= \xi_2 \tag{18}$$

The difference between a treated individual who does not prefer the information she receives and an otherwise identical non-treated individual is $\beta_2 + \sum_{j=1}^{J} (\gamma_{2,j} Z_{s,j})$. The difference between a treated individual who does prefer the information she receives and an otherwise identical non-treated individual is $\beta_2 + \xi_2 + \sum_{j=1}^{J} (\gamma_{2,j} Z_{s,j})$. The difference-in-difference between the two, that is the part of the treatment effect that only occurs in individuals with a preference for the treatment they receive is given by the coefficient ξ_k. This difference-in-difference is our measure of the 'information preference effect'.

Individuals with different information preferences need not have the same characteristics Z_i and W_i. The coefficient ξ_k measures the pure information preference effect net of controlling for these other characteristics. Hence, ξ_k can be interpreted as the effect we would expect if two individuals differed only in their information preference as in our thought experiment. However, our regression is more general than that and isolates the information preference effect controlling for a variety of respondent characteristics Z_i and W_i.

A.5 Heterogeneity of Information Preferences

This section investigates how individuals' information preferences vary with socio-demographic characteristics. Table A.10 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 most preferred information item and more likely to prefer information about the long-term average return of the DAX. Older individuals are more likely to prefer earnings growth information and less likely to prefer expert forecasts. 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 most preferred information item.

A.6 Heterogeneity of Information Costs

Table A.11 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.

A.7 Solution of the Optimal Portfolio Choice Problem

Approximate Analytical Solution Let us first recall the derivation of optimal portfolio share rules, such as equation 6. Such a rule can be derived from a standard model of portfolio choice, as in Campbell and Viceira (2003), in which individuals maximize the discounted value of the utility of consumption, C, under constant relative risk aversion preferences with parameter γ and a standard intertemporal budget constraint:

$$\max E_t \sum_{i=0}^{\infty} \delta^i \frac{C_{t+i}^{1-\gamma} - 1}{1-\gamma} \tag{19}$$

$$W_{t+1} = (1 + R_{p,t+1})(W_t - C_t) \tag{20}$$

$$R_{p,t+1} = \alpha_t R_{t+1} + (1 - \alpha_t) R_{f,t+1} \tag{21}$$

where wealth in period $t+1$, W_{t+1}, depends on the amount of savings from the previous period multiplied by the return on individuals' portfolio, $R_{p,t+1}$, which is a weighted average of the return on the risky asset, R_{t+1}, and the return on the risk-free asset, $R_{f,t+1}$, weighted by an individuals' portfolio share in the risky asset, α_t. Under the assumptions maintained in Campbell and Viceira (2003), this yields a familiar expression for the optimal portfolio share in the risky asset:

$$\alpha_t = \frac{E_t r_{t+1} - r_{f,t+1} + \sigma_t^2/2}{\gamma \sigma_t^2} \tag{22}$$

where lowercase letters denote the natural logarithm of the respective gross returns, i.e. $r_{t+1} = \ln(1 + R_{t+1})$, and one half of the conditional variance of the log risky gross return denoted, σ_t^2, is added to convert from expected log returns to log expected returns. This yields the optimal portfolio share as a linear function of the (log) expected equity premium scaled by its variance and individuals' risk aversion. The model's first order condition also implies that the equity premium is a product of relative risk aversion γ and the covariance between the return on the risky asset and individuals' consumption growth rate (see Campbell and Viceira, 2003). This link between portfolio shares and the equity premium suggests that solving the low portfolio share sensitivity puzzle might also contribute to explaining asset pricing puzzles, such as the equity premium puzzle or the excess volatility puzzle.

The key assumption used to derive this analytical solution is that the natural logarithm of the (risky) return is normally distributed. This assumption allows the modeler to linearly approximate portfolio returns and obtain an analytical solution for expected marginal utility which is a nonlinear function of the portfolio share *alpha*. Under log-normality, taking the expectation of a non-linear function implies the following Jensen's inequality correction, which is reflected in the formula for the opimal portfolio share, namely $E_t r_{t+1} - r_{f,t+1} + \sigma_t^2/2 = \ln E_t(1 + R_{t+1})/(1 + R_{f,t+1})$ (see Campbell and Viceira 2003).

Exact Solution Assume a simple one-period maximization problem (see Campbell and Viceira 2003). We allow for investor heterogeneity but omit an individual subscript throughout for ease of exposition. To simplify the exposition, we focus on a model with power utility of wealth, but we note that Campbell and Viceira 2003 derive identical portfolio rules for the model with power utility of consumption. Each investor chooses her portfolio share α such that it maximizes their expected utility of wealth, where expectations are taken with respect to the investors subjective system of beliefs:

$$\max_{\alpha} E_t U\left(W_{t+1}\right) \tag{23}$$

subject to the intertemporal law of motion for wealth:

$$W_{t+1} = (1 + R_{p,t+1})W_t \tag{24}$$

where the portfolio return, R_p, can be written as follows:

$$R_{p,t+1} = \alpha_t R_{t+1} + (1-\alpha_t)R_{f,t+1} = R_{f,t+1} + \alpha_t\left(R_{t+1} - R_{f,t+1}\right) \tag{25}$$

Next, we assume a CRRA utility function:

$$U = \frac{W^{1-\gamma}}{1-\gamma} \tag{26}$$

We can rewrite the optimization problem as:

$$\begin{aligned}
& \max_{\alpha} E_t U\left(W_{t+1}\right) && (27)\\
=\ & \max_{\alpha} E_t U\left((1+R_{p,t+1})W_t\right) && (28)\\
=\ & \max_{\alpha} E_t\left((1+R_{p,t+1})W_t\right)^{1-\gamma} / (1-\gamma) && (29)\\
\equiv\ & \max_{\alpha} E_t\left((1+R_{p,t+1})^{1-\gamma}\right) / (1-\gamma) && (30)
\end{aligned}$$

Hence, we note that $W_t^{1-\gamma}$ scales expected utility but does not affect optimality w.r.t. to the portfolio share α which depends simply on maximizing a non-linear function of the portfolio return.

The first-order condition for this maximization problem is:

$$\begin{aligned}
0 &= E_t\left[\frac{\partial U\left(R_{p,t+1}\right)}{\partial \alpha_t}\right] && (31)\\
&= E_t\left[\frac{\partial U\left(R_{p,t+1}\right)}{\partial R_{p,t+1}}\frac{\partial R_{p,t+1}}{\partial \alpha_t}\right] && (32)\\
&= E_t\left[\left((1+R_{p,t+1})\right)^{-\gamma}\left(R_{t+1}-R_{f,t+1}\right)\right] && (33)\\
&= E_t\left[\left((1+R_{f,t+1}+\alpha_t(R_{t+1}-R_{f,t+1}))\right)^{-\gamma}\left(R_{t+1}-R_{f,t+1}\right)\right] && (34)
\end{aligned}$$

Let us assume that the investor's beliefs about the risky return, R_{t+1}, are given by a discrete probability density function over $j = 1, \ldots, n$ states of the world with subjective probability mass w_j. For future reference, we denote individual's beliefs about the return probability distribution by, Ω^R. This implies the following subjective expectation for a nonlinear function $g(R_{t+1}, X)$, where expectations are taken over the future variable R_{t+1}, while X is a vector of variables that are certain from the perspective of period t, i.e. in our case $X = (\alpha_t, R_{f,t+1})$.

$$E_t g(R_{t+1}, X) = \sum_{j=1}^{n} w_j g(R_{t+1,j}, X) \tag{35}$$

The first order condition thus becomes:

$$0 = \sum_{j=1}^{n} w_j \left[(1 + R_{f,t+1} + \alpha_t (R_{t+1,j} - R_{f,t+1}))^{-\gamma} (R_{t+1,j} - R_{f,t+1}) \right] \tag{36}$$

If the equity premium is positive (negative), $R_{t+1,j} - R_{f,t+1} > 0 (< 0)$, for all states of the world to which the investor assigns positive probability, $w_j > 0$, the first order condition has no solution as the optimal portfolio share α would be infinite (negative infinite) in this case. There are indeed a number of individuals for which this is the case. Often, these individuals choose to fill only a small number of bins of the return distribution with non-zero probability mass.

We solve this optimization problem exactly using numerical methods. The first-order condition for the optimal portfolio share does not have an analytical solution when we relax the assumption that individuals believe that the return distribution is log-normal and instead replace it with each individual's belief about the perceived discrete probability distribution for returns from our survey, as shown in equation 36. When optimizing numerically, we can directly maximize expected utility in equation 23, subject to equations 24 through 26. In addition, we note that our survey question on individuals' portfolio choice only allows for non-negative portfolio shares. To reflect the reality of our survey, we therefore impose the additional condition that individual's optimal portfolio share is bounded between 0 and 1:

$$0 \leq \alpha \leq 1 \tag{37}$$

Each investor's optimization problem can be solved for the optimal portfolio share alpha as a function of individual's equity return beliefs, Ω^R (see above), the risk-free rate, and risk aversion. Our survey question fixed the risk-free rate for each individual's portfolio problem at 1% per annum. Hence, the theoretically optimal portfolio share for individual i given her return beliefs, Ω_i^R, and her risk aversion, γ_i, can be written as:

$$\alpha_i^\star = f\left(\Omega_i^R, \gamma_i\right) \tag{38}$$

where the functional relationship f results from the structure imposed by the above described portfolio optimization problem. Based on this exact, non-linear optimal portfolio share rule, we can back out each individual's risk aversion given her choices. Notice, that we observe individuals' portfolio share chosen in the survey and their return belief, but not their coefficient of relative risk aversion, γ_i. Hence, we can plug in each individual's portfolio share chosen in the survey for $\alpha^\star$ and solve the optimal portfolio rule in equation 38 for the coefficient of relative risk aversion, γ_i, that would rationalize individual's choice ex-post.

A.8 Additional Figures and Tables

Figure A.1: Learning Rates Split by Age

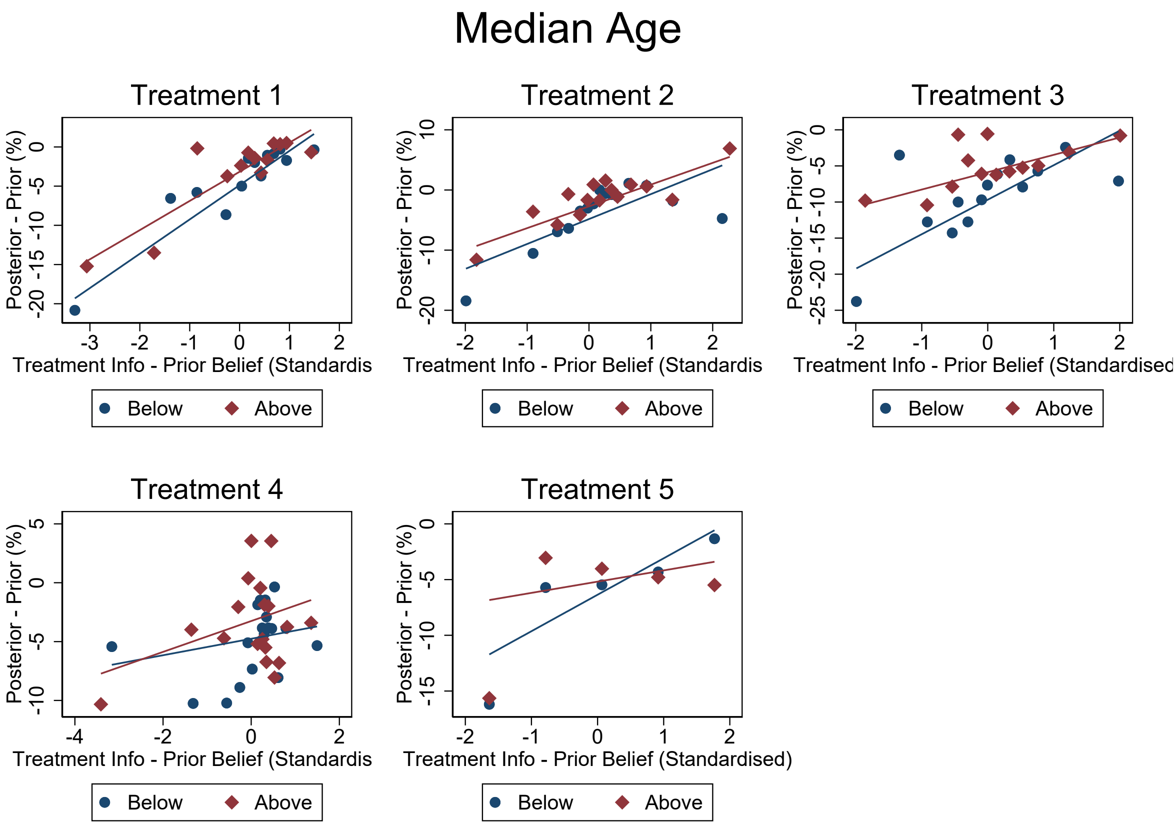

Figure A.2: NLLS Estimation of Risk Aversion Parameter

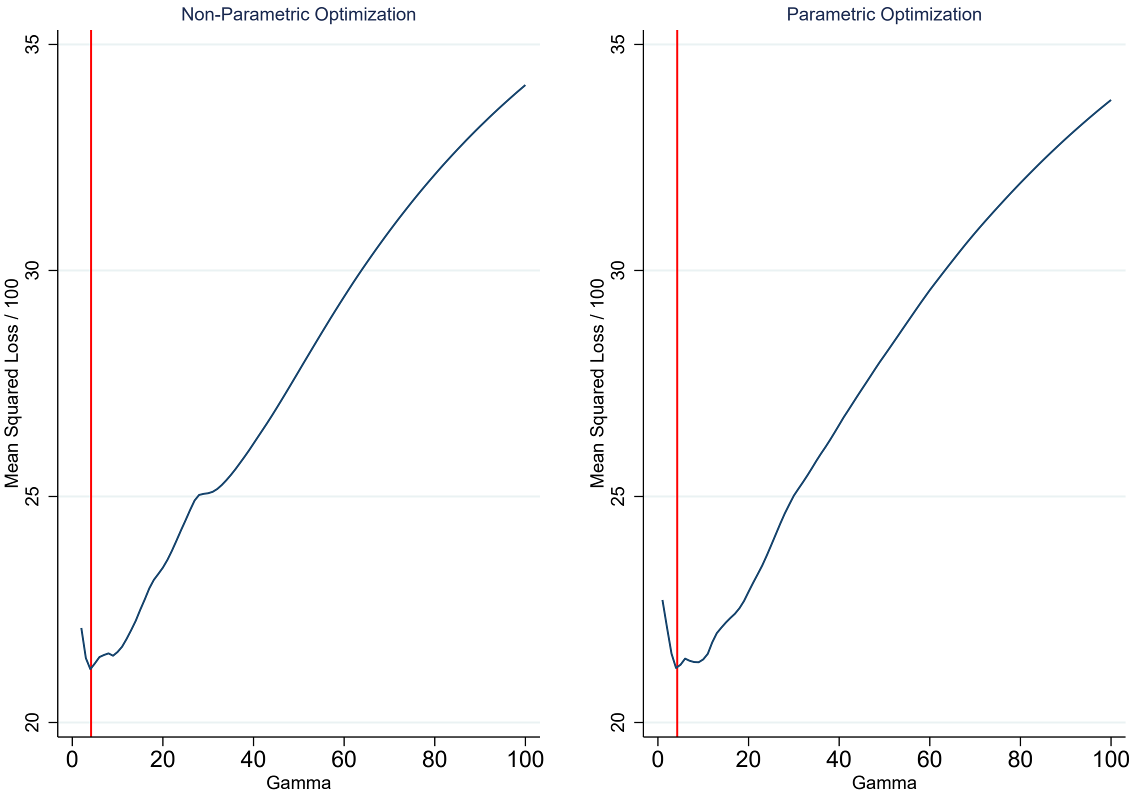

Table A.1: Sample Characteristics: First Wave

	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

Note: The table shows the share in % of survey participants with the respective characteristic.

Table A.2: 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

Note: The table shows the share in % of survey participants with the respective characteristic.

Table A.3: Learning Rate Regressions

	Posterior-Prior	
	(1)	(2)
T1	0.42	0.40
	(0.53)	(0.51)
T2	0.73	0.72
	(0.55)	(0.53)
T3	-3.17***	-3.22***
	(0.56)	(0.54)
T4	0.44	0.41
	(0.56)	(0.56)
T5	-1.42	-1.45*
	(0.88)	(0.87)
T1xGap		4.00***
		(0.76)
T2xGap		3.85***
		(0.67)
T3xGap		3.39***
		(0.53)
T4xGap		0.96*
		(0.52)
T5xGap		2.28**
		(1.00)
Constant	-4.47***	-4.47***
	(0.35)	(0.35)
R^2	0.02	0.11
N	3021	3021

Robust Standard errors in parentheses. T1 (DAX long-term), T2 (DAX past 12 months), T3 (Profits past 12 months), T4 (PE ratio) and T5 (Expert forecast next 12 months).

Table A.3: Financial Wealth

	mean	sd	p1	p10	p25	p50	p75	p90	p99
Cash acc.	23573	41704	0	0	1000	8000	25000	60000	250000
Cash	1852	5398	0	0	10	200	1000	5000	40000
Stock	21581	57559	0	0	0	0	12000	60000	380000
Bond	1965	9214	0	0	0	0	0	1	70000
Gold	1591	6876	0	0	0	0	0	2000	50000
Retirement	8616	20315	0	0	0	0	6000	30000	120000
Other	6728	26078	0	0	0	0	0	14000	200000
Total Wealth	65907	102491	0	100	5000	27850	80000	180000	510000
N	3198								

Note: Absolute amounts of financial wealth in Euro. Financial wealth data is winsorized at 1% tails. Total wealth is the sum of all asset classes. The table displays the mean, standard deviation, and various quantiles between 1% and 99% for each asset class.

Table A.4: 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

Table shows OLS regression estimates with robust standard errors in parentheses. Explanatory variables are dummy variables. Dependent variable is the standardised absolute value of the perception gap (zero mean, one standard deviation for each treatment group). 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: Profits Past 12 Months) and (prior belief current PE ratio - prior belief long-term PE ratio) - (23-15) (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: Profits 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).

Table A.5: OLS Subsample Heterogeneity: Posterior on Prior and Prior Interactions

	Baseline	Gender		Higher Education		Median Income		Median Risk Attitude		Interest	
	(1)	(2) Male	(3) Female	(4) No	(5) Yes	(6) Below	(7) Above	(8) Below	(9) Above	(10) No	(11) Yes
T1	0.56	0.11	1.17*	0.21	1.01*	0.30	0.53	1.31*	-0.34	-0.55	0.95*
	(0.41)	(0.51)	(0.69)	(0.54)	(0.61)	(0.74)	(0.50)	(0.67)	(0.52)	(0.68)	(0.53)
T2	2.04***	1.30**	2.93***	1.96***	1.76**	1.65**	2.01***	1.81***	2.00***	1.86**	1.73***
	(0.43)	(0.54)	(0.68)	(0.54)	(0.69)	(0.80)	(0.49)	(0.67)	(0.59)	(0.78)	(0.52)
T3	-3.22***	-2.33***	-4.31***	-3.43***	-2.96***	-4.23***	-2.61***	-3.97***	-2.37***	-4.08***	-2.67***
	(0.44)	(0.54)	(0.71)	(0.57)	(0.68)	(0.76)	(0.55)	(0.68)	(0.59)	(0.74)	(0.57)
T4	0.73	0.22	1.50**	0.95	0.21	0.43	0.96	1.19	0.43	-0.12	1.41**
	(0.46)	(0.59)	(0.71)	(0.62)	(0.63)	(0.82)	(0.59)	(0.75)	(0.60)	(0.78)	(0.60)
T5	1.63***	0.61	3.34***	1.41**	1.73***	1.51**	1.65***	2.25***	0.94	1.47**	1.57***
	(0.43)	(0.54)	(0.67)	(0.56)	(0.65)	(0.76)	(0.53)	(0.65)	(0.62)	(0.72)	(0.56)
Prior	0.36***	0.41***	0.28***	0.31***	0.47***	0.27***	0.41***	0.41***	0.33***	0.38***	0.36***
	(0.05)	(0.07)	(0.08)	(0.06)	(0.08)	(0.09)	(0.06)	(0.07)	(0.07)	(0.08)	(0.07)
T1xPrior	-0.14*	-0.07	-0.23	-0.14	-0.08	-0.12	-0.11	-0.25**	0.01	-0.03	-0.16
	(0.09)	(0.10)	(0.14)	(0.10)	(0.18)	(0.13)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)
T2xPrior	-0.17**	-0.12	-0.22*	-0.15*	-0.19	-0.08	-0.20**	-0.11	-0.20**	-0.30***	-0.05
	(0.07)	(0.09)	(0.12)	(0.09)	(0.12)	(0.12)	(0.09)	(0.10)	(0.10)	(0.11)	(0.09)
T3xPrior	0.04	0.03	0.06	0.04	0.07	0.09	-0.01	-0.06	0.08	-0.01	0.05
	(0.07)	(0.08)	(0.11)	(0.09)	(0.10)	(0.12)	(0.09)	(0.10)	(0.09)	(0.12)	(0.08)
T4xPrior	-0.07	-0.04	-0.12	-0.08	-0.05	-0.03	-0.12	-0.35***	0.07	-0.16	-0.06
	(0.08)	(0.10)	(0.12)	(0.10)	(0.11)	(0.14)	(0.10)	(0.12)	(0.09)	(0.11)	(0.10)
T5xPrior	-0.22***	-0.17*	-0.32***	-0.21**	-0.22*	-0.15	-0.26***	-0.35***	-0.14	-0.29**	-0.19**
	(0.07)	(0.09)	(0.12)	(0.09)	(0.13)	(0.13)	(0.09)	(0.11)	(0.10)	(0.13)	(0.09)
Constant	-1.71***	-1.22***	-2.46***	-1.57***	-1.76***	-1.64***	-1.69***	-0.23	-3.66	-3.72	0.32
	(0.28)	(0.37)	(0.43)	(0.36)	(0.44)	(0.50)	(0.34)	(3.28)	(3.09)	(3.23)	(2.70)
Socio-Demographics	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.15	0.22	0.13	0.12	0.29	0.12	0.18	0.18	0.21	0.17	0.21
N	3529	2105	1424	2372	1153	1391	2040	1520	1898	1283	2136

Robust Standard errors in parentheses. Winsorized (1% tails). T1 (DAX long-term), T2 (DAX past 12 months), T3 (Profits past 12 months), T4 (PE ratio) and T5 (Expert forecast next 12 months). Higher education means college education or higher.

Table A.6: OLS Subsample Heterogeneity: 12 Month Returns

	Baseline	Gender		Higher Education		Median Income		Interest	
	(1)	(2) Male	(3) Female	(4) No	(5) Yes	(6) Below	(7) Above	(8) No	(9) Yes
T1	-1.04	-1.11	-0.96	-1.71*	0.34	-1.70	-0.69	-2.22**	0.16
	(0.71)	(0.80)	(1.24)	(0.87)	(1.20)	(1.09)	(0.94)	(1.02)	(0.98)
T2	-2.41**	-1.14	-4.08**	-2.88**	-1.40	-4.80***	0.71	-1.51	-3.20**
	(1.03)	(1.15)	(1.82)	(1.20)	(2.00)	(1.44)	(1.49)	(1.52)	(1.39)
T3	0.40	-0.16	1.16	0.75	-0.39	-0.29	0.80	0.93	0.04
	(0.89)	(0.95)	(1.63)	(1.13)	(1.39)	(1.25)	(1.34)	(1.36)	(1.17)
Economic Growth	1.48**	2.08***	0.18	0.92	2.41***	0.28	2.44***	0.55	2.24***
	(0.58)	(0.68)	(0.97)	(0.76)	(0.89)	(0.93)	(0.75)	(0.93)	(0.73)
T1xGrowth	0.51	-0.35	3.09**	1.65	-1.21	2.33**	-0.72	2.06*	-0.77
	(0.77)	(0.86)	(1.55)	(1.01)	(1.21)	(1.18)	(1.03)	(1.23)	(0.98)
T2xGrowth	3.02**	2.24*	4.55*	3.52**	2.35	5.82***	0.45	3.99**	2.24
	(1.18)	(1.31)	(2.40)	(1.51)	(1.92)	(1.98)	(1.50)	(1.84)	(1.52)
T3xGrowth	-0.46	-0.48	0.23	0.40	-1.55	1.41	-1.88	-0.80	-0.43
	(0.88)	(1.01)	(1.62)	(1.13)	(1.39)	(1.33)	(1.21)	(1.46)	(1.09)
Stockholder	-0.21	0.25	-0.98	-0.15	-0.09	0.31	-0.65	0.63	-0.70
	(0.63)	(0.71)	(1.23)	(0.82)	(0.99)	(1.03)	(0.85)	(1.04)	(0.80)
T1xStockholder	-0.27	0.03	-0.61	-0.06	-0.87	0.01	-0.50	-0.36	-0.50
	(0.81)	(0.90)	(1.59)	(1.05)	(1.29)	(1.27)	(1.09)	(1.29)	(1.05)
T2xStockholder	2.26*	0.98	4.39*	3.41**	0.35	3.51*	0.15	0.73	3.53**
	(1.25)	(1.36)	(2.49)	(1.58)	(2.12)	(1.99)	(1.65)	(2.00)	(1.60)
T3xStockholder	-0.52	-0.07	-1.14	-1.25	0.80	-0.97	-0.20	-1.95	0.36
	(0.96)	(1.05)	(1.87)	(1.25)	(1.49)	(1.43)	(1.37)	(1.61)	(1.20)
Constant	5.26***	4.64***	6.05***	5.60***	4.51***	5.83***	4.95***	5.48***	5.00***
	(0.54)	(0.60)	(0.94)	(0.67)	(0.88)	(0.83)	(0.72)	(0.78)	(0.74)
R^2	0.02	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.03
N	3039	1934	1105	1874	1163	1440	1551	1302	1737

Note: Robust Standard errors in parentheses. Winsorized (1% tails). T1 (DAX past 5 years), T2 (Profits past 12 months) and T3 (PE ratio). Higher education means college education or higher.

Table A.7: OLS Subsample Heterogeneity: 5 Year Returns

	Baseline	Gender		Higher Education		Median Income		Interest	
	(1)	(2) Male	(3) Female	(4) No	(5) Yes	(6) Below	(7) Above	(8) No	(9) Yes
T1	0.15	0.05	0.06	-0.87	2.09	-0.23	0.48	-0.64	0.91
	(1.03)	(1.36)	(1.57)	(1.26)	(1.70)	(1.53)	(1.44)	(1.46)	(1.43)
T2	2.87**	4.74***	0.36	1.48	6.14***	0.60	5.88***	3.45*	2.37
	(1.25)	(1.63)	(1.92)	(1.47)	(2.36)	(1.78)	(1.81)	(1.84)	(1.70)
T3	0.71	-0.25	1.95	-0.22	2.32	-1.46	3.52*	-0.52	1.91
	(1.22)	(1.53)	(1.99)	(1.54)	(1.93)	(1.74)	(1.81)	(1.74)	(1.71)
Economic Growth	3.52***	4.23***	0.48	2.25	4.91***	2.33	4.48***	2.15	4.41***
	(1.05)	(1.30)	(1.74)	(1.38)	(1.60)	(1.68)	(1.38)	(1.64)	(1.37)
T1xGrowth	-0.97	-1.80	2.33	0.05	-2.21	-0.38	-1.39	0.57	-2.14
	(1.26)	(1.56)	(2.13)	(1.59)	(2.03)	(1.89)	(1.76)	(1.94)	(1.66)
T2xGrowth	1.08	-0.43	4.14	0.39	2.41	3.29	-0.89	1.49	0.79
	(1.74)	(2.09)	(3.17)	(2.17)	(2.90)	(2.73)	(2.33)	(2.71)	(2.27)
T3xGrowth	-1.63	-2.25	0.86	1.48	-5.45**	0.80	-4.12**	-0.41	-2.88
	(1.53)	(1.83)	(2.85)	(2.01)	(2.30)	(2.34)	(2.07)	(2.36)	(2.00)
Stockholder	3.40***	4.25***	1.21	1.77	5.48***	2.36	4.17***	3.20**	3.40**
	(1.03)	(1.30)	(1.66)	(1.33)	(1.55)	(1.66)	(1.36)	(1.60)	(1.38)
T1xStockholder	-2.52**	-2.68*	-1.62	0.28	-6.26***	-1.14	-3.48**	-2.28	-2.82*
	(1.25)	(1.57)	(2.04)	(1.56)	(2.00)	(1.90)	(1.73)	(1.89)	(1.68)
T2xStockholder	2.85*	1.65	4.80*	5.59***	-2.08	4.48*	0.62	1.09	4.16*
	(1.66)	(2.03)	(2.89)	(2.07)	(2.80)	(2.63)	(2.23)	(2.60)	(2.18)
T3xStockholder	0.04	1.45	-1.91	0.69	-1.14	1.25	-1.91	-0.49	0.15
	(1.50)	(1.83)	(2.55)	(1.91)	(2.32)	(2.24)	(2.10)	(2.30)	(2.02)
Constant	11.52***	11.34***	12.03***	12.11***	10.49***	12.37***	10.72***	11.68***	11.42***
	(0.84)	(1.10)	(1.29)	(1.05)	(1.28)	(1.28)	(1.12)	(1.19)	(1.16)
R^2	0.05	0.08	0.02	0.05	0.08	0.04	0.07	0.04	0.06
N	3039	1934	1105	1874	1163	1440	1551	1302	1737

Note: Robust Standard errors in parentheses. Winsorized (1% tails). T1 (DAX past 5 years), T2 (Profits past 12 months) and T3 (PE ratio). Higher education means college education or higher.

Table A.8: OLS Subsample Heterogeneity: 12 Month Dividend Growth

	Baseline	Gender		Higher Education		Median Income		Interest	
	(1)	(2) Male	(3) Female	(4) No	(5) Yes	(6) Below	(7) Above	(8) No	(9) Yes
T1	-0.76	-1.41	0.20	0.03	-2.42*	-1.85	0.13	-0.56	-1.00
	(0.89)	(1.15)	(1.38)	(1.10)	(1.46)	(1.25)	(1.27)	(1.16)	(1.37)
T2	-3.26***	-2.11	-4.54**	-3.54**	-2.85	-6.25***	1.10	-1.00	-5.14***
	(1.20)	(1.49)	(1.99)	(1.45)	(2.15)	(1.60)	(1.83)	(1.71)	(1.72)
T3	1.36	1.21	1.63	1.42	1.25	-0.56	2.90*	3.15**	-0.22
	(0.98)	(1.25)	(1.54)	(1.23)	(1.58)	(1.30)	(1.49)	(1.39)	(1.42)
Economic Growth	0.43	1.87*	-1.79	0.79	-0.02	-1.08	1.60	0.68	0.37
	(0.81)	(0.99)	(1.50)	(1.14)	(1.06)	(1.12)	(1.19)	(1.08)	(1.17)
T1xGrowth	0.60	0.13	2.09	1.41	-0.03	2.56*	-0.77	0.83	0.53
	(1.18)	(1.47)	(1.98)	(1.45)	(1.89)	(1.55)	(1.80)	(1.55)	(1.66)
T2xGrowth	2.48	2.73	0.30	3.30*	1.73	4.00*	1.15	-0.24	4.38**
	(1.59)	(1.86)	(3.16)	(1.95)	(2.63)	(2.35)	(2.21)	(2.29)	(2.19)
T3xGrowth	-1.56	-3.11**	1.96	-1.00	-2.51	2.97*	-4.94***	-2.74	-0.84
	(1.25)	(1.53)	(2.30)	(1.67)	(1.86)	(1.75)	(1.80)	(2.04)	(1.66)
Stockholder	-2.05**	-2.24**	-1.35	-1.67	-2.54**	-2.29**	-1.33	-0.51	-2.99**
	(0.81)	(0.99)	(1.39)	(1.20)	(1.00)	(1.10)	(1.15)	(1.09)	(1.19)
T1xStockholder	-0.51	0.41	-1.78	-0.82	0.45	0.47	-1.52	-1.22	0.12
	(1.17)	(1.46)	(1.89)	(1.51)	(1.81)	(1.55)	(1.70)	(1.58)	(1.66)
T2xStockholder	-0.63	-1.46	0.41	2.42	-4.88*	3.07	-5.40**	-2.23	0.60
	(1.59)	(1.88)	(2.87)	(2.05)	(2.56)	(2.29)	(2.20)	(2.32)	(2.18)
T3xStockholder	-1.49	0.04	-4.10*	-0.64	-2.32	-1.10	-1.82	-4.50**	0.63
	(1.23)	(1.50)	(2.09)	(1.73)	(1.76)	(1.80)	(1.73)	(1.86)	(1.67)
Constant	3.37***	2.27***	4.59***	3.17***	3.73***	4.91***	1.76**	3.16***	3.56***
	(0.62)	(0.80)	(0.99)	(0.81)	(0.89)	(0.88)	(0.87)	(0.77)	(1.02)
R^2	0.02	0.02	0.03	0.01	0.04	0.03	0.03	0.02	0.02
N	2996	1903	1093	1833	1161	1428	1522	1264	1732

Note: Robust Standard errors in parentheses. Winsorized (1% tails). T1 (DAX past 5 years), T2 (Profits past 12 months) and T3 (PE ratio). Higher education means college education or higher.

Table A.9: OLS Subsample Heterogeneity: 5 Year Dividend Growth

	Baseline	Gender		Higher Education		Median Income		Interest	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Male	Female	No	Yes	Below	Above	No	Yes
T1	1.07	0.67	1.63	1.61	-0.04	0.21	2.07	1.75	0.38
	(1.09)	(1.48)	(1.61)	(1.33)	(1.90)	(1.66)	(1.39)	(1.63)	(1.43)
T2	1.98	3.46**	0.08	1.80	2.59	-1.13	6.33***	1.72	2.16
	(1.25)	(1.65)	(1.91)	(1.49)	(2.27)	(1.76)	(1.82)	(1.90)	(1.64)
T3	0.42	-0.09	1.28	0.99	-0.77	-1.27	2.40	-0.53	1.24
	(1.24)	(1.66)	(1.88)	(1.59)	(1.99)	(1.85)	(1.65)	(1.79)	(1.73)
Economic Growth	1.38	2.69**	-1.75	1.63	1.12	0.07	2.30	0.76	1.78
	(1.09)	(1.34)	(1.85)	(1.56)	(1.46)	(1.65)	(1.48)	(1.59)	(1.47)
T1xGrowth	0.46	-0.53	3.00	0.21	0.84	1.32	0.04	0.31	0.59
	(1.36)	(1.70)	(2.20)	(1.88)	(1.94)	(2.00)	(1.90)	(2.13)	(1.78)
T2xGrowth	2.12	0.85	3.84	1.22	3.39	2.87	1.06	2.78	1.70
	(1.82)	(2.21)	(3.16)	(2.46)	(2.71)	(2.60)	(2.54)	(2.77)	(2.41)
T3xGrowth	-0.23	-2.17	3.77	0.33	-1.04	2.59	-2.34	2.43	-2.24
	(1.56)	(1.92)	(2.82)	(2.20)	(2.09)	(2.45)	(2.05)	(2.45)	(2.07)
Stockholder	0.92	0.77	0.97	1.84	-0.33	-1.99	3.49***	1.37	0.54
	(1.05)	(1.34)	(1.79)	(1.48)	(1.59)	(1.55)	(1.34)	(1.57)	(1.44)
T1xStockholder	-2.75**	-1.51	-4.79**	-3.12*	-2.00	0.14	-5.05***	-3.43*	-2.08
	(1.31)	(1.68)	(2.13)	(1.76)	(2.03)	(1.88)	(1.74)	(1.98)	(1.74)
T2xStockholder	0.68	0.34	0.97	0.94	-0.39	4.91**	-4.02*	0.21	0.97
	(1.69)	(2.12)	(2.86)	(2.24)	(2.66)	(2.50)	(2.35)	(2.64)	(2.23)
T3xStockholder	-0.47	2.44	-5.53**	-0.81	0.47	2.38	-2.76	-2.37	0.72
	(1.51)	(1.90)	(2.44)	(2.11)	(2.18)	(2.28)	(1.95)	(2.21)	(2.06)
Constant	9.33***	8.91***	9.92***	9.02***	10.00***	11.00***	7.37***	9.26***	9.44***
	(0.89)	(1.22)	(1.31)	(1.07)	(1.60)	(1.38)	(1.08)	(1.29)	(1.20)
R^2	0.01	0.02	0.02	0.01	0.03	0.01	0.03	0.02	0.02
N	2996	1903	1093	1833	1161	1428	1522	1264	1732

Note: Robust Standard errors in parentheses. Winsorized (1% tails). T1 (DAX past 5 years), T2 (Profits past 12 months) and T3 (PE ratio). Higher education means college education or higher.

Table A.10: Information Selection and Socio-demographic Characteristics

	(1) DAX long-term trend	(2) Profit in last 12 months	(3) Current PE Ratio	(4) Expert forecast	(5) DAX in the last 5 years
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

Note: The table shows the results of several ordered logit regressions. Robust standard errors are in parentheses. The dependent variable is coded (corresponding to the selected information source rank) as follows: 5 (rank 1), 4 (rank 2), ..., 1 (rank 5). Explanatory variables are gender (male dummy), above median age (dummy), college education or higher (dummy), full time employment (dummy), east/west Germany (dummy), children (dummy), household income (indicator for income bracket) and homeowner (dummy) and stockholder (dummy).

Table A.11: 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 y
	(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

Note: The table shows the results of several logit regressions. Robust standard errors are in parentheses. The dependent variable is 1 if the information source is perceived as being "difficult to get" and 0 otherwise. Explanatory variables are gender (male dummy), above median age (dummy), college education or higher (dummy), full time employment (dummy), east/west Germany (dummy), children (dummy), above median household income (dummy) and homeowner (dummy) and stockholder (dummy).