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Stock Market Beliefs and Portfolio Choice in the General Population

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The amount of risk that households take when investing their savings has long-term consequences for their financial well-being. However, a substantial share of observed heterogeneity in financial risk-taking remains unexplained by factors like risk aversion and wealth levels. This study explores whether subjective beliefs about stock market returns can close this knowledge gap. I make use of a unique data set that comprises incentivized, repeated elicitations of stock market beliefs and high-quality administrative asset data for a probability-based population sample. Households with more optimistic stock market expectations hold more risk in their portfolio, where the effect size is about half of the effect size of risk aversion. Furthermore, changes in expectations over time are related to changes in portfolio risk, which demonstrates that cross-sectional correlations are not driven by a time-invariant third variable. The results suggest that stock market expectations are an important component of portfolio choice. More generally, the study shows that subjective beliefs can be reliably measured in surveys and are related to actual high-stakes decisions.

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1 Introduction

The amount of risk that households take when investing their savings has long-term consequences for their financial well-being. However, despite much research, a large fraction of the variation in portfolio risk remains unexplained. For example, variation in risk aversion cannot explain observed levels of stock ownership and only a small part of individual heterogeneity (Barberis and Huang, 2008; Guiso and Sodini, 2013). Furthermore, participation costs help to understand the strong correlation between wealth levels and portfolio risk, but not why a substantial share of households do not invest in any risky assets despite considerable wealth (Campbell, 2006; Gomes, Haliassos, and Ramadorai, 2020). Portfolio decisions are also related to financial numeracy (van Rooij, Lusardi, and Alessie, 2011), but, altogether, a large share of observed differences in portfolio risk cannot be explained by these factors.

This study explores whether subjective beliefs about stock market returns can close this knowledge gap. There are at least four reasons why focusing on subjective beliefs as potential driver of portfolio choice is important. First, results inform how the financial decision-making of households should be represented in theoretical models. So far, those models often assume that households base their decisions on objective return distributions and do not consider individual differences in beliefs. Second, whether subjective beliefs play an important role for chosen portfolio risk has normative implications: under the assumption that past returns are accurate predictors of the future, some observed expectations are clearly irrational. If expectations drive portfolio choice, this would imply that not all households make optimal decisions for themselves. A related third point is that the results might give room for policy interventions. While preferences are arguably difficult to change, information campaigns or coachings could change the households' expectations and therefore improve their decisions, in the sense that decisions are based on rational expectations. More generally, the results also enable assessing whether subjective beliefs can be reliably measured in surveys. It has been criticized that self-reported stock market beliefs are measured with considerable noise and that they might not correspond to factors that individuals take into account when making actual decisions (e.g. Cochrane, 2011). This concern is especially relevant in broad population samples in which a substantial number of people show little comprehension of financial markets and numerical concepts (e.g. van Rooij, Lusardi, and Alessie, 2011).

For all of these reasons, earlier studies have already explored the relation of stock market expectations and portfolio risk. Dominitz and Manski (2007), Hurd, Rooij, and Winter (2011), Kézdi and Willis (2011), and Drerup, Enke, and von Gaudecker (2017) make use of broad population samples—like this study—and find a positive relation. However, they suffer from two potential problems. First, they use cross-sectional data only, and thence these findings could be biased by a third variable that drives both beliefs and portfolio choice. Potential candidates could be personality characteristics, family background, or risk aversion, if those are unobserved or measured with noise. Second, these studies rely on self-reported asset data, which is likely prone to survey response error (Hill, 2006; Johansson and Klevmarken, 2007; Meyer, Mok, and Sullivan, 2015).[1] Measurement error could bias results in studies based on self-reported asset data, as stressed by Campbell, Jackson, Madrian, and Tufano (2011).

Merkle and Weber (2014) and Giglio, Maggiori, Stroebel, and Utkus (2020) address these concerns by utilizing administrative asset data of asset management firms. These data sets contain detailed information about holdings of different assets, realized returns, and trading behavior. However, they are restricted to retail investors at the respective firm. Since those subjects are richer than average and all invest in risky assets, they are unrepresentative of the full population. The samples are well suited to answer a range of questions; for instance, about asset pricing, where prices are mostly driven by wealthy investors. However, for important economic questions such as the distributional effects of portfolio choice or foregone equity premia by households, it is crucial to understand portfolio choice within the full population. In particular, those data sets cannot give insights about the extensive margin of the holding of risky asset. Another shortcoming of these samples is that assets of the subjects at other banks are unobserved.

A natural next step is to extend the use of administrative asset data to a broad population sample when examining the relation between subjective beliefs and portfolio choice. To the best of my knowledge, this study is the first to do so. I address the aforementioned shortcomings of the related literature by leveraging a unique data set with four relevant features. First, I make use of a rich set of control variables including wealth levels, risk aversion, and financial numeracy, whereby I am able to examine the role of subjective beliefs in addition to other relevant characteristics. Second, I utilize repeated elicitations of beliefs. Analyzing changes in beliefs and associated changes in portfolio risk allows me to control for all time-invariant confounding variables.[2] Third, I make use of administrative asset data based on tax records to address concerns about the quality of self-reported asset data. Finally, I utilize a probability-based sample of the unity of households, which allows me to examine portfolio decisions for the broad population.

Based on these data, I show that differences in subjective beliefs about the stock market are an important component of portfolio choice. The results complement previous studies showing that subjective beliefs are related to other financial

1. This is confirmed in my data set: although not the main aspect of this paper, I find both substantial non-response in survey data and individual differences between survey and administrative data. Both sources of error vary systematically with observed characteristics. These results are summarized in Section C in the Online Appendix.

2. A similar approach has previously been used for experimental investment tasks (Drerup and Wibral, 2020) and investor samples (Merkle and Weber, 2014; Giglio et al., 2020). Laudenbach, Weber, and Wohlfart (2020) also make use of an investor sample, but leverage an information treatment to exogenously vary subjective beliefs.

choices such as borrowing decisions (Malmendier and Nagel, 2016), saving decisions (Heimer, Myrseth, and Schoenle, 2019), and corporate investment plans (Gennaioli, Ma, and Shleifer, 2016).

My data set comprises high-quality administrative data and detailed survey data, leveraging the individual advantages of both. The administrative data are provided by Statistics Netherlands (CBS) and contain a rich set of information about all households living in the Netherlands. They entail yearly asset and wealth data of those households, including a split between safe assets (bank and savings accounts) and risky assets (shares, funds, bonds, etc.). Since they are based on tax records for a wealth tax, misreporting the assets is potentially a criminal offense. This arguably makes these data much more reliable than self-reported asset data. My main measure of portfolio risk is the share of risky financial assets of total financial assets. Additionally, I also consider the extensive and intensive margin of risky asset holdings separately. I combine the tax data with survey data from a household panel (LISS), which is a probability sample of the Dutch adult population. The panel contains measures of stock market beliefs, background variables, and additional characteristics of subjects such as risk aversion and financial numeracy.

Beliefs about the distribution of stock market returns are elicited using a survey tool that has specifically been designed for use in internet panels. In an iterative procedure, subjects distribute 100 balls over eight bins that span the probability space. Choices are incentivized such that participants can win up to EUR 100, in addition to regular participation fees. In the analyses, I make use of the expected value and the standard deviation of the belief distribution, two key components of portfolio choice models. I estimate these parameters by fitting a log-normal distribution at the individual level. Overall, 82 % of households participating in the belief elicitation task can be linked to the administrative data.

I first confirm that expected stock market performance is positively related to portfolio risk in cross-sectional data. Importantly, this result is robust to adding a rich set of control variables including risk aversion and financial numeracy. Increasing the expected value by one standard deviation is associated with a 3.5 percentage point higher probability of holding any risky assets and an increase in the share of risky assets by 1.5 percentage points. These are substantial effect sizes: the latter corresponds to 15 % of the mean of the dependent variable and half of the effect size of risk aversion.

To control for potential confounders that might drive both beliefs and portfolio choice, I leverage a specific feature of my belief data, namely that subjects have the option to update their beliefs half a year after the first elicitation. This allows me to compare changes in beliefs with changes in portfolios. The analyses over time confirm the main findings based on cross-sectional data: changes in expected stock market development are related to changes in portfolio risk, whereby an increase in the expected value by one standard deviation predicts an increase in the risky asset share by 0.9 percentage points. These findings demonstrate that the cross-sectional correlation between stock market expectations and portfolio risk is not solely driven by a time-invariant third variable. I do not find an effect for the extensive margin of risky asset holding. Changes in expectations over this period seem to be insufficient for most non-stockholders to start buying risky assets, or vice versa.

The standard deviation of the belief distribution is not considerably related to portfolio choice, in both the cross-sectional analyses and over time. This aligns well with findings by Kézdi and Willis (2011) and Giglio et al. (2020). One reason could be that the estimated standard deviation of beliefs is likely measured with more noise. Besides, a high standard deviation of beliefs could not only express high perceived risk, but also high perceived ambiguity over the belief distribution. For future research, it would be interesting to differentiate between the two interpretations. Finally, I confirm that all findings are robust to different sample restrictions and non-parametric estimation of the belief parameters.

2 Data

I make use of three data sources, which I discuss in turn: stock market beliefs elicited in the Longitudinal Internet Studies for the Social Sciences (LISS), asset and background data based on administrative records from Statistics Netherlands (CBS), and additional survey data from the LISS.

2.1 Stock market beliefs

The first data source are beliefs about the development of the most important stock market index in the Netherlands, the AEX. Those function as a proxy for general beliefs about (potential) investment opportunities of Dutch households in risky assets like stocks or funds.[3] The beliefs are elicited in the LISS panel, an internet-based household panel administered by CentERdata (Tilburg University). Participating households are a probability sample of the Dutch population and they are financially compensated for their participation. The panel allows researchers to run individual surveys tailored to specific research questions such as the one used for this study.

During the first elicitation in August 2013, participants were asked about the value of a EUR 100 investment in the AEX in one year. To elicit the full distribution of beliefs, subjects placed 100 balls into seven partitions in an iterative procedure

3. This seems well justified as 69 % of the stocks held by households in the Netherlands are Dutch listed stocks (based on https://www.dnb.nl/en/news/news-and-archive/Statistischnieuws2018/dnb378222.jsp). Additionally, the development of stock markets across different countries is strongly correlated.

that was explicitly designed for usage in internet experiments (Delavande and Rohwedder, 2008). The procedure starts with a comparably accessible question when subjects are asked to split 100 balls between the events that the AEX goes up or down. Afterwards, each part is further divided until the seven bins are filled. See Figure 1 for an example of a filled-out response: the example subject put 38 balls in the interval indicating positive returns below 5 % and three balls in the bin for returns above 15 %. Drerup, Enke, and von Gaudecker (2017) collected the data and provide a more detailed description of the elicitation procedure (the belief measures are also used by Drerup and Wibral, 2020).

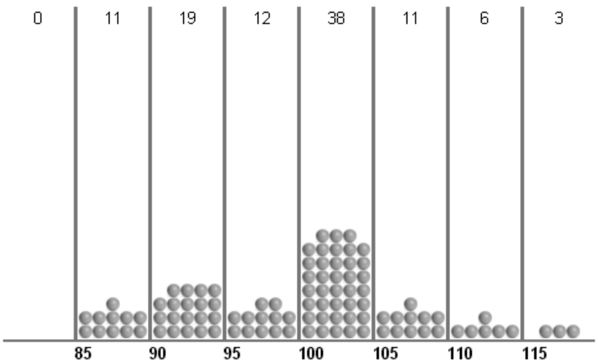

Figure 1. Survey tool

Notes: One example of an elicited belief distribution after a subject had completed all iteration steps and hence distributed all 100 balls. Subjects are asked for the value of a EUR 100 investment in the AEX in one year, including a fee of EUR 0.30.

The survey was sent to the self-reported financial deciders of 2,978 households who either reported total financial assets of at least EUR 1000 or whose financial assets observation was missing in 2012. 2,311 subjects filled out the complete first questionnaire. The answers are incentivized such that every tenth participant is paid up to EUR 100 one year later, depending on the accuracy of their prediction about the performance of the stock market. Payoffs are calculated based on the binarized scoring rule (Hossain and Okui, 2013), an incentive-compatible method for a wide range of utility functions.

When analyzing the relation between beliefs and portfolio choice, I make use of the expected value (μ_1) and the standard deviation (σ_1) of the belief distribution, two key components of portfolio choice models. The interpretation of the expected value is straightforward: ceteris paribus, higher return expectations should lead to higher investment in risky assets. Conversely, the standard deviation can play a role for at least two reasons. On the one hand, an observed high standard deviation of the belief distribution could be either an expression of actual high dispersion of the perceived return distribution and therefore a measure of perceived risk. On the other hand, it can express uncertainty over the distribution of beliefs (Ben-David, Fermand, Kuhnen, and Li, 2018). For both interpretations, a negative relation with portfolio risk is expected if subjects are on average risk averse and ambiguity averse.

I calculate the two belief parameters by fitting a log-normal distribution for each individual to the observed cumulative distribution function of beliefs. As the outer bins are open intervals, estimates of μ_1 and σ_1 for subjects with a high share of balls in these bins are potentially unreliable. In my main specification, I exclude all subjects with more than 80 % of the probability mass in the two outer bins (1.5% of the sample).

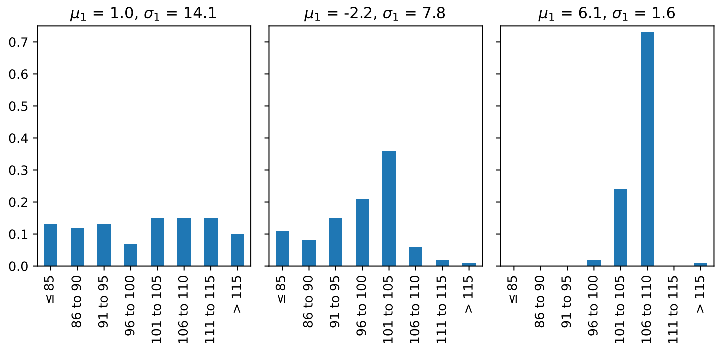

Figure 2. Distribution of beliefs and estimated parameters for three participants

Notes: The expected value (μ_1) and standard deviation (σ_1) are based on the first elicitation of beliefs and calculated by fitting a log-normal distribution. More of these plots are shown in Figure A.2 in the Online Appendix.

Figure 2 shows distributions of beliefs and the estimated parameters for three exemplary participants. The subject on the left expects that all bins are almost equally likely and I estimate a large standard deviation and a modestly positive μ_1. In the middle distribution, substantial mass is placed in bins with negative returns, which results in an estimated expected value below zero. Finally, the participant on the right places 70 balls on returns between +6 % and + 10 %. Compared with the other subjects, I hence estimate a higher μ_1 and a lower standard deviation. Summary statistics for the estimated parameters are presented in Table 1. Subjects expect on average that the AEX increases by 2.5%. While the distribution of μ_1 is roughly normally distributed, the distribution of σ_1 has a substantial mass at values close to zero and a large right tail.

I provide more details about the distribution of beliefs, the estimation of the log-normal distribution, and correlations between the belief parameters and demographic variables in Section A of the Online Appendix. Most notably, subjects underestimate both the expected value and the standard deviation of beliefs compared with empirical frequencies. The relations with background variables align well with previous studies (e.g. Manski, 2004; Hurd, 2009): Subjects with higher μ_1 tend to be male, university-educated, have higher numeracy skills, and a lower risk aver-

Table 1. Summary statistics of belief parameters

	Observations	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$
μ_1	1720	2.51	4.9	-2.21	1.84	8.19
σ_1	1720	6.24	3.27	2.23	5.96	9.82

Notes: The expected value (μ_1) and standard deviation (σ_1) are based on the first elicitation of beliefs and calculated by fitting a log-normal distribution. Sample: Can be linked to administrative data (see below), at most 80 balls in the two outer bins, and financial assets of at least EUR 1,000.

sion. On the other hand, a lower σ_1 is associated with high-numeracy subjects and unmarried couples.

In Section D of the Online Appendix, I replicate all analyses of the main paper using two alternative specifications. First, I increase the sample and exclude only subjects if all 100 balls are placed in the outer bins. Second, I make use of a non-parametric splines estimation based on Bellemare, Bissonnette, and Kröger (2012) to obtain the expected value and standard deviation of the distribution.

After half a year, in March 2014 another questionnaire was addressed to the participants in which they could update their belief about the performance between August 2013 and 2014. They received information about the performance during the first half of the period together with the belief distribution that they entered in August 2013 and could adjust their belief accordingly. The opportunity to change beliefs was incentivized and unexpected by the subjects. Figure 3 depicts the timing of the two belief elicitations.

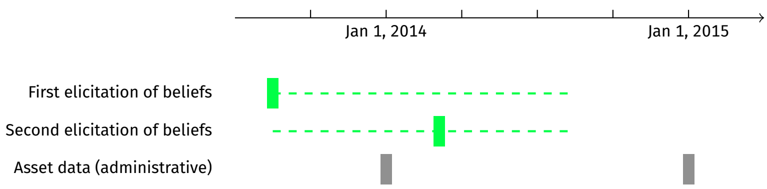

Figure 3. Timeline of data collection

Notes: The beliefs are elicited twice, in August 2013 and March 2014. Both questionnaires asked for the development of the AEX over the same time frame from August 2013 until August 2014.

I calculate the belief parameters of the second elicitation μ_2 and σ_2 as described above. Summary statistics about the updating of beliefs are presented in Section 4.

2.2 Asset and background data

Asset data is based on administrative records provided by Statistics Netherlands (CBS). The data cover a wide range of characteristics for the whole Dutch population and include—among others—gender, age, and income at the individual level, as well as the household composition. In contrast to administrative data in most other countries, the CBS data also contain detailed financial information about wealth, total financial assets as well as a split between safe assets (bank and savings accounts) and risky assets (shares, funds, bonds, etc.). The financial information is available at the household level and based on yearly tax records associated with the balances on January 1 of the respective year.

CBS provides an income equivalence scale based on the number of adults and children in the household. The factors are calibrated based on a budget survey (e.g. the factor for a couple without children is 1.37). I use this equivalence scale to standardize all asset and income variables. I make use of gross income as no measure of net income exists that is directly comparable between survey and administrative data. Finally, two measures of portfolio risk are calculated: a dummy variable indicating whether the household possesses any risky assets and the share of risky financial assets among total financial assets.

While the administrative data also contain information about the level of education achieved, this variable is missing for 58 % of the sample, especially for older persons who finished education before the collection of comprehensive administrative data started. Therefore, I do not use administrative educational information, but make use of the self-reported measures in the LISS panel.[4] The analyses are based on variables for the year 2013, where asset variables refer to the end of 2013. When focusing on the updating of beliefs in Section 5, I also use information from exactly one year later.

The LISS data can be linked to CBS data for 1,890 of 2,311 households that participated in the belief elicitation survey. The incomplete linkage is mostly caused by households that object to the procedure. While this might potentially introduce a bias in the administrative data, Sakshaug and Kreuter (2012) assess the linkage non-consent bias in a similar setting and find that it is very low compared with other sources of error like non-response or measurement error of the survey. I do not consider the non-consent bias further in this study and focus all analyses on the subset of households that can be linked to administrative records. Table 2 summarizes how the number of observations in the final sample emerges: 1,884 subjects can be linked to complete administrative income and asset data, of which 28 placed more than 80 % of the probability mass in the two outermost bins and are therefore excluded. In all regressions analyzing portfolio choice, only those 1,720 households holding financial assets of at least EUR 1,000 are considered. When examining the dynamics of beliefs, I can make use of 1,489 observations that participated in both waves.

Table 3 shows summary statistics of the dataset. The gender split is even. Subjects are on average 58 years old, with the 10 %-percentile at 36 and the 90 %-

4. For the subjects with available educational information from both sources, the data sources agree in 78 % of the cases, where some diverging answers are driven by a different aggregation of subcategories.

Table 2. Observations in final sample

Complete first elicitation	2311
(Thereof) linked to admin data	1890
(Thereof) complete income data	1884
(Thereof) at most 80 % of prob mass in outer events	1856
(Thereof) financial assets $\geq$ EUR 1000	1720
(Thereof) complete second elicitation	1489

Notes: For the cross-sectional analyses, 1,720 subjects are used. When examining changes in beliefs, 1,489 observations remain.

percentile at 77 years. One third of the subjects had achieved an upper secondary educational degree, while 0.38 percent of the sample had completed tertiary education. Furthermore, 58 % of financial deciders live together with a married partner, while about one in ten live together with an unmarried partner. In 30 percent of households, children are present at home. Income, assets, and wealth variables are aggregated at the household level and equivalized. More than one in ten households hold negative wealth. The final two rows show the main outcome variables: 29 percent of the households hold any risky asset, while the share of risky financial assets is 10 % on average. Compared with official statistics by CBS, my subjects are slightly older and more educated. The sample is also somewhat richer (in terms of both wealth and income) and more commonly hold any risky assets.[5] These differences are expected given the focus on financial deciders in each household and the requirement of financial assets of at least EUR 1,000.

2.3 Additional survey data

Finally, the study also makes use of additional survey variables elicited in the LISS panel to leverage individual variables not present in administrative data:

Risk aversion. A natural potential driver of portfolio risk is the aversion towards risk. The study employs the average of three standardized risk aversion measures that are based on Falk, Becker, Dohmen, Huffman, and Sunde (2016): a quantitative lottery choice task and two qualitative risk questions for general decisions under risk and financial decisions, respectively. The resulting risk aversion index is standard normalized.

Financial numeracy. The ability to reason quantitatively is potentially important for investment decisions, the elicitation of stock market expectations, and the updating of them after receiving new information. A set of questions by van Rooij, Lusardi,

5. Comparison based on the 2014 statistical yearbook of the Netherlands: https://www.cbs.nl/-/media/imported/documents/2014/27/2014-statistical-yearbook-of-the-netherlands.pdf?la=en-gb)

Table 3. Dataset

	Observations	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$
Female	1720	0.47				
Couple	1720	0.68				
Married	1720	0.58				
Has children at home	1720	0.30				
Education: lower secondary and below	1718	0.28				
Education: upper secondary	1718	0.33				
Education: tertiary	1718	0.38				
Age	1720	58.07	15.15	36	60	77
Gross income (thousands)	1720	2.92	1.72	1.15	2.65	4.88
Financial assets (thousands)	1720	50.50	97.61	3.43	19.82	117.18
Wealth	1720	132.99	274.08	-14.1	65.52	344.71
Has risky financial assets	1720	0.29				
Share of risky assets	1720	0.10	0.22	0	0	0.43

Notes: The education variable is taken from the LISS survey. All other variables are based on administrative records (CBS). All income and wealth variables are aggregated at the household level and equivalized.

and Alessie (2011) is used to elicit numeracy for basic financial calculations. The numeracy measure is standard normalized.

Besides, the survey data also contains self-reported asset data of the households, which is elicited bi-yearly. Section C in the Online Appendix describes the data collection and analyzes deviations between self-reported and administrative data. I find both substantial non-response in the survey data and individual differences between survey and administrative data. Both sources of error vary systematically with observed characteristics. This motivates the use of administrative asset data in this study.

3 Stock market beliefs and portfolio choice in the cross-section

I now focus on the relation between stock market beliefs and portfolio choice in a static setting. To gain a first impression of the relationship, I split the sample into five groups based on the quintiles of the expected value of stock market belief. Figure 4 shows the mean risky asset share of each group. Portfolio risk increases over the groups, from below 4.8 % for the most pessimistic to 14.5 % for the most optimistic group. Subjects who hold more optimistic beliefs about the development of the stock market tend to hold more risk in their portfolio. The difference between the highest and lowest bin is statistically significant at the 95 % level.

The previous finding supports the hypothesis that subjective beliefs drive portfolio choices. However, the relation could also be caused by other factors like financial numeracy, risk attitudes, or personal circumstances. Since these factors might drive

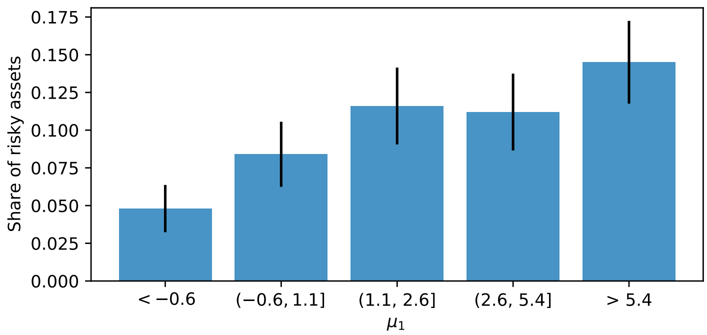

Figure 4. Risky asset share and stock market expectations

Notes: μ_1 is based on the first elicitation of beliefs and separated in five quintiles. The bars show the mean risky asset share for each bin, while the thin black lines depict 95 % confidence intervals.

both subjective beliefs and investment decisions directly, it is important to control for relevant personal and household characteristics. I therefore run a set of the following regressions:

$$a_{2013,i} = \beta_0 + \beta_1 \mu_{1,i} + \beta_2 \sigma_{1,i} + \beta X_{2013,i} + \epsilon_i$$

where $\mu_{1,i}$ and $\sigma_{1,i}$ are the individual expected value and standard deviation of elicited stock market beliefs, and $X_{2013,i}$ is a collection of background characteristics measured in 2013: household composition, education, age, gross income, wealth, risk aversion and financial numeracy. The dependent variable $a_{2013,i}$ is one of two measures of portfolio risk measured at the end of 2013: a dummy variable indicating whether the household possesses any risky assets or the share of risky assets of the total financial assets. While the first measure enables analyzing the decision to hold any risky investments (extensive margin), the risky asset share is a finer proxy of actual portfolio risk. Additionally, I analyze the risky asset share for the subset of households that hold any risky assets. This analysis allows me to look at the intensive margin separately.

Regression results are shown in Table 4. The belief parameters, financial numeracy, and risk aversion are standardized such that the reported coefficients show the predicted effect of a one standard deviation change in any of these variables. The coefficients of additional variables are excluded here, but shown in Table B.1 in the Online Appendix. Column 1 shows that when controlling for basic background variables, an increase in the expected value μ_1 by one standard deviation is related to a 4.5 percentage point higher probability of holding any risky assets. When additionally controlling for financial numeracy and risk aversion, the marginal effect is slightly lower at 3.5 percentage points. Although the sample drops by roughly 236 observations, the decrease is mainly driven by the inclusion of those control variables. The size of the coefficient corresponds to 12 percent of the mean of the dependent variable. A one standard deviation increase in μ_1 is also associated with a rise in the risky asset share by 1.5 percentage points (column 4), or 15 percent of the mean outcome variable. Compared with the effect of risk aversion, the absolute effect size is between 50 % (risky asset share) and 75 % (extensive margin) of it. Columns 5 and 6, restrict the sample to households that have any risky assets and hence focus solely on the intensive margin. The coefficients are similar but insignificant due to a reduced sample size.

Table 4. Portfolio choice and stock market beliefs

	Has risky financial assets		Share of risky assets			
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	0.045***	0.035***	0.021***	0.015***	0.023*	0.013
	(0.011)	(0.012)	(0.005)	(0.006)	(0.013)	(0.014)
σ_1	-0.008	0.000	-0.002	0.000	0.001	0.001
	(0.013)	(0.014)	(0.007)	(0.007)	(0.016)	(0.017)
Financial numeracy		0.018		0.001		-0.010
		(0.011)		(0.006)		(0.024)
Risk aversion		-0.044***		-0.029***		-0.053***
		(0.012)		(0.006)		(0.016)
N	1718	1482	1718	1482	500	425
R^2	0.138	0.137	0.107	0.112	0.073	0.102
Subset: has risky assets	No	No	No	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: For the first two columns, the dependent variable is a dummy indicating whether any risky assets are in the portfolio, while the remaining columns utilize the share of risky assets as the dependent variable. In the final two columns, the sample is restricted to households with any risky assets. The belief variables (expected value μ_1 and standard deviation σ_1) are only based on the first elicitation and standardized. Demographic controls are household composition, education, age, gross income, and wealth. The full regression table is shown in Table B.1 in the Online Appendix. All variables except education, beliefs, numeracy, and risk aversion are based on administrative records. Robust standard errors in parentheses.
* – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

While μ_1 is related to both the extensive margin of stock ownership and the share of risky assets, the relation with σ_1 is insignificant. This is also the case for interactions of σ_1 and μ_1 (not shown), which would be expected when interpreting σ_1 as a measure of perceived uncertainty over the belief distribution. Importantly, this does not need to indicate that differences in risk or ambiguity perceptions do not play a role here. Based on the negative effect of the risk aversion index, risk considerations seem to be important for the portfolio decision. It is likely that the aforementioned dual role of σ_1 as perceived risk or perceived ambiguity makes it difficult to find aggregate effects. Furthermore, stating the average level of subjective beliefs seems to be an easier task than reporting their variance. Hence, the estimated standard deviation of beliefs is likely measured with more noise. Kézdi and Willis

(2011) and Giglio et al. (2020) also find much smaller and mostly insignificant results for the standard deviation of beliefs.

To examine the robustness of the results in this section, I repeat the analysis for two alternative specifications in Section D of the Online Appendix. First, I relax the restriction that at most 80 % of the probability mass of the belief distribution is in the two extreme bins and include subjects that place more mass in those bins. Second, I make use of an alternative, non-parametric method to estimate μ_1 and σ_1. The results barely change accordingly.

Hence, I conclude that in the cross-section portfolio choice is related to stock market expectations, at both the extensive margin and the actual risky asset share. These findings are robust to adding a rich set of control variables, including financial numeracy and risk aversion. The standard deviation of stock market beliefs does not seem to play an important role. The relation found in cross-sectional data is a good indicator that stock market beliefs might be an important driver of portfolio choice. However, the findings could be biased by an unobserved variable that drives both beliefs and portfolio choice. Potential candidates are personality characteristics or the family background of respondents. In addition, if financial numeracy and risk aversion are measured with noise, controlling for it might be insufficient to eliminate the full potential bias. In Section 5, I make use of a second belief elicitation and address both issues by comparing changes in expectations with changes in portfolio risk.

4 Updating of stock market beliefs

Half a year after the first elicitation, subjects participated in another questionnaire in which they had the possibility to update their prediction of the stock market development, which they had not expected in advance. The questionnaire presents information about the performance of the AEX during the first half of the period together with the belief distribution that they entered in August 2013. Afterwards, participants could adjust those beliefs. Since the updated belief is used for incentive payments, the second belief elicitation was again incentivized. This section describes the distribution of changes in the belief parameters and examines how changes are related to characteristics of participants. I analyze the relation with changes in portfolio risk in the next section.

The actual AEX performance over this timeframe was +5 %, above both the mean historic six-month performance and the mean expected value at $t = 1$. The change in the reported distribution is depicted in Figure 5. Overall, subjects became more optimistic, whereby the expected return increased by 0.64 percentage points on average. This is in line with the positive performance over the first half of the year. However, roughly 45 % of the subjects do not adjust their belief at all. The standard deviation slightly decreased by 0.33 percentage points.

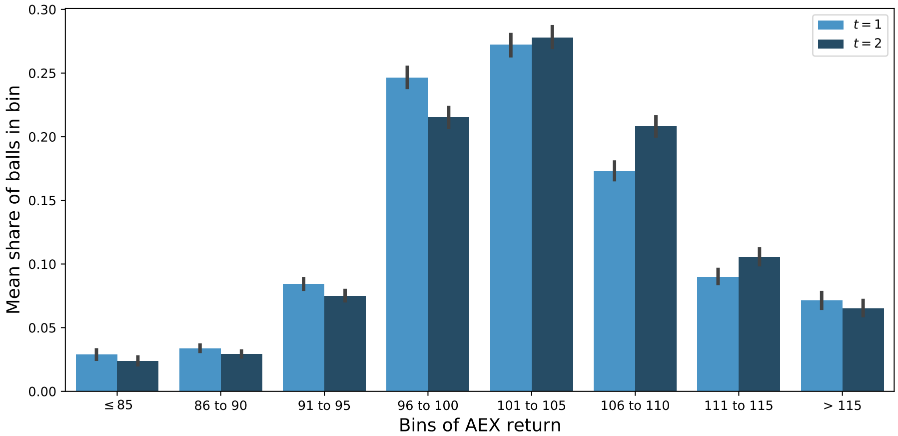

Figure 5. Mean share of balls in each bin in the first and second elicitation

Notes: The figure shows the average number of balls that are placed in each bin during the first (light blue) and second elicitation (dark blue). Bins correspond to the value of a EUR 100 investment in the AEX one year after it is invested. The black lines depict 95 % confidence intervals for each mean.

For the beliefs of the second elicitation, μ_2 and σ_2 are calculated in the same way as the equivalent parameters from time $t = 1$. Figure 6 shows the distribution of the difference between μ_2 and μ_1. The expected value increases for 40 % of the subjects and decreases for 16 % of the subjects. A large share of adjustments changed the expected value by no more than five percentage points, while 7 % of the subjects more strongly updated.

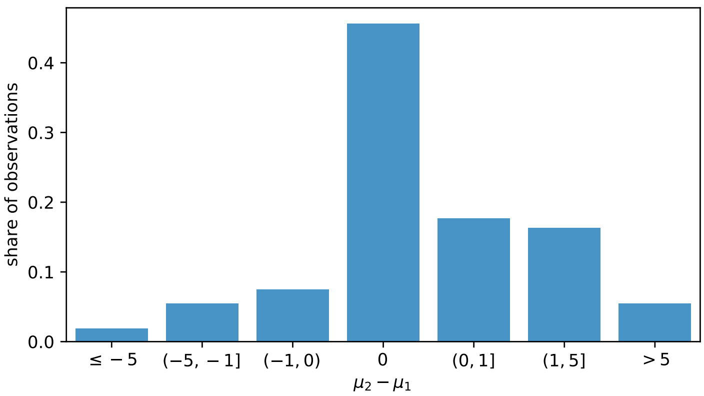

Figure 6. Distribution of changes in stock market expectations

Notes: The sample is split in seven groups based on the change in the respective expected value of stock market returns ($\mu_2 - \mu_1$). The respective numbers are shown in Table B.2 in the Online Appendix.

Next, I try to understand which subjects changed their beliefs and in which direction. Beliefs could have changed due to a variety of impressions and experiences that the individuals encountered during the six months. While these are mostly unobserved, I can look at the relation between changes and observed individual and household characteristics. In the first two columns in Table 5, I regress a binary variable indicating if the expected value is changed on several background variables. Not changing beliefs is associated with younger, less-educated, and low-numeracy subjects. High-educated and high-numeracy individuals might be more attentive to news about the stock market and therefore better able to adjust beliefs in response to such news. However, the low R-squared (0.07 in column 2) implies that only a small part of the changes systematically varies with observed characteristics. Most changes seem to be driven by other factors like the aforementioned individual specific experiences. In addition, some changes are likely also caused by measurement noise.

For the subset of participants who change their beliefs, I next look at the actual difference in expectations (Columns 3 and 4): high-income households tend to update their expected value more positively. Columns 5 and 6 reveal that less-educated households and those with negative wealth tend to increase the standard deviation of beliefs. In addition, a reversion to the mean can be detected for both belief parameters in the sense that subjects with a higher belief parameter at $t = 1$ are more likely to update downwards, and vice versa.[6]

5 Updating of beliefs and portfolio risk

The natural next question is how observed changes in beliefs translate to changes in portfolio risk. Figure 7 shows the mean change in the risky asset share for five bins of stock market expectation changes. The two groups with positive expectation changes also increase their risky asset share on average, by +0.4 percentage points for the group whose expectations increase by at most 3 percentage and +0.8 percentage points for the individuals who updated μ even more positively. The difference between the groups that updated their beliefs most positively and most negatively is significant at the 95 % level.

6. A different interpretation of beliefs in the second period would be to take the AEX return during the first six months into account when calculating the expected value over the second half only: if a subject expected +2 % during the first elicitation and did not change this response during the second elicitation, the implied expected value for the second part of the incentivized period is roughly −3 %, since the return so far was already +5 %. However, the data strongly suggests that participants do not give responses according to this interpretation. First, many people do not change their beliefs, which would be expected after the positive stock market development. Second, the distribution of expected values calculated as above would be strongly in the negative domain, and hence implausibly different from beliefs in the first period. An unrealistically high level of expected mean-reverting would be necessary to

Table 5. Updating of beliefs

	$\mu_2 \neq \mu_1$		$\mu_2 - \mu_1$		$\sigma_2 - \sigma_1$	
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	-0.000	-0.012	-0.472***	-0.477***		
	(0.013)	(0.014)	(0.057)	(0.059)		
σ_1	-0.006	0.007			-0.453***	-0.460***
	(0.013)	(0.014)			(0.059)	(0.060)
Female	-0.039	-0.002	0.057	0.081	0.045	0.022
	(0.028)	(0.030)	(0.049)	(0.055)	(0.047)	(0.050)
Age between 41 and 55	0.039	0.056	-0.030	0.001	-0.098	-0.093
	(0.046)	(0.049)	(0.083)	(0.093)	(0.069)	(0.077)
Age between 56 and 70	0.086*	0.118**	-0.094	-0.050	-0.011	-0.013
	(0.049)	(0.051)	(0.084)	(0.095)	(0.069)	(0.078)
Age above 70	0.080	0.118**	-0.053	-0.000	-0.070	-0.068
	(0.054)	(0.057)	(0.107)	(0.119)	(0.088)	(0.098)
Education: upper secondary	0.061*	0.037	0.037	0.003	-0.160***	-0.172***
	(0.035)	(0.036)	(0.073)	(0.079)	(0.062)	(0.066)
Education: tertiary	0.139***	0.092**	-0.006	-0.023	-0.256***	-0.259***
	(0.036)	(0.037)	(0.067)	(0.070)	(0.057)	(0.060)
Income between 1600 and 2500	0.029	0.024	0.205**	0.212**	-0.045	-0.021
	(0.039)	(0.040)	(0.083)	(0.086)	(0.067)	(0.073)
Income between 2500 and 3500	0.041	0.015	0.239***	0.254***	-0.054	-0.029
	(0.040)	(0.042)	(0.079)	(0.083)	(0.069)	(0.076)
Income above 3500	0.057	0.035	0.224***	0.240***	0.056	0.074
	(0.042)	(0.044)	(0.080)	(0.085)	(0.069)	(0.076)
Wealth below 0	0.004	0.025	0.020	-0.039	-0.180**	-0.183**
	(0.045)	(0.046)	(0.083)	(0.087)	(0.075)	(0.081)
Wealth between 50k and 200k	0.043	0.025	-0.004	-0.000	-0.046	-0.054
	(0.033)	(0.034)	(0.061)	(0.065)	(0.052)	(0.055)
Wealth above 200k	0.081**	0.041	-0.016	-0.029	-0.018	-0.013
	(0.038)	(0.039)	(0.067)	(0.072)	(0.062)	(0.066)
Financial numeracy		0.115***		0.076*		-0.031
		(0.014)		(0.040)		(0.037)
Risk aversion		0.010		-0.015		0.017
		(0.014)		(0.026)		(0.025)
N	1488	1357	809	742	809	742
R^2	0.033	0.072	0.371	0.376	0.415	0.423
Subset: $\mu_2 \neq \mu_1$	No	No	Yes	Yes	Yes	Yes
Household composition controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In the first two columns, the dependent variable is a dummy variable indicating whether the expected value changed at all. The next columns are restricted to those individuals who changed their beliefs. Columns 3 and 4 consider changes in μ and the final two columns consider changes in σ as the dependent variable. Robust standard errors in parentheses. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$

explain this. Hence, I only focus on the difference between first and second elicitation in the next section, as described above.

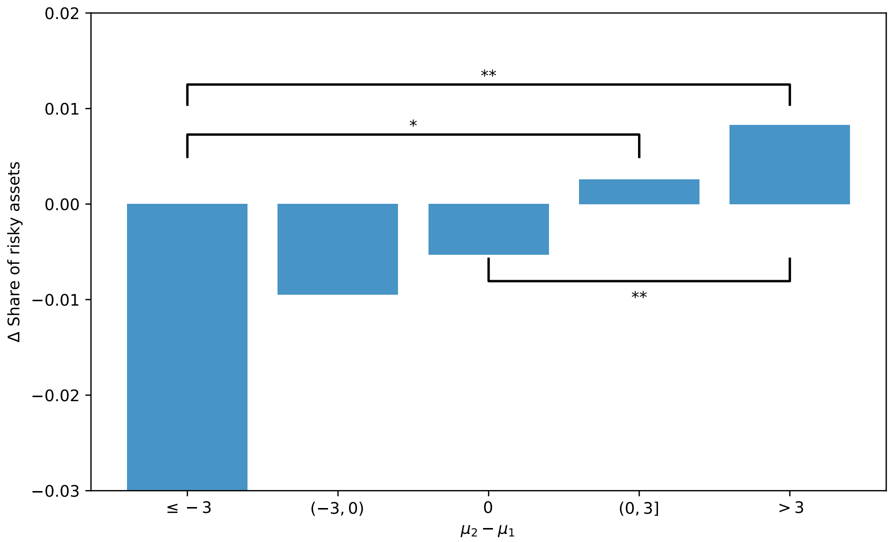

Figure 7. Changes in expectation and changes in portfolio risk

Notes: The changes in the expected value are grouped in five bins. The figure shows the mean change of the risky asset share for each bin. Brackets indicate significance levels between group means. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

Based on these observations, I run the following first difference regression:

$$a_{2014,i} - a_{2013,i} = \beta_0 + \beta_1 \left(\mu_{2,i} - \mu_{1,i}\right) + \beta_2 \left(\sigma_{2,i} - \sigma_{1,i}\right) + \beta \left(X_{2014,i} - X_{2013,i}\right) + \epsilon_i$$

The outcome variables are again measured at the end of 2013 and 2014, respectively. Most variables used as controls in the cross-section analysis are time-constant or only vary for very few households. Those are therefore left out and I control only for changes in household income and wealth. The changes of belief parameters are standardized based on the respective $t = 1$ distribution.

The results are presented in Table 6. The first three columns reveal that no statistically significant relation between changes in beliefs and the extensive margin of portfolio risk is detected (although the coefficient goes in the expected direction for μ). The belief changes over six months seem to be insufficient for most non-stockholders to start buying risky assets, or vice versa.

However, changes in the risky asset share are positively related to changes in the expected value. A one standard deviation increase in the expected values is associated with an increase of the risky share by 0.9 percentage points (column 4). The effect size does not change if I control for household income and wealth changes (column 5). A potential concern is that these effects could be driven by the few subjects who update their beliefs very strongly. I hence drop the 2.5 % strongest changes in μ and σ at both ends of the distribution in columns 6, altogether 124 individuals.

This leads to the coefficient for changes in μ increasing by 1.6 percentage points. To look separately at the intensive margin, the sample in the final three columns is restricted to households that hold risky assets in both periods. The coefficient is slightly higher than in the full sample, although it is only significant at the 10 % level due to lower sample size.

Increases in the standard deviation of beliefs again seem to have no effect on portfolio risk. For the share of risky assets, the coefficients tend to be even positive, although only statistically significant for the stockholder subset and at the 10 % level. When dropping the strongest updaters in column 6 and 9, the coefficient of σ becomes insignificant and negative. This suggests that the positive relations for the standard deviation are driven by outliers.

Finally, in Section D of the Online Appendix I again ensure that the results do not substantially change for a less restrictive sample selection and non-parametric belief parameter estimation. The results in this section strongly suggest that expectations are an important component of the decision of households concerning how much risk to take in their portfolio choice. When expectations increase, portfolio risk also tends to increase. This demonstrates that the relation found in cross-sectional data is not driven by any time-invariant third variable.

Table 6. Updating of beliefs and portfolio choice

	Δ Has risky financial assets			Δ Share of risky assets					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mu_2 - \mu_1$	0.010	0.010	0.011	0.009**	0.009**	0.016**	0.014*	0.014*	0.035
	(0.009)	(0.009)	(0.014)	(0.004)	(0.004)	(0.007)	(0.008)	(0.008)	(0.022)
$\sigma_2 - \sigma_1$	0.012	0.013	0.011	0.010	0.010	-0.005	0.032*	0.031*	-0.014
	(0.011)	(0.011)	(0.017)	(0.006)	(0.006)	(0.010)	(0.018)	(0.019)	(0.030)
Δ Income between 1600 and 2500		-0.021	-0.022		-0.012	-0.013		-0.003	-0.007
		(0.043)	(0.044)		(0.014)	(0.014)		(0.019)	(0.020)
Δ Income between 2500 and 3500		-0.015	-0.016		-0.001	-0.001		0.013	0.012
		(0.046)	(0.047)		(0.017)	(0.017)		(0.038)	(0.038)
Δ Income above 3500		0.020	0.024		0.002	0.008		0.015	0.023
		(0.047)	(0.048)		(0.020)	(0.021)		(0.050)	(0.052)
Δ Wealth below 0		-0.067**	-0.075**		-0.013	-0.014		-0.011	-0.011
		(0.033)	(0.036)		(0.015)	(0.017)		(0.061)	(0.060)
Δ Wealth between 50k and 200k		-0.002	-0.015		0.026	0.025		0.018	0.025
		(0.031)	(0.030)		(0.017)	(0.018)		(0.049)	(0.053)
Δ Wealth above 200k		0.014	0.003		0.019	0.017		0.013	0.010
		(0.038)	(0.038)		(0.028)	(0.028)		(0.074)	(0.076)
N	1489	1489	1365	1489	1489	1365	396	396	364
R^2	0.002	0.010	0.010	0.006	0.013	0.010	0.018	0.020	0.012
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes
Without strongest updaters	No	No	Yes	No	No	Yes	No	No	Yes

Notes: For the first three columns, the dependent variable is the difference between the end of 2014 and 2013 in the dummy indicating whether any risky assets are in the portfolio. The next columns use the change in the risky asset share. In the final three columns, the sample is restricted to those households that hold any risky assets in both years. In columns 3, 6, and 9, the 2.5 % strongest changes in μ and σ at both ends of the distribution are dropped. The changes in the expected value $\mu_2 - \mu_1$ and the standard deviation $\sigma_2 - \sigma_1$ of beliefs are standardized based on the respective $t = 1$ distribution. All variables except education, beliefs, numeracy, and risk aversion are based on administrative records. Robust standard errors in parentheses.
$* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$

6 Conclusion

This study shows that stock market expectations play a key role for the portfolio decision of households in a general population sample, while making two important contributions to the literature. First, I make use of administrative asset data complementing recent efforts to do so for samples of wealthy stockholders (e.g. Giglio et al., 2020). This is especially relevant as precedent analyses show substantial differences between self-reported asset data and administrative records. Second, I document that changes in beliefs over time are related to changes in portfolio risk. This analysis demonstrates that cross-sectional correlations between stock market expectations and portfolio risk are not driven by an unobserved time-invariant third variable. The effect size is substantial, whereby increasing the expected value by one standard deviation is associated with an increase in the share of risky assets by 1.5 percentage points. This corresponds to 15 % of the mean of the dependent variable and half of the effect size of risk aversion. In the analyses over time, the effect size is somewhat lower, at 0.9 percentage points.

The study suggests that stock market expectations are likely to be an important driver of portfolio choice for households, which should thus be taken into account in theoretical models of financial decision-making. Furthermore, it opens up the possibility of welfare-improving policy interventions that correct unrealistic stock market beliefs. In a more general sense, the results demonstrate that subjective beliefs can be reliably measured in surveys and are related to actual behavior. Subjective beliefs should also be used more often to understand decision-making in other contexts.

Similar to several earlier studies, I find no robust relationship between the standard deviation of belief and chosen portfolio risk. Disentangling the two interpretations of the standard deviation as perceived risk or perceived ambiguity about expectations would be very fruitful. Direct measures of perceived risk and/or perceived ambiguity could prove helpful in this matter. For a full understanding of different components of beliefs and related measures, it would be necessary to estimate a more complex decision model containing the expected value, standard deviation, risk aversion, and potentially ambiguity parameters.

I do not account for measurement error in the belief elicitation. Although strong care is taken to keep the elicitation procedure comprehensible for the heterogeneous subject pool and choices are incentivized, it is indisputable that some measurement error is present, which means that the coefficients found in the analysis represent a lower bound. More than two independent elicitations of beliefs would help to differentiate true beliefs from measurement noise and obtain more precise estimates.

For future research, it will be relevant to examine the causal effect of changes in expectations. This will require (quasi-)experimental variation of beliefs as studied by Laudenbach, Weber, and Wohlfart (2020) for a sample of stockholders.

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Appendix A Belief elicitation

This appendix provides more information about the distribution of stock market beliefs, the estimation of the belief parameters, and correlations between beliefs and demographic variables.

Figure A.1 shows the mean share of balls in each bin. As also noted by Drerup, Enke, and von Gaudecker (2017), the belief distributions are rather pessimistic compared with empirical frequencies. This is also found by Hurd (2009). Besides, the probability mass in the tail events is much lower than empirically observed (see Figure A.1).

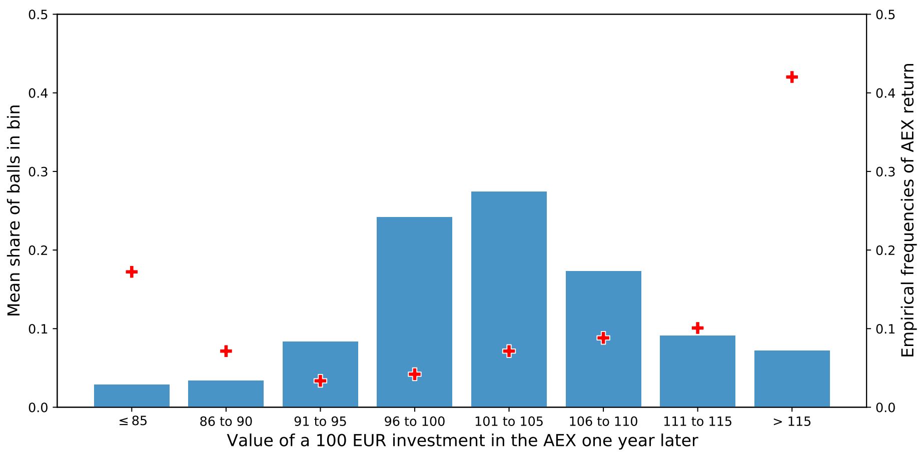

Figure A.1. Mean share of balls in each bin during the first elicitation

Notes: Subjects are asked for the value of a EUR 100 investment in the AEX in one year, including a fee of EUR 0.30. The red crosses depict historical frequencies calculated based on the yearly performance in each month between October 1992 and July 2013.

When analyzing the relation of beliefs and portfolio choice, I make use of the expected value (μ_1) and the standard deviation (σ_1) of the elicited distribution. These values are obtained by fitting a log-normal distribution. In particular, I minimize the sum of squared errors between the cumulative distribution function of a log-normal distribution with parameters $\widehat{\mu}_1$ and $\widehat{\sigma}_1$ and the observed cumulative distribution function

$$\min_{\widehat{\mu}_1,\widehat{\sigma}_1} \sum_i \left(\Phi\left(\frac{\ln(x_i) - \widehat{\mu}_1}{\widehat{\sigma}_1}\right) - F^{obs}(x_i)\right)^2 \tag{A.1}$$

where Φ is the cumulative distribution function of the standard normal distribution and the x_i are the thresholds of the bins (0.85, 0.9, ...). The expected value and standard deviation of the estimated distribution are obtained by

$$
\begin{aligned}
\mu_1 &= \exp\left(\widehat{\mu}_1 + \frac{\widehat{\sigma}_1^2}{2}\right) && \text{(A.2)} \\
\sigma_1 &= \sqrt{\left(\exp\left(\widehat{\sigma}_1^2\right) - 1\right)\exp\left(2\widehat{\mu}_1 + \widehat{\sigma}_1^2\right)} && \text{(A.3)}
\end{aligned}
$$

Figure A.2 displays the distribution of beliefs and the estimated parameters for 15 random participants.

Figure A.3 shows the joint distribution together with histograms for each parameter. While the distribution of μ_1 is roughly normally distributed, the distribution of σ_1 has a substantial mass at values close to zero and a large right tail.

Table A.1 shows the relation of stock market beliefs and demographics. Subjects with higher μ_1 tend to be male, went to university, have a higher numeracy, and a lower risk aversion. On the other hand, a lower σ_1 is associated with unmarried couples and high-numeracy subjects. These findings align well with previous studies (e.g. Manski, 2004; Hurd, 2009).

Table A.1. Stock market beliefs

	μ_1		σ_1	
	(1)	(2)	(3)	(4)
Female	-0.313***	-0.208***	0.074	0.033
	(0.051)	(0.056)	(0.052)	(0.056)
Couple	-0.043	-0.049	-0.104	-0.209**
	(0.086)	(0.091)	(0.088)	(0.093)
Married	0.034	0.059	0.103	0.199**
	(0.079)	(0.083)	(0.083)	(0.088)
Has children at home	0.030	0.031	-0.053	-0.019
	(0.061)	(0.064)	(0.064)	(0.065)
Age between 41 and 55	0.075	0.078	0.022	0.093
	(0.074)	(0.083)	(0.078)	(0.087)
Age between 56 and 70	0.043	0.041	-0.054	-0.043
	(0.085)	(0.093)	(0.086)	(0.093)
Age above 70	-0.113	-0.030	-0.078	-0.050
	(0.102)	(0.114)	(0.102)	(0.114)
Education: upper secondary	0.105	0.070	-0.062	-0.071
	(0.068)	(0.072)	(0.070)	(0.076)
Education: tertiary	0.239***	0.153**	-0.082	-0.044
	(0.065)	(0.070)	(0.065)	(0.069)
Income between 1600 and 2500	0.008	0.020	-0.006	0.012
	(0.074)	(0.081)	(0.080)	(0.088)
Income between 2500 and 3500	0.070	-0.004	-0.025	-0.033
	(0.073)	(0.081)	(0.079)	(0.086)
Income above 3500	0.143*	0.123	-0.094	-0.107
	(0.077)	(0.085)	(0.080)	(0.089)
Wealth below 0	0.122	0.155*	0.052	0.033
	(0.080)	(0.090)	(0.077)	(0.085)
Wealth between 50k and 200k	0.005	-0.009	-0.068	-0.052
	(0.062)	(0.066)	(0.063)	(0.067)
Wealth above 200k	0.084	0.058	-0.054	-0.033
	(0.073)	(0.079)	(0.077)	(0.083)
Financial numeracy		0.106***		-0.113***
		(0.026)		(0.030)
Risk aversion		-0.121***		-0.051
		(0.030)		(0.031)
N	1718	1482	1718	1482
R^2	0.059	0.079	0.009	0.027

Notes: Dependent variables are the belief parameters. The expected value is used in the first two columns and the standard deviation in the last two. All variables except education, beliefs, numeracy, and risk aversion are based on administrative records. Robust standard errors in parentheses.
* $-$ $p < 0.1$, ** $-$ $p < 0.05$, *** $-$ $p < 0.01$

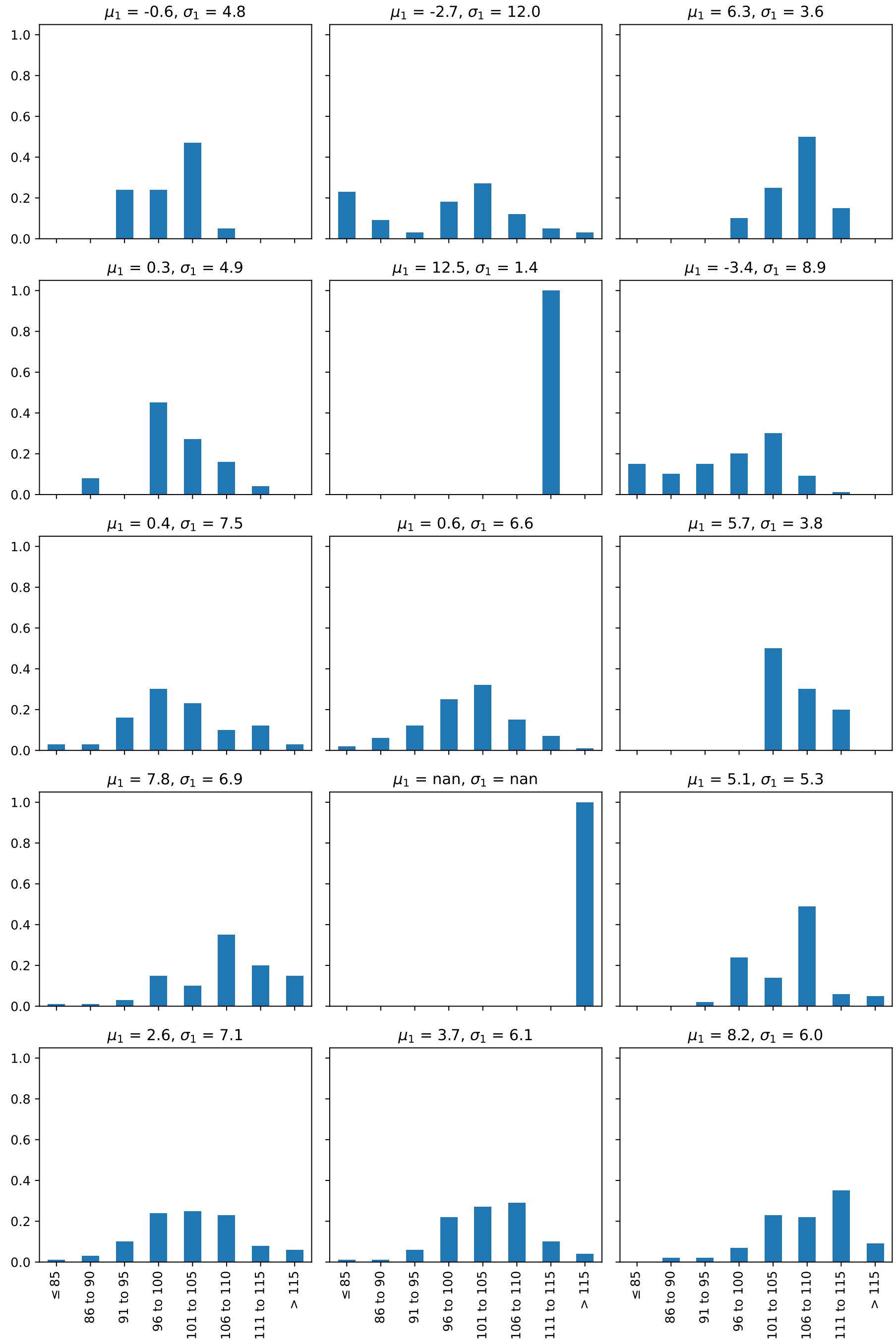

Figure A.2. Distribution of beliefs and estimated parameters for 15 random participants

Notes:

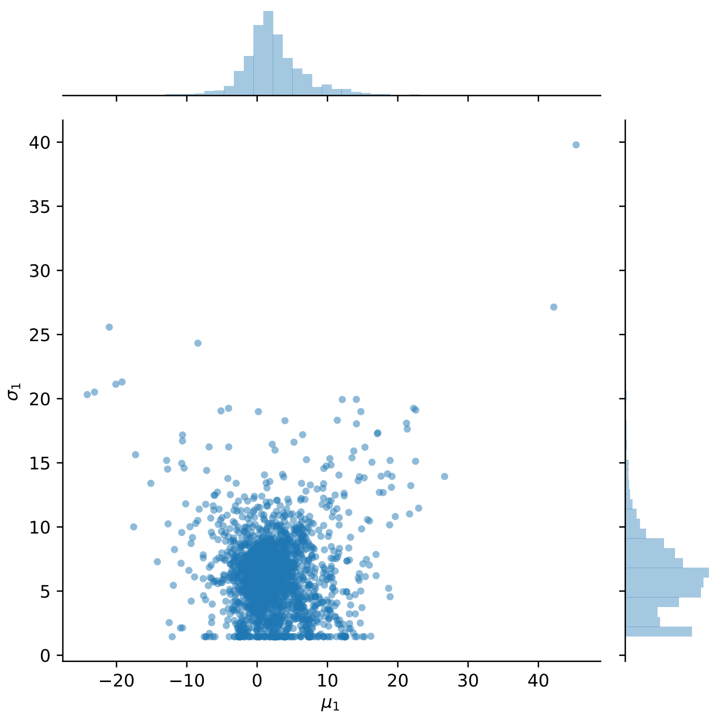

Figure A.3. Joint distribution of belief parameters

Notes: On the top and the right of the scatter plot are the histograms of the respective marginal distributions. Sample: Participants with at most 80 balls in the two outer bins.

Appendix B Main results

Table B.1. Portfolio choice and stock market beliefs

	Has risky financial assets			Share of risky assets					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.289***	0.078*	0.044	0.100***	0.014	-0.014	0.342***	0.277***	0.192***
	(0.011)	(0.048)	(0.054)	(0.005)	(0.023)	(0.025)	(0.013)	(0.070)	(0.074)
μ_1	0.065***	0.045***	0.035***	0.028***	0.021***	0.015***	0.017	0.023*	0.013
	(0.012)	(0.011)	(0.012)	(0.005)	(0.005)	(0.006)	(0.012)	(0.013)	(0.014)
σ_1	-0.024*	-0.008	0.000	-0.007	-0.002	0.000	0.003	0.001	0.001
	(0.014)	(0.013)	(0.014)	(0.008)	(0.007)	(0.007)	(0.016)	(0.016)	(0.017)
Female		-0.047**	-0.015		-0.012	0.001		0.008	0.031
		(0.022)	(0.024)		(0.011)	(0.012)		(0.028)	(0.033)
Couple		-0.018	0.008		-0.027	-0.025		-0.074	-0.101*
		(0.039)	(0.043)		(0.019)	(0.020)		(0.053)	(0.055)
Married		0.006	-0.017		0.006	0.009		0.003	0.048
		(0.038)	(0.041)		(0.018)	(0.019)		(0.048)	(0.050)
Has children at home		0.032	0.019		0.003	0.000		-0.017	-0.015
		(0.028)	(0.029)		(0.013)	(0.013)		(0.034)	(0.035)
Age between 41 and 55		0.092***	0.098**		0.060***	0.063***		0.119**	0.132***
		(0.035)	(0.039)		(0.016)	(0.017)		(0.047)	(0.049)
Age between 56 and 70		0.008	0.029		0.020	0.035*		0.084*	0.112**
		(0.038)	(0.041)		(0.017)	(0.018)		(0.051)	(0.053)
Age above 70		0.070*	0.091**		0.057***	0.070***		0.141**	0.162**
		(0.041)	(0.045)		(0.020)	(0.021)		(0.061)	(0.064)
Education: upper secondary		0.023	0.015		-0.006	-0.007		-0.064	-0.063
		(0.028)	(0.030)		(0.013)	(0.014)		(0.039)	(0.044)
Education: tertiary		0.125***	0.128***		0.048***	0.054***		0.010	0.025
		(0.030)	(0.033)		(0.015)	(0.016)		(0.039)	(0.043)
Income between 1600 and 2500		0.004	0.022		-0.004	0.009		-0.040	-0.003
		(0.029)	(0.031)		(0.014)	(0.015)		(0.046)	(0.048)
Income between 2500 and 3500		0.004	0.008		0.001	0.006		-0.014	-0.000
		(0.031)	(0.034)		(0.016)	(0.016)		(0.045)	(0.047)
Income above 3500		0.045	0.035		0.005	0.009		-0.035	-0.019
		(0.033)	(0.036)		(0.016)	(0.017)		(0.043)	(0.046)
Wealth below 0		0.016	0.016		0.037**	0.040**		0.131**	0.153**
		(0.034)	(0.038)		(0.017)	(0.019)		(0.054)	(0.060)
Wealth between 50k and 200k		0.123***	0.126***		0.044***	0.050***		0.026	0.053
		(0.025)	(0.027)		(0.011)	(0.012)		(0.038)	(0.041)
Wealth above 200k		0.344***	0.314***		0.148***	0.125***		0.078*	0.070
		(0.032)	(0.034)		(0.017)	(0.017)		(0.041)	(0.044)
Financial numeracy			0.018			0.001			-0.010
			(0.011)			(0.006)			(0.024)
Risk aversion			-0.044***			-0.029***			-0.053***
			(0.012)			(0.006)			(0.016)
N	1720	1718	1482	1720	1718	1482	501	500	425
R^2	0.021	0.138	0.137	0.016	0.107	0.112	0.004	0.073	0.102
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes

Notes: Full version of Table 4. Robust standard errors in parentheses.
$* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$

Table B.2. Distribution of changes in expectations

≤ -5	$(-5, -1]$	$(-1, 0)$	0	$(0, 1]$	$(1, 5]$	> 5
0.019	0.055	0.075	0.456	0.177	0.163	0.055

Notes: Shows numbers depicted in Figure 6

Appendix C Relations of portfolio risk, wealth, and demographics based on self-reported and administrative data

In this section, I document differences between self-reported and administrative asset data. I start by describing the elicitation method of asset data in the LISS panel. I then focus on item non-response analyzing the magnitude and how it is related to individual characteristics. For households for which both self-reported and administrative data is available, I then look at the difference between the two measures, which I interpret as response error. Next, basic regressions including asset data and demographic variables are compared for both data sets.

C.1 Self-reported asset data

Asset data in the LISS panel are elicited every other year. I employ the wave that was collected in October and November 2014. The subjects are asked about their financial and non-financial assets, as well as their debts on December 31, 2013, the same date on which the administrative data is based.[7]

For each asset class (e.g. safe financial assets), subjects are first asked whether they possess any assets of this category. In a second step, they are asked for the total balance on all accounts of this category. If they refuse or are unable to answer, they are presented a list of intervals and asked to select the bin in which the total value most likely falls. In case the subject refuse to answer again, the item is classified as missing; otherwise, I use the midpoint of the interval as the response value. The asset classes are then aggregated such that—for instance—total financial assets comprises safe and risky financial assets and wealth comprises financial assets plus non-financial assets minus debts. Every household member aged 16 years or older is asked for their personal assets. Additionally, the self-reported financial decider of the household is asked to enter the joint assets of the household. The household definition in the LISS is comparable to the administrative data. However, in a few households, not all members participate in the survey. For each household, I aggregate the individual LISS asset data based on the CBS household composition data and use the CBS equivalence scale to standardize all financial variables. This is done to ensure that observed differences in asset data are driven by the individual responses of the household members and the effect of differences in observed household composition is minimized. A household-level financial variable is missing if either no household member filled out the questionnaire or if one of the household members entered an invalid response.

All mentioned asset variables contained in the administrative records are also available in the survey data, including the split between safe and risky financial

7. Note that one wealth component—owner-occupied housing wealth and the respective mortgages—is elicited in a separate questionnaire, also administered in October and November 2014.

assets. Hence, I construct a second set of data that is solely based on survey information, which can be used to compare administrative and self-reported measures (see Table C.1)

Table C.1. Survey dataset

	Observations	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$
Female	1183	0.41				
Couple	1183	0.69				
Married	1183	0.60				
Has children at home	1183	0.29				
Education: lower secondary and below	1138	0.26				
Education: upper secondary	1138	0.31				
Education: tertiary	1138	0.43				
Age	1183	59.13	14.96	37	61	77
Gross income (thousands)	1167	2.63	1.57	1.13	2.38	4.26
Financial assets (thousands)	1183	53.89	260.02	2.58	18.25	109.71
Wealth	973	168.94	399.81	2.39	92.21	399.33
Has risky financial assets	1183	0.24				
Share risky assets	1183	0.10	0.22	0	0	0.42

Notes: All variables are based on the LISS survey.

C.2 Difference between self-reported and administrative asset data

Deviations in self-reported asset data may bias estimates of the drivers of portfolio risk in at least two ways. First, measurement error of portfolio risk can lead to a bias if it is non-standard, i.e. if it is correlated with either correlated the true value or with other variables of interest. Second, a high share of missing observations can be problematic if the non-response is not randomly distributed. In this case, the estimated relation could be different from the population of interest whenever wealth is added as an important control variable.

The analysis in this section is based on the sample of subjects that participated in the belief elicitation and can be linked to administrative records. In contrast to the later analysis, households with financial assets below EUR 1,000 are not excluded.

Income data are frequently log-transformed to—among others—reduce the effect of outliers. This proves difficult for asset variables as the logarithm is only defined for strictly positive values and wealth is negative for a substantial share of the population. To circumvent this problem, I make use of the inverse hyperbolic sine transformation $\left(\text{ihs}(x) = \ln\left(x + \sqrt{x^2+1}\right)\right)$ (see e.g. Pence, 2006; Bellemare and Wichman, 2020). The ihs transformation is similar to the natural logarithm for positive values in the sense that it approximates $\ln(2x)$, but allows for zero values ($\text{ihs}(0) = 0$) and—in case of the wealth variable—even negative values (where it approximates $-\ln(-2x)$).

C.2.1 Non-response. A well-known characteristic of survey data is non-response to particular items or a whole questionnaire. For simplicity, I do not differentiate between the two in the following. Table C.2 shows the number of missing observations for several asset variables. Information about financial assets is missing for 28 % of the sample. Wealth—which includes financial assets, non-financial assets like housing, and debts—is missing for even 41 % of the sample. By contrast, observations for labor income are available for almost all subjects as this variable is part of the background data set of the LISS, which is asked every month.

Table C.2. Missing observations for asset variables and income

		Present in LISS	Missing in LISS	Difference
		(1)	(2)	(3)
Wealth	Observations	1107	770	
	Mean	8.901	6.638	-2.263
		(0.226)	(0.336)	(0.405)
Total fin. assets	Observations	1383	501	
	Mean	10.262	10.190	-0.072
		(0.051)	(0.087)	(0.101)
Debts	Observations	1350	534	
	Mean	7.259	10.190	2.931
		(0.157)	(0.191)	(0.247)
Has rfa	Observations	1695	192	
	Mean	0.260	0.406	0.146
		(0.011)	(0.036)	(0.038)
Share rfa	Observations	1289	587	
	Mean	0.101	0.086	-0.015
		(0.006)	(0.009)	(0.011)
Income	Observations	1837	47	
	Mean	8.385	8.242	-0.143
		(0.027)	(0.111)	(0.114)

Notes: The first row for each variable shows the number of observations that are non-missing and missing in the LISS panel. 'rfa' stands for risky financial assets. The second row reports the mean according to CBS data in the two respective groups and the difference in the final column. Standard errors are in parentheses. Different total number of observations for the variables stem from missing observations in the CBS data. All variables except the portfolio risk variables (has rfa and share rfa) are ihs-transformed.

Concerning the later analyses, non-response leads to no bias if it is randomly distributed. In this case, only the power to detect relations between variables is reduced. By contrast, non-response that is correlated with observed or unobserved characteristics, makes the obtained results unrepresentative of the population of interest, which potentially leads to biased estimates. Comparing the means (based on CBS data) between observations that are missing and non-missing in the LISS reveals that a bias exists for several variables. For wealth, LISS respondents are substantially and significantly richer (ihs(wealth) = 8.9) than the missing sample (ihs(wealth) $= 6.6$), which implies that poor households are less likely to report complete wealth data. Furthermore, households with more debt or with risky financial assets are less likely to report the respective quantity. One reason for this finding could be that truthfully reporting a zero is trivial, while filling out the respective questionnaire is more demanding when people have substantial wealth of a specific category.

Since wealth is an aggregate of the other asset variables, wealth is missing whenever any other asset variable is missing. Hence, I focus on missing wealth observations and examine in Table C.3 which other observed characteristics of the households are related to it. The first column reveals that negative wealth is highly predictive of missing self-reported wealth. In columns 2 and 3, it is shown that older, more educated, and high-numeracy households are substantially more likely to report wealth information. The hypothesis of random non-response can be rejected (p-value < 0.001 for F-test). The R^2 for the full set of covariates is 0.081, which indicates that they explain a substantial part of the observed variation. However, importantly missing wealth information is not related to holding risky assets.

Bollinger, Hirsch, Hokayem, and Ziliak (2019) analyze non-response of self-reported income and find a U-pattern in non-response with higher non-reporting at both tails of the income distribution. While I can replicate this finding for wealth data at the lower tail, I do not find evidence of increased non-reporting of rich households. This does not change when I look at more than four wealth groups (not shown).

Note that the high rate of missing values for the wealth variable is partly a result of my strict way of aggregating the individual survey responses in the household. In case a household member reports that they possess a certain asset class but refuses to say how much, this variable is set to missing for the whole household. Under a relaxed policy in which the responses of the remaining household members were used instead, the missing rate would be lower, but the mean of the wealth variable would also be lower. This trade-off between sample size and accuracy is typical when working with self-reported data.

C.2.2 Response error. Next, I focus on households that respond to the survey and focus on the difference between self-reported and administrative quantities, which I interpret as response error.[8]

Under the assumption of classical measurement error, response error in the dependent variable does not introduce a bias (despite lowering the power), but error in an independent variable gives rise to attenuation bias. These well-known results do not apply if the measurement error is correlated with the true value or with

8. It seems intuitive that most reasons for measurement error in survey data do not apply to administrative records as most components are directly reported by banks and it would be a criminal offense for a household to hide part of their wealth.

Table C.3. Missing wealth information and individual characteristics

	Missing wealth obs.		
	(1)	(2)	(3)
Has risky financial assets	0.021	0.023	0.025
	(0.027)	(0.027)	(0.028)
Couple		0.009	0.026
		(0.042)	(0.044)
Married		0.003	-0.001
		(0.041)	(0.042)
Has children at home		0.002	0.013
		(0.030)	(0.031)
Age between 41 and 55		-0.031	-0.034
		(0.039)	(0.043)
Age between 56 and 70		-0.208***	-0.184***
		(0.040)	(0.044)
Age above 70		-0.238***	-0.241***
		(0.046)	(0.049)
Education: upper secondary		-0.051*	-0.018
		(0.030)	(0.031)
Education: tertiary		-0.127***	-0.084***
		(0.030)	(0.032)
Income between 1600 and 2500		-0.031	0.013
		(0.033)	(0.034)
Income between 2500 and 3500		-0.021	0.044
		(0.034)	(0.035)
Income above 3500		0.022	0.092**
		(0.035)	(0.038)
Wealth below 0	0.159***	0.093**	0.062
	(0.035)	(0.037)	(0.040)
Wealth between 50k and 200k	-0.023	0.009	0.015
	(0.029)	(0.029)	(0.030)
Wealth above 200k	-0.039	0.030	0.023
	(0.034)	(0.035)	(0.036)
Financial numeracy			-0.082***
			(0.013)
Risk aversion			-0.001
			(0.012)
N	1884	1882	1617
R^2	0.019	0.056	0.081

Notes: The dependent variable is a dummy that indicates if the wealth variable is missing in the survey data set. Robust standard errors in parentheses. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

other variables. In this general case, response error in the dependent variable can also introduce a bias. For example, this is the case if the measurement error of the dependent variable is mean-reverting or correlated with the independent variable of interest. See e.g. Bound, Brown, Duncan, and Rodgers (1994) for a more extensive discussion.

Table C.4 reports some statistics regarding the response error of several variables. Columns 2 and 3 reveal that there are large deviations between self-reported and administrative data. While 21 % of subjects report wealth that is more than 20 % below the administrative quantity, 47 % of respondents deviate upwards by more than 20 %. Both measures of portfolio risk tend to be rather reported too low than too high: about 10 % of the sample falsely report not having any risky assets, while only 2 % deviate in the other direction.

Table C.4. Response error

	N	Share rel. dev. $< -20\,\%$	Share rel. dev. $> 20\,\%$	Mean CBS	Mean LISS	Mean dev.	Corr. b/w dev. and CBS	λ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wealth	1107	0.205	0.47	8.901	9.522	0.621	-0.538	0.69
				(0.226)	(0.202)	(0.189)		
Total fin. assets	1383	0.395	0.262	10.262	9.388	-0.874	-0.039	0.271
				(0.051)	(0.095)	(0.082)		
Debts	1350	0.161	0.107	7.259	6.559	-0.699	-0.237	0.8
				(0.157)	(0.162)	(0.093)		
Has rfa	1695	0.104	0.021	0.260	0.177	-0.083	-0.546	0.757
				(0.011)	(0.009)	(0.008)		
Share rfa	1289	0.137	0.08	0.101	0.093	-0.008	-0.405	0.657
				(0.006)	(0.006)	(0.005)		
Income	1837	0.317	0.068	8.385	8.194	-0.192	-0.275	0.574
				(0.027)	(0.031)	(0.024)		

Notes: The first column shows the number of observations that are non-missing in the LISS data set. Columns 2 and 3 report the share of observations for which the relative deviation ($\frac{a^{LISS}-a^{CBS}}{|a^{CBS}|}$) (using untransformed values) is below -20 % and above 20 %, respectively. Division by a zero value is thereby treated as ∞ if the numerator is positve and $-\infty$ if it is negative. The next columns show the mean of the administrative variable, the mean of the survey variable and the mean of the individual response error. The respective standard errors are in parentheses. The final columns report the correlation coefficient between response error and administrative value and the reliability index λ introduced in equation C.1. All variables except the portfolio risk variables (has rfa and share rfa) are ihs-transformed.

The next columns report the mean of the administrative variable, the survey variable, and the individual response error. The respective standard errors are shown in parentheses. The mean response error is significantly different from 0 for all variables except the risky asset share. Financial assets, income, and debts are underreported, with the latter leading to wealth being overreported. The underreporting of debts has also been found by earlier studies (Karlan and Zinman, 2008; Brown, Haughwout, Lee, and van der Klaauw, 2011). Strikingly, the share of subjects that report having any risky assets is just 0.18 while this share is 0.26 for the CBS data.

A substantial share of subjects do not report the risky assets that they possess. Note that for the sample with total financial assets exceeding EUR 1,000 that is used for the main analysis later, the difference is much smaller (0.29 vs 0.24). The difference for the risky asset share is not significant, indicating that risky assets are not underreported over the full distribution, but rather that some individuals falsely claim not to have any risky financial assets. This interpretation is confirmed by Table C.6.

To understand the potential bias introduced by response error, the penultimate column in Table C.4 shows the correlation coefficient between the response error and the administrative quantity. The response error is strongly mean-reverting for all variables except total financial assets, meaning that households with a high value tend to underreport while households with a low value tend to overreport. Note that for the portfolio risk variables, this effect is mechanical since a dummy variable can—at the individual level—only deviate in one direction.

In the final column of Table C.4, the reliability

$$\lambda = \frac{\operatorname{cov}\left(X_j^{\text{Admin}}, X_j^{\text{Survey}}\right)}{\operatorname{Var}\left(X_j^{\text{Survey}}\right)} \tag{C.1}$$

is shown for each variable. Thereby, $1-\lambda$ is a measure of the attenuation bias introduced when this variable is used as an independent variable (Bound and Krueger, 1991). The reliability of wealth is 0.69, slightly above the reliability of household income.

Finally, we look at how these differences are related to other characteristics of the households. Table C.5 shows for wealth and the risky asset share the regression of the response error and the absolute value of it. For wealth, the error is higher (not in absolute terms) for households with risky assets, old respondents, and subjects with high numeracy. However, the strongest effect is that households with negative wealth tend to deviate upwards on average.[9] Response error for reporting any risky assets is positively related with high-income households, as well as high-numeracy and low risk aversion subjects (not shown). Conversely, for the risky asset share, no strong predictors for response error can be found (an F-test reveals that the variables other than the dummy 'has risky financial assets' are not jointly significant; p-value=0.129). Having strictly negative wealth predicts an increase in the absolute value of risky asset share response error, albeit which can be expected as a lower level of financial assets leads to more variation of the risky asset share over time.

9. The strong effect of having strictly negative wealth is supported by the ihs transformation, since deviations towards zero lead to a higher response error than deviations of the same untransformed value away from zero. However, when using a different metric that values deviations in both directions equally, the relative deviation ($\frac{a^{LISS}-a^{CBS}}{|a^{CBS}|}$), the results do not change (not shown).

Table C.5. Response error and individual characteristics

	|Dev. ihs(wealth)|	Dev. ihs(wealth)	|Dev. share rfa|	Dev. share rfa
	(1)	(2)	(3)	(4)
Has risky financial assets	0.606*	0.761**	0.150***	-0.093***
	(0.360)	(0.366)	(0.014)	(0.016)
Couple	1.950**	-0.453	0.012	-0.004
	(0.830)	(0.861)	(0.018)	(0.021)
Married	-2.168***	0.186	-0.013	0.015
	(0.812)	(0.849)	(0.018)	(0.021)
Has children at home	1.065**	-0.032	0.024*	0.017
	(0.502)	(0.521)	(0.013)	(0.014)
Age between 41 and 55	-0.419	0.954	-0.012	-0.039*
	(0.906)	(0.930)	(0.019)	(0.021)
Age between 56 and 70	-0.159	2.190**	-0.011	-0.017
	(0.851)	(0.863)	(0.017)	(0.020)
Age above 70	0.157	2.119**	0.007	-0.033
	(0.872)	(0.890)	(0.019)	(0.021)
Education: upper secondary	-0.253	0.166	0.016	0.010
	(0.375)	(0.388)	(0.012)	(0.014)
Education: tertiary	-0.406	-0.539	-0.008	0.011
	(0.370)	(0.382)	(0.012)	(0.013)
Income between 1600 and 2500	0.405	-0.346	-0.015	-0.003
	(0.452)	(0.480)	(0.013)	(0.015)
Income between 2500 and 3500	-0.201	0.133	-0.011	-0.007
	(0.446)	(0.463)	(0.015)	(0.017)
Income above 3500	-0.091	0.150	-0.001	0.028
	(0.485)	(0.507)	(0.016)	(0.018)
Wealth below 0	8.107***	11.476***	0.049***	-0.006
	(0.914)	(0.930)	(0.018)	(0.020)
Wealth between 50k and 200k	-0.689*	-0.654	0.006	0.006
	(0.387)	(0.411)	(0.010)	(0.011)
Wealth above 200k	-1.285***	-0.648	0.010	0.004
	(0.391)	(0.412)	(0.014)	(0.016)
Financial numeracy	-0.175	0.672***	-0.008	0.009
	(0.228)	(0.233)	(0.006)	(0.007)
Risk aversion	-0.019	-0.268*	-0.001	-0.005
	(0.144)	(0.149)	(0.005)	(0.005)
N	1060	1060	1208	1208
R^2	0.284	0.348	0.180	0.070

Notes: The dependent variable is the difference between the self-reported and administrative value. In columns 1 and 3, the respective absolute value is used as a dependent variable. Robust standard errors in parentheses. $* - p < 0.1$, $** - p < 0.05$, $*** - p < 0.01$

In summary, for the variables that I will use in the subsequent analysis, strong deviations between survey and administrative data can be found: the wealth variable is missing for a large share of respondents, most strongly for respondents with negative wealth. Furthermore, those low-wealth households that do respond over-report their wealth and the response error of the wealth variable is clearly not exogenous to other variables. However, the measures of portfolio risk are unrelated to asset variables being missing. Having any risky assets is in the full sample strongly underreported and related to other characteristics of the household. On the other hand, the share of risky assets is very similar over the data sets and the individual measurement error seems to be unrelated to other variables.

Table C.6 reports differences between self-reported and administrative data in more detail and for more variables.

Table C.6. CBS data, LISS data, difference between the data sets

		N	Mean	Std. dev.	$q_{0.1}$	$q_{0.5}$	$q_{0.9}$	share equals to 0
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Risky fin. assets	CBS	1884	2.648	4.499	0	0	10.546	0.725
	CBS (LISS sample)	1692	2.509	4.405	0	0	10.394	0.741
	CBS (missing)	192	3.873	1.163				
	LISS	1692	1.799	3.957	0	0	9.965	0.824
	LISS - CBS	1692	-0.710	3.236	-3.801	0	0	0.732
Save fin. assets	CBS	1884	10.066	1.878	7.877	10.337	12.001	0.006
	CBS (LISS sample)	1386	10.080	1.870	7.918	10.341	11.997	0.006
	CBS (missing)	498	10.027	1.902				
	LISS	1386	9.206	3.583	6.305	10.151	11.939	0.058
	LISS - CBS	1386	-0.874	3.091	-3.061	-0.087	0.927	0.009
Total fin. assets	CBS	1884	10.243	1.918	8.051	10.479	12.294	0.006
	CBS (LISS sample)	1383	10.262	1.904	8.094	10.476	12.278	0.006
	CBS (missing)	501	10.190	1.958				
	LISS	1383	9.388	3.542	6.377	10.282	12.16	0.056
	LISS - CBS	1383	-0.874	3.063	-2.993	-0.09	0.789	0.007
Debts	CBS	1884	8.089	5.569	0	11.492	12.821	0.305
	CBS (LISS sample)	1350	7.259	5.757	0	10.97	12.742	0.368
	CBS (missing)	534	10.190	4.417				
	LISS	1350	6.559	5.965	0	10.505	12.714	0.444
	LISS - CBS	1350	-0.699	3.435	-2.448	0	0.225	0.475
Wealth	CBS	1884	7.968	8.389	-10.321	11.686	13.409	0
	CBS (LISS sample)	1107	8.901	7.526	-9.329	11.85	13.445	0
	CBS (missing)	770	6.638	9.330				
	LISS	1107	9.522	6.723	0	11.972	13.527	0.014
	LISS - CBS	1107	0.621	6.279	-1.179	0.155	1.814	0.001
Has rfa	CBS	1887	0.275	0.447	0	0	1	0.725
	CBS (LISS sample)	1695	0.260	0.439	0	0	1	0.74
	CBS (missing)	192	0.406	0.492				
	LISS	1695	0.177	0.382	0	0	1	0.823
	LISS - CBS	1695	-0.083	0.343	-1	0	0	0.876
Share rfa	CBS	1876	0.096	0.218	0	0	0.417	0.723
	CBS (LISS sample)	1289	0.101	0.219	0	0	0.424	0.706
	CBS (missing)	587	0.086	0.216				
	LISS	1289	0.093	0.220	0	0	0.413	0.774
	LISS - CBS	1289	-0.008	0.181	-0.086	0	0.023	0.683
Income	CBS	1884	8.382	1.155	7.727	8.549	9.178	0.013
	CBS (LISS sample)	1837	8.385	1.163	7.733	8.552	9.181	0.013
	CBS (missing)	47	8.242	0.764				
	LISS	1837	8.194	1.332	7.533	8.409	8.995	0.02
	LISS - CBS	1837	-0.192	1.044	-0.44	-0.142	0.077	0.009

Notes: Summary statistics for different samples of several asset and wealth variables: CBS data, CBS data of all households with non-missing observations in the LISS, CBS data of all households that are missing in the LISS, LISS data, individual difference between LISS and CBS data. The final column reports the share of observations that are equal to 0.

C.3 Explaining self-reported wealth and portfolio risk

In Table C.7, I look at the relationship between wealth and other demographic characteristics. The first and third columns are regressions on the dummy variable if household wealth is strictly negative. Based on CBS data, this is predicted by being young, low education and high income. Only the first relation is also found based on self-reported data (column 3). In the next columns, I focus on the subset of households with non-negative wealth and use ihs-transformed wealth as dependent variables. Age, education, and income are predictive in both data sets, whereas the effects for age and income seem to be stronger in the LISS data set. Couple households are associated with higher wealth according to administrative data, which is not visible in the survey data.

Next, I focus on explaining portfolio risk in Table C.8. The effects are very similar across data sets, showing a strong positive relationship with education and wealth. Exceptions are that the CBS data implies that negative wealth households hold a higher risky asset share (compared with low-wealth households), while LISS data reveals a relation with high income. Furthermore, only in the administrative data can a relation between age and portfolio risk be detected: both middle-aged subjects and those above 70 hold more risky assets compared with young participants.

In sum, while the most important relations found in the administrative data are also visible in survey data, some associations are missed. Most of these deviations are related to households with negative wealth.

Table C.7. Wealth variables by demographics

	Has neg. wealth	ihs(wealth)	Has neg. wealth	ihs(wealth)
	(Admin)	(Admin)	(Survey)	(Survey)
Couple	0.041	0.701***	0.052	-0.791
	(0.036)	(0.151)	(0.036)	(0.679)
Married	-0.030	-0.163	-0.015	1.287*
	(0.035)	(0.141)	(0.036)	(0.665)
Has children at home	0.020	-0.092	-0.003	-0.125
	(0.024)	(0.106)	(0.026)	(0.420)
Age between 41 and 55	-0.257***	0.879***	-0.147***	1.825**
	(0.036)	(0.156)	(0.047)	(0.882)
Age between 56 and 70	-0.409***	1.564***	-0.255***	3.187***
	(0.033)	(0.150)	(0.042)	(0.797)
Age above 70	-0.435***	1.585***	-0.259***	2.950***
	(0.034)	(0.167)	(0.043)	(0.820)
Education: upper secondary	-0.017	0.370***	-0.022	0.657*
	(0.020)	(0.115)	(0.019)	(0.368)
Education: tertiary	-0.064***	0.640***	-0.009	0.623*
	(0.020)	(0.108)	(0.020)	(0.350)
Income between 1600 and 2500	0.015	0.024	-0.031	1.184***
	(0.021)	(0.133)	(0.021)	(0.417)
Income between 2500 and 3500	0.058**	0.581***	0.042	1.861***
	(0.023)	(0.125)	(0.028)	(0.438)
Income above 3500	0.111***	0.689***	0.011	2.161***
	(0.025)	(0.131)	(0.029)	(0.482)
N	1882	1563	1093	957
R^2	0.182	0.164	0.103	0.097
Subset: non-negative wealth	No	Yes	No	Yes

Notes: The first two columns are based on the main data set that uses administrative variables. The final two columns are based on the data set that uses survey data only. The first and third column use a dummy if household wealth is strictly negative as the dependent variable. In the second and fourth column, the sample is restricted to households with non-negative wealth and the dependent variable is ihs-transformed wealth. Robust standard errors in parentheses. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

Table C.8. Portfolio risk by demographics

	Has rfa	Share rfa	Has rfa	Share rfa
	(Admin)	(Admin)	(Survey)	(Survey)
Couple	0.001	-0.018	-0.035	-0.008
	(0.036)	(0.018)	(0.036)	(0.022)
Married	0.001	0.003	0.007	-0.011
	(0.035)	(0.017)	(0.036)	(0.023)
Has children at home	0.029	0.002	-0.007	0.016
	(0.026)	(0.012)	(0.033)	(0.019)
Age between 41 and 55	0.086***	0.057***	0.010	-0.001
	(0.032)	(0.015)	(0.043)	(0.024)
Age between 56 and 70	0.013	0.022	-0.029	0.001
	(0.034)	(0.016)	(0.041)	(0.023)
Age above 70	0.069*	0.055***	-0.012	0.023
	(0.037)	(0.018)	(0.044)	(0.025)
Education: upper secondary	0.030	-0.001	-0.007	0.006
	(0.025)	(0.012)	(0.029)	(0.016)
Education: tertiary	0.138***	0.053***	0.094***	0.055***
	(0.027)	(0.014)	(0.034)	(0.019)
Income between 1600 and 2500	0.022	-0.000	0.010	0.000
	(0.026)	(0.013)	(0.026)	(0.014)
Income between 2500 and 3500	0.028	0.007	0.058	0.029
	(0.029)	(0.014)	(0.035)	(0.021)
Income above 3500	0.084***	0.019	0.123***	0.047**
	(0.030)	(0.015)	(0.042)	(0.023)
Wealth below 0	0.003	0.032**	0.005	0.028
	(0.029)	(0.014)	(0.040)	(0.025)
Wealth between 50k and 200k	0.117***	0.041***	0.117***	0.060***
	(0.024)	(0.011)	(0.028)	(0.016)
Wealth above 200k	0.354***	0.151***	0.315***	0.135***
	(0.031)	(0.017)	(0.036)	(0.020)
N	1882	1871	1092	1039
R^2	0.134	0.101	0.147	0.100

Notes: The first two columns are based on the main data set, which uses administrative variables. The final two columns are based on the data set that uses survey data only. For each data set, three regressions are shown with the dependent variable being—first—the dummy if any risky assets are in the portfolio, and—second—the share of risky assets. Robust standard errors in parentheses.
* – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

Appendix D Main regressions for alternative specifications

I replicate the main results regarding the relation between stock market beliefs and chosen portfolio risk using two alternative specifications: First, I increase the sample and only exclude subjects if all 100 balls are placed in the outer bins.

Second, I make use of a non-parametric splines estimation that estimates μ_1 and σ_1 without functional form assumptions. I approximate the observed cumulative distribution function using a spline comprising several cubic polynomials. The method is based on Bellemare, Bissonnette, and Kröger (2012) and described in more detail by Drerup and Wibral (2020). Since the method requires all bins to be bounded, I set the bounds of the outer bins to the 2.5 % and 97.5 % quantiles of the empirical distribution of the AEX.

In the cross-section, the coefficients and significance levels are almost unchanged. For the analysis over time, the results are also very similar. In particular, the main result in column 5 remains unchanged. Two minor changes can be detected. First, when dropping the 2.5 % strongest updaters of μ and σ in column 6, the coefficient of the change in expectations is no longer significant, although the coefficient increases similarly as in the main specification. Second, when using non-parametric estimates of the belief parameters, the effects for the sample of stock holders are slightly smaller and no longer significant at the 10 % level.

Table D.1. Portfolio choice and stock market beliefs (less restrictive)

	Has risky financial assets		Share of risky assets			
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	0.041***	0.029**	0.018***	0.012**	0.021	0.012
	(0.013)	(0.013)	(0.006)	(0.005)	(0.016)	(0.016)
σ_1	-0.018	-0.010	-0.007	-0.004	-0.002	-0.002
	(0.013)	(0.013)	(0.006)	(0.006)	(0.016)	(0.017)
Female	-0.052**	-0.018	-0.014	-0.001	0.005	0.029
	(0.021)	(0.024)	(0.010)	(0.011)	(0.028)	(0.033)
Couple	-0.016	0.010	-0.026	-0.024	-0.077	-0.103*
	(0.039)	(0.043)	(0.019)	(0.020)	(0.052)	(0.055)
Married	0.005	-0.017	0.006	0.010	0.008	0.052
	(0.038)	(0.041)	(0.018)	(0.019)	(0.047)	(0.050)
Has children at home	0.028	0.016	0.002	-0.001	-0.016	-0.012
	(0.028)	(0.029)	(0.013)	(0.013)	(0.034)	(0.035)
Age between 41 and 55	0.092***	0.099**	0.060***	0.063***	0.121**	0.132***
	(0.035)	(0.039)	(0.016)	(0.017)	(0.047)	(0.049)
Age between 56 and 70	0.004	0.024	0.019	0.034*	0.088*	0.115**
	(0.037)	(0.041)	(0.017)	(0.018)	(0.051)	(0.053)
Age above 70	0.065	0.086*	0.054***	0.067***	0.139**	0.162**
	(0.041)	(0.045)	(0.020)	(0.021)	(0.061)	(0.064)
Education: upper secondary	0.021	0.012	-0.008	-0.009	-0.065*	-0.064
	(0.027)	(0.030)	(0.013)	(0.014)	(0.039)	(0.043)
Education: tertiary	0.127***	0.127***	0.048***	0.053***	0.009	0.023
	(0.030)	(0.032)	(0.015)	(0.016)	(0.039)	(0.043)
Income between 1600 and 2500	0.003	0.022	-0.006	0.008	-0.045	-0.007
	(0.029)	(0.031)	(0.014)	(0.015)	(0.046)	(0.048)
Income between 2500 and 3500	0.004	0.007	0.001	0.006	-0.013	0.001
	(0.031)	(0.034)	(0.016)	(0.016)	(0.045)	(0.047)
Income above 3500	0.047	0.038	0.006	0.009	-0.036	-0.021
	(0.033)	(0.036)	(0.016)	(0.017)	(0.043)	(0.046)
Wealth below 0	0.016	0.016	0.037**	0.041**	0.131**	0.152***
	(0.034)	(0.038)	(0.017)	(0.019)	(0.053)	(0.059)
Wealth between 50k and 200k	0.118***	0.120***	0.042***	0.048***	0.027	0.053
	(0.025)	(0.027)	(0.011)	(0.012)	(0.038)	(0.040)
Wealth above 200k	0.344***	0.314***	0.148***	0.126***	0.082**	0.074*
	(0.032)	(0.034)	(0.017)	(0.017)	(0.041)	(0.043)
Financial numeracy		0.019*		0.002		-0.011
		(0.011)		(0.006)		(0.024)
Risk aversion		-0.046***		-0.029***		-0.054***
		(0.012)		(0.006)		(0.016)
N	1731	1494	1731	1494	504	429
R^2	0.135	0.134	0.104	0.110	0.071	0.100
Subset: has risky assets	No	No	No	No	Yes	Yes

Notes: Conversely to the main specification, I only exclude subjects if all 100 balls are placed in the outer bins during the belief elicitation; otherwise, the same specification as in Table 4 is used. The threshold was 80 in the main specification. Robust standard errors in parentheses. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$

Table D.2. Portfolio choice and stock market beliefs (non-parametric splines estimation)

	Has risky financial assets		Share of risky assets			
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1	0.046***	0.038***	0.021***	0.015***	0.022*	0.011
	(0.011)	(0.011)	(0.005)	(0.005)	(0.013)	(0.013)
σ_1	-0.006	0.001	-0.004	-0.002	-0.009	-0.008
	(0.011)	(0.011)	(0.006)	(0.006)	(0.014)	(0.015)
Female	-0.047**	-0.015	-0.012	0.001	0.008	0.031
	(0.021)	(0.024)	(0.011)	(0.012)	(0.028)	(0.033)
Couple	-0.019	0.007	-0.027	-0.025	-0.075	-0.102*
	(0.039)	(0.043)	(0.019)	(0.020)	(0.053)	(0.055)
Married	0.006	-0.016	0.006	0.009	0.005	0.050
	(0.038)	(0.041)	(0.018)	(0.019)	(0.048)	(0.050)
Has children at home	0.031	0.020	0.003	0.000	-0.016	-0.013
	(0.028)	(0.029)	(0.013)	(0.013)	(0.034)	(0.035)
Age between 41 and 55	0.093***	0.099**	0.061***	0.064***	0.121**	0.134***
	(0.035)	(0.039)	(0.016)	(0.017)	(0.047)	(0.049)
Age between 56 and 70	0.009	0.030	0.020	0.036**	0.086*	0.113**
	(0.038)	(0.041)	(0.017)	(0.018)	(0.051)	(0.053)
Age above 70	0.070*	0.091**	0.056***	0.069***	0.141**	0.162**
	(0.041)	(0.045)	(0.020)	(0.021)	(0.061)	(0.064)
Education: upper secondary	0.022	0.015	-0.007	-0.008	-0.064	-0.062
	(0.028)	(0.030)	(0.013)	(0.014)	(0.040)	(0.044)
Education: tertiary	0.126***	0.128***	0.048***	0.054***	0.011	0.026
	(0.030)	(0.033)	(0.015)	(0.016)	(0.039)	(0.043)
Income between 1600 and 2500	0.004	0.022	-0.004	0.009	-0.041	-0.003
	(0.029)	(0.031)	(0.014)	(0.015)	(0.046)	(0.048)
Income between 2500 and 3500	0.004	0.008	0.001	0.006	-0.014	-0.000
	(0.031)	(0.034)	(0.016)	(0.016)	(0.045)	(0.047)
Income above 3500	0.045	0.036	0.005	0.009	-0.036	-0.020
	(0.033)	(0.036)	(0.016)	(0.017)	(0.043)	(0.046)
Wealth below 0	0.015	0.015	0.037**	0.040**	0.132**	0.153**
	(0.034)	(0.038)	(0.017)	(0.019)	(0.054)	(0.060)
Wealth between 50k and 200k	0.122***	0.125***	0.044***	0.050***	0.025	0.052
	(0.025)	(0.027)	(0.011)	(0.012)	(0.038)	(0.041)
Wealth above 200k	0.344***	0.315***	0.147***	0.125***	0.077*	0.069
	(0.032)	(0.034)	(0.017)	(0.017)	(0.041)	(0.044)
Financial numeracy		0.017		0.001		-0.011
		(0.011)		(0.006)		(0.024)
Risk aversion		-0.044***		-0.029***		-0.055***
		(0.012)		(0.006)		(0.016)
N	1719	1483	1719	1483	501	426
R^2	0.139	0.138	0.107	0.113	0.072	0.102
Subset: has risky assets	No	No	No	No	Yes	Yes

Notes: Conversely to the main specification, I use belief parameters that are non-parametrically estimated; otherwise, the same specification as in Table 4 is used. Robust standard errors in parentheses.
* $-$ $p < 0.1$, ** $-$ $p < 0.05$, *** $-$ $p < 0.01$

Table D.3. Updating of beliefs and portfolio choice (less restrictive)

	Δ Has risky financial assets			Δ Share of risky assets					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mu_2 - \mu_1$	0.009	0.010	0.014	0.008*	0.009**	0.015	0.019*	0.019*	0.027
	(0.008)	(0.009)	(0.018)	(0.004)	(0.004)	(0.010)	(0.010)	(0.011)	(0.029)
$\sigma_2 - \sigma_1$	0.010	0.011	0.013	0.009	0.009	0.003	0.029*	0.029*	0.009
	(0.010)	(0.010)	(0.020)	(0.006)	(0.006)	(0.016)	(0.016)	(0.017)	(0.045)
Δ Income between 1600 and 2500		-0.021	-0.022		-0.012	-0.012		-0.003	-0.001
		(0.043)	(0.044)		(0.014)	(0.014)		(0.019)	(0.020)
Δ Income between 2500 and 3500		-0.015	-0.016		-0.001	0.001		0.013	0.023
		(0.045)	(0.047)		(0.017)	(0.017)		(0.038)	(0.038)
Δ Income above 3500		0.019	0.023		0.002	0.003		0.013	0.016
		(0.046)	(0.048)		(0.020)	(0.022)		(0.050)	(0.052)
Δ Wealth below 0		-0.067**	-0.075**		-0.013	-0.014		-0.014	-0.008
		(0.033)	(0.036)		(0.015)	(0.017)		(0.056)	(0.060)
Δ Wealth between 50k and 200k		-0.002	-0.015		0.026	0.025		0.020	0.025
		(0.031)	(0.030)		(0.017)	(0.018)		(0.049)	(0.052)
Δ Wealth above 200k		0.014	0.003		0.019	0.018		0.009	0.014
		(0.038)	(0.038)		(0.027)	(0.028)		(0.074)	(0.076)
N	1500	1500	1377	1500	1500	1377	400	400	370
R^2	0.002	0.010	0.010	0.005	0.011	0.008	0.015	0.018	0.007
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes
Without strongest updaters	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Conversely to the main specification, I only exclude subjects if all 100 balls are placed in the outer bins during one of the belief elicitations; otherwise, the same specification as in Table 6 is used. The threshold was 80 in the main specification. Robust standard errors in parentheses. * – $p < 0.1$, ** – $p < 0.05$, *** – $p < 0.01$

Table D.4. Updating of beliefs and portfolio choice (non-parametric splines estimation)

	Δ Has risky financial assets			Δ Share of risky assets					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mu_2 - \mu_1$	0.007	0.007	0.021	0.009**	0.009**	0.012	0.012	0.012	0.008
	(0.008)	(0.009)	(0.018)	(0.004)	(0.004)	(0.010)	(0.009)	(0.009)	(0.027)
$\sigma_2 - \sigma_1$	0.013	0.013	0.007	0.008	0.008	-0.009	0.020	0.018	-0.038
	(0.010)	(0.010)	(0.012)	(0.006)	(0.006)	(0.009)	(0.018)	(0.018)	(0.028)
Δ Income between 1600 and 2500		-0.021	-0.022		-0.012	-0.012		-0.002	-0.004
		(0.043)	(0.044)		(0.014)	(0.014)		(0.018)	(0.017)
Δ Income between 2500 and 3500		-0.014	-0.016		-0.001	0.001		0.013	0.027
		(0.046)	(0.047)		(0.017)	(0.017)		(0.038)	(0.037)
Δ Income above 3500		0.019	0.021		0.001	0.003		0.009	0.013
		(0.047)	(0.048)		(0.020)	(0.021)		(0.050)	(0.052)
Δ Wealth below 0		-0.067**	-0.076**		-0.014	-0.014		-0.010	-0.006
		(0.033)	(0.037)		(0.015)	(0.017)		(0.060)	(0.059)
Δ Wealth between 50k and 200k		-0.002	-0.016		0.026	0.025		0.021	0.029
		(0.031)	(0.030)		(0.017)	(0.018)		(0.049)	(0.052)
Δ Wealth above 200k		0.014	-0.001		0.019	0.017		0.015	0.012
		(0.038)	(0.038)		(0.028)	(0.028)		(0.074)	(0.075)
N	1490	1490	1374	1490	1490	1374	397	397	364
R^2	0.002	0.009	0.010	0.004	0.010	0.009	0.008	0.010	0.010
Subset: has risky assets	No	No	No	No	No	No	Yes	Yes	Yes
Without strongest updaters	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Conversely to the main specification, I use belief parameters that are non-parametrically estimated; otherwise, the same specification as in Table 6 is used. Robust standard errors in parentheses. * $- p < 0.1$, ** $- p < 0.05$, *** $- p < 0.01$