

Huber, Jürgen; Kirchler, Michael; Steinbacher, Teresa

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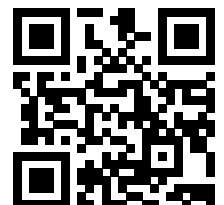
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Contact address of the editor:
Faculty of Economics and Statistics
University of Innsbruck
Universitaetsstrasse 15
A-6020 Innsbruck
Austria
Tel: + 43 512 507 96136
E-mail: Dean-EconStat@uibk.ac.at

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Knowledge and Beliefs About Behavioral Biases*

Jürgen Huber, Michael Kirchler, Teresa Steinbacher[†]

December 19, 2024

Abstract

In this study we explore the knowledge and beliefs regarding behavioral biases among behavioral scientists, financial professionals, and the general population. We investigate knowledge about ten prominent biases and collect beliefs about the knowledge levels of each of these subject pools by conducting an online survey with 547 participants. We find that knowledge about the selected biases is highest among behavioral scientists and lowest in the general population. Potential explanatory variables, such as age, gender, income, and financial literacy, show almost no impact on knowledge levels. Regarding accuracy of beliefs about knowledge of the own and the other groups, each subject pool has the highest accuracy rates for their own group, and behavioral scientists assessing other behavioral scientists have by far the highest accuracy rate.

JEL: C91, G40, G53

Keywords: Behavioral biases, expert beliefs, behavioral scientists, financial professionals.

*Our experimental software and the pre-analysis plan are stored in an OSF repository: <https://osf.io/gzdtq/>. Financial support from the Austrian Science Fund (SFB F63) is gratefully acknowledged. This study was ethically approved by the IRB of the University of Innsbruck (141/2024).

[†]Huber (corresponding author): University of Innsbruck, Department of Banking and Finance, Universitätsstraße 15, 6020 Innsbruck. E-mail: juergen.huber@uibk.ac.at.

Kirchler: University of Innsbruck, Department of Banking and Finance, Universitätsstraße 15, 6020 Innsbruck. E-mail: michael.kirchler@uibk.ac.at.

Steinbacher: University of Innsbruck, Department of Banking and Finance, Universitätsstraße 15. E-mail: teresa.steinbacher@uibk.ac.at.

1 Introduction

Understanding one’s own and other people’s biases in economic decision making can help to avoid potentially expensive pitfalls and mistakes. Baker et al. (2019), Croskerry et al. (2013), and Wang (2023) show that awareness of biases has the potential to directly or indirectly mitigate the negative effect of biases, thereby contributing to improved economic and financial decisions. In his influential book Kahneman (2011) suggests that individuals may improve their decision-making processes and reduce behavioral biases by developing a better understanding of how these biases affect their choices. For example, financial literacy not only leads to less biased decision-making, but is also crucial for improving overall financial behavior (Baker et al., 2019; Hsu et al., 2021; Zhang, 2023).

The main goal of this study is to investigate the levels of knowledge and beliefs about ten of the best-known behavioral biases in economic decision-making across three distinct and relevant groups: behavioral scientists (who should be acquainted with the concepts), financial professionals (who regularly make financial decisions), and the general population (whose daily decisions can be influenced by biases, but who might never have heard about them). We investigate behavioral biases across these groups through a pre-registered online survey including 547 participants. We consider this important because many daily individual, economic and social decisions are influenced by individuals’ behavioral biases and their beliefs about those of others. Thus, individuals’ proneness to biases is important for the quality of their decisions on an individual level. Even more importantly, their biases and their beliefs about the behavior and biases of others matter a lot for the decisions they take for third parties in principal-agent situations in economic environments, as financial professionals might regularly do.

In the 1950s, Herbert Simon introduced a starting point in the analysis of human behavior in economic and social interactions by defining the term “bounded rationality”, proposing that humans exhibit considerable irrational behavior (Simon, 1957). Behavioral economics and finance have gained popularity and importance over the subsequent decades in explaining financial behavior and the related behavioral patterns and biases (Hirshleifer, 2015). Behavioral finance integrates psychological and cognitive assumptions into traditional financial theories and principles, especially in the decision-making process (De Bondt et al., 2013; Suresh, 2024). It acknowledges that individuals may not always possess all relevant information and often rely on mental shortcuts to solve problems within a reasonable time frame (De Bondt et al., 2013; Tversky and Kahneman, 1974). Furthermore, errors and potential irrationality in decision-making frequently lead humans to rely on shortcuts and their intuition rather than calculations in their daily decisions (Suresh, 2024). Thus, behavioral finance does not only rely on rationality among agents but strongly considers actual human behavior in a financial context, where individuals also tend to make decisions influenced by, e.g., emotions, social influence, and stress levels (Shefrin, 2002; Statman et al., 2008).

There is evidence that the extent to which individuals are subject to behavioral biases can strongly depend on their demographic characteristics and profession (Haigh and List, 2005; Kaustia et al., 2008). We expect that knowledge about behavioral biases differs significantly between behavioral scientists, financial professionals, and the general population. Prior research further indicates that socio-demographic characteristics can significantly influence individual knowledge and decisions, with notable discrepancies between genders (Baker et al., 2019; Cronqvist and Siegel, 2014; Hsu et al., 2021). For instance, studies suggest that improving financial literacy can help mitigate the effects of behavioral biases on investment decisions (Baker et al., 2019; Fessler et al., 2020; Hsu et al., 2021).

Kruger and Dunning (1999) suggest that individuals with lower competence in a field often have difficulties in accurately assessing their own knowledge and the knowledge of others in that field. Behavioral scientists, who regularly conduct research and have extensive education in behavioral concepts likely have above-average expertise on behavioral biases (Kite and Whitley, 2012). Therefore, we expect that behavioral scientists have higher knowledge levels and are more likely to estimate the knowledge levels of their own and other subject pools more accurately compared to financial professionals and the general population.

In this study, we explore the understanding of behavioral biases among various population groups, namely behavioral scientists, financial professionals, and the general population. By further analyzing the impact of socio-demographic variables, financial literacy, math grade, and risk preferences, we contribute insights into how these factors influence knowledge about and attribution of prominent behavioral biases across various groups in society. We defined the following research questions in our pre-analysis plan:

RQ1a. “What is the level of knowledge concerning behavioral biases of behavioral scientists?”

RQ1b. “What is the level of knowledge concerning behavioral biases of financial professionals?”

RQ1c. “What is the level of knowledge concerning behavioral biases of the general population?”

RQ2. “To what extent are there disparities of knowledge concerning behavioral biases between behavioral scientists, financial professionals, and the general population?”

RQ3. “Do subject pools differ in their beliefs about the knowledge of their own and the other two subject pools with respect to behavioral biases?”

With the answers to these questions, our objective is to shed light on the differences and similarities in behavioral biases across various subject pools, offering deeper insights into the population’s ability to comprehend these biases in decision-making processes and to assess beliefs about the knowledge level of their own and other population groups about these biases.

To investigate our research questions, we run an online experiment with 547 participants from three subject pools—behavioral scientists, financial professionals, and the general population. We explore their knowledge of ten seminal behavioral biases—i.e., confirmation bias, hindsight bias, status quo bias, present bias, anchoring effect, self-serving bias, loss aversion, overconfidence, overweighting of small probabilities, and framing effect. Finally, we investigate

their beliefs about the knowledge of their own and the other subject pools about these behavioral biases.

We find that knowledge about these biases is highest among behavioral scientists and lowest in the general population with differences for most of the ten biases being significant. Other potential explanatory variables for differences in knowledge, such as age, gender, income, and financial literacy, have limited impact on the overall knowledge. Regarding beliefs about the three groups, significant differences are observed between behavioral scientists and the other groups. Regarding the accuracy of beliefs about knowledge of the own and the other groups, each subject pool has the highest accuracy rates for their own group, and behavioral scientists assessing other behavioral scientists have by far the highest accuracy rate.

This research adds to the literature on behavioral biases by assessing the level of knowledge about these biases across different important groups of the population. It provides findings on the understanding of behavioral biases in societal, economic and financial decisions. Moreover, our study examines how the different groups perceive and interpret behavioral biases of other groups in society. Thus, this study has important practical implications as, for instance, finance professionals and people representing the general population take plenty of daily individual, social, and economic decisions for themselves and for others. Thus, their proneness to biases is important for the quality of their decisions and, equally important, their beliefs about the behavior and biases of others matter a lot for the decisions they take for third parties. Therefore, educating people on behavioral biases and the ways to mitigate those to foster improved decision-making abilities would be an important avenue for improving decisions on a societal, company and governmental level.

2 Research Design

Our study is conducted as a cross-sectional online survey concentrated primarily in several European countries, including Austria, Germany, the Netherlands, Norway, and Sweden, but also a few participants from several Eastern European countries. Table 1 outlines details on the three subject pools.

The group of behavioral scientists comprises researchers who typically explore questions related to behavioral finance and economics. We recruited these subjects through the Society for Experimental Finance (SEF) and the Society for Judgment and Decision Making (JDM), ensuring that the responses come from individuals deeply engaged in academic and empirical behavioral research.

Financial professionals mainly include traders, fund managers, analysts, financial advisors, and private bankers at major European financial companies. These European professionals are sourced through the BEFORE-pool, a platform dedicated to scholarly research on behavioral finance and administered by the Department of Banking and Finance at the University of Inns-

bruck. Further recruitment channels were the CFA society Austria and three medium-sized financial institutions in the EU.

The general population sample includes individuals from diverse backgrounds across the countries mentioned above. The group represents a broad spectrum of socio-economic statuses, educational levels, and age groups. Participants from the general population were recruited through Prolific (Palan and Schitter, 2018), aiming to achieve a balanced gender distribution and a wide range of demographic characteristics.¹

In total, we collected 547 observations: 109 from behavioral scientists, 238 from financial professionals, and 200 from the general population. The survey was administered using QUALTRICS. It includes questions developed from established literature in behavioral science, focusing on ten of the best known behavioral biases (Peón et al., 2017; Peón and Antelo, 2021). Participants were provided with a brief explanation of each subject pool first before being asked about the following ten biases:

Confirmation Bias: is a cognitive form of selection bias manifesting as an inclination to seek or interpret information consistent with existing beliefs and expectations (Nelson and McKenzie, 2009). An explanation for this bias involves the tendency to avoid cognitive dissonance caused by contradictory evidence by selecting information that confirms one’s pre-existing beliefs (Russo et al., 1996).

Hindsight Bias: refers to a distortion of past events, where individuals possessing the knowledge of the outcome are more inclined to assign higher probabilities to the reported outcome than they would have done without prior knowledge (Guilbault et al., 2004; Hawkins and Hastie, 1990). This leads to a sensation of “I knew it all along” (Roese and Vohs, 2012).

Status Quo Bias: when individuals encounter different alternatives, the status quo bias suggests that they are inclined to stick to the current state or the existing course of action. Samuelson and Zeckhauser (1988) identified significant effects of the status quo bias on individual decision-making, revealing that the bias fluctuates depending on an individual’s preferences and the number of choices available.

Present Bias: is the inclination to prefer a smaller present reward to a larger later reward, but reverse this preference when both rewards are delayed equally (Chakraborty, 2021).

Anchoring Effect: although the anchoring effect as a cognitive bias in decision-making was first noted by Slovic (1967), its contemporary understanding largely stems from the work of Tversky and Kahneman (1974). It describes the significant influence of an initially presented value on decision-makers, leading them to form judgments biased toward that value (Slovic and Lichtenstein, 1971). Hence, possibly irrelevant and random information, often the first point of contact with this topic, impacts the decision-making process (Baker and Ricciardi, 2014).

¹To ensure that participants only take part in the study once, eligibility criteria are enforced using unique identifiers. The general population is tracked through a Prolific ID, while financial professionals and behavioral scientists register for payout using an email address. This method prevents duplicate participation for payment and maintains the integrity of the data collection process.

Characteristics	Behavioral Scientists	Financial Professionals	General Population	Full sample
Number of Subjects	109	238	200	547
	%	%	%	%
Gender				
Female	41.28	13.87	48.50	31.99
Male	58.72	85.71	50.00	67.28
Other ^a	0.00	0.42	1.50	0.73
Age \emptyset	37.44	42.26	32.61	37.77
Highest educational level				
<High school diploma	0.00	0.84	1.00	0.70
High school diploma	0.00	18.07	28.50	18.10
Bachelor's degree	6.42	4.62	33.00	15.36
Master's degree	37.61	70.17	34.00	50.46
Doctoral degree	55.96	5.04	3.50	14.63
Monthly net income				
up to 2,000€	19.27	2.94	44.00	21.21
2,000€ to 4,000€	38.52	38.66	47.17	39.12
4,000€ to 6,000€	18.35	26.05	7.50	17.73
6,000€ to 8,000€	8.26	13.87	1.50	8.23
8,000€ to 10,000€	3.67	1.68	0.50	1.65
Over 10,000€	8.26	7.56	1.00	5.30
Prefer not to say	3.67	9.24	5.50	6.76
Financial literacy score \emptyset	4.00	4.68	3.91	4.26
Risk preference \emptyset	5.26	7.01	5.13	5.97
Math grade ^b \emptyset	1.50	1.86	2.29	1.93

^a Answers “Prefer not to say” and “Non-binary / third gender”

^b On a scale of 1 to 5, where 1 is the best math grade

Table 1: Descriptive statistics of the three subject pools

Self-Serving Bias: also known as self-attribution bias; self-serving bias involves individuals attributing their successes to their own actions or abilities while assigning failures to external factors beyond their control (Shepperd et al., 2008). This bias can be understood as a combination of two distinct biases: the self-enhancing bias and the self-protecting bias (Pompian, 2012). This bias is therefore often more a means of explaining events by keeping self-esteem high, rather than a deliberate effort to deceive (Baker and Ricciardi, 2014; Duval and Silvia, 2002). Moreover, it can further enhance overconfidence (Baker and Ricciardi, 2014).

Loss Aversion: introduced within the framework of Prospect Theory; loss aversion is a key element that shapes individual behavior. Loss aversion indicates a stronger preference to avoid losses rather than achieving equivalent gains, demanding significantly higher potential gains to offset potential losses (Tversky and Kahneman, 1979, 1992). Research suggests that individuals generally feel the impact of losses roughly twice as strongly as the impact of gains (Pompian, 2012).

Overconfidence: “Overconfidence bias may cause people to overestimate their ability and knowledge” (Wang, 2023, p. 141). It is a cognitive bias that manifests in various forms, including over-precision, better-than-average bias, and over-optimism (Hirshleifer, 2015; Weinstein, 1980).

Overweighting of Small Probabilities: this bias, as mentioned within Prospect Theory, refers to the idea that individuals often assign more weight to small probabilities, perceiving them as more likely to occur than they actually are, while simultaneously underweighting moderate and high probabilities (Tversky and Kahneman, 1979, 1992).

Framing Effect: according to the framing effect, the presentation and perception of information influence decision-making, leading individuals to focus more on how information is presented rather than its content (Wang, 2023). According to rational choice, the preference for options should not be affected by the way they are presented (Tversky and Kahneman, 1981). However, people often reverse preference orders when decisions are framed in either a positive or negative way, although outcomes are identical (Tversky and Kahneman, 1981).

The biases were then elicited as follows (here, the statement for the confirmation bias is used): *“To what extent do you agree with this statement: ‘People usually have a tendency to seek, interpret, and favor information so that it confirms one’s prior beliefs or values’?”*

Responses were collected using a four point Likert scale ranging from “Strongly Agree” to “Strongly Disagree”.

After participants were asked to express their perception of each bias, they then stated their beliefs about what the majority response would be from each of the three demographic groups. The question for each bias was formulated as follows:

“Consider the three groups below. For each one, ask yourself: Which was the most frequently selected answer choice concerning the statement ‘People usually have a tendency to seek, interpret, and favor information so that it confirms one’s prior beliefs or values’?”

This needed to be answered once for each of the three subject pools. Response possibilities were again the four Likert scale items ranging from “Strongly Agree” to “Strongly Disagree”.

To test participants’ comprehension and mitigate any potential response biases, not all statements were formulated the same way. Specifically, five biases were presented in a way that, based on consensus in the literature, the statement is correct. The remaining five biases were formulated wrongly/negatively, hence disagreeing with the statement would be the correct answer. While for each participant the same five sentences were correct/wrong, the order of presentation of the statements was randomized for each.

The following five statements of biases were positively framed in the survey:

Confirmation Bias: People usually have a tendency to seek, interpret, and favor information so that it confirms one’s prior beliefs or values (Wason, 1960).

Hindsight Bias: People have the tendency to view past events as more predictable than they actually were (Fischhoff, 2003).

Status Quo Bias: People often choose an alternative simply because it is the default option,

rather than considering other alternatives (Samuelson and Zeckhauser, 1988).

Present Bias: People typically have a tendency to prefer a smaller present reward rather than waiting for a larger future reward (Laibson, 1997).

Anchoring Effect: People tend to rely too much on irrelevant reference points or arbitrary information when making decisions (Tversky and Kahneman, 1974).

The following five statements were wrongly/negatively framed:

Self-Serving Bias: People typically tend to own up to their failures more than take credit for their successes (Miller and Ross, 1975).

Loss Aversion: When evaluating gains and losses of equal size, people typically feel that gains loom larger than losses (Tversky and Kahneman, 1979).

Overconfidence: People usually underestimate their knowledge and abilities when making decisions (Lichtenstein et al., 1977).

Overweighting of Small Probabilities: People typically underweight small probabilities whilst they overweight high probabilities (Tversky and Kahneman, 1979).

Framing Effect: People are usually more risk-averse when it comes to losses and more risk-seeking concerning gains (Tversky and Kahneman, 1981).

Following the collection of knowledge and beliefs, the survey gathers control variables, beginning with responses to the “big-5” financial literacy questions (Lusardi and Mitchell, 2011). Participants also self-assessed their willingness to take risks and provided demographic information including age, gender, highest education level, math grade at the end of compulsory school, and monthly net income.

Incentives were structured as similarly as possible, but slight differences were necessary across subject pools to accommodate the varied methods of recruitment and compensation logistics.² The survey was conducted from April 28 to May 10 2024.

According to our pre-registration, data analysis for the collected data encompassed primary analysis, exploratory analysis, and robustness testing. Inspired by the study of Simons and Chabris (2011) we adopted a conservative power calculation with a lower standardized effect size of Cohen’s $d = 0.50$ (Cohen, 1969) in our pre-registration. The goal was to achieve a statistical power of at least 80% in detecting this effect size, with a Type I error rate of $\text{Alpha} = 0.05$, which required a sample size of at least 60 independent observations per condition.

²For the general population, recruited through Prolific, each participant received a flat payment of about 3 Euros (2.70 GBP) upon completing the survey. This payment method aligns with Prolific’s requirements. Financial professionals and behavioral scientists were subject to a slightly different incentive structure, where not everyone received a flat payment. Instead, they were entered into a lottery where 10% of the participants were randomly selected to receive 30 Euros, resulting in the same average payment of 3 Euros. This lottery approach significantly reduced the administrative burden of the financial department at the University of Innsbruck, which would otherwise face a very high volume of transactions. Additionally, behavioral scientists, financial professionals, and the general population were given the chance to earn a bonus payment. There was a 10% probability of receiving an additional 20 GBP (for Prolific) and 30 Euros (for behavioral scientists and financial professionals) if a participant’s response to a randomly selected survey question on beliefs matched the actual most common answer.

Data collection continued beyond the 60-participant threshold, fortunately resulting in a much larger sample size. The primary analysis was pre-registered prior to data collection to address our research questions. This analysis plan was pre-registered in a Pre-Analysis plan (available at <https://osf.io/gzdtq/files/osfstorage/662f406580d25c3774f91a09/?pid=gzdtq>) to ensure transparency in the applied methods.

3 Results

Table 2: Descriptions of positively framed bias statements along with the percentage distribution of respondents across each response category.

Statement	Group	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
Confirmation Bias: People usually have a tendency to seek, interpret, and favor information so that it confirms one’s prior beliefs or values	Behavioral Scientists	76.15	21.10	0.00	2.75
	Financial Professionals	67.23	30.67	0.84	1.26
	General Population	65.00	31.00	3.50	0.50
Hindsight Bias: People have the tendency to view past events as more predictable than they actually were	Behavioral Scientists	70.64	26.61	1.83	0.92
	Financial Professionals	67.23	30.67	0.84	1.26
	General Population	47.50	44.50	8.00	0.00
Status Quo Bias: People often choose an alternative simply because it is the default option, rather than considering other alternatives	Behavioral Scientists	55.06	41.28	1.83	1.83
	Financial Professionals	31.09	59.25	9.24	0.42
	General Population	24.50	64.00	11.00	0.50
Present Bias: People typically have a tendency to prefer a smaller present reward rather than waiting for a larger future reward	Behavioral Scientists	43.12	47.71	7.34	1.83
	Financial Professionals	35.29	47.48	15.13	2.10
	General Population	25.50	51.50	20.50	2.50
Anchoring: People tend to rely too much on irrelevant reference points or arbitrary information when making decisions	Behavioral Scientists	42.20	47.71	8.26	1.83
	Financial Professionals	28.15	60.09	11.34	0.42
	General Population	15.50	60.50	22.00	2.00

We organize the results by going from RQ1 to RQ3, following our pre-registered pre-analysis plan. Table 2 shows the distribution of responses for the five biases in which, based on existing literature, “Agree” would be the correct answer (separated by subject pool). We find that 75 to 98 percent of answers are “Strongly Agree” or “Mostly Agree” for each of the five questions. Hence, all subject pools mostly got the answers correct. However, there are still clear differences, as the share of correct answers by behavioral scientists is always the highest.

Table 3 gives the respective numbers for the negatively/wrongly formulated statements, i.e., the biases where “Disagree” would be the correct answer according to literature. We find that the distribution of results is not always that clear and correct. While for three biases 80 to 90 percent got the answer correct, for the remaining two biases the majority of participants across all subject pools agreed with the statements, even though to disagree would be the correct answer. The high share of wrong answers across all subject pools is likely due to a combination of low levels of knowledge among many participants, and – as we think – “inattentive reading”, which might have played a role.³

³For instance, some participants might immediately have recognized that a statement is about overweighting

Table 3: Descriptions of negatively framed bias statements along with the percentage distribution of respondents across each response category.

Statement	Group	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
Self-Serving Bias: People often admit their failures more readily than they take credit for their successes	Behavioral Scientists	1.83	7.34	33.03	57.80
	Financial Professionals	5.46	12.61	34.03	47.90
	General Population	8.00	11.00	48.50	32.50
Loss Aversion: When evaluating gains and losses of equal size, people typically feel that gains loom larger than losses	Behavioral Scientists	14.68	14.68	15.60	55.04
	Financial Professionals	15.13	22.69	23.53	38.65
	General Population	12.00	40.00	37.50	10.50
Overconfidence: People usually underestimate their knowledge and abilities when making decisions	Behavioral Scientists	3.67	13.77	41.28	41.28
	Financial Professionals	7.98	15.55	44.96	31.51
	General Population	13.00	34.00	42.50	10.50
Overweighting of small probabilities: People typically underweight small probabilities whilst they overweight high probabilities	Behavioral Scientists	32.11	24.77	22.94	20.18
	Financial Professionals	27.73	41.17	16.39	14.71
	General Population	24.00	58.50	13.50	4.00
Framing: People are usually more risk-averse when it comes to losses and more risk-seeking concerning gains	Behavioral Scientists	38.53	28.44	7.34	25.69
	Financial Professionals	58.83	30.67	6.30	4.20
	General Population	49.50	46.00	3.50	1.00

First, to analyze research questions 1a through 1c statistically, Likert scale answers for each bias are compared across subject pools. In particular, the Likert scores of all participants across the three subject pools are compared with the answer considered correct based on the literature. The factors “Strongly Agree” to “Strongly Disagree” are assigned numbers from 1 to 4. The expected correct answers for positively framed answers would therefore be close to 1 whereas negatively framed statements are considered closer to correct as they approach 4. As an exploratory analysis, we then test the aggregated knowledge of positively and negatively framed biases in each subject pool against the expected true value using a non-parametric Wilcoxon signed-rank test. This test allows us to determine whether there are significant differences between the answers provided by members of each subject pool and the correct answers for these biases.

Second, we use non-parametric Mann-Whitney U-tests to test for significant differences in responses across the subject pools and different behavioral biases in research questions 2 and 3. For all statistical tests, the significance levels are interpreted according to the guidelines provided by Benjamin et al. (2018), considering 5% as suggestive evidence and 0.5% as statistical significance.

To answer research questions 1a to 1c about knowledge concerning behavioral biases in the three distinct subject pools, the mean scores of each subject pool for each of the biases compared to the expected true answer are analyzed. These are given in Figure 1 for the five statements where “Agree” is correct, and for the five biases where “Disagree” is correct. We find that for

of small probabilities, but have been too inattentive to read carefully enough to see that we stated “underweight small probabilities” rather than “overweight”. However, we lack clear evidence on this possible explanation and have to leave a definite explanation to future research. Note that also on these questions (as on all others) the behavioral scientists have a higher share of correct answers than any of the other two subject pools.

the first five statements the shares of correct answers are consistently high, and clearly highest for behavioral scientists, while the general population has the lowest share of correct answers.

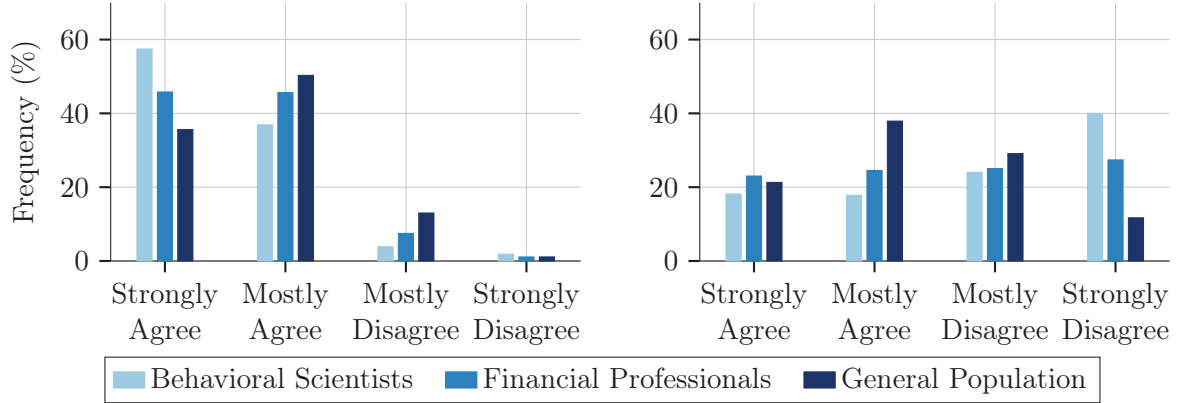


Figure 1: Mean answer scores aggregated over positively (left) and negatively (right) framed biases (in %).

For the second set of five biases the share of correct answers (“Disagree”) is markedly lower, while the pattern persists that behavioral scientists have the highest share of correct answers, the general population is on the correct side (“Mostly Disagree” and “Strongly Disagree” added up) in only about 40 percent of all cases.

To further examine the aggregated mean scores for both positively framed statements and negatively framed statements are calculated for each subject pool. These results can be seen in Table 4, while Table 5 gives the overall averages and the standard deviations of the answers.

Table 4: Mean knowledge scores of behavioral scientists, financial professionals, and the general population on positively and negatively framed statements of behavioral biases.

Positively Framed Biases	Behavioral Scientists	Financial Professionals	General Population
Confirmation Bias	1.29	1.36	1.34
Hindsight Bias	1.33	1.48	1.61
Status Quo Bias	1.51	1.80	1.88
Present Bias	1.68	1.84	2.00
Anchoring	1.70	1.84	2.11
Negatively Framed Biases			
Self-Serving Bias	3.47	3.24	3.06
Loss Aversion	3.11	2.86	2.47
Overconfidence	3.20	3.00	2.51
Overweighting	2.31	2.18	1.98
Framing	2.20	1.56	1.56

Behavioral scientists were closest to the correct answers (1.00 for positively framed biases; 4.00 for negatively framed ones) in both categories, with a mean score of 1.50 for positively framed statements and 2.89 for negatively framed statements. Financial professionals followed with aggregated mean scores of 1.66 and 2.57, respectively. The general population was further

Table 5: Mean scores of positively (MeanPositive) and negatively (MeanNegative) framed statements and standard deviation for positively (SdPositive) and negatively (SdNegative) framed statements.

Subject Pool	MeanPositive	SdPositive	MeanNegative	SdNegative
Behavioral Scientists	1.50	0.44	2.86	0.61
Financial Professionals	1.66	0.35	2.57	0.53
General Population	1.80	0.35	2.31	0.40

away from the true value, with mean scores of 1.80 and 2.31, respectively. While behavioral scientists were closest to the correct value, their standard deviation was also the highest in both categories (0.44 for positively framed statements and 0.61 for negatively framed statements), indicating higher variation in knowledge within this group.

This initial analysis provides a basic understanding of the knowledge levels in each subject pool. Looking at each of the 10 statements separately (see Figure A11 in the Appendix), behavioral scientists were closest to the correct value for each of the statements. Furthermore, the mean scores of the financial professionals were closer to the correct value than those of the general population in 9 out of 10 cases, though the differences were often small.

Knowledge across the subject pools varied strongly across the different biases, with knowledge about confirmation bias being relatively stable and good for all three groups (ranging between 1.29 and 1.40, with 1.00 being the “perfect” answer), whereas there were larger differences in knowledge concerning e.g., the anchoring effect (ranging between 1.70 and 2.11). As shown in Table A1, the non-parametric Wilcoxon signed-rank tests reveal significant differences between the knowledge of each subject group and the correct answers for both the aggregated positively and negatively framed biases. The same applies for individual biases. Despite behavioral scientists being the closest in their knowledge to the correct answers, there remain significant differences. This suggests that although behavioral scientists may have a better understanding of the biases, their knowledge does not fully align with the correct answers (or they may see ambiguities in some of the statements).

To answer research question 2, which focuses on the differences between the three subject pools, we first conduct pairwise non-parametric Mann-Whitney U-tests.

As we report in Table 6, most of the pairwise comparisons show significant differences between subject pools. Comparing behavioral scientists and financial professionals (BS - FP), behavioral scientists and the general population (BS - GP), and financial professionals and the general population (FP - GP) we see that behavioral scientists were always closer to the “correct” answer than financial professionals, significantly so for 6 of the 10 biases, and significantly closer than the general population in 9 of 10 cases. This attests to a higher level of knowledge about biases among behavioral scientists than among the other two subject pools. Furthermore, financial professionals are significantly closer to the “correct” answer than the general population for 7 of

Table 6: P-values and U-values from non-parametric double-sided Mann-Whitney U-tests for the comparison between subject groups. The comparisons include behavioral scientists vs. financial professionals (BS-FP), behavioral scientists vs. general population (BS-GP), and financial professionals vs general population (FP-GP).

Positive	n	Confirmation Bias	Hindsight Bias	Status Quo Bias	Present Bias	Anchoring
BS - FP	347	0.1111	0.0219*	0.0000**	0.0587	0.0236*
U-value		14073	14664.5	16292.5	14471	14712.5
BS - GP	309	0.0471*	0.0001**	0.0000**	0.0002**	0.0000**
U-value		12103.5	13513	14470	13480.5	14367
FP - GP	438	0.5461	0.0254*	0.1315	0.0208*	0.0000**
U-value		23142.5	21187.5	22081.5	20994	19019
Negative	N	Self-Serving Bias	Loss Aversion	Overconfidence	Overweighting	Framing
BS - FP	347	0.0338*	0.0241*	0.0511	0.3816	0.0000**
U-value		11296	11120	11391.5	12243.5	9242.5
BS - GP	309	0.0000**	0.0000**	0.0000**	0.0951	0.0000**
U-value		7901.5	6808.5	6178	25842.5	8098
FP - GP	438	0.0087*	0.0000**	0.0000**	0.0235*	0.2386
U-value		27015.5	29246	31285	9310	22422.5

Note: p-values below 0.05 are indicated with a single asterisk (*), and p-values below 0.005 are indicated with a double asterisk (**).

the 10 biases.

The Mann-Whitney U-tests for the aggregated mean scores revealed statistically significant differences in knowledge between all three pairings. Most of the differences of behavioral scientists and the other pools are significant on a 5% level. Overall, knowledge of behavioral biases of behavioral scientists is thus significantly higher than that of financial professionals and the general population, with significant differences also existing between the latter two.

To explore possible explanatory variables for these differences, we conduct an OLS regression where binary subject pool dummies are used for financial professionals and the general population, while behavioral scientists are used as the baseline category represented in the intercept. This analysis allows insights into differences in knowledge between the baseline category of behavioral scientists, financial professionals, and the general population. In addition, socio-demographic variables such as age, gender, education, and income along with math grade, risk preferences, and financial literacy scores, are included as control variables. This setup allows for the measurement of how these factors impact responses to the survey questions on behavioral biases. We conduct two regressions, one for the five positively framed biases and another one for the five negatively framed biases, with the results given in Table 7. The data suggests that belonging to a subject pool other than behavioral scientists results in a higher probability of responses being further away from the correct value, i.e., positive coefficients for the positively framed biases and negative coefficients for negatively framed biases.

More detailed OLS regressions including all control variables are given in the Appendix in

Tables A2 and A3. These regressions clearly show that age, gender, financial literacy, etc. impact knowledge about specific biases in a few cases, but these were not strong indicators of overall knowledge about behavioral biases.

Table 7: OLS regression results for positively and negatively framed biases

Coefficients	Positively Framed Biases			Negatively Framed Biases		
	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value
Financial Professionals	0.1604	0.0431	0.0002**	-0.2907	0.0584	0.0000**
General Population	0.2951	0.0444	0.0000**	-0.5467	0.0602	0.0000**
Adjusted R^2		0.073			0.132	
N	547					

Note: p-values below 0.05 are indicated with a single asterisk (*), and p-values below 0.005 are indicated with a double asterisk (**).

To address research question 3, which examines differences in beliefs about the choices of the own and the other two subject pools, we first illustrate the mean beliefs of each subject pool regarding the most frequent answer choice for each question in Figure A11. While simple guessing would have led to a share of 25 percent of correct answers (as we have four answer categories), behavioral scientists correctly guessed the most frequent answer of other behavioral scientists almost three quarters of the time. All guesses by all groups were clearly better than chance, and each subject pool was best at assessing its own subject pool (financial professionals and general population both guessed about 60 percent of their respective subject pool’s most frequent answer correctly). Furthermore, the beliefs of the five positively framed and five negatively framed biases are aggregated separately, and non-parametric Mann-Whitney U tests are conducted to examine differences between the beliefs of each subject pool and the actual answers of the subject pool the beliefs pertain to. This is presented in Table 8. The results highlight that there are no significant differences between the beliefs of behavioral scientists and their actual answers for both positively and negatively framed biases. Concerning financial professionals and the general population, no significant differences are observable for positively framed biases with differences between beliefs and the actual answers for negatively framed biases.

In Figure A12 the accuracy of each group’s beliefs about each of the three subject pools are given for each of the ten biases. To enhance clarity, accuracies of all ten biases are aggregated, and Mann-Whitney U tests are conducted on the differences between subject pools across that aggregated data, resulting in one statistical test for each pairwise comparison. Table A20 presents the p-values of the the Mann-Whitney U test for differences in beliefs about a specific subject pool between subject pools. This indicates that beliefs regarding the knowledge of behavioral scientists differ across all three subject pools and behavioral scientists hold distinct beliefs about the general population compared to financial professionals and the general population themselves.

Table 8: P-values for the comparison of beliefs about a subject pool with the corresponding subject pool’s actual answers for positively and negatively framed biases.

Subject Pool	Belief Group	Positively Framed Biases	Negatively Framed Biases
Behavioral Scientists	Behavioral Scientists	0.4410	0.2320
	Financial Professionals	0.0018**	0.0000**
	General Population	0.0000**	0.0000**
Financial Professionals	Behavioral Scientists	0.0000**	0.0410*
	Financial Professionals	0.3070	0.0211*
	General Population	0.1690	0.0000**
General Population	Behavioral Scientists	0.0000**	0.0000**
	Financial Professionals	0.0033**	0.0047**
	General Population	0.5470	0.0034**

Robustness Check

We conducted a robustness check on our OLS regression analysis of biases to further analyse RQ2 by applying a multiverse analysis approach, which varies data manipulation methods. This approach examines whether the observed differences between behavioral scientists and the other two subject pools (financial professionals and the general population) persist when different data manipulation techniques and control variable sets are applied. Specifically, the multiverse analysis involves excluding the top and bottom 1% and 5% of response times and testing different control variable sets (all control variables, financial literacy only, and socio-demographics only) for the positively and negatively framed biases. In Table 9, the p-values of the key comparison variables (financial professionals and the general population, relative to behavioral scientists as the reference group) are shown for the different variations of the OLS regression. These p-values indicate whether the differences between behavioral scientists and the other two groups in terms of the observed biases remain statistically significant across the various analytical paths. The results show that no significant differences emerge across the different analysis paths, confirming the stability and robustness of our findings regarding RQ2. This suggests that the observed biases in the behavioral scientists’ responses compared to the other two groups are not sensitive to the choice of data manipulation or control variables. Detailed regression results for the robustness test are available upon request.

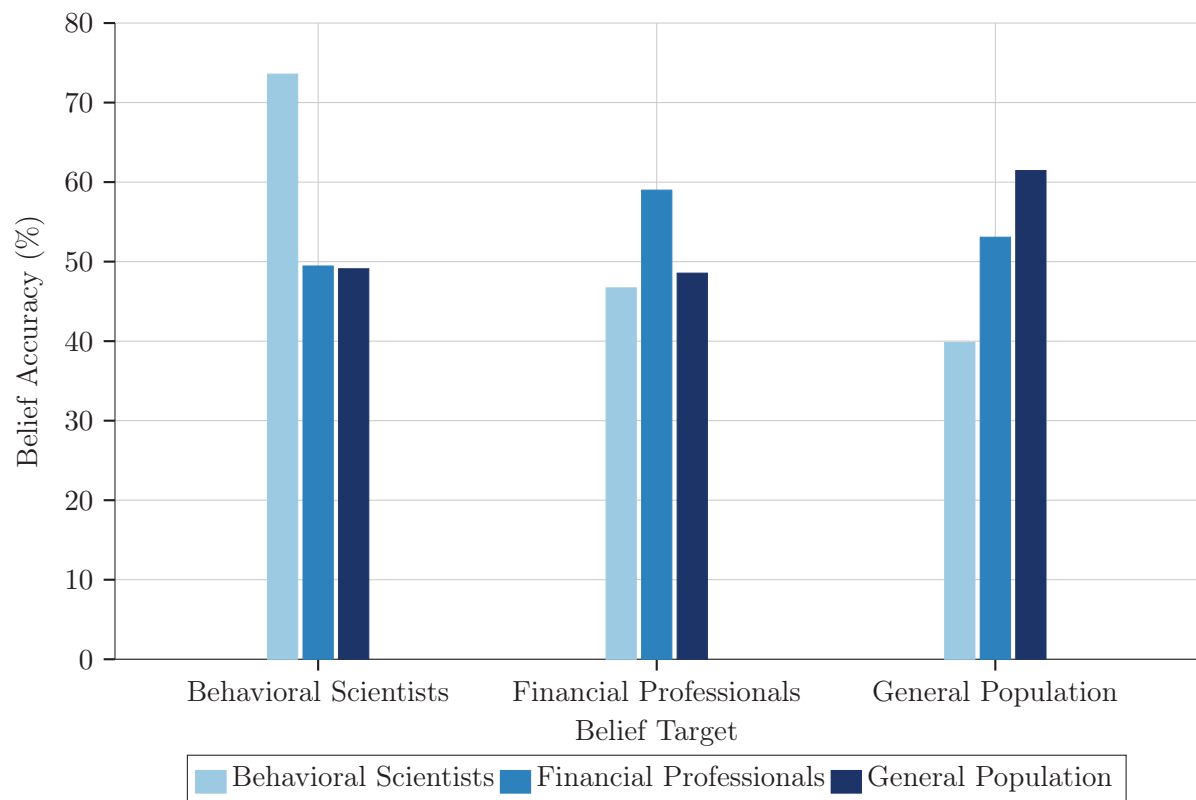


Figure 2: This figure shows the belief accuracy for the three subject pools: behavioral scientists, financial professionals, and the general population, with beliefs aggregated over the different biases.

Table 9: Multiverse analyses: Robustness check of positively and negatively framed biases, showing subject pool affiliation and the corresponding p-value for the different variations. “FP” stands for financial professionals and “GP” for the general population. Furthermore, the data manipulation variation is visible by the additions such as “all”, standing for the variation with all control variables, “FL” for the variation with only financial literacy, and “socio” for the variation with only sociodemographic variables.

Variation	Positively Framed Biases		Negatively Framed Biases		N
	p-value	R ²	p-value	R ²	
FP_1%_all	0.0006**	0.111	0.0006**	0.175	535
GP_1%_all	0.0000**		0.0000**		
FP_1%_FL	0.0000**	0.094	0.0000**	0.148	535
GP_1%_FL	0.0000**		0.0000**		
FP_1%_socio	0.0009**	0.113	0.0024*	0.165	535
GP_1%_socio	0.0000**		0.0000**		
FP_5%_all	0.0011*	0.109	0.0048*	0.180	491
GP_5%_all	0.0000**		0.0000**		
FP_5%_FL	0.0000**	0.094	0.0000**	0.149	491
GP_5%_FL	0.0000**		0.0000**		
FP_5%_socio	0.0020*	0.104	0.0089*	0.172	491
GP_5%_socio	0.0000**		0.0000**		

Note: p-values below 0.05 are indicated with a single asterisk (*), and p-values below 0.005 are indicated with a double asterisk (**).

4 Conclusion

In this study we examined the knowledge and beliefs about ten well-known behavioral biases among three different subject pools: behavioral scientists, financial professionals, and the general population. This was done in an online survey with a total of 547 participants. The analysis revealed that behavioral scientists had the highest overall level of knowledge about behavioral biases. Financial professionals in most cases demonstrated better knowledge than the general population. This aligns with related research – e.g., Kuilen and Wakker (2006) and List (2003) – and is in line with expectations, as both, behavioral scientists and financial professionals, have likely received more education on these topics than the general population. Control variables like income, financial literacy, gender or education had almost no explanatory power.

We also analyzed the accuracy of beliefs each of the participants had about the knowledge of the three subject pools. Beliefs of each subject pool were more accurate than pure chance, and each subject pool had the highest accuracy for their respective own subject pool, correctly guessing 59 to 74 percent of the most frequent answer category. This appears to contradict Kruger and Dunning (1999), who suggest that individuals with less expertise struggle to accurately assess their own knowledge. In our study this holds only partly, as each group was remarkably good in guessing the own groups' most frequent answer. Overall, behavioral scientists had the highest accuracy, especially for correctly guessing their own group's answers.

This research adds to the body of literature on behavioral biases by assessing the level of knowledge about these biases across different segments of the population. It provides insights into the overall understanding of behavioral biases in the context of economic decision-making, highlighting which biases are more widely recognized and which require further educational focus. Additionally, it examines how the different groups within the population perceive the knowledge of other groups regarding these biases. Thus, this study has important practical implications. Finance professionals and people representing the general population take plenty of daily individual, social, and economic decisions. Thus, their proneness to biases is important for the quality of their decisions on an individual level. More prominently, their biases and their beliefs about the behavior and biases of others matter a lot for the decisions they take for third parties in principal-agent situations, taking, for instance, decisions for their customers. Therefore, educating people on behavioral biases and the ways to mitigate those to reach better decisions would be an important avenue for improving decisions on a societal, company and governmental level.

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A Appendix

Table A1: P-values for the Wilcoxon signed-rank test for knowledge about biases aggregated for positively and negatively framed biases and the correct answer for the biases.

Subject Pool	Positively Framed Biases	Negatively Framed Biases
Behavioral Scientists	0.0000**	0.0000**
Financial Professionals	0.0000**	0.0000**
General Population	0.0000**	0.0000**

Table A2: OLS regression for positively framed biases

Coefficients	Estimate	Std. Error	t-value	p-value
Financial Professionals	0.1979	0.0580	3.4110	0.0007**
General Population	0.2131	0.0562	3.7930	0.0002**
Age	0.0027	0.0017	1.6180	0.1063
Gender Male	-0.0027	0.0377	-0.0720	0.9424
Gender Prefer not to say	-0.0233	0.3747	-0.0620	0.9504
Gender Non-binary / third gender	0.0188	0.2173	0.0860	0.9313
Education High school diploma or equivalent	-0.3212	0.1889	-1.7010	0.0896
Education Bachelor's degree or equivalent	-0.3176	0.1905	-1.6670	0.0961
Education Master's degree or equivalent	-0.3996	0.1879	-2.1270	0.0339*
Education Doctoral degree	-0.3879	0.1952	-1.9870	0.0474*
Education Other (please specify)	-0.1468	0.2609	-0.5630	0.5739
Income group 2,000€ to 4,000€	-0.0622	0.0605	-1.0280	0.3044
Income group 4,000€ to 6,000€	0.0882	0.0665	1.3260	0.1856
Income group 6,000€ to 8,000€	-0.0595	0.0671	-0.8870	0.3757
Income group 8,000€ to 10,000€	-0.0096	0.0533	-0.1810	0.8564
Income group over 10,000€	0.0788	0.0774	1.0180	0.3092
Income group Prefer not to say	0.0956	0.0742	1.2900	0.1977
Financial Literacy Score	-0.0366	0.0203	-1.8030	0.0720
Risk Preference	-0.0096	0.0080	-1.1980	0.2313
Math Grade	0.0126	0.0187	0.6750	0.5000
Adjusted R^2	0.108			
N	547			

A.1 Additional analyses

Table A3: OLS regression for negatively framed biases

Coefficients	Estimate	Std. Error	t-value	p-value
Financial Professionals	-0.2603	0.0783	-3.3240	0.0009**
General Population	-0.4253	0.0758	-5.6080	0.0000**
Age	-0.0011	0.0023	-0.4840	0.6288
Gender Male	0.1431	0.0508	2.8150	0.0051*
Gender Prefer not to say	1.2298	0.5056	2.4320	0.0153*
Gender Non-binary / third gender	0.2306	0.2933	0.7860	0.4320
Education High school diploma or equivalent	-0.1212	0.2549	-0.4760	0.6346
Education Bachelor's degree or equivalent	0.0566	0.2571	0.2200	0.8258
Education Master's degree or equivalent	0.1293	0.2536	0.5100	0.6104
Education Doctoral degree	0.2104	0.2634	0.7990	0.4247
Education Other (please specify)	0.0248	0.3521	0.0710	0.9438
Income group 2,000€ to 4,000€	0.0348	0.0816	0.4270	0.6699
Income group 4,000€ to 6,000€	0.0532	0.0898	0.5920	0.5539
Income group 6,000€ to 8,000€	-0.0262	0.0906	-0.2890	0.7729
Income group 8,000€ to 10,000€	0.1101	0.0719	1.5300	0.1265
Income group over 10,000€	0.1002	0.1044	0.9600	0.3375
Income group Prefer not to say	-0.0088	0.1001	-0.0880	0.9296
Financial Literacy Score	0.0723	0.0274	2.6370	0.0086*
Risk Preference	-0.0128	0.0108	-1.1860	0.2362
Math Grade	-0.0003	0.0253	-0.0110	0.9909
Adjusted R^2	0.172			
N	547			

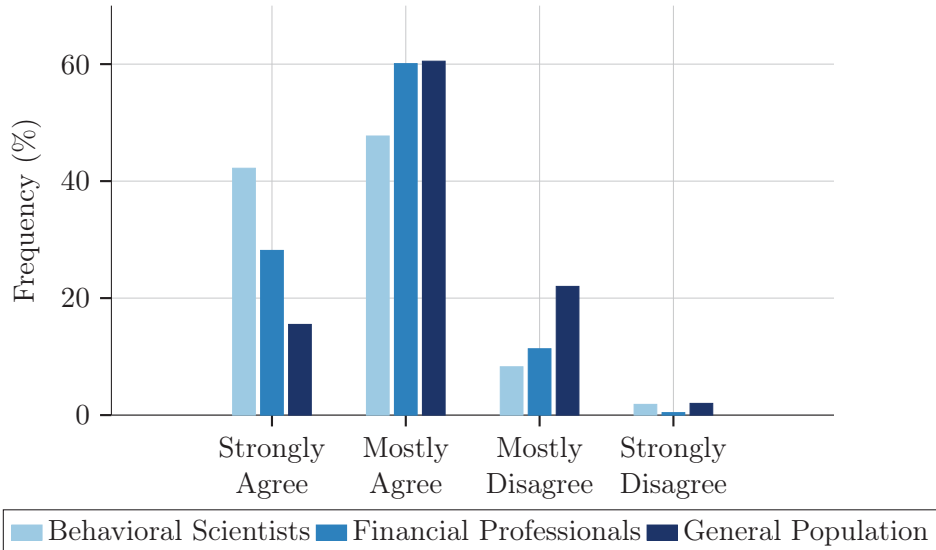


Figure A1: Response distribution for the anchoring effect across the different subject groups (in %)

Table A4: OLS results for the anchoring bias

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool_Financial Professionals	0.2600	0.1017	2.5560	0.0109*
SubjectPool_General Population	0.2889	0.0985	2.9320	0.0035**
Age	-0.0005	0.0029	-0.1570	0.8756
Gender_Male	-0.0595	0.0661	-0.9010	0.3682
Gender_Prefer not to say	0.4263	0.6570	0.6490	0.5167
Gender_Non-binary / third gender	0.3268	0.3811	0.8570	0.3916
Education_High school diploma	-0.0809	0.3312	-0.2440	0.8073
Education_Bachelor's degree	-0.1308	0.3341	-0.3920	0.6956
Education_Master's degree	-0.2925	0.3295	-0.8880	0.3751
Education_Doctoral degree	-0.0644	0.3423	-0.1880	0.8508
Education_Other	-0.2182	0.4575	-0.4770	0.6336
Income_2,000€ to 4,000€	0.0017	0.1061	0.0160	0.9871
Income_4,000€ to 6,000€	0.0705	0.1167	0.6040	0.5462
Income_6,000€ to 8,000€	-0.1693	0.1177	-1.4380	0.1510
Income_8,000€ to 10,000€	0.0881	0.0934	0.9430	0.3461
Income_over 10,000€	0.3824	0.1356	2.8190	0.0050**
Income_Prefer not to say	0.3662	0.1300	2.8160	0.0050**
Financial Literacy_Score	0.0298	0.0356	0.8380	0.4023
Risk_Preference	-0.0171	0.0140	-1.2170	0.2241
Math_Grade	-0.0171	0.0140	-1.2170	0.2241
Adjusted R^2	0.093			
N	547			

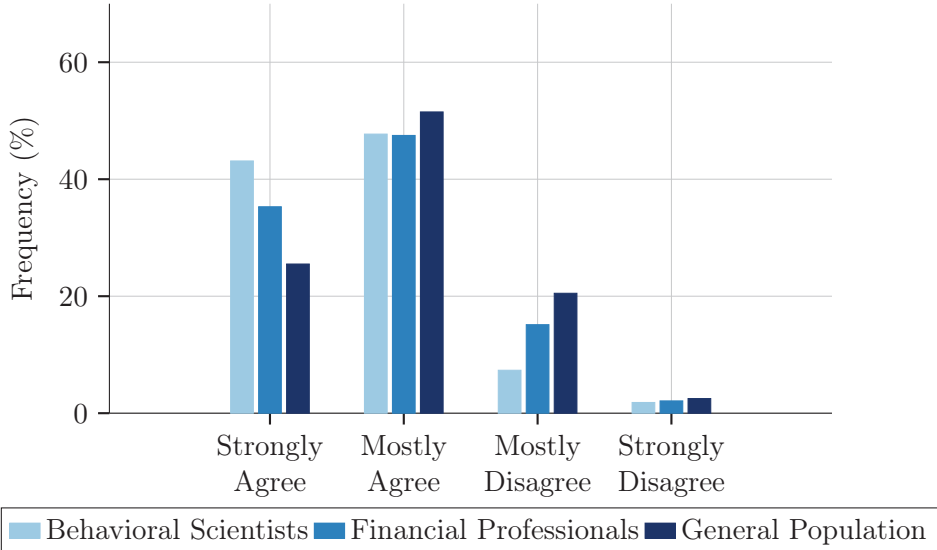


Figure A2: Response distribution for the present bias across the different subject groups (in %)

Table A5: OLS results for the confirmation bias

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool_Financial Professionals	0.1434	0.0914	1.5690	0.1173
SubjectPool_General Population	0.0567	0.0885	0.6410	0.5221
Age	0.0023	0.0026	0.8640	0.3880
Gender_Male	0.0337	0.0594	0.5680	0.5700
Gender_Prefer not to say	-0.2383	0.5904	-0.4040	0.6866
Gender_Non-binary / third gender	-0.1822	0.3424	-0.5320	0.5950
Education_High school diploma	-0.4195	0.2976	-1.4100	0.1593
Education_Bachelor's degree	-0.4765	0.3002	-1.5870	0.1131
Education_Master's degree	-0.4968	0.2961	-1.6780	0.0940
Education_Doctoral degree	-0.4326	0.3075	-1.4070	0.1602
Education_Other	0.1277	0.4111	0.3110	0.7562
Income_2,000€ to 4,000€	-0.0903	0.0953	-0.9470	0.3441
Income_4,000€ to 6,000€	0.0547	0.1048	0.5220	0.6019
Income_6,000€ to 8,000€	-0.0287	0.1058	-0.2710	0.7862
Income_8,000€ to 10,000€	0.0128	0.0840	0.1520	0.8789
Income_over 10,000€	0.1599	0.1219	1.3120	0.1902
Income_Prefer not to say	0.1102	0.1169	0.9430	0.3459
Financial Literacy_Score	-0.0920	0.0320	-2.8750	0.0042**
Risk_Preference	-0.0054	0.0126	-0.4270	0.6695
Math_Grade	0.0187	0.0295	0.6330	0.5272
Adjusted R^2	0.026			
N	547			

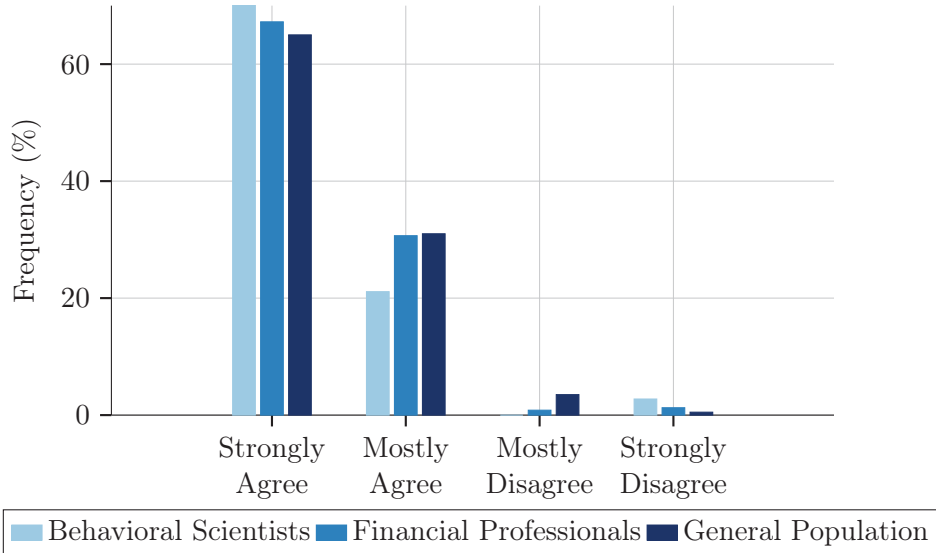


Figure A3: Response distribution for the confirmation bias across the different subject groups (in %)

Table A6: OLS results for the framing effect

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool_Financial Professionals	-0.3603	0.1317	-2.7350	0.0065*
SubjectPool_General Population	-0.3644	0.1276	-2.8560	0.0045**
Age	0.0019	0.0038	0.5060	0.6132
Gender_Male	0.1343	0.0855	1.5700	0.1169
Gender_Prefer not to say	0.6222	0.8508	0.7310	0.4649
Gender_Non-binary / third gender	-0.2902	0.4934	-0.5880	0.5567
Education_High school diploma	-0.4369	0.4289	-1.0190	0.3088
Education_Bachelor's degree	-0.5215	0.4326	-1.2050	0.2286
Education_Master's degree	-0.3983	0.4267	-0.9330	0.3510
Education_Doctoral degree	0.0818	0.4432	0.1850	0.8536
Education_Other	-1.0183	0.5924	-1.7190	0.0862
Income_2,000€ to 4,000€	-0.1408	0.1373	-1.0250	0.3059
Income_4,000€ to 6,000€	0.1045	0.1511	0.6920	0.4895
Income_6,000€ to 8,000€	-0.1634	0.1524	-1.0720	0.2842
Income_8,000€ to 10,000€	0.0580	0.1210	0.4790	0.6319
Income_over 10,000€	0.1563	0.1756	0.8900	0.3741
Income_Prefer not to say	0.1608	0.1684	0.9550	0.3402
Financial Literacy_Score	0.0107	0.0461	0.2330	0.8160
Risk_Preference	-0.0115	0.0181	-0.6330	0.5272
Math_Grade	-0.0339	0.0425	-0.7960	0.4263
Adjusted R^2	0.099			
N	547			

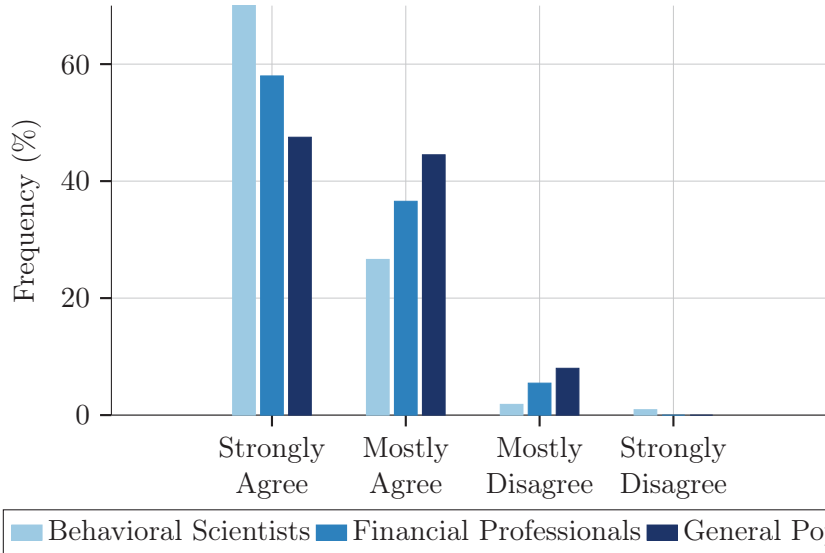


Figure A4: Response distribution for the hindsight bias across the different subject groups (in %)

Table A7: OLS results for the hindsight bias

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool_Financial Professionals	0.0774	0.0933	0.8300	0.4072
SubjectPool_General Population	0.0843	0.0904	0.9330	0.3515
Age	0.0094	0.0027	3.4930	0.0005**
Gender_Male	-0.1154	0.0606	-1.9040	0.0575
Gender_Prefer not to say	-0.5318	0.6028	-0.8820	0.3781
Gender_Non-binary / third gender	-0.1834	0.3496	-0.5250	0.6000
Education_High school diploma	-0.3805	0.3039	-1.2520	0.2111
Education_Bachelor's degree	-0.4556	0.3065	-1.4860	0.1378
Education_Master's degree	-0.5778	0.3023	-1.9110	0.0565
Education_Doctoral degree	-0.6702	0.3140	-2.1340	0.0333*
Education_Other	-0.3083	0.4198	-0.7340	0.4630
Income_2,000€ to 4,000€	-0.1075	0.0973	-1.1050	0.2696
Income_4,000€ to 6,000€	0.1780	0.1070	1.6630	0.0969
Income_6,000€ to 8,000€	0.0617	0.1080	0.5720	0.5678
Income_8,000€ to 10,000€	0.0065	0.0857	0.0760	0.9392
Income_over 10,000€	-0.0873	0.1245	-0.7010	0.4834
Income_Prefer not to say	-0.0460	0.1193	-0.3860	0.7000
Financial Literacy_Score	-0.0543	0.0327	-1.6630	0.0970
Risk_Preference	0.0026	0.0129	0.2000	0.8412
Math_Grade	0.0444	0.0301	1.4740	0.1410
Adjusted R^2	0.077			
N	547			

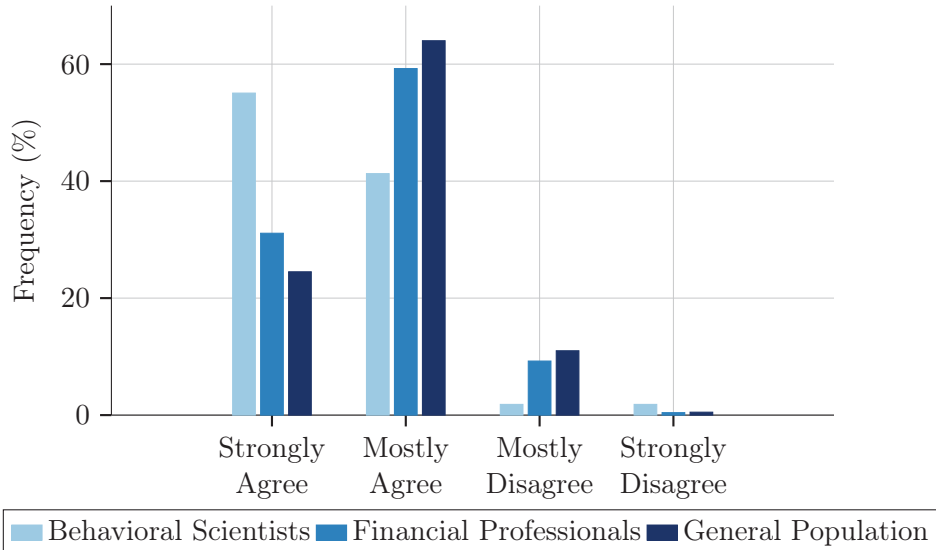


Figure A5: Response distribution for the status quo bias across the different subject groups (in %)

Table A8: OLS results for loss aversion

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool_Financial Professionals	-0.1437	0.1608	-0.8930	0.3721
SubjectPool_General Population	-0.5484	0.1557	-3.5210	0.0005**
Age	-0.0129	0.0047	-2.7770	0.0057*
Gender_Male	0.0368	0.1044	0.3520	0.7247
Gender_Prefer not to say	1.1107	1.0385	1.0690	0.2854
Gender_Non-binary / third gender	0.0274	0.6023	0.0450	0.9638
Education_High school diploma	0.0580	0.5236	0.1110	0.9119
Education_Bachelor's degree	0.1835	0.5281	0.3470	0.7284
Education_Master's degree	0.2825	0.5208	0.5420	0.5877
Education_Doctoral degree	0.3203	0.5410	0.5920	0.5541
Education_Other	-0.2578	0.7232	-0.3560	0.7216
Income_2,000€ to 4,000€	0.2810	0.1676	1.6760	0.0943
Income_4,000€ to 6,000€	-0.1695	0.1844	-0.9190	0.3583
Income_6,000€ to 8,000€	-0.3436	0.1861	-1.8470	0.0654
Income_8,000€ to 10,000€	0.0029	0.1477	0.0190	0.9846
Income_over 10,000€	0.4500	0.2144	2.0990	0.0363*
Income_Prefer not to say	0.3729	0.2056	1.8140	0.0703
Financial Literacy_Score	0.0553	0.0563	0.9820	0.3265
Risk_Preference	-0.0059	0.0221	-0.2680	0.7887
Math_Grade	-0.0162	0.0519	-0.3130	0.7548
Adjusted R^2	0.060			
N	547			

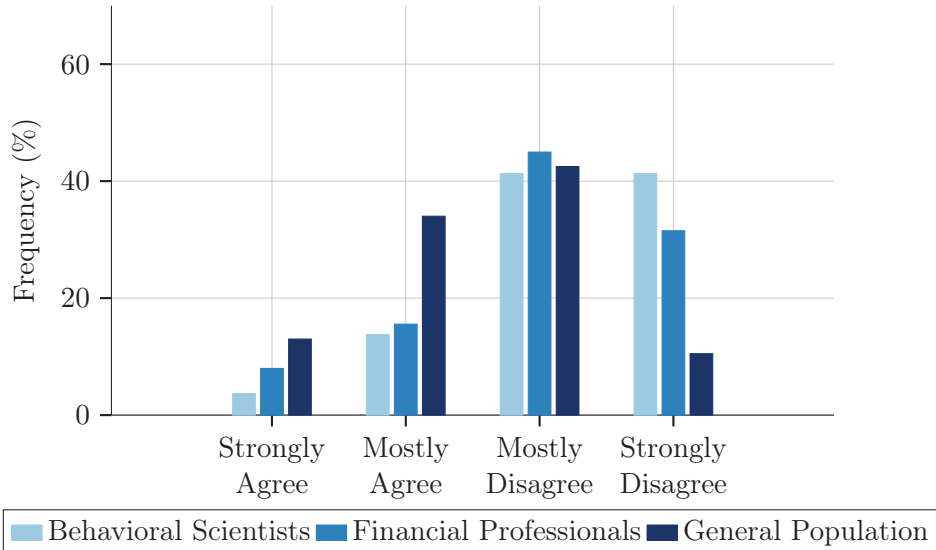


Figure A6: Response distribution for the overconfidence bias across the different subject groups (in %)

Table A9: OLS results for the overconfidence bias

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool_Financial Professionals	-0.3613	0.1346	-2.6840	0.0075*
SubjectPool_General Population	-0.5837	0.1304	-4.4770	0.0000**
Age	0.0065	0.0039	1.6560	0.0984
Gender_Male	0.0988	0.0874	1.1300	0.2590
Gender_Prefer not to say	1.1383	0.8694	1.3090	0.1910
Gender_Non-binary / third gender	0.1043	0.5042	0.2070	0.8362
Education_High school diploma	-0.0174	0.4383	-0.0400	0.9683
Education_Bachelor's degree	0.0952	0.4421	0.2150	0.8297
Education_Master's degree	0.3117	0.4360	0.7150	0.4750
Education_Doctoral degree	0.2222	0.4529	0.4910	0.6239
Education_Other	1.0411	0.6054	1.7200	0.0861
Income_2,000€ to 4,000€	0.0457	0.1403	0.3260	0.7448
Income_4,000€ to 6,000€	0.1417	0.1544	0.9180	0.3591
Income_6,000€ to 8,000€	0.0821	0.1558	0.5270	0.5982
Income_8,000€ to 10,000€	0.1128	0.1236	0.9120	0.3621
Income_over 10,000€	-0.0160	0.1795	-0.0890	0.9290
Income_Prefer not to say	-0.1657	0.1721	-0.9630	0.3361
Financial Literacy_Score	0.1325	0.0471	2.8140	0.0051*
Risk_Preference	0.0007	0.0185	0.0370	0.9706
Math_Grade	0.0181	0.0435	0.4160	0.6774
Adjusted R^2	0.119			
N	547			

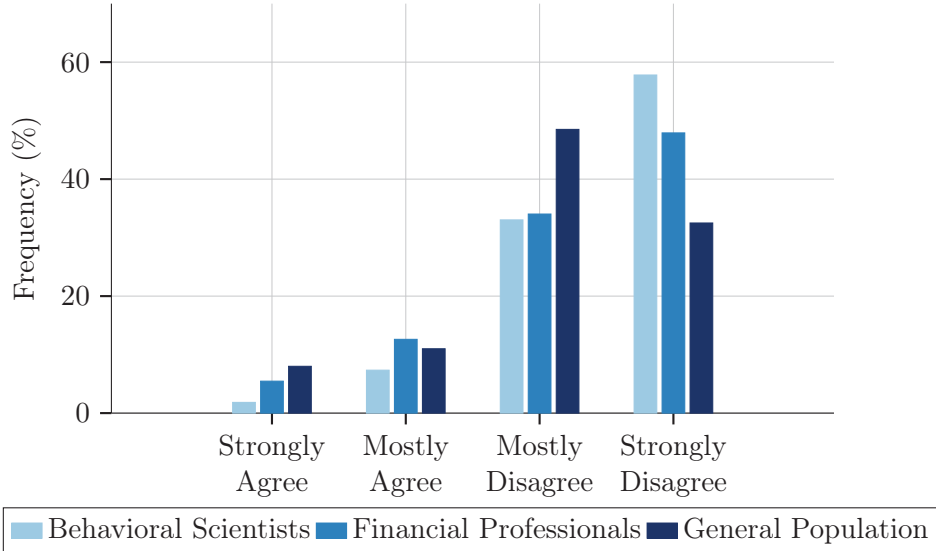


Figure A7: Response distribution for the self-serving bias across the different subject groups (in %)

Table A10: OLS results for overweighting of small probabilities

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool_Financial Professionals	-0.1622	0.1481	-1.0950	0.2740
SubjectPool_General Population	-0.2532	0.1435	-1.7650	0.0781
Age	0.0003	0.0043	0.0590	0.9533
Gender_Male	0.2906	0.0962	3.0220	0.0026**
Gender_Prefer not to say	2.1928	0.9566	2.2920	0.0223*
Gender_Non-binary / third gender	0.7304	0.5548	1.3170	0.1886
Education_High school diploma	-0.2318	0.4823	-0.4810	0.6309
Education_Bachelor's degree	0.1291	0.4864	0.2650	0.7907
Education_Master's degree	0.0757	0.4797	0.1580	0.8747
Education_Doctoral degree	0.1052	0.4983	0.2110	0.8329
Education_Other	-0.1781	0.6661	-0.2670	0.7892
Income_2,000€ to 4,000€	-0.0656	0.1544	-0.4250	0.6714
Income_4,000€ to 6,000€	0.1824	0.1699	1.0740	0.2834
Income_6,000€ to 8,000€	0.3092	0.1714	1.8040	0.0719
Income_8,000€ to 10,000€	0.1357	0.1360	0.9980	0.3188
Income_over 10,000€	-0.2278	0.1975	-1.1540	0.2492
Income_Prefer not to say	-0.3030	0.1893	-1.6000	0.1102
Financial Literacy_Score	0.0305	0.0518	0.5880	0.5571
Risk_Preference	-0.0172	0.0204	-0.8420	0.4000
Math_Grade	0.0037	0.0478	0.0770	0.9386
Adjusted R^2	0.030			
N	547			

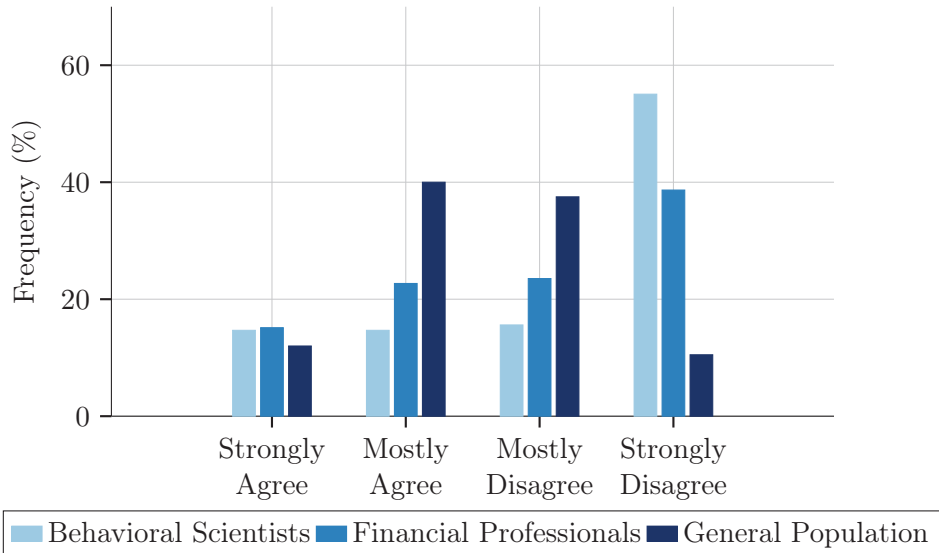


Figure A8: Response distribution for loss aversion across the different subject groups (in %)

Table A11: OLS results for the present bias

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool_Financial Professionals	0.1864	0.1184	1.5750	0.1159
SubjectPool_General Population	0.2940	0.1147	2.5640	0.0106*
Age	0.0027	0.0034	0.7840	0.4332
Gender_Male	0.0210	0.0769	0.2740	0.7846
Gender_Prefer not to say	0.0280	0.7646	0.0370	0.9708
Gender_Non-binary / third gender	-0.0421	0.4435	-0.0950	0.9245
Education_High school diploma	-0.2560	0.3855	-0.6640	0.5068
Education_Bachelor's degree	-0.2339	0.3888	-0.6020	0.5477
Education_Master's degree	-0.2276	0.3834	-0.5940	0.5530
Education_Doctoral degree	-0.3154	0.3983	-0.7920	0.4288
Education_Other	-0.1198	0.5324	-0.2250	0.8220
Income_2,000€ to 4,000€	-0.0148	0.1234	-0.1200	0.9046
Income_4,000€ to 6,000€	0.1516	0.1358	1.1170	0.2646
Income_6,000€ to 8,000€	-0.0843	0.1370	-0.6150	0.5388
Income_8,000€ to 10,000€	-0.1280	0.1087	-1.1770	0.2398
Income_over 10,000€	0.0030	0.1579	0.0190	0.9848
Income_Prefer not to say	0.0201	0.1513	0.1330	0.8944
Financial Literacy_Score	-0.0070	0.0414	-0.1690	0.8662
Risk_Preference	-0.0207	0.0163	-1.2700	0.2047
Math_Grade	-0.0446	0.0382	-1.1670	0.2439
Adjusted R^2	0.005			
N	547			

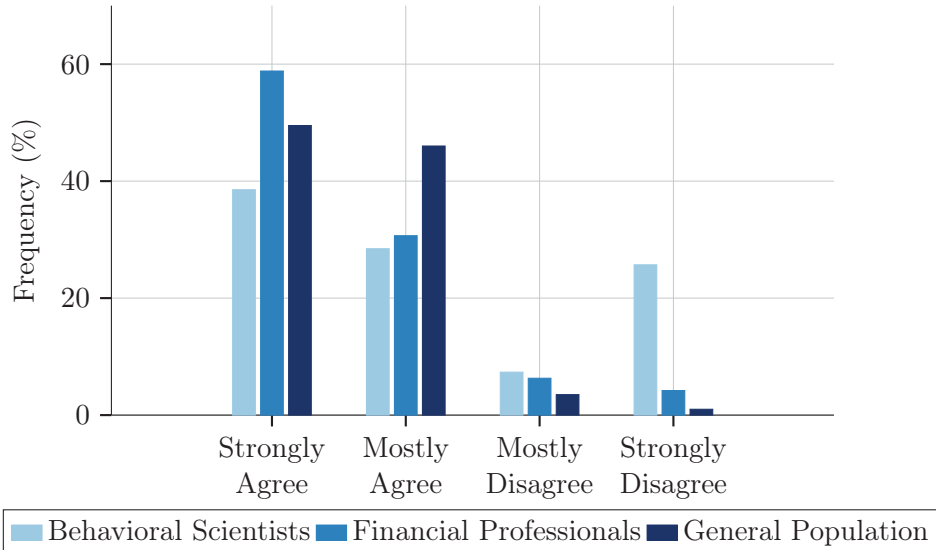


Figure A9: Response distribution for the framing effect across the different subject groups (in %)

Table A12: OLS results for the status quo bias

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool Financial Professionals	0.3223	0.0976	3.3010	0.0010**
SubjectPool General Population	0.3418	0.0946	3.6140	0.0003**
Age	-0.0004	0.0028	-0.1300	0.8968
Gender Male	0.1065	0.0634	1.6790	0.0937
Gender Prefer not to say	0.1991	0.6306	0.3160	0.7523
Gender Non-binary / third gender	0.1746	0.3658	0.4770	0.6332
Education High school diploma	-0.4691	0.3179	-1.4760	0.1406
Education Bachelor's degree	-0.2913	0.3207	-0.9080	0.3641
Education Master's degree	-0.4034	0.3163	-1.2760	0.2027
Education Doctoral degree	-0.4567	0.3285	-1.3900	0.1650
Education Other	-0.2155	0.4391	-0.4910	0.6239
Income group 2,000€ to 4,000€	-0.1000	0.1018	-0.9830	0.3263
Income group 4,000€ to 6,000€	-0.0138	0.1120	-0.1230	0.9018
Income group 6,000€ to 8,000€	-0.0771	0.1130	-0.6820	0.4955
Income group 8,000€ to 10,000€	-0.0277	0.0897	-0.3090	0.7573
Income group over 10,000€	-0.0643	0.1302	-0.4930	0.6219
Income group Prefer not to say	0.0277	0.1248	0.2220	0.8247
Financial Literacy Score	-0.0596	0.0342	-1.7450	0.0817
Risk Preference	-0.0073	0.0134	-0.5440	0.5868
Math Grade	-0.0368	0.0315	-1.1660	0.2441
Adjusted R^2	0.037			
N	547			

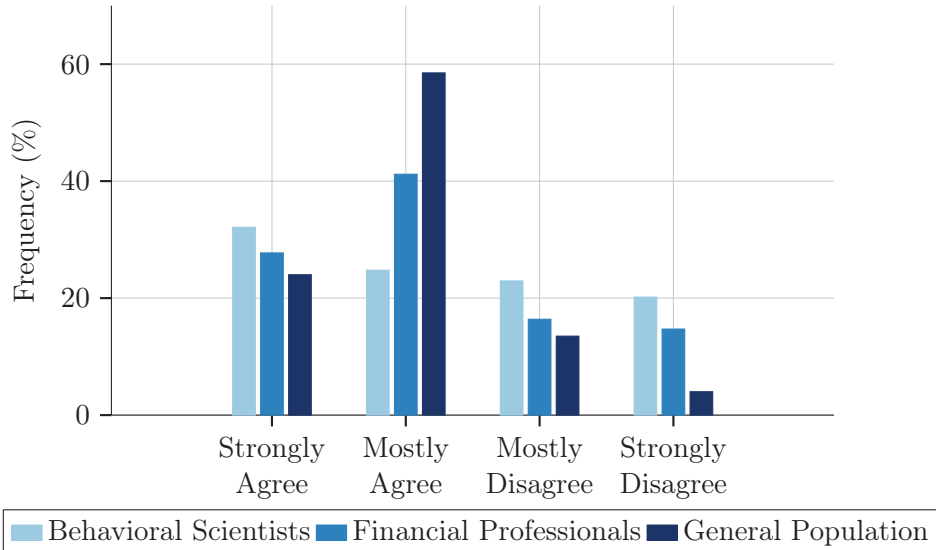


Figure A10: Response distribution for the overweighting of small probabilities across the different subject groups (in %)

Table A13: OLS results for the self-serving bias

Coefficients	Estimate	Std. Error	t-value	p-value
SubjectPool Financial Professionals	-0.2739	0.1316	-2.0810	0.0379*
SubjectPool General Population	-0.3767	0.1275	-2.9550	0.0033**
Age	-0.0012	0.0038	-0.3120	0.7555
Gender Male	0.1550	0.0855	1.8130	0.0704
Gender Prefer not to say	1.0850	0.8501	1.2760	0.2024
Gender Non-binary / third gender	0.5811	0.4930	1.1790	0.2391
Education High school diploma	0.0221	0.4285	0.0520	0.9589
Education Bachelor's degree	0.3968	0.4322	0.9180	0.3591
Education Master's degree	0.3748	0.4263	0.8790	0.3797
Education Doctoral degree	0.3227	0.4428	0.7290	0.4664
Education Other	0.5374	0.5919	0.9080	0.3644
Income group 2,000€ to 4,000€	0.0537	0.1372	0.3910	0.6959
Income group 4,000€ to 6,000€	0.0068	0.1509	0.0450	0.9639
Income group 6,000€ to 8,000€	-0.0150	0.1523	-0.0990	0.9214
Income group 8,000€ to 10,000€	0.2409	0.1209	1.9930	0.0468*
Income group over 10,000€	0.1387	0.1755	0.7900	0.4297
Income group Prefer not to say	-0.1092	0.1682	-0.6490	0.5167
Financial Literacy Score	0.1323	0.0461	2.8720	0.0042**
Risk Preference	-0.0300	0.0181	-1.6560	0.0983
Math Grade	0.0269	0.0425	0.6320	0.5275
Adjusted R^2	0.060			
N	547			

Table A14: Comparison of p-values for beliefs about behavioral scientists in positively framed statements. The comparisons include behavioral scientists vs. financial professionals (BS-FP), behavioral scientists vs. general population (BS-GP), and financial professionals vs. general population (FP-GP). The p-values were obtained using non-parametric double-sided Mann-Whitney U-tests.

Comparison	Confirmation Bias	Hindsight Bias	Status Quo Bias	Present Bias	Anchoring
BS - FP	0.0000**	0.0000**	0.0000**	0.0000**	0.0002**
BS - GP	0.0008**	0.0006**	0.0000**	0.0000**	0.0000**
FP - GP	0.4382	0.1526	0.4220	0.4152	0.3438

Table A15: Comparison of p-values for beliefs about financial professionals in positively framed statements. The comparisons include behavioral scientists vs. financial professionals (BS-FP), behavioral scientists vs. general population (BS-GP), and financial professionals vs. general population (FP-GP). The p-values were obtained using non-parametric double-sided Mann-Whitney U-tests.

Comparison	Confirmation Bias	Hindsight Bias	Status Quo Bias	Present Bias	Anchoring
BS - FP	0.0913	0.9687	0.0740	0.0007**	0.0435*
BS - GP	0.8443	0.7246	0.1483	0.0001**	0.0324*
FP - GP	0.0349*	0.7022	0.8474	0.2270	0.6125

Table A16: Comparison of p-values for beliefs about the general population in positively framed statements. The comparisons include behavioral scientists vs. financial professionals (BS-FP), behavioral scientists vs. general population (BS-GP), and financial professionals vs. general population (FP-GP). The p-values were obtained using non-parametric double-sided Mann-Whitney U-tests.

Comparison	Confirmation Bias	Hindsight Bias	Status Quo Bias	Present Bias	Anchoring
BS - FP	0.5329	0.2225	0.0458*	0.1990	0.0317*
BS - GP	0.5991	0.8792	0.0725	0.6668	0.3132
FP - GP	0.9394	0.1534	0.6948	0.2551	0.1091

Table A17: Comparison of p-values for beliefs about behavioral scientists in negatively framed statements. The comparisons include behavioral scientists vs. financial professionals (BS-FP), behavioral scientists vs. general population (BS-GP), and financial professionals vs. general population (FP-GP). The p-values were obtained using non-parametric double-sided Mann-Whitney U-tests.

Subject Group	Self-Serving Bias	Loss Aversion	Overconfidence	Overweighting	Framing
BS - FP	0.0018**	0.0010**	0.2923	0.9051	0.2398
BS - GP	0.0000**	0.0000**	0.0018**	0.2797	0.5652
FP - GP	0.0902	0.0001**	0.0086*	0.0638	0.4496

Table A18: Comparison of p-values for beliefs about financial professionals in negatively framed statements. The comparisons include behavioral scientists vs. financial professionals (BS-FP), behavioral scientists vs. general population (BS-GP), and financial professionals vs. general population (FP-GP). The p-values were obtained using non-parametric double-sided Mann-Whitney U-tests.

Subject Group	Self-Serving Bias	Loss Aversion	Overconfidence	Overweighting	Framing
BS - FP	0.5135	0.8028	0.9475	0.2334	0.0058**
BS - GP	0.2935	0.0012**	0.0597	0.0026**	0.0007**
FP - GP	0.5737	0.0000**	0.0248*	0.0195*	0.3293

Table A19: Comparison of p-values for beliefs about the general population in negatively framed statements. The comparisons include behavioral scientists vs. financial professionals (BS-FP), behavioral scientists vs. general population (BS-GP), and financial professionals vs. general population (FP-GP). The p-values were obtained using non-parametric double-sided Mann-Whitney U-tests.

Subject Group	Self-Serving Bias	Loss Aversion	Overconfidence	Overweighting	Framing
BS - FP	0.0285*	0.8809	0.4953	0.0036**	0.0000**
BS - GP	0.0292*	0.1174	0.0095**	0.0014**	0.0000**
FP - GP	0.8670	0.0707	0.0040**	0.8798	0.9748

Table A20: P-values for beliefs aggregated over all biases about behavioral scientists, financial professionals, and the general population. Comparisons include behavioral scientists vs. financial professionals (BS-FP), behavioral scientists vs. general population (BS-GP), and financial professionals vs. general population (FP-GP). P-values were calculated using non-parametric double-sided Mann-Whitney U-test.

Comparison	Behavioral Scientists	Financial Professionals	General Population
BS - FP	0.0000**	0.6317	0.0000**
BS - GP	0.0083**	0.2439	0.0000**
FP - GP	0.0139*	0.0431*	0.9028

Mean Beliefs about Knowledge across Subject Groups

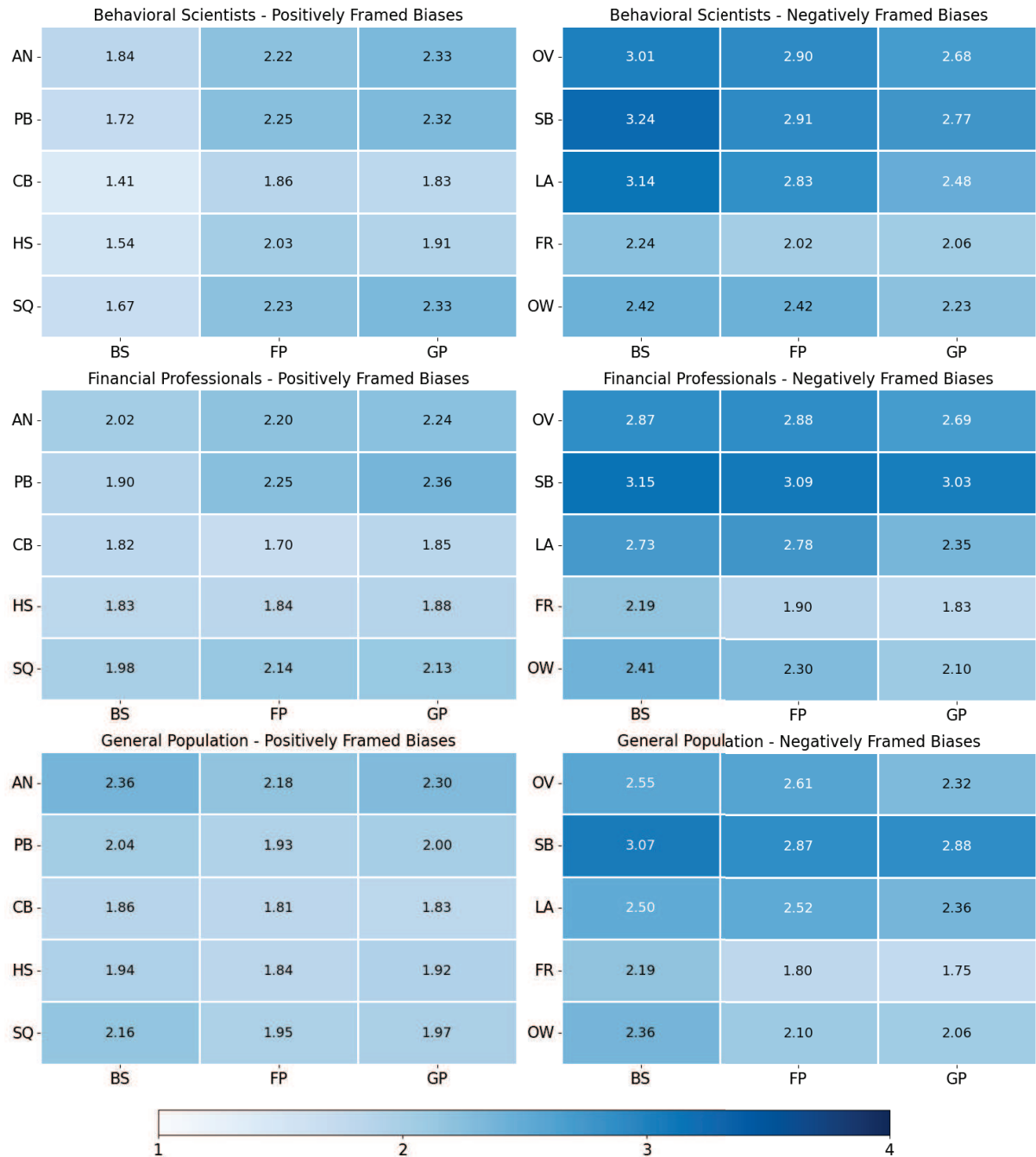


Figure A11: Mean beliefs of “BS” (behavioral scientists), “FP” (financial professionals), and the “GP” (general population) about these three subject pools are plotted. Responses range from 1 (“Strongly Agree”) to 4 (“Strongly Disagree”). The left column represents beliefs about positively framed biases, while the right column presents negatively framed biases. Headings for each graph indicate which subject pool the belief is about. Darker colors indicate a response closer to “Strongly Disagree”. Biases are abbreviated for clearer presentation in the order they have been presented in this thesis. “AN” stand for “Anchoring”, “PB” for “Present Bias”, “CB” for “Confirmation Bias”, “HS” for “Hindsight Bias”, “SQ” for “Status Quo Bias”, “OV” for “Overconfidence”, “SB” for “Self-Serving Bias”, “LA” for “Loss Aversion”, “FR” for “Framing” and “OW” for “Overweighting of small probabilities”

Accuracy of Beliefs Across Subject Groups and Biases (%)

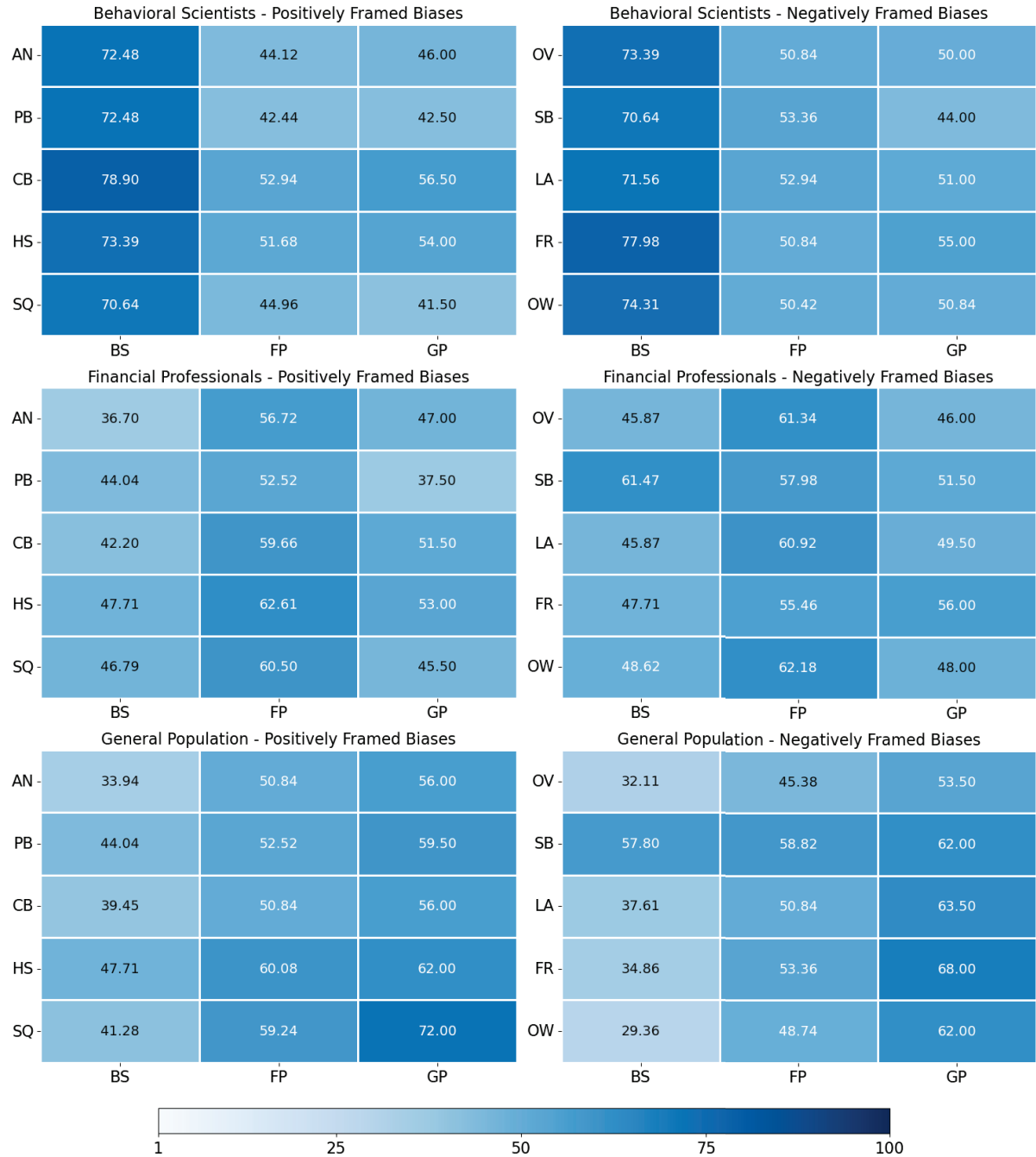


Figure A12: The percentage of correct beliefs of “BS” (behavioral scientists), “FP” (financial professionals), and “GP” (general population) across the subject pools and biases. The left column represents beliefs about positively framed biases, while the right column presents negatively framed biases. Headings for each graph indicate which subject pool the belief is about. Darker colors indicate a higher belief accuracy. Biases are abbreviated for clearer presentation in the order they have been presented in this thesis. “AN” stand for “Anchoring”, “PB” for “Present Bias”, “CB” for “Confirmation Bias”, “HS” for “Hindsight Bias”, “SQ” for “Status Quo Bias”, “OV” for “Overconfidence”, “SB” for “Self-Serving Bias”, “LA” for “Loss Aversion”, “FR” for “Framing” and “OW” for “Overweighting of small probabilities”.

A.2 Invitation E-Mail subjects

Appendix B: Invitation text (ESA/SEF, FinProf)

Dear BEFORE [ESA/SEF/CFA/EAM] member,

We would like to cordially invite you to participate in a short experiment which will take between 10 and 15 minutes.

Apart from helping science, as an incentive for your participation, there is the possibility of **financial compensation** (at least 30 Euros and up to 60 Euros for the 10% of participants drawn randomly) as well as optional feedback in the form of an **anonymized overview of the key results**.

Participation is voluntary and data analyses and presentation of results are fully anonymous!

Even in case of cross-postings/double invitation please participate only once in the experiment.

You can start the experiment here:

[Link to experiment]

The experiment includes content that is not displayed optimally on smartphones. We therefore ask you to answer the survey on a **desktop computer, laptop or tablet**, if possible.

**Thank you very much for your contribution to science and
good luck in the experiment!**

Prof. DDr. [Jürgen Huber](#) (University of Innsbruck)

Prof. Dr. [Michael Kirchler](#) (University of Innsbruck)

Teresa Steinbacher (University of Innsbruck)

Additional information:

Payments will be made no later than 12 weeks after the experiment is closed. As always, individual data will not be shared with third parties and used solely for research and experimental payment. For research publications and presentations aggregated and anonymized data will be made public in a way that does not allow for inferences about participating individuals, countries and institutions.

Figure A13: Invitation for Behavioral Scientists and Financial Professionals

A.3 Instructions of the experiment

Consent ★

Welcome to our survey!

Before you proceed, please take a moment to read through the following.

Purpose of Research: This study aims to gather information about financial decision-making.

Payment: By participating in this survey, you will receive a fixed compensation. Additionally, every 10th participant will receive a bonus payment of 20 GBP if their beliefs were correct.

Procedure: In this study you will first be asked about different aspects of financial decision-making and estimations on other groups of the population. We will then collect some information about your demographic data.

Your responses will remain confidential and will only be used for the purposes of this research. Your data will be securely stored in compliance with data protection regulations. It will be kept for the duration necessary to complete the research project and may be securely archived for future reference. Anonymized data may be shared with other researchers for academic purposes. However, your individual responses will not be identifiable.

Your participation is entirely voluntary, and you have the right to withdraw at any time without penalty. You can further withdraw your consent and request the removal of your data from the study at any time.

To do so and if you have any questions or concerns about this survey or your participation, please feel free to contact Teresa Steinbacher (teresa.steinbacher@uibk.ac.at).

If you agree to participate, please click 'I agree' to begin the survey.

☐ I agree

☐ I don't agree

Figure A14: First slide behavioral scientists and financial professionals

Consent

Welcome to our survey!

Before you proceed, please take a moment to read through the following.

Purpose of Research: This study aims to gather information about financial decision-making.

Payment: By participating in this survey, you will receive a fixed compensation. Additionally, every 10th participant will receive a bonus payment of 20 GBP if their beliefs were correct.

Procedure: In this study you will first be asked about different aspects of financial decision-making and estimations on other groups of the population. We will then collect some information about your demographic data.

Your responses will remain confidential and will only be used for the purposes of this research. Your data will be securely stored in compliance with data protection regulations. It will be kept for the duration necessary to complete the research project and may be securely archived for future reference. Anonymized data may be shared with other researchers for academic purposes. However, your individual responses will not be identifiable.

Your participation is entirely voluntary, and you have the right to withdraw at any time without penalty. You can further withdraw your consent and request the removal of your data from the study at any time.

To do so and if you have any questions or concerns about this survey or your participation, please feel free to contact Teresa Steinbacher (teresa.steinbacher@uibk.ac.at).

If you agree to participate, please click 'I agree' to begin the survey.

☐ I agree
 ☐ I don't agree

Figure A15: First slide general population

Captcha

Before you proceed with the survey, please click 'I'm not a robot' below


☐ I'm not a robot
 

Figure A16: reCAPTCHA

Explanation Groups

Please read all instructions and questions carefully, and complete this survey independently, without distractions.

Thank you for your participation!

This study is conducted with three distinct groups: the general population, financial professionals, and experimental scientists. Here are brief descriptions of each:

1. The General Population includes individuals from diverse backgrounds across Austria, Germany, the Netherlands, Sweden, and Norway. It represents a broad spectrum of socioeconomic statuses, educational levels, and age groups.
2. Financial Professionals are individuals who mainly work as traders, fund managers, analysts, financial advisors, private bankers, and/or work in the top- or middle management at European financial companies.
3. Experimental Scientists are researchers usually exploring questions related to behavioral finance and economics; often through experiments like this one. They are contacted through the Economic Science Association (ESA) and Society for Experimental Finance (SEF) mailing lists.

☐ Next

Figure A17: Explanation

OW1

★

To what extent do you agree with this statement:

'People typically underweight small probabilities whilst they overweight high probabilities'?

- ☐ Strongly Agree
- ☐ Mostly Agree
- ☐ Mostly Disagree
- ☐ Strongly Disagree

Page Break

OW2

💡 ★

Consider the three groups below. For each one, ask yourself:

Which was the most frequently selected answer choice with respect to the statement 'People typically underweight small probabilities whilst they overweight high probabilities'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A18: Overweighting of Small Probabilities

FR1

★

To what extent do you agree with this statement:

'People are usually more risk-averse when it comes to losses and more risk-seeking concerning gains'?

- ☐ Strongly Agree
- ☐ Mostly Agree
- ☐ Mostly Disagree
- ☐ Strongly Disagree

Page Break

FR2 Consider the three groups below. For each one, ask yourself: Which was the most frequently selecte

💡 ★

Consider the three groups below. For each one, ask yourself:

Which was the most frequently selected answer choice with respect to the statement 'People are usually more risk-averse when it comes to losses and more risk-seeking concerning gains'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A19: Framing

Anchoring

AN1 ★

To what extent do you agree with this statement:
'People tend to rely too much on irrelevant reference points or arbitrary information when making decisions'?

☐ Strongly Agree
☐ Mostly Agree
☐ Mostly Disagree
☐ Strongly Disagree

Page Break

AN2 💡 ★

Consider the three groups below. For each one, ask yourself:
Which was the most frequently selected answer choice with respect to the statement 'People tend to rely too much on irrelevant reference points or arbitrary information when making decisions'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A20: Anchoring

Loss aversion

LA1 ★

To what extent do you agree with this statement:
'When evaluating gains and losses of equal size, people typically feel that gains loom larger than losses'?

☐ Strongly Agree
☐ Mostly Agree
☐ Mostly Disagree
☐ Strongly Disagree

Page Break

LA2 💡 ★

Consider the three groups below. For each one, ask yourself:
Which was the most frequently selected answer choice with respect to the statement 'When evaluating gains and losses of equal size, people typically feel that gains loom larger than losses'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A21: Loss Aversion

Status Quo

SO1



To what extent do you agree with this statement:

'People often choose an alternative simply because it is the default option, rather than considering other alternatives'?

- ☐ Strongly Agree
- ☐ Mostly Agree
- ☐ Mostly Disagree
- ☐ Strongly Disagree

Page Break

SO2



Consider the three groups below. For each one, ask yourself:

Which was the most frequently selected answer choice with respect to the statement 'People often choose an alternative simply because it is the default option, rather than considering other alternatives'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A22: Status Quo Bias

Overconfidence

OV1



To what extent do you agree with this statement:

'People usually underestimate their knowledge and abilities when making decisions'?

- ☐ Strongly Agree
- ☐ Mostly Agree
- ☐ Mostly Disagree
- ☐ Strongly Disagree

Page Break

OV2



Consider the three groups below. For each one, ask yourself:

Which was the most frequently selected answer choice with respect to the statement 'People usually underestimate their knowledge and abilities when making decisions'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A23: Overconfidence

Present Bias

PB1★

To what extent do you agree with this statement:
'People typically have a tendency to prefer a smaller present reward rather than waiting for a larger future reward'?

☐ Strongly Agree

☐ Mostly Agree

☐ Mostly Disagree

☐ Strongly Disagree

Page Break

PB2💡 ★

Consider the three groups below. For each one, ask yourself:
Which was the most frequently selected answer choice with respect to the statement 'People typically have a tendency to prefer a smaller present reward rather than waiting for a larger future reward'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A24: Present Bias

Confirmation Bias

CB1★

To what extent do you agree with this statement:
'People usually have a tendency to seek, interpret, and favor information so that it confirms one's prior beliefs or values'?

☐ Strongly Agree

☐ Mostly Agree

☐ Mostly Disagree

☐ Strongly Disagree

Page Break

CB2💡 ★

Consider the three groups below. For each one, ask yourself:
Which was the most frequently selected answer choice with respect to the statement 'People usually have a tendency to seek, interpret, and favor information so that it confirms one's prior beliefs or values'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A25: Confirmation Bias

Hindsight

HS1★

To what extent do you agree with this statement:
'People have the tendency to view past events as more predictable than they actually were'?

☐ Strongly Agree

☐ Mostly Agree

☐ Mostly Disagree

☐ Strongly Disagree

Page Break

HS2💡★

Consider the three groups below. For each one, ask yourself:
Which was the most frequently selected answer choice with respect to the statement 'People have the tendency to view past events as more predictable than they actually were'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A26: Hindsight Bias

Self-serving

SS1★

To what extent do you agree with this statement:
'People often admit their failures more readily than they take credit for their successes'?

☐ Strongly Agree

☐ Mostly Agree

☐ Mostly Disagree

☐ Strongly Disagree

Page Break

SS2💡★

Consider the three groups below. For each one, ask yourself:
Which was the most frequently selected answer choice with respect to the statement 'People often admit their failures more readily than they take credit for their successes'?

	Strongly Agree	Mostly Agree	Mostly Disagree	Strongly Disagree
General Population	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Financial Professionals	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Experimental Scientists	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A27: Self-Serving Bias

FL1

★

Suppose you had €100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

☐ More than €102
 ☐ Exactly €102
 ☐ Less than €102
 ☐ Don't know

FL2

★

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

☐ More than today
 ☐ Exactly the same
 ☐ Less than today
 ☐ Don't know

FL3

★

Buying a single company's stock usually provides a safer return than a stock mutual fund.

☐ True
 ☐ False
 ☐ Don't know

Figure A28: Financial Literacy 1 to 3

FL4

★

If interest rates rise, what will typically happen to bond prices?

☐ They will rise
 ☐ They will fall
 ☐ They will stay the same
 ☐ There is no relationship between bond prices and the interest rate
 ☐ Don't know

FL5

★

A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less

☐ True
 ☐ False
 ☐ Don't know

Figure A29: Financial Literacy 4 and 5

FL6

★

Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

Not at all willing to take risk

0

1

2

3

4

5

6

7

8

9

10

very willing to take risk

☐
☐
☐
☐
☐
☐
☐
☐
☐
☐
☐

Figure A30: Risk preferences

Q80

Please proceed to answer a few demographic questions about yourself.

Age

★

What is your age?

Gender

★

Please select your gender identity from the options below.

- ☐ Male
- ☐ Female
- ☐ Non-binary / third gender
- ☐ Prefer not to say

Figure A31: Age and Gender

education

★

What is the highest level of education you have completed?

- ☐ Less than high school diploma
- ☐ High school diploma or equivalent
- ☐ Bachelor's degree or equivalent
- ☐ Master's degree or equivalent
- ☐ Doctoral degree
- ☐ Other (please specify)

income

★

What is your monthly net income (after taxes)?

- ☐ below 1,000€
- ☐ over 1,000€ to 2,000€
- ☐ over 2,000€ to 3,000€
- ☐ over 3,000€ to 4,000€
- ☐ over 4,000€ to 5,000€
- ☐ over 5,000€ to 6,000€
- ☐ over 6,000€ to 7,000€
- ☐ over 7,000€ to 8,000€
- ☐ over 8,000€ to 9,000€
- ☐ over 9,000€ to 10,000€
- ☐ over 10,000€
- ☐ Prefer not to say

Figure A32: Education and income

math grade

★

What was your grade in mathematics at the end of compulsory schooling? Please select the closest equivalent if your grading system does not match the options provided.

☐ A (Excellent)
 ☐ B (Good)
 ☐ C (Average)
 ☐ D (Below Average)
 ☐ F (Fail)
 ☐ Prefer not to say

Figure A33: math grade

Email

★

10% of participants will be randomly selected for payment. We will pay a fixed amount of EUR 30 plus a bonus of another EUR 30 to these participants (if a randomly selected belief question was answered correctly). If you would like to participate in the random draw please enter your e-mail below. The e-mail-address will not be shared with anybody, but is needed to either contact you (to ask for your IBAN) or for Payment via Wise/Paypal in case you are drawn for a payout. Additionally, your email is required if you wish to receive an anonymized overview of the key results.

Payments will be made no later than 12 weeks after the experiment is closed. As always, individual data will not be shared with third parties and used solely for research and experimental payment. For research publications and presentations aggregated and anonymized data will be made public in a way that does not allow for inferences about participating individuals, countries and institutions.

☒ ★ Yes, I want to enter my email address

☐ No, I don't want to enter my email address

Page Break

Q81

★

Display this question

If 10% of participants will be randomly selected for payment. We will pay a fixed amount of EUR 30 p... Text Response: Is Not Empty

Please indicate which payment method should be used.

☐ Wise
 ☐ Paypal
 ☐ Bank transfer
 ☐ I do not want to receive payment

Figure A34: Final slide 1 behavioral scientists and financial professionals

Q85

★

Display this question

If 10% of participants will be randomly selected for payment. We will pay a fixed amount of EUR 30 p... Text Response: Is Not Empty

Please indicate if you wish to receive an anonymized overview of the key results

☐ Yes, I want to receive an anonymized overview of the key results
 ☐ No, I don't want to receive an anonymized overview of the key results

Figure A35: Final slide 2 behavioral scientists and financial professionals

End of Survey

Q88

🔍

The survey is now finished. Thank you for your participation. If you are eligible for bonus payments and have accurately estimated the beliefs, you will receive your bonus after all participants have completed the survey.

Please click the button below to be redirected back to Prolific and register your submission.

Figure A36: Final slide general population

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Jürgen Huber, Michael Kirchler, Teresa Steinbacher

Knowledge and Beliefs About Behavioral Biases

Abstract

In this study we explore the knowledge and beliefs regarding behavioral biases among behavioral scientists, financial professionals, and the general population. We investigate knowledge about ten prominent biases and collect beliefs about the knowledge levels of each of these subject pools by conducting an online survey with 547 participants. We find that knowledge about the selected biases is highest among behavioral scientists and lowest in the general population. Potential explanatory variables, such as age, gender, income, and financial literacy, show almost no impact on knowledge levels. Regarding accuracy of beliefs about knowledge of the own and the other groups, each subject pool has the highest accuracy rates for their own group, and behavioral scientists assessing other behavioral scientists have by far the highest accuracy rate.

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