From Advice to Action: Drivers of Investor Behavior in the Age of Robo Advice

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General Introduction

The question of how and why individuals make certain decisions has long been a central focus of research. Spanning from disciplines like psychology to economics, researchers have aimed to understand the factors that influence human behavior. The Expected Utility Theory, with origins in the essay of Daniel Bernoulli (1738), provides an early framework for understanding decision-making under risk. Bernoulli introduced the idea that individuals aim to maximize their expected utility, rather than their expected monetary gains, while people experience diminishing marginal utility from wealth. This work laid the foundation for modern economic theories of decision-making. Bernoulli's work was expanded in the 20th century by von Neumann and Morgenstern (1944), who formalized the Expected Utility Theory. Their model provided a mathematical structure for how utility-maximizing individuals should make decisions when faced with risk. Building on this, Markowitz (1952) expanded the Expected Utility Theory to financial decision-making with the development of the Modern Portfolio Theory. In this context, the μ-σ-principle emerged as a key concept. The essence of this idea is that rational investors seek to maximize the expected return (μ) of their portfolios while minimizing the return variance (σ) as a measure of risk. This approach assumes that investors are inherently risk averse, meaning they will only accept higher levels of risk if compensated by higher expected returns. The concept of risk aversion itself was formalized by Pratt (1964) and Arrow (1971), who developed the Arrow-Pratt measure of risk aversion. This measure quantifies the degree of risk aversion exhibited by individuals based on the curvature of their utility functions.

However, real-world behavior often deviates from what would be the best decision as predicted by these frameworks. The emergence of behavioral finance in the late 20th century challenged the notion of an investor who maximizes expected utility based on an individual utility function as proposed by the aforementioned theories. In particular, the Prospect Theory of Kahneman & Tversky (1979), which was later extended to the Cumulative Prospect Theory (Kahneman & Tversky, 1992), introduces and mathematically formalizes two important concepts that were not captured by earlier works: loss aversion and probability weighting. Based on this idea, individuals exhibit loss aversion, where losses are weighted more heavily with a view to utility than equivalent gains. Furthermore, Kahneman & Tversky noticed that humans weigh probabilities non-linearly, meaning individuals tend to overweight small probabilities and underweight large probabilities. This explains why people might overvalue the likelihood of rare but highly impactful events (e.g., lottery wins), while undervaluing more probable outcomes. Behavioral finance further identifies a range of cognitive biases that influence decision-making and cannot yet be included into existing mathematically founded theories (e.g., Thaler, 1993; Shiller, 2000).

Based on the existence of all these biases, the role of financial advice has gained importance. Financial advisors can be seen as guides for helping individuals navigate their behavioral biases, aiming to steer them towards decisions that are more consistent with the principles of expected utility maximization coherent decision-making based on individual preferences. However, even with professional advice, investment mistakes persist, highlighting the complexity of aligning real-world behavior with theoretical expectations (e.g., Shapira & Venezia, 2001; Jansen et al., 2008; Foerster et al., 2017; Linnainmaa et al., 2021). The introduction of robo advice – algorithm-based, automated financial advisory services – has further transformed the investment landscape. However, the implications of robo advice for investor behavior largely remain unclear yet.

The papers presented in this work contribute to the existing literature in various ways, with each study rooted in experimental evidence. The first paper focuses on identifying which measures can serve as a proxy for actual decision-making and which risk preference and patience variables demonstrate the highest explanatory power concerning investment decisions. By using horserace regression analyses, the paper evaluates different question-based approaches to quantify risk preference and patience. The findings of this paper can thus be linked to the investor exploration phase of the advisory process. In the second paper, the impact of different robo advisor layouts and versions of investor exploration questionnaires on trust in the advisor and the subsequent acceptance of advice is analyzed. By exploring this relationship, the paper sheds light on how robo advisor design features can influence investor behaviors. Expanding on this topic, the third paper broadens the participant base and specifically analyzes how the presence of a human advisor can affect both trust levels and the acceptance of robo advisor recommendations. Employing structural equation modeling, this paper moreover offers insights into the connections among various dimensions of trust, the features of robo advisors, and advice acceptance. This contributes to a more comprehensive understanding of the topic. The fourth paper addresses the behavioral bias of overconfidence and its influence on the acceptance of advice within robo advice settings in detail. This study highlights how overconfidence can distort decision-making, even in contexts where robo advice is available, expanding the findings of Odean (1998) and Benos (1998) to robo advised investment decision-making.

In the following chapters of the introduction, a more detailed description of how behavioral biases relate to investment errors is presented. Furthermore, the introduction elaborates on how investment advice could potentially remedy erroneous decision-making processes while also addressing the inherent limitations and challenges associated with this approach. Moreover, the role of algorithm-generated advice is explained in greater detail. The main body of this dissertation consists of four research papers, which are briefly discussed at the end of the introduction. In this view, the individual contributions of each paper are clarified.

1. Irrational Behavior and Behavioral Biases

As noted before, decision-makers do not always choose the option that maximizes their individual expected utility, resulting in behavior that can be classified as irrational. Irrational behavior relates to behavioral biases, which in turn are the reason for the occurrence of systematic investment errors, even when decision-makers have access to information designed to help them in the process. In the context of investment decision-making, irrational behaviors can be divided into two categories: timing-related biases and selection-related biases. Timing-related biases are connected to when and how frequently stocks are traded, while selection-related biases concern which stocks are bought or sold. This section will focus on prominent biases that have gathered much attention in past research.

One of the earliest and most influential studies on behavioral biases in investment decisions is by Shefrin & Statman (1985). They identified the “disposition effect,” where investors tend to sell winning stocks too early and hold on to losing stocks for too long. This behavior is driven by loss aversion. Investors keep hoping that losing positions will recover, while accepting gains on winning positions “just to be safe.” The disposition effect with regard to profit can also be attributed to regret aversion, where investors avoid the negative emotion of regret that could arise if a winning stock price falls after not having sold it.

In the late 1990s and early 2000s, research on behavioral biases expanded. Odean (1998) and Benos (1998) showed that overconfidence in one's investment abilities leads to excessive trading, which – due to transaction costs – results in below-average expected returns. Odean (1999) and Barber & Odean (2000) further demonstrated the existence of this bias with the help of market data, confirming that overconfident investors tend to trade too frequently, eroding their expected returns, and with that, their portfolios' risk-adjusted performance. French (2008) quantified this by estimating that an active investor could increase returns by 67 basis points annually when switching to a passive strategy. This bias is more relevant among men, as Barber & Odean (2001) found that men are more likely to overestimate their investment abilities compared to women.

In terms of selection-related biases, closely akin to the disposition effect, Hartzmark (2015) identified that investors disproportionately often focus on extreme profit and loss positions in their portfolios, leading to poor trading decisions. Coval & Moskowitz (1999) discovered a home bias, where investors favor domestic stocks over foreign ones, resulting in under-diversification. Similarly, Barber & Odean (2008) found that investors tend to favor popular stocks (e.g., those in the news), which can also lead to suboptimal portfolio allocation. The researchers relate these biases to the scarcity of the resource of attention. At the level of information processing, Ehm et al. (2014) showed that while investors consider risk in their decisions, they often fail to understand risk-related information properly, hindering risk preference coherent decision-making. In addition to that, Calvet et al. (2007) observed that while the majority of Swedish private investors performed well overall, less experienced investors were more prone to investment errors, particularly in portfolio diversification. These errors resulted in below-average returns, a finding consistent with Campbell (2006), who, in addition to that, attributed better performance among experienced investors to an awareness of their cognitive limitations. Experienced investors thus tend to refrain from investing in financial products that they do not understand. The data from Badarinza et al. (2016) confirm these results in an international context. Ultimately, investment errors lead to high welfare losses (Calvet et al., 2007; Goetzmann & Kumar 2008).

2. The Role of Investment Advice

Given the existence of systematic errors in investment decisions and the fact that experienced investors tend to manage such situations better, professional investment advice can serve as a measure to address this problem. Financial services providers have recognized this possibility and offer a range of advisory services, including investment advice. There is evidence that professional advice helps to reduce investment errors (Hoechle et al., 2017), particularly by improving portfolio diversification (Bluethgen et al., 2008; Kramer, 2012). Research shows that less experienced investors, in particular, benefit from professional advice, managing to set up better portfolios when they receive advice compared to when they do not (von Gaudecker, 2015).

However, the process of delivering investment advice itself is prone to a number of shortcomings that can impair decision-making. To understand these challenges, it is important to define the typical structure of the investment advisory process. Investment advice for retail investors generally follows three steps. The first step is investor exploration, where the advisor collects data on the investor's financial situation and preferences by asking specific questions. Based on this information, the advisor sets up a profile of the investor to then tailor the investment recommendations. The second step involves providing the actual investment advice. In this step, the advisor recommends a portfolio that potentially offers an optimal risk-adjusted performance based on the investor's profile, considering individual constraints. Third, the investor makes the final investment decision. This is an important step as the whole process is essentially ineffective if the advice is not accepted. However, the question of what makes individuals accept advice, especially with a view to advice providers, has not finally been answered yet.

3. Human Advice vs. Robo Advice

Since the early 2010s, a new form of investment advice, robo advice, has emerged. Robo advisors use algorithms to analyze data provided by investors and to generate personalized investment recommendations. While the final investment decision still rests with the investor, the degree to which they can modify the robo advisor's recommendations varies by provider. Robo advice is generally much cheaper than traditional human advice. Studies such as those by Reher & Sun (2019) have shown that robo advisors help investors to build well-diversified portfolios, similar to traditional investment advisors. Additionally, D'Acunto et al. (2019) demonstrated that robo advice can reduce systematic investment errors, as studied at the example of an Indian brokerage house. However, there is an ongoing debate regarding the effectiveness of robo advice, particularly due to the heterogeneity in the services offered by different financial service providers.

Tertilt & Scholz (2018) criticize robo advisors for not adequately helping investors reflect on their own risk preferences, as they typically rely on a predefined set of questions that may overlook key factors for personalized advice. In contrast, human advisors could adapt to responses more flexibly, potentially leading to a better understanding of the clients' needs. Human advisors, however, are not without their own biases. For instance, Jansen et al. (2008)

found that human advisors often underestimate their clients' risk aversion, leading to suboptimal portfolio recommendations. Foerster et al. (2017) further observed that advisors sometimes base their recommendations on their own portfolios rather than their clients' needs. Such biases are potentially less likely to occur with robo advisors.

Both retail and professional investors are prone to systematic investment errors, although professional portfolios tend to be less affected (Shapira & Venezia, 2001; Linnainmaa et al., 2021). Nonetheless, professional advisors also exhibit cognitive biases which in turn lead to suboptimal advice and thus to erroneous decisions on the part of the investor. With robo advisors, investment errors are caused primarily by flaws in the underlying algorithm, which can be easier to monitor and to correct compared to human biases.

Concerning the integrity of the advisor, it has been shown that human advice can be affected by agency problems: because the compensation system may involve commissions, advisors may be tempted to recommend financial products that are not optimal for the investor but instead maximize their own profits. For example, the Council of Economic Advisors (2015) found that eliminating conflicted advice could increase returns on retirement accounts by about one percentage point per year on average. This problem is also conceivable in the context of robo advice if the algorithm is designed to prioritize the institution's profits over the clients', however, this area requires further research.

As explained above, a key challenge is that investors often do not fully follow the advice given to them. Particularly for inexperienced investors, not accepting advice may again lead to systematic errors and suboptimal portfolio performance, resulting in welfare losses. A lack of acceptance of advice thus entails the risk that investors will make systematic errors despite receiving advice.

Understanding why investors do not (fully) follow the advice requires examining the advisory process, often taking the form of a "judge-advisor system." In this system, the advisor offers recommendations, but the final decision rests with the so-called judge, in this case, the investor. A crucial aspect in this constellation is the acceptance of the advice, as the judge is not obliged to take the advisor's opinion into account. There is evidence that advice is "discounted," that is, advice influences the decision to some extent, but the decision-maker still incorporates his or her own ideas about the decision problem and merely shifts the actual decision in the direction of the advice to some degree (Yaniv & Kleinberger, 2000; Yaniv, 2004). The extent to which advice is discounted depends on several factors. Besides others, especially the degree of trust in the advisor appears to have a measurable impact on the extent of discounting. A number of studies have found that the greater the trust in the advisor, the more the advisor's recommendation is taken into account (Sniezek & Van Swol, 2001; Van Swol & Sniezek, 2005; Burke & Hung, 2021; Wang & Du, 2018). Moreover, a high level of confidence on the part of the decision-maker in their own predefined decision, which they perceive as "correct," increases the extent to which the advice is discounted (Wang & Du, 2018).

In theory, if we consider a boundedly rational investor in an otherwise perfect world with valid implications of Tobin's separation theorem, in which all information would be accessible to the advisor and each advisor would act exclusively in the investor's interest, the advisor would suggest, depending on the investor's risk preference, to invest one part in the market portfolio and the other part in a risk-free investment (for the assumptions and content of Tobin's separation theorem, see Tobin, 1958). Even in this world, the problem of acceptance of the advice would remain, which is why it is this problem that deserves special attention. This is why this dissertation focuses on the advisory process especially with a view to advice discounting.

In what follows, an executive summary of each paper presented in the main body of this dissertation is given. The content of every individual paper is described with a view to the research question and the findings. In addition to that, the contribution regarding the topic of the dissertation is clarified.

4. Executive Summary of Paper #1 – Measuring Risk-Taking and Patience in Financial Decision Making by Wolfgang Breuer, Thomas Renerken, and Astrid Juliane Salzmann

(published in: Review of Financial Economics, 2021; presented at: IFABS Conference 2019 in Angers, France)

4.1. Research Question and Contribution

The paper investigates financial decisions by studying survey-based items meant as a proxy for decision-making, comparing them to more lifelike decision situations based on an experimental setup. The central research question is whether simplified survey measures can provide reliable substitutes, predicting behavior in an actual financial decision-making context. The paper is moreover grounded on the literature on risk and time preferences in financial contexts and is specifically building on Kahneman & Tversky (1979) through Prospect Theory and Thaler's (1981) quasi-hyperbolic discounting models, trying to additionally answer the question which risk preference and patience elicitation methods provide the largest explanatory power regarding real-life decisions.

Previous research has suggested that simpler methods could potentially serve as a replacement for more complex approaches when it comes to predicting decision-making (Dohmen et al., 2011; Hyll & Irrek, 2015). However, there has been a considerable debate about the validity of these measures in the finance-related context, where behavior is influenced by a range of cognitive biases and environmental factors (Frey et al., 2017). This paper contributes to the literature by (i) exploring if simple survey questions that relate to hypothetical decision-making in a financial context can serve as a good proxy for actual financial behaviors observed in a controlled lab setting and (ii) analyzing the predictive power of easy-to-understand risk and time preference measures while comparing them to the more sophisticated ones.

The findings of the study suggest that simplified questions can serve as reliable proxies for actual decision-making, and that relatively easy-to-understand self-assessed measures of risk-taking and patience are superior to more complicated approaches with a view to explaining behavior.

4.2. Research Design

The research is based on a two-part methodological approach, combining a cross-national survey with a controlled laboratory experiment to validate the reliability of the measures used. Survey data collection was conducted with more than 700 participants from nine countries, ensuring diversity in terms of cultural and socio-economic backgrounds. This global sample allows us to account for cross-cultural differences in risk-taking and patience, with specific attention to Hofstede’s (2001) cultural dimensions framework, which emphasizes the role of culture in shaping decisions. Furthermore, data on 163 (additional) participants in a controlled laboratory experiment complete the database of this study.

The survey instrument employed straightforward questions designed to proxy participants’ decision-making. These questions were intended to capture intuitive patterns, similar to those used in earlier studies such as Donkers & van Soest (1999) and Bachmann et al. (2017). Moreover, a laboratory experiment was conducted in which participants made incentivized investment choices under risk and time constraints, closely related to real-life scenarios involving real monetary stakes, which were used as a benchmark for assessing the accuracy of proxies used in the survey.

The subjects were also asked to answer a set of questions intended to measure risk preferences and patience. Our questionnaire items were based on non-sophisticated and more difficult-to-understand approaches. We asked for a simple self-assessment of risk and time preferences on the one hand, while on the other hand, we used methods based on lottery questions, through which the relevant risk- and time-preference-related parameters had to be calculated first before relating these variables to decision-making.

The paper employs Tobit and Logit regression models to analyze the relationship between different risk and time preference measures and proxied decision-making. The same models were set up in a second step using experimental evidence and a more lifelike decision setup. Controls for age, gender, income, wealth, and cultural factors were included to account for socio-demographic influences. Then, we estimated horserace regressions to determine the predictive power of the different risk and time preference measures, and to judge the applicability of the survey instruments as a good substitute for actual decision-making tasks.

4.3. Findings

The central idea of the paper is that easy-to-understand survey questions relating to hypothetical decision situations will reliably proxy actual financial behavior. The empirical findings strongly support this notion. The regression results achieve a high comparability, no matter if we use the answer to our simplified survey question or more lifelike lab-measured data as the dependent variable in our analyses. This means that easy-to-employ survey questions proxy actual financial behavior in our models well. Second, the study compares simple self-assessments with lottery-based risk and time preference elicitation methods used in finance research (e.g., Hyll & Irrek, 2015), finding that the self-assessments outperform more complex methods in terms of predictive power. This suggests that the cognitive simplicity of the easy-to-understand methods enhances their reliability.

4.4. Contribution of Paper #1 to the Topic of this Thesis and Practical Relevance

One of the central challenges addressed in this work is the need for financial advisors to accurately measure their clients' risk and time preferences in order to provide tailored advice. The paper's finding is that non-sophisticated survey questions offer a practical solution to this challenge, enabling advisors to efficiently gather information about their clients' individual needs without using more time-consuming techniques. Thus, the demonstration that simple measures can reliably assess risk- and time-related preferences is of direct relevance to the thesis.

The practical impact of this contribution is particularly important in the context of the increasing reliance on robo advisors in the financial industry. As outlined in the thesis, robo advisors' investor exploration process is based on predefined, relatively easy-to-understand questionnaires to assess client preferences (Tertilt & Scholz, 2018). These tools were challenged in the way that they potentially do not manage to capture the complexity of individual preferences. This paper, however, provides empirical support for the utilization of rather non-sophisticated methods in large-scale investor exploration contexts, justifying current practices in robo advice that have been criticized before. In this view, the paper supports the thesis's broader goal of assessing the effectiveness of financial advisory processes.

In conclusion, the results have important implications for both academic researchers and practitioners, particularly in the context of the growing use of robo advisory platforms and the need for clarification concerning which measures of risk preference and patience to use in the investor exploration part of the advice process. With a view to the development of this thesis, easy-to-understand measures to determine individual preferences are therefore also used in the experiments employed in the following papers.

5. Executive Summary of Paper #2 – Drivers of Trust and Advice Discounting for Robo Advice by Claudia Breuer, Wolfgang Breuer, and Thomas Renerken

5.1. Research Question and Contribution

Paper #2 explores how the design and structure of robo advice services influence (i) the trust investors place in the advisor and (ii) the acceptance of advice. It investigates how certain characteristics – such as an emotional presentation of the interface and the length of the exploration questionnaire – affect the degree to which users follow advice.

The paper contributes to the emerging literature on robo advice by providing insights on what factors lead to greater acceptance of automated advice. While previous research has shown that there are different reasons why advice is disregarded, such as a lack of trust (e.g., Yaniv & Kleinberger, 2000; Sniezek & Van Swol, 2001), this paper focuses on the unique setting of robo advisors and offers evidence on the variables influencing advice acceptance. We develop several hypotheses regarding how interface layout and questionnaire detail impact both trust and advice discounting. The first hypothesis posits that participants will trust the robo advisor more when the questionnaire is detailed. The second hypothesis suggests that an emotionally engaging interface will lead to higher trust levels compared to a distanced interface. This hypothesis is based on the work of Hohenberger et al. (2019), who found that positive emotions increase trust in automated systems. The third and fourth hypotheses concern advice discounting. Hypothesis 3 proposes that participants will discount advice less when the questionnaire is detailed, while Hypothesis 4 suggests that an emotional interface will lead to lower discounting rates.

The study's contribution lies in its practical relevance for the financial services industry, particularly in the growing field of robo advisor software, which have become essential tools for investors with lower wealth and insufficient financial literacy (Fulk et al., 2018; Monticone, 2010; van Rooij et al., 2012). This research can therefore provide recommendations for robo advisory platforms. The findings ultimately suggest that user interface design should prioritize emotional engagement to increase advice acceptance, while the length of the questionnaire has no measurable impact in advice discounting.

5.2. Research Design

The research design consists of an incentivized experiment in which a total of 135 participants interacted with a custom-built robo advisor with the task of allocating an initial monetary endowment into different assets. The experiment varied two key factors: the length of the exploration questionnaire (detailed vs. superficial), and the design of the user interface (emotional vs. distanced). This 2x2 design created four treatment groups, allowing us to isolate the effects of each variable on both trust and advice discounting.

To be exact, participants were asked to allocate a hypothetical 50,000 € across several risky and risk-free assets in a series of portfolio decisions, each decision reflecting realistic situations using real-world historical stock price data. A total of four such situations were presented per participant. The initial investment decisions were made without any advice. After completing this first series of decisions, participants filled out an exploration questionnaire (either a detailed or a superficial one) and were then presented with the same decision situations again, this time with investment recommendations based on their questionnaire responses. These recommendations were generated by the robo advisor. After making their investment decisions, they were provided with information about the outcomes of their investment and then navigated to the next decision, until all four situations were completed. The emotional interface used eye-catching colors, informal language, and smiley faces, while the distanced interface was black-and-white with formal language and no visual emotive elements. This layout was kept constant for each participant during the whole advice process (exploration, advice, decision).

In order to measure advice acceptance, a modified version of Yaniv & Kleinberger's (2000) discounting measure was introduced with the goal to fit multidimensional decision situations. This measure involved calculating the Euclidian distance between participants' initial decisions and the robo advisor's recommendations, as well as the distance between the final decisions and the recommendations. The greater the shift from the initial decision towards the recommendations in the final decision, the lower the level of advice discounting. We furthermore collected data on trust using a Likert scale and elicited socio-demographic variables using an additional questionnaire. The design of this additional questionnaire was identical for each participant to avoid influences of different layouts in this part.

5.3. Findings

To determine the impact of our variables of interest on trust, we set up OLS regressions and ordered logistic regressions controlling for participant-specific socio-demographic, cultural and personality-related effects. The findings provide no support for our hypotheses concerning trust. Trust levels did not significantly differ between the detailed and superficial questionnaire groups and they were also unaffected by the interface design. This contradicts earlier studies (e.g., Harvey & Fischer, 1997). Concerning the acceptance of advice, we estimated several different models including random-effects Tobit and GLS regressions and we found robust evidence that while the length of the questionnaire did not significantly impact advice discounting, an emotional interface layout did result in lower discounting rates, reflecting a higher degree of advice acceptance – controlling for trust. This suggests that emotional engagement plays a more critical role in advice acceptance than the perceived thoroughness of the exploration process.

These findings challenge the notion that trust is the primary driver of advice acceptance (Sniezek & Van Swol, 2001), at least for automated settings. Instead, the paper argues that the design and presentation of the advice interface are crucial for determining how much users will follow the recommendations. However, it is conceivable that trust in an automated system cannot be measured in the same way as trust in a human and there might thus be a need for developing new trust scales for human-computer interactions. This is a matter of future research.

5.4. Contribution of Paper #2 to the Topic of this Thesis and Practical Relevance

As explained in Section 2 of this introductory chapter, the acceptance of the advice provided is of utmost importance, as it directly influences the effectiveness of financial advisory services in improving investor decision-making. In the realm of robo advisors, achieving high advice acceptance is essential for further reasons: robo advisors typically target an investor group that may have limited financial literacy and fewer financial resources compared to those seeking traditional, more expensive human advice (Fulk et al., 2018). As research shows (Monticone, 2010; van Rooij et al., 2012), less affluent clients tend to exhibit a higher number of errors when it comes to financial decision-making. The more affordable and accessible nature of robo advisors makes it a valuable solution for this demographic group, but the usefulness of these platforms depends heavily on whether clients actually follow the advice provided. Without high levels of advice acceptance, these investors may continue to make suboptimal financial decisions, counteracting the purpose of using a robo advisor in the first place.

By demonstrating that an emotionally engaging interface can significantly reduce advice discounting, the paper highlights a practical approach to increasing advice acceptance. Robo advisor users are likely to benefit from such design improvements, as emotionally appealing and user-friendly interfaces may help reduce the psychological barriers to following financial advice, thus leading to better investment behavior.

6. Executive Summary of Paper #3 – Each Betrayal Begins with Trust? The Impact of Human Involvement in Robo Advice by Claudia Breuer, Wolfgang Breuer, and Thomas Renerken

6.1. Research Question and Contribution

The third paper of this dissertation investigates how the presence of a human advisor during robo advisory interactions impacts trust and advice acceptance. It furthermore provides first-time evidence about the tension between algorithm aversion and betrayal aversion in an advised decision-making context, trying to determine whether investors are more likely to follow robo advice when a human is involved or when the advice is delivered exclusively by a robo advisor. To test these ideas, we set up different hypotheses. The first hypothesis is that trust levels are higher when a human advisor is involved compared to a purely robo advisor setting. This hypothesis is built on earlier research showing that humans are generally trusted more than machines (e.g., Promberger & Baron, 2006). The second set of hypotheses concerns advice discounting. Hypothesis 2a suggests that participants will discount advice more when it is delivered without human involvement due to algorithm aversion (Dietvorst et al., 2015). In contrast, Hypothesis 2b posits that participants will discount advice more when a human is involved due to betrayal aversion (Bohnet et al., 2008). The third set of hypotheses concerns the role of uncertainty avoidance in moderating the effects of human involvement, either because of the “black box” nature of algorithm advice development (Hypothesis 3a) or possibly caused by an increased risk of betrayal (Hypothesis 3b).

The findings reveal that while the presence of a human advisor increases trust, it leads to lower levels of advice acceptance. This may seem paradox at a first glance, but we attribute this to betrayal aversion – the idea is that investors may be more reluctant to follow advice from a human because of the perceived risk of being betrayed that increases with higher trust levels (Bohnet et al., 2008). The study furthermore contributes to the literature on trust in automated systems (see, for example, Promberger & Baron, 2006) by showing that while humans are generally trusted more than machines, the fear of betrayal can override this increased trust when it comes to following financial advice.

This paper thus adds research on robo advice by disentangling the effects of human involvement on investor behavior. It provides evidence that the benefits of human advisors – such as increased trust – can be offset by other factors, leading to lower acceptance of their advice in total.

6.2. Research Design

The research design is built upon the experiment presented in Section 5.2. of this dissertation, expanding the existing 2x2 scheme by conducting an additional experiment within the same framework to test the impact of human involvement in robo advice. The experimental design allowed us to isolate the effects of human presence and to test whether that presence would influence trust levels and advice discounting. 84 people participated in this second experiment, raising the total number of observed individuals to 219. In the baseline experiment, participants interacted solely with a robo advisor. In the additional experiment, participants received the same algorithm-generated robo advice based on their answers in the investor exploration part of the experiment, but a professional human advisor was present via video conferencing software, asking exploration questions and ultimately delivering the advice.

Both experiments involved the same portfolio allocation decisions and the same algorithm-generated advice, where participants were given a hypothetical sum of money to invest across various stocks and funds in different lifelike settings with and without advice. Participants in all cases had to rate the advisor in terms of trust, and their decisions were measured regarding advice discounting. Human advisors could not monitor participants' answers to questions on trust.

6.3. Findings

The findings show that trust levels – as based on OLS and ordered logistic regressions – are expected to be significantly higher in the presence of a human advisor, even though the advice was generated by the same algorithm (Hypothesis 1). However, the findings support Hypothesis 2b in contrast to Hypothesis 2a – based on the same regression approaches as described in Section 5.3., advice discounting is expected to be higher when a human advisor is present, suggesting that the risk of betrayal outweighs the participants' increased trust in the human advisor, and with that, overriding potential algorithm aversion as well. The study moreover found that participants with lower levels of uncertainty avoidance showed a lower extent of advice discounting when facing a human advisor. We attributed this to a smaller impact of the risk of being betrayed for those with lower uncertainty avoidance, supporting Hypothesis 3b.

To further validate these findings, we employed Structural Equation Modeling (SEM) to explore the relationship between trust, human involvement, and advice acceptance in more detail. The SEM allowed us to disentangle the different dimensions of trust that were also measured in the experiment – namely trust in the advisor's competence and trust in the advisor's integrity – and to assess how these factors contributed to the overall trust in the advisor, as well as their impact on advice discounting. Trust in integrity as well as trust in the advisor's competence were of significant influence on overall trust in the advisor, however, only trust in the advisor's integrity had a significant impact on advice discounting, underscoring the notion that people tend to be reluctant to follow advice when being unsure of the advisors' ethics. While a human advisor leads to higher trust in competence and integrity as well as overall trust, and higher trust in the advisor's integrity leads to less advice discounting, we could calculate the total effect of human presence on advice discounting. Our results show that this effect is significant, however, the statistics indicate that even though taking indirect effects into account, individuals discounted more when confronted with human advice.

Furthermore, when calculating advice discounting only with a view to the risky part of the investment and again estimating regression models, the paper shows that trust in the advisor is a highly significant influential factor when it comes to the acceptance of advice, with more trust leading to a lower degree of advice discounting only for the risky part of the investment. This led to the idea that people who are confronted with a human advisor, in general, might mainly lower the amount invested riskily but tend to stick to the structure of the advice in the risky part. By setting up another set of regressions, we confirmed this: when a human advisor was present, people invested significantly less money into risky assets. This reinforces the notion that betrayal aversion plays a role when it comes to human-advised decision-making, as investing money risk-free provides an opportunity to bypass a possible betrayal.

Expanding on the results of paper #2, we found that when taking the bigger pool of participants provided by the additional experiment into account and again performing OLS, GLS and Tobit regressions, a longer questionnaire led to significantly more advice discounting. We attributed this to the idea that a longer questionnaire might relate to a higher level of algorithm aversion with a view to an increased "black box" character of advice creation based on a larger set of questions. This, however, has still to be confirmed by generating additional evidence. The results concerning robo advisor layout stayed robust: participants discounted significantly less when confronted with a more emotional interface.

6.4. Contribution of Paper #3 to the Topic of this Thesis and Practical Relevance

The study provides valuable insights into why investors may be hesitant to follow advice from human advisors, even when they trust them more than machines. This contributes to the thesis's goal of identifying ways to improve the effectiveness of robo advisory services by reducing the potential for biased decision-making. The paper furthermore provides first-time experimental evidence on the balance between algorithm aversion and betrayal aversion when human advisors are integrated into robo advisory platforms.

For less wealthy clients, who are prone to exhibiting behavioral biases in investing, it is critical that robo advisors are perceived as unbiased and trustworthy sources of financial guidance to ensure a high acceptance of advice. The study's findings suggest that adding human elements to the advisory process can backfire, as it may lead to greater skepticism about the integrity of the advice. This paper is therefore important to the thesis's exploration of how to optimize robo advisors for investor needs. It can furthermore serve as a basis for future research concerning possible measures to avoid the pitfalls of betrayal aversion while still fostering trust. Ideas could be, for example, that renumeration schemes are transparently discussed with the investor before giving advice.

In terms of practical relevance, the research highlights the importance of designing advisory systems that build trust without introducing the “social risks” associated with human involvement.

7. Executive Summary of Paper #4 – Impact of Investor Overconfidence on Trading Volume in the Presence of Investment Advice by Thomas Renerken

7.1. Research Question and Contribution

The fourth paper of this dissertation analyzes the research question of how investor overconfidence affects trading volume when investors have access to robo advice. The study builds on existing research by Odean (1998) and Barber & Odean (2000), who found that overconfident investors tend to trade more frequently than their less confident counterparts, often leading to lower returns due to transaction costs.

The paper contributes to the literature by focusing on a topic that has received limited attention in previous studies. Most research on overconfidence has examined its effects on investment decisions of self-directed investors (e.g., Deaves et al., 2009; Pikulina et al., 2017; Inghelbrecht & Tedde, 2024), or the propensity to seek advice (e.g., Broekema & Kramer, 2021; Piehlmaier, 2022; Hsu, 2022). This paper expands the research by analyzing overconfidence and its effects on actual decision-making in the presence of financial advice. The first hypothesis suggests that investors classified as overconfident in the domain of overestimation will trade more than their non-overconfident counterparts, even though they have access to robo advice. The second hypothesis posits that a higher degree of overconfidence will lead to more excessive trading. These hypotheses build on the work of a diverse range of studies (e.g., Odean, 1998; Barber & Odean, 2000; Statman, 2006) who found that overconfident investors engage in excessive trading due to their belief in their superior knowledge or skills.

The study's contribution lies in its examination of how automated investment advice interacts with behavioral biases, particularly overconfidence. It provides evidence that robo advice does not completely mitigate the effects of overconfidence, suggesting that advisory systems need to account for this bias to prevent suboptimal trading behavior.

7.2. Research Design

The research design involves an incentivized trading experiment in which participants were asked to invest a hypothetical sum of money across several stocks, as explained in paper #2 and paper #3. The experiment used real-life market data to simulate a realistic trading environment. 219 participants took part in the experiment. In the specific experimental decision-situation analyzed in this paper, participants had to choose between a risk-free asset and five different stocks of rather unknown, German companies in order to avoid distortion based on other behavioral biases like home or media bias. Participants had to make a total of four such investment choices in this setting and they were charged 0.2 % of their trading volume as transaction costs. This number was taken from real-life data. As time progressed, investors were informed about the performance of their portfolio, and they could then change their allocation by buying or selling assets as they preferred. If participants followed the advice, there would be an initial allocation which would have only been altered by rebalancing the portfolio in later decisions, leading to a low trading volume. High levels of trading volume can therefore only occur when participants disregard advice.

Overestimation of own skills was measured using self-reported financial literacy and the actual performance on a financial literacy test based on Lusardi & Mitchel (2011). Individuals were classified as overconfident in the domain of overestimation if they rated their financial literacy equal to or higher than the median self-assessment while answering fewer or the median number of questions correctly; it was thus included as a dummy variable. Moreover, the degree of overconfidence was measured using information about the level of misjudgment of own skills (a measure relating to "overprecision", which is another dimension of overconfidence), which was operationalized as the discrepancy between a participants' self-assessed confidence to be correct and their actual performance on financial literacy questions. As the dependent variable, relative trading volume has been used, defined as the sum of asset values bought and sold in each round and then divided by the total portfolio value. Several robustness checks were conducted to verify the results of this study.

7.3 Findings

To account for upper and lower boundaries of the dependent variable, I used Tobit regression models to test the hypotheses. The findings support the hypothesized ideas: the models suggest that participants who were classified as overconfident in the domain of overestimation traded significantly more than their non-overestimating counterparts, even though all subjects received robo advice based on the same algorithm. This finding is not influenced by questionnaire length, advisor layout or the presence of a human advisor. The results further show that the interaction between the overestimation dummy and the extent of overprecision – to be interpreted as the degree of overconfidence – has a significant influence on trading volume, with more trading activity for those overestimating participants who misjudged their skills by a higher degree. This finding supports previous research by showing that overconfidence plays a critical role in determining trading behavior (e.g., Pikulina et al., 2017; Chui et al., 2010), extending the literature to robo advice situations.

I set up different robustness checks to test if factors like model choice, additional control variables or changes in the dependent variable influence the results. This was not the case; thus, the findings can be considered robust.

With a view to Sharpe ratios, literacy-overestimating participants did not perform significantly differently compared to the other subjects. However, trading costs in this experimental setting were relatively low compared to the analyses of earlier works such as Odean (1998), which might be a reason why I did not find the same detrimental effect of overtrading in this analysis.

7.4. Contribution of Paper #4 to the Topic of this Thesis and Practical Relevance

This paper's relevance to the thesis lies in its examination of investor overconfidence and its impact on advice acceptance and trading behavior, especially in the context of robo advisors. The findings of this paper underscore the notion that robo advisors cannot fully correct behavioral biases. For less affluent clients, who may already struggle with limited financial knowledge and resources but who are the key users of robo advice (Fulk et al., 2018), overconfidence can be a relevant barrier to achieving optimal financial outcomes. While robo advice can provide objective, data-driven recommendations, overconfident investors may still choose to ignore this advice and engage in excessive trading. This insight contributes to the thesis's discussion on the limitations of automated advisory systems and the need for additional mechanisms to address psychological biases in investment decisions. The paper thus underscores the importance of financial education as a crucial component for effective advisory services. This is an important issue especially for robo advisors, as they are targeted at this specific group of investors who are susceptible to an overestimation of their own skills. An interesting idea and a starting point for future research could be that robo advisors should include features that try to counteract overconfident behavior. By doing so, robo advisory platforms can better align with the needs of less financially literate investors, ensuring that the advice they provide is both accepted and acted upon in a way that promotes good investments.

In conclusion, this paper is relevant to the thesis as it gives an idea of how behavioral finance principles can be integrated into robo advisory systems. The findings reinforce the need for robo advice platforms to be proactive in addressing biases, ensuring that investors follow the advice and make better investment decisions.

8. Conclusion of the Thesis

All aspects considered, this dissertation provides insights into the robo advice process and investor decision-making. Paper #1 demonstrates that simple, easy-to-understand questions are most effective in determining investor preferences with a view to the investor exploration phase of the advisory process. Paper #2 presents evidence that the design of robo advisors significantly influences the acceptance of advice. Paper #3 reveals that while the involvement of humans in the advisory process increases trust, it lowers the acceptance of advice, likely due to the investors' fear of being betrayed. Paper #4 highlights that the issue of overconfident investors engaging in excessive trading persists, even within robo-advised investment decisions, independent of design features or the involvement of a human.

In conclusion, this work contributes to the field of behavioral finance and advised decision-making by extending research towards robo advice. The findings have important implications for both advice providers and policymakers. However, the issues explored in this thesis represent only a fraction of the factors affecting investment decisions when using algorithm-based advisory tools. Future research needs to dive deeper into these areas to ultimately develop more effective solutions for guiding individuals towards rational behavior.

References

Arrow, K. J. (1971). Essays in the Theory of Risk-Bearing. Markham Publishing Company, Markham.

Bachmann, K., Hens, T. & Stössel, R. (2017). Which measures predict risk taking in a multi-stage controlled investment decision process? *Financial Services Review* 26, 339-365.

Badarinza, C., Campbell, J. Y. & Ramadorai, T. (2016). International Comparative Household Finance. *Annual Review of Economics* 8, 111-144.

Barber, B. M. & Odean, T. (2000). Trading Is Hazardous to Your Wealth. The Common Stock Investment Performance of Individual Investors. *Journal of Finance* 55 (2), 773-806.

Barber, B. M. & Odean, T. (2001). Boys will be Boys. Gender, Overconfidence, and Common Stock Investment. *Quarterly Journal of Economics* 116 (1), 261-292.

Barber, B. M. & Odean, T. (2008). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies* 21 (2), 785-818.

Benos, A. V. (1998). Aggressiveness and survival of overconfident traders. *Journal of Financial Markets* 1, 353-383.

Bernoulli, D. (1738). Specimen Theoriae Novae de Mensura Sortis. *Commentarii Academiae Scientiarum Imperialis Petropolitanae*, 175-192.

Bluethgen, R., Gintschel, A., Hackethal, A. & Müller, A. (2008). Financial Advice and Individual Investors’ Portfolios. *European Business School Working Paper*.

Bohnet, I., Greig, F., Herrmann, B. & Zeckhauser, R. (2008). Betrayal Aversion: Evidence from Brazil, China, Oman, Switzerland, Turkey, and the United States. *The American Economic Review* 98 (1), 294-310.

Broekema, S. P. M. & Kramer, M. M. (2021). Overconfidence, Financial Advice Seeking and Household Portfolio Under-Diversification. *Journal of Risk and Financial Management* 14 (553), 1-15.

Burke, J. & Hung, A. (2021). Trust and Financial Advice. *Journal of Pension Economics and Finance* 20 (1), 9-26.

Calvet, L. E., Campbell, J. Y. & Sodini, P. (2007). Down or Out: Assessing the Welfare Costs of Household Investment Mistakes. *Journal of Political Economy* 115 (5), 707-747.

Campbell, J. Y. (2006). Household Finance. *Journal of Finance* 56 (4), 1553-1604.

Chui, A. C. W., Titman, S. & Wei, K. C. J. (2010). Individualism and Momentum around the World. *The Journal of Finance* 65 (1), 361-392.

Council of Economic Advisors (2015). The Effects of Conflicted Advice on Retirement Savings.

Coval, J. D. & Moskowitz, T. J. (1999). Home Bias at Home. Local Equity Preference in Domestic Portfolios. *Journal of Finance* 54 (6), 2045-2072.

D'Acunto, F., Prabhala, N. & Rossi, A. G. (2019). The Promises and Pitfalls of Robo-Advising. *Review of Financial Studies* 32 (5), 1983-2020.

Deaves, R., Lueders, E. & Luo, G. Y. (2009). An Experimental Test of the Impact of Overconfidence and Gender on Trading Activity. *Review of Finance* 13, 555-575.

Dietvorst, B. J., Simmons, J. P. & Massey, C. (2015). Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err. *Journal of Experimental Psychology* 144 (1), 114-126.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. & Wagner, G.G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association* 9, 522-550.

Donkers, B. & van Soest, A. (1999). Subjective measures of household preferences and financial decisions. *Journal of Economic Psychology* 20, 613-642.

Ehm, C., Kaufmann, C. & Weber, M. (2014). Volatility Inadaptability. Investors Care About Risk, but Cannot Cope with Volatility. *Review of Finance* 18, 1387-1423.

Foerster, S., Linnainmaa, J. T., Melzer, B. T. & Previtero, A. (2017). Retail Financial Advice: Does One Size Fit All? *Journal of Finance* 72 (4), 1441-1482.

French, K. R. (2008). Presidential Address. The Cost of Active Investing. *Journal of Finance* 63 (4), 1537-1570.

Frey, R., Pedroni, A., Mata, R., Rieskamp, J. & Hertwig, R. (2017). Risk preference shares the psychometric structure of major psychological traits. *Science Advances* 3, 1-13.

Fulk, M., Grable, J. E., Watkins, K. & Kruger, M. (2018). Who Uses Robo-Advisory Services, and Who Does Not? Financial Services Review 27 (2), 173-188.

Goetzmann, W. N. & Kumar, A. (2008). Equity Portfolio Diversification. *Review of Finance* 12 (3), 433-463.

Hartzmark, S. M. (2015). The Worst, the Best, Ignoring All the Rest. The Rank Effect and Trading Behavior. *Review of Financial Studies* 28 (4), 1024-1059.

Harvey, N. & Fischer, I. (1997). Taking Advice: Accepting Help, Improving Judgment, and Sharing Responsibility. *Organizational Behavior and Human Decision Processes* 70 (2), 117-133.

Hoechle, D., Ruenzi, S., Schaub, N. & Schmid, M. (2017). The Impact of Financial Advice on Trade Performance and Behavioral Biases. *Review of Finance* 21 (2), 871-910.

Hofstede, G. (2001). Culture's consequences: comparing values, behaviors, institutions, and organizations across nations. Sage Publications, Thousand Oaks.

Hohenberger, C., Lee, C. & Coughlin, J. F. (2019). Acceptance of robo-advisors: Effects of financial experience, affective reactions, and self-enhancement motives. *Financial Planning Review* 2019 (2), 1-14.

Hsu, Y.-L. (2022). Financial advice seeking and behavioral bias. *Finance Research Letters* 46, 1-9.

Hyll, W. & Irrek, M. (2015). The impact of risk attitudes on financial investments. *IWH Working Paper*.

Inghelbrecht, K. & Tedde, M. (2024). Overconfidence, financial literacy and excessive trading. *Journal of Economic Behavior and Organization* 219, 152-195.

Jansen, C., Fischer, R. & Hackethal, A. (2008). The Influence of Financial Advice on the Asset Allocation of Individual Investors. *EFA 2008 Athens Meetings Paper*.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica* 47 (2), 263-291.

Kahneman, D., & Tversky, A. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty* 5 (4), 297-323.

Kramer, M. M. (2012). Financial Advice and Individual Investor Portfolio Performance. *Financial Management* 41 (2), 395-428.

Linnainmaa, J. T., Melzer, B. & Previtero, A. (2021). The Misguided Beliefs of Financial Advisors. *Journal of Finance* 76 (2), 587-621.

Lusardi, A. & Mitchell, O. S. (2011). Financial Literacy and Retirement Planning in the United States. *Journal of Pension Economics and Finance* 10 (4), 509-525.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7 (1), 77-91.

Monticone, C. (2010). How Much Does Wealth Matter in the Acquisition of Financial Literacy? *Journal of Consumer Affairs* 44 (2), 403-422.

Odean, T. (1998). Volume, Volatility, Price, and Profit When All Traders Are above Average. *Journal of Finance* 53 (9), 1887-1934.

Odean, T. (1999). Do Investors Trade Too Much? *American Economic Review* 89 (5), 1279-1298.

Piehlmaier, D. M. (2022). Overconfidence and the adoption of robo-advice: why overconfident investors drive the expansion of automated financial advice. *Financial Innovation* 8 (14), 1-24.

Pikulina, E., Renneboog, L. & Tobler, P. N. (2017). Overconfidence and investment: An experimental approach. *Journal of Corporate Finance* 43, 175-192.

Pratt, J. W. (1964). Risk Aversion in the Small and in the Large. *Econometrica* 32 (1-2), 122-136.

Promberger, M. & Baron, J. (2006). Do Patients Trust Computers? *Journal of Behavioral Decision Making* 19, 455-468.

Reher, M. & Sun, C. (2019). Automated Financial Management: Diversification and Account Size Flexibility. *Journal of Investment Management* 17 (2), 63-75.

Shapira, Z. & Venezia, I. (2001). Patterns of Behavior of Professionally Managed and Independent Investors. *Journal of Banking & Finance* 25, 1573-1587.

Shefrin, H. & Statman, M. (1985). The Disposition to Sell Winners Too Early and Ride Losers Too Long. Theory and Evidence. *Journal of Finance* 40 (3), 777-790.

Shiller, R. J. (2000). Irrational Exuberance. Princeton University Press, Princeton.

Sniezek, J. A. & Van Swol, L. M. (2001). Trust, Confidence, and Expertise in a Judge-Advisor System. *Organizational Behavior and Human Decision Processes* 84 (2), 288-307.

Statman, M., Thorley, S. & Vorkink, K. (2006). Investor overconfidence and trading volume. *Review of Financial Studies* 19 (4), 1531-1565.

Tertilt, M. & Scholz, P. (2018). To Advise, or Not to Advise. How Robo-Advisors Evaluate the Risk Preferences of Private Investors. *Journal of Wealth Management* 21 (2), 70-84.

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics Letters* 8, 201-207.

Thaler, R. H. (1993). Advances in Behavioral Finance. Russell Sage Foundation, New York.

Tobin, J. (1958). Liquidity preference as behavior towards risk. *The Review of Economic Studies* 25 (2), 65-86.

Van Rooij, M. C. J., Lusardi, A. & Alessie, R. J. M. (2012). Financial Literacy, Retirement Planning, and Household Wealth. *The Economic Journal* 122 (5), 449-478.

Van Swol, L. M. & Sniezek, J. A. (2005). Factors affecting the acceptance of expert advice. *British Journal of Social Psychology* 44, 443-461.

Von Gaudecker, H.-M. (2015). How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice? *Journal of Finance* 70 (2), 489-507.

Von Neumann, J. & Morgenstern, O. (1944). Theory of Games and Economic Behavior. Princeton University Press, Princeton.

Wang, X. & Du, X. (2018). Why Does Advice Discounting Occur? The Combined Roles of Confidence and Trust. *Frontiers in Psychology* 9, 1-8.

Yaniv, I. (2004). Receiving other people's advice. Influence and benefit. *Organizational Behavior and Human Decision Processes* 93 (1), 1-13.

Yaniv, I. & Kleinberger, E. (2000). Advice Taking in Decision Making. Egocentric Discounting and Reputation Formation. *Organizational Behavior and Human Decision Processes* 83 (2), 260-281.

Paper #1: Measuring Risk-Taking and Patience in Financial Decision Making

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Abstract

We empirically compared the consistency among different kinds of measures for risk-taking and patience in a survey and an experiment. We evaluated how these variables relate to financial decisions, using a novel set of easy-to-apply survey questions as proxy. The main finding is that our results based on the novel survey questions describing financial behavior and on lifelike financial behavior in the laboratory are very similar. Therefore, relatively low-cost elicitation measures may be used to forecast decision-making, which, in turn, may be described by our novel set of survey questions.

Keywords: risk attitude; time preferences; decision-making; preferences.

JEL Classification: C81, D12, D81, G11

1. Introduction

The literature is rich in evidence of substantial heterogeneity in individual investment decisions, such as the choice of portfolio structure and savings behavior. The way individuals build their financial portfolios has been an increasingly relevant issue for economists and policy-makers alike. Economic theory suggests that household portfolio choice depends, among other things, on an individual's level of patience and willingness to take risk. These factors are also understood as the root of many economic phenomena (Donkers & van Soest, 1999).

The study on financial decision-making is challenging because individual preferences are difficult to measure. The literature has proposed distinct frameworks, such as the sophisticated models of the well-established prospect theory or the quasi-hyperbolic discounting model, to elicit relevant parameters. Collecting data on portfolio selection may also be complicated. Real-life data on portfolio choices can be difficult and expensive to obtain. Survey data is usually easier and cheaper to collect, but findings based on it cannot always be generalized. Incentivized laboratory experiments offer an interesting trade-off between generalizability and cost efficiency.

There is little consensus in the literature on how the level of patience and willingness to take risk should be measured to ensure consistent and reliable results. Financial advisors and private bankers still rely on rather rough estimates based on non-sophisticated measuring methods. Previous studies investigating different elicitation methods have revealed puzzling outcomes and large inconsistencies. A low correlation among different measures is a recurrent finding (see, for example, Crosetto & Filippin, 2016; Szrek, et al., 2012; Pedroni et al., 2017). Although self-reported measures for risk-taking show slightly higher consistency in the relative ordering, the empirical rank order induced by lottery-based measures is almost identical to that expected from random ranking (Frey et al., 2017).

Previous studies have compared the suitability of different measures to elicit an individual’s willingness to take risk and evaluated their usefulness for predicting financial behavior. Wärneryd (1996) asked questions on risk-taking, including self-descriptive measures and hypothetical lottery choices, but found that only the former are highly significant for explaining the riskiness of investment portfolios. Similarly, Hyll and Irrek (2015) concluded that simple measures of willingness to take risk appear to be more powerful predictors of portfolio allocation than complex lottery questions. Erner et al. (2013) examined whether the parameters of cumulative prospect theory are successful in predicting an individual’s preference for different structured financial products; they found low predictive power of the elicited parameters. Other studies have examined the validity of different measures for predicting risk-taking behavior in the laboratory. Lönnqvist et al. (2015) compared incentivized lottery choice tasks with non-incentivized measures and found that only the self-assessment measures relate to risk-taking. Vieider et al. (2015) showed that there are correlations between different measures of risk attitudes, pointing to the existence of one underlying actual risk preference. Galizzi et al. (2016) revealed similar findings, indicating correlations between different measures, but also mixed evidence concerning external validity in the context of financial behavior. Bachmann et al. (2017) used experimental data and demonstrated that self-assessed measures of risk tolerance are not suitable predictors of risk-taking.

The comparison between real-life, experimental, and survey data for financial decision-making, such as investment behavior, has not been sufficiently addressed in the previous literature. There is evidence that data collection method affects data quality (de Leeuw, 2005;

Duffy et al., 2005; Jäckle et al., 2010; Newman et al., 2021). The literature on the effect of incentivization on data quality is not coherent (Davern et al., 2003; van den Brakel et al., 2006; Stecklov et al., 2018). When comparing survey and experimental data, individuals answering survey questions seemed to unknowingly misreport or knowingly misrepresent data to a large extent (Goldman et al., 1989; Cosby & Bates, 2019). The literature concerning the comparison of experimental and real-life data is rather scarce. In financial decision-making, Li (2020) found that choices in the laboratory can predict, to a certain extent, real-life decisions.

Except for Bachmann et al. (2017), simple self-assessed measures seemed reliable when predicting actual risk-taking and patience. Given these conditions, easy-to-understand survey questions related to hypothetical investment behavior can be assumed to reflect behavior as, for example, in the laboratory. This is a potential finding that would make economic data collection rather easier than before.

First, this study contributes to the existing literature by proposing a novel and easy-to-apply survey measurement method to proxy actual risk-taking and patience. To this end, we investigated survey data of more than 700 individuals from nine different countries, thus ensuring sufficient variation in the dataset. Then we used an experimental setting to create a more lifelike environment with incentivized investment choices. This approach aimed to check whether our novel questions for describing investment behavior in our survey can, in fact, proxy conclusions drawn from actual decision-making in an experimental context. Second, this study expands the current literature by comparing the predictive power of different approaches on a large-scale basis while addressing both the complex problem of determining willingness to take risk and the easier issue of measuring the level of patience. This may validate the prevailing notion that elaborated decision-theoretical approaches only deliver a poor and inconsistent description of individuals' preferences. Along these lines, this study also investigated whether these poor descriptions exist because of an error-in-variables problem caused by mismeasurement.

The rest of our paper is organized as follows: Section 2 describes different measures to elicit willingness to take risk and the level of patience. Section 3 provides an overview of the dataset. Section 4 contains the empirical analysis of our survey data. Section 5 discusses the lab experiments. Section 6 addresses the error-in-variables problem. Section 7 is the conclusion.

2. Methods to Assess Willingness to Take Risk and Level of Patience

When comparing methods to predict risk-taking and patience, one can distinguish between sophisticated and simple measures. Sophisticated measures are widely used in decision-making theory and economic literature, whereas simple methods, such as self-assessments, are used by practitioners in the financial services sector. An example of the latter can be seen in the recent rise in algorithm-based investment advice, so-called “robo advice,” which offers automated investment recommendations based on less-sophisticated investor exploration questions. For the purpose of this study, it is necessary to understand the difference between these two approaches to assess willingness to take risk and level of patience.

2.1 Simple Self-Assessment

Haliassos & Bertaut (1995) used a straightforward behavioral measure of risk tolerance. Respondents evaluated the following questions:

> *Which of the following statements comes closest to the amount of financial risk you are willing to take when you save or make investments?*

- *I would take substantial financial risks expecting to earn substantial returns.*

- *I would take above average financial risks expecting to earn above average financial returns.*
- *I would take average financial risks expecting to earn average financial returns.*
- *I am not willing to take any financial risks.*

Haliassos & Bertaut (1995) used a similar formulation for self-descriptive patience:

> *Which of the following statements most applies to you if you needed to invest your money for a long period of time?*

- *I would tie up money for a long period of time to earn substantial returns.*
- *I would tie up money for an intermediate period of time to earn above average returns.*
- *I would tie up money for a short period of time to earn average returns.*
- *I am not willing to tie up money at all.*

A range of studies has employed similar measures and demonstrated their usefulness in predicting actual risk-taking behavior in financial matters (e.g., Donkers & van Soest, 1999; Dohmen et al., 2011; Barasinska et al., 2012). However, with respect to an individual's level of patience, we are not aware of similar works examining the predictive power of these self-assessments.

2.2 More Sophisticated Approaches

A more refined measurement of individual risk attitude is based on prospect theory. Its value function was introduced by Kahneman & Tversky (1979) and later extended to the cumulative prospect theory of Tversky & Kahneman (1992). Cumulative prospect theory is widely considered the most successful descriptive theory for decision-making under risk. According to Kahneman & Tversky (1979), individuals are risk-seeking for gains with low probabilities and for losses with high probabilities, and risk averse for gains with high probabilities and for losses with low probabilities. In addition, Tversky & Kahneman (1992) established the concept of rank-dependent probability weighting.

Based on these assumptions, a decision maker chooses the outcome that maximizes his or her rank-dependent utility $V = \sum \pi_i \cdot v(x_i)$ with *v* describing a value function and π specifying his or her decision weights. These are computed as

$$\pi_i = w\left(\sum_{j=i}^{n} p_j\right) - w\left(\sum_{j=i+1}^{n} p_j\right) \qquad i \in (1, \dots, n) \tag{1}$$

where *w* is a probability weighting function. The value function

$$v(x) := \begin{cases} x^{\alpha^+}, & x \geq 0 \\ -\lambda \cdot (-x)^{\alpha^-}, & x < 0 \end{cases} \tag{2}$$

classifies the outcomes relative to a reference point. Therefore, positive values of *x* denote gains and negative ones losses relative to a reference point. The value function is concave for gains (outcomes above the reference point) and convex for losses (outcomes below the reference point). The parameter λ causes the value function to be steeper for losses than for gains, thereby modeling the loss aversion phenomenon. The α^+ and α^- portray different degrees of (relative) risk aversion for gains and losses. Tversky and Kahneman's (1992) weighting function of probabilities is

$$w_\gamma(p) = \frac{p^\gamma}{\left(p^\gamma + (1-p)^\gamma\right)^{1/\gamma}} \tag{3}$$

and transforms the probability *p* of an outcome into a subjective probability weight using parameter γ. It models a pattern that underweighs high probabilities and overweighs small probabilities. Some researchers have distinguished between γ^+ and γ^-; however, we followed the reasoning of Tversky & Kahneman (1992) and assumed $\gamma^+ = \gamma^- = \gamma$.

We asked a series of questions in the form of a hypothetical binary lottery choice, similar to Barsky et al. (1997), to derive the relevant parameters. We applied the Gamble-Method by Currim & Sarin (1989) and the Certainty-Equivalent-Method. These methods were designed for our purposes, as well as relatively easy to comprehend and intuitively appealing. Winning probabilities and stakes vary to cover a range of outcomes with a minimum number of questions, because the length of the survey was limited. For the binary prospects that we used, the rank dependence can be ignored.

Owing to space restrictions, we could not reproduce a detailed survey in this paper. The English version of the questionnaire is presented in Appendix VI. Our raw data is available on request. Generally speaking, the questions used to compute the relevant parameters in this case were stated in a formal, quantitative manner. For example:

Please state the amount of Z for which you are indifferent between both lotteries.

Lottery A:
50 % chance to gain 20 $
50 % chance to gain 200 $

Lottery B:
50 % chance to gain Z $
50 % chance to gain nothing

Z should be ___________ $, such that lottery A is as attractive as lottery B.

These questions required more effort to understand the presented scenario compared with the self-assessment questions mentioned above. Because of the different nature of the question types and popularity of lottery-based questions, we decided to include them in our analysis. In this context, these questions could be considered a more sophisticated version of the simple self-assessment but with the same goal: to derive individual risk-taking parameters.

We were aware of the problems associated with calculating loss aversion parameters when using value functions as specified in (2). However, since it is the consistency with financial decision-making among different measures and not the exact values of these measures we wanted to study and compare, we still used the equations presented above. Although the absolute value of λ might depend, for example, on scaling (see, e.g., Wakker, 2010, for further information), demonstrating a higher loss aversion in our survey leads to a higher value for λ and, therefore, does not (ceteris paribus) influence statistic significance in our regressions.

We used the theory of the quasi-hyperbolic discounting model to derive individual patience-related measures. Although many other elicitation mechanisms exist, this method is among the most commonly used and relatively easy to implement. Individuals tend to prefer smaller but earlier rewards instead of larger but later rewards. Moreover, economists generally agree that people discount the near future with a higher discount rate per period than the far future (Thaler, 1981). Such a behavior can be described by a utility function of the following form:

$$U(x_0, x_1, \dots, x_T) = u(x_0) + \sum_{t=1}^{T} \beta \cdot \delta^t u(x_t). \qquad (4)$$

In (3), for $\beta = 1$ and $0 < \delta < 1$, the discount factor would be δ^t for any period t, and thus a corresponding constant discount rate $1/\delta - 1$ per period would result for all t. However, for $0 < \beta < 1$, the discount factor for the first period would only amount to $\beta \cdot \delta$, implying that the discount rate for the first period of $1/(\beta \cdot \delta) - 1$ is higher than $1/\delta - 1$. Therefore, when $0 < \beta < 1$ and $0 < \delta < 1$, people appear to be more patient in the long run and less patient in the immediate future. The parameter β is called the present bias, and δ refers to the long-term discount factor. For $\beta = 1$, there is no present bias problem, and we simply arrive at the neoclassical intertemporal utility function, as introduced by Samuelson (1937). We again positioned questions for a hypothetical set of circumstances in which participants could take some money now or wait until later. We then asked how much it would require making waiting as attractive as receiving the money now. The amount of money was kept constant, but the questions varied with respect to the length of time to wait, for example:

Please consider the following alternatives:

A: a payment of 200 $ now

B: a payment of X $ in one month from now

X has to be at least __________ $, such that B is as attractive as A.

A: a payment of 200 $ now

B: a payment of X $ in one year from now

X has to be at least __________ $, such that B is as attractive as A.

As can be seen, the questions were not as easy to understand as those in the simple self-assessment. These questions demanded some additional mental effort, making them a more sophisticated counterpart of the patience self-assessment.

We elicited the implicitly revealed parameters for both risk-taking and patience using a data-fitting approach, which is presented in detail in Appendix I.

An important concern arises from the fact that, as mentioned before, such parameter-related measurements are complicated and intellectually sophisticated. This particularly holds true for the determination of risk preferences based on (2) and (3). Respondents might misreport their preferences either knowingly or unknowingly. It is, therefore, probable that alternative survey instruments that are easier to understand can deliver similar (or even more) reliable information on individual preferences (Dohmen et al., 2011). Hence, we also refrained from employing more advanced versions of the models introduced above.

Previous studies have examined the consistency of the derived parameters with an individual's willingness to take financial risk but found no reliable evidence. Frijns et al. (2008)

demonstrated that risk aversion measured through lottery choice is a determining factor of portfolio selection. However, Dimmock & Kouwenberg (2010) found that loss aversion and portfolio allocation decisions are not related. Erner et al. (2013) found a low predictive power of prospect theory for financial risk-taking. To the best of our knowledge, literature on the role of patience in portfolio allocation decisions is non-existent.

3. Dataset

Our analysis was based on microeconomic data drawn from a specially designed survey to provide the most complete data. We elicited different measures of risk-taking and patience to obtain a rich set of information that is rarely available otherwise. In most cases, the survey was conducted at the beginning of a regular lecture at a university under the monitoring of a local field interviewer. The survey participants had mixed academic backgrounds; however, most of them were business students but at different stages of their studies. Participation was not mandatory. There was no explicit time limit for completing the survey. Individuals were able to be provided information on the results if they contacted the interviewer after participation. We surveyed individuals in nine different countries, namely China, Germany, India, Iran, Italy, Singapore, South Korea, Spain, and Russia. These countries were not part of a specific selection process but chosen based on the authors' existing academic connections. This approach yielded a high response rate and, as the results of our analysis show, a broad cultural basis for our study, thus avoiding any kind of country-specific bias. We collected information on more than 700 university students across nine countries from 2010 to 2013. Because of the nature of the internationally conducted surveys, the procedure took some time. Nevertheless, the data collection per country did not take longer than three months each. We attempted to keep this time span as narrow as possible. As we did not compare absolute values of risk and time measures across countries, we did not think that the stability of preferences would be an issue in our research.

The large sample size allowed us to attain a comprehensive scope of individual variability. The survey was translated into local languages. Monetary payoffs were adjusted according to each country's purchasing power to assure comparability of results across countries. We collected information on the monthly income and expenses of the local students to verify whether the calculated amounts make economic sense or need to be adjusted accordingly. We removed the responses from non-native students from our sample. We also excluded participants whose answers showed indications of violation of first-order stochastic dominance, more exactly violations of internality (Gneezy et al., 2006), or monotonicity (as a manifestation of response errors, such as choosing to play a binary lottery at low probabilities for a gain but refraining from playing a lottery at high probabilities for the same gain). These participants were excluded to reduce the influence of outlier responses, as we were aware that our approach of direct matching is prone to numerous biases (see also Rieger et al., 2017). We eliminated an observation if there was at least one strong internality or monotonicity violation while allowing any number of weak ones. For the difference between strong and weak violations in this regard, see Rieger et al. (2015).

To measure individual decision-making, we elicited answers to two novel and easy-to-apply hypothetical questions in our survey. These were related to the two facets of financial life in our analysis: risk and time.

> *Imagine you have an amount of 5,000 €. How much money would you invest in stocks/funds and fixed income assets?*
>
> *Stocks/Funds* __________

Fixed income assets __________

If you had the choice between a bond of one-year maturity with an interest rate of 3 % p.a. and a bond of five-year maturity with an interest rate of 4.5 % p.a., which option would you choose?

- o *Bond of one-year maturity*
- o *Bond of five-year maturity*

These questions have not been used in previous literature. All other questions used in our survey have already been introduced in the literature. Although one might assume a high persistency across the different questions our survey comprised of, empirical evidence with regard to stability is neither consistent nor conclusive (Eckel et al., 2005; Deck et al., 2013; Bradford et al., 2014; Gürdal et al., 2017).

We calculated our indicator for risk-taking as the ratio of money invested in stocks or investment funds, as answered in our novel question. We coded our self-assessed risk-taking variable correspondingly, such that a higher score indicates a higher propensity to take risk. Our measure for time-related behavior was a dummy variable that takes the value of 1 if the individual's answer to our novel question is to choose the bond with longer maturity; otherwise, it is 0. We again encoded the self-assessed patience measure in the same direction, so that a higher value relates to a more patient behavior. Although the measures of riskiness and time orientation of portfolios appear crude, they are easy to interpret and understand and apparently have some relevance to household finance.

The survey covered information on demographic, economic, and cultural characteristics that may influence investment and saving decisions. Overall, the age of respondents in our sample varied from 17 to 32 years, with a mean age of 23 years. Of the total respondents, 46.4% were men. The median monthly income after adjustments according to each country's purchasing power at the time the survey was conducted was 458.33 €. The median wealth after adjustments amounted to 2,000 €. Respondents were relatively evenly distributed among the countries. Although there were obvious discrepancies, the differences in the income and wealth of students from different countries were relatively small. Nevertheless, we controlled for such differences in the regressions. Table 1 provides an overview of some basic facts about the data.

>>> Insert Table 1 about here. <<<

We examined the extent to which measured risk-taking and patience predict the answers to our novel survey questions concerning hypothetical financial behavior. The econometric baseline specification was a Tobit model for risk-taking and a logit model for patience with robust standard errors, estimated on a cross-section of individuals and countries. The dependent variable indicated financial decision-making. As regressors, we used a broad set of parameters for risk-taking and patience, as outlined in Section 2. All our specifications controlled for a set of socioeconomic characteristics that existing theory and empirical studies suggest as relevant for household portfolio choice. More specifically, we included respondents' age, gender, wealth, and income. We also included country dummies and individually measured cultural dimensions to disentangle the observed effects from the impacts of the societal and cultural background. These cultural dimensions, according to Hofstede (2001), play a more important role in our analyses as there is evidence that they heavily influence individual decision-making (e.g., Ferris et al., 2013; Breuer et al., 2014; Lievenbrück & Schmid, 2014; Frijns et al., 2013; Rieger et al., 2015; Wang et al., 2016) despite a number of shortcomings (for an overview, see Bearden et al., 2006). We reported standardized coefficients so that the effects of different variables are easily comparable.

4. Survey Results

4.1 Correlations

To obtain an overview, we analyzed how the survey measures relate to each other and other demographic factors. We first used a Shapiro-Wilk test to determine the correct method to measure our correlations. Table A.1 in Appendix II shows that none of our variables were normally distributed ($p < 0.1$), which is why we ran a Spearman correlation test. Since gender represents a binary variable, it was excluded from the analyses in this section. The Spearman's correlations (see Table A.2 in Appendix II) indicated that our more sophisticated measures of patience correlated significantly with the demographic variables of age, income, and wealth. People of older age, with higher income, or with higher wealth demonstrated less patience. Interestingly, the self-assessed patience indicator was not significantly correlated with more sophisticated measures of patience. The corresponding statement about the self-assessed risk-taking indicator and other measures of risk-taking holds true as well. Risk aversion in gains was strongly positively correlated with risk aversion in losses, what one would expect. However, we found risk aversion in losses to be significantly negatively correlated with loss aversion. Our measure of probability weighting was significantly correlated with risk aversion in gains. We do not have explanations for the latter two observations at this point. In summary, this is first tentative evidence that our different measures for willingness to take risk and the level of patience were almost uncorrelated and thus described different measurement approaches. Therefore, we can assume large differences in the predictive power for the answers to our savings and investment decisions.[1]

[1] We would like to thank an anonymous reviewer for highlighting these issues in this section. Lack of space does unfortunately not permit us to elaborate deeper on these relationships.

4.2 Predicting Risk-Taking Behavior

We analyzed the distribution of the answers to our risk self-assessment question and found sufficient variation across countries. Therefore, we could conclude that the participants understood this question well and did not compare themselves with other people in the same country, which would have led to very similar distributions instead (for a closer look, see Figure A.1 in Appendix III). Patterns of known country differences were also found in our data, but there were exceptions; for example, participants from Russia assessed themselves as quite risk tolerant relative to the other countries, which is an unusual finding for their cultural background. However, the number of observations for some countries, including Russia, was relatively small and might not be completely representative of the respective country. As we were mainly interested in individual behavior and the possibilities of its prediction in the realm of saving and investment decisions, this finding did not pose too great a problem for our study. Moreover, we could not rule out that participants might have had different understandings of what "fixed income" means, but it was clear at all times that this option was the least risky one.

The next step of our empirical analysis regressed our newly introduced survey measure for risk-taking (named "*Risky Share*") on a set of socio-demographic variables in Model 1, Table 2. Subsequently, we added two different sets of variables that relate to risk-taking in Models 2 and 3. Moreover, in Model 5, we also added Hofstede's dimensions in the same way, as there is evidence that they exhibit an influence on risk-taking as well, as briefly described in Section 3. Finally, we ran a horserace regression in Model 5 that included the two sets of risk-taking variables plus Hofstede's dimensions at a time. Therefore, Model 5 was based on the following regression:

$$Risky\ Share = b_0 + b_1 \cdot SART + b_2 \cdot \alpha^+ + b_3 \cdot \alpha^- + b_4 \cdot \lambda + b_5 \cdot \gamma + b_6 \cdot UAI + b_7 \cdot LTO + b_8 \cdot PDI + b_9 \cdot IDV + b_{10} \cdot MAS + \boldsymbol{b} \cdot \boldsymbol{C} + \varepsilon \qquad (5)$$

with $SART$ referring to self-assessed risk-taking, and vector $\boldsymbol{C}$ describing all other control variables. Our analysis demonstrated that each set of measures for risk-taking and Hofstede's cultural dimensions had considerable predictive power with respect to the hypothetical risk-bearing choice of individuals. The explanatory power of the regression models increased significantly when we included indicators for risk propensity. The self-assessed risk-taking indicator thereby induced the highest increase in R^2. Of the four parameters that covered more sophisticated risk-taking measures, solely the probability bias appeared to have a significant impact on decision-making.

The horserace regression reconfirmed that the self-descriptive risk-taking indicator has a dominant influence on decision-making, although the impact of the probability bias in this special regression is significant as well. We noted that the sample size of the horserace regression ranked rather low, owing to a comparably high level of invalid responses for the implicitly estimated measures. Individuals appeared to incur difficulties in answering the underlying lottery questions consistently. Such violations of revealed measure conditions persisted evenly across all countries and were not uncommon when eliciting answers to lottery questions (Rieger et al., 2017).

>>> Insert Table 2 about here. <<<

The second step of our regression analysis subsequently added the significant variables from the previous regressions to the socio-demographic controls and substantiated our results. In this process, we restricted our analysis to the cross-section of data points for which we had data on all of these variables available. This procedure achieved a better comparability of the impact of different risk measures while using a large sample size. This also eliminated any possible sample composition bias. The sample size for the models was 420 individuals, of which the highest number of participants were from China (n = 89), followed by Germany (n = 66) and India (n = 51). The lowest number of observations was reported from Spain (n = 20), whereas the number of participants in all other countries considered ranged between 30 (Singapore) and 46 (Russia, see Table 1).

Results in Table 3 paint a consistent picture. The self-assessed risk-taking indicator could best explain hypothetical financial risk-taking, as measured by our novel question. The pseudo R^2 in the simple specification of Model 2 was 32.4% while the explanatory power of the other models hardly exceeded 20%. Besides self-assessment, other variables measuring risk-taking achieved a very meager increase in the pseudo R^2 of 7% at best of the baseline Model 1 that only included socio-demographic controls.

This confirmed our findings that self-assessed indicators are consistently most important for explaining hypothetical risk behavior, as measured by our novel question. Probability bias no longer had a significant influence. The explanatory power of this model yielded a solid 42.2%, and the control variables of the regression models were generally in line with what was expected based on the previous literature. Male participants appeared to be more risk-taking. Age, income, and wealth did not significantly influence risk behavior in the majority of our regression models. Hofstede dimensions only partly turned out to be significant, and the coefficients were relatively close to zero.

>>> Insert Table 3 about here. <<<

4.3 Predicting the Degree of Patience

With respect to the time self-assessment question, we found sufficient variation across countries (see Figure A.2 in Appendix III). In this case, patterns of known country differences in our data could not be spotted as easily as for the self-assessment of risk-taking.

One might object that there are reasons other than preferences for our participants to choose the shorter maturity bond over the longer one. Students might expect interest rates to change over the next few years, or they might be at different points in their studies, leading to an anticipated need for money in a fixed period of time. We checked these issues by analyzing the participants' bond choices. We compared a) the knowledge of financial markets, using investments in stocks, bonds, or funds against non-investors as proxies, and b) the group of participants who are planning to finish their studies within the next one to three semesters against those who are going to study longer than three semesters (see Figure 1). As can be seen at first glance, the distributions did not differ greatly from each other. We performed a t-test and could not reject the null hypothesis of equal means in either case. Therefore, we supposed that students did not decide in different ways based on their market knowledge using financial market participation as proxy or based on their remaining study time. We could not rule out possible misunderstandings of when exactly the bond coupon is paid. For the five-year-maturity option, participants might have understood the coupon payment to be made every year or alternatively to be paid as compound interest in one sum at the time of maturity. However, this did not cause too great a problem for our study since it was clear at all times that the initially invested amount of money, i.e., the principal, is to be blocked for one or five years, respectively.

>>> Insert Figure 1 about here. <<<

Our analysis of patience proceeded in a manner similar to that presented in the previous section. We first regressed hypothetical time behavior (described by the variable "*Longer Maturity*") on the two different sets of measurements for patience plus the Hofstede scores in Models 2 to 4. The combined regression equation of Model 4 is as follows:

$$Longer\ Maturity\ = b_0 + b_1 \cdot SAP + b_2 \cdot \beta + b_3 \cdot \delta + \ b_4 \cdot UAI + b_5 \cdot LTO + b_6 \cdot PDI + b_7 \cdot IDV + b_8 \cdot MAS + \boldsymbol{b} \cdot \boldsymbol{C} + \varepsilon \qquad (6)$$

with SAP referring to self-assessed patience, and vector $\boldsymbol{C}$ describing all other control variables.

>>> Insert Table 4 about here. <<<

Next, we established the relation between patience and survey-measured financial decision-making in a cross-section of exactly 700 data points for which we had data on all relevant variables available. As pointed out previously, this procedure provided a more consistent view. The highest number of observations can be reported from India (n = 118), followed by Italy (n = 100), Germany (n = 97), and China (n = 91). Relatively few participants were disclosed from Russia (n = 74), Iran (n = 65), Singapore (n = 59), South Korea (n = 54), and Spain (n = 42). In general, more individuals managed to answer our questions consistently compared with the risk-taking section, which might be traced back to an easier understanding.

Our findings were relatively consistent. The self-descriptive patience indicator consistently explained hypothetical individual decision-making, as measured by our novel question, at the best possible rate. This indicator was able to increase the pseudo adjusted R^2 from 3.4% in the baseline model to 4.7%. The horserace regression yielded 4.8% for the pseudo adjusted R^2. We did not observe a significant influence of gender or age in our regression models. An increase in income and wealth coincided with more patient time behavior.

>>> Insert Table 5 about here. <<<

The coefficient of the self-descriptive patience indicator was 1.504 in Model 2 in Table 5. A move to the next higher value on the time preference scale thus increased the likelihood that an individual hypothetically chooses the bond with the higher maturity by 50%. The main conclusion we draw from our results is that self-assessed indicators affected hypothetical financial behavior as measured by our novel questions in an obvious and intuitive manner.

As our results are similar with respect to both risk-taking and patience and as parameter elicitation regarding time discounting is somewhat easier than parameter determination regarding prospect theory, the low predictive power of these two approaches may not be completely caused by the high level of complexity. Moreover, we concluded that our newly introduced hypothetical questions about risk and time behavior turned out to deliver results that were in line with the existing literature, thus presumably offering an easy-to-apply method to reliably reflect decision-making in more realistic situations.

5. Lab Experiment

To compare the outcomes of a more lifelike situation with our novel, simple, and easy-to-use risk and time behavior elicitation method, we complemented our survey procedure through an experimental study. As described before, the extent to which preferences are misreported also depends on the data collection method. If our novel questions of hypothetical behavior are not subject to misreporting, we would expect the predictive power of the different risk and time measurements to be comparable for the survey and the experiment. Moreover, an experiment allowed us to address the following points that go beyond the scope of our survey:

- Offering performance-based monetary incentives

- Avoiding possible halo effects
- Determining risk and time decision-making in a single setup

As we have elaborated before, previous studies have found that, all other things being equal, incentivization does not necessarily lead to different outcomes (Rieger et al., 2015; Vieider et al., 2015). However, the literature in this regard is still inconclusive. Although laboratory experiments typically suffer from smaller sample sizes and self-selection biases, offering real monetary incentives might ensure that participants are motivated to give thoughtful answers. By further disassociating the risk-taking/patience measurements and the actual decision-making task, the experiment also helped avoid possible measurement errors that might solely arise because respondents tried to answer these questions consistently (halo effect). This might be particularly a problem with respect to patience because the simple investment problem presented in our novel question sounds, to some degree, similar to the self-assessment question. The experiment considered this in general and separated the corresponding questions sufficiently. Moreover, as described below, in the laboratory experiment, individuals now determine the risk and time structure of their portfolio simultaneously, loosening a potential mental connection to the previously answered self-assessment questions.

We conducted our lab experiment at a large German university using computers. Each participant completed the same questionnaire as described in Section 3. We removed our two hypothetical questions regarding financial behavior in terms of risk and time. Instead, participants were asked to make a portfolio allocation decision using the experimental task design of Kaufmann et al. (2013), given a hypothetical endowment of 5,000 €, for both one- and three-year maturity portfolios. All individuals knew that their final payments depended on their investment choices. The participants had to choose between the purchase of a riskless asset and a risky investment opportunity and state the share of money to be invested in each of those two options. The risk-free rates of return of the riskless asset were set at 1.5% p.a. for the one-year option and 2.0% p.a. for the three-year option. The risk-return profile of the risky investment opportunity was adapted from MSCI World Index data. First, a brief interactive introduction to probability distributions was provided, following the concept of Kaufmann et al. (2013). After making an allocation choice using a slider mechanism, a probability distribution of the possible outcomes of the chosen portfolio allocation based on a Monte Carlo simulation was presented. Participants could then decide to either change the allocation or accept the portfolio choice. This procedure was repeated for the allocation decision concerning a portfolio of longer maturity. Eventually, participants were asked to decide between either taking the one-year maturity portfolio and being paid one month after the event or taking the three-year maturity portfolio and being paid three months after the event. At this point, the allocation choices could no longer be altered. Moreover, participants could only see the probability distributions of their two portfolio choices involving the possible investment outcomes and the respective outcome probabilities at the time of maturity. The final payment, which was made via bank transfer, was then computed based on the probability distribution of the portfolio that the participant chose, while 500 € in the experiment corresponded to a real payment of 1 €. The final payments ranged between 8.07 € and 16.59 €, with an average payment of 12.03 € for an average of 45 minutes of work. Using this procedure, we could observe both, participants' risk decisions and time decisions in a single experimental setup. Two exemplary excerpts of the experiment are shown in Figures 2 and 3. Kaufmann et al. (2013) explained the experimental procedure in a more detailed way. This setup also allowed us to tackle the problem of different understandings of what "fixed income" means. The visualization component did not allow for any deviant interpretations, and the same reasoning could be adapted to possible misunderstandings of the coupon payment. The experimental validation might have been helpful in this context as well.

>>> Insert Figure 2 about here. <<<

>>> Insert Figure 3 about here. <<<

The final sample consisted of 163 observations. Again, participants whose answers indicated violation of first-order stochastic dominance because of response errors were excluded from the sample. This time, the share of excluded answers was considerably smaller because participants, in general, responded more consistently. This may be due to the fact that individuals participating in the laboratory experiment did so to earn money. Therefore, they might have felt obliged to read the questions very thoroughly and answer only after reflecting well. To this effect, incentivization may indeed be useful. However, as pointed out below, our main conclusions are not affected by incentivizing answers.

We defined the indicator of time-related behavior as a variable that takes the value of 1 if the individual chooses the investment with three-year maturity and otherwise 0, similar to our novel indicator of time-related behavior presented in Section 3. Since participants had to decide about the share to be invested in the respective investment options twice (once for one-year maturity and once for three-year maturity portfolios) in this analysis, the indicator of risk-related behavior was defined as each individual's mean share of money invested in the risky asset.

To allow for comparison between the two analyses presented in this study, we attempted to create a sample consisting of individuals of similar socio-economic backgrounds as in our first study. The mean age of the participants in the sample was 24.28 years. The median monthly income was 650.00 €, and the median wealth was 3,000.00 €. Our ratio of male participants, however, was slightly higher than that in our survey setting. Although our experimental sample mainly consisted of students of German descent, we controlled for existing country-specific differences. Since our sample is rather restricted regarding country differences compared with our sample of the analyses described in the previous sections, we included a dummy variable that is 1 if the participant is not of German nationality and 0 otherwise. As in our survey, we also gathered information about Hofstede scores.

Descriptive statistics and regression models are presented in Appendix IV. Compared with our survey findings, the results of our lab experiment mostly painted a consistent picture. In terms of risk-taking, the following results were found in all our models: the coefficient of the self-assessed measures had a significant impact; the findings for probability weighting were inconsistent; and the other measures were not significant at all. Concerning patience, only the self-assessed measure turned out to be highly significant, while no other relevant coefficient was of any significance, except for one single model in which the Hofstede cultural dimension of masculinity was significant at the 10%-level. Therefore, our findings strongly confirm the survey results and point to the fact that our newly introduced questions were able to proxy decision-making well enough to ensure delivering results that are comparable to lifelike situations. A second important observation is that self-assessed indicators worked best for predicting behavior.

6. Tackling the Error-in-Variables Problem

Because of the general nature of experiments and surveys, we could not rule out that there were measurement errors in the explanatory variables leading to biased estimators. We were aware of this problem. Regarding the complexity of lottery-choice-based questions and our results presented in the previous sections, and more precisely looking at the widely appearing non-significance of the variables derived from lottery-choice-based questions, we suspect that there might be measurement errors in the set of explanatory variables. In general, there are three possibilities to address this issue: one may use an instrumental variables approach, rely on the dynamic panel estimators of Arellano & Bond (1991), or apply the measurement error-consistent generalized method of moments/cumulants estimators (Erickson & Whited, 2000; Erickson et al., 2017), to our lottery-measured explanatory variables. The dynamic panel estimators from Arellano & Bond (1991) are based on lagged regressors and thus require panel data. Replacing the regressors we wanted to analyze with instrumental variables does not make sense. Therefore, for our purposes, only the third approach can be employed. Because this approach is not suited for binary dependent variables, it can only be applied to our risk-taking dataset.

The exact outcomes of our analysis are presented in the Appendix V. We found that our results were very sensitive to the choice of moments/cumulants and their highest order. Although there were indications that, when considering an error-in-variables model, lottery-based measures of risk-taking may gain reliability, the explanatory power of these results when applying the error-in-variables approach remains questionable. This is because there is no clear structure regarding the significance of other risk-taking measures besides self-assessment. The latter variable still had a consistent significant impact in all our models, except once. However, this may be an interesting starting point for future research.

7. Conclusion

A recurrent theme in economics is the description of individual risk-taking and patience measures and their relation to choice behavior. The novel feature of our study lies in linking different risk-taking and patience measures to a new and easy-to-use survey approach utilized to proxy lifelike investment situations. Moreover, we replicated and extended the existing literature concerning the predictive power of more or less sophisticated risk-taking and patience elicitation methods.

Our evidence was broadly consistent with the hypothesis that individual indicators play an important role in investment decisions. Analyses based on our novel survey questions regarding investment behavior achieved high comparability with those relying on actual decision-making in an experimental context. Another finding was that, in general, self-assessed indicators consistently generated the best predictions of behavior. It appears that the parameters based on more sophisticated elicitation methods have little importance in explaining the risk and time dimension of portfolio selection, and our results were inconsistent in this regard. A plausible explanation is that ordinary respondents may incur problems in answering more sophisticated choice questions between different alternatives. The relatively low number of observations for these questions because of many invalid answers supports this conjecture and casts doubt on such methods. We tried to tackle this issue with mixed results using special regression approaches for such a measurement problem regarding explanatory variables. Although this might increase the empirical relevance of lottery-choice-induced parameter computations, the results strongly depended on the manner by which such regression models are calibrated, and there is no straightforward way to unambiguously determine the best model variant. Apparently, there is a need for a regression method that considers the error-in-variables problem but yields more stable results than the methods currently available.

We tentatively conclude that economic data concerning financial decision-making can be generated reliably using low-cost survey questions that proxy actual decision-making in an experimental context. In addition, our results justify the current practices of financial advisors or private bankers, who use rather rough methods to measure their clients' risk-taking and patience attitudes. Our findings support prior evidence that demonstrates persistent discrepancies between the predictions of traditional, more sophisticated models and behavior (Andersen et al., 2006; Erner et al., 2013; Lönnqvist et al., 2015).

However, our data had some drawbacks. First, we only examined university students and not a representative sample of the total population. Although this caveat has to be kept in mind, we believe our study remains valuable in providing evidence on the explanatory power of different variables as this sample selection offers important advantages. On the one hand, because of their quantitative background, students of business administration and economics, as well as in the field of STEM (science, technology, engineering, and mathematics) can understand the numeric formulations of the questions without great difficulty. Asking a representative sample of the population the same numerical questions involving probabilities might have been less straightforward. Previous studies have demonstrated that student samples incur fewer violations of revealed measure conditions (von Gaudecker et al., 2011). On the other hand, they constitute a relatively homogeneous and comparable group across countries, helping to reduce the influence of country-level background variables, and they represent future investors. In addition, previous studies have documented that student samples reveal behavioral patterns that do not differ much from those of non-student samples (Druckman & Kam, 2011; Falk et al., 2013). Therefore, we are confident that our conclusions remain valid even for more heterogeneous samples. Second, we only compared survey and laboratory data; therefore, we cannot draw any direct conclusions about real-life portfolio selection decisions. There is a need to compare survey data based on our novel questions with genuine, real-life decision-making. However, we leave this issue for future research.

References

Andersen, S., Harrison, G.W., Lau, M.I. & Rutström, E.E. (2006). Elicitation using multiple price list formats. *Experimental Economics* 9, 383-405.

Arellano, M. & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58, 277-297.

Bachmann, K., Hens, T. & Stössel, R. (2017). Which measures predict risk taking in a multi-stage controlled investment decision process? *Financial Services Review* 26, 339-365.

Barasinska, N., Schäfer, D. & Stephan, A. (2012). Individual risk attitudes and the composition of financial portfolios: Evidence from German household portfolios. *The Quarterly Review of Economic and Finance* 42, 1-14.

Barsky, R.B., Juster, F.T., Kimball, M.S. & Shapiro, M.D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics* 112, 537-579.

Bearden, W.O., Money, R.B. & Nevins, J.L. (2006). Multidimensional versus unidimensional measures in assessing national culture values: The Hofstede VSM 94 example. *Journal of Business Research* 59, 195-203.

Bradford, D., Courtemanche, C., Heutel, G., McAlvanah, P. & Ruhm, C. (2014). Time preferences and consumer behavior. *Working Paper 20320, NBER*.

Breuer, W., Riesener, M. & Salzmann, A.J. (2014). Risk aversion vs. Individualism: What drives risk taking in household finance? *The European Journal of Finance* 20, 446-462.

Cozby, P.C. & Bates, S.C. (2019). Methods in behavioral research. New York, NY: McGraw-Hill Education.

Currim, I.S. & Sarin, R.K. (1989). Prospect versus utility. *Management Science* 35, 22-41.

Davern, M., Rockwood, T.H., Sherrod, R. & Campbell, S. (2003). Prepaid monetary incentives and data quality in face-to-face interviews: Data from the 1996 Survey of Income and program participation incentive experiment. *The Public Opinion Quarterly* 67, 139-147.

De Leeuw, E.G. (2005). To mix or not to mix data collection modes in surveys. *Journal of Official Statistics* 21, 233-255.

Deck, C., Lee, J., Reyes, J.A. & Rosen, C.C. (2013). A failed attempt to explain within subject variation in risk taking behavior using domain specific risk attitudes. *Journal of Economic Behavior & Organization* 87, 1-24.

Dimmock, S.G. & Kouwenberg, R. (2010). Loss-aversion and household portfolio choice. *Journal of Empirical Finance* 17, 441-459.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. & Wagner, G.G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association* 9, 522-550.

Donkers, B. & van Soest, A. (1999). Subjective measures of household preferences and financial decisions. *Journal of Economic Psychology* 20, 613-642.

Druckman, J.N. & Kam, C. (2011). Students as experimental participants: A defense of the 'narrow data base'. In: Green, D.P., Kuklinski, J.H. & Lupia, A. (eds.). *Cambridge Handbook of Experimental Political Science,* Cambridge University Press, 41-57.

Duffy, B., Smith, K., Terhanian, G. & Bremer, J. (2005). Comparing data from online and face-to-face surveys. *International Journal of Market Research* 47, 615-639.

Eckel, C., Johnson, C. & Montmarquette, C. (2005). Saving decisions of the working poor: Short- and long-term horizons. In: Harrison, G.W., Carpenter, J. & List, J.A. (eds.). *Field experiments in economics*, Emerald Group Publishing Limited, 219-260.

Erickson, T., Parham, R. & Whited, T.M. (2017). Fitting the errors-in-variables model using high-order cumulants and moments. *Stata Journal* 17, 116-129.

Erickson, T. & Whited, T.M. (2000). Measurement error and the relationship between investment and Q. *Journal of Political Economy* 108, 1027-1057.

Erner, C., Klos, A. & Langer, T. (2013). Can prospect theory be used to predict an investor's willingness to pay? *Journal of Banking and Finance* 37, 1960-1973.

Falk, A., Meier, S. & Zehnder, C. (2013). Do lab experiments misrepresent social preferences? The case of self-selected student samples. *Journal of the European Economic Association* 11, 839-852.

Ferris, S.P., Jayaraman, N. & Sabherwal, S. (2013). CEO overconfidence and international merger and acquisition activity. *Journal of Financial and Quantitative Analysis* 48, 137-164.

Frey, R., Pedroni, A., Mata, R., Rieskamp, J. & Hertwig, R. (2017). Risk preference shares the psychometric structure of major psychological traits. *Science Advances* 3, 1-13.

Frijns, B., Koellen, E. & Lehnert, T. (2008). On the determinants of portfolio choice. *Journal of Economic Behavior & Organization* 66, 373-386.

Frijns, B., Gilbert, A., Lehnert, T. & Tourani-Rad, A. (2013). Uncertainty avoidance, risk tolerance and corporate takeover decisions. *Journal of Banking & Finance* 37, 2457-2471.

Galizzi, M.M., Machado, S.R. & Miniaci, R. (2016). Temporal stability, cross-validity, and external validity of risk preferences measures: Experimental evidence from a UK representative sample. *Working Paper 67554, LSE.*

Gneezy, U., List, J.-A. & Wu, G. (2006). The uncertainty effect: When a risky prospect is valued less than its worst possible outcome. *The Quarterly Journal of Economics* 121, 1283-1309.

Goldman, N., Moreno, L. & Westoff, C.F. (1989). Collection of Survey Data on Contraception: An Evaluation of an Experiment in Peru. *Studies in Family Planning* 20, 147-157.

Gürdal, M., Kuzubaş, T. & Saltoğlu, B. (2017). Measures of individual risk attitudes and portfolio choice: Evidence from pension participants. *Journal of Economic Psychology* 62, 186-203.

Haliassos, M. & Bertaut, C.C. (1995). Why do so few hold stocks? *The Economic Journal* 105, 1110-1129.

Hofstede, G. (2001). Culture’s consequences: comparing values, behaviors, institutions, and organizations across nations. Sage Publications, Thousand Oaks.

Hyll, W. & Irrek, M. (2015). The impact of risk attitudes on financial investments. *Working Paper, IWH.*

Jäckle, A., Roberts, C. & Lynn, P. (2010). Assessing the effect of data collection mode on measurement. *International Statistic Review* 78, 3-20.

Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica* 47, 263-291.

Kaufmann, C., Weber, M. & Haisley, E. (2013). The role of experience sampling and graphical displays on one's investment risk appetite. *Management Science* 59, 323-340.

Li, K.K. (2020). A horse race of preferences for predicting portfolio choice. *Working Paper, SABS.*

Lievenbrück, M. & Schmid, T. (2014). Why do firms (not) hedge? Novel evidence on cultural influence. *Journal of Corporate Finance* 25, 92-106.

Lönnqvist, J.-E., Verkasalo, M., Walkowitz, G. & Wichardt, P.C. (2015). Measuring individual risk attitudes in the lab: Task or ask? An empirical investigation. *Journal of Economic Behavior and Organization* 119, 254-266.

Newman, A., Bavik, Y.L., Mount, M. & Shao, B. (2021). Data collection via online platforms: Challenges and recommendations for future research. *Applied Psychology,* 1-23.

Pedroni, A., Frey, R., Bruhin, A., Dutilh, G., Hertwig, R. & Rieskamp, J. (2017). The risk elicitation puzzle. *Nature Human Behaviour* 1, 803-809.

Rieger, M.O., Wang, M. & Hens, T. (2015). Risk preferences around the world. *Management Science* 61, 637-648.

Rieger, M.O., Wang, M. & Hens, T. (2017). Estimating cumulative prospect theory parameters from an international survey. *Theory and Decision* 82, 567-596.

Samuelson, P.A. (1937). A note on measurement of utility. *Review of Economic Studies* 4, 155-161.

Stecklov, G., Weinreb, A. & Carletto, C. (2018). Can incentives improve survey data quality in developing countries? Results from a field experiment in India. *Journal of the Royal Statistical Society* 181, 1033-1056.

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics Letters* 8, 201-207.

Tversky, A. & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5, 297-323.

Vieider, F., Chmura, T., Fisher, T., Kusakawa, T., Mattison Thompson, F. & Sunday, A. (2015). Within- versus between-country differences in risk attitudes: Implications for cultural comparisons. *Theory and Decision* 78, 209-218.

Van den Brakel, J.A., Vis-Visschers, R. & Schmeets, J.J.G. (2006). An experiment with data collection modes and incentives in the Dutch Family and Fertility Survey for young Moroccans and Turks. *Field Methods* 18, 321-334.

Von Gaudecker, H.-M., van Soest, A. & Wengstrom, E. (2011). Heterogeneity in risky choice behavior in a broad population. *American Economic Review* 101, 664-694.

Wakker, P. (2010). Prospect theory for risk and ambiguity. Cambridge University Press, Cambridge.

Wang, M., Rieger, M.O. & Hens, T. (2016). The impact of culture on loss aversion. *Journal of Behavioral Decision Making* 30, 270-281.

Table 1 Descriptive statistics, survey evidence (average values)

	all	**China**	**Germany**	**India**	**Iran**	**Italy**	**Singapore**	**South Korea**	**Spain**	**Russia**
male	0.48	0.34	0.46	0.56	0.59	0.53	0.52	0.47	0.52	0.36
age	23.13	18.61	24.81	26.62	23.11	22.96	22.48	22.85	23.34	23.50
income	681.32	665.57	693.05	1,139.92	922.27	443.33	1,027.54	487.12	662.95	329.70
wealth	8,357.66	1,805.18	9,004.55	12,872.50	7,3152.15	6,619.68	9,872.11	8,101.59	6,197.28	9,505.47
ratio of risky assets in individual portfolios	0.40	0.38	0.38	0.39	0.39	0.46	0.54	0.41	0.30	0.42
ratio of individuals choosing the higher maturity bond	0.45	0.48	0.56	0.38	0.10	0.57	0.47	0.44	0.58	0.43
self-assessed risk-taking	2.43	2.25	1.85	3.64	2.35	2.06	2.72	2.33	1.75	2.40
self-assessed patience	3.01	2.80	3.00	3.13	2.75	3.14	3.18	3.10	2.87	2.65
risk aversion (gains)	0.51	0.55	0.59	0.66	0.16	0.48	0.60	0.48	0.62	0.37
risk aversion (losses)	0.60	0.63	0.79	0.67	0.17	0.60	0.72	0.55	0.75	0.45
loss aversion	1.73	1.60	1.63	2.12	1.41	2.10	2.17	2.03	1.73	1.66
probability weighting	0.65	0.62	0.53	0.57	0.84	0.49	0.70	0.68	0.70	0.66
present bias parameter	0.40	0.26	0.58	0.52	0.50	0.13	0.73	0.41	0.25	0.39
long-term discount factor	0.82	0.82	0.85	0.84	0.81	0.79	0.85	0.84	0.80	0.82
uncertainty avoidance	65.46	104.65	53.91	55.16	56.33	73.52	33.43	47.61	82.66	41.07
long-term orientation	46.91	49.14	44.90	29.74	55.32	46.68	46.27	57.57	59.00	44.23
power distance	20.52	-1.87	27.04	26.09	34.95	22.05	26.54	12.33	20.33	29.91
individualism	72.67	62.96	73.42	71.18	83.39	73.18	90.96	60.27	62.19	96.68
masculinity	58.58	48.78	18.21	56.41	80.77	104.18	0.76	17.21	53.58	141.11
# observations in Table 3	420	89	66	51	36	39	30	43	20	46
# observations in Table 5	700	91	97	118	65	100	59	54	42	74

Table 2 *Tobit analysis of risk behavior and risk-taking indicators, first step, survey evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
male	0.074***	*0.023*	0.048**	*0.022*	0.046	*0.043*	0.071***	*0.023*	0.068	*0.042*
age	0.000	*0.004*	0.003	*0.004*	0.003	*0.008*	-0.001	*0.004*	0.004	*0.008*
income	0.000	*0.000*	0.000	*0.000*	0.000**	*0.000*	0.000	*0.000*	0.000**	*0.000*
wealth	0.000	*0.000*	0.000***	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
self-assessed risk-taking			0.113***	*0.015*					0.072**	*0.034*
risk aversion (gains)					0.156	*0.112*			0.066	*0.110*
risk aversion (losses)					0.004	*0.076*			0.040	*0.080*
loss aversion					0.015	*0.026*			0.012	*0.021*
probability weighting					0.181**	*0.073*			0.181**	*0.071*
uncertainty avoidance							-0.001***	*0.000*	0.000	*0.000*
long-term orientation							-0.001	*0.001*	-0.003**	*0.001*
power distance							0.000	*0.000*	0.000	*0.000*
individualism							0.000**	*0.000*	0.000	*0.000*
masculinity							0.000	*0.000*	0.000	*0.000*
country dummies	yes		yes		yes		yes		yes	
observations	642		637		155		609		153	
pseudo R^2	0.121		0.302		0.280		0.200		0.504	
F statistic	7.313		12.380		2.390		4.730		2.949	
p-value	0.000		0.000		0.003		0.000		0.000	

The dependent variable is the ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and three different sets of variables for risk-taking as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table 3 *Tobit analysis of risk behavior and risk-taking indicators, second step, survey evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**	
male	0.089***	*0.028*	0.062**	*0.027*	0.088***	*0.028*	0.084***	*0.028*	0.099***	*0.028*	0.084***	*0.028*	0.064**	*0.027*
age	-0.003	*0.005*	0.001	*0.005*	-0.003	*0.005*	-0.001	*0.005*	-0.004	*0.005*	-0.003	*0.005*	0.002	*0.005*
income	0.000	*0.000*	0.000	*0.000*	0.000*	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
wealth	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
self-assessed risk-taking			0.117***	*0.018*									0.109***	*0.018*
probability weighting					0.071*	*0.038*							0.035	*0.037*
uncertainty avoidance							-0.001***	*0.000*					-0.001***	*0.000*
long-term orientation									-0.002**	*0.001*			-0.001**	*0.001*
individualism											0.000	*0.000*	0.000	*0.000*
country dummies	yes		yes		yes		yes		yes		yes		yes	
observations	420		420		420		420		420		420		420	
pseudo R^2	0.149		0.324		0.162		0.214		0.179		0.159		0.422	
F statistic	3.709		7.174		3.955		4.558		3.794		3.695		7.475	
p-value	0.000		0.000		0.000		0.000		0.000		0.000		0.000	

The dependent variable is the ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and those variables for risk-taking that gained significance in Table 2. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table 4 *Logit analysis of time behavior and patience indicators, first step, survey evidence*

	Model 1		Model 2		Model 3		Model 4		Model 5	
male	1.041	*0.167*	1.061	*0.174*	1.069	*0.181*	0.970	*0.162*	1.036	*0.187*
age	0.959	*0.027*	0.973	*0.028*	0.965	*0.029*	0.968	*0.028*	0.991	*0.032*
income	1.000*	*0.000*	1.000**	*0.000*	1.000**	*0.000*	1.000**	*0.000*	1.000***	*0.000*
wealth	1.000*	*0.000*	1.000**	*0.000*	1.000*	*0.000*	1.000	*0.000*	1.000	*0.000*
self-assessed patience			1.523***	*0.163*					1.501***	*0.175*
present bias parameter					1.337	*0.391*			1.299	*0.399*
long-term discount factor					1.737	*1.539*			2.921	*2.712*
uncertainty avoidance							1.001	*0.001*	1.002	*0.001*
long-term orientation							1.007*	*0.004*	1.004	*0.004*
power distance							1.000	*0.002*	1.000	*0.002*
individualism							1.002	*0.002*	1.002	*0.002*
masculinity							1.001	*0.001*	1.001	*0.001*
country dummies	yes		yes		yes		yes		yes	
observations	722		711		668		685		628	
χ^2	50.290		63.980		49.170		47.270		57.420	
p-value	0.000		0.000		0.000		0.000		0.000	
pseudo R^2	0.064		0.081		0.067		0.070		0.088	
pseudo R^2 *adjusted*	0.037		0.052		0.034		0.031		0.039	
specificity	69.700		68.540		63.970		66.670		60.900	

The dependent variable is the probability that an individual chooses the higher maturity bond. The independent variables consist of a group of socio-demographic variables and three different sets of variables for patience as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table 5 *Logit analysis of time behavior and patience indicators, second step, survey evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**	
male	0.976	*0.159*	1.015	*0.167*	0.945	*0.155*	0.985	*0.164*
age	0.968	*0.028*	0.975	*0.028*	0.971	*0.028*	0.977	*0.028*
income	1.000**	*0.000*	1.000**	*0.000*	1.000**	*0.000*	1.000**	*0.000*
wealth	1.000**	*0.000*	1.000**	*0.000*	1.000**	*0.000*	1.000**	*0.000*
self-assessed patience			1.504***	*0.162*			1.491***	*0.162*
long-term orientation					1.007*	*0.004*	1.006*	*0.004*
country dummies	yes		yes		yes		yes	
observations	700		700		700		700	
χ^2	47.460		60.910		48.550		61.010	
p-value	0.000		0.000		0.000		0.000	
pseudo R^2	0.061		0.076		0.065		0.080	
pseudo R^2 *adjusted*	0.034		0.047		0.036		0.048	
specificity	70.650		67.010		69.350		69.610	

The dependent variable is the probability that an individual chooses the higher maturity bond. The independent variables consist of a group of socio-demographic variables and those variables for patience that gained significance in Table 4. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Figure 1 *Distributions of survey bond choices*

Figure 1 shows the distributions of bond choices (1 = longer maturity) by remaining study time and financial market participation

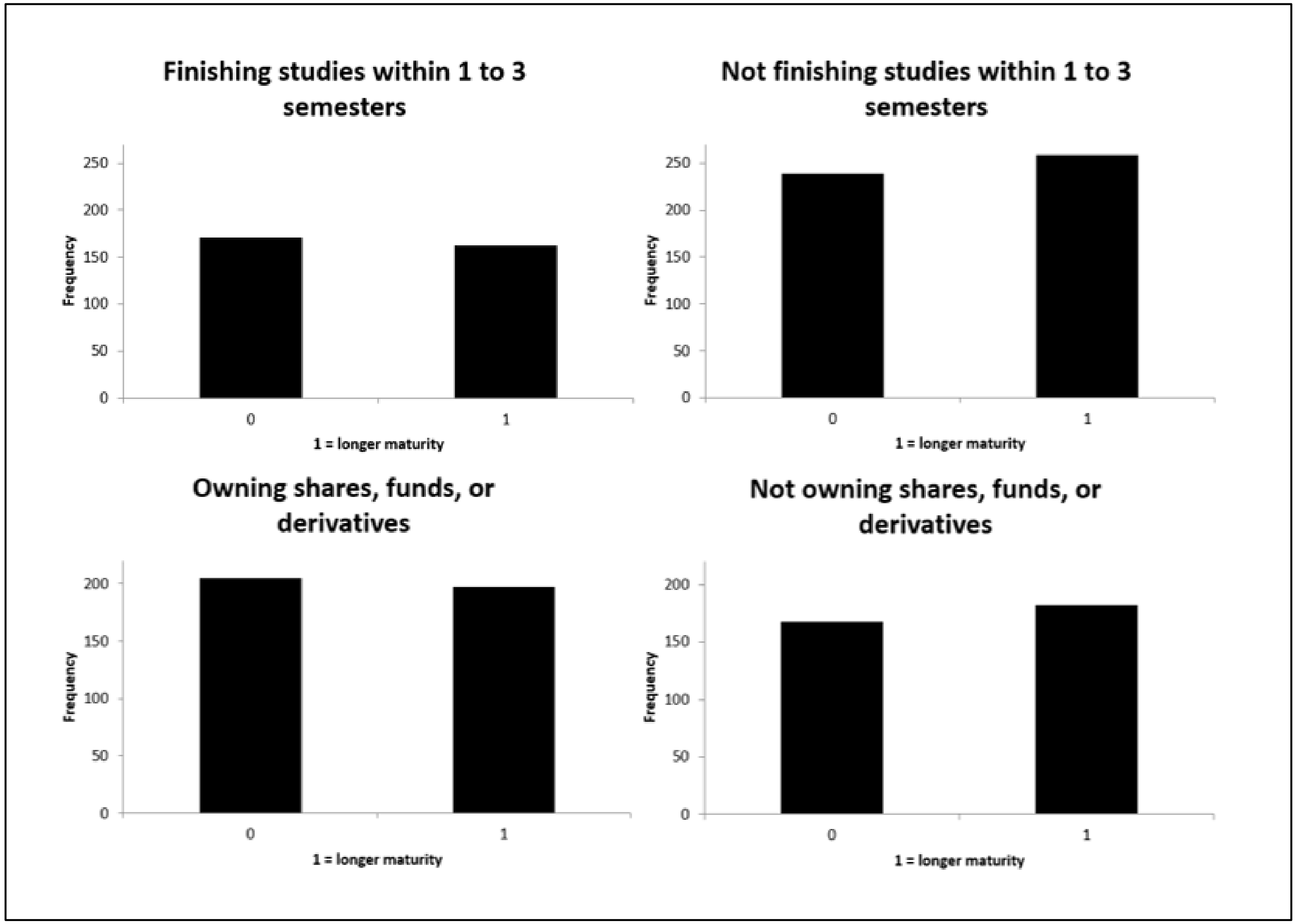


***Figure 2** Experiment: Allocation mechanism*

Figure 2 shows the slider mechanism used by participants of the experiment to make an allocation decision.

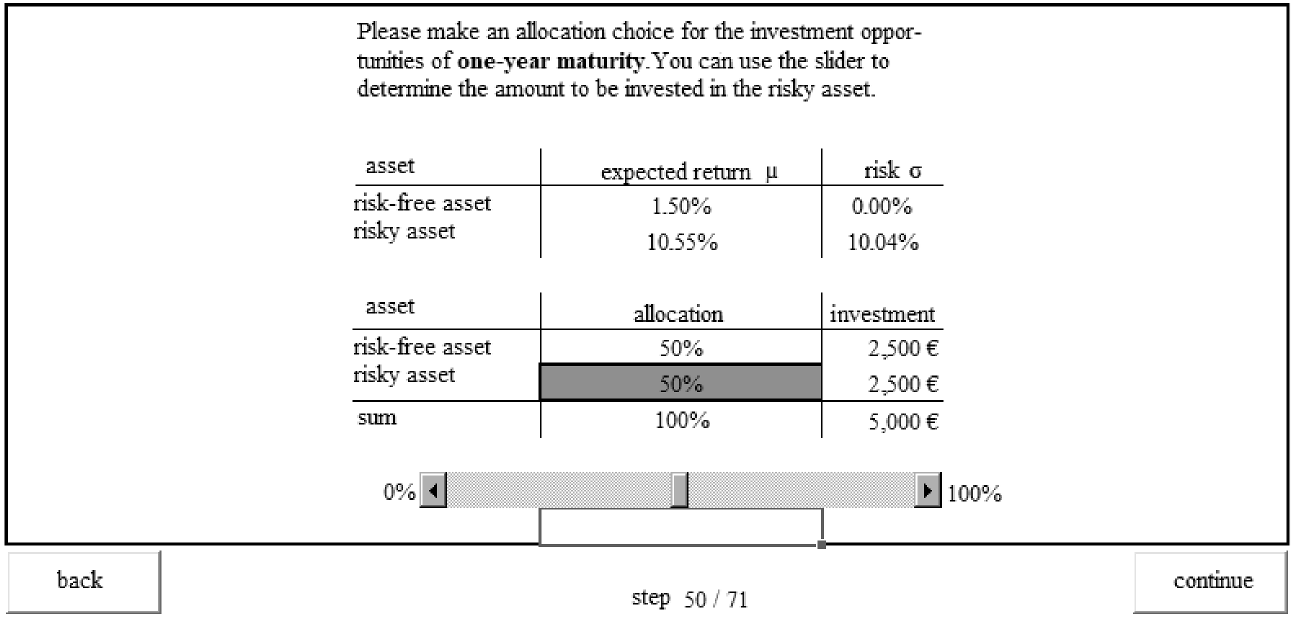
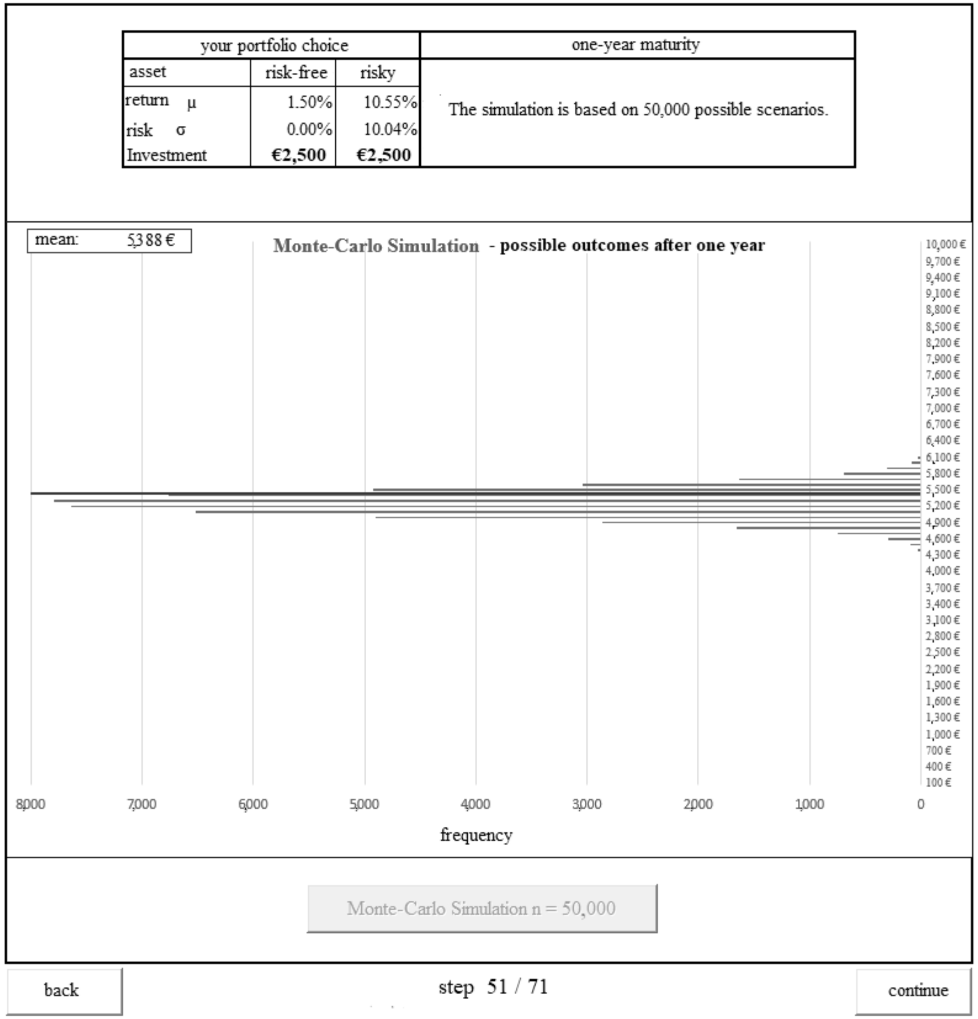


Figure 3 *Experiment: Presentation of the probability distribution*

Figure 3 shows how the concept of a probability distribution has been presented to participants of the experiment.



Appendix

I Elicitation of Parameters for Risk-Taking Behavior and Patience

To elicit risk-taking parameters, we employ a simple task for every parameter with three sub-questions. The main assignment for risk aversion towards gains has the following form:

> *"For each lottery comparison, please state the amount of Z for which you are indifferent between both lotteries.*
>
> *Lottery A: 50% chance to gain 20 €, 50% chance to gain 200 €*
>
> *Lottery B: 50% chance to gain Z €, 50% chance to gain nothing*
>
> *Z should be __________ €, such that lottery A is as attractive as lottery B."*

Using Prospect Theory by Kahneman & Tversky and three different lotteries of the form (*x,* 0.5; *y*, 0.5) and (*z*, 0.5; 0, 0.5) with *x, y* > 0, we calculate the risk aversion towards gains:

$$\pi(0.5) \cdot v(x) + \pi(0.5) \cdot v(y) = \pi(0.5) \cdot v(z) + \pi(0.5) \cdot v(0). \qquad \text{(A1)}$$

With $v(0)$ = 0 it follows:

$$v(x) + v(y) = v(z). \qquad \text{(A2)}$$

Now the function $v(x)$ has to be adjusted. For every value of the parameter α (exogenously given) the sum of the differences between the calculated value and the real value given through the questionnaire is calculated. The value of α for which this sum is minimal is the optimal value of the parameter. The higher the value of α, the smaller is the risk aversion towards gains, since the shape of the function is getting more concave with smaller α. For α = 1 the investor is neutral towards risk. We apply the same procedure to determine risk aversion in losses. We can then use three subsequent questions of the form (*x*, 0.5; – *y*, 0.5) and (– *z*, 0.5; 0, 0.5) with *x* = *y* to calculate λ, the loss aversion.

$$v(x) + v(-y) = v(-z)$$

$$\Leftrightarrow x^{\alpha^+} - \lambda \cdot y^{\alpha^-} = -\lambda \cdot z^{\alpha^-} \tag{A3}$$

$$\Leftrightarrow \lambda = \frac{x^{\alpha^+}}{y^{\alpha^-} - z^{\alpha^-}}.$$

For the calculation of the probability weighting parameter *γ* we use a well-known formula that has also been used in Tversky & Kahneman (1992):

$$\pi_\gamma(p) = \frac{p^\gamma}{((p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}. \tag{A4}$$

The treatment of probabilities differs between expected utility theory and prospect theory. In expected utility theory, the utility of an uncertain outcome is weighted by its probability. In prospect theory, the probability is replaced by a decision weight *π(p)* that is not a probability. We use questions of the form (*x*, *p*; 0, 1 – *p*) and ask the respondents for their certainty equivalent *z*. For the sake of completeness, please note that *π(p)* = *w(p)* for binary prospects. With $v(0)$ = 0 it follows:

$$\pi(p) \cdot v(x) + \pi(1-p) \cdot v(0) = v(z)$$

$$\Leftrightarrow \pi(p) = \frac{v(z)}{v(x)}. \tag{A5}$$

Since $v(x)$ and $v(z)$ are known, $\pi(p)$ and thus *γ* can be determined by variation of *p*, using the same procedure that has been utilized for the calculation of risk aversion α.

Concerning patience, we use the theory of the quasi-hyperbolic discount-model. Following this model, that has been confirmed in a large number of experiments, individuals tend to prefer smaller, but earlier rewards instead of larger, but later rewards. The function describing the subjective discount factor over time does not follow the shape of exponential discounting (as implied on capital markets by arbitrage freeness conditions) but a hyperbolic shape. Mathematically, quasi-hyperbolic discounting can be described as:

$$U(x_o, x_1, \ldots, x_T) = u(x_o) + \sum_{t=1}^{T} \beta \cdot \delta^t \cdot u(x_t), \tag{A6}$$

where U is an individual's overall utility consisting of discounted utility values u at times $t = 0$ to $t = T$ that result from rewards x_t. β and δ are constants between 0 and 1 utilized for subjective discounting purposes. The parameter β is called the present bias because this factor describes the patience of the individual between this period and the next period. A larger β implies a smaller present bias. The other parameter δ is called long-term discount factor and characterizes the patience between any two future periods.

For the calculation of these parameters the following two questions were used:

> *"Please consider the following alternatives:*
>
> *Payment A: A payment of 100 € now*
>
> *Payment B: A payment of F € in one year (ten years)*
>
> *F_{1year} ($F_{10years}$) should be __________ €, such that payment A is as attractive as payment B."*

Both parameters can be inferred from the individual's responses F_{1year} and $F_{10years}$:

$$\delta = \left(\frac{F_{1year}}{F_{10years}}\right)^{\frac{1}{9}}, \tag{A7}$$

$$\beta = \frac{100}{\delta \cdot F_{1year}}. \tag{A8}$$

II Correlation Analysis of Survey Data

Table A.1 *Shapiro-Wilk test for normal distribution*

Variable	*Observations*	*W*	*V*	*z*	*p-value*
age	995	0.953	29.488	8.378	0.000
income	866	0.449	304.787	14.080	0.000
wealth	802	0.093	467.955	15.087	0.000
self-assessed risk-taking	976	0.996	2.503	2.269	0.012
self-assessed patience	968	0.994	3.723	3.351	0.001
risk aversion (gains)	711	0.978	10.338	5.703	0.000
risk aversion (losses)	486	0.951	15.928	6.645	0.000
loss aversion	327	0.817	41.976	8.808	0.000
probability weighting	635	0.867	55.575	9.761	0.000
present bias parameter	962	0.898	61.944	10.202	0.000
long-term discount factor	962	0.975	15.145	6.719	0.000
uncertainty avoidance	966	0.997	1.871	1.549	0.061
long-term orientation	976	0.995	2.840	2.582	0.005
power distance	961	0.997	2.006	1.721	0.043
individualism	980	0.995	3.203	2.881	0.002
masculinity	969	0.997	1.954	1.657	0.049

Table A.2 *Spearman's correlations*

Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*
(1) age	1.000															
(2) income	0.107	1.000														
(3) wealth	0.576***	0.220***	1.000													
(4) self-assessed risk-taking	0.029	-0.049	0.050	1.000												
(5) self-assessed patience	0.181**	0.072	0.206***	0.165**	1.000											
(6) risk aversion (gains)	-0.191**	0.032	-0.122	-0.043	0.027	1.000										
(7) risk aversion (losses)	-0.094	0.053	0.027	-0.152	0.005	0.661***	1.000									
(8) loss aversion	0.004	0.015	-0.051	0.063	0.013	-0.124	-0.140*	1.000								
(9) probability weighting	0.095	-0.001	0.105	0.085	0.023	-0.254***	-0.120	-0.048	1.000							
(10) present bias parameter	0.299***	0.160**	0.284***	0.025	0.028	0.050	0.023	-0.059	0.120	1.000						
(11) long-term discount factor	0.139*	0.182**	0.160*	0.029	0.021	0.070	0.029	-0.069	-0.011	0.342***	1.000					
(12) uncertainty avoidance	-0.305***	0.113	-0.195**	-0.100	-0.095	0.125	0.121	-0.007	-0.031	-0.124	-0.062	1.000				
(13) long-term orientation	-0.146*	-0.050	-0.058	-0.283***	-0.144	-0.044	-0.006	-0.017	0.084	0.053	0.054	-0.139*	1.000			
(14) power distance	0.236***	-0.015	0.176**	-0.119	0.078	-0.242***	-0.051***	0.010	0.071	0.032	-0.018	0.011	-0.146*	1.000		
(15) individualism	0.182**	0.126	0.211***	0.157*	0.080	-0.077	-0.212***	0.077	0.029	0.101	0.054	-0.163*	0.018	-0.014	1.000	
(16) masculinity	0.061	-0.153*	0.013	0.199**	-0.068	-0.193**	-0.223***	-0.097	0.086	-0.035	-0.013	-0.180**	-0.107	-0.007	0.119	1.000

***, **, and * denote significance at 1, 5, and 10%, respectively.

III Distribution Analysis of Survey Data: Self-Assessed Indicators

Figure A.1 *Risk preference self-assessment distributions per country*

Figure A.1 shows the distributions of answers to our survey risk preference self-assessment question clustered by country

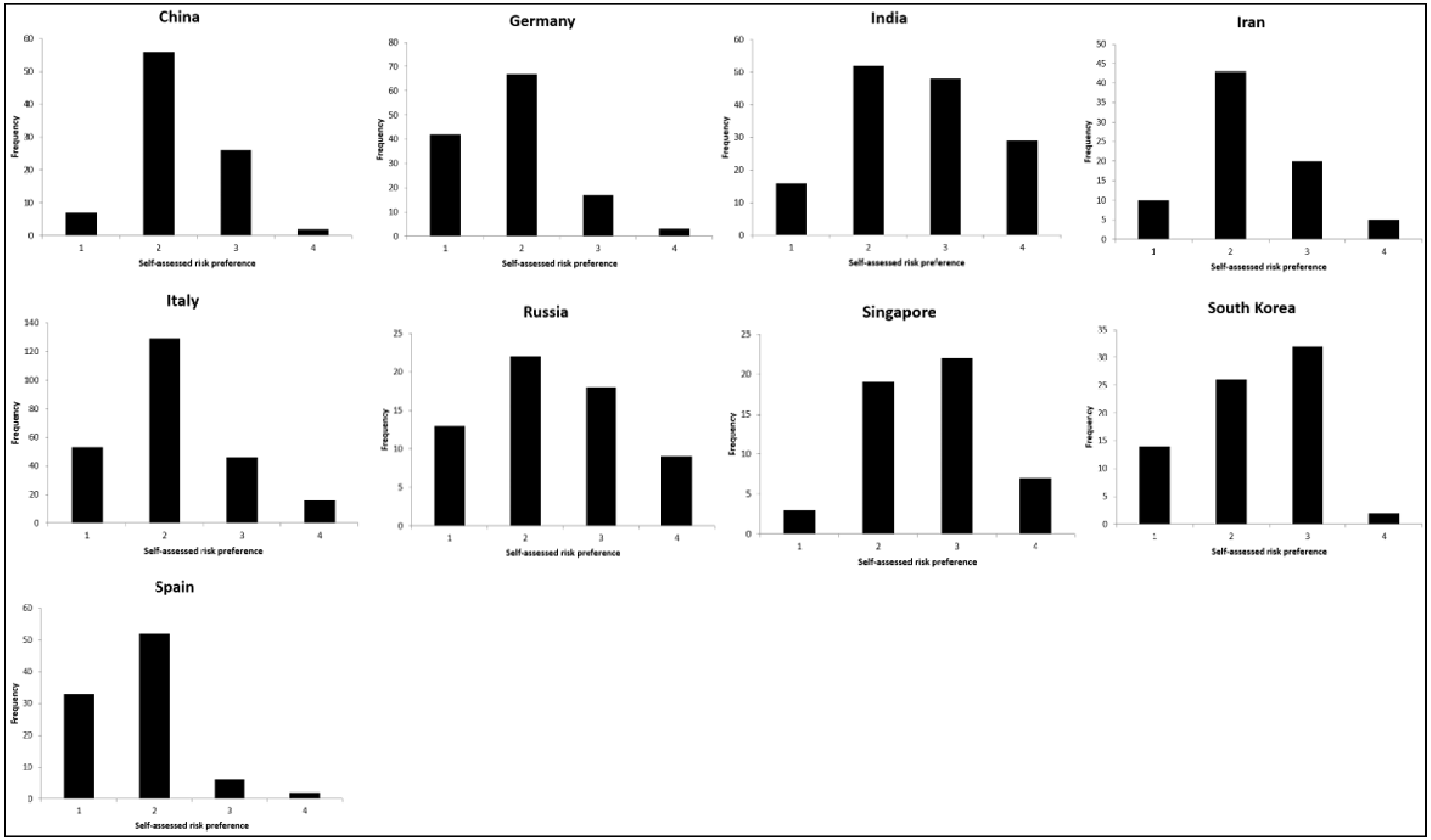
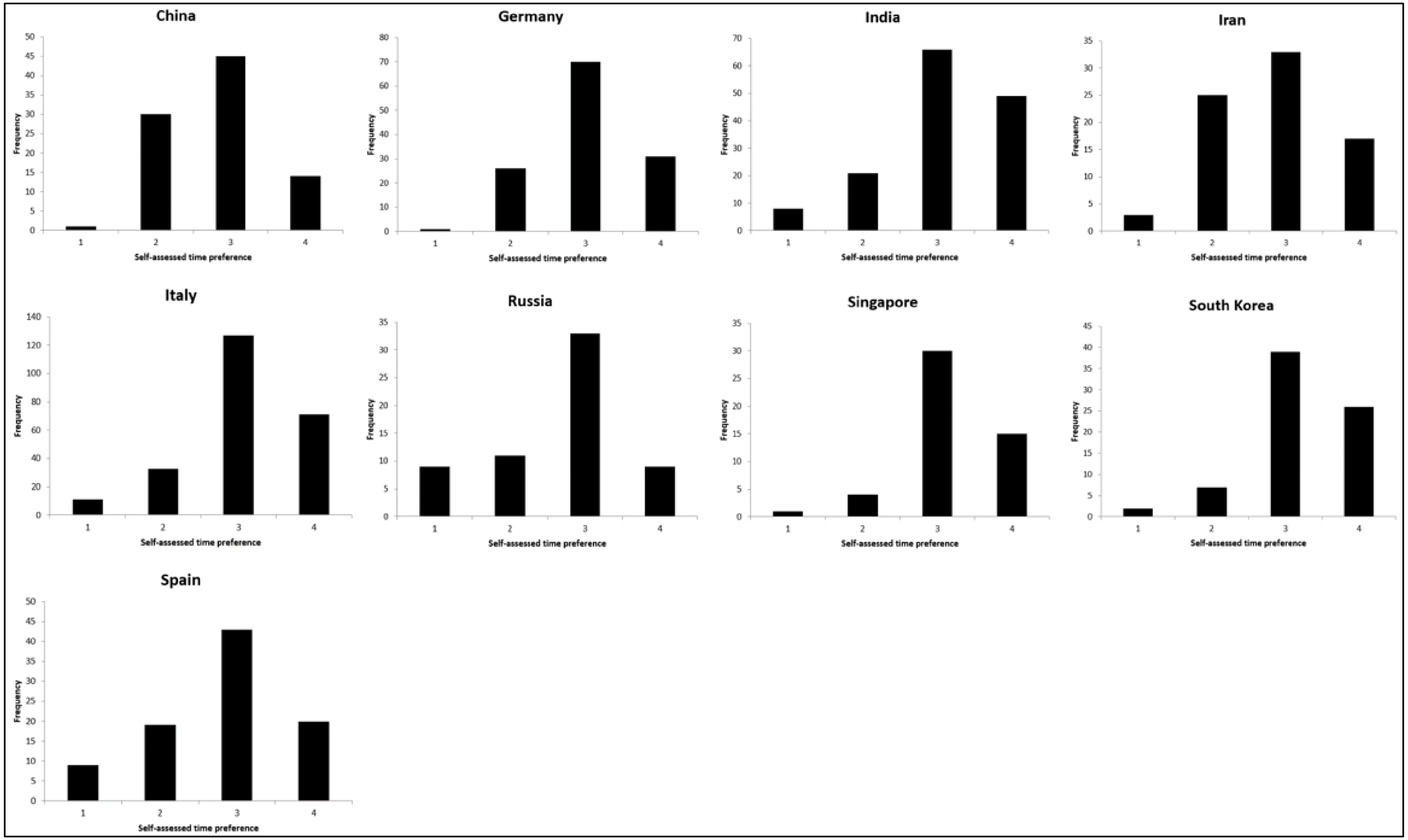


Figure A.2 *Time preference self-assessment distributions per country*

Figure A.2 shows the distributions of answers to our survey time preference self-assessment question clustered by country



IV Descriptive Statistics and Results of Lab Experiment

Table A.3 provides an overview of descriptive statistics of our experimental sample. As can be seen, the participants in the lab experiment show higher average wealth and income levels than survey participants. The survey data also reveal smaller present bias and probability weighting parameters as well as less loss aversion. Moreover, survey participants demonstrate less risky and less future-oriented financial behavior. The higher future orientation exhibited by participants in the lab might be a consequence of just waiting only two additional months (instead of two additional years) for relatively higher overall returns. However, the difference between the ratio of participants who opt for the longer maturity portfolio, which is 0.77 according to Table A.3, compared to the ratio of participants who decide for the longer maturity bond, which is 0.56 for the German subsample according to Table 1, is not too large and of a similar magnitude as the corresponding difference between the ratio of the risky assets according to Tables 1 and A.3 (0.38 versus 0.63).

>>> Insert Table A.3 about here. <<<

We conduct our additional analyses the same way as done before and as presented in Section 3. The choice of regression models as well as the choice of independent variables stays the same to ensure comparability. Additional controls are added in certain models to verify the results.

Our findings concerning the prediction of individual's risk behavior are consistent with our previous ones. Similar to the survey analysis of the prediction of individuals' risk behavior based on our novel questions, we can find significant regression coefficients for the variables of the self-assessed risk-taking indicator, probability weighting, and uncertainty avoidance. While in the first step of our regression series, the increase in pseudo R^2 is not the highest when including the self-assessed risk-taking indicator compared to models with other risk-taking measures, it is so in our second step. Furthermore, when including more than one measure of risk-taking at a time in the regression, the self-assessed risk-taking indicator appears to be statistically significant on a higher level compared to other measures in both, the first and the second step of our analysis.

>>> Insert Table A.4 about here. <<<

>>> Insert Table A.5 about here. <<<

To verify our findings, we set up a model with an enhanced set of control variables. All additional variables are dummy variables. We include a variable concerning the job-related workload, which takes the value of 1 if the participant works 15 hours or more per week as a professional, a variable which is 1 if the subject studies business administration, a variable which is 1 if the participant saved money during the last year, and a variable which is 1 if the participant is currently investing a (positive) share of his/her wealth in stocks, funds or financial derivatives. All dummy variables take the value of 0 if the particular condition stated above is not fulfilled.

We find that including these additional variables emphasizes the relevance of the self-assessed risk-taking indicator for explaining risk behavior in the experiment. While this variable still is significant on a 5%-level, all the other risk-related variables lose significance in this extended regression. Overall, our results of Section 4.2 are confirmed and we can state that the variable of the self-assessed risk-taking indicator performed consistently best in all our analyses.

>>> Insert Table A.6 about here. <<<

Regarding individuals' patience measures and time behavior, we again find similar evidence as in our previous analyses. The highest increase in pseudo R^2 as well as in adjusted pseudo R^2 can be observed when including the self-assessed patience indicator in the regression. In all regression models including the self-assessed patience indicator, we find this variable to be highly significant. Therefore, we can state that the self-assessed patience indicator serves consistently as the best predictor for time behavior in our analyses. These findings are supported in the second step of the regression series.

>>> Insert Table A.7 about here. <<<

>>> Insert Table A.8 about here. <<<

When including additional control variables, our findings remain stable. We can thus draw the same conclusion that our new and easy-to-use approach offers reliable results, which are comparable to lifelike decision-making in an experimental environment.

>>> Insert Table A.9 about here. <<<

Table A.3 *Descriptive statistics, laboratory evidence (average values)*

	mean	**std. dev.**	**10%-percentile**	**median**	**90%-percentile**
male	0.60	0.49	0.00	1.00	1.00
age	24.28	3.75	20.00	24.00	28.00
income	709.18	341.51	300.00	650.00	1,200.00
wealth	11,388.27	31,424.66	110.00	3,000.00	29,000.00
job-related workload	0.26	0.44	0.00	0.00	1.00
business studies	0.15	0.35	0.00	0.00	1.00
saver	0.71	0.45	0.00	1.00	1.00
Investment experience	0.48	0.50	0.00	0.00	1.00
ratio of risky assets in individual portfolios	0.63	0.28	0.20	0.70	1.00
ratio of individuals choosing the long-term portfolio	0.77	0.42	0.00	1.00	1.00
self-assessed risk-taking	1.94	0.70	1.00	2.00	3.00
self-assessed patience	3.03	0.78	2.00	3.00	4.00
risk aversion (gains)	0.63	0.24	0.29	0.62	1.00
risk aversion (losses)	0.63	0.18	0.44	0.63	0.80
loss aversion	4.55	7.55	0.05	0.59	15.12
probability weighting	1.56	0.90	0.57	1.47	2.88
present bias parameter	0.56	1.77	0.13	0.55	1.03
long-term discount factor	0.84	0.12	0.73	0.83	0.96
uncertainty avoidance	56.56	61.37	-14.00	55.00	138.00
long-term orientation	51.66	25.82	20.00	60.00	80.00
power distance	24.48	47.67	-34.00	20.00	83.00
individualism	91.75	46.96	31.00	95.00	150.00
masculinity	0.25	95.60	-128.00	0.00	120.00
foreign dummy	0.23	0.42	0	0	1
# observations	163	163	163	163	163

Table A.4 *Tobit analysis of risk behavior and risk-taking indicators, first step, laboratory evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
male	0.195***	*0.045*	0.169***	*0.045*	0.282***	*0.059*	0.182***	*0.048*	0.241***	*0.065*
age	-0.002	*0.008*	0.001	*0.008*	-0.009	*0.010*	-0.000	*0.008*	-0.003	*0.010*
income	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
wealth	-0.000	*0.000*	-0.000	*0.000*	-0.000	*0.000*	-0.000	*0.000*	-0.000	*0.000*
self-assessed risk-taking			0.077**	*0.034*					0.091**	*0.043*
risk aversion (gains)					-0.227	*0.146*			-0.190	*0.141*
risk aversion (losses)					0.126	*0.145*			0.058	*0.154*
loss aversion					0.001	*0.005*			-0.000	*0.004*
probability weighting					0.071**	*0.038*			0.064*	*0.036*
uncertainty avoidance							-0.001***	*0.000*	-0.000	*0.001*
long-term orientation							0.001	*0.001*	0.000	*0.001*
power distance							0.001	*0.000*	0.001	*0.001*
individualism							0.000	*0.000*	0.000	*0.001*
masculinity							0.000	*0.000*	0.000	*0.000*
foreign dummy	yes		yes		yes		yes		yes	
observations	163		163		115		163		115	
pseudo R^2	0.198		0.251		0.253		0.299		0.334	
F statistic	4.820		5.030		3.450		4.190		3.170	
p-value	0.000		0.000		0.001		0.000		0.000	

The dependent variable is the mean ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and three different sets of variables for risk-taking as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.5 *Tobit analysis of risk behavior and risk-taking indicators, second step, laboratory evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
male	0.226***	*0.051*	0.194***	*0.053*	0.226***	*0.052*	0.206***	*0.051*	0.177***	*0.053*
age	-0.004	*0.009*	-0.001	*0.008*	-0.004	*0.090*	-0.001	*0.008*	0.002	*0.009*
income	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
wealth	-0.000	*0.000*	-0.000	*0.000*	-0.000	*0.000*	-0.000	*0.000*	-0.000	*0.000*
self-assessed risk-taking			0.078**	*0.038*					0.074**	*0.037*
probability weighting					0.024	*0.025*			0.010	*0.025*
uncertainty avoidance							-0.001**	*0.000*	-0.001*	*0.000*
foreign dummy	yes		yes		yes		yes		yes	
observations	137		137		137		137		137	
pseudo R^2	0.192		0.238		0.200		0.230		0.276	
F statistic	4.200		4.400		3.950		4.490		4.120	
p-value	0.001		0.000		0.001		0.000		0.000	

The dependent variable is the mean ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and those variables for risk-taking that gained significance in Table A.4. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.6 *Tobit analysis of risk behavior and risk-taking indicators including additional control variables, laboratory evidence*

male	0.239***	*0.066*
age	-0.006	*0.010*
income	0.000	*0.000*
wealth	-0.000	*0.000*
job-related workload	0.093	*0.061*
business studies	-0.064	*0.080*
saver	-0.055	*0.068*
investment experience	-0.007	*0.060*
self-assessed risk-taking	0.091**	*0.044*
risk aversion (gains)	-0.158	*0.136*
risk aversion (losses)	0.107	*0.157*
loss aversion	-0.001	*0.005*
probability weighting	0.051	*0.038*
uncertainty avoidance	-0.000	*0.001*
long-term orientation	0.001	*0.001*
power distance	0.001	*0.001*
individualism	0.000	*0.001*
masculinity	0.000	*0.000*
foreign dummy	yes	
observations	115	
pseudo R^2	0.369	
F statistic	2.780	
p-value	0.001	

The dependent variable is the mean ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables including additional ones and three different sets of variables for risk-taking as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.7 *Logit analysis of time behavior and patience indicators, first step, laboratory evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
male	1.495	*0.390*	1.493	*0.403*	1.509	*0.392*	2.120*	*0.448*	2.514*	*0.481*
age	0.962	*0.051*	0.959	*0.054*	0.961	*0.051*	0.950	*0.054*	0.932	*0.058*
income	1.000	*0.001*	1.000	*0.001*	1.000	*0.001*	1.000	*0.001*	1.000	*0.001*
wealth	1.000	*0.000*	1.000	*0.000*	1.000	*0.000*	1.000	*0.000*	1.000	*0.000*
self-assessed patience			2.104***	*0.254*					2.639***	*0.282*
present bias parameter					1.151	*0.293*			1.268	*0.257*
long-term discount factor					2.275	*1.723*			2.547	*1.811*
uncertainty avoidance							1.001	*0.003*	1.002	*0.004*
long-term orientation							0.998	*0.008*	0.999	*0.008*
power distance							1.005	*0.004*	1.007	*0.005*
individualism							0.996	*0.004*	0.994	*0.005*
masculinity							0.997	*0.002*	0.996*	*0.002*
foreign dummy	yes		yes		yes		yes		yes	
observations	163		163		163		163		163	
χ^2	8.894		18.010		9.537		12.277		26.469	
p-value	0.113		0.006		0.216		0.267		0.015	
pseudo R^2	0.080		0.158		0.086		0.110		0.226	
pseudo R^2 *adjusted*	0.053		0.105		0.057		0.073		0.150	
specificity	2.600		7.900		2.600		5.300		13.200	

The dependent variable is the probability that an individual chooses the long-term portfolio. The independent variables consist of a group of socio-demographic variables and three different sets of variables for patience as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.8 *Logit analysis of time behavior and patience indicators, second step, laboratory evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**	
male	1.495	*0.390*	1.493	*0.403*	1.707	*0.413*	1.850	*0.432*
age	0.962	*0.051*	0.959	*0.054*	0.954	*0.052*	0.944	*0.056*
income	1.000	*0.001*	1.000	*0.001*	1.000	*0.001*	1.000	*0.001*
wealth	1.000	*0.000*	1.000	*0.000*	1.000	*0.000*	1.000	*0.000*
self-assessed patience			2.104***	*0.254*			2.253***	*0.260*
masculinity					-0.998	*0.002*	0.996	*0.002*
foreign dummy	yes		yes		yes		yes	
observations	163		163		163		163	
χ^2	8.894		18.010		9.984		20.435	
p-value	0.113		0.006		0.125		0.005	
pseudo R^2	0.080		0.158		0.090		0.178	
pseudo R^2 *adjusted*	0.053		0.105		0.059		0.118	
specificity	2.600		7.900		2.600		10.500	

The dependent variable is the probability that an individual chooses the long-term portfolio. The independent variables consist of a group of socio-demographic variables and those variables for patience that gained significance in Table A.7. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.9 *Logit analysis of time behavior and patience indicators including additional control variables, laboratory evidence*

male	2.631**	*0.494*
age	0.895*	*0.062*
income	1.000	*0.001*
wealth	1.000	*0.000*
job-related workload	0.767	*0.507*
business studies	0.284**	*0.615*
saver	0.507	*0.534*
investment experience	0.905	*0.456*
self-assessed patience	2.946***	*0.320*
present bias parameter	1.258	*0.239*
long term discount factor	2.664	*1.779*
uncertainty avoidance	1.004	*0.004*
long-term orientation	1.001	*0.008*
power distance	1.008*	*0.005*
individualism	0.994	*0.005*
masculinity	0.996	*0.003*
foreign dummy	yes	
observations	163	
χ^2	33.348	
p-value	0.010	
Pseudo R^2	0.279	
Pseudo R^2 *adj.*	0.185	
specificity	21.100	

The dependent variable is the probability that an individual chooses the long-term portfolio. The independent variables consist of a group of socio-demographic variables including additional ones and three different sets of variables for patience as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

V The Error-in-Variables Problem

One requirement for the use of the error-in-variables model is that the supposedly flawed variables are not normally distributed, which we checked, and ruled out. As exemplarily presented in Table A.10, when applying this model, it turns out that our results are very sensitive to the chosen method of calculation (high-order moments or cumulants) and the choice of the highest order of moments or cumulants, which might be due to our comparatively small number of observations, especially for our lab experiment. One may try to address this issue with the help of a further distribution analysis of our variables. In our case, however, this does not lead to meaningful results. Erickson et al. (2017) suggest using cumulants and checking the sensitivity of the estimates to different maximum orders case by case, since there is no way to determine ex ante the "right" model choice. They propose to use cumulants of fifth or higher order, but also point out that the choice of the order depends on the number of observations. In general, the more observations one has, the higher the order which can be applied. Following the advice of Erickson et al. (2017), in our case, we make use of the fourth-order-cumulants calculation method.

>>> Insert Table A.10 about here. <<<

To ensure comparability, we create a similar set of horserace regressions as presented before. According to Table A.11, for our survey evidence, the results hardly differ at all from our previous findings of Table 2. Compared to Model 3, Table 2, the coefficient of probability weighting in Model 3, Table A.11, is still significant. However, when taking measurement errors into account, the significance level of this coefficient increases, and risk aversion in losses also gains significance. Looking at the combined Models 5 in Table 2 and Table A.11, we find significance for exactly the same variables. However, the significance level of probability weighting is still higher when using the error-in-variables model. The R^2 of the error-in-variables model is considerably smaller, and the low value of the Sargan-Hansen *J* statistic *p*-value shows that this model is not really appropriate in terms of eliminating measurement errors. The comparison of the combined models in the second step of our horserace regression, presented in Model 7, Table 3, and Model 8, Table A.12, does not reveal any notable differences, either. In both cases, the measures related to prospect theory lose their statistical significance, while the self-assessed risk-taking indicator retains it on a 1%-level. When looking at the Sargan-Hansen *J* statistic *p*-value, this model is better than Model 5 of Table A.11. Generally speaking, this supports our previous findings.

>>> Insert Table A.11 about here. <<<

>>> Insert Table A.12 about here. <<<

For our experimental evidence, the outcomes regarding the first step of the horserace regression are again similar. Comparing Tables A.4 and A.13, we can see that the regressors which are significant in Table A.4 are significant in Table A.13 as well. Additionally, in our error-in-variables Model 3, Table A.13, loss aversion becomes significant, and in Model 5 of Table A.13, this is true for risk aversion (gains). In general, the significance levels of our lottery-measured risk-taking variables are higher when applying a regression model which accounts for the error-in-variables problem. However, when comparing the second steps of our laboratory evidence horserace regressions, we find some differences. In the combined Models 5, Table A.5, and 7, Table A.14, the coefficient for the self-assessed risk-taking indicator loses its significance in the latter one, while in the former one, it is still significant on a 5%-level. The very high *p*-value of the Sargan-Hansen *J* statistic in Model 7, Table A.14, confirms the relevance of this model. While this seems to be quite a reliable result at first glance, it actually is very sensitive to the choice of the highest order as well. Model 1, Table A.15, shows the results of the same combination of regressors using only third-order cumulants instead of fourth-order cumulants. We can see that in this case, a simple self-assessment still seems to be the best choice for determining personal risk-taking. Note that the R^2 is even higher than in Model 7, Table A.14, and the Sargan-Hansen *J* statistic *p*-value is sufficiently high to consider this a good model.

All in all, the regression method of Erickson & Whited (2000) seems to be a good starting point for further research, but as long as the results are that sensitive to the choice of the highest order, the explanatory power remains questionable – although there are indications that, when considering an error-in-variables model, lottery-based measuring of risk-taking may gain reliability.

>>> Insert Table A.13 about here. <<<

>>> Insert Table A.14 about here. <<<

>>> Insert Table A.15 about here. <<<

Table A.10 *Exemplary error-in-variables analysis of risk behavior and risk-taking indicators using high-order cumulants and moments, laboratory evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**	
male	0.263***	*0.516*	0.238***	*0.053*	0.221***	*0.069*	0.213***	*0.066*
age	-0.009	*0.244*	-0.008	*0.008*	-0.006	*0.009*	-0.005	*0.010*
income	0.000*	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
wealth	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000**	*0.000*
risk aversion (gains)	-0.653	*0.516*	-0.067	*0.137*	0.000	*0.112*	0.240*	*0.138*
risk aversion (losses)	0.471*	*0.244*	-0.171	*0.090*	0.556*	*0.076*	1.009***	*0.324*
loss aversion	-0.012*	*0.007*	0.007***	*0.002*	-0.007	*0.026*	0.000	*0.004*
probability weighting	0.015	*0.063*	0.071***	*0.023*	-0.006	*0.073*	0.100***	*0.034*
foreign dummies	yes		yes		yes		yes	
observations	115		115		115		115	
pseudo R^2	0.201		0.182		0.203		0.325	
Sargan-Hansen J statistic	5.600		33.946		10.794		5332.976	
p-value J statistic	0.469		0.567		0.095		0.000	
degrees of freedom J statistic	6		36		6		36	
τ^2_1	0.219		2.809		1.210		0.838	
τ^2_2	0.404		0.403		0.282		0.156	
τ^2_3	0.159		0.218		0.256		55.121	
τ^2_4	8.697		0.700		2.162		0.225	
method	cumulants		cumulants		moments		moments	
highest order of cumulants/moments	3		4		3		4	

The dependent variable is the mean ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and a set of variables for risk-taking as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.11 *Tobit and error-in-variables analysis of risk behavior and risk-taking indicators, first step, survey evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
male	0.074***	*0.023*	0.048**	*0.022*	0.037	*0.038*	0.071***	*0.023*	0.059	*0.037*
age	0.000	*0.004*	0.003	*0.004*	0.002	*0.007*	-0.001	*0.004*	0.004	*0.006*
income	0.000	*0.000*	0.000	*0.000*	0.000***	*0.000*	0.000	*0.000*	0.000**	*0.000*
wealth	0.000	*0.000*	0.000***	*0.000*	0.000*	*0.000*	0.000	*0.000*	0.000	*0.000*
self-assessed risk-taking			0.113***	*0.015*					0.068**	*0.030*
risk aversion (gains)					0.103	*0.088*			0.141	*0.096*
risk aversion (losses)					0.104*	*0.061*			0.070	*0.066*
loss aversion					-0.017	*0.014*			-0.004	*0.017*
probability weighting					0.240***	*0.054*			0.209***	*0.060*
uncertainty avoidance							-0.001***	*0.000*	-0.000	*0.000*
long-term orientation							-0.001	*0.001*	-0.002**	*0.001*
power distance							0.000	*0.000*	0.000	*0.000*
individualism							0.000**	*0.000*	0.000	*0.000*
masculinity							0.000	*0.000*	-0.000	*0.000*
country dummies	yes		yes		yes		yes		yes	
observations	642		637		155		609		153	
pseudo R^2	0.121		0.302		0.202		0.200		0.303	
F statistic	7.313		12.380				4.730			
p-value F statistic	0.000		0.000				0.000			
Sargan-Hansen J statistic					45.416				54.164	
p-value J statistic					0.135				0.026	
degrees of freedom J statistic					36				36	
τ^2_1					0.501				0.387	
τ^2_2					0.166				0.079	
τ^2_3					0.329				2.352	
τ^2_4					0.705				0.796	

The dependent variable is the ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and three different sets of variables for risk-taking as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.12 *Tobit and error-in-variables analysis of risk behavior and risk-taking indicators, second step, survey evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**		**Model 8**	
male	0.075*	*0.039*	0.062	*0.038*	0.015	*0.055*	0.091*	*0.052*	0.074*	*0.038*	0.091**	*0.039*	0.071*	*0.039*	0.078**	*0.037*
age	-0.004	*0.006*	0.001	*0.006*	0.007	*0.009*	-0.014	*0.012*	-0.002	*0.006*	-0.004	*0.006*	-0.004	*0.006*	-0.000	*0.006*
income	0.000**	*0.000*	0.000**	*0.000*	0.000***	*0.000*	0.000***	*0.000*	0.000**	*0.000*	0.000**	*0.000*	0.000**	*0.000*	0.000**	*0.000*
wealth	0.000*	*0.000*	0.000*	*0.000*	0.000*	*0.000*	-0.000	*0.000*	0.000*	*0.000*	0.000	*0.000*	0.000*	*0.000*	0.000	*0.000*
self-assessed risk-taking			0.110***	*0.027*											0.081***	*0.022*
risk aversion (losses)					0.837*	*0.500*									-0.008	*0.186*
probability weighting							0.887	*0.584*							0.148	*0.108*
uncertainty avoidance									-0.001***	*0.000*					-0.001***	*0.000*
long-term orientation											-0.002***	*0.001*			-0.001**	*0.001*
individualism													0.001	*0.000*	0.000	*0.000*
country dummies	yes		yes		yes		yes		yes		yes		yes		yes	
observations	246		246		246		246		246		246		246		246	
pseudo R^2	0.113		0.217		0.187		0.207		0.158		0.159		0.126		0.230	
F statistic	2.030		3.390						2.680		2.290		2.170			
p-value F statistic	0.022		0.000						0.002		0.007		0.012			
Sargan-Hansen J statistic					1.439		0.280								5.894	
p-value J statistic					0.487		0.869								0.659	
degrees of freedom J statistic					2		2								8	
τ^2_1					0.324										9.584	
τ^2_2							0.253								0.555	

The dependent variable is the ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and those variables for patience that gained significance in Table A.11. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

__Table A.13__ Tobit and error-in-variables analysis of risk behavior and risk-taking indicators, first step, laboratory evidence

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
male	0.195***	*0.045*	0.169***	*0.045*	0.238***	*0.053*	0.182***	*0.048*	0.213***	*0.056*
age	-0.002	*0.008*	0.001	-0.008	-0.008	*0.010*	-0.000	*0.008*	-0.003	*0.008*
income	0.000	*0.000*	0.000	0.000	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
wealth	-0.000	*0.000*	-0.000	0.000	0.000	*0.000*	-0.000	*0.000*	0.000	*0.000*
self-assessed risk-taking			0.077**	*0.034*					0.081**	*0.035*
risk aversion (gains)					-0.067	*0.137*			-0.320**	*0.143*
risk aversion (losses)					-0.171	*0.090*			-0.122	*0.090*
loss aversion					0.007***	*0.002*			0.001	*0.003*
probability weighting					0.071***	*0.023*			0.101***	*0.035*
uncertainty avoidance							-0.001***	*0.000*	-0.000	*0.000*
long-term orientation							0.001	*0.001*	0.000	*0.001*
power distance							0.001	*0.000*	0.001	*0.001*
individualism							0.000	*0.000*	0.000	*0.001*
masculinity							0.000	*0.000*	0.000	*0.000*
foreign dummy	yes		yes		yes		yes		yes	
observations	163		163		115		163		115	
pseudo R^2	0.198		0.251		0.182		0.299		0.263	
F statistic	4.820		5.030				4.190			
p-value F statistic	0.000		0.000				0.000			
Sargan-Hansen J statistic					33.946				38.072	
p-value J statistic					0.567				0.375	
degrees of freedom J statistic					36				36	
τ^2_1					2.809				0.814	
τ^2_2					0.403				0.273	
τ^2_3					0.218				0.207	
τ^2_4					0.700				0.853	

The dependent variable is the mean ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and three different sets of variables for risk-taking as outlined in Section 3. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.14 *Tobit and error-in-variables analysis of risk behavior and risk-taking indicators, second step, laboratory evidence*

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**	
male	0.252***	*0.058*	0.218***	*0.059*	0.160**	*0.073*	0.206***	*0.052*	0.221***	*0.060*	0.234***	*0.057*	0.171***	*0.053*
age	-0.006	*0.010*	-0.003	*0.010*	-0.000	*0.013*	-0.003	*0.009*	-0.004	*0.010*	-0.003	*0.010*	-0.000	*0.009*
income	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000*	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
wealth	-0.000	*0.000*	-0.000	*0.000*	-0.000	*0.000*	0.000	*0.000*	-0.000	*0.000*	-0.000	*0.000*	-0.000**	*0.000*
self-assessed risk-taking			0.094**	*0.043*									0.053	*0.038*
risk aversion (gains)					0.823	*0.803*							0.259	*0.201*
loss aversion							-0.013	*0.012*					0.008**	*0.003*
probability weighting									0.201	*0.242*			0.064*	*0.033*
uncertainty avoidance											-0.001*	*0.000*	-0.001*	*0.000*
foreign dummy	yes		yes		yes		yes		yes		yes		yes	
observations	117		117		117		117		117		117		117	
pseudo R^2	0.198		0.250		0.128		0.150		0.218		0.227		0.208	
F statistic	4.310		4.530								4.460			
p-value F statistic	0.001		0.000								0.000			
Sargan-Hansen J statistic					0.403		0.780		0.216				9.889	
p-value J statistic					0.817		0.677		0.898				0.956	
degrees of freedom J statistic					2		2		2				19	
τ^2_1					0.064								0.581	
τ^2_2							0.282						0.116	
τ^2_3									0.202				0.141	

The dependent variable is the mean ratio of risky assets in individual portfolios. The independent variables consist of a group of socio-demographic variables and those variables for risk-taking that gained significance in Table A.13. ***, **, and * denote significance at 1, 5, and 10%, respectively. Robust standard errors are reported in italics.

Table A.15 *Exemplary error-in-variables analysis of risk behavior and risk-taking indicators using third-order cumulants, laboratory evidence*

	Model 1	
male	0.183***	*0.059*
age	0.000	*0.008*
income	0.000	*0.000*
wealth	0.000	*0.000*
self-assessed risk-taking	0.093**	*0.042*
risk aversion (gains)	-0.332	*0.549*
loss aversion	-0.008	*0.006*
probability weighting	0.004	*0.062*
uncertainty avoidance	-0.001	*0.000*
foreign dummy	yes	
observations	117	
pseudo R^2	0.221	
Sargan-Hansen J statistic	0.740	
p-value J statistic	0.864	
degrees of freedom J statistic	3	
τ^2_1	0.216	
τ^2_2	0.305	
τ^2_3	19.726	
method	cumulants	
highest order	3	

VI Questionnaire

Questionnaire

In this questionnaire we would kindly ask you to answer different types of questions:

In **Part A** general statistical data are collected. **Part B** deals with your time preferences. **Part C** is concerned with your own risk preferences. **Part D** asks questions on your household finance. **Part E** deals with your personal attitudes. **Part F** is for financial statistics.

Please note the following: Remember there are no right or wrong answers. I am only interested in your own preference and attitudes. The answers will not be analysed and will remain confidential.

Part A: Statistical Data

The survey will remain confidential but it is important to understand how different population groups think and behave, i.e. men and women, younger and older people, working people and pensioners, etc. Therefore we would like to know some specifics about yourself.

1 Gender

☐ Male
☐ Female

2 Nationality

☐ South Korean
☐ Others: ____________________

3 How do you describe your ethnic origin?

☐ African
☐ English-Speaking
☐ Confucian
☐ South Asia
☐ Middle East
☐ East Europe
☐ West Europe
☐ Latin America
☐ Others: ____________________

4 How would you describe your religious beliefs?

☐ Christian

☐ Jewish
☐ Muslim
☐ Buddhism
☐ Hinduism
☐ Others: ________________________

5 What is your date of birth?

___/____/_____
(DD/ MM / YYYY)

6 Which of the following statements concerning living conditions apply to you?

☐ I live at my parents' home.
☐ I live together with my partner.
☐ I live in a flat share with other people.
☐ I live in a student accommodation on campus.
☐ I live on my own.

7 Do you live in rented accommodation or do you own your own property?

☐ Rented accommodation
☐ Own property

8 How many hours do you regularly work per week in a part-time job?

☐ 0 hours
☐ 1 – 15 hours
☐ 16 – 35 hours
☐ More than 35 hours

9 What school are you majoring in?

☐ Arts and Social Sciences
☐ Business and Economics
☐ Computing
☐ Dentistry
☐ Architecture and Civil Engineering
☐ Engineering
☐ Law
☐ Medicine
☐ Music
☐ Science
☐ Others: ________________________

10 How many more semesters will it take you to complete your studies (please include the current semester as well)?

____ semester

11 Which degree are you working towards?

☐ Bachelor
☐ Diploma

- ☐ Ph.D.
- ☐ Magister
- ☐ Master

Part B: Time Preferences

Please note: *A* ***payment*** *is defined as money that you receive.*

Please consider the following alternatives:

1 A: a payment of 200 $ now
B: a payment of X $ in one month from now
X has to be at least __________ $, such that B is as attractive as A.

2 A: a payment of 200 $ now
B: a payment of X $ in one year from now
X has to be at least __________ $, such that B is as attractive as A.

3 A: a payment of 200 $ now
B: a payment of X $ in ten years from now
X has to be at least __________ $, such that B is as attractive as A.

Part C: Risk Preferences

For each lottery comparison, please state the amount of Z for which you are indifferent between both lotteries.

1 **Lottery A:**
50 % chance to gain 20 $
50 % chance to gain 200 $
Lottery B:
50 % chance to gain Z $
50 % chance to gain nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

2 **Lottery A:**
50 % chance to gain 100 $
50 % chance to gain 400 $
Lottery B:
50 % chance to gain Z $
50 % chance to gain nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

3 **Lottery A:**
50 % chance to gain 200 $
50 % chance to gain 800 $
Lottery B:

50 % chance to gain Z $
50 % chance to gain nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

4 **Lottery A:**
50 % chance to lose 40 $
50 % chance to lose 240 $
Lottery B:
50 % chance to lose Z $
50 % chance to lose nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

5 **Lottery A:**
50 % chance to lose 80 $
50 % chance to lose 480 $
Lottery B:
50 % chance to lose Z $
50 % chance to lose nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

6 **Lottery A:**
50 % chance to lose 160 $
50 % chance to lose 640 $
Lottery B:
50 % chance to lose Z $
50 % chance to lose nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

7 **Lottery A:**
50 % chance to gain 100 $
50 % chance to lose 100 $
Lottery B:
50 % chance to lose Z $
50 % chance to gain nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

8 **Lottery A:**
50 % chance to gain 200 $
50 % chance to lose 200 $
Lottery B:
50 % chance to lose Z $
50 % chance to gain nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

9 **Lottery A:**
50 % chance to gain 400 $
50 % chance to lose 400 $

Lottery B:
50 % chance to lose Z $
50 % chance to gain nothing
Z should be __________ $, such that lottery A is as attractive as lottery B.

Imagine you are offered the Lotteries below. Please indicate the maximum amount you are willing to pay for the lottery.

10 0,1 % chance to gain 2000 $
99,9 % chance to gain nothing
I am willing to pay at most __________ $ to play the lottery.

11 10 % chance to gain 100 $
90 % chance to gain nothing
I am willing to pay at most __________ $ to play the lottery.

12 90 % chance to gain 20 $
10 % chance to gain nothing
I am willing to pay at most __________ $ to play the lottery.

13 70 % chance to gain 60 $
30 % chance to gain nothing
I am willing to pay at most __________ $ to play the lottery.

14 98 % chance to gain 200 $
2 % chance to gain nothing
I am willing to pay at most __________ $ to play the lottery.

Part D: Household Finance

1 ***Imagine you have got an amount of 10,000 $. How much money would you invest in stocks/funds and fixed income assets?***

Stocks/Funds ________________ $

Fixed income assets ________________ $

2 ***If you had the choice between a bond of one-year maturity with an interest rate of 3 % p.a. and a bond of five-year maturity with an interest rate of 4.5 % p.a., which option would you choose?***

☐ Bond of one-year maturity

☐ Bond of five-year maturity

3 ***Which of the following statements most applies to you if you needed to invest your money for a long period of time?***

☐ I would tie up money for a long period of time to earn substantial returns.

☐ I would tie up money for an intermediate period of time to earn above average returns.

☐ I would tie up money for a short period of time to earn average returns.

☐ I am not willing to tie up money at all.

4 ***Please indicate what percentage of your total wealth is currently invested in each of the following categories (the total must sum to 100):***

Savings _________%

Stocks _________%

Mutual Funds _________%

Life Insurance _________%

Pension Funds _________%

Financial Derivatives _________%

5 ***Which of the following statements comes closest to the amount of financial risk you are willing to take when you save or make investments?***

☐ I would take substantial financial risks expecting to earn substantial returns.

☐ I would take above average financial risks expecting to earn above average financial returns.

☐ I would take average financial risks expecting to earn average financial returns.

☐ I am not willing to take any financial risks.

	Please evaluate the following statements:	strongly disagree	disagree	undecided	agree	strongly agree
6	In comparison to my environment I am more willing to take risks.	☐	☐	☐	☐	☐
7	In the last year my expenditure exceeded my income.	☐	☐	☐	☐	☐
8	It is important to me that I am allowed to pull back invested money if needed.	☐	☐	☐	☐	☐

		1 month	the next couple of months	1 year	the next couple of years	more than 5 years from now
9	***Which of the time frames mentioned is most important to you with regard to planning expenditure and savings?***	☐	☐	☐	☐	☐

Part E: Attitudes

Please think of your ideal job, disregarding your present job, if you have one. **In choosing an ideal job, how important would it be to you to ...**

	Please mark only one answer in each row.	of no importance	of little importance	of moderate importance	very important	of utmost importance
1	*have sufficient time for your personal or family life.*	☐	☐	☐	☐	☐
2	*have good physical working conditions (good ventilation and lighting, adequate work space, etc.).*	☐	☐	☐	☐	☐
3	*have a good working relationship with your direct superior.*	☐	☐	☐	☐	☐
4	*have security of employment.*	☐	☐	☐	☐	☐
5	*work with people who co-operate well with one another.*	☐	☐	☐	☐	☐
6	*be consulted by your direct superior in his/her decisions.*	☐	☐	☐	☐	☐
7	*have an opportunity for advancement to higher level jobs.*	☐	☐	☐	☐	☐
8	*have an element of variety and adventure in the job.*	☐	☐	☐	☐	☐

In your private life, how important is each of the following for you?

	Please mark one answer in each row.	of no importance	of little importance	of moderate importance	very important	of utmost importance
9	*Thrift*	☐	☐	☐	☐	☐
10	*Respect for tradition*	☐	☐	☐	☐	☐

	Please mark one answer in each row.	never	seldom	some-times	usually	always
11	***How often do you feel nervous or tense at work?***	☐	☐	☐	☐	☐

	Please mark one answer in each row.	very sel-dom	seldom	some-times	frequently	very fre-quently
12	***How frequently, in your experience, are subordinates afraid to express dis-agreement with their superiors?***	☐	☐	☐	☐	☐

To what extent do you agree or disagree with each of the following statements?

	Please mark one answer in each row.	strongly disagree	disagree	undecided	agree	strongly agree
13	*Most people can be trusted.*	☐	☐	☐	☐	☐
14	*One can be a good manager without having precise answers to most ques-tions that subordinates may raise about their work.*	☐	☐	☐	☐	☐
15	*An organisation structure in which cer-tain subordinates have two bosses should be avoided at all costs.*	☐	☐	☐	☐	☐
16	*Competition between employees usu-ally does more harm than good.*	☐	☐	☐	☐	☐
17	*A company's or organisation's rules should not be broken - not even when the employee thinks it is in the com-pany's best interest.*	☐	☐	☐	☐	☐
18	*When people have failed in life it is of-ten their own fault.*	☐	☐	☐	☐	☐

	Please mark one answer in each row.	dissatis-fied	slightly dissatis-fied	neutral	somehow satisfied	very satis-fied
19	***How satisfied are you overall with your present life?***	☐	☐	☐	☐	☐

Part F: Financial Values

This survey will remain confidential and its purpose is purely for analytical use. It is important to understand how different population groups (with e.g. high, middle or lower income) think and behave. Therefore, I would like to ascertain the following financial information in the strictest of confidence.

1	***What is your actual total wealth?***	__________ $
2	***How much money do you have at your disposal per month?***	__________ $

3 How much money did you put aside in the last month? __________ $

4 Did you put money aside in the past 12 months?

☐ yes

☐ no

Thank you for your time and your valuable participation!

Paper #2: Drivers of Trust and Advice Discounting for Robo Advice

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Abstract

We compare the levels of trust as well as the acceptance of advice in the context of robo-advised individual portfolio allocation decisions with respect to the impact of certain layout and questionnaire characteristics. We moreover introduce an easy-to-replicate measure for the acceptance of advice in multidimensional decision-making situations. Our data is based on an incentivized experiment. The results show that a more emotional design of the advice software leads to a higher level of advice acceptance, while trust in the advisor, on the other hand, is not influenced by layout or questionnaire features and does not seem to play an important role when it comes to advice acceptance, contradicting the findings of existing literature. We therefore suggest that robo advice providers should primarily focus on the development of informal interfaces to enhance the use of robo advice.

Keywords: robo advice; advice discounting; judge-advisory-system; investment advice, portfolio allocation.

JEL Classification: D14, D81, D83, G11, G4

1. Introduction

There is empirical evidence that the investment decisions of individuals are prone to irrational behavioral patterns, resulting in systematic errors that ultimately lead to suboptimal portfolio allocations. However, there might be a simple way to remedy this issue: Literature suggests that financial advice plays a crucial role in preventing systematic investment errors to some extent (Hoechle et al., 2017). Currently, the financial services industry is facing the emergence of algorithm-based robo advice solutions, which represent a disruptive innovation. In 2017, the combined assets under management (AuM) of all robo advisors were estimated to be around US$240 billion globally. By 2023, this value had increased more than tenfold to an estimated US$2.76 trillion. By 2027, the value is projected to be around US$4.66 trillion, nearly a twentyfold increase in just ten years (Statista, 2023). Against the backdrop of this surge, one question remains largely unanswered: What impact do robo advice services actually have on investment decisions? This paper aims to investigate what characteristics a robo advisor should have to ensure that advice is considered as much as possible, based on data taken from an experiment in a controlled environment.

Currently, there is limited research focusing on robo advice within the context of portfolio allocation. In this area, Stolper and Walter (2017) observe that "surprisingly, however, the question of whether advisees in fact implement the advice they receive is still largely unanswered […]." Evidence exists that people generally "discount" advice offered to them to a certain extent, for a variety of reasons (Yaniv & Kleinberger, 2000).

Research regarding investor behavior in the context of robo advice is additionally important because, unlike conventional wealth management services, robo advice is typically accessible to less affluent clients. Compared to clients of traditional management services, individuals using robo advice services tend to have lower income and wealth levels (Fulk et al., 2018). Statistically, there is a positive correlation between wealth and financial literacy as well as experience acting on the capital markets (Monticone, 2010; van Rooij et al., 2012) – and inexperienced investors are shown to be particularly prone to systematic investment errors. The existing robo advice services mainly differ based on the user interface and on the content of the interaction. However, research on how robo advice characteristics influence decision-making is basically non-existent. Bringing together the particularly vulnerable group of inexperienced individuals, who heavily rely on advice, with an advisory system structured to possibly favor high discount rates, could lead to particularly undesirable outcomes; however, even for more experienced investors, a low discount rate, thus a high level of advice acceptance, is favorable.

We expand the current literature on the acceptance of advice with a view to investment advice and portfolio composition in general and regarding the use of robo advice in particular. We address how user interface characteristics and questionnaire length influence decision-making. That could help to create an "optimal" advice process with the goal to maximize advice acceptance. We find evidence that an emotional, rather informal layout implies a higher acceptance of advice.

Our work is structured as follows: We review existing literature in Section 2. Based on this, we form hypotheses, which are presented in Section 3. Section 4 describes our experimental setup; consecutively, we show the outcomes of our statistical analyses in Section 5. These results are discussed in Section 6, after which a brief conclusion is presented in Section 7.

2. Literature Review

Looking at portfolio composition, Calvet et al. (2007) found that while the majority of retail investors in their dataset seem to invest successfully overall, less experienced investors in particular have great difficulties when it comes to investment decisions, especially with regard to diversifying their portfolios. Accordingly, the annual returns for inexperienced investors are more often below average. Campbell (2006) also attributes the better performance of experienced investors to the fact that they are more aware of their respective cognitive abilities and refrain from investing in financial products that they do not understand. Data of Badarinza et al. (2016) confirm these findings in an international context. As a consequence, suboptimal investment behavior leads to high welfare losses (Calvet et al., 2007; Goetzmann & Kumar 2008).

Considering the numerous existing systematic errors in investment decisions and the fact that more experienced investors are better able to deal with such situations, it can be concluded that professional investment advice might be a useful measure to address the problem. Financial service providers have recognized this possibility and offer their clients a wide range of financial advice, including investment advice. As already noted, there is evidence that professional investment advice generally helps to reduce the tendency to make investment mistakes (Hoechle et al., 2017) and, in particular, to improve portfolio diversification (Bluethgen et al., 2008; Kramer, 2012). In fact, it has been found that especially the group of less experienced investors achieves, on average, a higher return after advice than in situations without advice (von Gaudecker, 2015). Since around the beginning of the 2010s, a new form of investment advice has been entering the market: robo advice. With the help of algorithms and on the basis of personal information about the investor collected by software, the providers generate a recommendation for the allocation of the desired investment amount with regard to various investment products. The final investment decision is then made by either the software (if the investor does not completely step back from following the investment advice), not allowing any deviations from the recommended portfolio composition (so called “full service robo advisors”), or by the investors themselves, making it possible to adapt changes to the advised portfolio (“half service robo advisors”). Robo advice is usually significantly cheaper than traditional advice. Reher & Sun (2019) relied on real market data to show that robo advice helps investors to build a well-diversified portfolio just like traditional investment advice. D’Acunto et al. (2019) studied the implementation of a robo advice tool in an Indian brokerage house in 2015 and compared the portfolios of advised clients before and after using this tool. They found that the incidence of systematic investment errors can be reduced by using robo advice.

In order to understand why people do not follow advice, one has to look at the advice process, which is often carried out in the form of a so-called Judge-Advisor-System (JAS). The JAS consists of two actors: one gives advice (advisor) and the other actor takes advice (also called decision-maker, advisee, or judge). The decision-maker is then – as the name suggests – responsible for the final decision; the advisor does not make a decision, but can openly express what he or she considers to be the best decision from the decision-maker’s point of view (see Sniezek & Buckley, 1995, for more information). One important aspect of this constellation is the acceptance of advice, since the decision-maker is not obliged to take the advisor’s opinion into account. There is evidence that advice is “discounted,” that is, advice influences the decision to some extent, but the decision-maker still incorporates his or her own ideas about the decision problem and merely shifts the actual decision towards the advice to some degree (Yaniv & Kleinberger, 2000; Yaniv, 2004), while higher discounting rates refer to lower advice acceptance.

The degree to which advice is accepted depends on several factors. Experienced decision-makers appear to be less likely to follow advice, while greater experience known to the advised person on the part of the advisor leads to lower discounting (Harvey & Fischer, 1997). In addition, Harvey and Fischer (1997) found that the higher the potential loss associated with an error, the less the advice is discounted. Importantly, several authors show that the degree of trust in the advisor also appears to have a measurable negative impact on the extent of discounting. In general, the advisor's recommendation was found to be considered more strongly, the greater the trust in the advisor (Sniezek & Van Swol, 2001; Van Swol & Sniezek, 2005; Burke & Hung, 2021; Wang & Du, 2018). From the decision-maker's perspective, the expectation of feeling ex post regret based on a suboptimal decision also leads to a lower discounting rate (Tzini & Jain, 2018). It has further been found that a high level of self-confidence on the part of the advisor (known to the advisee) with respect to his or her own investment advice increases the willingness to accept advice on the part of the decision-maker and thus also leads to a lower discounting rate (Sniezek & Van Swol, 2001; Van Swol & Sniezek, 2005). On the other hand, high confidence on the part of the decision-maker in his or her predefined own views perceived as "right" increases the extent to which advice is discounted (Wang & Du, 2018). Emotions experienced by the advice recipient, whether positive or negative, are also determinants of advice discounting in the context of robo advice (Hohenberger et al., 2019), while lower discounting rates are associated with positive emotions and higher ones with negative emotions. Thus, it is conceivable that the design and presentation of the user interface of a robo advisor could influence the acceptance of advice, particularly considering that some providers feature a more informal, colorful user interface in which smileys are used to convey emotions. Furthermore, it has been observed – especially with regard to algorithm-based investment advice – that personal characteristics of the recipient can influence the acceptance of the advice (Cheng, 2020; Piehlmaier, 2022; Figà-Talamanca et al., 2022).

Tertilt & Scholz (2018) have found that the number of questions asked by robo advisors before giving advice can vary between rather superficial or detailed questionnaires. Moreover, user interfaces differ greatly with a view to the use of language, colors and emoticons. Our research question therefore is: To what extent do various levels of detail in the exploration questionnaire or the chosen type of user interface influence the acceptance of advice from robo advice services?

3. Hypotheses

As already described in the literature review, the acceptance of advice, in general, is based on several factors. However, trust in the advisor is of particular interest in this context. It is intuitively plausible that an advisor who bases his or her advice on a broader range of information could be trusted more. Our first hypothesis concerning trust is therefore:

Hypothesis 1: Decision-makers will trust an advice service that uses a detailed exploration questionnaire to a greater extent than one whose advice is based on a superficial questionnaire.

Furthermore, according to Hohenberger et al. (2019), positive emotions are associated with more trust. Since an emotional type of presentation with the help of appropriate coloring, smileys, and a less distant written expression could trigger positive emotions in the participant, it can be assumed that subjects feel a higher level of trust here.

Hypothesis 2: Decision-makers will trust an emotionally oriented advice service to a greater extent than a distanced one.

Following the suggestions of the existing literature presented before, further hypotheses concerning the discounting of advice can be made.

Hypothesis 3: Decision-makers will discount the advice of an advice service based on a detailed exploration questionnaire less than the advice created using a superficial questionnaire.

Hypothesis 4: Decision-makers will discount the advice of an emotionally oriented advice service less compared to a distanced one.

4. Experimental Design

We set up a robo advice software with the help of oTree (Chen et al., 2016) and asked the participants to invest their money, allocating it to a choice of stocks or funds. The experiment described in this section has been conducted online and participants have been acquired using the database of a large German university. Thus, the experiment has been carried out in German.

On the one hand, we varied the number of questions in the exploration questionnaire with regard to the level of detail ("detailed" vs. "superficial" questionnaire), on the other hand, the presentation of the user interface differed ("emotional" vs. "distanced" interface). This 2x2-design led to a total number of four treatment groups. Both the composition of the questionnaires and the design were copied from real robo advice services from the German-speaking robo advice market.

The superficial questionnaire consisted of one single question about the participants' risk tolerance. The detailed questionnaire contained the same question, but in addition 22 further questions regarding income, wealth, risk-bearing capacity and various others on risk tolerance and previous experience in trading. Details on the exploration questionnaires can be found in the appendix of this paper.

The distanced interface was characterized by an exclusively black and white, austere color scheme including formal language and no use of smileys on the one hand, the emotional one, on the other hand, by a colorful scheme, colloquial language and the presence of smiley faces. The interface layout the participants were confronted with was kept constant during the experiment. Figure 1 illustrates the differences in presentation using excerpts from the exploration questionnaire in the emotional (top) and distanced (bottom) versions.

>>> Insert Figure 1 about here. <<<

After being assigned to one of these treatment groups, the subjects were first presented with an allocation decision before the exploration questions were asked. Participants had to make a selection from five or six available stocks or funds after being provided with a hypothetical budget of 50,000 € and a fictitious investment horizon of one year per decision situation. For this purpose, the subjects received information about the performance of the available stocks/funds over the past two years. Participants had to go through four different decision situations, each involving different stocks/funds. They could also decide to invest their budget completely or partially with a risk-free interest rate of 0.5% per year. If the subjects decided to invest in a risky investment alternative, transaction costs of 0.2% based on the amount allocated to the risky investment were charged, about which the subjects were informed in advance. These values were derived from real-life data at the time the experiment was conducted. Figure 2 depicts the user interface of one decision situation.

>>> Insert Figure 2 about here. <<<

We varied the decision situations in order to represent a number of real-life decisions with the goal for our results to be better generalizable. As said before, the subjects had to make a total of four such allocation decisions: (1) a choice between an MSCI World fund and four well-known country-specific stock index funds including the German stock index DAX (all being blue chip stock indices), (2) a choice between a CDAX fund (blue chip plus mid-cap stock index) and four different German sector index funds, (3) a choice between six stocks in total, three stocks each referring to well-known or less well-known DAX companies[2], respectively, and (4) a choice between a total of five stocks of consistently rather unknown CDAX companies. All decision situations were based on real data on the performance of the various investment alternatives at points in time between 2012 and 2017. Due to the impact of the Covid-19 pandemic and the Russian invasion in Ukraine, we decided not to use more recent data. Therefore, any statements on the DAX also refer to the DAX30 before the index reform in 2021. Furthermore, the order of the decision situations and the respective years they referred to were randomized across all treatment groups to avoid order- or time-specific influences on the decision. The year to which the respective decision situations corresponded was not disclosed in order to ensure that the ex post best allocation decision was not determined by an Internet search. With the goal to avoid such an in-depth search, the subjects were given a maximum selection time of five minutes per allocation decision. After the respondent had made and confirmed the allocation decision, the next decision situation was immediately presented until all four situations had been completed.

[2]The level of popularity of the DAX companies was determined on the basis of the number of Google search results for the name of the respective company. The three DAX companies with the most search results and the three with the fewest were selected. Companies whose name has its own, different meaning, such as "Linde," which is (also) the German name of a tree species, were sorted out.

The consequences of the allocation decision with respect to the performance of the portfolio were not presented at the initial decision, because the same decision situations were to be presented again under the availability of advice later in the experiment with the goal to determine how individuals shifted their final decision towards the direction of the advice. The first allocation decision – without the existence of advice – was then followed by the exploration questionnaire in order to determine an investment recommendation. In all cases, this recommendation was based solely on the answer to the one question on risk tolerance that was identical across all treatment groups. It has already been established that not all questions of a robo advice service are also considered in the recommendation during the exploration process (Tertilt & Scholz, 2018). Thus, this procedure is not uncommon. The subjects were not aware of how exactly the recommendation was made; this also corresponds to the general process of robo advice.

Depending on the answer to this question, the proportion of risk-free or risky investments recommended was varied. The subjects were then presented again with the decision situations already shown before the exploration, this time with investment advice. At the very beginning of the experiment, the participants had been informed that the investment decisions influenced the payout amount as this depended on the performance of the created portfolio; 10,000 € in the experiment corresponded to a payout amount of 2.40 € in reality. This led to final payouts in the range of 11.71 € to 36.57 €, with a mean payout of 15.90 €. Figure 3 shows a decision situation with advice. The amount of riskless lending was simply determined as the residual after subtracting all risky investments from the initial monetary endowment in each period.

>>> Insert Figure 3 about here <<<

The recommendations concerning the risky share of the portfolio varied with respect to the decision situation presented. In the decision situations where the MSCI World and country-specific stock indices were available for selection, we recommended exclusively the MSCI World for the risky part of the investment in order to achieve the greatest possible global diversification without too great a focus on specific regions. The same applied to our recommendation regarding the CDAX and specific German sector indices: Here, we exclusively recommended investing in the CDAX in order to avoid an excessive concentration on specific sectors. Our investment recommendations with respect to the other two decision situations were somewhat more complex: We recommended a portfolio allocation based on the market capitalization of the available stocks compared to the others open for selection (see also the decision situation in Figure 3). The theoretical basis of this approach is the utilization of diversification effects as known from the Capital Asset Pricing Model according to Sharpe (1964), Lintner (1965), and Mossin (1966) and the underlying Markowitz Portfolio Theory, which will not be discussed further here. However, assuming at least weak form efficiency of the capital market, broad diversification is the best which can be done by investors. Although using historical stock data, we formed our recommendation without including information about future stock prices. The participants were free to decide to what extent they wanted to follow the recommendations; after each decision situation, they now received feedback on the performance of their portfolio (see Figure 4).

>>> Insert Figure 4 about here <<<

The value of the portfolio was carried over to the next decision situation and could be invested entirely in the set of newly available stocks.

Trust in the robo advisor was measured after receiving advice and making the final investment decision for the first time, but before providing any information about the outcomes to avoid biases. Also, following the investment experiment, participants were asked to complete an additional questionnaire that was presented somewhat separately from the experiment itself to prevent the number of questions in this questionnaire from distorting the influences of the number of questions in the exploration questionnaire (see appendix 2 of this paper for the full questionnaire). The interface of this separate questionnaire was kept constant across all treatment groups, regardless of the design before. In addition to demographic data such as the age or gender of the subjects, certain cultural characteristics (Hofstede, 2011) and the Big 5 personality traits (Digman, 1990, German translation by Körner et al., 2008) were also collected in this follow-up questionnaire. In addition, participants' social value orientation (Murphy & Ackermann, 2014), general interpersonal trust (Beierlein et al., 2012), and financial literacy (Lusardi & Mitchell, 2011), among others, were also gathered to be used as control variables in the analysis.

5. Results

5.1 Data

We recruited 135 participants. In terms of gender identification, 63 individuals identified as female, 59 as male, and three did not identify as either male or female. Regarding employment status, 10 people were employed full-time, 118 worked part-time, and 7 were unemployed. With a view to nationality, the majority (103) were German, 12 participants were Turkish, and the remaining 20 individuals represented 15 other nationalities in total. Participants were confronted with 13 financial-literacy-related questions adapted from Lusardi & Mitchell (2011) and answered, on average, 9.1 questions correctly, suggesting a strong level of financial literacy. This was possibly influenced by their academic background, as we recruited our participants at a large university. We calculated the acceptance of advice by computing an advice discounting measure based on Yaniv & Kleinberger (2000). However, since the decision in our experiment was multidimensional (participants could decide how to invest their money offering more than two options and not only one risky and one risk-free possibility), we had to adjust the existing measurement of advice discounting to fit our decision problem. We first calculated the (Euclidean) distance between the final decision and the recommendation as well as between the initial decision and the recommendation. This means, the distance between two points in space $p = (p_0, \ldots, p_n)^T$ and $q = (q_0, \ldots, q_n)^T$, whereas $p_{0,\ldots n}$ and $q_{0,\ldots n}$ reflect the relative share invested in a risk-free way (index 0) and in each of the respective risky investment opportunities (indexes 1 to n) and $n+1$ describes the resulting dimension, can be measured as follows:

$$Distance(p, q) = \sqrt{\sum_{k=0}^{n}(p_k - q_k)^2}. \tag{1}$$

Then, we computed an advice discounting variable for each participant i and each decision situation j as:

$$AD_{ij} = \frac{Distance(Final, Recommendation)_{ij}}{Distance(Initial, Recommendation)_{ij}}. \tag{2}$$

A score of 0 indicates complete reliance on the advisor's recommendation for the final portfolio allocation. A score of 1 reflects an exact replication of the initial allocation decision, and any value between 0 and 1 describes the extent to which the investors adjusted their decision in alignment with the advice. For instance, a score of 0.4 implies that 40% of the initial deviation still persists in the ultimate allocation decision. Values greater than 1 happened in some cases, which means that in these situations, the investors decided to move the final decision even further away from the recommendation than it has initially been (e.g., the initial decision was to buy 10 units of share A, we recommended buying 5 units and the final decision was to buy 15 units of A). In general, we can state that a lower advice discounting means a higher acceptance of advice. To our best knowledge, this easy-to-replicate multidimensional approach has never been used in the decision-making literature before, expanding the possibilities to calculate an advice discounting measure with a view to more complex decision-making situations.

We describe all variables we used in our analyses in Table 1. Descriptive data on advice discounting as well as on other important variables such as cultural dimensions or personality traits can be seen in Table 2.

>>> Insert Table 1 about here <<<

>>> Insert Table 2 about here <<<

5.2 Statistical Analyses

Based on our hypotheses in Section 3, we first want to find out whether the design and/or the questionnaire length has an impact on trust in the advisor, which in turn might influence advice discounting. To check this, we set up an OLS regression model with the level of trust in the advisor as the dependent variable. The model is thus based on the following equation:

$$Trust\ Overall_i = b_0 + b_1 \cdot Emotional_i + b_2 \cdot Detailed_i + \boldsymbol{b} \cdot \boldsymbol{C_i} + \varepsilon_i, \qquad (3)$$

Whereas $Emotional_i$ and $Detailed_i$ are dummy variables that take the value of 1 for participant *i* if the design was emotional or the questionnaire version was detailed, respectively; the vector $\boldsymbol{C_i}$ describes all other control variables. The dependent variable, $Trust\ Overall_i$, was defined as the answer to the question: “How much do you trust your advisor overall?” measured on a scale of 1 to 5 with a higher value indicating higher trust levels. Our regression model was created including control variables to account for differences in individual characteristics such as age and financial literacy as well as cultural and personality traits (see Table 1), as there is evidence that personal characteristics might influence how others are trusted (Burke & Hung, 2021). Since we include a relatively high number of control variables, we first checked for multicollinearity, but this is not an issue in our data. In all our models, we use robust standard errors to account for heteroscedasticity.

>>> Insert Table 3 about here <<<

Table 3 shows that the design of the user interface as well as the length of the questionnaire do not significantly influence trust. However, since our dependent variable is measured on an ordinal scale, OLS regression assumptions are violated, which is why we set up an ordered logistic regression model to verify our results (see Table 3 as well). Using the same control variables, as can be seen, our results remain stable. We therefore cannot verify any significant effect of questionnaire length (*Hypothesis 1*) or type of presentation (*Hypothesis 2*) on trust.

Subsequently, we want to find out how the variables *Emotional*, *Detailed*, and *Trust* influence the acceptance of advice. We measure the dependent variable by computing advice discounting (*AD*) as presented in Section 5.1. First, we set up a pooled OLS regression model based on the following equation:

$$AD_{ij} = b_0 + b_1 \cdot Trust\ Overall_{ij} + b_2 \cdot Emotional_{ij} + b_3 \cdot Detailed_{ij} + \boldsymbol{b} \cdot \boldsymbol{C_{ij}} + \varepsilon_{ij}, \quad (4)$$

whereas AD_{ij} describes the advice discounting measure of participant *i* in decision situation *j* ($j \in 1, 2, 3, 4$). We use the same control variables as we did before. Additionally, in this model, we control for the respective decision situation, as we calculated one advice discounting value for each situation.

>>> Insert Table 4 about here <<<

The results in Table 4 show that without controlling for personality- and culture-related variables, there is no significant effect of all our variables of interest on advice discounting. When including personality- and culture-related controls, we can see that our results change: In this model, $Emotional_{ij}$ and gains significance on a 5 %-level. Controlling for the aforementioned variables, an emotional design therefore leads to a higher acceptance of advice, ceteris paribus. Keeping all other variables constant at means, we would expect an individual that has been confronted with the emotional layout to discount advice by 56.46% versus 68.41% for someone who encountered the distanced scheme.

We moreover perform a pooled Tobit regression analysis to account for the boundaries of AD_{ij}, which are zero to infinity. The findings validate our previous results (see Table 5), however, the variables $Trust\ Overall_{ij}$ and $Detailed_{ij}$ gain significance on a 10%-level as well.

>>> Insert Table 5 about here <<<

In order to control for serial correlation and to check for consistency, we run a random-effects GLS regression model with the same variables, grouped by participant. A fixed effects model would not make sense in this case, as our variables of interest do not change throughout the experimental procedure. Again, the findings concerning $Emotional_{ij}$ confirm our OLS regression results (see Table 6). To further validate this, we run a random-effects Tobit regression model (see Table 7). The results are once more almost completely identical to those presented in Table 4.

Regarding our hypotheses, we thus cannot confirm that a detailed questionnaire leads to less advice discounting (*Hypothesis 3*) as the evidence is rather mixed, but we can state that this holds true for an emotional design (*Hypothesis 4*). It is somewhat surprising that *Trust Overall*$_{ij}$ does not seem to influence advice discounting significantly, at least not in most of our models.

>>> Insert Table 6 about here <<<

>>> Insert Table 7 about here <<<

6. Discussion

One thing to keep in mind concerning our analyses is that it is not yet clear which design characteristics represent the most important influential factors when it comes to the impact on trust and advice acceptance. We do not vary a large number of certain components of the design as we only use two different interfaces. Moreover, the level of detail of the questionnaire has been described by only two extremes as well: an extraordinarily superficial and a very detailed questionnaire. It might be possible that insignificant results only occur when looking at those extreme values, while setting up a slightly different experiment with a more diverse range of questions could lead to different results.

The level of trust does not have an impact on advice discounting in nearly all our analyses. This is something we did not expect beforehand since there is ample research on this relationship indicating a dependency between those two variables. It could be imaginable that the concept of trust cannot easily be transferred to the relationship between a human and a machine, and therefore our question concerning the level of trust did not reflect the complexity of trust relationships well enough, leading to unreliable measures. Further research is needed to address this issue, especially because the number of participants in our experiment has not been extraordinarily high. Recruiting a larger number of participants might help to paint a more comprehensive picture in this case.

The subjects further tend to be young academics who, due to their educational background, sometimes have intensive prior knowledge of issues relevant to financial decision-making. This relatively homogenous age structure could be the reason why no significant age-related differences exist in our analyses. It is imaginable that older individuals react differently to, for example, an emotional design using emoticons than younger ones. Nevertheless, this social class of young academics represents future investors on the capital market. Thus, our findings can be deemed as useful. Replicating this study using a more international and/or more representative sample could still make a nice extension of the existing literature.

In general, the advice discounting rate is relatively high (about 61.3%, see Table 1). On average, the advisees seem to give more weight to their own initial decision than to the advice. Although this basically corresponds to the values calculated in comparable analyses (Yaniv & Kleinberger, 2000), it remains to be investigated whether these values can be lowered by using different advice characteristics we did not include in our analyses.

7. Conclusion

All things considered, we can state that, based on our research, robo advice providers should use a rather informal interface in order to ensure a higher level of advice acceptance. The questionnaire length, on the other hand, does not seem to have a significant influence on advice acceptance. Furthermore, in contrast to the majority of other studies in the advice discounting literature, trust in the advisor does not play an important role in our sample. However, we do not include actual human interaction, which most of the prior research on trust and advice discounting was based on. The absence of significant correlations between trust and advice acceptance in robo advice settings might be caused by some kind of unique dynamics of human-computer interaction in financial decision-making. We believe that this might be one reason why the relationship between trust and advice acceptance did not turn out to be statistically significant for the case of robo advice. Most investment advice still relies on human involvement from the advisor’s side. Therefore, exploring the implications of this human presence in the investment advice process could provide an interesting starting point for future research. Moreover, our data suggests that personal characteristics and cultural variables play a role in our analyses (see Tables A.2 to A.5), a finding we do not focus on in this paper. With a view to machine-generated advice and advice discounting, this relationship has not achieved much attention yet. In our view, it could be promising to research the interplay between individual attributes or culture and decision-making in the context of situations with algorithm-generated advice. Future research could also explore the integration of artificial intelligence algorithms to copy human-like interaction. By using natural language processing tools and machine learning, these systems could simulate a more lifelike “human” conversation, potentially closing the gap between automated and human advice.

References

Badarinza, C., Campbell, J. Y. & Ramadorai, T. (2016). International Comparative Household Finance. *Annual Review of Economics* 8, 111-144.

Beierlein, C., Kemper, C. J., Kovaleva, A. & Rammstedt, B. (2012). Kurzskala zur Messung des zwischenmenschlichen Vertrauens: Die Kurzskala Interpersonales Vertrauen (KUSIV3). GESIS - Leibniz-Institut für Sozialwissenschaften, Mannheim.

Bluethgen, R., Gintschel, A., Hackethal, A. & Müller, A. (2008). Financial Advice and Individual Investors' Portfolios. *European Business School Working Paper*: http://ssrn.com/abstract=968197.

Burke, J. & Hung, A. (2021). Trust and Financial Advice. *Journal of Pension Economics and Finance* 20 (1), 9-26.

Calvet, L. E., Campbell, J. Y. & Sodini, P. (2007). Down or Out: Assessing the Welfare Costs of Household Investment Mistakes. *Journal of Political Economy* 115 (5), 707-747.

Campbell, J. Y. (2006). Household Finance. *Journal of Finance* 56 (4), 1553-1604.

Chen, D.L., Schonger, M. & Wickens, C. (2016). oTree - An open-source platform for laboratory, online and field experiments. *Journal of Behavioral and Experimental Finance* 9 88-97.

Cheng, Y.-M. (2020). Will robo-advisors continue? Roles of task-technology fit, network externalities, gratifications, and flow experience in facilitating continuance intention. *Kybernetes* 50 (6), 1751-1783.

D'Acunto, F., Prabhala, N. & Rossi, A. G. (2019). The Promises and Pitfalls of Robo-Advising. *Review of Financial Studies* 32 (5), 1983-2020.

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology* 41, 417–440.

Figà-Talamanca, G., Tanzi, P. M. & D'Urso, E. (2022). Robo-advisor acceptance: Do gender and generation matter? *PLoS One* 17 (6), 1-13.

Fulk, M., Grable, J. E., Watkins, K. & Kruger, M. (2018). Who uses robo-advisory services, and who does not? *Financial Services Review* 27, 173-188.

Goetzmann, W. N. & Kumar, A. (2008). Equity Portfolio Diversification. *Review of Finance* 12 (3), 433-463.

Harvey, N. & Fischer, I. (1997). Taking Advice: Accepting Help, Improving Judgment, and Sharing Responsibility. *Organizational Behavior and Human Decision Processes* 70 (2), 117-133.

Hoechle, D., Ruenzi, S., Schaub, N. & Schmid, M. (2017). The Impact of Financial Advice on Trade Performance and Behavioral Biases. *Review of Finance* 21 (2), 871-910.

Hofstede, G. (2011). Dimensionalizing Cultures: The Hofstede Model in Context. *Online Readings in Psychology and Culture* 2 (8).

Hohenberger, C., Lee, C. & Coughlin, J. F. (2019). Acceptance of robo-advisors: Effects of financial experience, affective reactions, and self-enhancement motives. *Financial Planning Review* 2019 (2), 1-14.

Körner, A., Geyer, M., Roth, M., Drapeau, M., Schmutzer, G., Albani, C., Schumann, S. & Brähler, E. (2008). Persönlichkeitsdiagnostik mit dem NEO-Fünf-Faktoren-Inventar: Die 30-Item-Kurzversion (NEO-FFI-30). *Psychother Psych Med* 58, 238-245.

Kramer, M. M. (2012). Financial Advice and Individual Investor Portfolio Performance. *Financial Management* 41 (2), 395-428.

Lintner, J. (1965). Security Prices, Risk, and Maximal Gains From Diversification. *Journal of Finance* 20 (4), 587-615.

Lusardi, A. & Mitchell, O. S. (2011). Financial Literacy and Retirement Planning in the United States. *Journal of Pension Economics and Finance* 10 (4), 509-525.

Monticone, C. (2010). How Much Does Wealth Matter in the Acquisition of Financial Literacy? *Journal of Consumer Affairs* 44 (2), 403-422.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica* 34 (4), 768-783.

Murphy, R. O. & Ackermann, K. A. (2014). Social Value Orientation: Theoretical and Measurement Issues in the Study of Social Preferences. *Personality and Social Psychology Review* 18 (1), 13-41.

Piehlmaier, D. M. (2022). Overconfidence and the adoption of robo-advice: why overconfident investors drive the expansion of automated financial advice. *Financial Innovation* 8 (14), 1-24.

Reher, M. & Sun, C. (2019). Automated Financial Management: Diversification and Account Size Flexibility. *Journal of Investment Management* 17 (2), 63-75.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory Of Market Equilibrium Under Conditions Of Risk. *Journal of Finance* 19 (3), 425-442.

Statista (2023). Robo-Advisors worldwide: https://www.statista.com/outlook/dmo/fintech/digital-investment/robo-advisors/worldwide (20.09.2023).

Stolper, O. A. & Walter, A. (2017). Financial literacy, financial advice, and financial behavior. *Journal of Business Economics* 87, 581-643.

Sniezek, J. A. & Buckley, T. (1995). Cueing and cognitive conflict in judge-advisor decision making. *Organizational behavior and human decision processes* 62 (2), 159-174.

Sniezek, J. A. & Van Swol, L. M. (2001). Trust, Confidence, and Expertise in a Judge–Advisor System. *Organizational Behavior and Human Decision Processes* 84 (2), 288-307.

Tertilt, M. & Scholz, P. (2018). To Advise, or Not to Advise. How Robo-Advisors Evaluate the Risk Preferences of Private Investors. *Journal of Wealth Management* 21 (2), 70-84.

Tzini, K. & Jain, K. (2018). The Role of Anticipated Regret in Advice Taking. *Journal of Behavioral Decision Making* 31, 74-86.

Van Rooij, M. C. J., Lusardi, A. & Alessie, R. J. M. (2012). Financial Literacy, Retirement Planning, and Household Wealth. *The Economic Journal* 122 (5), 449-478.

Van Swol, L. M. & Sniezek, J. A. (2005). Factors affecting the acceptance of expert advice. *British Journal of Social Psychology* 44, 443-461.

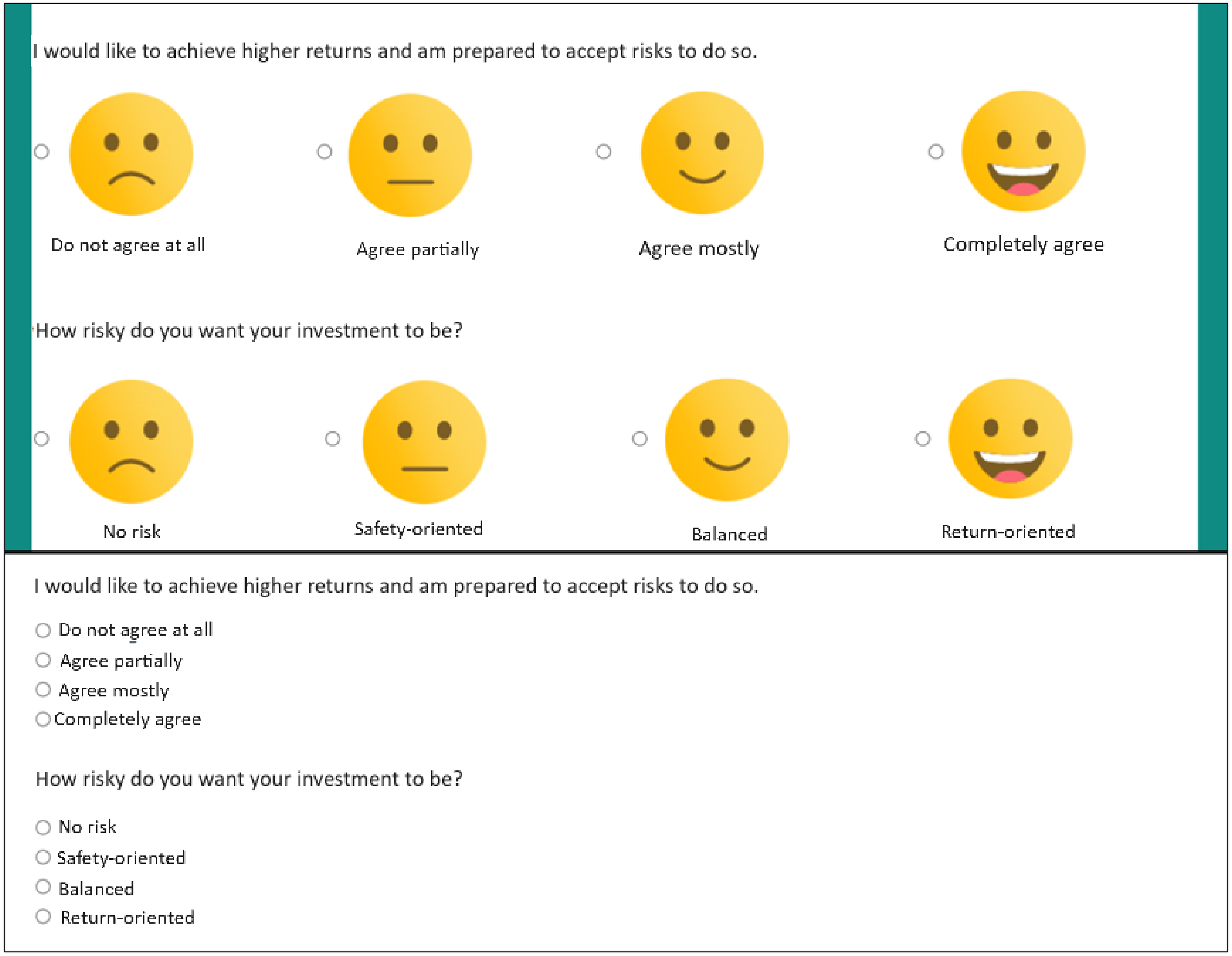
Von Gaudecker, H.-M. (2015). How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice? *Journal of Finance* 70 (2), 489-507.

Wang, X. & Du, X. (2018). Why Does Advice Discounting Occur? The Combined Roles of Confidence and Trust. *Frontiers in Psychology* 9, 1-8.

Yaniv, I. (2004). Receiving other people's advice. Influence and benefit. *Organizational Behavior and Human Decision Processes* 93 (1), 1-13.

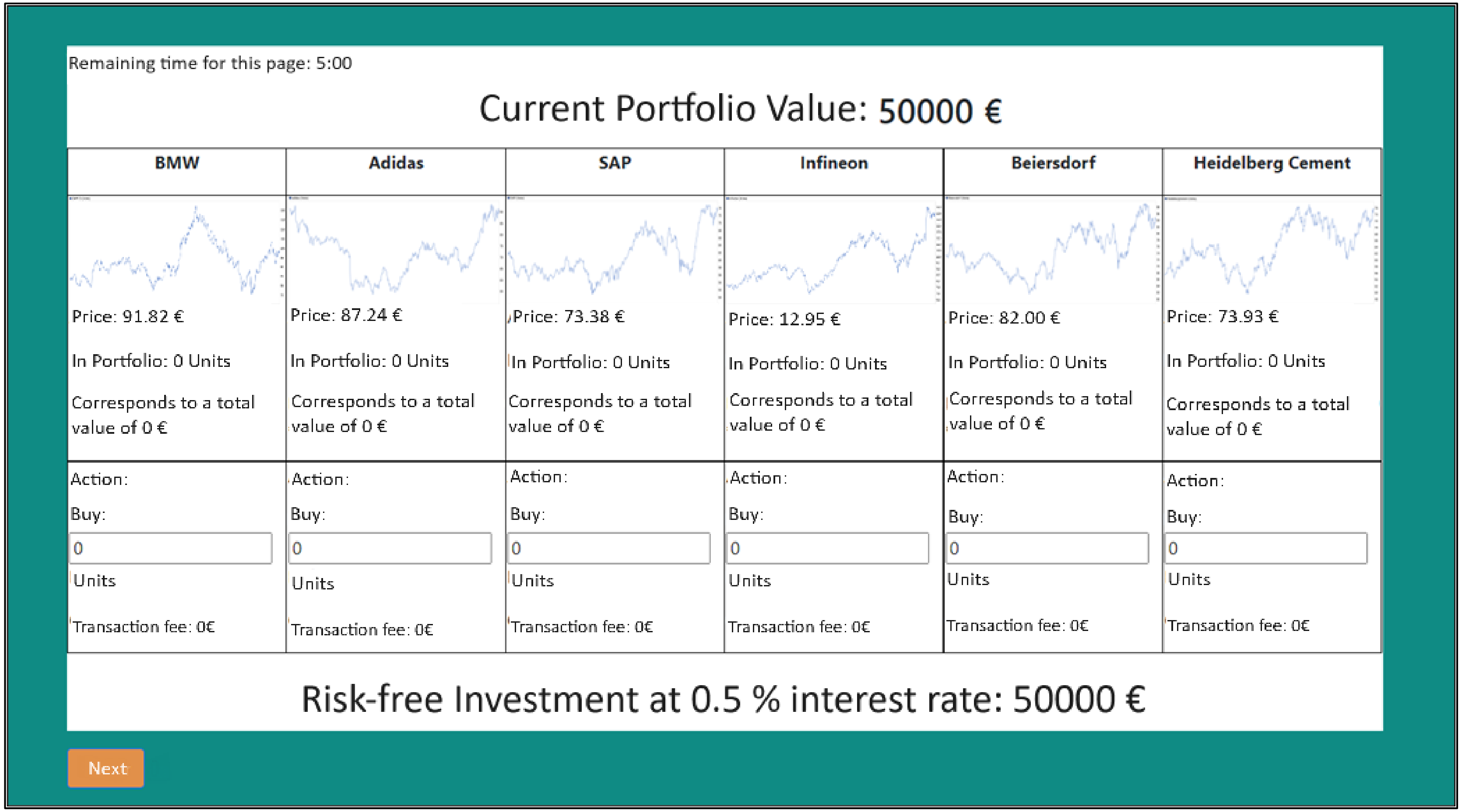
Yaniv, I. & Kleinberger, E. (2000). Advice Taking in Decision Making. Egocentric Discounting and Reputation Formation. *Organizational Behavior and Human Decision Processes* 83 (2), 260-281.

Figure 1 *Excerpt from the exploration questionnaire, emotional (top) vs. distanced (bottom) versions*



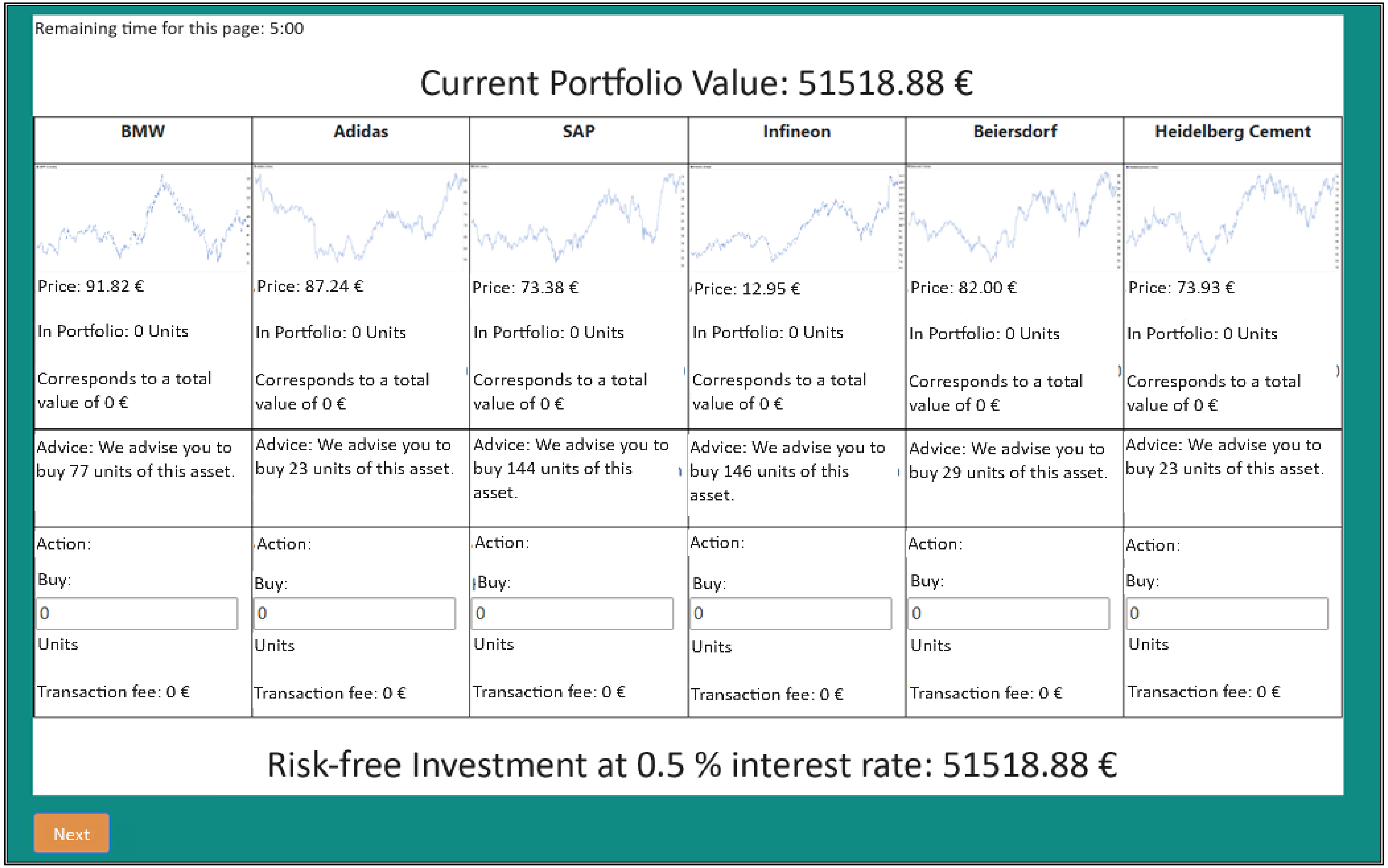
This figure shows the design of the two questionnaire versions exemplarily. The emotional design can be seen at the top half of the figure, the distanced design is depicted on the bottom half.

Figure 2 *User interface, initial decision, emotional design*



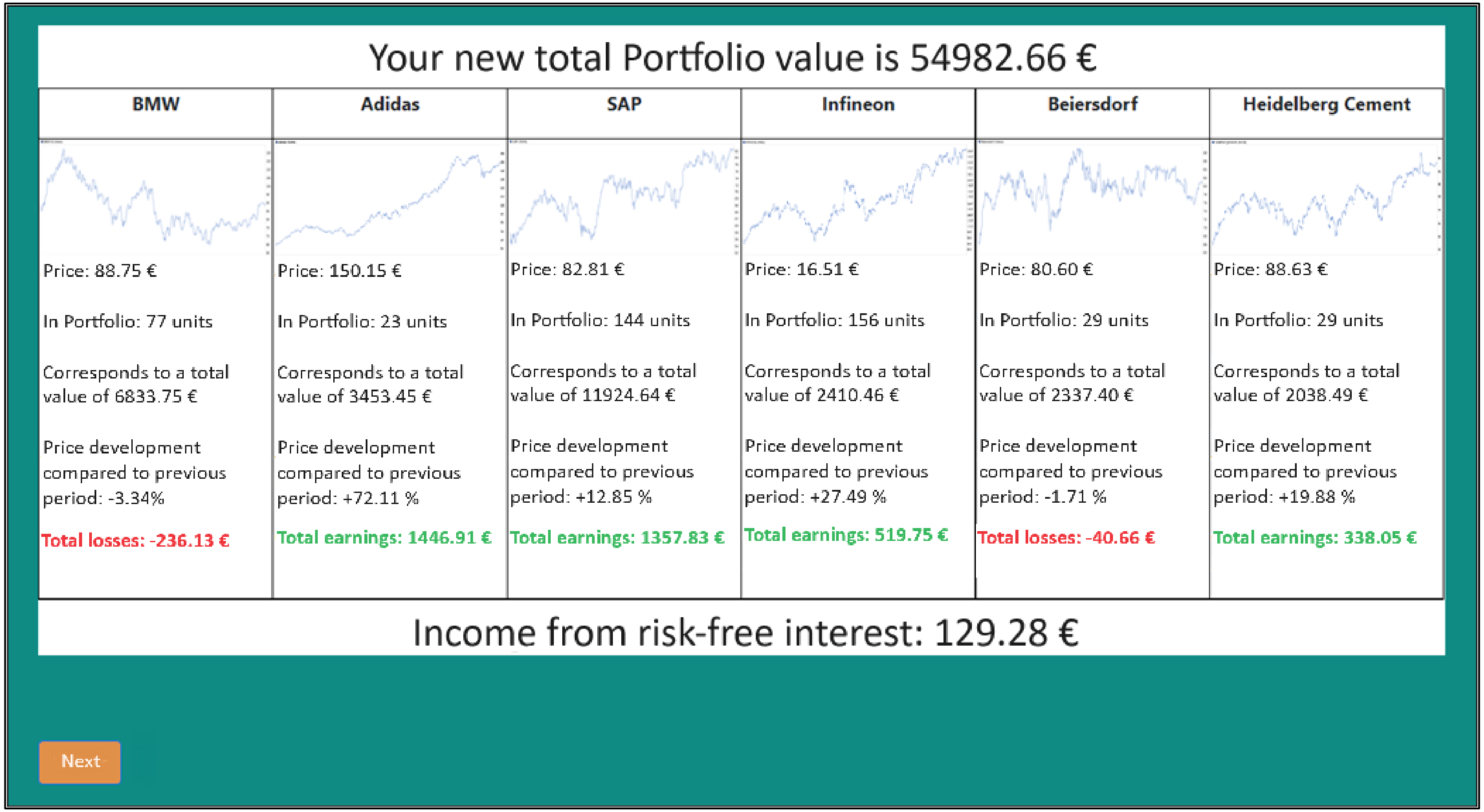
This figure shows a screenshot of the user interface participants were confronted with when making a first investment decision without advice. The screenshot is taken from the emotional layout version of the experiment.

Figure 3 *User interface with given advice, emotional design*



This figure shows a screenshot of the user interface participants were confronted with when making an investment decision including advice. The screenshot is taken from the emotional layout version of the experiment.

Figure 4 Exemplary feedback on portfolio after investment decision, emotional design



This figure shows a screenshot of the user interface participants were confronted with when being informed about the outcome of their investment decision. The screenshot is taken from the emotional layout version of the experiment.

Table 1 *Overview of variables used in our analyses*

Variable	Description
<u>**Variables of key interest**</u>	
AD	Advice discounting, the measurement of advice acceptance as a numerical value.
Emotional	Equals 1 if the questionnaire layout is emotional, 0 otherwise.
Detailed	Equals 1 if the questionnaire is detailed, 0 otherwise.
Trust Overall	Overall trust in advisor, measured on a scale of 1 (very low) to 5 (very high).
<u>**Control Variables**</u>	
Basic controls	
Gender	Participants‘ gender, measured as a categorial variable that can take the value "female", "male", or "other".
Age	Participants' age, measured as a numerical value.
Marital status	Participants' marital status, measured as a categorial variable that can take the value "single", "in a relationship", "married", "divorced", or "other".
Working hours	Participants' hours worked per week in the context of gainful employment, measured as a categorial variable that can take the value "0", "1 to 15", "16 to 25", "26 to 35", or "more than 35".
Living conditions	Participants‘ living conditions, measured as a categorial variable that can take the value "with parents", "with partner", "shared apartment", "stu-dent accommodation", or "alone".
Financial Literacy	Participants' knowledge of finance-related topics, measured as a numerical value between 0 and 13 based on the number of correct answers to financial literacy questions of Lusardi & Mitchell (2011).
Self-assessed risk preference	Self-assessment of participants' risk preference, measured on a scale of 1 (strong risk aversion) to 4 (weak risk aversion).
Advice	Advised share to be invested riskily based on exploration questionnaire, measured as a percentage value between 0 and 100.
Decision situation	Investment options, only used in analyses concerning *AD,* measured as a categorial variable that can take the value "Situation MSCI", "Situation CDAX", "Situation Known vs. Unknown", "Situation Ony Unknown", see section 4.1 for details.
Culture-related controls	
Power distance	Hofstede dimension "Power Distance", individual-level data, measured as a numerical value, see Hofstede (2011) for details.
Individualism	Hofstede dimension "Individualism", individual-level data, measured as a numerical value, see Hofstede (2011) for details.
Masculinity	Hofstede dimension "Masculinity", individual-level data, measured as a numerical value, see Hofstede (2011) for details.
Uncertainty avoidance	Hofstede dimension "Uncertainty avoidance", individual-level data, measured as a numerical value, see Hofstede (2011) for details.
Long-term orientation	Hofstede dimension "Long-term orientation", individual-level data, measured as a numerical value, see Hofstede (2011) for details.
Indulgence vs. restraint	Hofstede dimension "Indulgence vs restraint", individual-level data, measured as a numerical value, see Hofstede (2011) for details.
Personality-related controls	
Neuroticism	Personality trait "Neuroticism", individual-level data, measured as a numerical value, see Digman (1990) for details.
Agreeableness	Personality trait "Agreeableness ", individual-level data, measured as a numerical value, see Digman (1990) for details.

Extraversion	Personality trait “Extraversion “, individual-level data, measured as a numerical value, see Digman (1990) for details.
Conscientiousness	Personality trait “Conscientiousness“, individual-level data, measured as a numerical value, see Digman (1990) for details.
Openness	Personality trait “Openness”, individual-level data, measured as a numerical value, see Digman (1990) for details.
General interpersonal trust	General level of trust in other people, individual-level data, measured as a numerical value, see Beierlein at al. (2012) for details.
Social value orientation	Social value orientation, individual-level data, measured as a numerical value, see Murphy & Ackermann (2014) for details.

This table shows definitions of all variables we used in our analyses including basic controls, personality- and culture-related controls as well as our variables of key interest. Information includes a brief description of the variable and details on the measurement.

Table 2 *Descriptive statistics of most important variables*

	# observations	mean	std. dev.	min	max
Variables of key interest					
Advice discounting	135	0.613	0.592	0	5.983
Emotional	135	0.593	0.493	0	1
Detailed	135	0.452	0.500	0	1
Trust overall	135	3.207	0.931	1	5
Basic controls					
Age	135	25.444	4.113	19	42
Self-assessed risk preference	135	2.741	0.657	1	4
Financial literacy	135	9.104	1.975	2	12
Advice	135	0.530	0.237	0	1
Culture-related controls					
Power distance	135	12.852	59.061	-155	180
Individualism	135	7.000	50.918	-175	140
Masculinity	135	-23.852	61.468	-175	140
Uncertainty avoidance	135	-39.111	69.663	-220	120
Long-term orientation	135	-13.370	61.728	-155	145
Indulgence vs. restraint	135	57.000	60.459	-145	225
Personality-related controls					
Openness	135	11.252	2.585	3	19
Conscientiousness	135	14.674	3.097	6	21
Extraversion	135	13.585	4.113	2	23
Agreeableness	135	9.733	3.456	4	23
Neuroticism	135	9.104	3.984	0	20
General interpersonal trust	135	2.983	0.857	1	5
Social value orientation	135	0.550	0.184	0.203	1.141

This table shows average values and standard deviations as well as minimum and maximum values of the variables used in our analyses. The variables *gender*, *marital status*, *working hours*, *living conditions*, and *decision situation* do not appear here due to their categorical nature.

Table 3 *OLS and ordered logistic regression results, dependent variable: Trust Overall*

	OLS		***Ordered logistic regression***	
	Trust Overall		***Trust Overall***	
Emotional	-0.102	*0.198*	-0.071	*0.453*
Detailed	0.232	*0.180*	0.633	*0.414*
Controls	yes		yes	
# observations	135		135	
R^2	0.221		0.098	

This table shows the results of an OLS and an ordered logistic regression that evaluate the effect of advisor layout and questionnaire on overall trust in the advisor. All models include control variables. Dependent variables appear in the second row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. Full regression results are available in the appendix of this paper (Table A.1).

Table 4 *Pooled OLS regression results, dependent variable: AD*

	AD		***AD***	
	(1)		(2)	
Trust Overall	-0.044	*0.035*	-0.055	*0.036*
Emotional	-0.071	*0.064*	-0.119**	*0.057*
Detailed	0.068	*0.069*	0.082	*0.065*
Basic controls	yes		yes	
Culture-related controls	no		yes	
Personality-related controls	no		yes	
# observations	540		540	
R^2	0.077		0.124	

This table shows the results of a pooled OLS regression that evaluates the effect of overall trust, advisor layout and questionnaire length on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Table 1. Full regression results in the appendix of this paper (Table A.2).

Table 5 Pooled Tobit regression results, dependent variable: AD

	AD		***AD***	
	(1)		(2)	
Trust Overall	-0.050	*0.038*	-0.063*	*0.038*
Emotional	-0.079	*0.058*	-0.137**	*0.057*
Detailed	0.101	*0.063*	0.121*	*0.062*
Basic controls	yes		yes	
Culture-related controls	no		yes	
Personality-related controls	no		yes	
# observations	540		540	
Pseudo R^2	0.041		0.066	

This table shows the results of a pooled Tobit regression that evaluates the effect of overall trust, advisor layout and questionnaire length on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Table 1. Full regression results in the appendix of this paper (Table A.3).

Table 6 *Random-effects GLS regression results, dependent variable: AD*

	AD (1)		***AD*** (2)	
Trust Overall	-0.044	*0.035*	-0.055	*0.036*
Emotional	-0.071	*0.064*	-0.120**	*0.057*
Detailed	0.068	*0.069*	0.082	*0.065*
Basic controls	yes		yes	
Culture-related controls	no		yes	
Personality-related controls	no		yes	
# observations	540		540	
# groups	135		135	
Overall R^2	0.077		0.098	

This table shows the results of a random-effects GLS regression that evaluates the effect of overall trust, advisor layout and questionnaire length on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Table 1. Full regression results in the appendix of this paper (Table A.4).

Table 7 Random-effects Tobit regression results, dependent variable: *AD*

	AD (1)		***AD*** (2)	
Trust Overall	-0.048	*0.042*	-0.061	*0.041*
Emotional	-0.078	*0.083*	-0.136*	*0.082*
Detailed	0.104	*0.078*	0.126	*0.077*
Basic controls	yes		yes	
Culture-related controls	no		yes	
Personality-related controls	no		yes	
# observations	540		540	
# groups	135		135	

This table shows the results of a random-effects Tobit regression that evaluates the effect of overall trust, advisor layout and questionnaire length on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Table 1. Full regression results in the only appendix of this paper (Table A.5).

Appendix

Appendix 1.1: Question used in superficial exploration questionnaire, English translation

1. How risky do you want your investment to be?

- No risk
- Safety-oriented
- Balanced
- Return-oriented

Appendix 1.2: Questions used in long exploration questionnaire, English translation

1. How much is your monthly disposable income?

- Up to 250 €
- 250 € - 500 €
- 500 € - 750 €
- Over 750 €

2. How much are your liquid assets in Euro?

- Up to 20.000 €
- 20.000 € - 50.000 €
- 50.000 € - 100.000 €
- Over 100.000 €

3. We recommend keeping at least two months' salary in reserve for unforeseen expenses. Beyond that, how long can you live off your reserves?

- Not at all

- One month

- Two months

- Over two months

4. The risk of losing some of my money weighs heavily on me.

- Do not agree at all

- Agree partially

- Agree mostly

- Completely agree

5. The security of my investment is most important to me.

- Do not agree at all

- Agree partially

- Agree mostly

- Completely agree

6. I am reluctant to take risks in financial matters.

- Do not agree at all

- Agree partially

- Agree mostly

- Completely agree

7. Even small losses make me nervous.

- Do not agree at all

- Agree partially

- Agree mostly

- Completely agree

8. I would like to achieve higher returns and am prepared to accept risks to do so.

- Do not agree at all

- Agree partially

- Agree mostly

- Completely agree

9. How risky do you want your investment to be?

- No risk

- Safety-oriented

- Balanced

- Return-oriented

10. The return on investments can change every year. Acceptable for me is the following range:

- Between -5 % and +5 %

- Between -10 % and +10 %

- Between -15 % and +15 %

- Below -15 % to above +15 %

11. What knowledge and experience do you have with investments?

- I already have knowledge.

- I do not have any knowledge yet.

12. Do you already have knowledge about direct investments in single stocks / precious metals?

- Yes

- No

13. How many transactions do you make per year in these investments?

- None

- Up to 2

- 3 to 5

- More than 5

14. For how many years have you been doing these transactions?

- Up to 2 years

- 3 to 5 years

- Over 5 years

15. The volume per transaction was:

- Up to 5,000 €

- Up to 25,000 €

- Up to 50,000 €

- Over 50,000 €

16. Do you already have knowledge about investments in funds containing equity, mixed funds or funds on precious metals?

- Yes

- No

17. How many trades do you make per year in these investments?

- None

- Up to 2

- 3 to 5

- More than 5

18. For how many years have you been doing these transactions?

- Up to 2 years

- 3 - 5 years

- Over 5 years

19. The volume per transaction was:

- Up to 5,000 €

- Up to 25,000 €

- Up to 50,000 €

- Over 50,000 €

20. Do you already have knowledge about direct investments in bonds or bond funds?

- Yes

- No

21. How many transactions do you make per year in these investments?

- None

- Up to 2

- 3 to 5

- More than 5

22. For how many years have you (you) been doing these transactions?

- Up to 2 years

- 3 to 5 years

- Over 5 years

23. The volume per transaction was:

- Up to 5,000 €

- Up to 25,000 €

- Up to 50,000 €

- Over 50,000 €

Appendix 2: Full Questionnaire

Which gender do you feel you belong to?

☐ Male

☐ Female

☐ Other

What is your nationality?

____

Which religion do you belong to?

☐ Christianity

☐ Islam

☐ Judaism

☐ Non-denominational

☐ Other: ________________________

When were you born?

DD.MM.YYYY

Which statement regarding your marital status applies to you?

☐ Single

☐ In a relationship

☐ Married

☐ Divorced

☐ Other: ______________________

Which statement regarding your living conditions applies to you?

☐ I live with my parents.

☐ I live with my partner.

☐ I live in a shared apartment.

☐ I live in student accommodation.

☐ I live alone.

How many hours in total do you regularly work per week?

☐ 0

☐ 1 - 15

☐ 16 - 25

☐ 26 - 35

☐ More than 35

What degree are you working towards in your current degree program?

☐ Bachelor

☐ Diploma

☐ Master

☐ PhD

☐ I have never studied before

☐ I have already completely finished my studies

In how many semesters do you expect to complete your studies (please include the current semester)?

In __________________________ semesters

What subject are you studying?

☐ Arts and social sciences

☐ Economic sciences

☐ Computer science

☐ Dentistry

☐ Architecture and civil engineering

☐ Engineering sciences

☐ Law

☐ Medicine

☐ Music

☐ Natural sciences

☐ Other, namely: ______________________

Please rate yourself on the following statements on a scale from 0 (strongly disagree) to 4 (strongly agree).

	do not agree at all ...			... completely agree	
I often feel inferior to others.					
I like having lots of people around me.					
I find philosophical discussions boring.					
I often get into arguments with my family and colleagues.					
I keep my things tidy and clean.					
When I'm under a lot of stress, I sometimes feel like I'm going to collapse.					
I am easy to make laugh.					
I am inspired by the motifs I find in art and in nature.					
Some people think I'm selfish and complacent.					
I can manage my time quite well so that I finish my business on time.					
I often feel tense and nervous.					
I like to be at the center of the action.					
Poetry makes little or no impression on me.					
I tend to be cynical and skeptical about the intentions of others.					
I try to carry out all the tasks assigned to me very conscientiously.					
Sometimes I feel completely worthless.					
I often feel like I'm bubbling over with energy.					
When I read literature or look at a work of art, I sometimes feel a chill or a wave of enthusiasm.					
Some people think I'm cold and calculating.					

If I make a commitment, you can definitely rely on me.					
Too often I get discouraged and want to give up when something goes wrong.					
I am a cheerful, good-humored person.					
I have little interest in speculating about the nature of the universe or the state of humanity.					
I always try to act considerately and sensitively.					
I am a hard-working person who always gets the job done.					
I often feel helpless and wish I had someone to solve my problems					
I am a very active person.					
I often enjoy playing with theories or abstract ideas.					
To get what I want, I am prepared to manipulate people if necessary.					
I will probably never be able to bring order into my life.					

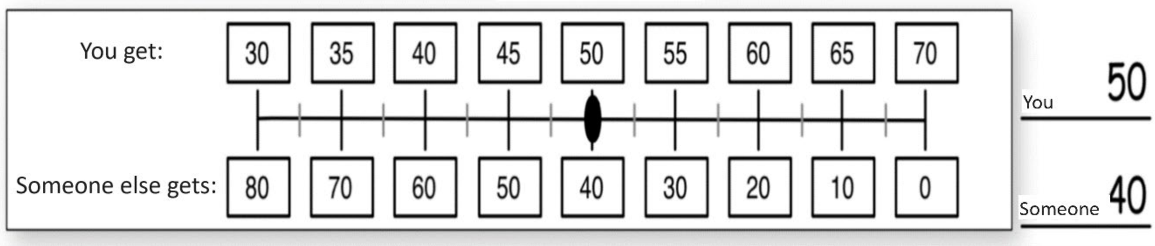
Instructions

In this task, you will determine how you would like to divide certain hypothetical amounts of money between yourself and another person. In the following, we will simply refer to this other person as the hypothetical **"someone else."** This someone is a person whom you do not know and who will remain anonymous. All their decisions are completely confidential. **For each of the following questions, please indicate the distribution of money that you would prefer.**

In the example below, one person has decided to split the money so that they receive 50 Euro while the anonymous other person receives 40 Euro.

There are no right and wrong answers in this task, it is all about personal preference. Once you have made your decision, **mark the corresponding position using the slider.** You can only mark one item per question. As you can see, your decision affects both the amount of money you receive and the amount of money the other person receives.

Example:



1.

85	85	85	85	85	85	85	85	85	You get: 85
85	76	68	59	50	41	33	24	15	Someone else gets: 85

2.

85	87	89	91	93	94	96	98	100	You get: 85
15	19	24	28	33	37	41	46	50	Someone else gets: 15

3.

50	54	59	63	68	72	76	81	85	You get: 50
100	98	96	94	93	91	89	87	85	Someone else gets: 100

4.

50	54	59	63	68	72	76	81	85	You get: 50
100	89	79	68	58	47	36	26	15	Someone else gets: 100

5.

100	94	88	81	75	69	63	56	50	You get: 100
50	56	63	69	75	81	88	94	100	Someone else gets: 50

6.

100	98	96	94	93	91	89	87	85	You get: 100
50	54	59	63	68	72	76	81	85	Someone else gets: 50

7.

100	96	93	89	85	81	78	74	70	You get: 100
50	56	63	69	75	81	88	94	100	Someone else gets: 50

8.

90	91	93	94	95	96	98	99	100	You get: 90
100	99	98	96	95	94	93	91	90	Someone else gets: 100

9.

100	94	88	81	75	69	63	56	50	You get: 100
70	74	78	81	85	89	93	96	100	Someone else gets: 70

10.

100	99	98	96	95	94	93	91	90	You get: 100
70	74	78	81	85	89	93	96	100	Someone else gets: 70

11.

70	74	78	81	85	89	93	96	100	You get: 70
100	96	93	89	85	81	78	74	70	Someone else gets: 100

12.

50	56	63	69	75	81	88	94	100	You get: 50
100	99	98	96	95	94	93	91	90	Someone else gets: 100

13.

50	56	63	69	75	81	88	94	100	You get: 50
100	94	88	81	75	69	63	56	50	Someone else gets: 100

14.

100	96	93	89	85	81	78	74	70	You get: 100
90	91	93	94	95	96	98	99	100	Someone else gets: 90

15.

90	91	93	94	95	96	98	99	100	You get: 90
100	94	88	81	75	69	63	56	50	Someone else gets: 100

Please think of an ideal professional activity. Please disregard your current professional activity if you are employed. How important is it for you when choosing a professional activity?

1 = most important
2 = very important
3 = fairly important
4 = less important
5 = unimportant

	of the utmost importance ...			... slightly important or unimportant	
have enough time for yourself personally or for your private life					
Having a direct supervisor who you can respect					
Receive recognition for good work performance					
having a secure job					
working with nice people					
to do an interesting job					
to be consulted by your direct superior on decisions affecting your work					
to live in a pleasant environment					
have enough time for yourself personally or for your private life					
Having work that is respected by family and friends					

How important is the following for you in your private life?

1 = most important
2 = very important
3 = fairly important
4 = less important
5 = unimportant

	of the utmost importance ...			... slightly important or unimportant	
Keeping time free for pleasure					
Moderation: having few wishes					
to be there for my friends					
Modesty (not spending more money than necessary)					

How often do you feel nervous or tense?

☐ always

☐ mostly

☐ sometimes

☐ rare

☐ never

Are you a happy person?

☐ always

☐ mostly

☐ sometimes

☐ rare

☐ never

Do other people or circumstances ever stop you from doing what you really want to do?

☐ yes, always

☐ yes, usually

☐ sometimes

☐ no, rather rare

☐ no, never

How would you describe your current state of health overall?

☐ Very good

☐ good

☐ mediocre

☐ bad

☐ very bad

How proud are you to be a citizen of your country?

☐ very proud

☐ quite proud

☐ reasonably proud

☐ not very proud

☐ not proud at all

In your experience, how often are employees afraid to contradict their supervisor (or teacher for pupils/students)?

☐ never

☐ rare

☐ sometimes

☐ usually

☐ always

To what extent do you agree or disagree with the following statements?

1 = absolutely agree
2 = agree
3 = undecided
4 = disagree
5 = absolutely disagree

	absolutely agree ...			... absolutely disag-ree	
You can be a good manager without being able to give precise answers to all the questions that subordinates have about their work					
Consistent effort is the surest way to success					
An organizational structure in which certain employees have two superiors should be avoided at all costs					
Company or organizational policies should not be broken, even if an employee believes it is in the best interest of the company					

Now it’s about your attitudes towards other people. For each statement, please indicate the extent to which you agree with it.

1 = strongly disagree
2 = somewhat disagree
3 = somewhat agree
4 = fairly agree
5 = strongly agree

	do not agree at all ...			... agree wholehe-artedly	
I am convinced that most people have good intentions.					
You can’t rely on anyone these days.					
In general, you can trust people.					

For each of the following lottery comparisons, please indicate how large Z must be for you to be indifferent between the two lotteries. Z can be entered as a negative or positive number. A negative win corresponds to a loss, while a negative loss corresponds to a win.

1.	**Lottery A:**	
	50% probability	Win 10 €
	50% probability	Win 100 €
	Lottery B:	
	50% probability	Win Z €
	50% probability	Win 0 €
	The amount Z should be _____________ so that I am indifferent between the lotteries.	

2.	**Lottery A:**	
	50% probability	Win 50 €
	50% probability	Win 200 €
	Lottery B:	
	50% probability	Win Z €
	50% probability	Win 0 €
	The amount Z should be _____________ so that I am indifferent between the lotteries.	

3.	**Lottery A:**	
	50% probability	Win 100 €
	50% probability	Win 400 €
	Lottery B:	
	50% probability	Win Z €
	50% probability	Win 0 €
	The amount Z should be _____________ so that I am indifferent between the lotteries.	

4.	**Lottery A:**	
	50% probability	Loss 20 €
	50% probability	Loss 120 €
	Lottery B:	
	50% probability	Loss Z €
	50% probability	Loss 0 €
	The amount Z should be _____________ so that I am indifferent between the lotteries.	

5.	**Lottery A:**	
	50% probability	Loss 40 €
	50% probability	Loss 240 €
	Lottery B:	

	50% probability	Loss Z €
	50% probability	Loss 0 €
	The amount Z should be ____________ so that I am indifferent between the lotteries.	

6.	**Lottery A:**	
	50% probability	Loss 80 €
	50% probability	Loss 320 €
	Lottery B:	
	50% probability	Loss Z €
	50% probability	Loss 0 €
	The amount Z should be ____________ so that I am indifferent between the lotteries.	

7.	**Lottery A:**	
	50% probability	Win 50 €
	50% probability	Loss 50 €
	Lottery B:	
	50% probability	Loss Z €
	50% probability	Win 0 €
	The amount Z should be ____________ so that I am indifferent between the lotteries.	

8.	**Lottery A:**	
	50% probability	Win 100 €
	50% probability	Loss 100 €
	Lottery B:	
	50% probability	Loss Z €
	50% probability	Win 0 €
	The amount Z should be ____________ so that I am indifferent between the lotteries.	

9.	**Lottery A:**	
	50% probability	Win 200 €
	50% probability	Loss 200 €
	Lottery B:	
	50% probability	Loss Z €
	50% probability	Win 0 €
	The amount Z should be ____________ so that I am indifferent between the lotteries.	

Imagine you are offered the following lotteries. Enter the maximum amount you would be willing to pay to take part in each lottery once.

10.	0.1% probability	Win 1000 €
	99.9% probability	Win 0 €

	I would pay _____________ € to take part in the lottery.

11.	10% probability	Win 50 €
	90% probability	Win 0 €
	I would pay _____________ € to take part in the lottery.	

12.	90% probability	Win 10 €
	10% probability	Win 0 €
	I would pay _____________ € to take part in the lottery.	

13.	70% probability	Win 30 €
	30% probability	Win 0 €
	I would pay _____________ € to take part in the lottery.	

14.	98% probability	Win 100 €
	2% probability	Win 0 €
	I would pay _____________ € to take part in the lottery.	

Imagine you are offered the following lotteries. Enter the maximum amount you would be willing to pay to avoid the lotteries once.

15.	0.1% probability	Loss 1000 €
	99.9% probability	Loss 0 €
	I would pay _____________ € to avoid the lottery.	

16.	10% probability	Loss 50 €
	90% probability	Loss 0 €
	I would pay _____________ € to avoid the lottery.	

17.	90% probability	Loss 10 €
	10% probability	Loss 0 €
	I would pay _____________ € to avoid the lottery.	

18.	70% probability	Loss 30 €
	30% probability	Loss 0 €
	I would pay _____________ € to avoid the lottery.	

19.	98% probability	Loss 100 €
	2% probability	Loss 0 €
	I would pay _____________ € to avoid the lottery.	

Which of the following statements comes closest to the amount of financial risk you are willing to take when saving money or making investments?

☐ I take considerable risks in order to achieve substantial gains.

☐ I take above-average risks in order to achieve above-average gains.

☐ I take average risks to achieve average financial gains.

☐ I am not prepared to take any financial risks.

Each of the following questions offers two or three possible answers. After answering each question, please indicate how certain you are about your answer. For a question with three possible answers, 33.3% means that you do not know the answer, you are therefore completely unsure and your choice would therefore only be correct by chance. For a question with two possible answers, 50% means that you do not know the answer. In both cases, 100% would mean that you are completely sure that your answer is correct.

1. Imagine you have €100 in a savings account and the interest rate is 2% per year. How much money do you think you would have after five years if you left the money and the interest earned in the savings account?

☐ More than €102

☐ Exactly €102

☐ Less than €102

How confident are you? _______% (33.3-100)

2. Imagine you had €100 in a savings account, the interest rate was 20% per year and you never withdrew any money or interest from the account. How much money do you think you would have in your account after five years?

☐ More than €200

☐ Exactly €200

☐ Less than €200

How confident are you? _______% (33.3-100)

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

☐ More than today

☐ Exactly the same amount

☐ Less than today

How confident are you? _______% (33.3-100)

4. Imagine that a friend of yours inherits €10,000 today, while his brother inherits €10,000 in exactly three years' time. Who will be richer on the basis of this inheritance, given that there are positive interest rates for savings?

☐ The friend

☐ His brother

☐ They are both equally rich

How confident are you? _______% (33.3-100)

5. Imagine that both your income and all goods prices have doubled in 2025. How much will you be able to buy with your income in 2025?

☐ More than today

☐ The same as today

☐ Less than today

How confident are you? _______% (33.3-100)

6. Which of the following statements describes the main function of a stock exchange?

☐ The stock exchange helps to predict income from securities.

☐ The stock market results from an increase in security prices.

☐ The stock exchange brings potential buyers and sellers of securities together.

How confident are you? _______% (33.3-100)

7. Which of the following statements is correct?

☐ As soon as you invest in an open-ended investment fund, you cannot withdraw your money in the first year.

☐ Open-ended investment funds can invest in different types of securities, for example in both equities and bonds.

☐ Open-ended investment funds pay out a guaranteed return, which depends on past performance.

How confident are you? _______% (33.3-100)

8. How would bond prices develop as expected if the key interest rate falls?

☐ They rise

☐ They fall

☐ They remain the same

How confident are you? _______% (33.3-100)

9. Right or wrong? Holding shares in a single company usually provides safer returns than holding shares in an equity fund.

☐ Correct

☐ Wrong

How confident are you? _______% (50-100)

10. Right or wrong? Equities are usually riskier than bonds.

☐ Correct

☐ Wrong

How confident are you? _______% (50-100)

11. Which of these asset classes usually has the highest return over a long investment horizon (e.g. 10 or 20 years)?

☐ Savings accounts

☐ Bonds

☐ Shares

How confident are you? _______% (33.3-100)

12. Which of these asset classes normally exhibit the highest fluctuations in value?

☐ Savings accounts

☐ Bonds

☐ Shares

How confident are you? _______% (33.3-100)

13. How does the risk of losing money change when an investor divides his assets between different asset classes?

☐ The risk of loss increases

☐ The risk of loss decreases

☐ The risk of loss remains the same

How confident are you? _______% (33.3-100)

How would you rate your own understanding of economic relationships?

Very low ☐ ☐ ☐ ☐ ☐ ☐ ☐ Very high

Appendix 3: Regression Tables

Table A.1 *OLS and ordered logistic regression results, dependent variable: Trust Overall*

	OLS		***Ordered logistic regression***	
	Trust Overall		***Trust Overall***	
Emotional	-0.102	*0.198*	-0.071	*0.453*
Detailed	0.232	*0.180*	0.633	*0.414*
Gender (0 = female)				
Male	-0.132	*0.226*	-0.302	*0.539*
Other	0.021	*0.649*	0.168	*1.151*
Marital status (0 = single)				
In a relationship	-0.036	*0.232*	0.167	*0.547*
Married	0.616	*0.422*	1.498	*1.002*
Working hours (0 = zero hours)				
1 to 15 hours	-0.139	*0.241*	-0.423	*0.588*
16 to 25 hours	0.198	*0.283*	0.370	*0.698*
26 to 35 hours	0.159	*0.377*	0.363	*0.882*
More than 35 hours	0.223	*0.431*	0.896	*1.001*
Living conditions (0 = with parents)				
With partner	0.082	*0.374*	0.287	*0.823*
Shared apartment	0.296	*0.336*	0.591	*0.691*
Student accommodation	0.391	*0.417*	0.942	*0.956*
Alone	0.338	*0.393*	0.870	*0.895*
Age	-0.016	*0.027*	-0.029	*0.059*
Financial Literacy	-0.033	*0.053*	-0.078	*0.132*
Self-assessed risk preference	0.261*	*0.149*	0.651*	*0.362*
Advice	-0.092	*0.520*	0.108	*1.230*
Power distance	0.000	*0.001*	-0.001	*0.003*
Individualism	0.002	*0.002*	0.001	*0.005*
Masculinity	0.001	*0.002*	0.000	*0.003*
Uncertainty avoidance	0.000	*0.001*	-0.000	*0.003*
Long-term orientation	-0.000	*0.001*	-0.001	*0.003*
Indulgence vs. restraint	-0.001	*0.002*	-0.002	*0.003*
Neuroticism	0.025	*0.029*	0.057	*0.068*
Agreeableness	-0.034	*0.026*	-0.067	*0.062*
Extraversion	0.032	*0.027*	0.047	*0.060*
Conscientiousness	0.004	*0.034*	0.031	*0.079*
Openness	0.011	*0.036*	0.034	*0.086*
General interpersonal trust	-0.094	*0.130*	-0.125	*0.304*
Social value orientation	0.482	*0.509*	1.195	*1.215*
Constant	2.583	*1.156*		
# observations	135		135	
R^2	0.221		0.099	

This table shows the results of an OLS and an ordered logistic regression that evaluate the effect of advisor layout and questionnaire length on overall trust in the advisor. All models include control variables. Dependent variables appear in the second row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.2 *Pooled OLS regression results, dependent variable: AD*

	AD		***AD***	
	(1)		(2)	
Trust Overall	-0.044	*0.035*	-0.055	*0.036*
Emotional	-0.071	*0.064*	-0.120**	*0.057*
Detailed	0.068	*0.069*	0.082	*0.065*
Decision situation (0 = situation MSCI)				
Situation CDAX	-0.094**	*0.047*	-0.094*	*0.048*
Situation known/less known	0.010	*0.077*	-0.001	*0.078*
Situation only less known	-0.011	*0.060*	-0.011	*0.061*
Gender (0 = female)				
Male	0.114	*0.074*	0.088	*0.083*
Other	-0.150	*0.226*	-0.241	*0.209*
Marital status (0 = single)				
In a relationship	-0.080	*0.082*	-0.100	*0.084*
Married	-0.137	*0.136*	-0.101	*0.123*
Working hours (0 = zero hours)				
1 to 15 hours	0.031	*0.118*	0.025	*0.119*
16 to 25 hours	0.008	*0.110*	0.064	*0.099*
26 to 35 hours	0.030	*0.138*	0.022	*0.143*
More than 35 hours	-0.011	*0.123*	0.005	*0.161*
Living conditions (0 = with parents)				
With partner	0.169	*0.110*	0.159	*0.102*
Shared apartment	0.005	*0.131*	0.012	*0.116*
Student accommodation	0.059	*0.113*	0.048	*0.114*
Alone	0.105	*0.108*	0.034	*0.100*
Age	-0.011	*0.009*	-0.012	*0.010*
Financial Literacy	-0.045**	*0.020*	-0.043**	*0.020*
Self-assessed risk preference	-0.118**	*0.045*	-0.148***	*0.045*
Advice	0.014	*0.117*	0.035	*0.116*
Power distance			0.001	*0.000*
Individualism			0.000	*0.001*
Masculinity			-0.001**	*0.001*
Uncertainty avoidance			0.001	*0.001*
Long-term orientation			-0.000	*0.000*
Indulgence vs. restraint			-0.001	*0.001*
Neuroticism			-0.001	*0.010*
Agreeableness			-0.008	*0.009*
Extraversion			0.021***	*0.007*
Conscientiousness			-0.017	*0.011*
Openness			-0.002	*0.010*
General interpersonal trust			-0.093**	*0.044*
Social value orientation			0.138	*0.172*
Constant	1.663***	*0.352*	2.150***	*0.587*
# observations	540		540	
R^2	0.077		0.124	

This table shows the results of a pooled OLS regression that evaluates the effect of overall trust, advisor layout and questionnaire length on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.3 *Pooled Tobit regression results, dependent variable: AD*

	AD		***AD***	
	(1)		(2)	
Trust Overall	-0.050	*0.038*	-0.063*	*0.038*
Emotional	-0.079	*0.058*	-0.137**	*0.057*
Detailed	0.101	*0.063*	0.121*	*0.062*
Decision situation (0 = situation MSCI)				
Situation CDAX	-0.073	*0.077*	-0.074	*0.074*
Situation known/less known	0.026	*0.089*	0.027	*0.087*
Situation only less known	0.020	*0.077*	0.020	*0.074*
Gender (0 = female)				
Male	0.116	*0.076*	0.097	*0.088*
Other	-0.227	*0.249*	-0.380	*0.246*
Marital status (0 = single)				
In a relationship	-0.050	*0.068*	-0.069	*0.070*
Married	-0.142	*0.102*	-0.091	*0.105*
Working hours (0 = zero hours)				
1 to 15 hours	0.021	*0.101*	0.018	*0.104*
16 to 25 hours	-0.009	*0.088*	0.053	*0.084*
26 to 35 hours	-0.012	*0.118*	-0.029	*0.125*
More than 35 hours	0.011	*0.078*	0.035	*0.081*
Living conditions (0 = with parents)				
With partner	0.232**	*0.113*	0.219	*0.112*
Shared apartment	0.035	*0.125*	0.039	*0.122*
Student accommodation	0.099	*0.134*	0.094	*0.134*
Alone	0.140	*0.111*	0.058	*0.115*
Age	-0.013	*0.008*	-0.014	*0.009*
Financial Literacy	-0.048**	*0.024*	-0.045*	*0.024*
Self-assessed risk preference	-0.146***	*0.043*	-0.180***	*0.046*
Advice	0.028	*0.118*	0.055	*0.122*
Power distance			0.001	*0.000*
Individualism			0.001	*0.001*
Masculinity			-0.001***	*0.001*
Uncertainty avoidance			0.001*	*0.000*
Long-term orientation			0.000	*0.000*
Indulgence vs. restraint			-0.001**	*0.000*
Neuroticism			0.001	*0.010*
Agreeableness			-0.010	*0.009*
Extraversion			0.022***	*0.008*
Conscientiousness			-0.016	*0.010*
Openness			-0.006	*0.010*
General interpersonal trust			-0.120***	*0.040*
Social value orientation			0.165	*0.169*
Constant	1.178***	*0.340*	2.291***	*0.390*
# observations	540		540	
Pseudo R^2	0.041		0.066	

This table shows the results of a pooled Tobit regression that evaluates the effect of overall trust, advisor layout and questionnaire length on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.4 *Random-effects GLS regression results, dependent variable: AD*

	AD (1)		***AD*** (2)	
Trust Overall	-0.044	*0.035*	-0.055	*0.036*
Emotional	-0.071	*0.064*	-0.120**	*0.057*
Detailed	0.068	*0.069*	0.082	*0.065*
Decision situation (0 = situation MSCI)				
Situation CDAX	-0.094**	*0.047*	-0.094*	*0.048*
Situation known/less known	0.001	*0.077*	0.001	*0.078*
Situation only less known	-0.011	*0.060*	-0.011	*0.061*
Gender (0 = female)				
Male	0.114	*0.074*	0.088	*0.083*
Other	-0.150	*0.226*	-0.241	*0.209*
Marital status (0 = single)				
Liased	-0.080	*0.082*	-0.100	*0.084*
Married	-0.137	*0.136*	-0.101	*0.113*
Working hours (0 = zero hours)				
1 to 15 hours	0.031	*0.118*	0.025	*0.119*
16 to 25 hours	0.008	*0.110*	0.064	*0.099*
26 to 35 hours	0.030	*0.138*	0.022	*0.143*
More than 35 hours	0.000	*0.073*	0.007	*0.080*
Living conditions (0 = with parents)				
With partner	0.169	*0.110*	0.159**	*0.102*
Shared apartment	0.005	*0.131*	0.012	*0.116*
Student accommodation	0.059	*0.123*	0.048	*0.114*
Alone	0.105	*0.108*	0.034	*0.100*
Age	-0.011	*0.009*	-0.012	*0.010*
Financial Literacy	-0.045**	*0.020*	-0.043**	*0.020*
Self-assessed risk preference	-0.118***	*0.045*	-0.148**	*0.045*
Advice	0.014	*0.117*	0.035	*0.119*
Power distance			0.001	*0.000*
Individualism			0.000	*0.001*
Masculinity			-0.001**	*0.001*
Uncertainty avoidance			0.001	*0.001*
Long-term orientation			-0.000	*0.000*
Indulgence vs. restraint			-0.001	*0.001*
Neuroticism			-0.001	*0.010*
Agreeableness			-0.008	*0.009*
Extraversion			0.021***	*0.007*
Conscientiousness			-0.017	*0.011*
Openness			-0.002	*0.010*
General interpersonal trust			-0.093**	*0.044*
Social value orientation			0.138	*0.172*
Constant	1.663***	*0.352*	2.150***	0.437
# observations	540		540	
# groups	135		135	
Overall R^2	0.077		0.124	

This table shows the results of a random-effects GLS regression that evaluates the effect of overall trust, advisor layout and questionnaire length on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.5 Random-effects Tobit regression results, dependent variable: *AD*

	AD (1)		*AD* (2)	
Trust Overall	-0.048	*0.042*	-0.061	*0.041*
Emotional	-0.078	*0.083*	-0.136*	*0.082*
Detailed	0.104	*0.078*	0.126	*0.077*
Decision situation (0 = situation MSCI)				
Situation CDAX	-0.074	*0.071*	-0.075	*0.071*
Situation known/less known	0.025	*0.071*	0.026	*0.071*
Situation only less known	0.020	*0.071*	0.021	*0.071*
Gender (0 = female)				
Male	0.123	*0.087*	0.107	*0.094*
Other	-0.268	*0.277*	-0.384	*0.270*
Marital status (0 = single)				
In a relationship	-0.044	*0.109*	-0.063	*0.108*
Married	-0.139	*0.188*	-0.086	*0.185*
Working hours (0 = zero hours)				
1 to 15 hours	0.027	*0.106*	0.021	*0.103*
16 to 25 hours	-0.006	*0.111*	0.053	*0.113*
26 to 35 hours	-0.006	*0.146*	-0.028	*0.147*
More than 35 hours	0.022	*0.112*	-0.095	*0.117*
Living conditions (0 = with parents)				
With partner	0.236	*0.148*	0.225	*0.143*
Shared apartment	0.033	*0.141*	0.038	*0.137*
Student accommodation	0.101	*0.159*	0.100	*0.159*
Alone	0.138	*0.144*	0.058	*0.145*
Age	-0.014	*0.010*	-0.015	*0.011*
Financial Literacy	-0.048**	*0.020*	-0.045**	*0.020*
Self-assessed risk preference	-0.149**	*0.064*	-0.181***	*0.066*
Advice	0.037	*0.168*	0.066	*0.165*
Power distance			0.001	*0.001*
Individualism			0.001	*0.001*
Masculinity			-0.001**	*0.001*
Uncertainty avoidance			0.001	*0.001*
Long-term orientation			0.000	*0.001*
Indulgence vs. restraint			-0.001	*0.001*
Neuroticism			0.001	*0.012*
Agreeableness			-0.010	*0.012*
Extraversion			0.023**	*0.010*
Conscientiousness			-0.015	*0.014*
Openness			-0.007	*0.016*
General interpersonal trust			-0.122**	*0.048*
Social value orientation			0.167	*0.214*
Constant	1.723***	*0.439*	2.266***	*0.647*
# observations	540		540	
# groups	135		135	

This table shows the results of a random-effects Tobit regression that evaluates the effect of overall trust, advisor layout and questionnaire length on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Paper #3: Each Betrayal Begins with Trust? The Impact of Human Involvement in Robo Advice

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Abstract

Our research addresses investment decision-making with the help of robo advisors. We generate our data using incentivized experiments in a controlled environment, including human interaction with professional investment advisors via video conferencing software during the trials. The results demonstrate that although all individuals in our experiment received automated investment advice based on the same algorithm, the presence of a human advisor influences trust levels significantly positive but leads to a lower acceptance of advice in total. The latter finding is moderated by uncertainty avoidance. We attribute this to the idea that a human involved in the process is seen as an additional source of uncertainty concerning a possible betrayal, leading to "algorithm affinity" in the case of robo advice.

Keywords: robo advice; advice discounting; judge-advisory-system; investment advice, portfolio allocation.

JEL Classification: D14, D81, D83, G11, G4

1. Introduction

In recent years, the landscape of investment decision-making has undergone a transformation with the rise of robo advice platforms. Central to the significance of robo advice is its role in mitigating the problematic impact of behavioral biases on investment decisions. These biases, rooted in cognitive and emotional factors, often lead investors to deviate from rational decision-making, resulting in suboptimal investment choices. However, to some extent, this negative impact can be remedied by seeking financial advice (Hoechle et al., 2017). Robo advice addresses this challenge, offering objective and rational investment guidance, while being cheaper than traditional advice. The constraints of time, accessibility and cost associated with traditional advisory services have fueled the importance of robo advice as a more efficient and accessible alternative for investors seeking personalized financial guidance.

Amidst an exponential growth of robo-advised assets under management in the last ten years (Statista, 2024), a fundamental question remains unanswered: What impact does a lack of human involvement in investment advice have on investment decisions? Based on laboratory experiments in controlled settings, we seek to uncover the underlying factors influencing the acceptance of financial advice.

To date, research comparing the degree of acceptance of human advice with that of robo advice in the context of portfolio allocation is scarce. In general, the literature shows that decision-makers "discount" advice, meaning that individuals do not follow advice completely but merely shift their final decision to the direction of the advice, with the degree of acceptance depending on different factors (Yaniv & Kleinberger, 2000). Predicting the willingness to follow robo advice compared to human advice poses challenges, as conflicting factors may come into play. In situations including computer-assisted decision-making, on the one side, there's a behavioral pattern called "algorithm aversion," where individuals exhibit reluctance to accept automatically generated advice and often prefer human guidance, despite evidence in the literature showing the superior performance of purely data-driven advice on average (e.g., Dawes et al., 1989; Bartlett & McCarley, 2017). Yet, it remains unclear whether algorithm aversion persists in the context of portfolio composition involving robo advice. Furthermore, there is evidence that people tend to trust a human more than a machine (Promberger & Baron, 2006) and higher trust is generally connected to a higher level of advice acceptance (Sniezek & Van Swol, 2001; Van Swol & Sniezek, 2005; Burke & Hung, 2021; Wang & Du, 2018). However, it is yet unclear if this relationship holds for the case of robo advice (Breuer et al., 2024).

On the other side, because of this higher level of trust, another factor might influence the acceptance of advice: betrayal aversion. With higher trust comes higher vulnerability to betrayal; therefore, individuals anticipating a possible betrayal might in turn follow human advice less than machine-related advice, in order to avoid the possible negative feeling of being betrayed (Bohnet et al., 2008). It is therefore yet unclear whether human involvement in investment advice leads to a higher level of advice acceptance due to algorithm aversion or to a lower level because of betrayal aversion. These effects need to be disentangled.

Tauchert & Mesbah (2019) find that in a hypothetical setting of stock price prediction tasks with no actual human presence, when being told that the advice originates from a human, decision-makers would follow the advice less compared to a robo-generated advice. However, the researchers do not actually include human interaction or individualized advice, nor do they derive causalities in this regard. The study of Tauchert & Mesbah has a set of drawbacks we want to address, contributing to the existing literature and delivering first-time evidence of advice-taking in a more lifelike portfolio composition task using robo advice and including actual communication with a professional human investment advisor.

We expand the current literature on the acceptance of advice with a view to how the presence of a human advisor influences the acceptance of advice. After presenting relevant literature in Section 2, we form our hypotheses in Section 3. We briefly describe our experimental setup in Section 3 and continue by showing the results of our analyses in Section 5. In Section 6, our results are discussed. Section 7 concludes.

2. Literature Review

Literature shows that people tend to exhibit a behavioral pattern that Dietvorst et al. (2015) refer to as “algorithm aversion” (for an overview see Jussupow et al., 2022). Individuals sometimes are reluctant to accept automatically generated advice and tend to prefer human advice over algorithm-based advice, although there is ample evidence in the literature comparing human and algorithm-based advice that the latter outperforms the former (e.g., Bartlett & McCarley, 2017), with one reason for this being the “black box” nature of the algorithmic advice generation (Mahmud et al., 2022). It is, however, yet unclear, if algorithm aversion also occurs in a portfolio composition context that involves robo advice. Trust in the advisor, at least, has been found to be lower in human-computer interactions than in human-human interactions (Promberger & Baron, 2006). At a time when professional robo advisors did not exist yet, Önkal et al. (2009) found that individuals who received advice from an algorithm-based software discounted the computer-based advice much more compared to human advice concerning a prediction task in a relatively easy-to-understand financial decision-making context. Since trust is considered a crucial factor for the acceptance of advice, Önkal et al.

(2009) also deem lack of trust in a non-human advisor as a possible reason for a higher discounting rate. However, recent studies show that this relationship may not be incontrovertible. Prahl & van Swol (2017) found that advice from algorithm-based sources was not discounted more than human advice regarding health-related decision-making in hospitals. With respect to investment decisions, Germann & Merkle (2020) showed in an experimental setting that when asked by whom they would like to be advised, individuals did not prefer human over robo advisors, suggesting that participants did not exhibit algorithm aversion. Logg et al. (2019) found that individuals even prefer algorithmic advice to human advice in certain settings, but did not examine situations in the financial advice context with the specifics relevant here. The results of previous studies on the discounting of advice in situations with human and computer-assisted advice cannot simply be transferred to robo advice, since different variables such as personal risk attitude or risk-bearing capacity influence the behavior in investment decisions individually. This is not the case in other decision situations with clearly defined, generally valid best solutions.

While there is evidence that on the one hand, higher trust in human advisors leads to less advice discounting, on the other hand, those higher trust levels might imply an increasing vulnerability to possible betrayal, as indicated before. The ex-post feeling of betrayal causes a "psychological loss" (Bohnet et al., 2008). Decision-makers tend to avoid this psychological loss, adjust their decision accordingly and thus exhibit so-called "betrayal aversion" (Koehler & Gershoff, 2003). Trusting someone is, in this view, always a decision under uncertainty including a "social risk" (Gambetta, 1988). Biased decision-making on the side of the advisor can occur in certain situations and is often unobservable to the investor. With a view to integrity, it has been shown that financial advice situations with human advisors may be subject to agency problems, as the compensation system may include commissions, tempting advisors to recommend financial products that maximize their own profits rather than being optimal for the investor (Council of Economic Advisors, 2015). Studies have found that people are less willing to expose themselves to a social risk when facing a human compared to AI. Candrian & Scherer (2022) examined the willingness to delegate decisions, forcing participants to choose between a human or an AI agent. They found that participants preferred to delegate to AI, attributing this to the perception that AI is more likely to act in an unbiased manner. This effect might also explain why the results of the existing studies concerning advice discounting are inconsistent.

With a view to advisor competence, systematic investment errors can be observed not only among retail investors but also among professional investors and advisors, although the extent to which professionally managed portfolios are affected by investment errors is lower than that of non-professionally managed portfolios (Shapira & Venezia, 2001; Linnainmaa et al., 2021). However, advisors themselves exhibit forms of systematic errors in investment decisions sometimes, leading to suboptimal advice and erroneous decisions by clients (Shapira & Venezia, 2001). Participants might anticipate this problem, which would then result in a different level of advice acceptance when a human is present.

Summarizing, there seems to be an interplay between algorithm aversion and betrayal aversion in decision-making. We extend the current literature by investigating whether individuals are more inclined to follow advice when delivered exclusively by a robo advisor or when human involvement is part of the process, trying to link our results to the influences of algorithm aversion and betrayal aversion.

3. Experimental Design

Two experiments have been conducted to determine the effects of the existence of a human advisor, who is present via video conferencing software and passes on the (robo) advice to the advised person, on two dependent variables: trust and advice discounting. A robo advice software was set up and the participants were asked to invest their money, allocating it to a choice of stocks or funds (for a more detailed description see Breuer et al., 2024). Participants have been acquired using the database of a large German university. The experiments both were conducted online and in German. They were set up using oTree (Chen et al., 2016).

In the first experiment, participants were given a hypothetical amount of 50,000 € and had to make investment decisions in four different scenarios, at first without advice and then under the existence of an automated allocation proposal without any human involvement. Breuer et al. (2024) varied the length of the exploration questionnaire and the user interface in a 2x2 treatment group design to check for effects rooted in the robo advisor setup. Details will not be discussed here; they are available in the abovementioned literature. Participants were paid based on their portfolio performance.

The second experiment was based on the design of the first experiment. With the help of this additional experiment, we wanted to determine what influences the acceptance of advice in situations where advisees are confronted with actual human advisors. The procedure was similar to that of the first experiment: One by one, as in the first experiment, the possible investment scenarios were presented, and before receiving advice, also as in the first experiment, an initial portfolio allocation decision was made with respect to four different decision situations.

The decision-makers were then asked by a human advisor – who is present via a video conferencing software, simply shares the screen and uses the robo advice software from the first experiment – to answer personal questions in the investor exploration part. The choice of questions corresponded to the setting in the first experiment, so that the results remain comparable. After that, the subjects orally and visually received investment advice. Finally, the participants were asked to make an allocation decision for all four decision scenarios again, this time receiving investment advice. Equivalent to the first experiment, the decisions determined the amount of the individual payoff of the investors. The advisors were recruited amongst employees of a large German bank. They all had former experience with regard to investment advice and customer service and they were paid a flat fee of 30.00 € per hour. The renumeration scheme was not known to the investors. Advisors were instructed to mainly use a set of predefined wordings and to not give more information than the user interface provides in order to avoid biases and to achieve a better comparability to the first experiment. Just like in this first experiment, data on trust in the advisor was collected: information about overall trust, trust in the advisor's integrity and trust in the advisor's competence. To avoid mismeasurements, the investors received a link they had to click at a certain point in time in order to be directed to an online survey about trust levels which the advisor could not monitor. This was known to the participants.

As already pointed out, to ensure comparability of advice, the human advisors entered the investors' information into the robo advice software used in the first experiment while sharing the screen. We also included all the different treatment groups just as in Experiment 1, to keep the outcomes comparable. An individual allocation proposal was then displayed, based on the same algorithm that was used in the first experiment (for details, see Breuer et al., 2024). Human advisors repeated this investment proposal orally, stating that this is what they would recommend the investors to do. The fact that the investment proposal was calculated solely by the software was not pointed out specifically and the allocation proposal was given without further explanation of the process. The two experiments were conducted only a few months apart. Possible differences in the discounting of advice can thus be explained by the fact that the advice was given through different channels: solely with the help of a software or under the presence of a human.

Just as Breuer et al. (2024) did, we gathered some additional data to be used in our analyses as, for example, control variables (see Table 1 in Breuer et al., 2024, for descriptions of all the data collected; the full questionnaire can be seen in the Appendix of Breuer et al., 2024). Additionally, we included the variable *Video* which is a dummy variable that has the value of 1 if the individual took part in our second experiment and was therefore confronted with a human advisor in a video conference.

4. Hypotheses

Based on the existing literature, which consistently shows that humans are more trusted than machines, the following hypothesis can be formulated:

Hypothesis 1: Decision-makers trust a human advisor more than a robo advisor.

Furthermore, there are two potential scenarios to consider: either algorithm aversion outweighs betrayal aversion, or the reverse holds true. The first scenario suggests that humans may be trusted more than machines, leading to a rejection of algorithm-generated advice and, therefore, less utilization of pure robo advice compared to advice including human interaction. In the second scenario, decision-makers follow human advice less due to an increased trust in humans, which heightens the perceived social risk. This increased perceived risk is based on the belief that involving a human in the decision-making process introduces the possibility of a betrayal. Therefore, two opposing hypotheses can be formulated:

Hypothesis 2a: Decision-makers will discount pure robo advice to a greater extent than advice including human interaction.

Hypothesis 2b: Decision-makers will discount advice including human interaction to a greater extent than pure robo advice.

In both cases, the level of uncertainty avoidance is likely to play a crucial role. On one hand, individuals may be hesitant to trust machine-generated advice due to uncertainty about the algorithmic advice creation process, resulting in algorithm aversion (Mahmud et al., 2022). On the other hand, a human advisor may introduce uncertainty due to the associated social risk (Koehler & Gershoff, 2003; Gambetta, 1988), which could lead to betrayal aversion and a preference for algorithmic advice ("algorithm affinity"). Since individuals tend to avoid uncertainty regarding both the advice creation process and the potential for betrayal, Hofstede's (2011) uncertainty avoidance index scores were used to check if they could moderate the extent to which advice is accepted in both cases. This, again, leads to two opposing hypotheses:

Hypothesis 3a: Decision-makers discount pure robo advice less when the values of Hofstede's uncertainty avoidance index are lower.

Hypothesis 3b: Decision-makers discount advice including human interaction less when the values of Hofstede's uncertainty avoidance index are lower.

5. Results

5.1 Data

All in all, 219 subjects took part in the experiments. 135 of them completed the first one, while 84 others participated in the second experiment. The age of our participants ranged between 19 and 42, whereas the average age was about 26 years, which is due to the fact that people were acquired at a university. Out of all 219 participants, 100 individuals identified as female, 116 as male and three people did not identify themselves as either male or female. 15 people worked full-time, 187 worked part-time, and 17 did not work at all. Out of 13 financial-literacy-related questions based on Lusardi & Mitchell (2011), participants gave the correct answer to an average of 9.26 questions, which is quite much. Again, this could be due to their academic background. Concerning nationality, 173 individuals were German, 12 were Turkish and the remaining 34 participants all in all represented a total of 23 other nationalities. The average payoff across all experiments was 15.59 €. We measured the acceptance of advice by computing an advice discounting variable, replicating the multi-dimensional approach of Breuer et al. (2024) and defining advice discounting of the individual *i* in the respective decision situation *j* as the (Euclidean) distance between the final and the recommended decision divided by the distance between the initial and the recommended decision:

$$AD_{i,j} = \frac{Distance(Final,Recommendation)_{i,j}}{Distance(Initial,Recommendation)_{i,j}}. \tag{1}$$

For more information on the logic behind this, see also Yaniv & Kleinberger (2000). Descriptive data on advice discounting as well as on other important variables such as cultural dimensions or personality traits can be seen in Table 1.

>>> Insert Table 1 about here <<<

5.2 Statistical Analyses

5.2.1 Testing for Hypotheses

Based on our hypotheses in Section 3, we first want to find out whether the presence of a human via video conferencing software has an impact on trust in the advisor, which in turn might influence advice discounting through different channels. To check this, we set up an OLS regression model with *Trust Overall* as the dependent variable. The model is thus based on the following equation:

$$Trust\ Overall_i = b_0 + b_1 \cdot Emotional_i + b_2 \cdot Detailed_i + b_3 \cdot Video_i + \boldsymbol{b} \cdot \boldsymbol{C_i} + \varepsilon_i, \tag{2}$$

Our data allows us to expand the results of Breuer et al. (2024) concerning robo advisor layout and questionnaire length and we therefore include the variables $Emotional_i$ and $Detailed_i$. Whereas $Emotional_i$, $Detailed_i$ and $Video_i$ are dummy variables that take the value of 1 for participant *i* if the robo advisor design was emotional, the questionnaire version was detailed, or if a human was present via a conferencing software, respectively; the vector $\boldsymbol{C_i}$ describes all other control variables. We use the same variables and variable measurements as Breuer et al. (2024). In all our models, we deploy robust standard errors to account for heteroscedasticity.

>>> Insert Table 2 about here <<<

Table 2 shows that while the design of the user interface as well as the length of the questionnaire do not significantly influence trust (which confirms the results of Breuer et al., 2024), people who were confronted with an experimental setup including the presence of a human advisor reported significantly higher trust levels. Based on our OLS model, we would expect that participants, on average, score 0.426 units higher on the trust scale when there is human involvement, ceteris paribus.

However, since our dependent variable is measured on an ordinal scale, OLS regression assumptions are violated, which is why we set up an ordered logistic regression model to verify our results.

Using the same control variables, as can be seen, our results remain stable. Keeping all other variables constant at mean, based on this model, we would expect the trust level distributions by $Video_j$ as shown in Table 3.

>>> Insert Table 3 about here <<<

All in all, our results indicate that trust levels are reported significantly higher when an actual human is involved in the process (*Hypothesis 1*).

Subsequently, we want to find out how the variables *Emotional*, *Detailed*, *Video*, and *Trust Overall* influence the acceptance of advice. We measure the dependent variable by computing advice discounting (*AD*) as presented before. First, we set up a pooled OLS regression model based on the following equation:

$$AD_{ij} = b_0 + b_1 \cdot Trust\ Overall_{ij} + \ b_2 \cdot Emotional_{ij} + b_3 \cdot Detailed_{ij} + b_4 \cdot Video_{ij} + \boldsymbol{b} \cdot \boldsymbol{C_{ij}} + \varepsilon_{ij}, \quad (3)$$

whereas AD_{ij} describes the advice discounting measure of participant *i* in decision situation *j* ($j \in 1, 2, 3, 4$). We use the same control variables as we did in our previous regressions. Additionally, in this model, we control for the respective decision situation, as we calculated one advice discounting value for each situation. The results in Table 4 show that without controlling for personality- and culture-related variables, *Trust Overall*$_{ij}$ leads to significantly less advice discounting, thus more acceptance of advice, while *Detailed*$_{ij}$ has a significantly positive effect on the dependent variable. The coefficients of *Emotional*$_{ij}$ and *Video*$_{ij}$ are not significantly different from zero.

When including personality- and culture-related controls, we can see that our results change: In this model, additionally, *Emotional*$_{ij}$ and *Video*$_{ij}$ gain significance on a 10%-level. We observe that controlling for the aforementioned variables, an emotional design leads to less advice discounting, while the existence of a human leads to a higher value, ceteris paribus. In general, with a view to the influence of layout, questionnaire length and trust, this is somewhat different to what Breuer et al. (2024) found out, as they did not observe a significant influence of the two latter variables in most of their models. Furthermore, our findings suggest that – controlling for trust – advice including human interaction is considered less, which contradicts much literature on algorithm aversion but confirms the findings of Tauchert & Mesbah (2019). Our findings therefore support *Hypothesis 2b*. It seems that betrayal aversion overcompensates algorithm aversion. *Hypothesis 2a* (and with that, *Hypothesis 3a*) seem to not hold true for our sample.

This underlines the idea that a human is rather seen as a source of "social risk" (Gambetta, 1988), so we set up an additional model controlling for a moderating effect of Hofstede's uncertainty avoidance index score (*UAI*), which we measured individually:

$$\begin{aligned} AD_{ij} = {} & b_0 + b_1 \cdot Trust\ Overall_{ij} + b_2 \cdot Emotional_{ij} + b_3 \cdot Detailed_{ij} \\ & + b_4 \cdot Video_{ij} + b_5 \cdot UAI_{ij} + b_6 \cdot UAI_{ij} \times Video_{ij} + \boldsymbol{b} \cdot \boldsymbol{C_{ij}} + \varepsilon_{ij}. \end{aligned} \tag{4}$$

Looking at the results in Model 3, Table 4, our coefficients of interest stay significant and the direction of the effect does not change. We can confirm that *UAI*$_{ij}$ has a moderating effect.

With a view to the marginal effect, we conclude that we would expect people who are confronted with a human advisor to discount their advice by 0.188 + 0.001·*UAI* units, ceteris paribus. Note that *UAI* can be smaller than zero, ranging between –220 and +120 in our sample (see Table 1). This means that only for people who exhibit very low uncertainty avoidance levels, advice from a human advisor is taken into account more than advice from a robo advisor.

We moreover perform a pooled Tobit regression analysis to account for the boundaries of AD_{ij}, which are zero to infinity. The findings validate our previous results (see Table 5).

>>> Insert Table 4 about here <<<

>>> Insert Table 5 about here <<<

In order to control for serial correlation and to check for consistency, we run a random-effects GLS regression model with the same variables, grouping by participant. A fixed effects model would not make sense in this case as our variables of interest do not change throughout the experimental procedure. Again, the findings confirm our OLS regression results (see Table 6). To further validate this, we run a random-effects Tobit regression model (see Table 7). The results are almost completely identical to those presented in Table 5. However, in Model 3, Table 7, the coefficient of the interaction term is not statistically significantly different from zero anymore ($p = 0.106$).

Regarding our hypotheses with a view to the influence of human presence, we can state that a “real” human advisor present during the process may lower advice discounting only for people with low uncertainty avoidance scores, thus supporting *Hypothesis 3b*.

>>> Insert Table 6 about here <<<

>>> Insert Table 7 about here <<<

Finally, comparing the risk-adjusted performance, the realized Sharpe Ratio of portfolios that were advised by a pure robo advisor was 0.979, while under the influence of a human advisor, this value is 1.073 and thus a bit higher. However, we performed a t-test and the difference is not statistically significant ($p > 0.1$).

5.2.2 Structural Equation Model

It seems that on the one hand, trust in the advisor has an important impact on advice discounting, whereas on the other hand, the presence of a human advisor influences trust. Literature suggests that following the so-called "reputation characterization" of trust (McKnight et al., 1998) there are several trust dimensions: trust in the integrity of the advisor and trust in the competence of the advisor, which form a measure of overall trust. In our experiment, we asked the subjects how much they trust the integrity/competence of the advisor as well as how much they trust the advisor overall, each on a scale of 1 ("I do not trust at all") to 5 ("I trust completely"). See Table 1 for details. Expanding our analyses in the previous sections and using structural equation modeling, we want to shed a light on the effects driving advice acceptance with a view on the dimensions of trust. With this approach, we can disentangle the effects of questionnaire length, layout and human presence on trust in advisor integrity and competence and, as a second step, check how this affects overall trust in the advisor, defining overall trust as a resultant of trust in integrity and competence. Both integrity and competence are non-observable by the investor, and integrity is a crucial factor when it comes to a possible betrayal. Furthermore, uncertainty avoidance seems to have a moderating effect as suggested in the previous section. This is why we set up a more comprehensive moderated mediation model (see Figure 1).

>>> Insert Figure 1 about here <<<

We use pooled linear regression models, robust standard errors and the same control variables that we included in our analyses presented in Section 5.2.1, comprising basic, personality- and culture-related controls. Looking at the direct effect of the variables influencing trust, our model shows that *Video* has a significant positive influence on all three dimensions of trust (see Table 8). *Detailed* has a significant positive effect on trust in the integrity ($p < 0.1$). It seems intuitively reasonable, at least, that advisors who base their advice on more information are considered to act with more integrity. *Emotional* does not significantly influence any of the three dimensions of trust. With a view to the influential factors of advice discounting, we see that the discounting rate is driven by trust in the integrity of the advisor. The coefficients reflecting overall trust and trust in the advisor's competence are not statistically significant. The results align with findings from the prior analyses: advice discounting decreases with an emotional design, while a more detailed questionnaire increases it. Additionally, as observed across all analyses, the presence of a human advisor reduces advice acceptance, ceteris paribus. The moderating effect of uncertainty avoidance also persists.

>>> Insert Table 8 about here <<<

We can now calculate an indirect effect of *Video* on *AD*, since the presence of a real advisor leads to more trust and in turn, via this channel, to a decrease in advice discounting. However, this effect does not offset the higher discounting rate when advised by a human: The coefficient of the indirect effect of all dimensions of trust on *AD* combined is –0.024 and statistically significant on a 10%-level. The total effect coefficient of *Video* on *AD* thus is 0.187–0.024 = 0.163 ($p < 0.01$); under the presence of a human advisor, individuals discount around 16.3 percentage points more compared to pure robo advice, ceteris paribus. The total marginal effect including the moderation is 0.163 + 0.001·*UAI*. This means that, for example, using the value of the 20%-percentile for *UAI* (= -115), less uncertainty avoidant individuals would discount the advice from a human source around 4.8 percentage points more compared to pure robo advice, while for more uncertainty avoidant individuals and using the value of the 80%-percentile for UAI (= 10), this value would add up to 17.3 percentage points, keeping all other variables at constant levels. Our conclusion concerning *Video* still stands: Only people with (very) low uncertainty avoidance levels discount less when a human advisor is present, ceteris paribus. We attribute this to betrayal aversion.

6. Discussion

One thing to keep in mind is that we argue that betrayal aversion and algorithm aversion are crucial factors in the decision-making process, yet we do not measure these variables directly. However, due to the indirect approach using *UAI* as a moderating variable and the effects of trust in the advisor's integrity, we think that our point is comprehensible. Future research might repeat our experiment, adding additional questions concerning these two factors and address this issue.

We moreover base our reasoning concerning the moderating effect of uncertainty avoidance on the uncertainty avoidance index as measured by Hofstede (2011). We are aware that Hofstede's cultural dimensions were not intended to be measured and analyzed on individual levels. Despite that, the dimensions are still widely used in this context, although there are a number of shortcomings (see Bearden et al., 2006, for an overview). There is an ongoing discussion about this method, still, and additional uncertainty avoidance measures might be used in the future to verify our results.

It must be kept in mind that the sample in this study is not representative of the general public. As we had to tell participants upfront that during the experiment, they needed to accept to join a Zoom meeting if asked to, we cannot exclude a possible sample selection bias towards people who are less socially distant.

Looking at our results, it is striking that *Detailed* has a significantly positive impact on *AD* in nearly all our analyses. This is a surprising outcome and a finding that we did not expect beforehand. It is conceivable that there is an optimum number of questions that lies between the two extremes presented in the experiment, as just one question might appear too superficial, while too many questions – without further explanation – might lead to intransparency concerning the advice generation. Transparency is known to be a crucial factor influencing the use of advice (Burton et al., 2020; Glikson & Woolley, 2020; van de Merwe et al., 2022). Beyond transparency, perceived algorithm complexity seems to play an important role as well (Lehmann et al., 2022). It is at least imaginable that a long questionnaire might have had an effect on perceived algorithm complexity, adding to confusion about the "black box" advice creation process in our experiment. More research is needed to address this issue. Following an idea that more experienced investors might grasp the reasoning behind a large number of questions about risk attitudes differently compared to less experienced participants, we checked if financial literacy or previous investment experience had a significant moderating effect on the relationship between questionnaire length and advice acceptance, but this was not the case. This also addresses the thought that some sort of priming effect influences investment decision-making in the detailed questionnaire treatment group, as more experienced investors might realize their superior level of experience only while answering a large number of questions about their investment history. However, as we did not find the moderating effects described above, this could be ruled out. Furthermore, we noticed that a detailed questionnaire leads to more trust in the advisor's integrity ($p < 0.1$, see Table 8). More trust in integrity, moreover, leads to lower advice discounting ($p < 0.05$), which raises questions on the indirect effect and the sign of the total effect of a detailed questionnaire on advice discounting. However, in this case, the indirect effect is –0.009 ($p < 0.1$) and thus the total effect of a long questionnaire on advice discounting is 0.102–0.009 = 0.093 ($p < 0.05$), which is still larger than zero.

As an addition to our analyses in Section 5.2, we investigated more closely how the existence of a human advisor influences the investment decision. To do this, we calculated *AD* in two additional, slightly different ways and performed further regressions (see Table 9). First, we measured *AD* only with regard to the part that has been invested in risky investment opportunities, checking for deviations within the riskily invested share of the portfolio, leaving out the part that has been invested in a risk-free way. We call this variable *ADOnlyRisky*. Second, we calculated advice discounting comparing the percentage that has been invested with no risk to the share that has been invested in the risky investment opportunities, referring to this as *ADRiskySafe*. We sorted out undefined values for advice discounting which could happen if the denominator of equation (1) is zero (see Section 5.1). We then balanced the panel. As can be seen, the allocation within the risky investment share is only significantly influenced by *Trust Overall*. However, looking at the results for *ADRiskySafe*, the findings are comparable to our insights presented in Section 5.2: participants discount more when a human advisor is present, and this effect also depends on uncertainty avoidance. Checking the average share of the total budget invested in the risky investment opportunities, we found that individuals that have been advised by a human choose to invest, on average, 53.44% riskily while this value amounts to 59.27% for the robo advice treatment group. We performed a t-test which showed that the difference is significant ($p < 0.01$). The subjects seem to be reluctant to invest riskily when a human is involved, which again supports the idea that participants try to avoid being betrayed, as betrayal can only happen when investing riskily (provided that there is a credible risk-free investment opportunity).

>>> Insert Table 9 about here <<<

This study deepens the analyses of Breuer et al. (2024). It has therefore to be kept in mind that possible differences with a view to the results might be rooted in the number of participants, which we increased from 135 to 219 in total. The analyses in this paper are based on a larger database and can thus be considered to be more accurate. However, these differences mainly concern the insignificance of certain coefficients in Breuer at al. (2024), which are significant in the regressions presented in this work. Using the same variables as Breuer et al. (2024) did and repeating the regressions on this broader dataset does not lead to different outcomes either, which is something we checked. The results do not contradict each other.

7. Conclusion

All things considered, we provide evidence that the integration of human communication plays an important role when it comes to the actual advice acceptance, while also influencing trust in the advisor. However, the relationship between human involvement and advice utilization is not as straightforward as one might initially think: the presence of a human does not lead to more but less acceptance of advice. Additional analyses show that sufficient diversification can be achieved similarly through both human and robo advisory formats, as evidenced by comparable levels of advice discounting within the risky portion of the portfolio. This suggests that, in terms of managing portfolio risk through diversification, human and robo advisors can be equally effective. However, the regression models indicate that in our experimental context, robo advice may be more effective in increasing overall stock engagement among investors, potentially due to human presence being seen as an additional factor causing uncertainty about a possible betrayal. Further research is needed to determine whether this presumed fear of betrayal can be reduced by, for example, additional information about the advisors’ motives or payment schemes.

Looking to the future, it would also be helpful to investigate how different setups of robo advice with the aid of augmented or virtual reality influence the extent of trust and discounting. Here, it would be conceivable to have a human-like avatar act as an advisor. It is imaginable that such an avatar, located in a virtual reality office and appearing like a professional human advisor, could influence the level of trust and the extent of discounting. The exact effects of such an approach are yet to be studied; however, it could potentially combine the trust-enhancing benefits of human influence with the higher advice acceptance seen in purely robo-advised settings. Furthermore, future research could focus on the comparison of the acceptance of robo advice compared to “traditional” in-office financial advice.

References

Bartlett, M. L. & McCarley, J. S. (2017). Benchmarking aided decision making in a signal detection task. *Human Factors* 59 (6), 881-900.

Bearden, W.O., Money, R.B. & Nevins, J.L. (2006). Multidimensional versus unidimensional measures in assessing national culture values: The Hofstede VSM 94 example. *Journal of Business Research* 59, 195-203.

Bohnet, I., Greig, F., Herrmann, B. & Zeckhauser, R. (2008). Betrayal Aversion: Evidence from Brazil, China, Oman, Switzerland, Turkey, and the United States. *The American Economic Review* 98 (1), 294-310.

Breuer, C., Breuer, W. & Renerken, T. (2024). Drivers of Trust and Advice Discounting for Robo Advice. Working Paper.

Burke, J. & Hung, A. (2021). Trust and Financial Advice. *Journal of Pension Economics and Finance* 20 (1), 9-26.

Burton, J. W., Stein, M.-K. & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented Decision making. *Journal of Behavioral Decision Making* 33 (2), 220-239.

Candrian, C. & Scherer, A. (2022). Rise of the machines: Delegating decisions to autonomous AI. *Computers in Human Behavior* 134, 1-16.

Chen, D.L., Schonger, M. & Wickens, C. (2016). oTree - An open-source platform for laboratory, online and field experiments. *Journal of Behavioral and Experimental Finance* 9, 88-97.

Council of Economic Advisors (2015). The Effects of Conflicted Advice on Retirement Savings.

Dawes, R. M., Faust, D. & Meehl, P. E. (1989). Clinical Versus Actuarial Judgment. *Science* 243, 1668-1674.

Dietvorst, B. J., Simmons, J. P. & Massey, C. (2015). Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err. *Journal of Experimental Psychology* 144 (1), 114-126.

Gambetta, D. (1988). Can we trust trust? in: *Trust. Making and breaking cooperative relationships*, 213–237, Oxford: Basil Blackwell.

Germann, M. & Merkle, C. (2022). Algorithm Aversion in Delegated Investing. *Journal of Business Economics, forthcoming.*

Glikson, E. & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals* 14 (2), 627-660.

Hoechle, D., Ruenzi, S., Schaub, N. & Schmid, M. (2017). The Impact of Financial Advice on Trade Performance and Behavioral Biases. *Review of Finance* 21 (2), 871-910.

Hofstede, G. (2011). Dimensionalizing Cultures: The Hofstede Model in Context. *Online Readings in Psychology and Culture* 2 (8).

Jussupow, E., Benbasat, I. & Heinzl, A. (2020). Why are we averse towards algorithms? A comprehensive literature review on algorithm aversion. *ACIS Research Papers* 168, 1-16.

Koehler, J. J. & Gershoff, A. D. (2003). Betrayal aversion: When agents of protection become agents of harm. *Organizational Behavior and Human Decision Processes* 90, 244–261.

Lehmann, C. A., Haubitz, C. A., Fügener, A. & Thonemann, U. W. (2022). The risk of algorithm transparency: How algorithm complexity drives the effects on the use of advice. *Production and Operations Management* 31 (9), 3419-3434.

Linnainmaa, J. T., Melzer, B. & Previtero, A. (2021). The Misguided Beliefs of Financial Advisors. Journal of Finance 76 (2), 587-621.

Logg, J. M., Minson, J. A. & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes* 151, 90-103.

Lusardi, A. & Mitchell, O. S. (2011). Financial Literacy and Retirement Planning in the United States. *Journal of Pension Economics and Finance* 10 (4), 509-525.

Mahmud, H., Islam, A. K. M. L., Ahmed, S. I. & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting & Social Change* 175, Paper No. 121390, 1-26.

McKnight, D. H., Cummings, L. L. & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *Academy of Management Review* 23 (3), 473-490.

Önkal, D., Goodwin P., Thomson, M., Gönül, S. & Pollock, A. (2009). The Relative Influence of Advice From Human Experts and Statistical Methods on Forecast Adjustments. *Journal of Behavioral Decision Making* 22, 390-409.

Prahl, A. & Van Swol, L. (2017). Understanding algorithm aversion: When is advice from automation discounted? *Journal of Forecasting* 36 (6), 691-702.

Promberger, M. & Baron, J. (2006). Do Patients Trust Computers? *Journal of Behavioral Decision Making* 19, 455-468.

Shapira, Z. & Venezia, I. (2001). Patterns of Behavior of Professionally Managed and Independent Investors. Journal of Banking & Finance 25, 1573-1587.

Statista (2023). Robo-Advisors worldwide: https://www.statista.com/outlook/dmo/fintech/digital-investment/robo-advisors/worldwide (20.09.2023).

Sniezek, J. A. & Buckley, T. (1995). Cueing and cognitive conflict in judge-advisor decision making. *Organizational behavior and human decision processes* 62 (2), 159-174.

Sniezek, J. A. & Van Swol, L. M. (2001). Trust, Confidence, and Expertise in a Judge–Advisor System. *Organizational Behavior and Human Decision Processes* 84 (2), 288-307.

Tauchert, C. & Mesbah, N. (2019). Following the Robot? Investigating Users' Utilization of Advice from Robo-Advisors. *ICIS 2019 Proceedings* 40 (8).

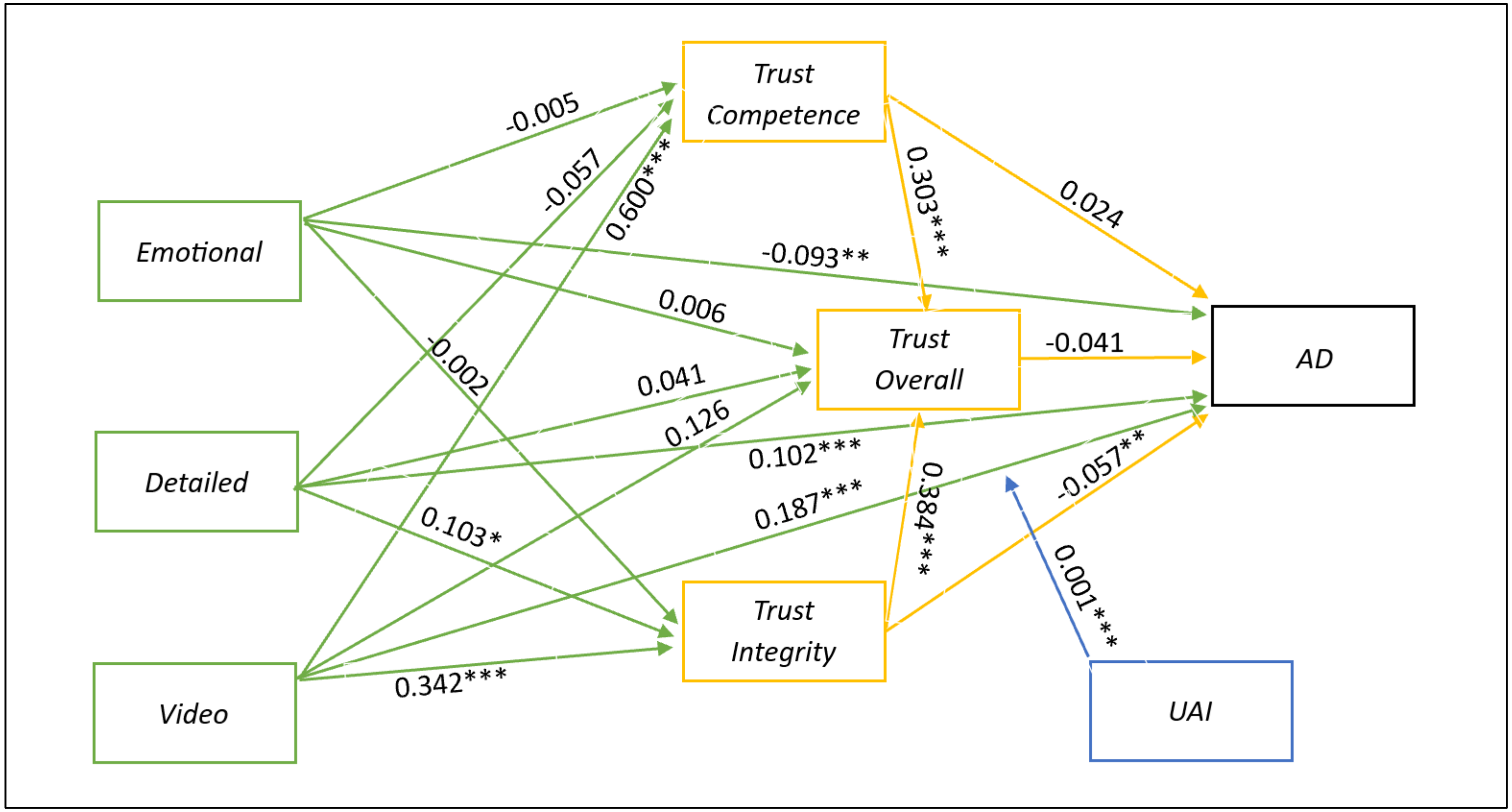
Van de Merwe, K., Mallam, S. & Nazir, S. (2022). Agent Transparency, Situation Awareness, Mental Workload, and Operator Performance: A Systematic Literature Review. *Human Factors* 66 (1), 180-208.

Van Swol, L. M. & Sniezek, J. A. (2005). Factors affecting the acceptance of expert advice. *British Journal of Social Psychology* 44, 443-461.

Wang, X. & Du, X. (2018). Why Does Advice Discounting Occur? The Combined Roles of Confidence and Trust. *Frontiers in Psychology* 9, 1-8.

Yaniv, I. & Kleinberger, E. (2000). Advice Taking in Decision Making. Egocentric Discounting and Reputation Formation. *Organizational Behavior and Human Decision Processes* 83 (2), 260-281.

***Figure 1** Mediated Moderation Model, overview*



This figure shows the relationships between the variables *Emotional*, *Detailed, Video* and three dimensions of trust as well as their effect on the acceptance of advice based on a mediated moderation model as presented in Section 5.2.3. Uncertainty avoidance is included as a moderator of the effect of *Video* on *AD*. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. See Breuer et al. (2024) for details concerning the variables used in this figure.

***Table 1** Descriptive statistics of most important variables*

	# observations	mean	std. dev.	min	max
Variables of key interest					
Advice discounting	219	0.655	0.548	0	5.983
Emotional	219	0.562	0.497	0	1
Detailed	219	0.484	0.501	0	1
Video	219	0.384	0.487	0	1
Trust overall	219	3.338	0.896	1	5
Trust competence	219	3.374	0.980	1	5
Trust integrity	219	3.242	0.939	1	5
Basic controls					
Age	219	25.680	4.195	19	42
Self-assessed risk preference	219	2.758	0.691	1	4
Financial literacy	219	9.260	1.965	2	12
Advice	219	0.527	0.255	0	1
Culture-related controls					
Power distance	219	9.262	58.679	-165	190
Individualism	219	24.292	60.067	-175	145
Masculinity	219	-15.662	58.458	-175	140
Uncertainty avoidance	219	-51.187	71.969	-220	120
Long-term orientation	219	-13.927	62.001	-160	195
Indulgence vs. restraint	219	74.909	75.410	-145	260
Personality-related controls					
Openness	219	11.178	2.517	3	19
Conscientiousness	219	15.037	3.007	6	21
Extraversion	219	13.534	3.902	2	23
Agreeableness	219	9.626	3.430	4	23
Neuroticism	219	8.991	4.247	0	23
General interpersonal trust	219	3.088	0.862	1	5
Social value orientation	219	0.563	0.186	0.158	1.141

This table shows average values and standard deviations as well as minimum and maximum values of the variables used in our analyses. The variables *gender*, *marital status*, *working hours*, *living conditions*, and *decision situation* do not appear here due to their categorical nature.

Table 2 *OLS and ordered logistic regression results, dependent variable: Trust Overall*

	OLS		***Ordered logistic regression***	
	Trust Overall		***Trust Overall***	
Emotional	0.004	*0.139*	0.096	*0.328*
Detailed	0.098	*0.126*	0.243	*0.295*
Video	0.426**	*0.177*	0.935**	*0.435*
Controls	yes		yes	
# observations	219		219	
R^2	0.177		0.075	

This table shows the results of an OLS and an ordered logistic regression that evaluate the effect of advisor layout, questionnaire length and existence of a human advisor on overall trust in the advisor. All models include control variables. Dependent variables appear in the second row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. Full regression results are available in the online appendix of this paper (Table A.1).

Table 3 Distribution of trust levels based on ordered logistic regression

Trust Overall level	1	2	3	4	5
Probability if *Video* = 0	0.027	0.162	0.434	0.343	0.034
Probability if *Video* = 1	0.011	0.073	0.310	0.524	0.082

This table shows the expected distribution of the categorial variable *trust overall* as based on the ordered logistic regression model presented in *Table 2*, conditional on the existence of a human advisor who is present via a video conferencing software.

Table 4 *Pooled OLS regression results, dependent variable: AD*

	AD		***AD***		***AD***	
	(1)		(2)		(3)	
Trust Overall	-0.067**	*0.029*	-0.065**	*0.028*	-0.062**	*0.027*
Emotional	-0.047	*0.049*	-0.084*	*0.047*	-0.093**	*0.047*
Detailed	0.106**	*0.051*	0.104**	*0.048*	0.099**	*0.049*
Video	0.043	*0.062*	0.117*	*0.063*	0.188**	*0.078*
UAI			0.001***	*0.000*	0.001	*0.000*
UAI × Video					0.001**	*0.001*
Basic controls	yes		yes		yes	
Culture-related controls	no		yes		yes	
Personality-related controls	no		yes		yes	
# observations	876		876		876	
R^2	0.063		0.095		0.102	

This table shows the results of a pooled OLS regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Breuer et al. (2024). Full regression results in the online appendix of this paper (Table A.2).

Table 5 Pooled Tobit regression results, dependent variable: AD

	AD (1)		***AD*** (2)		***AD*** (3)	
Trust Overall	-0.085***	*0.028*	-0.083***	*0.027*	-0.079***	*0.027*
Emotional	-0.056	*0.044*	-0.100**	*0.045*	-0.109**	*0.047*
Detailed	0.145***	*0.045*	0.146***	*0.044*	0.141***	*0.049*
Video	0.038	*0.053*	0.115**	*0.056*	0.195***	*0.078*
UAI			0.001***	*0.000*	0.001**	*0.000*
UAI × Video					0.001**	*0.001*
Basic controls	yes		yes		yes	
Culture-related controls	no		yes		yes	
Personality-related controls	no		yes		yes	
# observations	876		876		876	
Pseudo R^2	0.037		0.056		0.058	

This table shows the results of a pooled Tobit regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Breuer et al. (2024). Full regression results in the online appendix of this paper (Table A.3).

Table 6 *Random-effects GLS regression results, dependent variable: AD*

	AD (1)		***AD*** (2)		***AD*** (3)	
Trust Overall	-0.067**	*0.029*	-0.065**	*0.028*	-0.062**	*0.027*
Emotional	-0.047	*0.049*	-0.084*	*0.047*	-0.093**	*0.047*
Detailed	0.106**	*0.051*	0.104**	*0.048*	0.099**	*0.049*
Video	0.043	*0.063*	0.117*	*0.063*	0.188**	*0.078*
UAI			0.001***	*0.000*	0.001	*0.000*
UAI × Video					0.001**	*0.001*
Basic controls	yes		yes		yes	
Culture-related controls	no		yes		yes	
Personality-related controls	no		yes		yes	
# observations	876		876		876	
# groups	219		219		219	
Overall R^2	0.063		0.098		0.102	

This table shows the results of a random-effects GLS regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Breuer et al. (2024). Full regression results in the online appendix of this paper (Table A.4).

Table 7 Random-effects Tobit regression results, dependent variable: *AD*

	AD		***AD***		***AD***	
	(1)		(2)		(3)	
Trust Overall	-0.085**	*0.034*	-0.082**	*0.033*	-0.079**	*0.033*
Emotional	-0.055	*0.062*	-0.099	*0.061*	-0.108*	*0.061*
Detailed	0.149**	*0.059*	0.151***	*0.058*	0.145**	*0.057*
Video	0.035	*0.072*	0.113	*0.079*	0.192**	*0.092*
UAI			0.001***	*0.000*	0.001	*0.001*
UAI × Video					0.001	*0.001*
Basic controls	yes		yes		yes	
Culture-related controls	no		yes		yes	
Personality-related controls	no		yes		yes	
# observations	876		876		876	
# groups	219		219		219	

This table shows the results of a random-effects Tobit regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Breuer et al. (2024). Full regression results in the only appendix of this paper (Table A.5).

__Table 8__ Mediated Moderation Model, direct effects

	Trust Competence		***Trust Integrity***		***Trust Overall***		***AD***	
	(1)		(2)		(3)		(4)	
Emotional	-0.006	*0.069*	-0.002	*0.064*	0.006	*0.047*	-0.093**	*0.039*
Detailed	0.057	*0.064*	0.103*	*0.058*	0.041	*0.042*	0.102***	*0.037*
Video	0.600***	*0.083*	0.342***	*0.074*	0.126*	*0.070*	0.187***	*0.058*
Trust Competence					0.303***	*0.041*	0.024	*0.025*
Trust Integrity					0.384***	*0.042*	-0.057**	*0.027*
Trust Overall							-0.041	*0.028*
UAI	-0.001	*0.001*	0.000	*0.000*	-0.001*	*0.000*	0.001**	*0.000*
UAI × Video							0.001***	*0.000*
Basic controls	yes		yes		yes		yes	
Culture-related controls	yes		yes		yes		yes	
Personality-related controls	yes		yes		yes		yes	
# observations	876		876		876		876	
R^2	0.168		0.192		0.462		0.108	

This table shows the results of a mediated moderation regression model that evaluates the direct effect of advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on trust in the advisor's competence, trust in the advisor's integrity and overall trust as well as the aforementioned variables plus the three dimensions of trust in the advisor on advice discounting. All models include basic control variables and culture- as well as personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Breuer et al. (2024). Full regression results in the online appendix of this paper (Table A.6).

Table 9 *Pooled OLS regression results, dependent variables: ADOnlyRisky and ADRiskySafe*

	ADOnlyRisky		***ADOnlyRisky***		***ADOnlyRisky***		***ADRiskySafe***		***ADRiskySafe***		***ADRiskySafe***	
	(1)		(2)		(3)		(4)		(5)		(6)	
Trust Overall	-0.077***	*0.021*	-0.072***	*0.022*	-0.071***	*0.022*	-0.084***	*0.027*	-0.083***	*0.027*	-0.079***	*0.027*
Emotional	-0.047	*0.040*	-0.054	*0.040*	-0.062	*0.040*	-0.053	*0.046*	-0.075	*0.049*	-0.087*	*0.050*
Detailed	-0.038	*0.036*	-0.026	*0.036*	-0.032	*0.036*	0.168***	*0.047*	0.158***	*0.048*	0.154***	*0.048*
Video	-0.012	*0.042*	0.014	*0.048*	0.067	*0.054*	0.024	*0.056*	0.127**	*0.064*	0.210***	*0.073*
UAI			0.000	*0.000*	-0.000	*0.000*			0.001**	*0.000*	0.001	*0.000*
UAI × Video					0.001*	*0.001*					0.001**	*0.001*
Basic controls	yes		yes		yes		yes		yes		yes	
Culture-related controls	no		yes		yes		yes		yes		yes	
Personality-related controls	no		yes		yes		yes		yes		yes	
# observations	824		824		824		811		811		811	
R^2	0.062		0.078		0.081		0.063		0.094		0.099	

This table shows the results of a pooled OLS regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting in only the risky part of the investment (Models 1 to 3) and on advice discounting calculated using the percentage that has been invested risklessly compared to the share that has been invested in the risky investment opportunities (Models 4 to 6). All models include basic control variables. Models 2, 3, 5 and 6 additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics. For details concerning basic, culture- and personality-related controls see Breuer et al. (2024). Full regression results in the online appendix of this paper (Table A.7).

Appendix

Appendix 1: Regression Tables

Table A.1 *OLS and ordered logistic regression results, dependent variable: Trust Overall*

	OLS		***Ordered logistic regression***	
	Trust Overall		***Trust Overall***	
Emotional	0.004	*0.139*	0.096	*0.328*
Detailed	0.098	*0.126*	0.243	*0.295*
Video	0.426**	*0.177*	0.935**	*0.435*
Gender (0 = female)				
Male	-0.152	*0.151*	-0.376	*0.371*
Other	0.181	*0.465*	0.465	*1.111*
Marital status (0 = single)				
In a relationship	0.150	*0.181*	0.254	*0.442*
Married	0.340	*0.311*	0.646	*0.747*
Working hours (0 = zero hours)				
1 to 15 hours	0.294	*0.287*	0.826	*0.735*
16 to 25 hours	0.332	*0.303*	0.911	*0.788*
26 to 35 hours	0.541*	*0.288*	1.140*	*0.766*
More than 35 hours	0.619	*0.400*	1.172*	*1.031*
Living conditions (0 = with parents)				
With partner	0.110	*0.258*	0.291	*0.587*
Shared apartment	0.271	*0.245*	0.606	*0.545*
Student accommodation	0.297	*0.299*	0.628	*0.744*
Alone	0.348	*0.264*	0.868	*0.607*
Age	-0.010	*0.018*	-0.017	*0.042*
Financial Literacy	-0.064*	*0.034*	-0.162*	*0.087*
Self-assessed risk preference	0.181	*0.103*	0.430*	*0.256*
Advice	0.018	*0.115*	-0.013	*0.273*
Power distance	0.001	*0.001*	0.001	*0.002*
Individualism	0.001	*0.001*	0.003	*0.003*
Masculinity	0.001	*0.001*	0.002	*0.003*
Uncertainty avoidance	-0.001	*0.001*	-0.002	*0.003*
Long-term orientation	-0.000	*0.001*	-0.001	*0.003*
Indulgence vs. restraint	-0.000	*0.001*	-0.000	*0.003*
Neuroticism	0.013	*0.020*	0.025	*0.047*
Agreeableness	-0.024	*0.021*	-0.047	*0.050*
Extraversion	0.008	*0.020*	-0.002	*0.046*
Conscientiousness	-0.015	*0.025*	-0.028	*0.059*
Openness	0.031	*0.024*	0.089	*0.059*
General interpersonal trust	-0.007	*0.087*	0.055	*0.212*
Social value orientation	0.315	*0.389*	0.785	*0.966*
Constant	2.688**	*1.157*		
# observations	219		219	
R^2	0.177		0.075	

This table shows the results of an OLS and an ordered logistic regression that evaluate the effect of advisor layout, questionnaire length and existence of a human advisor on overall trust in the advisor. All models include control variables. Dependent variables appear in the second row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.2 *Pooled OLS regression results, dependent variable: AD*

	AD		***AD***		***AD***	
	(1)		(2)		(3)	
Trust Overall	-0.067**	*0.029*	-0.065**	*0.028*	-0.062**	*0.027*
Emotional	-0,047	*0.049*	-0.084*	*0.047*	-0.093**	*0.047*
Detailed	0.106**	*0.051*	0.104**	*0.048*	0.099**	*0.049*
Video	0.043	*0.062*	0.117*	*0.063*	0.188**	*0.078*
Decision situation (0 = situation MSCI)						
Situation CDAX	-0.097**	*0.038*	-0.097**	*0.038*	-0.097**	*0.034*
Situation known/less known	-0.030	*0.054*	-0.030	*0.054*	-0.030	*0.054*
Situation only less known	0.002	*0.047*	0.002	*0.048*	0.002	*0.048*
Gender (0 = female)						
Male	0.053	*0.062*	0.067	*0.064*	0.073	*0.063*
Other	-0.121	*0.231*	-0.204	*0.198*	-0.210	*0.187*
Marital status (0 = single)						
In a relationship	-0.066	*0.063*	-0.099	*0.067*	-0.101	*0.067*
Married	-0.048	*0.102*	0.008	*0.102*	0.012	*0.106*
Working hours (0 = zero hours)						
1 to 15 hours	0.028	*0.107*	-0.012	*0.106*	-0.049	*0.102*
16 to 25 hours	0.052	*0.104*	-0.019	*0.109*	-0.053	*0.105*
26 to 35 hours	0.005	*0.107*	-0.011	*0.110*	-0.045	*0.106*
More than 35 hours	-0.001	*0.150*	-0.043	*0.160*	-0.080	*0.155*
Living conditions (0 = with parents)						
With partner	0.267***	*0.097*	0.191**	*0.088*	0.182**	*0.087*
Shared apartment	0.135	*0.106*	0.113	*0.099*	0.105	*0.099*
Student accommodation	0.130	*0.108*	0.099	*0.095*	0.071	*0.093*
Alone	0.232**	*0.098*	0.145	*0.091*	0.132	*0.089*
Age	-0.004	*0.006*	-0.007	*0.006*	-0.006	*0.006*
Financial Literacy	0.031*	*0.016*	-0.023	*0.016*	-0.022	*0.016*
Self-assessed risk preference	-0.068*	*0.040*	-0.079**	*0.038*	-0.076**	*0.038*
Advice	0.018	*0.038*	0.018	*0.037*	0.005	*0.038*
Power distance			0.000	*0.000*	0.000	*0.000*
Individualism			0.000	*0.000*	0.000	*0.000*
Masculinity			-0.001	*0.000*	-0.001	*0.000*
Uncertainty avoidance			0.001***	*0.000*	0.001	*0.000*
Long-term orientation			0.000	*0.000*	0.000	*0.000*
Indulgence vs. restraint			-0.001	*0.000*	-0.001*	*0.000*
Neuroticism			-0.004	*0.008*	-0.006	*0.008*
Agreeableness			-0.007	*0.008*	-0.008	*0.008*
Extraversion			0.015***	*0.006*	0.017***	*0.006*
Conscientiousness			-0.002	*0.009*	-0.002	*0.009*
Openness			0.006	*0.009*	0.007	*0.008*
General interpersonal trust			-0.080**	*0.032*	-0.081**	*0.031*
Social value orientation			-0.059	*0.146*	-0.065	*0.144*
UAI × Video					0.001**	*0.001*
Constant	1.130***	*0.304*	1.464***	*0.437*	1.151***	*0.444*
# observations	876		876		876	
R^2	0.063		0.095		0.102	

*This table shows the results of a pooled OLS regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.*

Table A.3 *Pooled Tobit regression results, dependent variable: AD*

	AD (1)		***AD*** (2)		***AD*** (3)	
Trust Overall	-0.085***	*0.028*	-0.083***	*0.027*	-0.079***	*0.027*
Emotional	-0,056	*0.044*	-0.100**	*0.045*	-0.109**	*0.047*
Detailed	0.145***	*0.045*	0.146***	*0.044*	0.141***	*0.049*
Video	0.038	*0.053*	0.115**	*0.056*	0.195***	*0.078*
Decision situation (0 = situation MSCI)						
Situation CDAX	-0.093	*0.057*	-0.094*	*0.056*	-0.094*	*0.056*
Situation known/less known	-0.027	*0.065*	-0.027	*0.063*	-0.027	*0.063*
Situation only less known	0.022	*0.059*	0.022	*0.058*	0.022	*0.058*
Gender (0 = female)						
Male	0.057	*0.057*	0.075	*0.062*	0.083	*0.062*
Other	-0.220	*0.239*	-0.330	*0.300*	-0.338	*0.226*
Marital status (0 = single)						
In a relationship	-0.045	*0.052*	-0.077	*0.056*	-0.078	*0.057*
Married	-0.030	*0.079*	0.040	*0.084*	0.044	*0.085*
Working hours (0 = zero hours)						
1 to 15 hours	0.023	*0.087*	-0.017	*0.087*	-0.059	*0.085*
16 to 25 hours	0.044	*0.081*	-0.034	*0.085*	-0.071	*0.084*
26 to 35 hours	-0.002	*0.085*	-0.025	*0.087*	-0.063	*0.086*
More than 35 hours	-0.042	*0.127*	-0.098	*0.135*	-0.139	*0.134*
Living conditions (0 = with parents)						
With partner	0.330***	*0.090*	0.238***	*0.086*	0.228***	*0.086*
Shared apartment	0.165	*0.095*	0.138	*0.092*	0.189	*0.092*
Student accommodation	0.157	*0.102*	0.130	*0.100*	0.098	*0.099*
Alone	0.272***	*0.092*	0.177*	*0.091*	0.162*	*0.090*
Age	-0.006	*0.006*	-0.009	*0.056*	-0.008	*0.006*
Financial Literacy	-0.033*	*0.017*	-0.025	*0.017*	-0.023	*0.017*
Self-assessed risk preference	-0.079**	*0.035*	-0.094***	*0.035*	-0.090***	*0.035*
Advice	0.025	*0.053*	0.021	*0.035*	0.007	*0.035*
Power distance			0.000	*0.000*	0.000	*0.000*
Individualism			0.000	*0.000*	0.000	*0.000*
Masculinity			-0.001*	*0.000*	-0.001*	*0.000*
Uncertainty avoidance			0.001***	*0.000*	0.001**	*0.000*
Long-term orientation			0.000	*0.000*	0.000	*0.000*
Indulgence vs. restraint			-0.001*	*0.000*	-0.001**	*0.000*
Neuroticism			-0.004	*0.007*	-0.007	*0.007*
Agreeableness			-0.009	*0.007*	-0.011	*0.008*
Extraversion			0.018***	*0.006*	0.019***	*0.006*
Conscientiousness			0.003	*0.008*	0.002	*0.008*
Openness			0.005	*0.008*	0.006	*0.008*
General interpersonal trust			-0.098***	*0.029*	-0.099***	*0.029*
Social value orientation			-0.057	*0.131*	-0.065	*0.131*
UAI × Video					0.001**	*0.001*
Constant	1.168***	*0.298*	1.535***	*0.390*	1.576***	*0.390*
# observations	876		876		876	
Pseudo R^2	0.037		0.056		0.058	

This table shows the results of a pooled Tobit regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.4 *Random-effects GLS regression results, dependent variable: AD*

	AD (1)		***AD*** (2)		***AD*** (3)	
Trust Overall	-0.067**	*0.029*	-0.065**	*0.028*	-0.062**	*0.027*
Emotional	-0,047	*0.049*	-0.084*	*0.047*	-0.093**	*0.047*
Detailed	0.106**	*0.051*	0.104**	*0.048*	0.099**	*0.049*
Video	0.043	*0.063*	0.117*	*0.063*	0.188**	*0.078*
Decision situation (0 = situation MSCI)						
Situation CDAX	-0.097***	*0.038*	-0.097**	*0.038*	-0.097**	*0.038*
Situation known/less known	-0.030	*0.054*	-0.030	*0.054*	-0.030	*0.054*
Situation only less known	0.002	*0.047*	0.002	*0.048*	0.002	*0.048*
Gender (0 = female)						
Male	0.053	*0.062*	0.067	*0.064*	0.073	*0.063*
Other	-0.121	*0.231*	-0.204	*0.198*	-0.210	*0.187*
Marital status (0 = single)						
Liased	-0.067	*0.063*	-0.099	*0.067*	-0.101	*0.067*
Married	-0.048	*0.102*	0.008	*0.102*	0.012	*0.106*
Working hours (0 = zero hours)						
1 to 15 hours	0.028	*0.107*	-0.012	*0.106*	-0.049	*0.102*
16 to 25 hours	0.052	*0.104*	-0.019	*0.109*	-0.053	*0.105*
26 to 35 hours	0.005	*0.107*	-0.011	*0.110*	-0.045	*0.106*
More than 35 hours	-0.001	*0.150*	-0.043	*0.160*	-0.080	*0.155*
Living conditions (0 = with parents)						
With partner	0.267***	*0.097*	0.191**	*0.088*	0.182**	*0.087*
Shared apartment	0.135	*0.106*	0.114	*0.099*	0.105	*0.099*
Student accommodation	0.130	*0.108*	0.099	*0.095*	0.071	*0.093*
Alone	0.232**	*0.098*	0.145	*0.091*	0.132	*0.089*
Age	-0.004	*0.006*	-0.007	*0.006*	-0.006	*0.006*
Financial Literacy	-0.031*	*0.016*	-0.023	*0.016*	-0.022	*0.016*
Self-assessed risk preference	-0.068*	*0.040*	-0.079**	*0.038*	-0.076**	*0.038*
Advice	0.018	*0.038*	0.018	*0.063*	0.005	*0.038*
Power distance			0.000	*0.000*	0.000	*0.000*
Individualism			0.000	*0.000*	0.000	*0.000*
Masculinity			-0.001	*0.000*	-0.001	*0.000*
Uncertainty avoidance			0.001***	*0.000*	0.001	*0.000*
Long-term orientation			0.000	*0.000*	0.000	*0.000*
Indulgence vs. restraint			-0.001	*0.000*	-0.001*	*0.000*
Neuroticism			-0.004	*0.008*	-0.006	*0.008*
Agreeableness			-0.007	*0.008*	-0.008	*0.008*
Extraversion			0.016***	*0.006*	0.017***	*0.006*
Conscientiousness			-0.002	*0.009*	-0.002	*0.009*
Openness			0.006	*0.009*	0.007	*0.008*
General interpersonal trust			-0.079**	*0.032*	-0.081**	*0.031*
Social value orientation			-0.080	*0.146*	-0.065	*0.144*
UAI × Video					0.001**	*0.001*
Constant	1,130***	*0.304*	1.464***	0.437	1,506***	*0.444*
# observations	876		876		876	
# groups	219		219		219	
Overall R^2	0.063		0.098		0.102	

This table shows the results of a random-effects GLS regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.5 Random-effects Tobit regression results, dependent variable: *AD*

	AD (1)		***AD*** (2)		***AD*** (3)	
Trust Overall	-0.085**	*0.034*	-0.082**	*0.033*	-0.079**	*0.033*
Emotional	-0,055	*0.062*	-0.099	*0.061*	-0.108*	*0.061*
Detailed	0.149**	*0.059*	0.151***	*0.058*	0.145**	*0.057*
Video	0.035	*0.072*	0.113	*0.079*	0.192**	*0.092*
Decision situation (0 = situation MSCI)						
Situation CDAX	-0.094*	*0.053*	-0.095*	*0.053*	-0.095*	*0.053*
Situation known/less known	-0.027	*0.053*	-0.027	*0.053*	-0.027	*0.053*
Situation only less known	0.022	*0.052*	0.022	*0.053*	0.022	*0.052*
Gender (0 = female)						
Male	0.062	*0.066*	0.083	*0.069*	0.091	*0.069*
Other	-0.216	*0.271*	-0.325	*0.264*	-0.333	*0.263*
Marital status (0 = single)						
In a relationship	-0.044	*0.085*	-0.074	*0.085*	-0.075	*0.084*
Married	-0.024	*0.139*	0.048	*0.138*	0.052	*0.137*
Working hours (0 = zero hours)						
1 to 15 hours	0.023	*0.124*	-0.015	*0.124*	-0.056	*0.126*
16 to 25 hours	0.046	*0.127*	-0.029	*0.128*	-0.066	*0.129*
26 to 35 hours	-0.001	*0.129*	-0.023	*0.127*	-0.050	*0.129*
More than 35 hours	-0.037	*0.175*	-0.095	*0.172*	-0.135	*0.173*
Living conditions (0 = with parents)						
With partner	0.332***	*0.115*	0.240**	*0.114*	0.230**	*0.114*
Shared apartment	0.164	*0.113*	0.137	*0.111*	0.128	*0.111*
Student accommodation	0.152	*0.129*	0.126	*0.126*	0.095	*0.127*
Alone	0.269**	*0.116*	0.175	*0.115*	0.161	*0.114*
Age	-0.006	*0.008*	-0.009	*0.008*	-0.008	*0.008*
Financial Literacy	-0.033**	*0.016*	-0.024	*0.016*	-0.023	*0.016*
Self-assessed risk preference	-0.078*	*0.045*	-0.094**	*0.045*	-0.090**	*0.045*
Advice	0.035	*0.044*	0.024	*0.045*	0.010	*0.045*
Power distance			0.000	*0.000*	0.000	*0.000*
Individualism			0.000	*0.001*	0.000	*0.001*
Masculinity			-0.001	*0.001*	-0.001	*0.001*
Uncertainty avoidance			0.001***	*0.000*	0.001	*0.001*
Long-term orientation			0.000	*0.000*	0.000	*0.000*
Indulgence vs. restraint			-0.001	*0.000*	-0.001	*0.000*
Neuroticism			-0.004	*0.009*	-0.006	*0.009*
Agreeableness			-0.009	*0.010*	-0.010	*0.010*
Extraversion			0.018**	*0.008*	0.020**	*0.008*
Conscientiousness			0.003	*0.011*	0.002	*0.011*
Openness			0.004	*0.012*	0.006	*0.012*
General interpersonal trust			-0.100***	*0.035*	-0.101***	*0.035*
Social value orientation			-0.054	*0.165*	-0.061	*0.164*
UAI × Video					0.001	*0.001*
Constant	1.168***	*0.357*	1.508***	*0.518*	1.552***	*0.515*
# observations	876		876		876	
# groups	219		219		219	

This table shows the results of a random-effects Tobit regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting. All models include basic control variables. The second and the third model additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.6 *Mediated Moderation Model, direct effects*

	Trust Competence		***Trust Integrity***		***Trust Overall***		***AD***	
	(1)		(2)		(3)		(4)	
Emotional	-0.006	*0.069*	-0.002	*0.064*	0.006	*0.047*	-0.093**	*0.039*
Detailed	0.057	*0.064*	0.103*	*0.058*	0.041	*0.042*	0.102***	*0.037*
Video	0.600***	*0.083*	0.342***	*0.074*	0.126*	*0.070*	0.187***	*0.058*
Trust Competence					0.303***	*0.041*	0.024	*0.025*
Trust Integrity					0.384***	*0.042*	-0.057**	*0.027*
Trust Overall							-0.041	*0.028*
Decision situation (0 = situation MSCI)								
Situation CDAX							-0.097**	*0.047*
Situation known/less known							-0.030	*0.055*
Situation only less known							0.002	*0.051*
Gender (0 = female)								
Male	-0.097	*0.077*	0.132*	*0.074*	-0.173***	*0.047*	0.086	*0.055*
Other	-0.574***	*0.131*	0.060	*0.262*	0.332**	*0.158*	-0.197	*0.153*
Marital status (0 = single)								
In a relationship	0.152*	*0.088*	-0.020	*0.085*	0.111*	*0.059*	-0.108**	*0.049*
Married	0.065	*0.165*	0.843***	*0.140*	-0.003	*0.137*	0.051	*0.081*
Working hours (0 = zero hours)								
1 to 15 hours	0.301**	*0.132*	-0.018	*0.138*	0.210**	*0.089*	-0.064	*0.072*
16 to 25 hours	0.489***	*0.142*	-0.011	*0.145*	0.188*	*0.110*	-0.073	*0.070*
26 to 35 hours	0.467***	*0.133*	-0.056	*0.141*	0.421***	*0.104*	-0.072	*0.072*
More than 35 hours	0.485**	*0.202*	-0.160	*0.204*	0.533***	*0.135*	-0.114	*0.116*
Living conditions (0 = with parents)								
With partner	-0.245**	*0.128*	0.160	*0.116*	0.123*	*0.072*	0.194***	*0.068*
Shared apartment	-0.059	*0.120*	0.252**	*0.125*	0.193***	*0.068*	0.115	*0.076*
Student accommodation	0.014	*0.138*	0.193	*0.134*	0.219***	*0.084*	0.075	*0.081*
Alone	-0.005	*0.131*	0.450***	*0.126*	0.177**	*0.074*	0.150**	*0.070*

Age	-0.002	*0.008*	-0.021***	*0.008*	-0.002	*0.005*	-0.007	*0.005*
Financial Literacy	-0.058***	*0.015*	-0.072***	*0.016*	-0.019	*0.012*	-0.023	*0.015*
Self-assessed risk preference	0.052	*0.049*	0.110**	*0.047*	0.124***	*0.038*	-0.075***	*0.028*
Advice	0.104	*0.054*	-0.002	*0.052*	-0.049	*0.037*	0.003	*0.003*
Power distance	-0.001***	*0.001*	0.000	*0.001*	0.001***	*0.000*	0.000	*0.000*
Individualism	0.002***	*0.001*	0.000	*0.001*	0.001	*0.000*	0.000	*0.000*
Masculinity	0.001**	*0.001*	0.000	*0.001*	0.001	*0.000*	-0.001**	*0.000*
Uncertainty avoidance	-0.001	*0.001*	0.000	*0.000*	-0.001*	*0.000*	0.001**	*0.000*
Long-term orientation	0.001	*0.001*	0.002***	*0.001*	-0.001***	*0.000*	0.000	*0.000*
Indulgence vs. restraint	0.000	*0.001*	0.001	*0.001*	-0.001	*0.000*	-0.001**	*0.000*
Neuroticism	0.006	*0.010*	0.024**	*0.010*	0.002	*0.006*	-0.005	*0.005*
Agreeableness	-0.024**	*0.010*	-0.029***	*0.010*	-0.006	*0.007*	-0.008	*0.006*
Extraversion	0.020**	*0.009*	0.023**	*0.009*	-0.007	*0.007*	0.017***	*0.005*
Conscientiousness	-0.027**	*0.013*	-0.018	*0.012*	0.000	*0.008*	-0.002	*0.007*
Openness	0.032**	*0.013*	0.046***	*0.012*	0.003	*0.008*	0.009	*0.007*
General interpersonal trust	0.079**	*0.038*	0.077**	*0.040*	-0.061**	*0.031*	-0.078***	*0.024*
Social value orientation	-0.030	*0.180*	0.074	*0.172*	0.295***	*0.134*	-0.066	*0.117*
UAI × Video							0.001***	*0.000*
Constant	2.695***	*0.528*	2.889***	*0.559*	0.764**	*0.366*	1.552***	*0.323*
# observations	876		876		876		876	
R^2	0.168		0.192		0.462		0.108	

This table shows the results of a mediated moderation regression model that evaluates the direct effect of advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on trust in the advisor's competence, trust in the advisor's integrity and overall trust as well as the aforementioned variables plus the three dimensions of trust in the advisor on advice discounting. All models include basic control variables and culture- as well as personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table A.7 Pooled OLS regression results, dependent variables: ADOnlyRisky and ADRiskySafe

	ADOnlyRisky		***ADOnlyRisky***		***ADOnlyRisky***		***ADRiskySafe***		***ADRiskySafe***		***ADRiskySafe***	
	(1)		(2)		(3)		(4)		(5)		(6)	
Trust Overall	-0.077***	*0.021*	-0.072***	*0.022*	-0.071***	*0.022*	-0.084***	*0.027*	-0.083***	*0.027*	-0.079***	*0.027*
Emotional	-0.047	*0.040*	-0.054	*0.040*	-0.062	*0.040*	-0.053	*0.046*	-0.075	*0.049*	-0.087*	*0.050*
Detailed	-0.038	*0.036*	-0.026	*0.036*	-0.032	*0.036*	0.168***	*0.047*	0.158***	*0.048*	0.154***	*0.048*
Video	-0.012	*0.042*	0.014	*0.048*	0.067	*0.054*	0.024	*0.056*	0.127**	*0.064*	0.210***	*0.073*
Decision situation (0 = situation MSCI)												
Situation CDAX	-0.048	*0.050*	-0.048	*0.050*	-0.048	*0.050*	-0.023	*0.064*	-0.034	*0.063*	-0.033	*0.063*
Situation known/less known	-0.016	*0.047*	-0.016	*0.047*	-0.016	*0.048*	-0.078	*0.064*	-0.083	*0.064*	-0.083	*0.064*
Situation only less known	0.052	*0.048*	0.052	*0.048*	0.052	*0.048*	-0.024	*0.062*	-0.030	*0.062*	-0.031	*0.062*
Gender (0 = female)												
Male	0.050	*0.038*	0.060	*0.042*	0.063	*0.042*	0.077	*0.049*	0.040	*0.057*	0.044	*0.057*
Other	0.023	*0.181*	-0.007	*0.185*	-0.011	*0.184*	-0.082	*0.262*	-0.165	*0.245*	-0.176	*0.241*
Marital status (0 = single)												
In a relationship	-0.064	*0.045*	-0.067	*0.046*	-0.070	*0.046*	0.036	*0.061*	0.002	*0.061*	0.000	*0.062*
Married	-0.090	*0.078*	-0.049	*0.081*	-0.044	*0.082*	-0.048	*0.105*	-0.010	*0.107*	-0.008	*0.108*
Working hours (0 = zero hours)												
1 to 15 hours	-0.047	*0.069*	-0.014	*0.074*	-0.044	*0.074*	-0.132	*0.091*	-0.137	*0.089*	-0.172**	*0.086*
16 to 25 hours	-0.021	*0.073*	-0.024	*0.078*	-0.051	*0.077*	-0.017	*0.097*	-0.058	*0.097*	-0.089	*0.093*
26 to 35 hours	-0.057	*0.073*	-0.071	*0.073*	-0.096	*0.073*	-0.007	*0.100*	-0.017	*0.098*	-0.050	*0.095*
More than 35 hours	0.099	*0.106*	0.065	*0.110*	0.035	*0.111*	-0.170	*0.114*	-0.200**	*0.118*	-0.235**	*0.115*
Living conditions (0 = with parents)												
With partner	0.204***	*0.071*	0.172**	*0.074*	0.161**	*0.075*	0.254***	*0.086*	0.197**	*0.087*	0.187**	*0.087*
Shared apartment	0.074	*0.073*	0.059	*0.073*	0.052	*0.073*	0.130	*0.087*	0.143	*0.089*	0.136	*0.089*
Student accommodation	0.053	*0.077*	0.041	*0.076*	0.019	*0.078*	0.270***	*0.102*	0.231**	*0.100*	0.206**	*0.099*
Alone	0.079	*0.073*	0.062	*0.076*	0.053	*0.076*	0.267***	*0.087*	0.191**	*0.089*	0.178**	*0.088*
Age	-0.002	*0.004*	-0.000	*0.005*	0.000	*0.005*	-0.000	*0.006*	-0.002	*0.006*	-0.001	*0.007*
Financial Literacy	-0.008	*0.010*	-0.001	*0.010*	0.000	*0.011*	-0.022*	*0.012*	-0.012	*0.013*	-0.009	*0.013*
Self-assessed risk preference	-0.050*	*0.027*	-0.051*	*0.026*	-0.050*	*0.026*	-0.033	*0.034*	-0.033	*0.034*	-0.029	*0.034*
Advice	0.014	*0.027*	0.013	*0.029*	0.004	*0.030*	0.038	*0.036*	0.038	*0.038*	0.025	*0.038*

Power distance			-0.000	*0.000*	-0.000	*0.000*			0.001*	*0.000*	0.001	*0.000*
Individualism			-0.000	*0.000*	-0.000	*0.000*			-0.000	*0.000*	-0.000	*0.000*
Masculinity			-0.001*	*0.000*	-0.001*	*0.000*			0.000	*0.000*	0.000	*0.000*
Uncertainty avoidance			0.000	*0.000*	-0.000	*0.000*			0.001**	*0.000*	0.001	*0.000*
Long-term orientation			-0.000	*0.000*	-0.000	*0.000*			0.000	*0.000*	0.000	*0.000*
Indulgence vs. restraint			-0.000	*0.000*	-0.001	*0.000*			-0.000	*0.000*	-0.001*	*0.000*
Neuroticism			-0.005	*0.006*	-0.006	*0.006*			-0.010	*0.007*	-0.012*	*0.007*
Agreeableness			0.008	*0.006*	0.007	*0.006*			-0.005	*0.009*	-0.006	*0.009*
Extraversion			0.007	*0.005*	0.008	*0.006*			0.012*	*0.007*	0.013**	*0.007*
Conscientiousness			0.010	*0.007*	0.010	*0.007*			-0.004	*0.010*	-0.004	*0.010*
Openness			0.005	*0.008*	0.006	*0.008*			0.007	*0.010*	0.008	*0.010*
General interpersonal trust			-0.030	*0.021*	-0.030	*0.021*			-0.103***	*0.029*	-0.104***	*0.028*
Social value orientation			0.131	*0.101*	0.134	*0.100*			-0.058	*0.145*	-0.067	*0.145*
UAI × Video					0.001*	*0.001*					0.001**	*0.001*
Constant	0.954***	*0.212*	0.556*	*0.321*	0.584*	*0.321*	0.929***	*0.268*	1.327	*0.403*	1.352***	*0.404*
# observations	824		824		824		811		811		811	
R^2	0.062		0.078		0.081		0.063		0.094		0.099	

This table shows the results of a pooled OLS regression that evaluates the effect of overall trust, advisor layout, questionnaire length, existence of a human advisor and uncertainty avoidance on advice discounting in only the risky part of the investment (Models 1 to 3) and on advice discounting calculated using the percentage that has been invested risklessly compared to the share that has been invested in the risky investment opportunities (Models 4 to 6). All models include basic control variables. Models 2, 3, 5 and 6 additionally include culture- and personality related controls. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Paper #4: Impact of Investor Overconfidence on Trading Volume in the Presence of Investment Advice

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Abstract

Using data from an incentivized experiment involving 219 participants, which has been conducted in a realistic trading environment with real-life data, this study is set up to understand how overconfidence in the field of financial literacy influences trading behavior when investors receive advice. The findings reveal a significant positive relationship between investor overconfidence and trading volume: individuals with higher levels of overconfidence tend to engage in higher trading activities, suggesting that the more overconfident an investor is, the more is traded. These results support the findings of Odean (1998), reinforcing the notion that overconfidence leads to excessive trading, expanding on situations with advice.

Keywords: robo advice; overconfidence; judge-advisory-system; investment advice, portfolio allocation; trading.

JEL Classification: D14, D81, D83, G11, G41

1. Introduction

The dynamics of investor behavior have long been a subject of interest within the field of finance, especially the role of psychological factors such as overconfidence. Overconfidence has been consistently linked to increased trading activity. Odean's (1998) work first highlighted this relationship, demonstrating that overconfident investors trade more frequently than their non-overconfident counterparts. However, the investment landscape has evolved fundamentally since Odean's study, with the rising importance of advisory services and the appearance of robo advisors changing how investors make decisions. The emergence of robo advisors, which offer low-cost algorithm-based financial services with minimal human intervention, underscores a shift towards more accessible and machine-driven advice solutions.

Despite this evolution, existing research has primarily focused on the propensity of investors to seek advice, rather than examining investor behavior in scenarios where advice is actively provided (e.g. Broekema & Kramer, 2021, Hsu, 2022, Piehlmaier, 2022). This study aims to fill the research gap by exploring the impact of investor overconfidence on trading volume in actual investment decision-making contexts. By employing an incentivized experiment with 219 participants in a lifelike setting using real-life stock market data, insights into how overconfidence influences trading behavior when investment advice is available are provided. The findings validate that more overconfident individuals engage in higher trading activity.

This study contributes to the existing literature by not only reaffirming the link between overconfidence and trading volume but also by contextualizing this relationship within the modern landscape of investment advice. Understanding these dynamics is crucial for financial advisors, robo advisor developers, and policymakers aiming to optimize advisory services and mitigate the potentially detrimental effects of overconfidence on trading behavior.

The paper is structured as follows: In Section 2, the current state of literature is analyzed. Based on this, hypotheses are presented in Section 3. Section 4 describes the experimental design, and statistical analyses are shown in Section 5. A discussion is provided in Section 6. Section 7 concludes.

2. Literature Review

The relationship between overconfidence and trading volume has been an important topic in financial research. Odean (1998), as mentioned before, was the first to empirically demonstrate that overconfident investors tend to trade more frequently than their non-overconfident counterparts. This study laid the foundation for following research and Odean's study was supported by Barber & Odean (2000), who found that overconfident investors not only trade more but also achieve lower net returns due to excessive trading costs. Subsequent studies have continued to explore the relationship between overconfidence and trading in different contexts. Research by Statman et al. (2006) suggests that overconfident investors are more likely to chase trends, which in turn also leads to an increased trading volume. Biais et al. (2005) have explored the role of overconfidence in diverse market settings. Their research indicated that overconfidence could also affect market prices and liquidity, linking this to the (faulty) belief that overconfident investors have an informational advantage. They furthermore find that trading behavior is influenced by gender, while men trade more than women and are more affected by personality-related influences. Deaves et al. (2009) extended this line of research by examining the role of gender in overconfidence and trading in more detail. They found that men are generally more overconfident than women in financial decision-making contexts, with this being the main cause they observe higher trading volumes for male investors. Their research also showed that this overconfidence results in larger transaction costs and lower net returns, further confirming the adverse effects of this bias on investment outcomes. In a cross-cultural study, Chui et al. (2010) examined overconfidence and found that cultural factors influence overconfident behavior. They discovered that investors in countries with higher levels of individualism tend to exhibit more overconfident trading behaviors, resulting in higher trading volumes. Concerning personality-related influences, Durand et al. (2013) found that the Big 5 personality traits influence overconfidence and with that, investment behavior. Expanding on this research, the impact of overconfidence levels on trading behavior have been tested in laboratory experiments and using real-life data, delivering similar results: overconfidence leads to more excessive trading (Pikulina et al., 2017; Inghelbrecht & Tedde, 2024). Overall, the existing research supports the idea of a robust link between overconfidence and trading volume, which is also influenced by gender, and by psychological and cultural factors.

Overconfidence manifests in three different forms: overplacement, overprecision and overestimation (Moore & Healy, 2008). Overplacement will not be addressed in more detail, since it is defined as one’s overestimation of personal abilities, knowledge or control over events in comparison to others, which is not relevant to this study. Overprecision involves excessive certainty in the accuracy of one’s beliefs, and it is measured using confidence intervals, a method that often proves problematic due to the general public’s limited understanding of the statistical concept of said confidence intervals. This misunderstanding may lead to miscalibrated interval values – either too narrow or too broad – that do not reflect true confidence levels (e.g., Juslin at al., 2000). Because of this problem, the overestimation form of overconfidence – describing that individuals overestimate their actual abilities, knowledge, or control over events – has received particular attention in the context of financial literacy and decision-making. Measuring overconfidence in the form of overestimation involves comparing individuals’ self-reported knowledge with objective measures of their actual performance, which is, in general, a method that is relatively easy to implement in surveys and experiments.

In the particular case of financial literacy, overestimation refers to an individual’s tendency to overrate the understanding of financial concepts and finance-related mathematics. Studies have shown that individuals tend to believe they are more knowledgeable about financial matters than they actually are, which can result in overconfident trading behavior and, ultimately, suboptimal financial outcomes (Lusardi & Mitchell, 2011).

A number of studies have shown that behavioral biases in investment can be influenced when the decision-maker receives advice (Bhattacharya et al., 2012; Hoechle et al., 2017). The provision of investment advice has traditionally been an important financial service, with the goal to guide investors through the decision-making process. However, Bhattacharya et al. (2012) also found that those who would most be in need of advice tend to ignore it, and the studies mentioned before did not specifically address the role of overconfidence. Actual investment decisions in this context are often only examined indirectly, with researchers attempting to address the influence of overconfidence on advised investment decision-making through the non-straightforward way of looking at the propensity to seek advice (e.g., Broekema & Kramer, 2021; Piehlmaier, 2022; Hsu, 2022). In general, research in this area is still scarce and the aforementioned indirect approach highlights a significant research gap since the willingness of a person to be advised is not necessarily a good proxy for actual advised decision-making, as it leaves the use of advice disregarded. However, the relatively large number of papers trying to examine the effect of overconfidence on advised decision-making with the help of this “detour” shows that the research question is a relevant one. While the link between overconfidence and trading volume in situations without advice is well-established, it is striking that this specific influence remains underexplored in advisory contexts addressing lifelike decision-situations. The research gap is particularly important given the evolving landscape of financial advisory services. This is especially true considering the rise of digitalized advisory services like robo advisors, which have revolutionized the accessibility of investment advice. Merkle (2020) highlighted that robo advisors offer cost-effective, data-driven financial planning, making professional advice accessible to a broader and less financially sophisticated audience. This growing importance of automated investment advice leads to the question of the impact of such a form of advice on actual investment decisions. Piehlmaier (2022) has identified this research gap as well, stating that “these comparably new financial services are critically understudied,” but also only examines the propensity to seek robo advice in his work. There is thus a need to address investment decisions in the context of robo advice.

To summarize, this study aims to close a research gap by testing if overconfidence affects trading volume in scenarios where automated investment advice is provided. By using an incentivized experiment with a realistic setting and using real-life stock market data, the aim of this work is to check if overconfidence leads to higher trading volumes even when investment advice is available, therefore examining the persistence of this psychological bias despite the presence of guidance.

3. Hypotheses

Based on the existing literature discussed before, which consistently shows investors classified as overconfident trade more frequently due to their overestimation of knowledge and abilities and considering that advice is ignored mostly by those who would need it the most, the following hypothesis is set up:

Hypothesis 1: Despite receiving advice, overconfident decision-makers trade more than non-overconfident individuals.

As the level of overconfidence increases, literature suggests that the expected trading volume increases as well, which leads to a second hypothesis.

Hypothesis 2: Despite receiving advice, a higher the degree of overconfidence leads to a higher trading volume.

As indicated before, these hypotheses are being checked using experimental data.

4. Experimental Design

The experiment was designed to explore what drives decision-making in investment situations with advice. Participants were asked to invest a hypothetical sum of money by distributing it across various stocks or funds and a risk-free investment. They were compensated based on the performance of their portfolios. Furthermore, a 2x2x2 treatment group design that manipulated the length of the exploration questionnaire, the user interface, and the presence of a human advisor via video was introduced to control for different aspects of a robo advisor setup (for further details about the experiment, see Breuer et al., 2024a; Breuer et al., 2024b). The participants were recruited at a large German university and therefore the experiment was conducted in German. It was programmed using the oTree framework (Chen et al., 2016).

Among other investment scenarios which are less relevant to this paper, participants were tasked with allocating a hypothetical sum of money across five different company shares from the CDAX, all representing relatively unknown firms. Participants made investment decisions over four consecutive rounds, with each progressing round representing an additional year in time, based on real historical stock data. They had the possibility to adjust their investments according to the results from previous rounds. Participants were given stock prices from the past two years but received no additional information. Moreover, they could select a risk-free investment offering an annual interest rate of 0.5%, reflecting a prevalent number at both the time of the historical data and when the experiment was conducted. Using the internet in order to acquire more knowledge about the companies was forbidden. Participants received individualized investment advice based on their answers to an exploration questionnaire which had to be answered once before receiving advice for the first time (for more details, see Breuer et al., 2024a).

During Round 1, participants could only buy shares (see Figure 1 for a screenshot). After finalizing their allocations with advice available, participants clicked “Next” and were immediately informed of the outcomes of their investments. In Rounds 2 through 4, participants could buy additional shares or sell shares they had previously purchased (see Figure 2 for a screenshot). They were charged a transaction fee that amounted to 0.2% of the trading volume. After each allocation decision, they were once again shown their updated portfolio value, which incorporated their gains or losses from the earlier decision. The dynamic nature of the experiment allowed them to either maintain, modify, or reverse their prior choices. This iterative process was created to simulate a real-world investment scenario. Participants were given a time limit of five minutes per allocation decision in order to avoid in-depth Internet searches that could have distorted our results due to differences in participants’ information at the time of the decision.

>>> Insert Figure 1 about here <<<

>>> Insert Figure 2 about here <<<

Additional data, to be used as control variables, was also gathered to enhance the quality of the analyses (refer to Breuer et al., 2024a, Table 1, for details on the collected data; the full questionnaire is available in the Appendix of Breuer et al., 2024a).

5. Results

5.1 Data

In the experimental setup described above, individual-level data on 219 participants' social and demographic attributes has been collected, as well as their Big 5 personality traits (Digman, 1990, German translation by Körner et al., 2008) and cultural dimensions (Hofstede, 2011). To assess the measure of financial literacy, a set of 13 questions based on the methodology developed by Lusardi & Mitchell (2011) has been used. Participants correctly answered an average of 9.26 questions, which indicates a relatively high level of prior financial knowledge. After each question, the individuals were additionally asked to indicate a confidence level in their answer on a scale ranging from 33% (for questions with three answer options) or 50% (for two answer options) to 100%. A value of 33% or 50%, respectively, indicated a complete guess, while 100% indicated certainty. This confidence scale was carefully explained to ensure participants fully understood its implications. Confidence intervals were not used because of the general problems that come with a potentially limited understanding of those measures, as explained before. Individuals were also asked to rate their own financial literacy on a Likert scale from 1 (very low) to 7 (very high).

Following the approach used by Porto & Xiao (2016), a variable reflecting overconfident behavior has been set up by comparing participants' self-assessed financial literacy based on the Likert scale with their actual performance. This variable thus relates to the overconfidence domain of overestimation. As Porto & Xiao (2016) propose to use this measure, it was defined as a dummy variable, taking the value of 1 if participants rated their own financial literacy equal to or above the median of the Likert scale question (≥ 4) but correctly answered at maximum the median number of right answers (≤ 9). Based on this methodology, 28 participants were classified as overconfident in the domain of overestimation, which relates to a relative share of 12.79%. As it is extensively used in the literature (e.g., Atlas et al., 2019; Aristei & Gallo, 2022; Pearson & Korankye, 2023), this variable is considered as the key measure to determine if an individual acts in an overconfident way or not. Studies have demonstrated that overestimation is not only practical to measure but also predictive of financial behavior. Mallik et al. (2017) found that overestimation is highly relevant to financial decision-making. Tang et al. (2014) observed a connection between visualization and interactivity in financial tools and overestimation, which is important to this study with a view to the different robo advisor features applied in the experiment.

The drawback of the aforementioned, widely used measure of overestimation is its binary nature. Therefore, the confidence values that have been stated after each literacy-related question have been used to calculate how many questions participants were expected to have answered correctly. For example, if a participant's average confidence was 75%, one would expect them to correctly answer 75% of the questions. In this regard, the variable relates to a certain form of overprecision, not measured by using confidence intervals but by a judgment of participants' certainty to be right. This expected value was then compared to the actual results to calculate an *Overprecision* variable:

$$Overprecision = \frac{(expected\ correct\ answers - correct\ answers)}{total\ number\ of\ questions} \tag{1}$$

On average, participants misjudged (or, "overprecised") by 0.0502, indicating that their overall judgment was relatively appropriate, as this number is close to zero.

The inclusion of an overprecision variable adds depth to the analysis by capturing a different dimension of overconfidence, making it possible to measure overconfidence in a non-binary way. However, relevant studies connecting overprecision to financial decision-making do not exist yet, which is why this variable is treated only as an addition to the analyses involving overestimation. In this context, an interaction term between *Overestimation* and *Overprecision* has been created to be interpreted as the degree of overconfidence. The idea is that a higher *Overprecision* value within the group of participants that tend to overestimate their abilities can be described as a higher degree of overconfidence, which is a new approach. As mentioned before, this interaction term goes beyond a simple binary overconfidence classification and offers a more refined measure which takes two domains of overconfidence into account.

Data on participants' trading behavior was also collected. Total trading volume was calculated by summing up all sales and purchases in one round. On average, participants traded assets worth approximately 8,931.72 € in each of Rounds 2 through 4, with total trading values ranging from 0 € to 125,050.30 € per round. This corresponds to an average relative trading volume of 15.12% of participants' total portfolio value per round. The distinction between total and relative trading volume is important since participants might have had different monetary endowments, as those values were based on prior investment decisions and their respective outcomes. In order to take this possibly result-distorting issue into account, since it is imaginable that people who own more money trade more in absolute numbers, the relative trading volume has been used in the main analyses, whereas the use of the absolute trading volume is limited to robustness checks only. It is furthermore worth noting that the total trading volume could theoretically range from 0 up to twice the portfolio value, since participants were able to simultaneously sell and buy assets. If participants had followed the advice provided, their trading activity would have been much lower than what has been observed, consisting only of portfolio rebalancing. Trading volume in Round 1 has not been used for the analyses, as the decision made in this round is not comparable to the ones in Rounds 2 through 4, since in Round 1, only buying assets was possible, therefore the upper boundary of the trading volume variable differed. This way, the total number of observations used in the analyses amounts to 657 – three for each individual. Additional details on participants' social and demographic characteristics, as well as their personality and culture-related traits and information concerning the other variables used in the analyses, can be found in Breuer et al. (2024b).

In terms of descriptive statistics with a view to the individuals that have been defined as overconfident in the domain of overestimation compared to all others, Table 1 reveals no notable differences between overestimating and non-overestimating participants regarding age, cultural dimensions, or personality-related variables. Among the 28 people identified as overestimators, 16 are male (57.14%), 11 are female (39.29%), and one identifies as another gender. This distribution differs slightly from the remaining participants, of whom 89 identified as female (46.60%), 100 as male (52.36%), and two as a different gender. Further distinctions show that 57.59% of non-overestimating participants encountered the emotional layout, and 47.64% completed the long questionnaire. For overestimating participants, these figures shift slightly, with 46.43% exposed to the emotional layout and 53.57% to the long questionnaire. However, these differences in layout and questionnaire length should not have influenced the overestimation classification, as the questions used to determine the dummy variable originated from a separate, standardized questionnaire given to all participants regardless of treatment group, ensuring consistency in length and layout. A notable difference appears in financial literacy levels, which – by design – are directly connected to the classification criteria.

Additionally, overestimating participants demonstrated a higher mean trading volume, which relates to an average of 25.11% of their total portfolio value per round, compared to 13.65% among non-overconfident participants. The mean overprecision of participants that overestimated their knowledge amounted to 0.1527, while the average overprecision value of all other participants was 0.0352. This difference is statistically significant ($p < 0.01$).

>>> Insert Table 1 about here <<<

5.2 Statistical Analyses

Examining the pairwise correlations in Table 2, one can observe significant positive relationships between *Overestimation* and *Relative Trading Volume*, between *Overprecision* and *Relative Trading Volume*, and between *Overestimation* and *Overprecision*. Additionally, *Financial Literacy* has a significant negative correlation with both *Overestimation* and *Overprecision*. These initial findings provide evidence that the variables of interest are connected with each other and play a role in the decision-making process. In particular, the results support the idea that overconfident individuals tend to engage in higher trading activity.

>>> Insert Table 2 about here <<<

However, pairwise correlations do not account for the influence of other variables in the system, and it is plausible that multiple factors simultaneously affect investment decisions. To address this, a multivariable regression approach is employed, with *Relative Trading Volume* as the dependent variable. Since the dependent variable is bounded both at the upper and lower level, ordinary least squares (OLS) regression assumptions are violated. Therefore, a Tobit regression model is used to account for the boundaries (0 to two times the total portfolio value for each decision situation). Given that each participant i provides three observations j, a random-effects model is applied to control for both within- and between-group variability, allowing for a better estimation of the relationship between the variables of interest and *Relative Trading Volume*. To determine if overconfidence in the field of overestimation influences trading behavior, the following model has been set up:

$$Relative\ Trading\ Volume_{ij} = b_0 + b_1 \cdot Overestimation_{ij} + \boldsymbol{b} \cdot \boldsymbol{C_{ij}} + \varepsilon_{ij}. \qquad (2)$$

The vector $\boldsymbol{C_{ij}}$ describes all control variables used. Furthermore, with the goal to go beyond the scope of a simple binary classification and thus to analyze the effects of the degree of overconfidence on trading activity, an additional random-effects Tobit regression model is set up including an interaction term between *Overprecision* and *Overestimation* to be interpreted as the degree of overconfidence, as explained before:

$$Relative\ Trading\ Volume_{ij} = b_0 + b_1 \cdot Overestimation_{ij} + b_2 \cdot Overprecision_{ij} + b_3 \cdot Overestimation_{ij} \times Overprecision_{ij} + \boldsymbol{b} \cdot \boldsymbol{C_{ij}} + \varepsilon_{ij}. \qquad (3)$$

The results of these two models are presented in Table 3. Model 1 of Table 3 shows that one would expect people being overconfident in the domain of overestimation to indeed trade more than their non-overconfident counterparts. However, *Overestimation* is not significant in Model 2 (as well as *Overprecision*), but the coefficient of the interaction term is significant and positive ($p < 0.01$). This means that individuals who overestimate their knowledge do not inherently exhibit higher trading volumes, but they are strongly influenced by the degree of overprecision. This is an interesting notion which has not been described in the previous literature on overconfidence. Furthermore, the magnitude of this effect is relatively large. The coefficient is 0.812. Calculating the average marginal effect, keeping all other variables constant at means, amounts to 0.811, suggesting that for each additional percentage point increase in the interaction term – seen as the “degree of overconfidence” – one would expect a participant to trade 0.811 percentage points more of their total portfolio value, on average. With a view to the hypotheses, being classified as overconfident in the domain of overestimation leads to a higher trading volume but only for those who overprecise the accuracy of their financial literacy (Hypothesis 1). Within the group of overestimating participants, there is evidence that higher degrees of overconfidence, as measured by a higher overprecision, indeed lead to higher trading volumes (Hypothesis 2). It is worth noting that in terms of Sharpe ratios after subtracting transaction costs, non-overestimating individuals in the sample have an average Sharpe ratio of 0.267, while overestimating participants exhibit a mean Sharpe ratio of 0.143. However, this difference is not statistically significant ($p > 0.1$).

>>> Insert Table 3 about here <<<

5.3 Robustness Checks

Additional models were set up to account for a larger number of control variables, specifically including those related to personality and culture-specific effects. As shown in Table 4, the results remain consistent. *Overestimation* is only significant in Model 1, while in Model 2, the interaction term is significant, with both *Overprecision* and *Overestimation* being non-significant.

>>> Insert Table 4 about here <<<

Moreover, the same random-effects Tobit regression models were estimated with and without additional controls, using the absolute value of participants' trading volume per round as the dependent variable (see Table 5). The results remain robust across all versions.

>>> Insert Table 5 about here <<<

Although the assumptions of OLS regression are technically violated due to the bounded nature of the dependent variable, a linear random-effects OLS regression can still be employed as a robustness check to validate the consistency of the results, allowing for an additional layer of comparison. Using OLS as a robustness check helps to ensure that the relationships observed are not model-dependent. Tables 6 and 7 show the results of such an approach. While Table 6 is dedicated to *Relative Trading Volume*, Table 7 presents the outcomes with *Absolute Trading Volume* being the dependent variable. Once again, the analyses paint a consistent picture.

>>> Insert Table 6 about here <<<

>>> Insert Table 7 about here <<<

The interpretation of the coefficients in Table 7 is somewhat more straightforward in the case of linear regressions. Based on Model 4, Table 7, participants who overestimate their abilities and who misjudged their performance by one question (out of the thirteen asked) are expected to trade $\frac{1}{13} \cdot 49{,}915.07 = 3{,}839.62$ € more per round compared to non-overestimating individuals, who misjudged their performance by the same degree.

All in all, the results are robust to additional control variables, to a change in the dependent variable and to using alternative statistical models.

6. Discussion

The measure of defining an individual as overconfident in the domain of overestimation used in the study could be considered as quite simple. Overconfidence is a complex construct that works in various ways such as overestimation of knowledge or skills, overplacement relative to others, and overprecision, which is normally measured by using confidence intervals, as mentioned before. According to Glaser & Weber (2007), different types of overconfidence can have different influences on trading. Therefore, a more nuanced measurement that further distinguishes between these forms might provide a clearer understanding of how overconfidence influences trading volume. This study moreover only focuses on overconfidence in the domain of financial literacy, which may not account for all kinds of overconfidence that affect trading behavior. By expanding the scope to include different overconfidence measures, future research could provide a more comprehensive picture.

The findings moreover suggest a decrease in trading volume for later rounds, as the controls for Round 3 and 4 (compared to Round 2) are significantly negative in all of the analyses, which might indicate the existence of a learning effect. This aligns with the findings of Nicolosi et al. (2009), who observed that individual investors learn from their trading experiences and adjust their behavior accordingly. A moderating effect of the overconfidence measures was checked, but could be ruled out. In this study, the observed decline in trading volume in later experimental rounds could reflect participants' growing awareness of the inability to make better choices than what is being advised (that is, following a buy and hold strategy and only rebalancing the portfolio), independent of being overconfident. It is yet unclear if and how strong this learning effect would have been in situations without advice. Future research might address this idea.

It is striking that the influence of personality traits on trading volume does not align with expectations based on the literature. For instance, traits like extraversion and conscientiousness have been linked to trading behavior in previous studies (e.g., Durand et al., 2013). However, in the analyses performed in this paper, said personality variables do not show significant effects on trading volume. This discrepancy might be due to the homogeneity of the sample or the context-specific factors of the experiment. Further research is needed to explore these relationships more deeply, possibly considering a more diverse sample or different contextual settings to better capture the effects of personality traits and culture on trading behavior. Generally speaking, the participants' homogeneity might have limited the generalizability of the results. I furthermore checked if personality- as well as culture-related controls moderate any of the connections between overconfidence and trading volume. However, no significant effects could be found.

Considering only models with additional control variables, there is a finding that more trading occurs when participants are confronted with a more emotional, colorful interface, possibly reflecting an influence of some form of gamification on trading behavior. Gamification involves applying playful design elements in non-game contexts to enhance motivation (Deterding et al., 2011). A colorful, engaging interface can make trading feel more like a game, encouraging more frequent interactions. This aligns with research indicating that gamified environments can increase user engagement and activity (for an overview, see, e.g., Hamari et al., 2014). However, this could also lead to excessive trading driven by entertainment reasons rather than thoughtful decision-making, which is an interesting idea to be possibly addressed by future research. Again, a potential moderating effect of specific robo advisor features was tested to assess if these might amplify or mitigate the influence of overconfidence on trading volumes. However, the analyses did not yield statistically significant results, providing no support to this idea.

There is evidence that Sharpe ratios do not differ significantly between overestimating and non-overestimating individuals, although one would expect overestimating participants to trade more based on their level of overconfidence, and thus, show lower levels of returns net of fees, influencing Sharpe ratios ceteris paribus. The idea Odean (1998) had was based on this logic. However, when transaction costs are relatively low, as they were in this case (0.2% of the trading volume), the "penalty" for frequent trading is less severe. As a result, the negative impact of excessive trading on portfolio performance may be less pronounced. Low transaction costs, especially compared to earlier periods like 1998, reduce the performance gap between frequent and non-frequent traders. An iteration-based approach yields that the difference would have been statistically significant ($p < 0.1$) for all fees larger than 1.34% of the trading volume and highly significant ($p < 0.01$) for fees that excess 3.59%, ceteris paribus. The calculation does not account for the behavioral consequences of higher trading costs; however, it exemplarily shows that Barber's & Odean's reasoning seems correct for trading costs that were common in the 1990's, which at that time amounted to about 2% per trade on average (Barber & Odean, 2000).

With a view to the practical implications of this paper, it can be stated that robo advice does not manage to fully annihilate behavioral biases in investment decision-making. Especially regarding the socio-demographic background of robo advice users, who are rather less financially literate with no extensive prior knowledge of capital markets and investments (Fulk et al., 2018; Monticone, 2010; van Rooij et al., 2012), there seems to be a necessity to address this issue. Research is needed to determine if features such as real-time feedback on trading volume, alerts for excessive trades, or even education modules aimed at improving financial literacy could help mitigate the impact of overconfidence and promote better financial outcomes.

7. Conclusion

All things considered, the findings reaffirm the significant effect of overconfidence on trading behavior in situations with advice, a finding that closes a research gap and underscores the consistency of the impact of this behavioral bias in investing. This might have important implications for robo advisor developers and policymakers aiming to optimize advisory services and trading platforms, as overconfidence seems to be a problem that needs to be addressed. The analysis also pointed towards the existence of a learning effect, as indicated by the significant decrease in trading volume in later experiment rounds. This suggests that participants adjust their trading behavior based on prior experiences, changing it as time progresses. Analyzing if this is caused or supported by advice might be an interesting starting point for future research. This study, however, has some drawbacks. One notable limitation is that it does not specifically examine advice discounting, i.e., the acceptance level of advice provided to the participants. Given the relevance of advice acceptance in understanding the effectiveness of advisory systems (Breuer et al., 2024a; Breuer et al., 2024b), future research should integrate this perspective and analyze the impact of overconfidence on advice acceptance in financial-decision making. Moreover, the influence of personality traits and culture on trading volume was less clear, with many expected relationships from the literature not observed here. The discrepancy could be due to the homogeneity of the sample, which might have limited some variability necessary to detect these effects. Future research should therefore consider more diverse samples. However, the results can still be considered helpful as young academics form a very important investor group, to date as well as in the future.

References

Aristei, D. & Gallo, M. (2022). Assessing gender gaps in financial knowledge and self-confidence: Evidence from international data. *Finance Research Letters* 46A, 1-15.

Atlas, S. A., Lu, J., Dorin Micu, P. & Porto, N. (2019). Financial Knowledge, Confidence, Credit Use, and Financial Satisfaction. *Journal of Financial Counseling and Planning* 30 (2), 175-190.

Barber, B. M. & Odean, T. (2000). Trading Is Hazardous to Your Wealth. The Common Stock Investment Performance of Individual Investors. *Journal of Finance* 55 (2), 773-806.

Bhattacharya, U., Hackethal, A., Kaesler, S. Loos, B. & Meyer, S. (2012). Is Unbiased Financial Advice to Retail Investors Sufficient? Answers from a Large Field Study. *The Review of Financial Studies* 25 (4), 976-1032.

Biais, B., Hilton, D., Mazurier, K. & Pouget, S. (2005). Judgemental overconfidence, self-monitoring, and trading performance in an experimental financial market. *The Review of Economic Studies* 72 (2), 287-312.

Breuer, W., Breuer, C. & Renerken, T. (2024a). Drivers of Trust and Advice Discounting for Robo Advice. Working Paper.

Breuer, W., Breuer, C. & Renerken, T. (2024b). Each Betrayal Begins with Trust? The Impact of Human Involvement in Robo Advice. Working Paper.

Broekema, S. P. M. & Kramer, M. M. (2021). Overconfidence, Financial Advice Seeking and Household Portfolio Under-Diversification. *Journal of Risk and Financial Management* 14 (553), 1-15.

Chen, D.L., Schonger, M. & Wickens, C. (2016). oTree - An open-source platform for laboratory, online and field experiments. *Journal of Behavioral and Experimental Finance* 9, 88-97.

Chui, A. C. W., Titman, S. & Wei, K. C. J. (2010). Individualism and Momentum around the World. *The Journal of Finance* 65 (1), 361-392.

Deaves, R., Lueders, E. & Luo, G. Y. (2009). An Experimental Test of the Impact of Overconfidence and Gender on Trading Activity. *Review of Finance* 13, 555-575.

Deterding, S., Dixon, D., Khaled, R. & Nacke, L. (2011). From Game Design Elements to Gamefulness: Defining “Gamification”. *Proceedings of the 15th International Academic MindTrek Conference* 11, 9-15.

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology* 41, 417–440.

Durand, R., Newby, R. Tant, K. & Trepongkaruna, S. (2013). Overconfidence, overreaction and personality. *Review of Behavioral Finance* 5 (2), 104-133.

Fulk, M., Grable, J. E., Watkins, K. & Kruger, M. (2018). Who Uses Robo-Advisory Services, and Who Does Not? Financial Services Review 27 (2), 173-188.

Glaser, M. & Weber, M. (2007). Overconfidence and Trading Volume. *Geneva Risk Insurance Review* 32, 1-36.

Hamari, J, Koivisto, J. & Sarsa, H. (2014). Does Gamification Work? – A Literature Review of Empirical Studies on Gamification. *Proceedings of the 47th Hawaii International Conference on System Sciences*, 3024-3034.

Hoechle, D., Ruenzi, S., Schaub, N. & Schmid, M. (2017). The Impact of Financial Advice on Trade Performance and Behavioral Biases. *Review of Finance* 21 (2), 871-910.

Hofstede, G. (2011). Dimensionalizing Cultures: The Hofstede Model in Context. *Online Readings in Psychology and Culture* 2 (8).

Hsu, Y.-L. (2022). Financial advice seeking and behavioral bias. *Finance Research Letters* 46, 1-9.

Inghelbrecht, K. & Tedde, M. (2024). Overconfidence, financial literacy and excessive trading. *Journal of Economic Behavior and Organization* 219, 152-195.

Juslin, P., Winman, A. & Olsson, H. (2000). Naive Empiricism and Dogmatism in Confidence Research: A Critical Examination of the Hard-Easy Effect. *Psychological Review* 107 (2), 384-396.

Körner, A., Geyer, M., Roth, M., Drapeau, M., Schmutzer, G., Albani, C., Schumann, S. & Brähler, E. (2008). Persönlichkeitsdiagnostik mit dem NEO-Fünf-Faktoren-Inventar: Die 30-Item-Kurzversion (NEO-FFI-30). *Psychother Psych Med* 58, 238-245.

Lusardi, A. & Mitchell, O. S. (2011). Financial Literacy and Retirement Planning in the United States. *Journal of Pension Economics and Finance* 10 (4), 509-525.

Mallik, K. A., Munir, M. A. & Sarwar, S. (2017). Impact of Overconfidence and Loss Aversion Biases on Investor Decision-Making Behavior: Mediating Role of Risk Perception. *International Journal of Public Finance, Law & Taxation* 1 (1), 13-24.

Merkle, C. (2020). Robo-Advice and the Future of Delegated Investment. *Journal of Financial Transformation* 51, 20-27.

Monticone, C. (2010). How Much Does Wealth Matter in the Acquisition of Financial Literacy? *Journal of Consumer Affairs* 44 (2), 403-422.

Moore, D. A. & Healy, P. J. (2008). The Trouble with Overconfidence. *Psychological Review* 115 (2), 502-517.

Nicolosi, G., Peng, L. & Zhu, N. (2009). Do individual investors learn from their trading experience? *Journal of Financial Markets* 12, 317-336.

Odean, T. (1998). Volume, Volatility, Price, and Profit When All Traders Are Above Average. *Journal of Finance* 53 (9), 1887-1934.

Pearson, B. & Korankye, T. (2023). The association between financial literacy confidence and financial satisfaction. *Review of Behavioral Finance* 15 (6), 935-946.

Piehlmaier, D. M. (2022). Overconfidence and the adoption of robo-advice: why overconfident investors drive the expansion of automated financial advice. *Financial Innovation* 8 (14), 1-24.

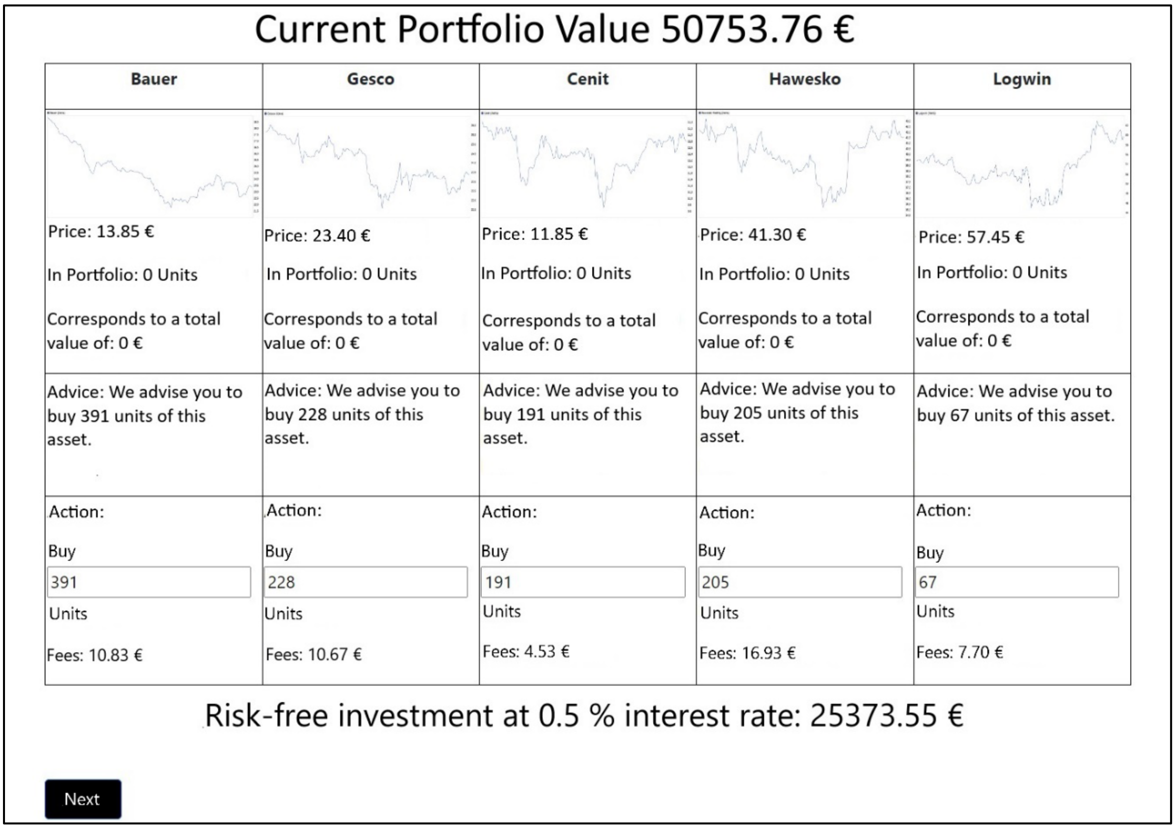
Pikulina, E., Renneboog, L. & Tobler, P. N. (2017). Overconfidence and investment: An experimental approach. *Journal of Corporate Finance* 43, 175-192.

Statman, M., Thorley, S. & Vorkink, K. (2006). Investor overconfidence and trading volume. *Review of Financial Studies* 19 (4), 1531-1565.

Tang, F., Hess, T. J., Valacich, J. S. & Sweeney, J. T. (2014). The Effects of Visualization and Interactivity on Calibration in Financial Decision-Making. *Behavioral Research in Accounting* 26 (1), 25-58.

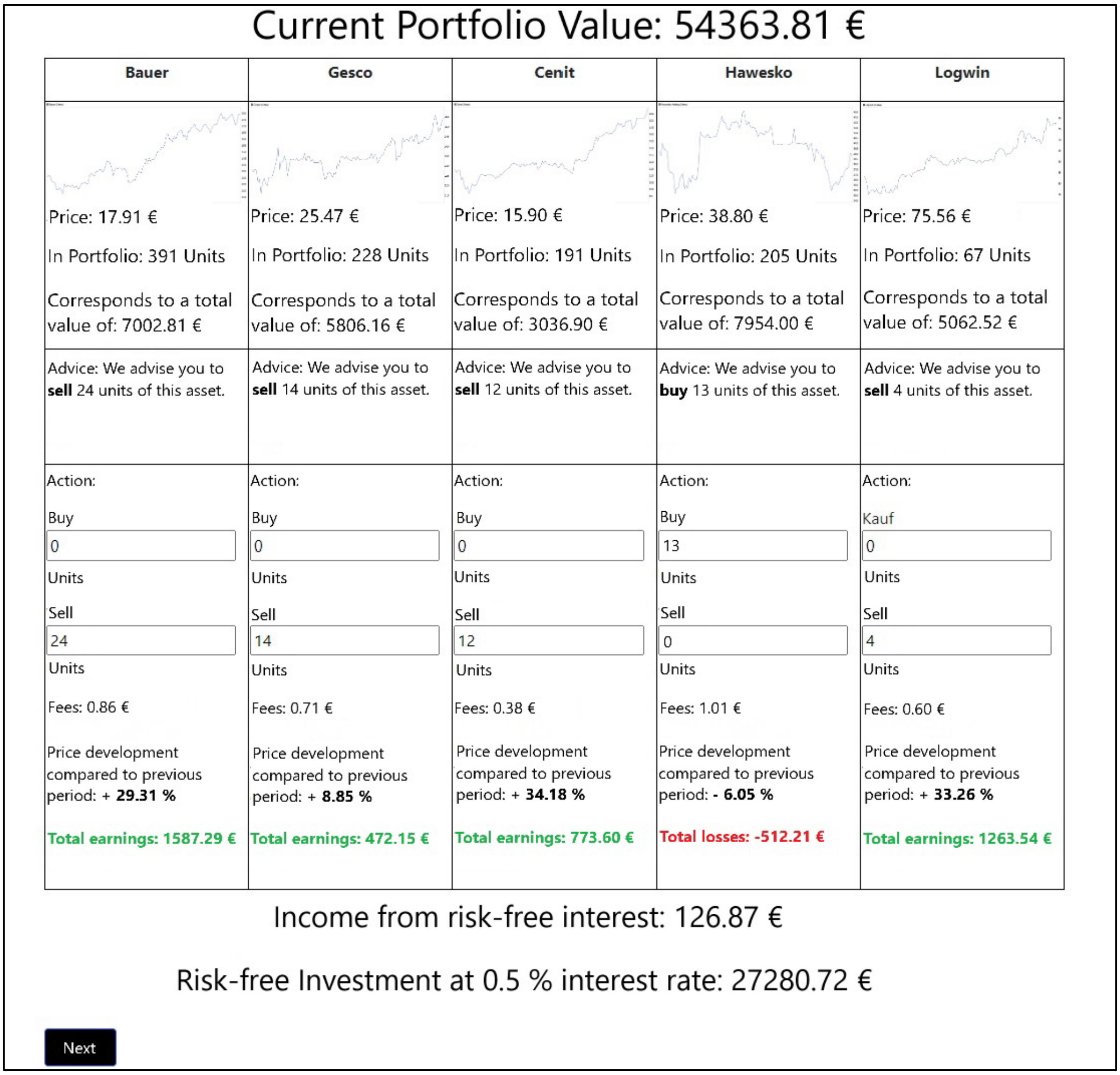
Van Rooij, M. C. J., Lusardi, A. & Alessie, R. J. M. (2012). Financial Literacy, Retirement Planning, and Household Wealth. *The Economic Journal* 122 (5), 449-478.

Figure 1 *Screenshot of decision situation without sale possibility*



This figure shows a screenshot of the user interface participants were confronted with when making an investment decision with possibility to buy only.

Figure 2 *Screenshot of decision situation with sale possibility*



This figure shows a screenshot of the user interface participants were confronted with when making an investment decision with possibility to buy and sell.

Table 1 *Descriptive statistics grouped by Overconfidence*

	***Overestimation* = 0** n = 191		***Overestimation* = 1** n = 28		
	mean	**std. dev.**	**mean**	**std. dev.**	**p-value (t-test)**
Variables of key interest					
Relative Trading Volume	0.137	*0.230*	0.251	*0.336*	*0.000*
Financial literacy	9.424	*1.980*	8.143	*1.458*	*0.001*
Overprecision	0.035	*0.135*	0.153	*0.141*	*0.000*
Basic controls					
Emotional	0.576	*0.496*	0.464	*0.508*	*0.268*
Detailed	0.476	*0.501*	0.536	*0.508*	*0.560*
Video	0.387	*0.488*	0.357	*0.488*	*0.760*
Trust overall	3.340	*0.914*	3.321	*0.772*	*0.917*
Age	25.607	*4.279*	26.179	*3.591*	*0.502*
Self-assessed risk preference	2.827	*0.679*	2.286	*0.600*	*0.000*
Advice	0.519	*0.258*	0.580	*0.236*	*0.241*
Culture-related controls					
Power distance	9.162	*59.565*	10.000	*53.229*	*0.944*
Individualism	26.753	*61.382*	7.500	*47.968*	*0.114*
Masculinity	-16.492	*59.527*	-10.000	*51.171*	*0.584*
Uncertainty avoidance	-49.005	*71.740*	-66.071	*73.072*	*0.242*
Long-term orientation	-11.780	*62.448*	-28.571	*57.797*	*0.181*
Indulgence vs. restraint	74.110	*77.553*	80.357	*59.627*	*0.683*
Personality-related controls					
Openness	11.115	*2.533*	11.607	*2.409*	*0.335*
Conscientiousness	14.979	*3.042*	15.429	*2.781*	*0.461*
Extraversion	13.529	*3.812*	13.571	*4.541*	*0.957*
Agreeableness	9.544	*3.491*	10.170	*2.982*	*0.362*
Neuroticism	9.089	*4.283*	8.321	*4.000*	*0.373*
General interpersonal trust	3.129	*0.849*	2.809	*0.981*	*0.067*
Social value orientation	0.568	*0.186*	0.526	*0.182*	*0.268*

This table shows average values and standard deviations of the variables used in my analyses grouped by *Overestimation*. P-values of a two-sample t-test are presented in the right column. The variables *gender*, *marital status*, *working hours*, *living conditions*, and *round* do not appear here due to their categorical nature.

Table 2 *Pairwise Correlations*

Variables	*Relative Trading Volume*	*Overestimation*	*Overprecision*	*Trust*	*Emotional*	*Detailed*	*Video*	*Age*	*Financial Literacy*	*Self-assessed risk preference*
Relative Trading Volume	1.000									
Overestimation	0.171***	1.000								
Overprecision	0.090**	0.279***	1.000							
Trust	-0.064	-0.007	-0.130***	1.000						
Emotional	0.044	-0.075*	0.048	-0.057	1.000					
Detailed	-0.054	0.040	-0.054	0.104***	0.119	1.000				
Video	-0.069*	-0.021	0.097**	0.185***	-0.079**	0.082	1.000			
Age	-0.013	0.046	0.069*	0.009	-0.054	0.004	0.072*	1.000		
Financial Literacy	-0.044	-0.218***	-0.403***	-0.186***	0.033	-0.091**	0.101*	0.005	1.000	
Self-assessed risk preference	-0.125***	-0.262***	-0.271***	0.170***	-0.163***	0.048	0.032	-0.051	-0.095**	1.000

This table shows pairwise correlations of the most important variables used in our analyses. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels.

Table 3 *Random-effects Tobit regression results, dependent variable: Relative Trading Volume*

	Relative Trading Volume (1)		***Relative Trading Volume*** (2)	
Overestimation	0.126***	*0.047*	0.011	*0.065*
Overprecision			-0.109	*0.135*
Overestimation × Overprecision			0.812***	*0.315*
Trust Overall	0.001	*0.017*	0.001	*0.017*
Emotional	0.055*	*0.031*	0.060**	*0.031*
Detailed	-0.038	*0.029*	-0.041	*0.029*
Video	0.028	*0.035*	0.028	*0.035*
Advice	0.010	*0.022*	0.011	*0.022*
Financial Literacy	-0.006	*0.008*	-0.006	*0.009*
Self-assessed risk preference	-0.003	*0.023*	0.002	*0.023*
Age	-0.004	*0.004*	-0.004	*0.004*
Gender (0 = female)				
Male	0.052	*0.032*	0.059*	*0.032*
Other	-0.051	*0.130*	-0.004	*0.129*
Marital status (0 = single)				
In a relationship	-0.005	*0.042*	-0.005	*0.042*
Married	-0.071	*0.070*	-0.026	*0.071*
Working hours (0 = zero hours)				
1 to 15 hours	0.059	*0.062*	0.053	*0.062*
16 to 25 hours	0.140**	*0.063*	0.146**	*0.063*
26 to 35 hours	0.106	*0.065*	0.106	*0.064*
More than 35 hours	0.161*	*0.088*	0.162*	*0.086*
Living conditions (0 = with parents)				
With partner	0.066	*0.057*	0.071	*0.056*
Shared apartment	0.012	*0.055*	0.019	*0.055*
Student accommodation	0.060	*0.063*	0.064	*0.062*
Alone	0.037	*0.057*	0.043	*0.056*
Round (0 = Round 2)				
Round 3	-0.046***	*0.017*	-0.046***	*0.017*
Round 4	-0.055***	*0.017*	-0.055***	*0.017*
Constant	0.086	*0.182*	0.071	*0.185*
# observations	657		657	
# groups	219		219	

This table shows the results of a random-effects Tobit regression that evaluate the effect of overestimation and overprecision on relative trading volume. All models include control variables which are explicitly stated in the table. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Standard errors in italics.

Table 4 *Random-effects Tobit regression results including additional controls, dependent variable: Relative Trading Volume*

	Relative Trading Volume (1)		***Relative Trading Volume*** (2)	
Overestimation	0.135***	*0.046*	0.025	*0.064*
Overprecision			-0.051	*0.140*
Overestimation × Overprecision			0.735**	*0.309*
Trust Overall	0.002	*0.017*	0.004	*0.017*
Emotional	0.076**	*0.030*	0.080***	*0.030*
Detailed	-0.049*	*0.028*	-0.059*	*0.028*
Video	0.028	*0.038*	0.029	*0.038*
Advice	0.017	*0.022*	0.018	*0.022*
Financial Literacy	-0.002	*0.008*	-0.001	*0.009*
Self-assessed risk preference	0.002	*0.023*	0.008	*0.023*
Age	-0.001	*0.004*	-0.002	*0.004*
Gender (0 = female)				
Male	0.045	*0.039*	0.046	*0.034*
Other	-0.061	*0.126*	-0.018	*0.125*
Marital status (0 = single)				
In a relationship	-0.011	*0.042*	-0.014	*0.041*
Married	-0.062	*0.070*	-0.019	*0.071*
Working hours (0 = zero hours)				
1 to 15 hours	0.048	*0.061*	0.043	*0.061*
16 to 25 hours	0.123*	*0.064*	0.128**	*0.063*
26 to 35 hours	0.107*	*0.064*	0.106*	*0.063*
More than 35 hours	0.149*	*0.086*	0.152*	*0.085*
Living conditions (0 = with parents)				
With partner	0.062	*0.056*	0.066	*0.056*
Shared apartment	-0.000	*0.055*	0.007	*0.054*
Student accommodation	0.042	*0.062*	0.046	*0.061*
Alone	0.036	*0.056*	0.041	*0.055*
Round (0 = Round 2)				
Round 3	-0.046***	*0.017*	-0.046***	*0.017*
Round 4	-0.055***	*0.017*	-0.055***	*0.017*
General Interpersonal Trust	-0.004	*0.017*	-0.005	*0.017*
Social Value Orientation	0.126	*0.081*	0.127	*0.083*
Power Distance	-0.000	*0.000*	-0.000	*0.000*
Individualism	-0.001**	*0.000*	-0.001***	*0.000*
Masculinity	0.000	*0.000*	0.000	*0.000*
Uncertainty Avoidance	0.000	*0.000*	0.000	*0.000*
Long Term Orientation	0.001***	*0.000*	0.001***	*0.000*
Indulgence vs. Restraint	0.001**	*0.000*	0.001**	*0.000*
Neuroticism	0.001	*0.004*	0.001	*0.004*
Agreeableness	0.002	*0.005*	0.002	*0.005*
Extraversion	-0.001	*0.004*	-0.002	*0.004*
Conscientiousness	-0.007	*0.006*	-0.007	*0.006*
Openness	0.005	*0.006*	0.005	*0.006*
Constant	-0.071	*0.256*	-0.092	*0.262*
# observations	657		657	
# groups	219		219	

This table shows the results of random-effects Tobit regressions that evaluate the effect of overestimation and overprecision on relative trading volume. All models include additional control variables which are explicitly stated in the table. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Standard errors in italics.

Table 5 *Random-effects Tobit regression results, dependent variable: Absolute Trading Volume*

	Absolute Trading Volume		***Absolute Trading Volume***		***Absolute Trading Volume***		***Absolute Trading Volume***	
	(1)		(2)		(3)		(4)	
Overestimation	4,802.527*	*2,673.057*	-3,505.803	*3,672.07*	4,959.187*	*2,671.920*	-3,201.230	*3,689.762*
Overprecision			-5,393.151	*7,588.855*			-3,143.554	*8,009.891*
Overestimation × Overprecision			57,789.750***	*17,866.530*			55,037.810***	*17,729.550*
Trust Overall	-1,687.191*	*972.828*	-1,563.035	*974.064*	1,668.977*	*953.615*	-1,482.172	*950.565*
Emotional	348.117	*1,765.855*	772.006	*1,729.562*	889.894	*1,760.639*	1,292.593	*1,726.077*
Detailed	-871.340	*1,663.880*	-1,001.155	*1,629.247*	-757.331	*1,634.952*	-821.466	*1,603.692*
Video	-2,540.563	*1,990.010*	-2,654.012	*1,999.086*	-2,761.175	*2,198.199*	-2,707.304	*2,180.817*
Advice	1,431.817	*1,262.896*	1,541.461	*1,238.282*	2,039.550	*1,280.941*	2,185.148*	*1,257.978*
Financial Literacy	-243.320	*453.682*	-176.601	*519.269*	42.187	*460.854*	199.906	*548.876*
Self-assessed risk preference	-1,555.889	*1,311.839*	-1,084.876	*1,317.822*	-1,161.267	*1,322.735*	-655.922	*1,328.775*
Age	172.239	*221.051*	131.887	*216.541*	292.734	*222.617*	237.045	*218.590*
Gender (0 = female)								
Male	3,469.445*	*1,827.040*	3,834.270**	*1,811.350*	3,418.145*	*1,940.076*	3,427.141*	*1,921.141*
Other	-3,569.439	*7,354.492*	-537.031	*7,249.775*	-6,004.931	*7,225.931*	-2,911.242	*7,141.457*
Marital status (0 = single)								
In a relationship	-2,417.999	*2,378.643*	-2,483.959	*2,353.077*	-2,531.144	*2,372.801*	-2,704.356	*2,347.556*
Married	-33.468	*4,095.238*	3,461.646	*4,173.453*	1,446.850	*4,090.813*	4,810.513	*4,183.047*
Working hours (0 = zero hours)								
1 to 15 hours	-2,089.410	*3,525.728*	-2,531.370	*3,460.643*	-2,179.641	*3,537.965*	-2,412.827	*3,470.003*
16 to 25 hours	471.490	*3,601.028*	846.043	*3,540.221*	-153.090	*3,671.353*	253.766	*3,596.354*
26 to 35 hours	-246.018	*3,691.341*	-294.102	*3,619.930*	-71.258	*3,663.681*	-88.414	*3,583.283*
More than 35 hours	-1,738.649	*4,985.713*	-1,365.948	*4,869.857*	-2,246.429	*4,964.128*	1,740.291	*4,857.956*
Living conditions (0 = with parents)								
With partner	2,343.578	*3,254.354*	2,621.558	*3,179.241*	1,241.607	*3,252.260*	1,544.293	*3,182.661*
Shared apartment	-2,661.589	*3,149.195*	-2,231.947	*3,093.765*	-3,240.628	*3,144.368*	-2,685.039	*3,094.246*
Student accommodation	1,924.331	*3,595.944*	2,380.034	*3,510.994*	1,128.978	*3,556.367*	1,566.137	*3,480.292*
Alone	-995.140	*3,228.422*	-643.360	*3,158.701*	-1,601.340	*3,227.898*	-1,182.960	*3,161.494*
Round (0 = Round 2)								
Round 3	-3,128.574***	*1,001.763*	-3,070.871***	*999.971*	-3,114.053***	*1,000.869*	-3.055,714***	*999.270*
Round 4	-3,159.324***	*1,006.308*	-3,137.748***	*1,003.833*	-3,161.724***	*1,005.326*	-3.140,124***	*1,003.029*

General Interpersonal Trust					-1,868.989*	*1,013.012*	-1,852.172*	*991.398*
Social Value Orientation					5,445.08	*4,638.902*	5,745.457	*4,767.002*
Power Distance					-10.633	*14.169*	-9.048	*13.928*
Individualism					-11.152	*14.922*	-14.150	*14.667*
Masculinity					14.351	*15.231*	11.322	*14.945*
Uncertainty Avoidance					2.211	*13.567*	-1.212	*13.315*
Long Term Orientation					29.774**	*13.929*	26.655*	*13.720*
Indulgence vs. Restraint					18.305	*13.531*	14.497	*13.299*
Neuroticism					199.608	*242.972*	173.566	*241.331*
Agreeableness					211.109	*270.711*	278.506	*265.915*
Extraversion					153.714	*230.243*	58.396	*227.251*
Conscientiousness					-116.527	*323.643*	-109.436	*319.118*
Openness					327.824	*342.180*	360.171	*335.909*
Constant	17,452.93*	*10,378.13*	15,082.64	*10,476.10*	4.010,48	*14,878.72*	968.25	*15,120.59*
# observations	657		657		657		657	
# groups	219		219		219		219	

This table shows the results of random-effects Tobit regressions that evaluate the effect of overestimation and overprecision on absolute trading volume. All models include control variables which are explicitly stated in the table. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Standard errors in italics.

__Table 6__ Random-effects OLS regression results, dependent variable: Relative Trading Volume

	Relative Trading Volume		***Relative Trading Volume***		***Relative Trading Volume***		***Relative Trading Volume***	
	(1)		(2)		(3)		(4)	
Overestimation	0.096**	*0.044*	-0.010	*0.045*	0.101**	*0.043*	-0.002	*0.044*
Overprecision			-0.094	*0.152*			-0.031	*0.154*
Overestimation × Overprecision			0.752***	*0.292*			0.697***	*0.264*
Trust Overall	-0.008	*0.013*	-0.008	*0.015*	-0.009	*0.013*	-0.007	*0.014*
Emotional	0.030	*0.023*	0.035	*0.023*	0.046*	*0.024*	0.050**	*0.024*
Detailed	-0.026	*0.023*	-0.028	*0.023*	-0.032	*0.023*	-0.032	*0.023*
Video	0.001	*0.028*	0.001	*0.027*	0.002	*0.034*	0.002	*0.031*
Advice	0.010	*0.018*	0.010	*0.017*	0.016	*0.019*	0.017	*0.018*
Financial Literacy	-0.007	*0.006*	-0.007	*0.009*	-0.002	*0.006*	-0.000	*0.009*
Self-assessed risk preference	-0.009	*0.015*	-0.004	*0.015*	-0.005	*0.017*	0.001	*0.018*
Age	-0.001	*0.003*	-0.002	*0.003*	0.001	*0.003*	0.000	*0.003*
Gender (0 = female)								
Male	0.052*	*0.029*	0.058*	*0.032*	0.045	*0.033*	0.045	*0.035*
Other	-0.044	*0.060*	-0.000	*0.056*	-0.058	*0.062*	-0.017	*0.060*
Marital status (0 = single)								
In a relationship	-0.020	*0.030*	-0.020	*0.027*	-0.025	*0.030*	-0.028	*0.029*
Married	-0.039	*0.054*	0.001	*0.055*	-0.024	*0.055*	0.015	*0.056*
Working hours (0 = zero hours)								
1 to 15 hours	0.017	*0.038*	0.010	*0.039*	0.013	*0.044*	0.013	*0.044*
16 to 25 hours	0.083**	*0.042*	0.088**	*0.045*	0.071	*0.049*	0.071	*0.049*
26 to 35 hours	0.056	*0.041*	0.055	*0.042*	0.059	*0.044*	0.059	*0.044*
More than 35 hours	0.076	*0.059*	0.077	*0.059*	0.065	*0.061*	0.065	*0.061*
Living conditions (0 = with parents)								
With partner	0.052	*0.046*	0.055	*0.047*	0.044	*0.048*	0.044	*0.048*
Shared apartment	-0.009	*0.047*	-0.003	*0.050*	-0.016	*0.049*	-0.016	*0.049*
Student accommodation	0.035	*0.051*	0.038	*0.052*	0.022	*0.050*	0.022	*0.050*
Alone	0.017	*0.045*	0.022	*0.046*	0.012	*0.046*	0.012	*0.046*
Round (0 = Round 2)								
Round 3	-0.042***	*0.016*	-0.042***	*0.016*	-0.042***	*0.016*	-0.042***	*0.016*
Round 4	-0.048***	*0.016*	-0.048***	*0.016*	-0.048***	*0.016*	-0.048***	*0.016*

General Interpersonal Trust					-0.005	*0.013*	-0.012	*0.013*
Social Value Orientation					0.119	*0.077*	0.122*	*0.074*
Power Distance					-0.000	*0.000*	-0.000	*0.000*
Individualism					-0.000**	*0.000*	-0.001***	*0.000*
Masculinity					0.000	*0.000*	0.000	*0.000*
Uncertainty Avoidance					0.000	*0.000*	0.000	*0.000*
Long Term Orientation					0.001***	*0.000*	0.001***	*0.000*
Indulgence vs. Restraint					0.000**	*0.000*	0.000**	*0.000*
Neuroticism					0.001	*0.004*	0.001	*0.004*
Agreeableness					0.003	*0.005*	0.003	*0.005*
Extraversion					-0.000	*0.003*	-0.002	*0.003*
Conscientiousness					-0.005	*0.004*	-0.005	*0.004*
Openness					0.006	*0.007*	0.006	*0.007*
Constant	0.192	*0.132*	0.178	*0.155*	0.030	*0.242*	0.030	*0.242*
R^2	0.088		0.109		0.142		0.159	
# observations	657		657		657		657	
# groups	219		219		219		219	

This table shows the results of random-effects OLS regressions that evaluate the effect of overestimation and overprecision on relative trading volume. All models include control variables which are explicitly stated in the table. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.

Table 7 *Random-effects OLS regression results, dependent variable: Absolute Trading Volume*

	Absolute Trading Volume		***Absolute Trading Volume***		***Absolute Trading Volume***		***Absolute Trading Volume***	
	(1)		(2)		(3)		(4)	
Overestimation	6,840.615**	*3,096.260*	-824.564	*2,855.097*	7,150.537**	*2,968.634*	-184.866	*2,781.449*
Overprecision			-6,310.691	*10,057.670*			-3,574.551	*10,015.270*
Overestimation × Overprecision			54,214.640**	*21,438.750*			49,915.070***	*19,130.130*
Trust Overall	-963.855	*953.132*	-929.168	*966.834*	-1,004.436	*910.969*	-878.479	*931.544*
Emotional	1,707.173	*1,488.948*	2,055.981	*1,455.194*	2,607.731*	*1,522.577*	2,927.357*	*1,499.333*
Detailed	-1,530.064	*1,498.394*	-1,622.083	*1,527.796*	-1,793.741	*1,474.349*	-1,837.223	*1,487.698*
Video	491.299	*1,743.286*	442.522	*1,652.760*	-72.992	*2,162.384*	-1.193	*1,966.809*
Advice	692.342	*1,139.665*	732.905	*1,066.041*	1,219.548	*1,167.444*	1,297.951	*1,120.915*
Financial Literacy	-281.022	*375.175*	-280.709	*570.405*	-57.768	*352.629*	29.271	*559.139*
Self-assessed risk preference	-590.064	*1,006.877*	-212.249	*972.340*	-314.011	*1,084.856*	99.460	*1,096.902*
Age	-60.514	*196.997*	-86.825	*190.710*	90.296	*195.018*	45.365	*194.943*
Gender (0 = female)								
Male	2,655.715	*2,004.445*	3,066.197	*2,093.871*	2,226.222	*2,210.045*	2,284.384	*2,296.306*
Other	-4,784.003	*3,855.149*	-1,657.072	*3,286.490*	-6,416.577	*4,296.643*	-3,443.119	*3,807.085*
Marital status (0 = single)								
In a relationship	-424.414	*2,367.439*	-443.657	*2,142.993*	-667.727	*2,408.948*	-809.427	*2,278.510*
Married	-1,782.332	*3,493.096*	1,112.989	*3,650.055*	-931.054	*3,467.471*	1,802.446	*3,524.780*
Working hours (0 = zero hours)								
1 to 15 hours	921.609	*3,253.455*	440.791	*3,291.202*	683.315	*3,595.145*	333.949	*3,583.544*
16 to 25 hours	4,461.618	*3,085.290*	4,811.479	*3,329.286*	3,622.714	*3,624.031*	3,963.079	*3,700.828*
26 to 35 hours	3,049.913	*3,089.828*	3,003.967	*3,196.542*	3,245.085	*3,211.670*	3,208.194	*3,196.158*
More than 35 hours	4,553.904	*3,971.424*	4,613.495	*3,989.141*	3,817.981	*3,980.217*	4,037.392	*3,941.003*
Living conditions (0 = with parents)								
With partner	2,747.752	*2,732.703*	2,939.521	*2,793.796*	2,008.782	*2,929.441*	2,233.325	*2,910.985*
Shared apartment	-344.247	*2,825.107*	10.721	*3,045.889*	-1,023.345	*2,883.040*	-565.273	*3,002.934*
Student accommodation	3,713.251	*3,662.504*	3,905.281	*3,662.297*	2,755.883	*3,442.454*	2,964.011	*3,426.571*
Alone	842.227	*2,602.125*	1,201.390	*2,661.002*	440.629	*2,739.888*	822.874	*2,763.071*
Round (0 = Round 2)								
Round 3	-2,196.884**	*941.216*	-2,196.884**	*942.706*	-2,196.884**	*951.032*	-2,196.884**	*952.570*
Round 4	-2,481.973**	*1,050.552*	-2,481.973**	*1,052.216*	-2,481.973**	*1,061.509*	-2,481.973**	*1,063.225*

General Interpersonal Trust					-1,009.641	*887.594*	-1,045.795	*863.640*
Social Value Orientation					6,301.933	*4,958.767*	6,306.664	*4,738.668*
Power Distance					-6.142	*12.431*	-4.697	*12.568*
Individualism					-23.121*	*12.462*	-25.083**	*11.796*
Masculinity					20.822*	*12.380*	18.417	*11.926*
Uncertainty Avoidance					5.688	*18.234*	2.527	*17.988*
Long Term Orientation					42.723***	*15.436*	39.322***	*14.838*
Indulgence vs. Restraint					31.168**	*12.460*	27.724**	*11.608*
Neuroticism					102.660	*256.187*	72.862	*232.105*
Agreeableness					103.109	*298.734*	159.325	*294.098*
Extraversion					-38.362	*207.187*	-131.422	*210.984*
Conscientiousness					-261.390	*232.167*	-256.561	*237.915*
Openness					327.001	*195.018*	347.417	*410.774*
Constant	10,772.32	*8,920.72*	9,585.29	*10,245.44*	1,600.51	*15,012.60*	420.81	*15,680.33*
R^2	0.081		0.108		0.137		0.159	
# observations	657		657		657		657	
# groups	219		219		219		219	

This table shows the results of random-effects OLS regressions that evaluate the effect of overestimation and overprecision on absolute trading volume. All models include control variables which are explicitly stated in the table. Dependent variables appear in the first row of the table. ***, **, and *, respectively, describes statistical significance at the 1 %, 5 %, and 10 % levels. Robust standard errors in italics.