“In Design and Humans we Trust“? – Drivers of Trust and Advice Discounting for Robo Advice

Claudia Breuer[1]

Wolfgang Breuer[2]

Thomas Renerken[2]*

[1]Hochschule für Finanzwirtschaft & Management, Simrockstraße 4, 53113 Bonn, Germany.

[2]Department of Finance, RWTH Aachen University, Templergraben 64, 52062 Aachen, Germany.

****Corresponding author. Tel.: +49 241 80 94774;***

thomas.renerken@bfw.rwth-aachen.de.

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Abstract. We compare 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 as well as the involvement of a human. Our data are based on incentivized experiments. The results show that a more emotional design of the advice software leads to a higher level of advice acceptance, whereas a detailed exploration questionnaire reduces the level of acceptance. The presence of a human 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.

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 not only what characteristics a robo advisor should have to ensure that advice is taken into account as much as possible, but also compares the acceptance of advice under the presence of a human advisor via video conferencing software compared to the situation without human involvement. Using experiments in controlled environments, we investigate the factors on which the acceptance of financial advice depends.

To date, there is few research that compares the degree of acceptance of human advice with the acceptance of robo advice in a portfolio allocation context. Evidence exists that people generally “discount” advice offered to them to a certain extent, for a variety of reasons (Yaniv & Kleinberger, 2000). However, the willingness to follow a robo advice compared to a human advice cannot be easily predicted, as there may be different countervailing effects at work. On

the one side, literature suggests that people generally exhibit a behavioral pattern that Dietvorst et al. (2015) refer to as “algorithm aversion” (for an overview see Jussupow et al., 2022). People 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 on average (e.g., Dawes et al., 1989). It is, however, yet unclear, if algorithm aversion also occurs in a portfolio composition context that involves robo-advice.

On the other side, as there is evidence that people tend to trust a human more than a machine (Promberger & Baron, 2006), 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.

With regard to the acceptance of financial advice, Stolper & Walter (2017) generally state that “surprisingly, however, the question of whether advisees in fact implement the advice they receive is still largely unanswered […].” Tauchert & Mesbah (2019) try to address this research gap by investigating the acceptance of investment advice comparing human and robo advice. They 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, they 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 investment advice and portfolio composition in general and regarding the use of robo advisors in particular. We address how user interface layout, questionnaire length and the presence of a human advisor influence the acceptance of advice. This could help to create an "optimal" advice process with the goal to maximize advice acceptance. We find evidence that an emotional, rather informal layout as well as a short exploration questionnaire implies a higher acceptance of advice, while the involvement of a human leads to higher levels of trust in the advisor, but has a negative impact on advice acceptance. We attribute the latter finding to betrayal aversion.

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 a 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 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.

The existing robo advice services differ based on the user interface and the content of the interaction. 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 colors, pictures and emoticons. This might influence the acceptance of advice as well.

In order to understand why people do not (fully) 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 in this constellation is the acceptance of the 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).

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. The degree of trust in the advisor also appears to have a measurable negative impact on the extent of discounting. In several research papers, 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).

In this context, trust in the advisor 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) 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 with regard to 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 advisors 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 situations, but did not examine situations in the financial advice context with the particular 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 investment advice, since various 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). Studies have found that people are less willing to expose themselves to this social risk when facing a human compared to AI, since the AI is considered to act in a more unbiased way (Candrian & Scherer, 2022). This effect, which contradicts the finding that higher trust levels, in general, lead to a higher acceptance of advice, might explain why the results of the existing studies are inconsistent. In consequence, these effects need to be disentangled in our research.

3 Hypotheses

As already described in the literature review, the acceptance of advice is based on several decisive factors. 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 T1: 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 T2: Decision-makers will trust an emotionally oriented advice service to a greater extent than a distanced one.

Based on the existing literature, further hypotheses can also be formulated, which relate to the comparison of robo advice with human advice. With respect to algorithm aversion and its impact on trust, we assume that the advisees trust a real human more than a machine.

Hypothesis T3: Decision-makers trust a human advisor more than a robo advisor.

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

Hypothesis D1: 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 D2: Decision-makers will discount the advice of an emotionally oriented advice service less compared to a distanced one.

However, as elaborated in the previous section, we think that – controlling for trust – decision-makers follow advice from a human less, due to betrayal aversion, as they might see a human involved in a process as a source of a possible betrayal.

Hypothesis D3: Decision-makers will discount advice including human interaction to a greater extent than pure robo advice.

We suspect that the level of uncertainty avoidance may play a crucial role, because a human advisor might be seen as an additional factor of uncertainty concerning a possible social risk (Koehler & Gershoff, 2003; Gambetta, 1988), potentially leading to betrayal aversion on the side of the decision-maker and, with that, to "algorithm affinity" rather than algorithm aversion. Assuming that individuals are uncertain about a possible betrayal and therefore follow the advice to a smaller extent, the acceptance of advice originating from human sources can thus be moderated by uncertainty avoidance.

Hypothesis D4: Decision-makers discount advice including human interaction less when the values of Hofstede's uncertainty avoidance index are lower.

4 Experimental Design

We conducted two experiments to determine the effects of the questionnaire length, the design of the user interface, and 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 the

two dependent variables trust and advice discounting. We set up a robo advice software and asked the participants to invest their money, allocating it to a choice of stocks or funds (see Section 4.1 for a more detailed description). All the experiments described in Sections 4.1 and 4.2 have been conducted online and participants have been acquired using the database of a large German university. Thus, the experiments have been carried out in German.

4.1 Experiment 1: Acceptance of advice based on design and structure of robo advice

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). This 2x2-design lead 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.

We set up the questionnaire variants either as “superficial” or “detailed.” 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 online appendix of this paper on pages A.1 to A.5.

The design can be described either as “distanced” or “emotional.” The distanced one 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 advice, on the other hand, by a colorful scheme, colloquial language and the presence of smiley faces. The design was used

for the entire experiment in which allocation decisions play a role. Figure 1 exemplarily 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 per year 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 exemplarily 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 local, 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[1], 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 with the help of 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 allocation decisions had been completed.

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

[1] 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.

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 single 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 influence 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 15.59 €. 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.

>>> 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 focus 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 available 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 using 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 new available stocks.

Trust in the robo advisor was measured after receiving advice and making the final investment decision for the first time, but before receiving 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 online appendix 2 of this paper for the full questionnaire). In addition to demographic data such as the age or gender of the subjects, as already presented in Table 1, certain cultural characteristics (Hofstede, 2011) and the

Big Five personality traits (Digman, 1990, German translation by Körner et al., 2008) were also collected in this questionnaire. In addition, participants' so-called “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.

4.2 Experiment 2: Acceptance of Advice based on the involvement of human interaction

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 human advisors. The procedure was similar to that of the first experiment: One by one, as in the first experiment, the possible investment options 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 an actual advisor – who is present via a video conferencing software, simply shares the screen and uses the robo advice software from our first experiment – to answer personal questions in the exploration part of the experiment. 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, as outlined in the previous section. Finally, the participants were asked to make an allocation decision for all four decision situations under the impact of existing 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. They 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 our first experiment. Just like in this first experiment, data on trust in the advisor was collected. To avoid further biases, 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. They also had to answer the same personality- and demographics-related questions compared to the first experiment. In contrast to Experiment 1, this questionnaire had to be filled out a few days upfront instead of directly after the experiment in order to firstly, avoid possible biases when a human is present, and secondly, to limit the contact time with the advisors due to budget restrictions and the relatively high payouts for the professional bank employees.

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 (including all the different treatment groups just as in Experiment 1) while sharing the screen. An individual allocation proposal was then displayed, based on the same algorithm that was used in the first experiment. 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. Possible differences in the discounting of advice can thus only 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.

5 Results

5.1 Data

All in all, 219 subjects took part in our 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 van Rooij et al. (2012), participants gave the correct answer to an average of 9.26 questions, which is quite much. Again, this could be connected with their academic background. Concerning nationality, 173 individuals were German, 12 were Turkish and the other 34 participants all in all represented a total of 23 other nationalities. We calculated the acceptance of advice by computing an advice discounting measure based on Yaniv & Kleinberger (2000). However, as our decision was multidimensional (participants could decide how to invest their money offering multiple options and not only one risky and one risk-free possibility), we had to adjust the existing measurement of advice discounting based on 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:

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

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

$$AD_{i,j} = \frac{Distance(Final,Recommendation)_{i,j}}{Distance(Initial,Recommendation)_{i,j}}. \quad (2)$$

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 investor 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

5.2.1 Testing for Hypotheses T1 to T3

Based on our hypotheses in Section 3, we first want to find out whether the design and/or the questionnaire length as well as 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* as the dependent variable. The model is thus based on the following equation:

$$TrustOverall_i = b_0 + b_1 \cdot Emotional_i + b_2 \cdot Detailed_i + b_3 \cdot Video_i + \boldsymbol{b} \cdot \boldsymbol{C_i} + \varepsilon_i, \quad (3)$$

Whereas $Emotional_i$, $Detailed_i$ and $Video_i$ are dummy variables that take the value of 1 for participant *i* if the 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. The dependent variable, $TrustOverall_i$, 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). As 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 while the design of the user interface as well as the length of the questionnaire do not significantly influence trust, 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 expect that participants would, 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 4.

>>> Insert Table 4 about here <<<

We therefore cannot verify any significant effect of questionnaire length (Hypothesis T1) or type of presentation (Hypothesis T2) on trust, but our results show that trust levels are reported significantly higher when an actual human is involved in the process (Hypothesis T3).

5.2.2 Testing for Hypotheses D1 to D3

Subsequently, we want to find out how the variables *Emotional*, *Detailed*, *Video*, 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:

$$AD_{ij} = b_0 + b_1 \cdot Trust_{ij} + b_2 \cdot Emotional_{ij} + b_3 \cdot Detailed_{ij} + b_4 \cdot Video_{ij} + \boldsymbol{b} \cdot \boldsymbol{C_{ij}} + \varepsilon_{ij}, \quad (4)$$

whereas AD_{ij} describes the advice discounting measure of participant i in decision situation j (j ∈ 1, 2, 3, 4). We use the same control variables as we did in our regressions in Section 5.2.1. 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 5 show that without controlling for personality- and culture-related variables, $Trust_{ij}$ 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 of the dependent variable, ceteris paribus. This suggests that advice including human interaction is considered less, which contradicts much literature on algorithm aversion but supports the findings of Tauchert & Mesbah (2019).

This might relate to the idea the idea that a human is 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:

$$AD_{ij} = b_0 + b_1 \cdot Trust_{ij} + b_2 \cdot Emotional_{ij} + b_3 \cdot Detailed_{ij} + b_4 \cdot Video_{ij} + b_5 \cdot UAI_{ij} + b_6 \cdot UAI_{ij} \times Video_{ij} + \boldsymbol{b} \cdot \boldsymbol{C_{ij}} + \varepsilon_{ij}. \quad (5)$$

Looking at the results in Model (3), Table 5, 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 2). 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 $AD_{i,j}$, which are zero to infinity. The findings validate our previous results (see Table 6).

>>> Insert Table 5 about here <<<

>>> Insert Table 6 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 7). To further validate this, we run a random-effects Tobit regression model (see Table 8). The results are almost completely identical to those presented in Table 6. However, in Model (3), Table 8, the coefficient of the interaction term is not statistically significantly different from zero anymore (p = 0.106).

Regarding our hypotheses, we thus cannot confirm that a detailed questionnaire leads to less advice discounting (Hypothesis D1), but there is evidence that this holds true for an emotional

design (Hypothesis D2). With a view to the influence of human presence, we can state that a "real" advisor present during the process may lower advice discounting (at best) only for people with low uncertainty avoidance scores (Hypotheses D3 and D4).

>>> Insert Table 7 about here <<<

>>> Insert Table 8 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 ($p > 0.1$).

5.2.3 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. Furthermore, the 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 trust in general. 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"). 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. Using structural equation modeling, 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 by the previous tables. This is why we set up a more comprehensive moderated mediation model (see Figure 5).

>>> Insert Figure 5 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 and 5.2.2, 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 effect on all three dimensions of trust (see Table 9). *Detailed* has a significant positive effect on trust in the integrity ($p < 0.1$), which seems intuitively reasonable. *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 on overall trust and trust in the advisor's competence are not statistically significant. Following our hypotheses, we would expect advice discounting to be lower when the design is emotional (Hypothesis D2) and when the exploration questionnaire is detailed (Hypothesis D3). Indeed, the former is supported, but not the latter. Furthermore, as it was the case in our previous analyses, the presence of a human leads to more advice discounting, ceteris paribus. The moderating effect of uncertainty avoidance also persists.

>>> Insert Table 9 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 $0.163 + 0.001 \cdot UAI$. 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 concerning our analysis 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 components of the design within the treatment group who received the emotional or distant type of presentation. Moreover, the level of detail of the questionnaire is described by only two extremes: An extraordinarily superficial and a very detailed questionnaire. Looking at our results, it is striking that *Detailed* has a significantly positive impact on *AD* in nearly all of 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 these two extremes, 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 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 only realize their superior level of experience by answering a large number of questions. 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 9). 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.

We base our reasoning concerning the moderating effect of uncertainty avoidance on the uncertainty avoidance index as measured by Hofstede (2011). However, we are aware that Hofstede's cultural dimensions were not intended to be measured and analyzed on individual

levels, however, the dimensions are still widely used in this context, despite 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. The subjects further tend to be young academics who, due to their educational background, sometimes have intensive prior knowledge of issues relevant to the financial decision-making. This relatively homogenous age structure could also 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 or the presence of a human advisor 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. 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 analysis.

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 additional regressions (see Table 10). 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 risklessly 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 (2) 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 *Overall Trust*. 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 advisor 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 highly 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.

7 Conclusion

All things considered, we provide evidence that the setup of the robo advisor with regard to layout and exploration questionnaire length as well as integration of human communication plays an important role when it comes to the actual advice acceptance, with the latter one

also influencing trust in the advisor. However, the relationship between robo advisor characteristics, human involvement and advice utilization is not as straightforward as one might think: A more detailed exploration and the presence of a human does not lead to more but less acceptance of advice. We believe that human presence might be an additional factor causing uncertainty about a possible betrayal, ultimately leading to less advice utilization depending on the level of uncertainty avoidance. Moreover, we introduce an advice discounting measure for multidimensional decision-making situations that has not been used before, expanding the current literature on the acceptance of advice and offering further possibilities for future research.

Looking to the future, it would 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. Furthermore, future research could focus on the comparison of the acceptance of robo advice compared to "traditional" in-office financial advice.

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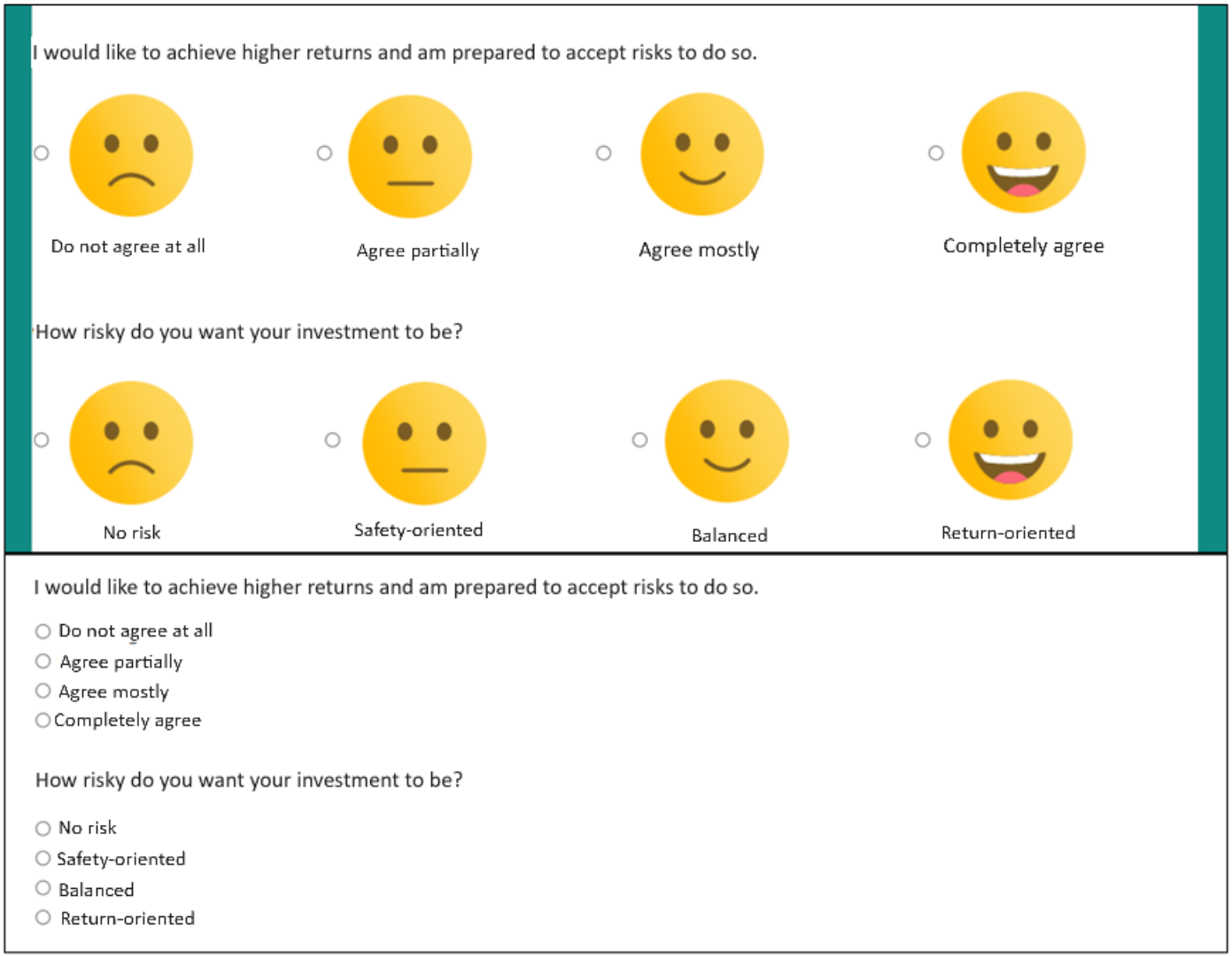
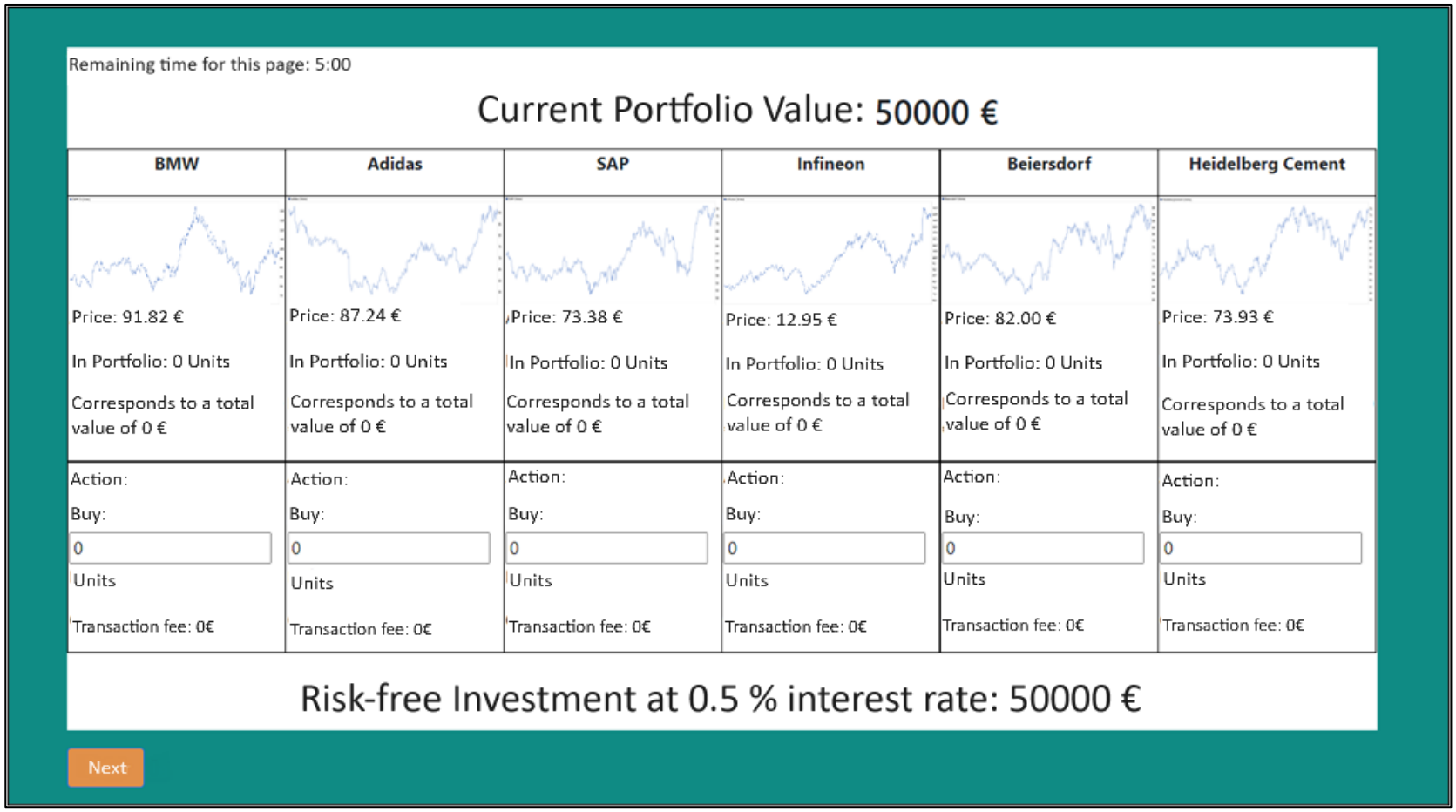
Figure 1 *Excerpt from the exploration questionnaire, emotional (top) vs. distanced (bottom) versions*



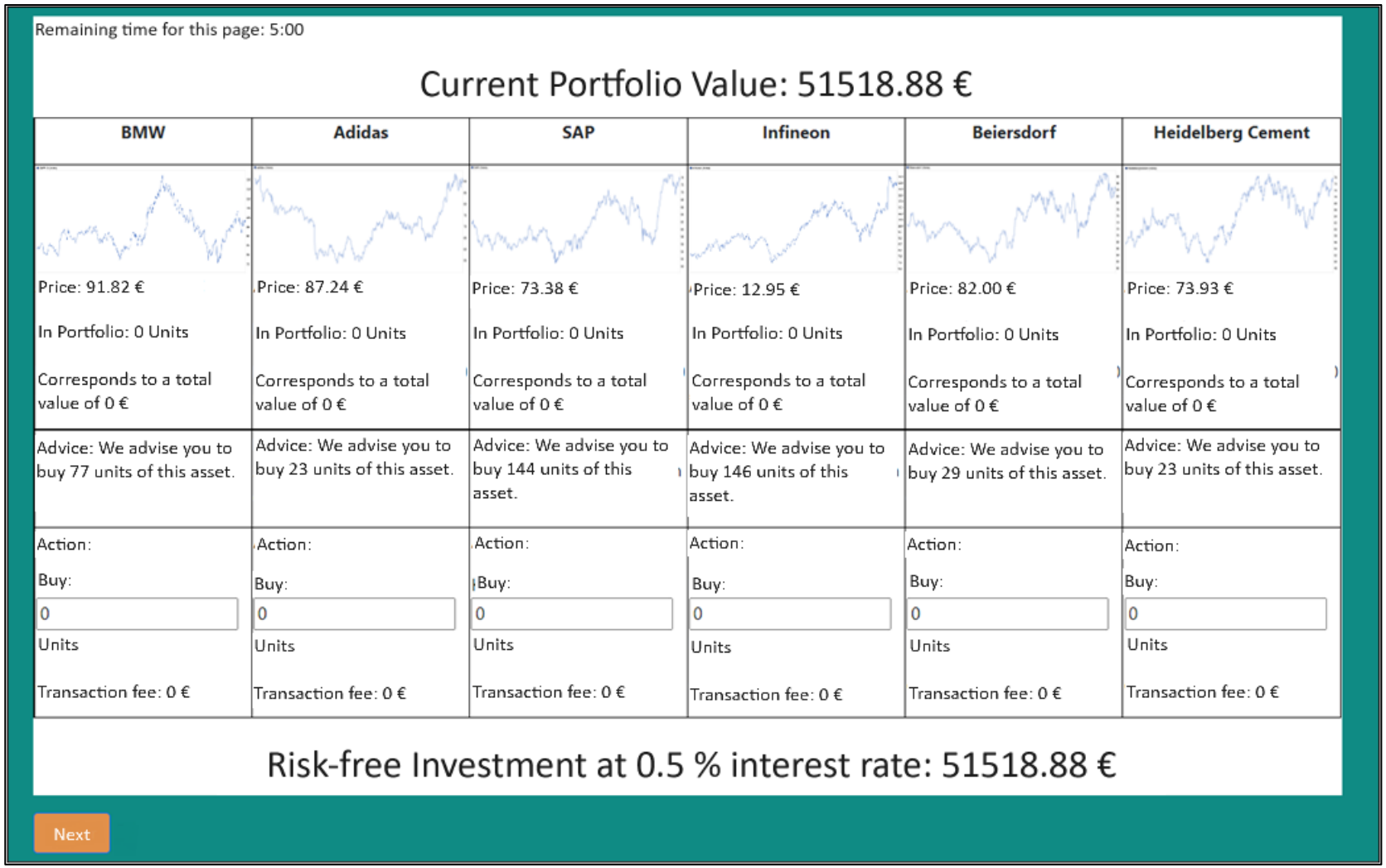
This figure shows the design of the two questionnaire versions exemplarily. The emotional design can be seen at the top half of the figure, the distanced design is depicted on the bottom half.

Figure 2 *User interface, emotional design*



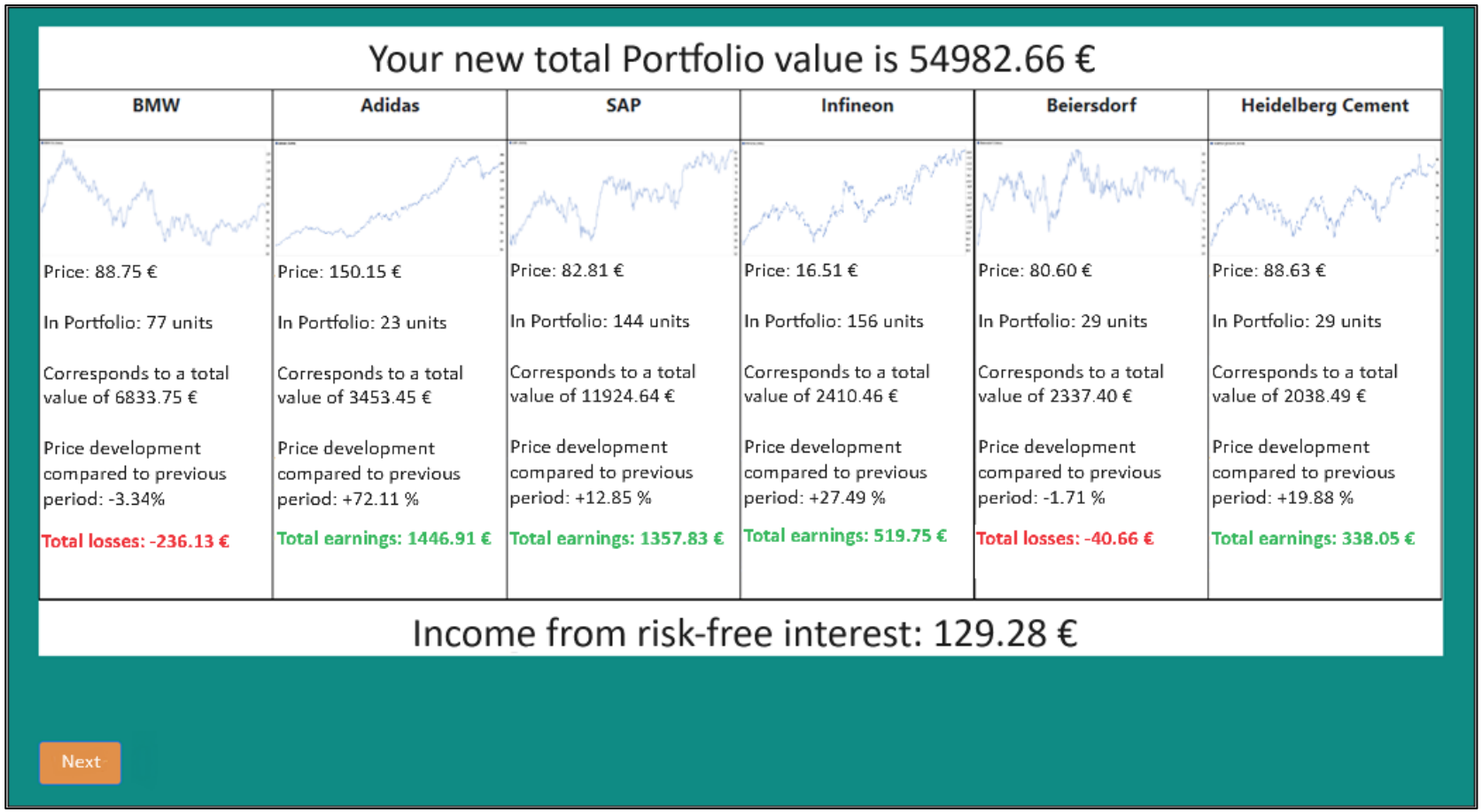
This figure shows a screenshot of the user interface participants were confronted with when making a first investment decision without advice. The screenshot is taken from the emotional layout version of the experiment.

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



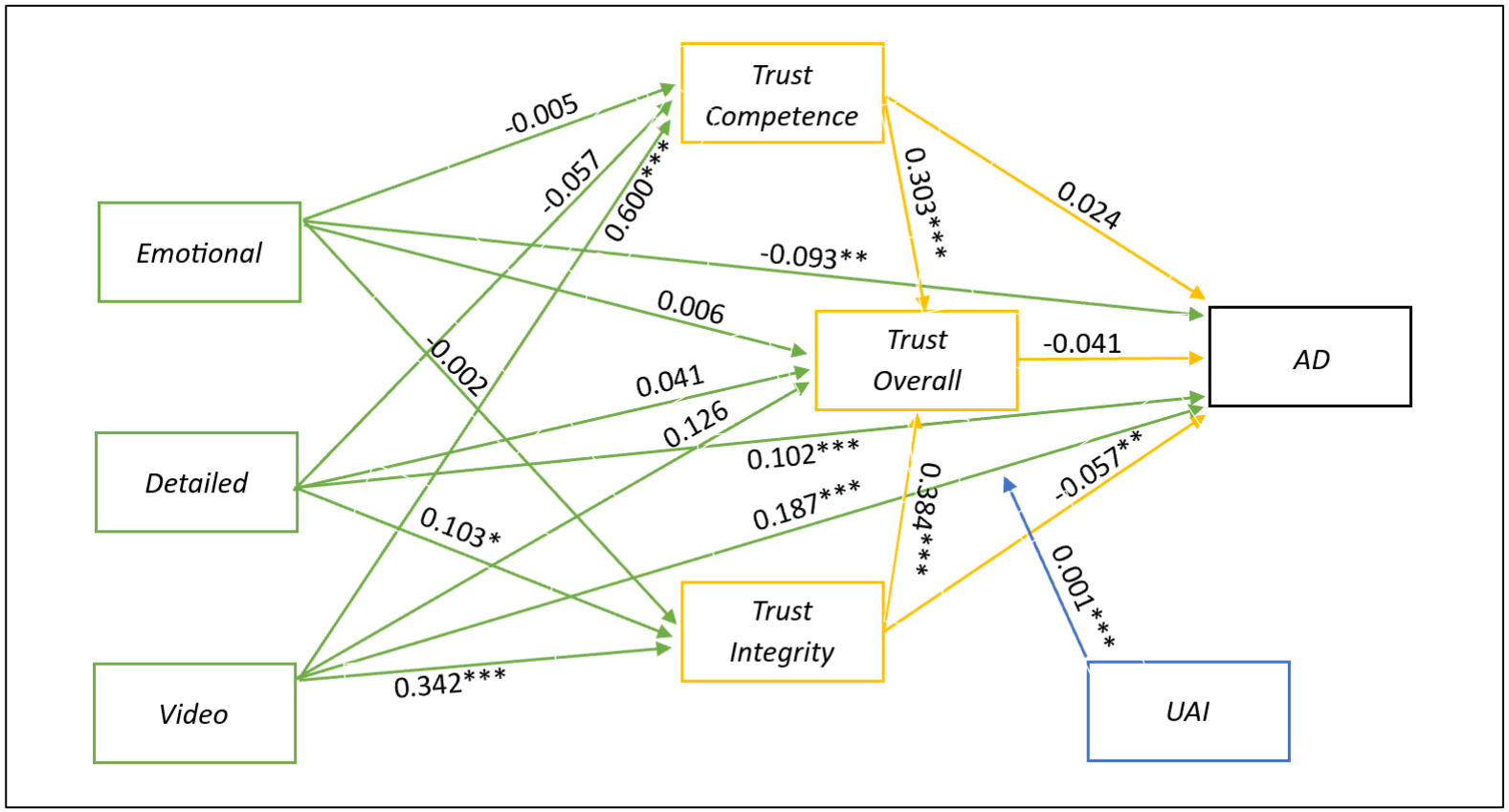
This figure shows a screenshot of the user interface participants were confronted with when making an investment decision including advice. The screenshot is taken from the emotional layout version of the experiment.

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.

Figure 5 *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 Table 1 for details concerning the variables used in this figure.

Table 1 *Overview of variables used in our analyses*

Variable	Description
Variables of key interest	
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.
Video	Equals 1 if a human advisor was present via video conferencing software, 0 otherwise.
Trust Overall	Overall trust in advisor, measured on a scale of 1 (very low) to 5 (very high).
Trust Competence	Trust in advisor's competence, measured on a scale of 1 (very low) to 5 (very high), see Section 5.2.3 for details.
Trust Integrity	Trust in advisor's integrity, measured on a scale of 1 (very low) to 5 (very high), see Section 5.2.3 for details.
Control Variables	
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", "student 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	219	0.655	0.548	0	4.474
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 3 *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 4 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 3*, conditional on the existence of a human advisor who is present via a video conferencing software.

Table 5 *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 Table 1. Full regression results in the online appendix of this paper (Table A.2).

Table 6 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 Table 1. Full regression results in the online appendix of this paper (Table A.3).

Table 7 *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 Table 1. Full regression results in the online appendix of this paper (Table A.4).

Table 8 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*
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 Table 1. Full regression results in the only appendix of this paper (Table A.5).

Table 9 *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 Table 1. Full regression results in the online appendix of this paper (Table A.6).

Table 10 *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 Table 1. Full regression results in the online appendix of this paper (Table A.7).

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.					

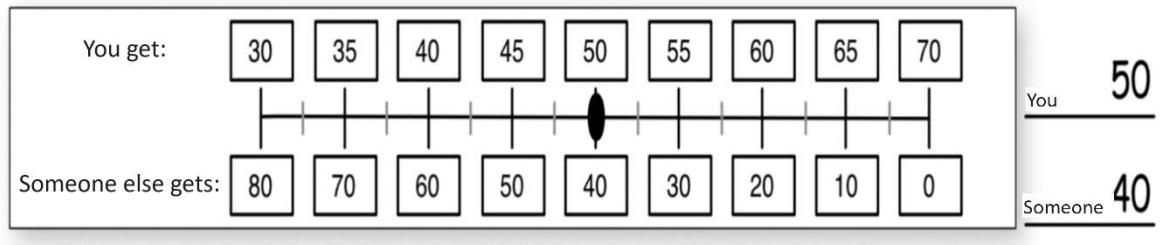
Instructions

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.**

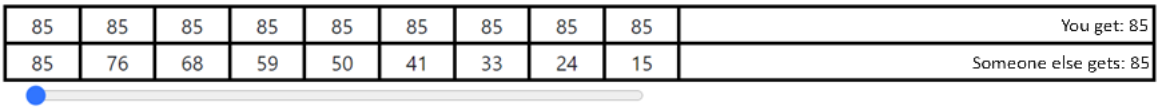
In the example below, one person has decided to split the money so that they receive 50 Euro while the anonymous other person receives 40 Euro.

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.



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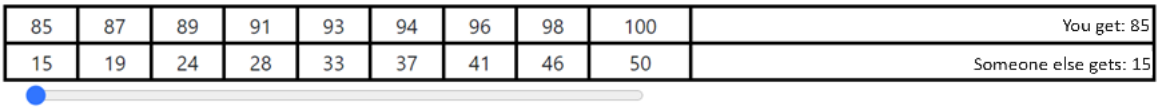
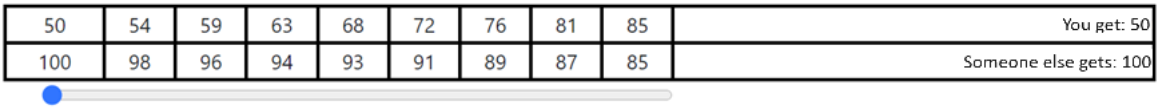


3.



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 disagree
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 wholeheartedly
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	0.004	*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. For details concerning basic, culture- and personality-related controls see Table 1. Full regression results in the online appendix of this paper (Table A.7).