Essays on Risk and Uncertainty Preferences

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Contents

List of Figures

List of Tables

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Chapter 1

Introduction

Uncertainty is an all-embracing challenge for individuals and society as a whole. Many decisions - especially those regarding the future - are made under uncertainty: decisions on production, health care, pension plans and even finding your spouse. Since human beings are heterogeneous, they react differently in uncertain situations. That is why, since early on, economists have been investigating decision making under uncertainty. In 1738 the Swiss mathematician Bernoulli disentangled the concepts of utility and expected value.[1] He states that two subjects facing the same lottery may evaluate the same uncertain situation differently. To illustrate his point Bernoulli uses an example with lotteries containing fair coin tosses. Bernoulli argues that the value an individual assigns to such a lottery depends on the individual traits towards uncertainty. Given Bernoulli's concept von Neumann and Morgenstern (1947) develop four axioms for preferences under which a subject evaluates a lottery by the expected value over all outcomes. We refer to this concept as the expected utility theory.

A major restriction of von Neumann and Morgenstern's theory is the fact that in order to compute the expected value, the probability distribution over the

[1] For an English translation see Bernoulli (1954).

set of outcomes must exist and be known to the decision maker. Savage (1954) argues that this is not a problem per se as long as the decision maker has a subjective probability distribution in mind that satisfies the assumptions of the expected utility theory.

Knight (1921) changes the understanding of uncertainty, as in his view the measurability of the probability plays an important role. He introduces the concept of ambiguity (or Knightian uncertainty). While under the expected utility theory the probability distribution is known and unique, under ambiguity a decision maker might not be able to assign a unique (subjective) probability distribution over the potential outcomes. Ellsberg (1961) presents thought experiments which illustrate that in an ambiguous situation behavior may occur for which no such subjective beliefs exist. This is not only a theoretical exercise as many experimental validations of the Ellsberg experiments show that a large share of subjects exhibits behavior which is inconsistent with expected utility theory (see Camerer and Weber 1992 or Oechssler and Roomets 2013).

When we think of real decision making situations the probabilities are only rarely known. Individuals face decisions in an uncertain environment in various real life situations. Prominent examples are decisions in which the payoffs realize in the future. Consider a situation in which an individual has to decide over a pension plan when entering the job market in a young age. Hence, for the decision maker it is essential that the decision made today fits her preferences when the payoff materializes in the future. Therefore, either the preferences need to be stable between the time of the decision and the payoff or the decision maker has to anticipate correctly a change in preferences over time when making the decision. While the literature provides some insights into the stability of risk preferences (Zeisberger et al. 2012), it is mainly quiet with respect to ambiguity attitudes. We tackle these research questions in chapter 3.

We analyze the stability of ambiguity preferences experimentally. To elicit ambiguity aversion, we use a standard tool of the ambiguity literature, the 3-color urn from Ellsberg's thought experiment. For the intertemporal stability, we repeatedly elicit ambiguity attitudes towards multiple 3-color urns over a period of two months. In our data, 57% of the choices are consistent with stable preferences over the time of two months. This share is significantly higher than random choices would suggest, but also far away from a full consistency. In order to isolate the pure time effect on the consistency level we use a control treatment whose structure is identical to the main treatment but omits the time delay of two months. With this treatment, we estimate a statistically significant drop of the consistency level by 14% over two months. In order to measure if subjects are able to anticipate a change in preference correctly we separate payoffs and decisions and move the payoffs into the future. We do not find any effects on consistency. Of course, the time frame in our experiment is relatively short compared to a pension plan, but the results show a significant effect on consistency even after such a short period. In a further task, we elicit the subjects' capacity to recall their choices made two months before. Surprisingly, for subjects who are able to recall their decision correctly, the share of consistent choices does not drop significantly over time.

In contrast to chapter 3, which deals with attitudes towards ambiguity, chapters 4, 5 and 6 investigate behavior towards risk. Chapter 4 and 5 are based on a common artefactual field experiment. Similar to the case of ambiguity, individuals permanently have to make decisions under risk. Many of these decisions are complex and made under the assistance of professional advisors. This is also because individuals prefer having assistance of an advisor when making a decision (see Schotter 2003). Prominent examples are the choice of pension plans or medical treatments.[2] In an experiment Powdthavee and Riyanto (2012) show that even in a game with purely random payoffs subjects are willing to pay for advice. As subjects give advice such a high priority, it is important for the advisor's advice to match the preferences of the advisee. In chapters 4 to 6 we investigate subjects' ability to "read out" others' risk preferences. This is the link that spans over these three chapters. In all chapters, we test the ability to predict the risk preferences of others under various conditions. Subjects have to make the predictions while we manipulate the available information.

There is a large body of literature that studies the correlation between risk preferences and demographics (see Harrison and Rutström 2008, Croson and Gneezy 2009 or von Gaudecker et al. 2011). Furthermore, behavior under risk such as financial decisions, smoking and occupational choices can be predicted by risk preferences (Dohmen et al. 2011). In chapter 4 and 5 we study whether professional advisors know these correlations between demographics and risk attitudes and use this knowledge when giving their advice. As the following papers focus on a setting of financial advisory we apply an artefactual field experiment. Our subject pool contains financial professionals as well as non-professionals. We choose this design as there is evidence that occupational potential sorting may induce a selection bias on financial professionals (see Dohmen and Falk 2011).

In chapter 4 we explore differences between financial professionals and non-professionals. Although we do not find any statistical differences in the risk attitudes between financial professionals and non-professionals, we do detect differences in their knowledge regarding the correlations of demographics and risk preferences. Therefore, we compare the subjects' perceived correlation of

[2] More and more assets are managed by institutions instead of private individuals. For example, according to *TheCityUK*, a British lobby group, the assets under management doubled from 2002 to 2011 (see www.thecityuk.com/assets/Uploads/Fund-Management-2012.pdf, accessed on May 3rd 2013).

a certain demographic characteristic (or stereotype) with the true correlation. We find that experienced professionals are less aware of these correlations than non-professionals. Young professionals show a better knowledge of these correlations relative to non-professionals.

In contrast to chapter 4, where we investigate the relationship between different demographic characteristics and risk attitudes separately, in chapter 5 we look at demographic profiles as a whole. We inspect whether the advisors are capable to "read out" a real person's risk preferences given their demographic profile. By using multiple demographic profiles we account for correlations within the demographic categories (e.g., older people are more likely to be parents). A main feature of this experiment is that we use "real" profiles which we collect from a survey. By design we are able to compare these profiles to a large-scale dataset. This offers the opportunity to construct representative demographic profiles. As a result, the financial professionals show a higher precision when predicting the risk attitudes of these profiles. When analyzing the beliefs regarding the risk attitudes of these profiles we find a significant false consensus effect. In fact, the advisors' own risk preferences correlate significantly with their beliefs. This effect is the strongest for experienced professionals and might reflect a paternalistic trait of experienced advisors.

While in chapter 6 we focus on differences between financial professionals and non-professionals when predicting others' risk attitudes, in chapter 4 and 5 we inspect whether this prediction improves when having a personal conversation between advisor and advisee at hand. In this experiment we have three treatments. In all treatments the subjects' task is to predict the risk preferences of another person. First, similar to chapter 5, the prediction is made given demographic information only. Second, two subjects meet and have a personal chat. Subsequently, the prediction is made. Third, the subjects have to make the prediction given a transcribed conversation between two subjects only. As we want to isolate the effect of a conversation, the comparison between the first and the second treatment may be misleading because in a personal chat the advisor possibly receives additional information and is in a "hot state" (see Loewenstein 2005 or Bohnet and Frey 1999). In the second and the third treatment the information is similar but the third treatment lacks the emotional involvement of the personal contact. When we compare the predictions of the first with those of the third treatment we measure the effect of additional information transmitted in a conversation. Our results confirm that the additional information provided in a chat decreases the prediction errors. Comparing the second to the third treatment it is the emotional involvement we measure. Surprisingly, when comparing the second to the third treatment we find that the prediction errors increase. This is interesting for online banking applications where communication is less vivid and the costumer is not as identifiable as in a personal conversation, for example.

The remainder of this dissertation is organized as follows: In chapter 2 we introduce the preference measures which are applied in the experiments of the following chapters. Each of the following chapters is independent and can be read on its own.

All chapters are based on work with co-authors. Chapter 3 is a joint project with Peter Dürsch and Daniel Römer (see Duersch et al. 2013). All authors contributed to this paper in equal shares and in all parts of research. My main contributions are in the fields of the experimental design, the execution of the experiment and the empirical analysis. Chapters 4[3], 5[4] and 6[5] are based on three papers which are co-authored by Andrea Voskort. Both authors contributed to

[3]Roth and Voskort (2012b)

[4]Roth and Voskort (2012a)

[5]Roth and Voskort (2013)

these papers in equal shares to the design, execution, data analysis and writing. In these papers I have an over average stake in the programming work.

Although the chapters are independent they share a common appendix and the bibliography. The appendix contains the experimental instructions and supplementary material at the end of the thesis.

Chapter 2

Measurement of Uncertainty Preferences

For all experiments in this dissertation we use experimental preference measures. In this chapter we introduce and briefly discuss the methods we apply. Section 1 explains our experimental measure for ambiguity preferences, while section 2 discusses the different elicitation methods for risk preferences.

1 Ambiguity preferences

Chapter 3 investigates the stability of ambiguity preferences. We elicit ambiguity preferences by using a 3-color urn. This method is an experimental implementation of a thought experiment proposed by Ellsberg (1961). The experiment has the following structure: Consider an urn containing thirty balls. Ten balls are yellow (Y). The remaining twenty balls are either green (G) or blue (B) balls in an unknown distribution. In order to elicit the preferences, the subject faces two bets. For each bet the experimenters randomly draw a ball from the urn.[1] If the subject's bet coincides with the draw we pay €4 and

[1] After each draw the ball is returned to the urn.

otherwise €0. In the first bet the subject faces two possible choices: either to bet on Y or to bet on B. In the second bet the subject bets either on Y *or* G or on B *or* G. The above choices translate into ambiguity preferences according to table 2.1.

Ambiguity preference	Averse	Neutral	Neutral	Loving
Bet 1	Y	Y	B	B
Bet 2	B *or* G	Y *or* G	B *or* G	Y *or* G

Table 2.1: Classification of choices

Note that there are no beliefs that justify strictly preferring Y in bet 1 and B *or* G in bet 2 under the assumption of expected utility maximizing behavior. Rather, by preferring Y over B and B *or* G over Y *or* G a subject opts for choices with a known number of balls over choices where the number of winning balls is ambiguous. Such a subject is called ambiguity averse. Analogously, a subject preferring B over Y in bet 1 and Y *or* G over B *or* G in bet 2 is called ambiguity loving. Finally, Y and Y *or* G as well as B and B *or* G are the only choice combinations for which probability distributions of beliefs exist that satisfy subjective expected utility theory. Subjects showing this behavior are hence classified as ambiguity neutral.

Indifference The 3-color urn is not able to identify subjects who are indifferent in any bet. To tackle this issue, we add two non-incentivized questions to each bet. The questions are non-incentivized in order to exclude any possibility of hedging and to maintain the incentive-compatibility of the 3-color urn. In a first step, we follow Dominiak et al. (2012) and ask subjects about their confidence when making the bet.[2] This confidence measure ranges from

[2]The exact wording is "How confident (from "not confident at all" to "very confident") are you with this decision?".

"not confident at all" to "very confident" on a five point Likert-scale (denominated as confidence henceforth). Furthermore, we elicit a subject's hypothetical willingness to change the bet to the other choice (we will refer to this task as WTA).[3]

2 Risk preferences

In all chapters we elicit an individual's risk preference. There are various methods to measure risk preferences (Harrison and Rutström 2008 provide an excellent overview). In our experiments we use the measure of Holt and Laury (2002) and Dohmen et al. (2011), which we discuss in the following.

2.1 Multiple price lists

In all experiments subjects complete a risk preference measure in a multiple price list design (abbreviated MPL, see Holt and Laury 2002). Consider figure 2.1 for a graphical illustration for this mechanism. In the following we refer to this task as HL-task or MPL task. In this mechanism a subject faces choices between two lotteries (option A or option B). Option A pays €2 in the first state and €1.60 in the second state. Option B pays €3.85 in the first and €0.10 in the second state. The payoff of option A exhibits a lower variance than the payoff of option B. In the tenth row the expected payoff of option B strictly dominates the expected payoff of option A as the amount of €3.85 is paid for sure. Hence, every rational individual prefers B over A at least in row ten. An increasing row number indicates a higher probability that the first state is paid out. The more rows a subject opts for option B, i.e., the earlier a subject switches from

[3] The exact wording in the instructions is: "You will be paid-off according to your decision above. But, hypothetically asked, how much should we pay you such that you change your decision above?" The answers are scaled from €0 to €4.

TABLE 1 (Please choose for each row either A or B!)

	Option A						Option B		
Row	Payoff	Probability	Payoff	A	or	B	Payoff	Probability	Payoff
1	2 €	10% 90%	1,60 €	O		O	3,85 €	10% 90%	0,10 €
2	2 €	20% 80%	1,60 €	O		O	3,85 €	20% 80%	0,10 €
3	2 €	30% 70%	1,60 €	O		O	3,85 €	30% 70%	0,10 €
4	2 €	40% 60%	1,60 €	O		O	3,85 €	40% 60%	0,10 €
5	2 €	50% 50%	1,60 €	O		O	3,85 €	50% 50%	0,10 €
6	2 €	60% 40%	1,60 €	O		O	3,85 €	60% 40%	0,10 €
7	2 €	70% 30%	1,60 €	O		O	3,85 €	70% 30%	0,10 €
8	2 €	80% 20%	1,60 €	O		O	3,85 €	80% 20%	0,10 €
9	2 €	90% 10%	1,60 €	O		O	3,85 €	90% 10%	0,10 €
10	2 €	100%	1,60 €	O		O	3,85 €	100%	0,10 €

Figure 2.1: HL-task

option A to option B, the higher the subject's risk tolerance. For the subject's payoff experiment, one row is randomly chosen and a lottery according to the probability distribution of this row is played.

In chapter 3 and in the surveys of chapter 4 and 5 we use the HL-task as described above. For each subject we elicit ten separate decisions. However in chapter 4, 5 and 6, our experimental design requires the switching point to be singleton. In order to enforce monotonicity of the risk preferences we use a switching MPL or sMPL instead of the classic design (Andersen et al. 2006). Whereas in the MPL design a subject makes a separate decision for each of the ten rows, in the sMPL the subject is only asked for the marginal row switching from A to B.[4] We apply the sMPL as we want to compute the average decision later on.[5] This mechanism has been tested to measure risk attitudes outside the lab consistently (Harrison and List 2004, Harrison et al. 2007). The payoff procedure is the same as in the classical HL-task. An illustration of how this mechanism is presented to the subjects can be found in figure 2.1 in the ap-

[4] Holt and Laury (2002) do not find any significant effects for subjects with non-monotonic answers.

[5] See section 2.4 in appendix 2 for a graphical illustration of the sMPL mechanism.

pendix.

Although there are some concerns that this elicitation mechanism is prone to framing effects (see Harrison and Rutström 2008, Lévy-Garboua et al. 2011) a major advantage of the MPL measure is its symmetry. A subject always compares two lotteries having equal probability distributions but different payoffs. In other tasks subjects face a trade-off between a lottery and a certainty equivalent (e.g., Gneezy and Potters 1997 or Dohmen et al. 2011). This could potentially bias (e.g., less sophisticated) subjects towards the certainty equivalent as the single value is easier to evaluate than the more complex structure of the lottery.

2.2 €100,000 question

The second mechanism (hereafter: "€100,000 question") we apply is taken from the German socioeconomic panel (SOEP). We use this measure as it provides the opportunity to relate our experimental data to the large-scale data base of the SOEP survey. The exact wording of this risk task is as follows:

€100,000 question *Please consider what you would do in the following situation: Imagine that you had won €100,000 in the lottery. Almost immediately after you collect the winnings, you receive the following financial offer, the conditions of which are as follows: There is the chance to double the money. It is equally possible that you could lose half of the amount invested. You have the opportunity to invest the full amount, part of the amount or reject the offer. What share of your lottery winnings would you be prepared to invest in this financially risky, yet lucrative investment?*
Your Decision *€100,000 - €80,000 - €60,000 - €40,000 - €20,000 - Nothing, I would decline the offer.*

The elicitation mechanism is an ordered lottery selection design in which subjects can invest €100,000 into a lottery that doubles or halves the amount with equal probabilities. In order to provide incentives to take the decision thoroughly in the lab experiment, for the actual payoff we convert the €100,000 into €2.50, €80,000 into €2 etc. The reliability of this measure has been validated via a lab experiment with substantial stakes (Dohmen et al. 2011). In contrast to the lottery this design is very easy but it captures only preferences on the risk averse domain.

For a better comparability, the €100,000 measure is rescaled in the analysis. We will present the amount invested in an inverse order and refer to it as the amount *not* invested in the lottery in units of €10,000. By this, a value of 10 indicates that nothing is invested whereas a value of 0 means that €100,000 are invested into the lottery. Hence, in both measures a higher value indicates a higher degree of risk aversion.

Chapter 3

Intertemporal Stability of Ambiguity Preferences

1 Introduction

People who prefer alternatives with known probabilities over alternatives with unknown probabilities are ambiguity averse. In his seminal paper, Ellsberg (1961) described a thought experiment designed to test an individual's ambiguity aversion. Since then, the topic has received considerable attention in the literature (Etner et al. 2012). The thought experiment has been conducted many times with real subjects and incentives (see Camerer and Weber 1992, Oechssler and Roomets 2013 and Trautmann and Kuilen 2013). The usual result is that a majority of subjects are indeed ambiguity averse. As a consequence, ambiguity is taken into account to better explain real world phenomena and to make better predictions. Increasingly, ambiguity aversion models are applied to economic problems such as the stock market (Epstein and Schneider 2008) or climate change (see Weitzman 2009 or Millner et al. 2012).

In any model that makes predictions based on preferences, an often unmentioned, but important assumption is the stability of said preferences. To draw conclusions from previous observations to future behavior, we have to assume that an individual chooses according to the same rules at both points in time. When designing policies, for example in the context of the choice of pension plans or climate protection, we can only observe choices today while the payoffs realize in the future, often involving uncertainty. While the literature provides some insights into the stability of risk preferences (Zeisberger et al. 2012), it is mainly quiet with respect to ambiguity attitudes. The scarcity of real life choice situations with precise probabilities stresses the importance of an extension of the analysis to preferences on ambiguity. Since it is impossible, so far, to directly "read out" these preferences from the subject's mind, we repeatedly use a standard tool of the ambiguity literature, the 3-color Ellsberg urn, to classify and compare behavior over time. If subjects possess preferences for ambiguity, and if those preferences are stable, we expect choices to be consistent. That is, we expect subjects to reveal identical ambiguity preferences at two different points in time. To apply the strictest possible test, we use a design that allows us to obtain two measures of ambiguity aversion using the same elicitation procedure for one and the same, physically identical, urn.

Our experimental design allows us to study preference stability under different conditions. In our main comparison, we analyze the stability of ambiguity preferences by comparing choices on two 3-color Ellsberg urns over a period of two months. Moreover, we also look at two variations where the time interval between choices is reduced to a few minutes only. In the first variation, we repeat the same elicitation procedure directly after the first choices to test for the effect of time on stability. In a second variation, we keep the shorter time interval, but additionally delay the draws and the payoffs for one urn by two months to study the effect of deferred payoffs.

Overall, we find that individual choices are more stable than random choices would suggest. However, far from all subjects are consistent across all choices. Moving payoffs to the future does not significantly impact stability, but separating choices by two months' time leads to lower consistency. We even find reduced consistency when moving from back-to-back decisions to decisions that are taken roughly 10 minutes apart. Interestingly, for subjects recalling their choices after two months, we do not find time effects on stability.

In section 2, we briefly review the related literature. Section 3 explains the experimental design. In section 4 and 5 we present the results of our experiment. Finally, section 6 concludes.

2 Literature

There is a large number of studies that address the general question of preference stability. With respect to preferences on uncertainty, the majority of papers deals with expected utility theory and prospect theory (see Zeisberger et al. (2012) for a more detailed survey on this literature). To study stability, most papers compare choices at two different points in time. Wehrung et al. (1984) elicit hypothetical investment decisions of 90 business men with a delay of one year. They find a small but highly significant positive correlation ($\rho = 0.36$) for the corresponding personal risk measures. Smidts (1997) elicited Dutch farmers' certainty equivalents for 50/50 lotteries concerning the market price for potatoes in two consecutive years. Comparing the Arrow-Pratt measures of absolute risk aversion across the two years he observes a positive and significant correlation ($\rho = 0.44$). Harrison et al. (2005) conduct lab experiments and elicit risk preferences according to the Holt and Laury (2002) framework twice, with a delay of 20 to 28 weeks in between. By using a structural maximum likelihood model, they estimate coefficients of constant relative risk aversion and do not find any significant difference of the aggregate parameter between both points in time. Note, however, that they do not study individual stability. Andersen et al. (2008) elicit risk preferences over a 17-month period from a representative sample of the adult Danish population, using four different elicitation tasks. They find a positive and significant correlation (ranging from $\rho = 0.34$ to $\rho = 0.58$, depending on the actual task), but do not identify a general tendency for risk attitudes to change over time. In a related paper, Baucells and Villasís (2010) study the stability of risk preferences in a prospect theory framework. They observe a stable pattern of preferences on the aggregate level, while the percentage of individuals that change their responses across sessions is quite high (63%).

There are only few studies that address the stability of ambiguity aversion. None of them systematically investigates identical situations over distinct points in time. Eliaz and Ortoleva (2012) elicit multiple ambiguous decisions with one decision appearing three times in the same session. Here, 71% of subjects give consistent answers while the remaining 29% change their view when faced with the decision for the second or third time.[1] However, there is no variation in the time dimension in this study. Some other papers test for the stability of ambiguity aversion across different choice situations.[2] Stahl (2013) compares both classical variants of the Ellsberg urn and finds a lower number of ambiguity averse subjects in the 3-color urn (55%) than in the 2-color urn (70%). Moreover, he shows that the number of ambiguity averse choices drops as the relative payoffs of the ambiguous urn rises. Based on the observed choices

[1] In the experimental literature on ambiguity aversion, broader classifications (averse, neutral, loving) are more common than the estimation of a more specific parameter, which makes the use of a correlation coefficient less meaningful.

[2] Note that this approach cannot rule out the possibility that observed instabilities are driven by differences in the tasks and sources applied.

in these different situations, he classifies 60% of the subjects to be choosing "almost random", while 26% of choice patterns are consistent with expected utility and only 12% represent ambiguity averse choices. Binmore et al. (2012) also analyze decision behavior in different conditions and test the explanatory power of different theories. They find only weak evidence for consistent ambiguity aversion and explain this result by a stricter consistency requirement as they analyze two different (but related) comparisons in choices. Dimmock et al. (2011) compare ambiguity attitudes from different elicitation tasks and find at least 35% inconsistent classifications across the tasks. Summarizing, the literature suggests that choices under ambiguity contain a large share of randomness, at least when comparing behavior across different tasks.

3 Design

The experiment is designed as a sequence of two parts. The first part was run in November 2012 (November sessions) while the second part took place in January 2013 (January sessions). The time lag between the two parts varies from 47 to 59 days depending on the specific sessions the subject was assigned to. All sessions took place in the AWI lab at Heidelberg University. Subjects were recruited via the local ORSEE platform (Greiner 2004) and were informed in the invitation that the experiment would consist of two parts. To increase retention in the second part, we offered a €4 show up fee and fourteen different time slots in January for which the subjects received up to three invitations by e-mail.

The experiment was executed in a paper and pencil design. The complete instructions were distributed at the beginning of each session and remained with the subjects for the whole experiment. All random draws were made by means of physical devices and in the presence of the subjects.

Our measure for ambiguity preferences we use the standard 3-color urn proposed by Ellsberg (1961). We outline the procedures of the experimental task in chapter 1.

3.1 Main experiment

The main experiment contains multiple elicitations of ambiguity attitudes at different points in time. By comparing choices over time we can evaluate preference stability. Note, however, that not every change in behavior must be due to instable preferences in the strictest sense. When faced with a new urn, subjects might simply expect different (sets of) probability distributions and adjust their behavior accordingly. Therefore, we wanted to disentangle this confound and designed the experiment in a way that allows us to use the same urn at two different points in time. Comparing two measures of ambiguity aversion elicited by the same procedures and based on the physically identical urn is the strictest possible test for stability we can think of. In the following we describe the experimental procedures and start by introducing the different choice conditions used in the experiment.

Choice conditions We differentiate between three choice conditions (compare figure 3.1). Each condition consists of two urns. The two urns are identical in appearance and we do not provide any information on how the urns are filled.[3] The conditions differ with respect to the timing of decisions and payoffs. In condition *Present* (short: P), choices are made today and corresponding payoffs are realized today as well. In condition *Present-Future* (short: PF), choices are made today but random draws and payoffs are deferred to the future. In

[3]The pictures in figure 7.1 in the appendix show an example.

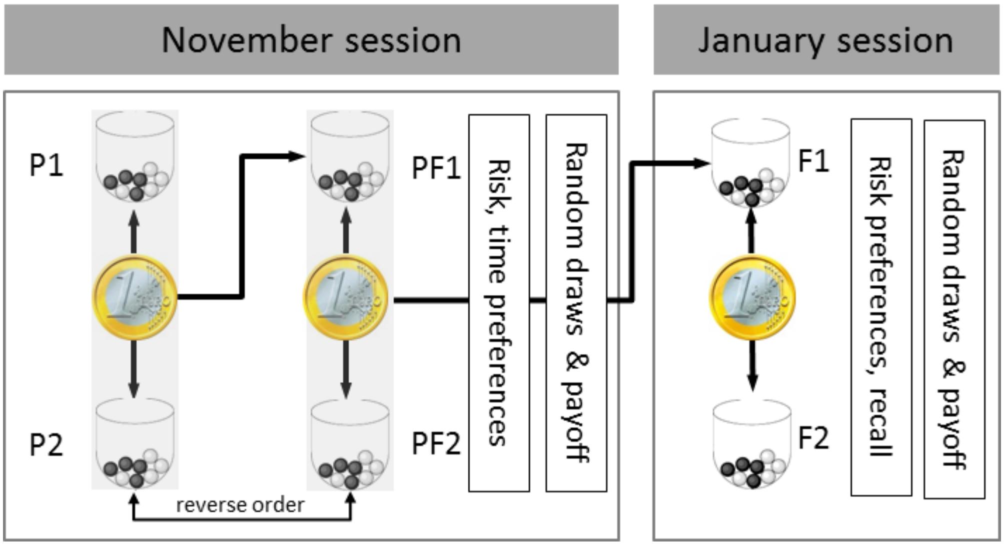


Figure 3.1: Course of actions

condition *Future* (short: F), both choices and payoffs take place in the future. Note that conditions P and F are structurally equivalent and only occur at different points in time. Hence, the comparison of P and F is the natural test for the stability of preferences over time.

Procedures Initially, subjects are seated and informed about the complete structure of the design at the beginning of each session. In the first part of the November sessions, in P, we ask subjects to make their choices for two urns (*P1* and *P2*). In this condition subjects make decisions in the present for the present, that is choices and payoffs happen in the same session (in November). After collecting the subjects' decisions, a coin is flipped and either *P1* or *P2* is determined for payment. The remaining urn is used again as *PF1*. In *PF*, subjects again have to make their choices for two urns, the relabeled urn (*PF1*) and a new urn (*PF2*). However, in this condition, choices are made in the present for the future, that is random draws and payoffs are postponed to the January sessions. After collecting the subjects' decisions, another coin flip decides which of the two *PF* urns will be paid off in January.

Roughly two months after the *P* and *PF* conditions, we run the January sessions. In condition *F*, we reintroduce the non-paid urn from *PF*, which is now labeled as *F1*. Additionally, a new urn is brought in (*F2*). We ask subjects to make choices for both urns. In this condition subjects make a decision in the future for the future, that is choices and payoffs happen in the same session (in January). When subjects have made their choices, a coin flip decides which of the urns is paid out.

Our design allows us to observe repeated choices on a physically identical urn without distorting the incentives. In particular, by moving an urn from *P* to *PF* we are able to observe incentive compatible choices for a physically identical urn under both *P* and *PF*. Similarly, by moving an urn from *PF* to *F* we observe choices of a physically identical urn in *PF* and *F*. Additionally, by eliciting ambiguity attitudes towards two urns in each choice condition, we get information on the stability of preferences across time within the smallest time interval possible: in two back-to-back decisions.

Reverse order In order to control for order effects within the November sessions, we randomized and counterbalanced the order in which subjects received the conditions *P* and *PF*.[4]

Credibility Since we elicit the ambiguity attitudes on a physically identical urn twice, a major concern is that subjects have to trust the experimenters that urns are not tampered. To tackle this issue, we take pictures of the urns in front of the subjects. Each picture carries a physical and unique time stamp. After finishing the experiment, all pictures are sent out to the subjects to verify that

[4]Note that the randomization procedure also affects the urn that is moved between the different conditions. In standard order, a *P* urn is moved to *PF* and a *PF* urn is moved to *F*. In reversed order, a *PF* urn is moved to *P* and a *P* urn is moved to *F*.

the urns have remained the same when moved between choice conditions.[5]

3.2 Treatment *single session*

In order to establish a strict test for the time effect, we also run an additional treatment omitting the time lag of two months. Applying the above coin flip procedure, we elicit ambiguity attitudes on four urns with immediate payoffs in a *single session*.

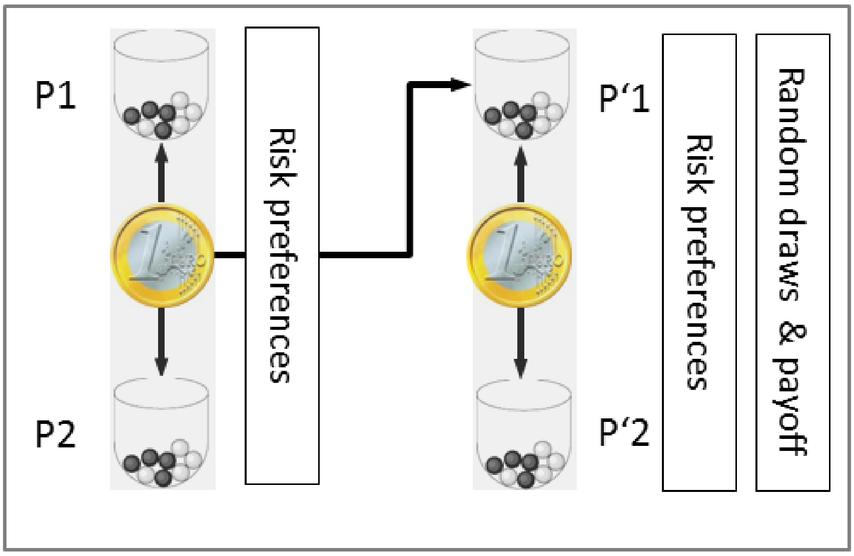


Figure 3.2: *Single session*: Course of actions

The structure is similar to the main experiment. First, we elicit ambiguity preferences on two urns denoted by *P1* and *P2* (see figure 3.2). After the decision is made, a coin flip decides which urn is paid out. The urn not chosen for payment is moved to the next choice condition *P'* which is identical to the first condition *P*: again, both choices and payoffs are realized today. *P'* represents a second elicitation of immediately paid choices and hence replaces *F* from the main experiment.[6] However, in contrast to the main experiment,

[5] In the appendix, we depict examples for these pictures.

[6] Note that in *single session* there is no counterpart to the *PF* condition with deferred payments as all choices and payments take place in the same session.

between P and P' approximately ten minutes elapse whereas between P and F there is a time span of two months. Therefore, comparing consistency levels between P and P' to those between P and F in the main experiment serves as a test for the effect of time.

3.3 Further measures

We elicit several additional variables to control for their potential impact on ambiguity preferences and their temporal stability.

Risk preferences In both experiments, after eliciting the ambiguity preferences, subjects complete a risk preference measure in a multiple price list design (Holt and Laury 2002). For a detailed discussion we refer to chapter 2.

Time preferences Moreover, in the November sessions, subjects are given a choice list that involves deferred payoffs (see figure 3.3). Option A pays €2 at date P for all ten decisions. Option B is paid out in the January sessions with payoffs ranging from €2 in the first decision to €3 in the tenth decision. A random draw chooses one payoff relevant decision. Any subject who discounts the future chooses option A in the first decision. Depending on their time preference, they will switch to B in later rows, or even stay with A all along for extreme time preferences.

	Option A			Option B	
row	Payoff today	A	or	B	Payoff in January
1	2,00 €	O		O	2,00 €
2	2,00 €	O		O	2,05 €
3	2,00 €	O		O	2,10 €
4	2,00 €	O		O	2,15 €
5	2,00 €	O		O	2,20 €
6	2,00 €	O		O	2,30 €
7	2,00 €	O		O	2,40 €
8	2,00 €	O		O	2,60 €
9	2,00 €	O		O	2,80 €
10	2,00 €	O		O	3,00 €

Figure 3.3: Elicitation of time preferences

Sociodemographic information In both experiments, as a last task, we survey sociodemographic information of the subjects including gender, age, body height, studentship and whether statistics, econometrics, or game theory classes had been taken.

Recall questions In the January sessions, two urns of the November sessions play a role: The *PF* urn which is chosen for payment and - depending on the order - the *PF* or *P* urn which was moved to the *F* condition (see figure 3.1). Therefore, in January, we elicit a subject's ability to recall the choices made in the November session. This task is incentivized as we pay €0.25 for each choice that is recalled correctly.

4 Main results

4.1 General information

In the November sessions of the main experiment 110 subjects participated, of which 105 returned to the January sessions. This amounts to a retention rate of 95%.[7] In the *single session* experiment 35 subjects participated. Fourteen subjects participated in both experiments.[8] The sample is balanced on gender (51% males) while 95% of the subjects are students. The average payoff was €6.87 in November, €17.34 in January and €13.44 in the *single session* treatment.

Averaged over all ambiguity tasks, we find 52.7% ambiguity averse, 37.4% neutral and 9.9% ambiguity loving choices. These numbers are in line with results other studies have found before (see Camerer and Weber 1992 and Oechssler and Roomets 2013).

In terms of recall capacity, we find 58.1% of the subjects remembering their preferences for the payoff relevant *PF* urn correctly (*recall* henceforth). This share is higher than in the case of random answers (N=103, p <0.001, binomial test).[9]

4.2 Descriptives: Consistency

Our main interest is the share of consistent choices with respect to the revealed ambiguity attitude. We define two choices to be consistent if they reveal the same ambiguity attitude in two different choice situations.[10]

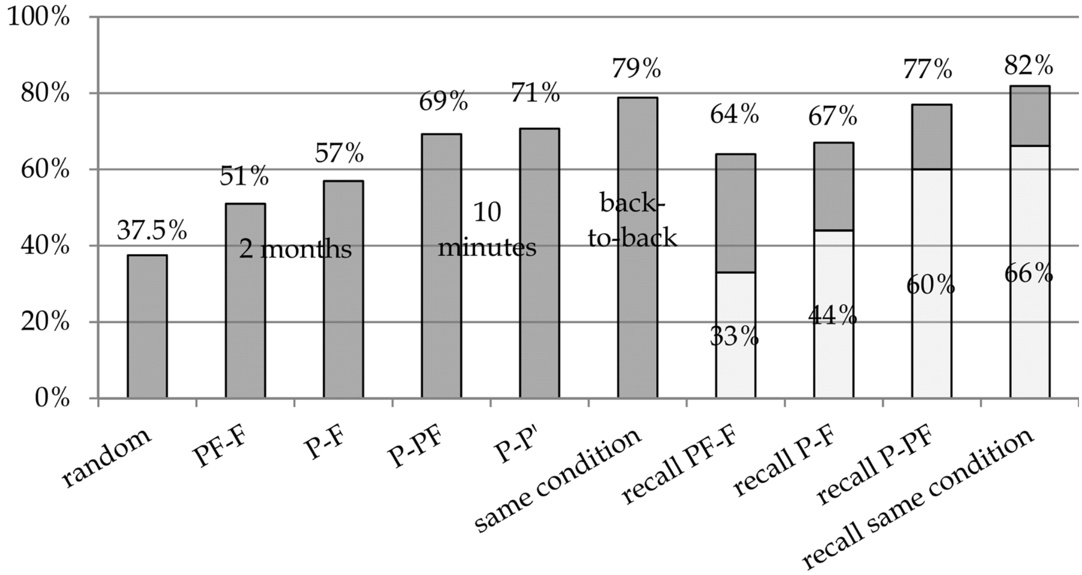
[7]Due to a mistake in the instructions we had to drop ten observations in one session. A few other observations were dropped on a case-by-case basis for some tests when decision sheets or questionnaires were returned incomplete.

[8]We invited subjects from *single session* to the main experiment with the intention of creating additional within subject comparisons. Due to the low rate of retention from *single session* to the main experiment, we drop this analysis. We successfully added additional incentives to increase subject retention in the main experiment. In the regressions, we cluster on the subject level.

[9]For the remainder of the paper we focus on the recall of the *PF* urn given its payoff relevance. In the other recall task, subjects performed similarly. 52.5% remember their preferences of the *P* urn that is moved to January. Also here, this share is statistically different from 25%, which would be expected for random answers (N=59, p <0.001, binomial test). Moreover, the correlation between both measures turns out to be $\rho = 0.48$.

[10]Note that there are two different choice combinations which are classified as ambiguity neutral (see table 2.1). For being consistent we do not require the same choices but the same revealed ambiguity attitude in two conditions.

Figure 3.4 shows the consistency levels for choices when comparing different situations (e.g., *PF-F* compares condition *PF* with condition *F*). First, we discuss differences in consistency while econometric tests are provided in the next section.



Last four bars: dark (light) bars for subjects that recall correctly (incorrectly). "2 months" etc.: time lag between decisions.

Figure 3.4: Consistency over choice conditions

Note that our subjects are in general more consistent than one would expect under random choice (37.5%, bar *random*).[11] However, they are also not fully consistent in their choices. Consistency varies with the time interval between decisions. Deferring the payoffs is less relevant for consistency.

Moreover, we can compare choices with different time lags. Here, the main difference is between decisions taken in the same session, with a delay of 10 minutes, and those taken in two different sessions, with a two months' lag in between. For the longer time lag we compare decisions in the November session with the decisions taken in the January session. Here, we find low levels of

[11] In each 3-color urn a subject can make four possible choices (one ambiguity loving, one ambiguity averse and two ambiguity neutral). Hence, when randomizing with equal probabilities over the four choice combinations we would expect a consistency level of 37.5%.

consistency represented by the bars *PF-F* (51%) and *P-F* (57%).

The level of consistency is higher when we consider decisions taken only 10 minutes apart. Bar *P-PF* depicts the consistency levels across decisions taken during the November session (69%). A second within session measure, bar *P-P'*, comes from the *single session* treatment and shows a very similar level (71%). Last we can analyze a third, even shorter time lag between decisions in the experiment. Remember that, in each choice condition, we asked subjects to state their preferences for two Ellsberg urns. This was done on a single decision sheet. That is, these decisions were taken back-to-back without any time delay.[12] For back-to-back decisions we find even higher levels of consistency (bar *same condition*[13], 79%). It seems that even a small time delay between decisions reduces consistency in behavior.

A very good predictor of consistent decision making is the subjects' ability to recall their previous decisions after two months. Bars *recall PF* and *recall P-PF* report the consistency levels for *PF-F*, *P-F* and *P-PF* when splitting the sample in subjects who remember their previous decision (light bars) and subjects who do not (dark bars). The recall ability especially affects consistency in decisions with two months' time delay. Subjects who, after 2 months, do not recall their previous decisions, have a consistency level similar to random behavior.

4.3 Econometric analysis

Data structure and consistency measures Before presenting the econometric results, we briefly describe the data structure. When assessing the consistency of choices in two conditions, we need to keep in mind that the subjects were asked to decide for two Ellsberg urns in each condition. Hence, denot-

[12]Since subjects could change their first urn decisions after answering for the second urn, one could also argue that the decisions where simultaneous.

[13]Pooled over all conditions (*P, PF, F, P'*).

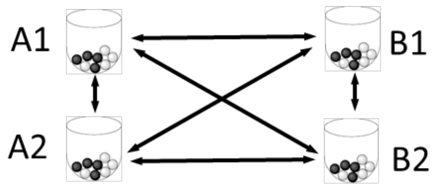


Figure 3.5: Data structure

ing the two conditions A and B, this involves four urns: *A1*, *A2*, *B1* and *B2*. Therefore, there are four possible comparisons between A and B corresponding to the horizontal and diagonal arrows in figure 3.5. We use all of these four comparisons in our regressions. That is, for each subject and each combination of conditions, we have four observations of the dependent variable *consistent*, set to one if the revealed ambiguity attitudes for the two corresponding urns coincide and 0 otherwise.

Further, our experimental design guarantees that subsequent choice conditions always share one identical urn (compare figures 3.1 and 3.2). Therefore, when comparing subsequent choice conditions, one out of the four arrows in figure 3.5 represents a comparison of decisions for a physically identical urn. In this case, the dummy variable *ident* is equal to 1. The dummy variable *reverse order* is set to one if *PF* choices were elicited first to counterbalance the order in the November sessions. Finally, we can compare the ambiguity attitude between the two urns within one condition (the vertical arrows in figure 3.5). These decisions are not part of comparisons across conditions. Instead, they form the comparison group *same condition*.

All consistency comparisons are necessarily within subject. We can compare conditions P to F, P to PF and PF to F, since subjects made decisions for all three cases P, F and PF. Hence, we gain multiple observations for each subject. As the independent unit of observation is the subject in the regression models below, we cluster standard errors on the subject level.[14]

An exception is the treatment *single session*, which is done in a different experiment and therefore provides an across subject comparison. Here we evaluate the differences between *P* and *P'* (figure 3.2).

As a robustness check, in section 5.1, we define consistency as having the same ambiguity attitude in all four urns (that is, being consistent along all arrows in figure 3.5 connecting *A* and *B*).

Regressions We test for differences in consistency levels across time lags via the regressions in table 3.1. In a probit model, with standard errors clustered on subjects, we explain *consistent* behavior, coded as a binary variable. Independent variables in our main model (1) are dummy variables representing different pairs of choice conditions *PF-F, P-PF, P-P'* and *same condition*. The omitted category is *P-F*. We add the *ident* dummy to test the effect of being consistent across two decisions for a physically identical urn whereas the *reverse order* dummy accounts for a possible order effect.

The significance of the coefficients confirms the visual impressions from figure 3.4. *P-F* and *PF-F* both feature a time lag of two months and are not significantly different from each other. However, *P-F* is significantly different both from comparisons with a time lag of 10 minutes (at 1% level comparing to *P-PF* and at 5% level comparing to *P-P'*) and from the comparisons without a time lag (0.1% level comparing to *same condition*). We run additional Wald tests (see table 7.1 in the appendix) to test the non-omitted categories against each other. We find a similar result as for *P-F* for the second condition with a two months' time lag, *PF-F*: It is significantly different from *P-PF* (p <0.001), from *P-P'* (p =0.003), and from *same condition* (p <0.001). *P-PF*, with a time lag

[14] The results are qualitatively robust when using random effects models for the estimation.

	(1)	(2)	(3)	(4)	(5)	(6)
	PROBIT	PROBIT	OLS	OLS	PROBIT RECALL	PROBIT RECALL
Dep. Var.	*consistent*	*consistent*	*consistent*	*consistent*	*consistent*	*consistent*
PF-F	-0.13	-0.12	-0.056	-0.05	-0.29*	-0.31*
	0.072	0.077	0.029	0.03	0.13	0.14
P-PF	0.35**	0.35**	0.13**	0.12*	0.41	0.42
	0.13	0.13	0.047	0.049	0.21	0.23
P-P'	0.47*	0.48*	0.15**	0.14*		
	0.19	0.22	0.056	0.065		
same condition	0.57***	0.59***	0.19***	0.20***	0.61***	0.66**
	0.11	0.12	0.037	0.04	0.19	0.2
recall P-F					0.59**	0.67**
					0.2	0.21
recall PF-F					0.81***	0.96***
					0.2	0.2
recall P-PF					0.48*	0.57*
					0.21	0.23
recall same condition					0.45*	0.52*
					0.19	0.2
ident	-0.044	-0.0074	-0.016	-0.00049	-0.057	-0.025
	0.072	0.073	0.027	0.027	0.082	0.083
reverse order		0.045		0.017		-0.095
		0.15		0.055		0.16
HL		-0.027		-0.012		-0.13
		0.36		0.13		0.37
HL_inconsistent		0.026		0.0093		0.016
		0.045		0.016		0.043
confidence		0.15*		0.054*		0.19*
		0.066		0.023		0.08
WTA		-0.032		-0.011		-0.047
		0.06		0.021		0.06
Constant	0.16	-1.59	0.57***	-0.053	-0.15	-0.73
	0.099	2.25	0.038	0.75	0.14	2.22
demographics	No	Yes	No	Yes	No	Yes
Observations	1,800	1,644	1,800	1,644	1,590	1,511

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$, robust standard errors clustered at subjects' level
Demographics: age, male, semester, game, econmajor, statistics, econometrics, height. *P-F* omitted

Table 3.1: Differences in consistency

of 10 minutes, is not significantly different from *P-P'*, also with a time lag of 10 minutes (p =0.573), but is significantly different from *same condition*, which has no time lag (p =0.021). The only comparison which is not different across time delays is *P-P'*, with a time lag of 10 minutes, versus *same condition*, no time lag, which are not significantly different (p =0.625).

Surprisingly to us, the *ident* variable is not significant. When evaluating subjects' consistency, the fact whether the two decisions are made for one and the same urn or for two different urns does not matter. Hence, subjects do not seem to treat different urns differently when the information on the urn is kept constant. In our experimental design, we spend considerable effort to come up with a comparison of physically identical urns. Our result on *ident* is important for future experiments: The effort to compare physically identical urns is not necessary, as it suffices to use urns with the same information structure.

In model (2) we add sociodemographic measures (year of birth, being male, number of semesters studied, having participated in a game theory or statistics course, being an economics major and body height in cm).[15] Furthermore, we add the subjects' risk preferences elicited by the HL-task (*HL_inconsistent* is a binary variable that carries a one if incomplete answers or non-monotonic preferences were returned in the HL-task).[16] Neither of these variables is significant, nor do they change the significant results of our condition variables.

Finally, we add the variables *confidence* and *WTA*. Both of them are the confidence measures introduced in section 2. Measuring consistency between two urns generates data on four bets. The variables reported are the averages over these four bets. In the results we find a significant and positive effect of the

[15]Since Dohmen et al. (2011) find correlations between height, age and risk aversion, this raises the issue of multicolinearity. When testing the variance inflation factors we do not detect such effects in any model.

[16]For the HL-task we use the first row in which a subject switches from option A to B. Lower values represent a higher risk tolerance.

confidence variable in all models. Therefore, subjects who show higher levels of *confidence* in their choices are also more likely to show consistent behavior. However, we do not detect a relevant effect for the *WTA* variable. It is insignificant in all models. As a robustness check, we repeat model (1) and (2) as an OLS specification, see model (3) and (4). The results stay qualitatively unchanged.

Overall, whenever the time lag between two compared choice conditions is different, the level of consistency is significantly different as well - with one exception, *P-P'* versus *same condition.* And when the time lag between two compared conditions is similar, consistency is not significantly different, too. This shows how consistency depends on the time lag between decisions, even when the amount of time passed is only 10 minutes.

Since time differences are a driving force behind different levels of consistency, we look at the effect of being able to recall past decisions. To measure recall, we asked subjects in the main experiment to recall their decisions on this specific Ellsberg urn in choice condition *PF*, which was selected to be paid in the January session. In *single session* no such question was asked as we did not reinvite subjects. Subjects did have an incentive to recall their own decisions, since this allowed them to verify their payment in the January session. If a subject correctly recalled all their past decisions in the *PF* condition, the variable *recall* takes the value 1, and 0 otherwise. In models (5) and (6) we test whether subjects who recalled their previous decisions correctly differ from those who did not. To do so, we reduce the sample to observations from the main experiment and add interaction terms of *recall* with all available comparisons.[17] The results show that subjects who are able to recall past own actions are more consistent in condition *P-F*, with a two months' time lag, than those how are not. Performing

[17]Note that we do not control for *P-P'* as this comparison is only available for *single session.*

a Wald test for the *PF-F* dummy versus its interaction with recall shows that the same holds true for decisions in this comparison (p <0.001). So, for both consistency values with a two months' time lag, we find a significant effect of recall. In fact, subjects who do not recall their previous actions act not significantly different from random.[18] What about consistency levels with a time lag of 10 minutes (*P-PF*) or with no time lag (*same condition*)? While we see some difference in figure 3.4, the effect is not significant (p =0.860/p =0.604). This is not surprising: *Recall* is measured over a time period of two months. Recalling actions over 10 minutes must be considerably easier, such that we would not expect a strong difference between groups here.

We can also test whether subjects who are able to correctly remember previous choices are still affected by the different time lags. Interestingly, based on the estimates in model (5), not a single difference across choice conditions is still significant![19] That is, for those subjects who, after two months, still recall their decisions, we do not detect a time effect on consistency. Again, adding sociodemographics and risk aversion in model (6) does not alter these results in terms of significance.[20]

Non-parametric tests In the following we will present non-parametric tests as a robustness check for the regression models above.

In general, our consistency measure is a binary variable which shows a one if a subject has the same ambiguity preferences in two urn tasks. According to figure 3.5 we observe four realizations for any comparison between two choice conditions. When considering *single session* we gain six observations. In order

[18] If we restrict model 3 to subjects who do not recall, *PF-F* and *P-F* are not significantly different from 37.5%.

[19] Wald test p-values for the comparisons are 0.686 (*P-F* vs. *P-PF*), 0.146 (*P-F* vs. *PF-F*), 0.568 (*P-F* vs. *same condition*), 0.164 (*PF-F* vs. *P-PF*), 0.152 (*PF-F* vs. *same condition*) and 0.881 (*P-PF* vs. *same condition*).

[20] See table 7.1 in the appendix.

to boil down these multiple observations to apply non-parametric tests we average over each choice condition for each subject.

We begin by testing whether subjects behave more consistent than under random choice. We use χ^2-goodness-of-fit tests to compare behavior to the benchmark of 37.5%. It rejects random behavior for all choices at the 0.1% level (N=102, $p < 0.001$).[21]

Consistency across choice conditions					Consistency and recall$^{\triangle}$	
	same condition	*P-P'*$^{\triangle}$	*P-PF*	*P-F*		
PF-F	0.000	0.017	0.002	0.10	*PF-F*	0.000
N	102	137	102	102	N	102
P-F	0.002	0.076	0.058		*P-F*	0.006
N	137	137	102		N	102
P-PF	0.423	0.671			*P-PF*	0.015
N	102	137			N	102
P-P'$^{\triangle}$	0.991				*same condition*	0.014
N	137				N	102

We use a two-sided Wilcoxon signed-rank test for paired data. For comparisons indicated by $^{\triangle}$ we apply a two-sided Wilcoxon–Mann–Whitney test for independent observations.
For all tests the null hypothesis is that the consistency level is not different across two comparisons - for recalling and non-recalling subjects.

Table 3.2: P-values for non-parametric tests

In table 3.2 we present p-values and numbers of observations of our tests (compare figure 3.4). Similar to the results based on regressions, consistency is significantly lower when choices are separated by two months (*PF-F* and *P-F*) compared to choices that are only a few minutes apart (*P-PF* and *P-P'*) or when the decisions are back-to-back (*same condition*). Although significance is lower compared to section 4.3, we find these results significant at least at the 10%-level. However, we do no longer detect a significant difference between choice conditions *P-PF*, *P-P'* and *same condition*. Therefore, we do not find a difference in consistency when ten minutes elapse between two decisions com-

[21] Instead of assuming equal probabilities for all urn choices, we can alternatively assume that the probability of showing any ambiguity preference in a single urn is equal to the observed frequency in the experiment, but that there is no further correlation across urns. This would amount to a consistency level of 42.74%. χ^2-goodness-of-fit tests reject (N=102, $p < 0.0001$ in all tests) random behavior for this case as well.

pared to back-to-back decisions.

When considering the results on recall, we find our earlier results unanimously confirmed on reasonably high levels of significance. Although we lose variance by averaging on the subject level, these non-parametric tests largely confirm our findings from section 4.3.

5 Further results and robustness

5.1 Consistency over four Ellsberg urns

In the above section we analyze consistency based on pairwise comparisons of urns. In the following we present a robustness check by applying a stricter measure for consistency. Here, we consider a subject to be consistent if the attitude towards ambiguity is the same in all four decisions associated with immediate payment, corresponding to the P and F decisions in the main experiment and to P and P' in *single session.*[22] This approach yields an alternative dependent variable *cons_all*, consisting of one observation for each subject, which is set to one if all choices are consistent and 0 otherwise. Overall, we find a consistency level of 40.8% in the main experiment and a level of 62.9% in the *single session* treatment.

In table 3.3, we present estimates from different models using *cons_all* as dependent variable and including controls similar to the analysis in section 4.3. In line with the findings in section 4.3, we find a higher level of consistency in the *single session* treatment as the significant coefficient in all six models shows. Even under the stricter specification, consistency decreases when decisions are separated by a longer time interval.

[22] We do not consider the PF data, as we do not have corresponding observations in *single session.*

	(1)	(2)	(3)	(4)	(5)	(6)
	PROBIT	PROBIT	OLS	OLS	PROBIT	PROBIT
Dep. Var.	*cons_all*	*cons_all*	*cons_all*	*cons_all*	*cons_all*	*cons_all*
single session	0.56*	0.76*	0.22*	0.28*	1.06***	1.32***
	0.24	0.31	0.093	0.11	0.3	0.4
recall					0.81**	1.01***
					0.27	0.3
reverse order		0.19		0.072		0.029
		0.27		0.099		0.28
HL		0.96		0.32		1.14
		0.66		0.23		0.72
HL_inconsistent		0.095		0.03		0.11
		0.071		0.025		0.079
Constant	-0.23	3.88	0.41***	1.26	-0.73***	3.91
	0.13	4.62	0.049	1.15	0.21	4.17
demographics	No	Yes	No	Yes	No	Yes
Observations	138	137	138	137	138	137
R-squared			0.037	0.141		

* p <0.05; ** p <0.01; *** p <0.001, robust standard errors clustered at subjects' level
Demographics: age, male, semester, game, econmajor, statistics, econometrics, height

Table 3.3: Consistency over four urns

We argue in the above section that consistency is not affected by time for subjects that remember their decisions. Here, we tackle this issue in model (5) and (6) by including the subjects' ability to correctly *recall* previous decisions. We detect a highly significant effect (at 1% in model (5) and 0.1% in model (6)) in the expected direction. Again, subjects recalling their decisions are more likely to be consistent. Additionally, a Wald test reveals that the *single session* variable is not statistically different from the *recall* variable (p =0.36). Subjects in the main experiment that are able to remember past decisions are as consistent over two months as the average subject is in a setting with a delay of 10 minutes only.

As a further result, the only significant effect of demographic variables we observe is a mild age effect. Although the coefficient is not reported, we find the year of birth significant on the 5%-level in all models. Younger subjects are less likely to be consistent. When computing the marginal effects (p =0.017 for model 2), the probability of being consistent decreases for every year of birth by 3.2%. Restrictively, the age variation is quite small since we observe 95% students in our sample. Nonetheless, the effect is a pure age effect as we control for the seniority at university. Similar to the models in table 3.1, *reverse order* and the risk preferences (*HL*) have no effect on consistency.

To sum up, this robustness check bolsters the results from section 4.3. With an even stricter measure of consistency, we confirm both the general time effect on consistency and the mitigating role of the individual recall capacity. Furthermore, we find a slightly positive age effect on consistency.

5.2 Ambiguity preferences

Preferences in aggregate After having analyzed the individual consistency of preferences, we take a look at the overall distributions of ambiguity attitudes in the different choice conditions. As figure 3.6 shows, the distribution of ambiguity attitudes is broadly similar over the different choice conditions. Although we find that time has an effect on the individual consistency above, this does not imply that the preferences change in the aggregate. Observe, however, that finding differences over a period of two months would suggest an extreme effect of aging.

Ambiguity preferences In table 3.4 we present six probit models for the different types of ambiguity preferences. The underlying data is organized and stacked by urns and we consider data from the main experiment only. Depending on the retention to the January sessions, each subject decides on up to six urns corresponding to up to six observations for each subject in the dataset. The models are computed with standard errors clustered on the subject level to control for multiple observations.

The dependent variable is a binary variable that carries a one if the subject

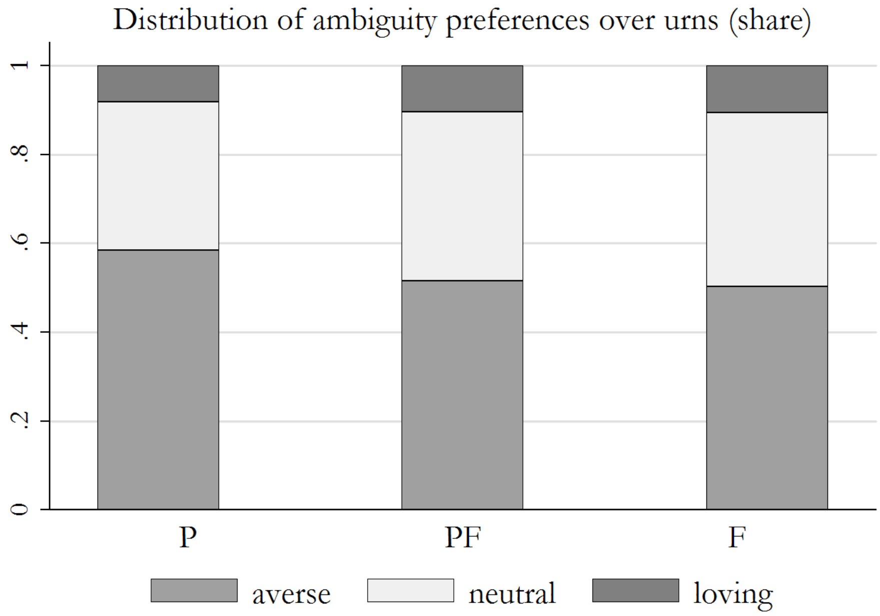


Figure 3.6: Ambiguity preferences over choice conditions

shows the respective preference in the urn. Model (1) and (4) investigate ambiguity averse (AA), (2) and (5) ambiguity neutral (AN) and (3) and (6) ambiguity loving (AL) attitudes.

For the explanatory part we include two different sets of variables. First, in order to evaluate the time effects on the ambiguity attitudes, we include binary variables to control for the choice conditions (PF, F). The omitted category is P. While model (1) to (3) are probit models, models (4) to (6) are estimated by OLS as a robustness check. Second, similar to regressions in the previous section, we include several personal control variables.

As figure 3.6 suggests, there are no large effects on the distribution of ambiguity attitudes. When considering the tests in the regressions in model (1) and model (4) in table 3.4, we find a mild reduction of ambiguity aversion in PF. This finding is in line with Onay et al. (2012).

We detect mild correlations between demographics and ambiguity preferences while *time* preferences do not have a significant impact. Furthermore, the mod-

	(1)	(2)	(3)	(4)	(5)	(6)
	PROBIT	PROBIT	PROBIT	OLS	OLS	OLS
Dep. Var.	AA	AN	AL	AA	AN	AL
PF	-0.25*	0.17	0.19	-0.088*	0.061	0.026
	0.11	0.1	0.19	0.04	0.036	0.027
F	-0.23	0.15	0.23	-0.081	0.05	0.031
	0.15	0.15	0.2	0.053	0.053	0.031
HL	0.14*	-0.13*	-0.0001	0.050*	-0.049*	-0.001
	0.061	0.053	0.065	0.021	0.019	0.012
HL_inconsistent	0.46	-0.81	0.5	0.17	-0.3	0.13
	0.55	0.54	0.52	0.19	0.21	0.12
reverse order	0.29	-0.16	-0.33	0.11	-0.057	-0.051
	0.19	0.19	0.19	0.07	0.068	0.029
time	0.017	-0.01	-0.014	0.0057	-0.0031	-0.0025
	0.028	0.025	0.03	0.01	0.0091	0.0045
confidence	0.1	-0.066	-0.044	0.037	-0.023	-0.013
	0.095	0.092	0.099	0.035	0.034	0.02
WTA	-0.006	0.016	-0.0028	-0.0009	0.006	-0.0051
	0.087	0.083	0.089	0.031	0.031	0.016
Constant	-4.17	2.62	-7.17	-1	1.44	0.56
	2.46	2.32	5.62	0.85	0.8	0.32
demographics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	607	607	607	607	607	607
R-squared				0.117	0.062	0.07

* p <0.05; ** p <0.01; *** p <0.001, standard errors clustered on subjects' level. P omitted. Demographics: age, male, semester, game, econmajor, statistics, econometrics, height

Table 3.4: Ambiguity attitudes in aggregate

els show a correlation between the risk task and ambiguity attitudes. For ambiguity averse choices we find a significant correlation with risk averse behavior whereas ambiguity neutral choices are positively associated with risk tolerance. For ambiguity lovers we do not find any significant effects. In general, these results coincide with the findings of Lauriola and Levin (2001) and Chakravarty and Roy (2008) who find ambiguity and risk aversion positively associated. However, this relationship is not undisputed since Di Mauro and Maffioletti (2004) find only a low correlation and Cohen et al. (1985) no relationship at all. The *time* coefficients are insignificant in all models.

Model	(1) PROBIT	(2) PROBIT	(3) OLS	(4) OLS
Dep. Var.	*cons_HL*	*cons_HL*	*cons_HL*	*cons_HL*
consistent	-0.014	-0.097	-0.004	-0.0046
	0.44	0.5	0.11	0.12
recall	0.22	0.32	0.053	0.07
	0.34	0.4	0.084	0.091
reverse order		-0.062		-0.013
		0.36		0.083
confidence		0.032		0.007
		0.23		0.048
WTA		-0.33		-0.061
		0.2		0.045
Constant	0.91**	2.82	0.82***	1.11
	0.3	5.11	0.077	1.37
demographics	No	Yes	No	Yes
Observations	91	90	91	90
R-squared			0.005	0.099

* p <0.05; ** p <0.01; *** p <0.001, standard errors clustered on subjects' level. *P* omitted. Demographics: age, male, semester, game, econmajor, statistics, econometrics, height

Table 3.5: Ambiguity and risk attitudes

5.3 Consistency of uncertainty: Risk and ambiguity

Above, we argue that the ability to recall choices correlates with consistent ambiguity preferences. In the following we will explore two questions: First, whether the ability to recall also affects consistency in risk preferences. Second, whether having consistent ambiguity attitudes correlates with consistent risk preferences.

In the experiment, we elicited risk preferences in the *P* and the *F* session. Therefore we are able to investigate the *P*-*F* consistency for ambiguity as well as for risk preferences.

For this analysis, we construct a binary variable that carries a one if a subject is consistent between both risk tasks (*cons_HL*). Hence, we consider a subject to be consistent if the deviation in rows switching from option A to B between the two tasks is smaller or equal than one. Using this variable, we find a consistency level of 85% between the two risk tasks.[23] This is considerably higher compared to the 57% we find for ambiguity preferences for *P-F* (see figure 3.4).[24]

In table 3.5 we present two binary choice models investigating the relationship between the consistency in risk and ambiguity preferences. The dependent variable measures the consistency in risk preferences over the choice conditions *P* and *F* (*cons_HL*).[25] The independent variable of interest is our previous measure for consistent ambiguity preferences (*consistent*). Additionally, model (1) controls for subjects who remember their decision in the *PF* urn whereas model (2) includes a set of demographic variables.[26] Model (3) and (4) are robustness checks estimated by OLS. We find no significant relationship between the consistency of risk and ambiguity preferences since *consistent* is insignificant. The fact that subjects remember their decision in the ambiguity task has also no effect on the consistency of risk preferences as *recall* is significant.

Although we find a correlation between risk and ambiguity preferences, we do not find a correlation in the corresponding levels of consistency.

5.4 Order effects

A concern when eliciting multiple urns per subject is that subjects may decide differently in repeated tasks. The models in table 3.6 investigate whether the sequence in which urns are presented does affect the subjects' ambiguity preferences. The independent variables consist of binary variables indicating the

[23] By using a structural maximum likelihood model (Harrison and Rutström 2008) we do not find significant differences in CRRA coefficients (assuming $u(x) = x^{\alpha}$) between November (0.88) and January (0.89) in aggregate. This is in line with Andersen et al. (2008).

[24] The results do not change qualitatively or in significance if we use an alternative measure of consistency for risk preferences: A subject is considered to be consistent when showing risk averse, neutral or loving preferences in both HL-tasks. Here we find a consistency level of 87.9%.

[25] We restrict the analysis to *P-F* since we do not observe an HL decision with a delayed payment. However, a comparable setting is tested by Noussair and Wu (2006), who find that subjects are less averse toward future risks.

[26] See section 4.3 for the description.

	(1) PROBIT	(2) PROBIT	(3) PROBIT	(4) OLS	(5) OLS	(6) OLS
Dep. Var.	AA	AN	AL	AA	AN	AL
urn_nb_1	0.01	0.09	-0.23	0.004	0.033	-0.037
	0.12	0.12	0.21	0.049	0.045	0.034
urn_nb_2	-0.023	0.15	-0.29	-0.0092	0.055	-0.046
	0.12	0.11	0.21	0.049	0.042	0.033
urn_nb_3	-0.082	0.042	0.087	-0.032	0.015	0.017
	0.09	0.099	0.16	0.036	0.036	0.032
Constant	0.15	-0.44***	-1.23***	0.56***	0.33***	0.11***
	0.12	0.12	0.16	-.048	0.045	0.03
Observations	438	438	438	438	438	438
R-squared				0.001	0.002	0.008

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$, standard errors clustered at subjects' level, *urn_nb_4* omitted

Table 3.6: Order effects on multiple elicitations

position in the sequence of presentation regardless of the choice condition. For example, *urn_nb_1* carries a one for the first urn in the experiment and a zero otherwise. The dependent variables are also on a binary scale and show a one if the subject's preference is ambiguity averse (model 1), neutral (model 2) or loving (model 3). While models (1) to (3) are probit estimations, (4) to (6) are OLS models which are presented for robustness. The results show that there are no significant and systematic order effects.[27]

6 Conclusion

In an experiment designed to test the stability of subjects' ambiguity preferences, we find that the consistency of choices is well above the benchmark of random behavior. Consistency decreases as the time lag between choices increases, from 79% for back-to-back choices to 57% for two months. The decrease in consistency over time is mitigated by subjects' ability to recall their previous choices. For subjects who successfully recall their previous choices, there is no significant difference between longer and shorter time lags. Overall,

[27] In an alternative test we include urn_nb in the models of table 3.4. While losing the January observations in these regressions we again do not find an order effect.

the consistency results leave a mixed picture: Subjects are consistent to some degree, but not fully. A large amount of individual inconsistency can remain hidden when only aggregate results are taken into account.

Apart from the observed levels of consistent choices, we are also interested in the drivers of stability. Here, we can reject our initial concern that the comparison across different urns might introduce a bias: Subjects' consistency over the same urn is not different from the consistency for physically not identical urns. This suggests that it is acceptable to forgo the effort of constructing experiments where one and the same urn is used multiple times in an incentive compatible way. Moreover, we identify two correlates of stability. One is self-reported confidence in the choice which turned out to be a significant predictor of stability. Hence, including a question like the one used in our experiment might be helpful in predicting individual behavior. Second, subjects who recall their behavior are associated with more consistent behavior, in particular as the time span increases. These subjects might deliberately choose consistently with their previous choices, either to appear consistent, or to avoid having to make up their minds again. However, since we only find a correlation, other causal effects are also possible. The subjects using easy to remember heuristics (Gigerenzer and Gaissmaier 2011) could lead to a reverse direction of causality: Subjects are consistent because they use the same heuristic at both times. And they are able to recall their previous decisions not because they remember the action, but remember using the same heuristic as before.

Chapter 4

Stereotypes and Risk Attitudes of Financial Professionals: Evidence from the Lab and the Field

1 Introduction

The correlation between risk attitudes and sociodemographic characteristics has been actively studied in recent years (Dohmen et al. 2011, Gaudecker et al. 2011). These findings give rise to the question of whether subjects are aware of the correlation between risk preferences and sociodemographic information.

Risk attitudes are important for decision making, for example for buying stocks or for financial decisions in general (e.g., Dohmen et al. 2011). However, previous studies suggest that financial literacy is limited (Rooij et al. 2007), which shows the importance of professional advice (Shiller 2008). And indeed, when making their decisions, individuals are increasingly relying on professionals - such as doctors in the health domain, insurance agents, and in particular financial consultants (c.f. Allen 2001, Bhattacharya et al. 2012). Of course, agency problems, which have been discussed in the theoretical literature (Bhattacharya and Pfleiderer 1985 or Inderst and Ottaviani 2012), are of major influence in the counseling interview. However, these models assume that the risk preferences or some distribution over risk preferences are common knowledge. Our research starts by tackling this assumption.

We study a subject's ability to identify the major demographic correlates with risk preferences. We conduct an artefactual field experiment[1] in which three types of subjects participate: senior financial advisors, junior financial advisors and non-professionals. In particular, we assess professionals' knowledge about people's risk preferences and seek to ascertain if they attach importance to other characteristics than subjects without advice experience. Studying these groups allows us to explore potential experience and training effects in the financial sector (c.f. Haigh and List 2005).

The experiment consists of two parts. The first part is based on a survey conducted on the web and a large-scale survey (SOEP) of Germany. By using these data we estimate risk preferences of certain subgroups of the population (e.g., older versus younger, female versus male). In the second part, we run a computerized lab experiment. The lab experiment consists of two stages. At first we elicit the subjects' risk attitudes using the risk measures of Holt and Laury (2002) and Dohmen et al. (2011). In the second stage, we elicit the subjects' stereotypes (or perceived correlations) of risk preferences of sociodemographic groups (such as gender). By augmenting the subject pool with financial professionals we are able to study behavioral differences between financial advisors and non-professionals.

In a further task subjects are asked to rank their individual risk attitude relative to the population mean of the survey. This is to measure their self-assessment

[1] Artefactual field experiments use the tools of a standard lab experiment with a non-standard subject pool (Harrison and List 2004).

of risk taking.

The results of the experiment show that subjects recognize the correlation between particular sociodemographic variables and risk preferences rather consistently. The subjects are able to assess with a high precision how their own risk attitude relates to the average risk attitude of the representative population. Although we find professional subjects to be more risk tolerant than non-professionals, these differences are not statistically significant. However, senior professionals are significantly less successful in recognizing the correlations between risk attitudes and demographics found in the data. They assume a zero correlation of a characteristic and even more often they mispredict the direction of the correlation. Additionally, senior professionals are less successful in ranking their own risk attitude relative to the population mean. In contrast, the junior professionals are significantly more accurate in predicting the correlations of demographics and their own position in the distribution of preferences.

The remainder of the paper is structured as follows: In the next section (section 2), we discuss the literature. Section 3 explains the experimental design of the study while section 4 presents the results. Finally, we conclude in section 5.

2 Literature

Recent research on risk preferences has detected significant linkages between sociodemographic characteristics and risk attitudes. It is largely undisputed that women are more risk averse than men (e.g., Byrnes et al. 1999, Croson and Gneezy 2009). By using German micro data (SOEP) Dohmen et al. (2011) find that individuals are more risk averse if they are older, married, or are parents. The authors report that individuals are more risk loving if they have a high school diploma or higher income. However, regarding the relationship of education or income and risk tolerance, the findings of other literature are ambiguous (c.f. Barsky et al. 1997, Belzil and Leonardi 2007, Hartog et al. 2002). In addition, Dohmen et al. (2011) report a significant correlation between stated risk preferences and real-life decisions e.g., holding risky financial assets, smoking, and being self-employed.

A strategy to figure out others' preferences is "stereotyping". By intuition, a subject assumes a correlation between an observable characteristic and the risk preference. This perceived correlation does not necessarily need to coincide with the true correlation. Regarding the knowledge about the correlation between risk preferences and sociodemographic information, Eckel and Grossman (2008) study gender stereotypes. Their results are twofold: First, in line with previous results, females tolerate less risk than males. And second, the beliefs[2] over gender are consistent since women are perceived to be less risk tolerant. In this setup the judged person is fully visible to the judging subject. If the belief formation is based on groups (e.g., males) instead of individuals, subjects overestimate males' risk tolerance, while females' is correctly assessed (Siegrist et al. 2002). In terms of cultural stereotypes people perceive Chinese to be less risk tolerant than Americans. Interestingly, the actual experimental data shows that the opposite is true (Hsee and Weber 1999).

Previous studies on financial decision making suggest that especially financial professionals are less prone to behavioral biases, such as anchoring effects, when forming expectations about long-term stock returns (Kaustia et al. 2008). They show a higher degree of analytical behavior than the general population (Nofsinger and Varma 2007). However, there is contradictory evidence regarding the degree of myopic loss aversion of financial professionals compared to student subjects (Eriksen and Kvaloy 2009, Haigh and List 2005). Financial profession-

[2] In the literature 'prediction', 'forecast' and 'belief' are used interchangeably.

als are better in assessing the quality of public information, while students more closely follow Bayes' Rule (Alevy et al. 2007). Nevertheless, artefactual field experiments which allow observing financial professionals and students in an identical situation are scarce.

This study contributes to the existing literature by investigating subjects' perceived correlation of risk preferences and six demographic characteristics. It is the first study that takes up this question by using an "artefactual field experiment" as the subject pool is augmented by financial professionals. This setup allows exploring differences in behavior between these subject groups.

3 Experimental design

This experiment is designed to study differences of subjects' "perceived" correlations between risk preferences and sociodemographic groups (or stereotypes) and the "true" correlations. In order to find these true correlations we use data from two surveys. Having computed correlations between sociodemographic groups and risk preferences in the survey data, we go to the lab and elicit the subjects' stereotypes. As we use a non-standard subject pool we compare these stereotypes of financial advisors and non-professionals.

At first, in the treatment SELF, we measure the subjects' own risk preferences. Subsequently, the treatment STEREOTYPE contains two tasks: First, we investigate the subjects' ability to self-assess their own risk attitudes. For this we ask them to rank their willingness to take risk in the distribution of risk attitudes. Second, we check whether the subjects' perceived relationship between risk preferences and demographics and the true correlations coincide. A time line of the experiment is provided in figure 4.1.

Throughout the experiment we use two preference elicitation methods: The

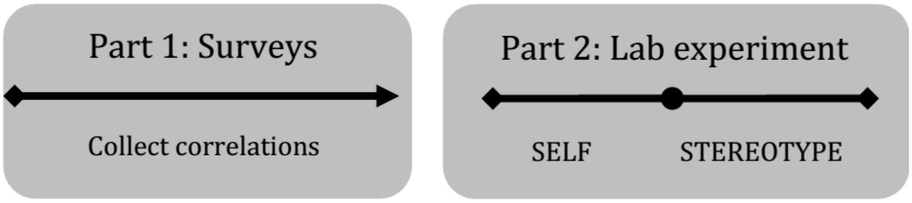


Figure 4.1: Experimental design: Course of actions

method borrowed from the German large-scale survey SOEP (see Dohmen et al. (2011)) and the multiple price list by Holt and Laury (2002). Both methods are discussed in detail in chapter 2.

3.1 Part 1: Surveys

One major restriction we face with our design is that there is no publicly available survey containing the HL-task. Therefore we run our own online survey to collect sociodemographic information and risk preferences.

First, for the €100,000 question we make use of the German Socioeconomic Panel (SOEP), which is publicly available.[3] Second, for the HL-task we employ a web-based survey which can easily be distributed to different people via e-mail.[4] The distribution of the survey ran over university and private e-mail lists.[5] The survey collects risk preferences (in the HL-task as well as the €100,000 question) and sociodemographic information and it ran from November to December 2010.

The second and the third column in table 4.1 show the descriptive statistics of the surveys. The data show heterogeneity within the surveys especially in the categories age, parenthood and university education. The subjects in the SOEP survey are significantly older and thus more often have a partner and children.

[3]We use data from 2009. See www.diw.de/soep for more details.

[4]Consult the appendix for the complete instructions.

[5]Participants were recruited via e-mail and were asked to further distribute the survey. For the completion of the web-based survey we raffled off €50 among the participants.

	Part 1: Reference decisions				Part 2: Lab experiment					
	Web survey		SOEP survey		Non-prof.		Junior prof.		Senior prof.	
Variable	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
N	84	-	20750	-	77	-	52	-	38	-
Year born	1979	10.0	1959	17.71	1986	6.29	1989	1.06	1973	11.0
Female	0.57	0.56	0.52	0.50	0.56	0.50	0.46	0.50	0.18	0.39
Partner	0.41	0.62	0.77	0.42	0.26	0.44	0.23	0.43	0.66	0.48
Parenthood	0.20	0.40	0.62	0.49	0.05	0.22	0.02	0.14	0.47	0.51
High income*	0.02	0.15	0.01	0.07	0	0	0	0	0.11	0.31
Uni degree	0.59	0.50	0.21	0.41	0.94	0.25	1.00	0.00	0.63	0.49
Counsel. exp. (years)	-	-	-	-	-	-	1.02	1.07	10.97	8.27
CRRA$^{\Upsilon}$	0.20	-	-	-	0.32	-	0.25	-	0.28	-
HL$^{\triangle}$	6.11	1.68	-	-	6.81	1.56	6.33	1.78	6.32	2.08
100,000	7.61	2.70	9.08	1.98	4.70	3.29	6.00	2.44	6.89	3.18

* refers to a monthly net income above €6,000 (approx. $8460).
$^{\Upsilon}$ See section 4.2 for estimation details. The survey is not incentivized.
$^{\triangle}$ refers to the row in which Option B was chosen for the first time in the lottery.

Table 4.1: Descriptive statistics of surveys and subjects

3.2 Part 2: Lab experiment

General information and subject pool In the lab, subjects first play SELF and STEREOTYPE subsequently. When entering the lab, subjects are randomly allocated to a computer slot. During the experiment there is no interaction and no feedback about the payoff.[6]

The experimental sessions took place in 2011 and 2012. In total 167 subjects participated in the lab experiment. In the subject pool of the lab experiment we have three types of subjects: senior professional advisors, junior professional advisors and non-professionals. The non-professionals are mainly students recruited via the AWI-lab at Heidelberg University, where all sessions with non-professionals were run.[7] The senior professional advisors are recruited from a German financial advisory agency and from local banks. The junior advisors come from a banking specific advanced training institution.[8] After finishing high school, the junior professionals enter a study program in financial advisory. This takes place at an applied university, and practical counseling makes up 50% of their training. Since these subjects are currently students, their age

[6]We treat each subject as an independent observation.
[7]The experiment is programmed on a PHP-platform. A transcribed version of all instructions can be found in the appendix.
[8]We ran seven sessions with professionals - three in the lab and four on-site.

and educational level are comparable to the non-professional advisors.

An experimental session lasts approximately 50 minutes; on average subjects earn €11.92.

SELF The SELF treatment elicits the subjects' own demographics and their risk tolerance. First, subjects answer the questions about their demographics. Then they play the €100,000 question and the HL-task. Both measures are incentivized as described in chapter 2.

STEREOTYPE After finishing the SELF treatment, subjects move on to STEREOTYPE.[9] In the first task, we are interested in finding out whether subjects are able to locate their own risk attitudes in the (representative) distribution of risk preferences. We ask the subjects to assess whether their own decision in the two preference elicitation tasks is riskier, less risky, or bears the same risk compared to the advisees' average decision in the surveys of part 1. Our instructions explicitly mention that the reference decisions are based on surveys. The exact wording for the €100,000 question is:

Approx. 22,000 participants answered the Game Decision I in a preceding survey.[10] *Do you think the average participant of the preceding survey invested more, less, or the same amount of money as you did in the first game decision?*
Your decision: *I think that the average participant of the preceding survey invested (please choose): More, less, the same amount of money as I did in the first game decision.*

For the risk task we use the average choices in the web survey to determine the advisees' average decision, for the €100,000 question choices from the SOEP survey are employed. However, only the SOEP survey constitutes a representative sample of the German population.[11] For all tasks in STEREOTYPE we

[9]After STEREOTYPE two more treatments are executed which are not reported here. The results of these treatments are reported in chapter 5.

[10]Here, the instructions include Barsky et al. 1997, a repetition of the €100,000 question.

[11]We are aware that there are significant differences in the sample size of both surveys. We account for this in the design by explicitly mentioning the data count in the instructions.

pay €0.25 for a correct answer.

In a second task, we study stereotypes of risk preferences of different subsamples. The subjects' task is to correctly predict the subsample that makes the riskier decision. To determine whether the subjects' stereotypes are correct, we use the data from the surveys of part 1. The average decisions of different subsamples formed in the categories 'age', 'gender', 'family status', 'education', 'parenthood' and 'income' are computed. The different subsamples and the exact wording are presented in table 4.2. Two subsamples are formed per category. For these categories we calculate the average decisions and infer which subsample takes the riskier decision. For example, we compute the average decision among advisees that are 40 years old and above and the average of advisees that are below 40 years of age.[12] The averages are computed for both risk measures separately.

In table 4.2 an asterisk (triangle) indicates the subgroup making the riskier decision for the HL-task (the €100,000 question).[13]

€100,000 question: Which group invested more money in the lottery?
lottery: Which group switched to option B earlier?

Category	Choice 1	Choice 2	Choice 3
Age	younger than 40*$^{\Delta}$	40 and older	both equal
Gender	male*$^{\Delta}$	female	both equal
Family status	single*$^{\Delta}$	partner/married	both equal
Education	university degree*$^{\Delta}$	no university degree	both equal
Parenthood	having no children*$^{\Delta}$	having children	both equal
Net income	up to €1,000*	more than €1,000$^{\Delta}$	both equal

The *riskier* average decision (correct answer) for the HL-task is denoted by an asterisk (*), for the €100,000 question by a triangle ($^{\Delta}$).

Table 4.2: STEREOTYPE: Average choices of subsamples

12 The cut-off values of the categories are designed to be close to the median. E.g., the median age in the survey is 44. For a better comprehensibility we choose 40 years.

13 The true correlations of both samples differ only in the income variable. This is in line with the ambiguous findings in the literature. Hartog et al. (2002) find that risk aversion decreases with income and wealth. In contrast to that, Barsky et al. (1997) identify an inverse U-shape relation of risk aversion and income.

4 Results

In the following section we present the results of the experiment. While we explore the differences in preferences between financial advisors and non-professionals in section 4.1, we investigate the differences in their self-assessment and the stereotypes of the subject groups in section 4.2.

4.1 SELF

One of the main features of this experiment is the non-standard subject pool containing financial advisors. In figure 4.2 we present the distributions of the subjects' choices in both risk elicitation mechanisms for each subject group.[14] Considering the €100,000 question (table 4.1), non-professionals invest much less (€47,000) in the lottery compared to the junior professionals (€60,000) and the senior professionals (€69,000). However, a two-sample Kolmogorov-Smirnov test[15] for equal distributions does not detect any significant differences between the different subject groups for the €100,000 question.

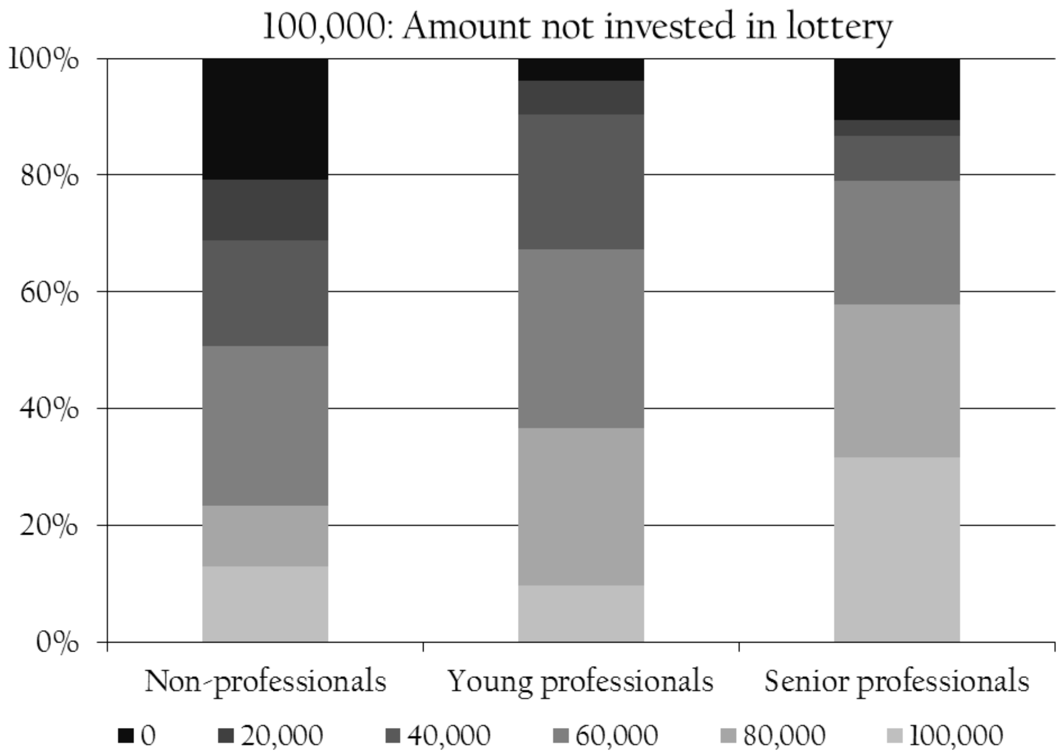
The same is true when considering the HL-task, as we do not recognize any systematic differences between the subject groups in the preference distribution (see figure 4.2). The intersection of the risk neutral prediction (black solid line) with the actual distribution of the subjects' choices in figure 4.2 indicates that up to 13% of the subjects exhibit risk loving choices.[16] On average, the subjects exhibit risk averse preferences.

This is backed by a structural maximum likelihood model to estimate the coefficient of relative risk aversion. For this we follow the procedure proposed by

[14]As discussed in chapter 2 we present the scale of the €100,000 question in an inverse order.

[15]H_0: Student=Junior, N=126, p=0.25, H_0: Non-prof.=Senior, N=115, p=0.42, H_0: Senior=Junior, N=90, p=0.64

[16]This is in line with Holt and Laury (2002), who find 20% of subjects to exhibit risk loving choices.



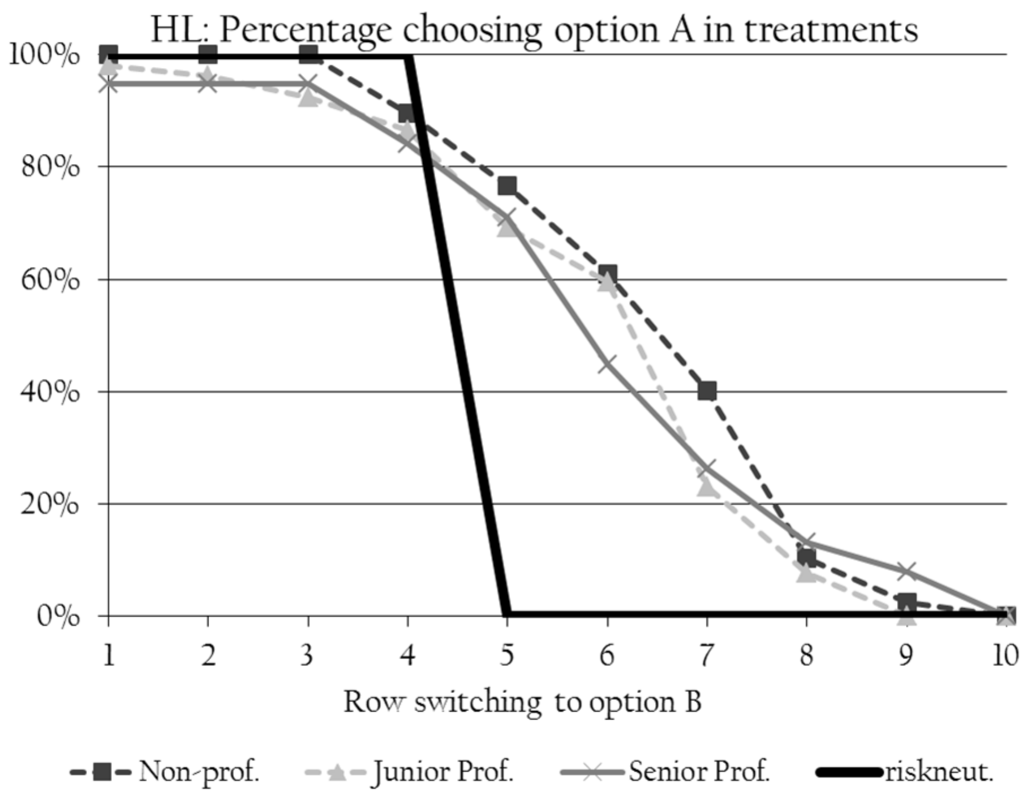


Figure 4.2: Subjects' risk attitudes in €100,000 question and HL-task

Model	1	2	3	4	5	6
Subject:	Non-prof.	Junior	Senior	Non-prof.	Junior	Senior
α	0.68***	0.75***	0.72***	-1.13	21.9	-4.88
	0.031	0.038	0.059	8.49	86.7	10.3
female				-0.11	-0.031	0.063
				0.067	0.079	0.1
uni				-0.18		-0.16
				0.13		0.096
low inc.				-0.019	-0.047	
				0.054	0.086	
yob				0.001	-0.011	0.0028
				0.0043	0.044	0.0052
partner				0.081	0.11	0.34***
				0.071	0.08	0.089
children				-0.15	-0.33***	-0.2
				0.23	0.09	0.14
Observations	77	52	38	77	52	38

Robust standard errors, *** p<0.001, ** p<0.01, * p<0.05

Note: In model 5 uni, in model 6 low income, are omitted because of colinearity.

Table 4.3: SELF: CRRA coefficients

Harrison and Rutström (2008) and assume a power utility function in the form $u(x) = x^{\alpha}$.[17] Given the data of the HL-task we present the estimation results in table 4.3. The models 1 to 3 present the fitted parameters of the underlying utility function for the different subject groups. The results we obtain are in line with the €100,000 question: With a CRRA of 0.32, the non-professionals show the lowest risk tolerance compared to the junior professionals with r=0.25 and the senior professionals with r=0.28. However, these values are not significantly different when we estimate the three equations in a system and compare the coefficients. In model 4 to 6 we include demographic controls. Surprisingly, beside parenthood in model 5 and having a partner in model 6, the usual covariates do not show up to be significant in our data. Hence, the differences in the estimates are not driven by the demographics, and as the differences are insignificant there is no evidence for potential sorting in our sample.

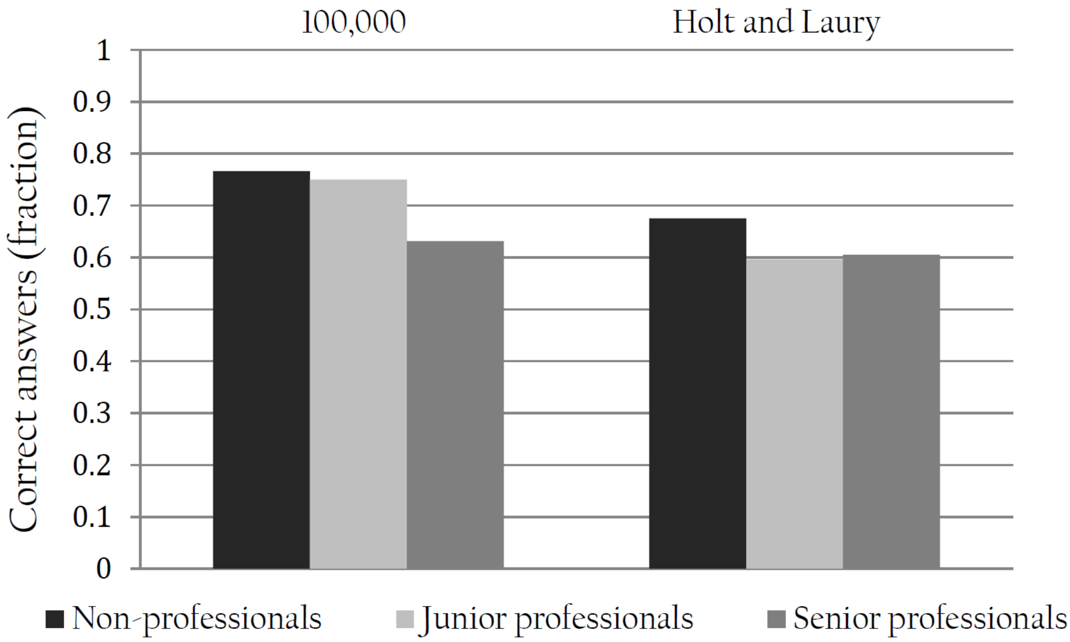
[17]For this functional form the CRRA coefficient is $r = 1 - \alpha$.

4.2 STEREOTYPE

In the following chapter we will focus on the prediction of risk preferences. In the first task subjects have to self-assess their risk attitude relative to the sample average. In the second task subjects predict the risk attitudes of distinct demographic groups.

Self-assessment and the population mean Figure 4.3 shows the percentage of subjects which are able to locate themselves correctly in the distribution of risk preferences. The figure is split up into the different subject groups and the two elicitation tasks. On the left, we present the fractions of correct answers in the €100,000 question. The results indicate that over three quarters of the non-professionals and the junior professionals rank their risk tolerance relative to the mean choice of the subjects in the web survey and SOEP survey correctly. For senior professionals this value is lower but still amounts to 63%.
Decisions in the HL-task show a similar pattern. Approximately 60% of the professionals and 67% of the non-professionals assess their risk tolerance correctly. All values are significantly larger than random answers would suggest. As there are three possible answers, under random answers we would expect a share of 33%. We test for this with binomial tests for both risk measures and all subject groups. We reject random answers with $p<0.001$ for all tests. When testing for differences between the subject groups we do not find any significant effects. As a further robustness check we run regression models including demographics to predict a correct self-assessment.[18] In line with figure 4.3 these models show only significant effects for the €100.000 question.

[18]Consult appendix 2.1 for details.

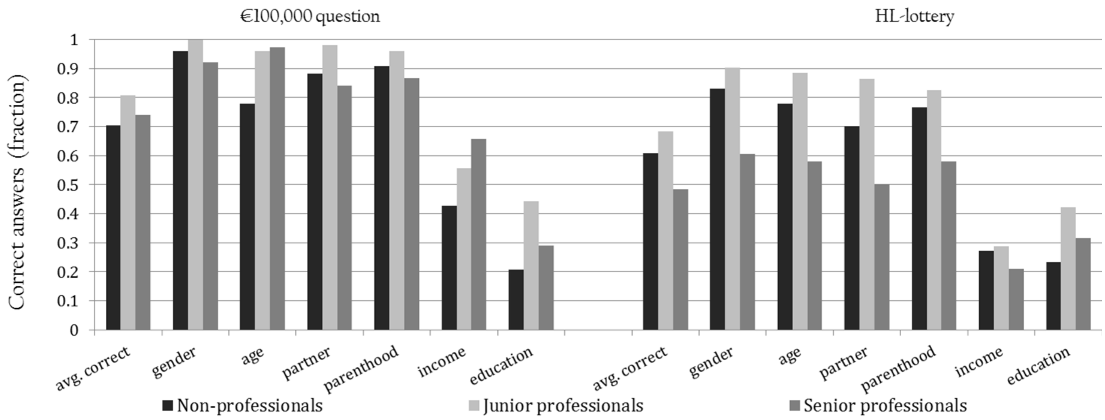


Note: The columns denote the percentage of subjects that are able to correctly answer the question *"What do you think, did people in the pretest invest more, less or the same amount respectively switch earlier, later or at the same point as you?"* split by the mechanism of elicitation. Answers of the participants in the SOEP and web survey are framed as *pretest*.

Figure 4.3: Subjects' self-assessment compared to the population mean

When considering the coefficients, we find the senior professionals to be less successful in locating their own risk attitude in the distribution of risk preferences compared to the other subject groups. However, when testing this result statistically, there is only a mildly significant structural difference.

Stereotypes on demographics In the following section we investigate the subjects' stereotypes on the risk attitudes of certain demographic groups. Table 4.2 outlines the different subsamples and their attitudes towards risk. In figure 4.4 we present the fraction of subjects who are able to identify this correlation correctly in the experiment. The column labeled by 'avg. correct' displays the average of correct answers summarized over all six categories. It is followed by the fraction of correct answers in the six different subsamples.



Note: The columns denote the percentage of subjects that are able to correctly answer the question *"What do you think, on average, which of the two groups invests more/ switches earlier, or do both groups switch at the same time/invest the same amount?"*. The column "avg. correct" averages the correct answers over the six characteristics.

Figure 4.4: Distribution of correct answers

On average, for the €100,000 question, the stereotypes of the junior professionals coincide more often with the true correlations than for the other subjects. Regarding the HL-task, again junior professionals on average answer the most questions correctly, followed by non-professionals and senior professionals. Over both elicitation mechanisms, junior professionals recognize the correlation between sociodemographic information and risk preferences with higher precision than non-professionals or senior professionals.

Considering the category 'gender' in figure 4.4, nearly all subjects are aware of the fact that men tolerate more risk than women; in the €100,000 question even 100% of the junior professionals judge this correctly. On the other hand, in the HL-task 61% of the senior professionals correctly believe that males, on average, tolerate more risk. Considering the categories 'age', 'family status' or 'parenthood', around 70% to nearly 100% of subjects assess the statistical relationship in the €100,000 question correctly. The percentage of correct answers is lower for the HL-task in these categories with around 50 to 90%.

Whereas the data delivers fairly clear results for the first four categories, in the 'education' and 'income' category the results are less clear.[19] Approximately 20% of the non-professionals and 30 to 40% of the professional groups identify the effect of a university degree correctly.[20] While in the €100,000 question 50% to 65% are aware of the correct correlation with 'income', for the HL-task less than 30% of answers are accurate. The 'income' category is a special case as the correct answer is "high income" to the €100,000 question and "low income" to the HL-task. Our study finds that only 7% recognize this pattern correctly and answer that a different subgroup exhibits the riskier choice.

In order to explore the differences between the subject groups, in table 4.4 we set up four regression models. The dependent variable is the number of correctly predicted categories.[21] While model 1 and 2 use data of the €100,000 question, model 3 and 4 investigate the HL-task. In model 1 and 3 we apply a negative binomial regression model to account for the count data structure of the dependent variable. The data are on a integer scale and range from 0 (no category is predicted correctly) to 6 (all categories are predicted correctly). In model 2 and 4 we present OLS estimations as a robustness check. The set of independent variables contains two dummy variables to identify the subject groups (senior and junior for the professionals). The omitted category is non-professional. Additionally, we include demographic variables as in model 4.3.

When we consider the regression results we find the junior and senior coefficients to be significant in all models. The senior professionals predict fewer

[19] If subjects chose their answers randomly we would expect 33% of correct answers. In both mechanisms, for all categories beside income and education a t-test rejects the null-hypothesis at reasonable levels of significance. Even when we apply a stricter test and exempt the answer "both equal", the correct answers of junior and non-professionals are significantly different from 50% except for income and education.

[20] Regarding education, the correlations found in the literature are - as for income - ambiguous. Dohmen et al. (2011) show that higher educated people are more risk tolerant. In contrast to that, Belzil and Leonardi (2007) find only modest evidence for the hypothesis that higher risk tolerance relates to higher education levels, whereas Barsky et al. (1997) find a U-shaped relationship between completed years of education and the willingness to take risk.

[21] This is a linear transformation of "avg. correct" in figure 4.4 but allows us to use count data models.

Table 4.4: STEREOTYPE: Quality of prediction

Model	1	2	3	4
Dep. Var	# correct €100.000		# correct HL	
Method	Neg.Bin	OLS	Neg.Bin	OLS
senior	-0.165***	-0.769***	-0.321***	-1.237***
	0.0578	0.283	0.111	0.44
junior	0.128***	0.623***	0.123**	0.548**
	0.0324	0.159	0.0526	0.239
female	-0.0472	-0.224	-0.0526	-0.226
	0.0316	0.154	0.0527	0.23
year of birth	-0.0007	-0.0028	-0.0014	-0.0044
	0.00275	0.013	0.00527	0.0228
single	0.00315	0.0133	-0.00127	-0.00467
	0.0361	0.173	0.0697	0.292
parent	0.0411	0.182	0.173	0.65
	0.0722	0.339	0.144	0.585
low income	-0.0583	-0.298	0.0391	0.104
	0.0527	0.27	0.0824	0.352
uni	0.00901	0.0394	-0.046	-0.177
	0.0594	0.268	0.108	0.423
constant	2.981	10.54	4.247	13.09
	5.459	25.84	10.43	45.12
Observations	167	167	167	167
R-squared		0.167		0.15

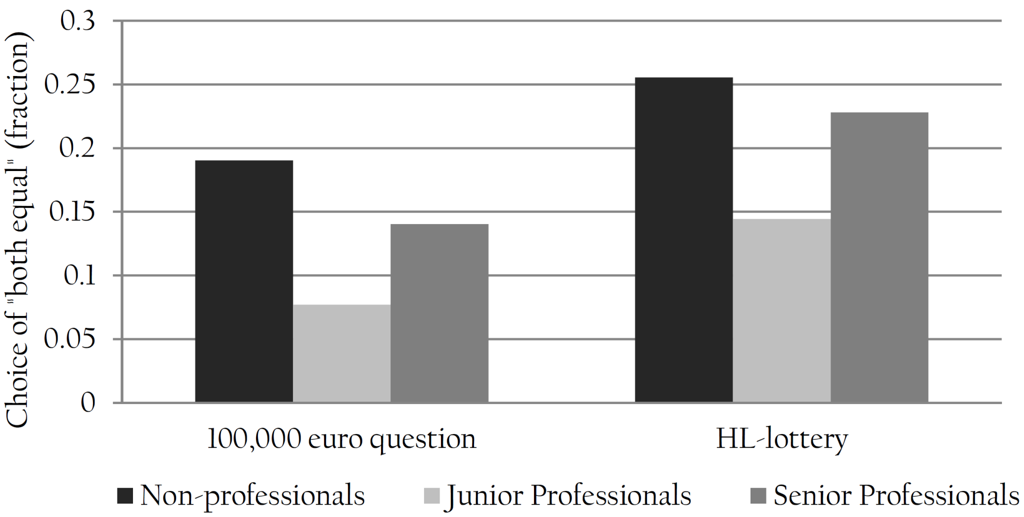
Robust standard errors, *** p<0.001, ** p<0.01, * p<0.05

categories correctly than the non-professionals. The opposite is true for the junior professionals. On average, junior professionals are successful in more categories compared to the omitted non-professionals. When testing the professionals against each other, we find that senior professionals get on average less categories right.[22] Note that all comparisons between the subject groups are significant at least on the 5%-level or higher. In contrast, for the demographic controls we do not find any significant effects. The only correlation we detect comes from the different subject groups. Of particular interest is the insignificance of the income variable. A potential concern of our design is the incentive structure: We pay the same €-amounts to all subject groups. As the senior professionals have a higher income on average, the incentives relative to

[22]When applying a Wald test (H_0: Senior=Junior) we find for model 1: (N=167) p<0.0001, for model 2: (N=167) p<0.0001, model 3: (N=167) p<0.0001, model 4: (N=167) p<0.0001.

their income are lower. Since in all models in table 4.4 the income coefficient is insignificant, there is no problem with biased incentives.

To sum up, we interpret these finding that senior professionals have less knowledge on the correlations of risk preferences and demographics.



Note: Answers to the question *"What do you think, on average, which of the two groups invests more/switches earlier, or do both groups switch at the same time/invest the same amount?"* with "both groups switch at the same time/invest the same amount", averaged over all categories and split by subjects' type and elicitation mechanism.

Figure 4.5: Distribution of answer "both equal": €100,000 question and HL-task

So far we have focused the analysis on the correlations of certain demographic groups and risk attitudes. In the following we will look at subjects' confidence regarding these correlations. As in STEREOTYPE the task allows the answer "both groups switch at the same time/invest the same amount". In fact, this answer indicates that subjects do not assign any correlation - in either way - to the variable. Subjects choosing this option do not attach informational content to this category. In figure 4.5 we show how often subjects choose this option on average. With 7% (€100,000 question) and 14% of cases (HL-task) junior professionals pick this option the least often. The non-professionals and senior professionals choose this answer with shares between 14% and 25% nearly twice as often. As a result we find that the junior professionals, the group which shows the best knowledge on correlations and demographics, chooses the "both equal" option the least often.

5 Conclusion

This experiment studies whether the behavior of financial professionals deviates from non-professionals when predicting the correlations between certain demographic groups and risk preferences. Our subject pool contains senior professionals with a long experience in financial counseling, junior professionals with an experience of roughly one year and non-professionals. We find that subjects identify the relationship between gender, age, family status, parental status and risk taking correctly while the effect of education and income is more often predicted incorrectly.

In a further task subjects are asked to rank their own risk preference relative to the population mean of two surveys. The large majority of the subjects is able to identify their behavior correctly.

As a main result we find significant differences between the different subject groups. Senior professionals are least successful in identifying the relationship between demographics and risk attitudes. There is also mild evidence that this is true for their self-assessment relative to the population mean. In contrast, junior professionals are most exact when predicting the relationship between demographic groups and risk preferences or self-assessing their preferences relative to the population mean. Interestingly, we do not find any significant differences in the risk attitudes between the groups.

Throughout the whole analysis we control for subjects' demographics. Hence, all effects come from the differences in the subject groups and are not driven by observed demographics. Junior professionals show the most accurate predictions, senior professionals the lowest. A possible explanation could be that with a larger experience financial advisors develop other strategies which are outside the control of this experiment to figure out the risk attitudes of a potential advisee. An alternative explanation could be that a trait of paternalism comes into play with an ongoing experience. These lines of reasoning could be a topic for further investigations.

Chapter 5

Does Good Advice Come Cheap? - On the Assessment of Risk Preferences in the Lab and the Field

1 Introduction

Every day, people have to decide among multiple risky options. An important aspect is that people make a decision not only based on their own knowledge and experience, but also based on advice. Especially in the financial sector, products are becoming more and more complex and at the same time, financial literacy is limited (Rooij et al. 2007). Thus, individuals are increasingly relying on professionals - such as financial consultants, insurance agents, but also doctors in the health domain - when making their decisions (c.f. Allen 2001, Bhattacharya et al. 2012).

An integral determinant of individuals' decision making is their risk preferences.

Behavior such as financial decisions, smoking and occupational choices can be predicted by risk preferences (e.g., Dohmen et al. 2011).

These developments give rise to the question of whether an advisor is capable of assessing the risk preferences of an advisee correctly. This is the aim of this study. We analyze whether good advice is possible if risk preferences are not obvious to the advisor. Explicitly, we abstain from any agency problems on which the theoretical literature has focused so far (c.f. Bhattacharya and Pfleiderer 1985, Inderst and Ottaviani 2012, or Ottaviani and Sorensen 2006). Our objective is to start a step earlier. If the advisor's only goal is to correctly gauge the risk preferences of the advisee, is the advisor able to do so?

Advice is usually given by professional advisors. Therefore we employ an artefactual field experiment[1] in which three types of subjects participate: senior financial advisors, junior financial advisors and non-professionals. These groups allow us to explore potential behavioral differences, in particular as the counseling experience differs and sorting of employees into the financial sector could be an issue (c.f. Bonin et al. 2007, Dohmen and Falk 2011, Haigh and List 2005)

Several aspects are studied: First, we inspect how advisors form beliefs about the risk preferences of specific advisees given sociodemographic information. We also check whether advisors' beliefs are subject to false consensus (Hsee and Weber 1997, Hadar and Fischer 2008) regarding their own risk preferences. This would indicate that they overestimate the extent to which other people are similar to themselves. Furthermore, we investigate how precise the advisors' beliefs are. Instead of analyzing whether the advisors' stated beliefs coincide with the advisees' actual decisions, we make use of the data of a German large-scale representative survey (SOEP) in order to generalize our result. Therefore, we compare the advisor's belief with the average decision of subjects in the

[1] Artefactual field experiments use the tools of a standard lab experiment with a non-standard subject pool (Harrison and List 2004).

SOEP data conditional on the sociodemographic characteristics of the observed advisees.

In the experiment, subjects in two different roles participate: advisors, or subjects who form beliefs, and subjects on whom beliefs are formed - advisees. Our experimental design incorporates these two roles as it consists of two main parts. First, we use a web-based survey to collect data on potential advisees. In the second part, we run an artefactual field experiment consisting of four treatments. In the first treatment, we elicit the advisor's own risk attitude. In the subsequent treatments, we vary the information available to the advisor when forming beliefs about the risk preferences of a specific advisee as collected in the survey of part one. In the second and the third treatment advisors are able to draw on several sociodemographic variables.

The results of the experiment show a false consensus bias of the advisors. Indeed, the advisors' own risk preferences positively correlate with their beliefs on the advisees. Interestingly, this is especially pronounced for experienced financial advisors and non-professionals. Besides the advisors' own risk preferences, the advisees' gender and the self-assessment of risk are considered to be important by the advisors when forming beliefs. In general, advisees are perceived as less risk tolerant than the advisors are themselves.

In a further step we investigate whether the advisors' beliefs coincide with the advisees' actual choices. We find that information on family status and the advisee's self-assessment on risk improve the predictions of risk preferences. Furthermore, the precision increases if more information is available. Professionals exhibit a significantly higher accuracy in the forecast than non-professionals.

Our paper is the first to observe the process of forming beliefs about risk preferences of others based on several sociodemographics in detail. We can explicitly control for the available information. A major advantage is the subject pool of financial advisors.

The remaining paper is structured as follows: In the next section (section 2), we discuss the literature on risk preferences and advice. Section 3 explains the experimental design, while section 4 presents the results followed by concluding remarks in section 6.

2 Literature

When making risky decisions subjects strongly react to advice (Allen 2001, Schotter 2003). Furthermore, people prefer to have advice when making a decision. Surprisingly, this is even true when it is common knowledge that the advisor does not have any information advantage in the field of the decision (Nyarko et al. 2006, Schotter and Sopher 2007). A prominent example is that subjects even demand advice for the outcome of a fair coin-flip (Powdthavee and Riyanto 2012). One explanation why subjects are keen on advice is that during the advice process people rethink their decision problem more in-depth and are therefore able to make better decisions (Schotter 2003).

To give good advice it is essential for the advisor to know the advisee's preferences. Recent research on risk preferences has detected significant linkages between sociodemographic characteristics and risk attitudes. It is largely undisputed that women are more risk averse than men (e.g., Byrnes et al. 1999, Croson and Gneezy 2009). Furthermore, individuals are found to be more risk averse if they are older, married, or have children (Dohmen et al. 2011). Regarding the relationship of education or income and risk tolerance the findings in the literature are ambiguous (c.f. Belzil and Leonardi 2007, Barsky et al. 1997, Dohmen et al. 2011, Hartog et al. 2002).

In contrast to the above research that studies *actual* correlations, advisors form their beliefs according to their *perceived* correlation between an advisee's sociodemographics and his or her risk attitude. One strategy to figure out somebody's preferences is stereotyping. Eckel and Grossman (2008) study gender stereotypes. In their study, females tolerate less risk than males. Furthermore, the beliefs about gender are consistent since women are perceived to be less risk tolerant. If, instead of *individuals'* stereotypes, *groups'* stereotypes are elicited, subjects overestimate the risk tolerance of the male group, while the female group is correctly assessed (Siegrist et al. 2002). In terms of cultural stereotypes, people perceive Chinese to be less risk tolerant than Americans. Interestingly, the actual experimental data shows an opposite correlation (Hsee and Weber 1999).

Studying the beliefs on others' risk preferences is particularly interesting with respect to financial decision making. Regarding financial advice, Faro and Rottenstreich (2006) inspect how subjects predict others' risky choices. Their findings show a systematic bias towards risk neutrality when estimating the risk preferences of others. In their experiment - in contrast to the setting of Eckel and Grossman (2008) - the advisors have to assess how a randomly chosen subject decided. Hsee and Weber (1997) study differences between a subject's own risk preferences and the subject's beliefs about others' risk preferences. The authors show that the differences increase with social distance. If subjects have to assess an abstract, randomly chosen subject from the session, the self-other discrepancy occurs. It is absent if the judging subject has visual contact with the judged subject. No further information is transmitted in both situations; the judging subject is unknown to the judge.

Another aspect that is raised in the literature is the false consensus bias in belief formation (Hsee and Weber 1997, Hadar and Fischer 2008). Subjects' beliefs about the risk preferences of another person are consistently biased towards their own risk attitude. A restriction of these studies is that no monetary incentives are used to elicit the advisors' risk aversion or the advisors' belief. Daruvala (2007) explores gender differences in beliefs when predicting risk preferences of others. She finds that gender stereotypes as well as the subject's own risk attitudes affect the belief. However, there is no incentive compatible mechanism applied to elicit the beliefs on others in this design. Chakravarty et al. (2011) inspect risk taking in delegated decisions by using lottery gambles. The subjects have to judge the risk preferences of other participants of the experiment. Judging and judged subject are seated in different rooms, and again, no further information on the judged subject is provided. When making the lottery decision for this anonymous advisee, advisors exhibit a significantly higher risk aversion compared to their own risk attitude. In addition, the increase in risk aversion is relative to their own risk preferences, which again supports the false consensus hypothesis.

There is evidence that financial professionals exhibit a different behavior in decision making than the average population (Haigh and List 2005, Nofsinger and Varma 2007, Slovic et al. 2004). People choose their job according to their preferences (Dohmen and Falk 2011). It is argued that individuals which are willing to take more risk sort into occupations with a higher variance in income (Bonin et al. 2007, Fuchs-Schündeln and Schündeln 2005) or even with a higher mortality risk (Deleire and Levy 2004). The premium dependent incentive schemes in the financial sector could be a reason for the sorting of financial professionals.

This study contributes to the literature in several ways: First, in our experiment advisors are provided with a *set* of sociodemographic characteristics of specific and vivid advisees. In the literature so far, only a single sociodemographic information is presented and varied. Based on this information, advisors form their belief about the risk preferences of the advisees. We can study the advisors' belief formation process while explicitly controlling for the information available. Second, incentives are provided for the elicitation of the advisors' risk preferences *and* beliefs, while this is not the case in previous studies. A major advantage of our approach is our subject pool consisting of financial professionals and non-professionals. This allows us to study behavioral differences of subjects familiar and unfamiliar with giving advice.

3 Experimental design

The experiment investigates beliefs about the risk preferences of others.[2] This involves two distinct roles: subjects who form beliefs (advisors) and subjects about whom beliefs are formed (advisees). Therefore our experimental setup consists of two main parts (c.f. figure 5.1).[3] In a first part, we collect data on risk preferences of advisees in a web-based survey as described in section 3.1. From this data, we choose the advisees that are presented to advisors in the second part. We augment this information by survey data from the German Socioeconomic Panel (SOEP) to control for representativity as discussed in section 3.2. Especially, we borrow our risk measure (€100.000 question) from the survey, which enables us to relate our data to the data coming from the SOEP. As robustness check we also include the measure of Holt and Laury (2002). A detailed discussion of our risk measures is given in chapter 2.

In the second part, we run an experiment consisting of three treatments. When entering the lab the advisors are randomly assigned to a computer and then log on to the experimental software. All treatments are played one after another without interaction between the advisors. Hence, we treat each subject as an independent observation. The payoffs of the whole experiment are shown after

[2]In the literature 'prediction', 'forecast' and 'belief' are used interchangeably.

[3]The instructions of both parts of the experiment can be found in appendix.

all treatments are finished to avoid learning effects. At first treatment SELF is played, which asks for the advisors' sociodemographic information and their own risk attitude using two risk measures.[4] These two risk tasks are described in section 2. In the second (RANK) as well as in the third treatment (PAY) advisors forecast the risk preferences of four advisees' profiles, each chosen from the web survey of part 1. For each advisee profile we present a screen with the advisee's sociodemographic information. Subsequently, the advisor is asked to predict the advisee's actual decision in the same two risk measures used in SELF. RANK and PAY differ in the way the sociodemographics are presented to the advisor. A detailed description is given in section 3.2.

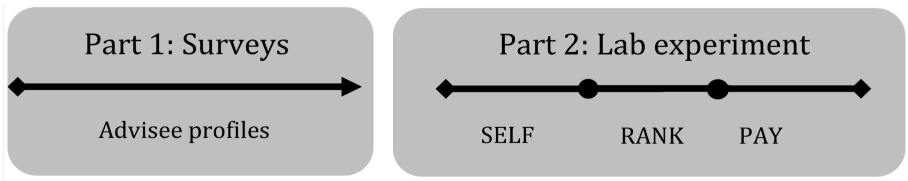


Figure 5.1: Experimental design: Course of actions

3.1 Part 1: Surveys

Our main objective is to study how advisors assess the risk preferences of specific advisees. As we analyze how the variation of sociodemographic information is incorporated into the assessment of the advisees' risk preferences, it is crucial to achieve sufficient sociodemographic heterogeneity in the pool of advisees.

To collect the subject pool from which the advisees' profiles are then selected, we ran a web-based survey in November and December 2010.[5] This allows us to generate a heterogeneous sample in several sociodemographic characteristics.

[4]There are two more treatments. SELF, as well as PAY, is followed by a further treatment. We do not expect interference for the presented results as the advisors do not receive any feedback from this further treatment.

[5]Participants were recruited via e-mail and were asked to further distribute the survey. Among all participants who completed the web-based survey we raffled off €50.

Furthermore, we ask the participants about their sociodemographics and elicit their choices in the €100,000 question.

In the course of the experiment, we make use of the fact that the €100,000 question is also part of the German Socioeconomic Panel (SOEP) survey, which allows us to generalize our results.[6] This large-scale dataset surveys approximately 20,750 subjects yearly and is therefore a powerful and representative tool for our purpose. At first, we will compare the advisees selected for presentation to the advisors with subjects in the SOEP to ensure that the advisees do not differ from the population in general. Second, in section 4.3 we analyze whether the advisors' beliefs coincide with the advisees' actual choices. To assess whether advisors' beliefs are correct, we compute the average risk preferences of a subsample of the SOEP population which are comparable to the actual advisee's sociodemographics and take this as a benchmark. This allows us to conclude whether advisors are able to assess average advisees.

	Part 1: Surveys				Part 2: Lab experiment					
	Web survey		SOEP survey		Non-prof.		Junior prof.		Senior prof.	
Variable	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
N	84	-	20,750	-	77	-	52	-	38	-
Year born	1979	10.0	1959	17.71	1986	6.29	1989	1.06	1973	11.0
Gender (female=1)	0.57	0.56	0.52	0.50	0.56	0.50	0.46	0.50	0.18	0.39
Partner (yes=1)	0.41	0.62	0.77	0.42	0.26	0.44	0.23	0.43	0.66	0.48
Parent (yes=1)	0.20	0.40	0.62	0.49	0.05	0.22	0.02	0.14	0.47	0.51
High income* (yes=1)	0.02	0.15	0.01	0.07	0	0	0	0	0.11	0.31
Uni degree (yes=1)	0.59	0.50	0.21	0.41	0.94	0.25	1.00	0.00	0.63	0.49
Counsel. Exp. (in years)	-	-	-	-	-	-	1.02	1.07	10.97	8.27
Stated risk attitude$^{\theta}$	3.54	1.81	1.90	2.13	5.26	1.39	5.08	1.52	4.68	1.71
100,000$^{\psi}$	2.38	2.70	0.91	1.98	4.70	3.29	4.00	2.44	3.11	3.18

* refers to a monthly net income above €6,000 (approx. 8,460$).
$^{\theta}$ Subjects chose on a scale from 0 (=risk averse) to 10 (=fully prepared to take risks).
$^{\psi}$ refers to the the amount invested into the €100,000 question in €10,000.

Table 5.1: Descriptive statistics

While the SOEP survey is a representative sample of the German population, this does not hold for the web survey as can be observed by comparing the descriptive statistics of the sociodemographics in table 5.1, column two and three.

[6]C.f. www.diw.de/soep for further information. The €100,000 question was included in the year 2009.

However, the heterogeneity of sociodemographic characteristics within these two pools is large compared to a sample that mainly consists of students as table 5.1 (compare column 'non-professionals', which mainly consists of students) shows.

Selection of advisees In total, eight profiles are used in RANK and PAY - four for each treatment. These profiles are chosen from the web-based survey and are displayed in table 5.2. The sequence in which these eight profiles are

Age	Education	Family status	Net income (in €)	Gender	Child.	Risk index$^{\theta}$	100, 000$^{\psi}$	SOEP mean$^{\psi}$
64	university	married	>6,000	male	yes	1	2	2.55
38	training	single	1,001-3,000	female	no	2	0	0.83
25	econ student	partner	<1,000	male	no	5	4	1.29
30	training	married	1,001-3,000	male	yes	1	4	1.01
36	adv training	single	3,001-6,000	male	no	1	2	3.24
57	university	married	3,001-6,000	female	yes	0	4	0.62
41	university	divorced	>6,000	female	no	1	2	2.50
21	econ student	single	<1,000	female	no	4	0	1.59

$^{\theta}$ Advisees chose on a scale from 0 (=risk averse) to 10 (=fully prepared to take risks).
$^{\psi}$ refers to the the amount invested into the €100,000 question in €10,000.

Table 5.2: Profiles of advisees

shown to the advisors is random. That is, a profile could appear as the second advisee to be assessed in RANK but also as the fourth in PAY, for example. Nonetheless, *every* advisor sees *all* eight profiles in random order in RANK or PAY.

Within the described experimental design it is vital to choose the set of our advisees thoughtfully. The eight advisees are chosen out of the 84 subjects of the web survey in order to achieve a balanced and diversified sample over age, education, family status, income, gender, and parenthood as presented in table 5.2. The column '100,000' depicts the individual choices in the €100,000 question.

Only if the advisees do not show any exceptional risk preferences, it becomes a feasible task for the advisor to correctly assess the advisee. Hence, we have to assure that our advisee sample is approximately coherent with the population. The large SOEP panel allows to accomplish this issue. We reduce the whole SOEP population to subjects that are similar to our specific advisees in the sociodemographic characteristics age, education, family status, income, gender, and parenthood as presented in table 5.2. From this subsample we calculate the average of the answer to the €100,000 question. Consider for example the advisee in the second row of table 5.2. In order to compute the risk tolerance of the 'representative counterpart' of this advisee (consider column 'SOEP mean'), we compute the mean of the answers in the €100,000 question given a subsample of all SOEP observations with these characteristics.[7] This subsample contains all females, aged between 32 and 43 who are single, have an income between €1,000 and €3,000 and are skilled by a vocational training. On average, people with these characteristics invest €8,300 in the lottery. By this procedure we incorporate two design features: First, the advisors assess real-life advisees which, second, do not show extraordinary risk attitudes. We show the differences between the individual risk preferences and the respective population average in column '100,000' and 'SOEP mean'.

3.2 Part 2: Lab experiment

The experimental sessions took place between April 2011 and January 2012. In total, 167 subjects in the role of advisors participated.[8] In the subject pool we have three types of advisors: senior professional advisors, junior professional advisors and non-professionals. The non-professionals are mainly students and hired via the AWI-lab at Heidelberg University where all sessions with non-professionals were run.[9] The senior professional advisors were recruited from

[7]Means are weighted with a dataset-specific weighting function which considers cross-sectional personal weights of each subject.

[8]The experiment involves no interaction among the advisors, therefore each advisor is treated as an independent observation.

[9]The experiment was programmed on a PHP-platform and accessible via a Web Browser.

a large German financial advisory agency and from local banks. The junior advisors were recruited from a banking specific advanced training institution.[10] After finishing high school, the junior professionals enter a study program in financial advisory at an applied university which contains practical counseling in up to 50% of time. Since these advisors are students, regarding age and education, they are comparable to the non-professional advisors. Detailed information on the advisor pool and descriptives are given in table 5.1. The experiment lasted approximately 50 minutes. The average payoff was €11.92. In the following we present the three treatments (SELF, RANK, PAY). RANK and PAY differ in the way the information is provided to the advisor. As discussed in the previous section, the information in RANK and PAY is drawn from the following categories of the advisees' sociodemographic characteristics: age, education, family status, income, gender, having children and self-assessment of risk-taking in financial matters. The possible realizations of these variables are shown in table 5.3.

Age	age in years
Education	university, advanced training, training, in training, no formal training
Family status	single, partner, married, divorced, living separated, widowed
Net income	up to €1,000, €1,001-€3,000, €3,001-€6,000, more than €6,000
Gender	male, female
Parenthood	having children, having no children
Risk Index	Self-assessment of risk with the question: *Regarding financial matters, are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?(0=risk averse to 10=fully prepared to take risks)*

Table 5.3: Information/Categories in RANK and PAY

SELF In the SELF treatment, the advisors' own sociodemographics and their risk preferences are elicited. At first, advisors answer the questions on their

[10] We ran seven sessions with professionals - three in the lab and four on-site. In all sessions, the conditions (no communication among participants, the distance between computers, the visual presentation of the experiment) were identical.

sociodemographics. Subsequently, they play the €100,000 question.

RANK For this treatment, we randomly choose four out of the eight profiles in table 5.2. The incentivized task is to correctly assess the risk preferences of an advisee. In the following analysis we want to estimate the effect of the demographic characteristics of table 5.3 on the adviors' beliefs. For this we need variation in the advisee profiles. Therefore we randomly assign the number of visible characteristics. As some characteristics may be more informative the advisors can influence the probability that a specific characteristic is uncovered. For this we apply the following mechanism. The advisors rank all characteristics (e.g., 1. age , 2. gender, 3. income, 4. risk index,...). Then a random number is drawn from a uniform distribution on the interval [1,7]. If for example, the random number is two and we are dealing with the advisee of the last row of table 5.2, the computer displays the following information: age: *21 years old* and gender: *female*. Then the advisor has to assess how this specific advisee has decided in the €100,000 question. For this advisee the correct answers would be *0* for the €100,000 question (see table 5.2). If the answers are correct, the advisor is paid €0.50 for each risk task.
In total, this procedure is repeated for four advisee profiles. The ranking stated at the beginning is kept for all profiles. However, for each profile a new random number is drawn and, of course, a new advisee profile is presented. Hence, the advisors evaluate four profiles one after another before moving on to the PAY treatment.

PAY In the PAY treatment, advisors can freely choose the number and kind of available characteristics that they want to be presented. In contrast to RANK, the advisors have to pay for each category they want to see in each round separately (c.f. figure 5.2). The characteristics are priced according to a convex

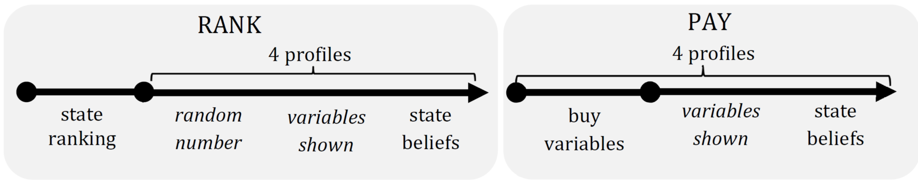


Figure 5.2: Course of actions

pricing rule. The first characteristic costs €0.01 while buying all seven characteristics amounts to €0.99 in total.[11] When entering the PAY treatment, the advisor are asked which categories they want to buy. If, for example, the advisor wants to see age and gender, the total price amounts to €0.03. On the next screen the categories are shown (e.g., age: *21 years old* and gender: *female* for the above example) and the advisor is asked to assess the risk preference of this profile. Again, the advisor earns €0.50 for each correctly assessed risk task. On the subsequent screen, the advisor is asked to buy the sociodemographic characteristics for the next profile. As in RANK, this procedure is repeated for four profiles in total.

4 Results

After introducing the different treatments, the following section presents the results. In this section we contribute to three questions. Section 4.1 studies differences in the belief formation in the different treatments and sheds a light on self-other discrepancies. Secondly, in section 4.2 we investigate how information on the advisee's sociodemographic characteristics affects the advisor's belief. Finally, in section 4.3 we inspect if the advisors' beliefs are correct. For this we combine representative survey data with lab data.

[11]Price for the second characteristic: €0.02, the third: €0.03, the fourth: €0.06, the fifth: €0.12, the sixth: €0.24, the seventh: €0.50. As the minimum earnings that are generated before the PAY treatment amount to €4, net losses are excluded.

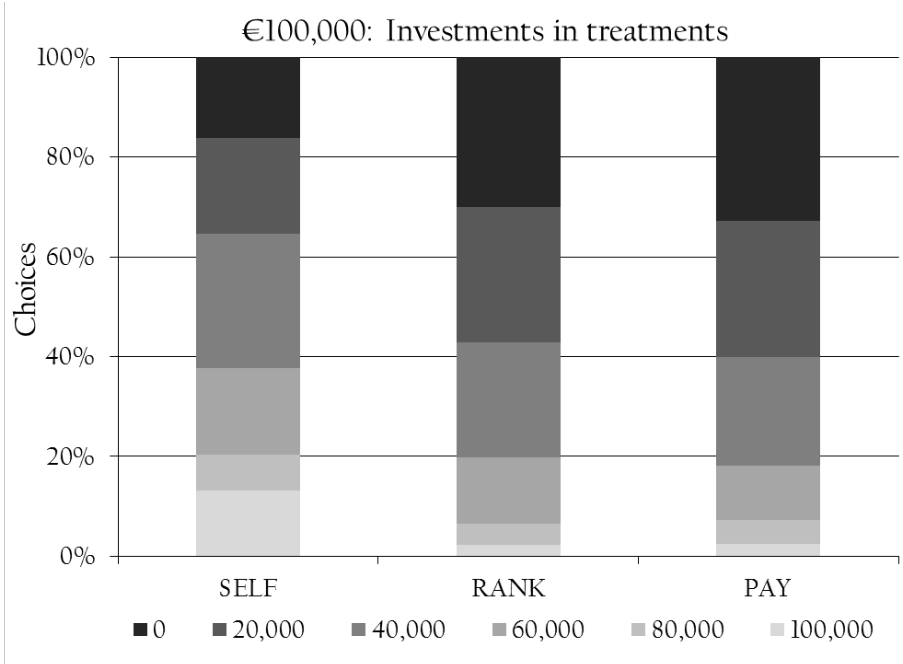


Figure 5.3: Advisors' risk preferences and beliefs (€100,000 question)

4.1 Self-assessment and beliefs

In this section, we analyze how the advisors' own risk preferences relate to their beliefs. The term self-other discrepancy refers to a systematic misperception between the advisor's own risk tolerance and the *perceived* risk tolerance of the advisee. This effect is found by Hsee and Weber (1997) but also discussed by Eckel and Grossman (2008), Faro and Rottenstreich (2006) and Eriksen and Kvaloy (2009). Regarding the process of giving advice it is important to analyze whether advisors judge themselves to be more or less risk tolerant than the advisees evaluated.

In order to investigate this effect, we present the advisor's self-assessment in the €100,000 question (SELF) compared to their beliefs separately for the two treatments RANK and PAY in figure 5.3. The decisions are aggregated for all three groups of advisors. The first column 'SELF' indicates the advisor's own decision. The second column denotes the beliefs for the RANK treatment, the third represents the beliefs for the PAY treatment. A Wilcoxon signed-rank test does not detect a statistical difference between the beliefs in RANK and PAY (p=0.43). We conclude that the way we let advisors rank and select the sociodemographic information does not affect the belief formation.

However, we find statistically different distributions for the comparison of SELF vs. RANK and PAY at the 1%-level. The results indicate that the advisors on average take more risk in their own decisions compared to the beliefs about their advisees' risk preferences. In other words, the advisors perceive their advisees to be less risk tolerant. If analyzed individually, 80% of the beliefs in RANK and PAY exhibit either the same risk or are more risk averse than the advisors' own choice. A self-other discrepancy does indeed exist.

4.2 How do advisors form beliefs?

In order to analyze how the advisors assess others' risk preferences based on sociodemographics, we set up three regression models which are presented in table 5.4. The data of RANK and PAY is pooled in the regressions since we do not find statistically significant differences in the beliefs.[12] As the 167 advisors have to judge four randomly chosen advisees in each treatment, the pooled decisions sum up to 1,336 observations.

[12]Furthermore, we control for potential differences with a dummy variable.

Model		*(1)*	*(2)*	*(3)*
dependent variable		belief	belief	belief
$\mathbb{1}\{seen{=}1\}$	Year of birth	-19.48	-15.26	-12.2
		15.63	15.16	15.11
	No uni degree	0.222	0.171	0.166
		0.230	0.210	0.205
	Single	-0.00252	-0.0251	-0.0312
		0.185	0.171	0.170
	Low income	-0.00822	-0.0794	-0.0812
		0.159	0.148	0.148
	Male	0.666***	0.651***	0.654***
		0.224	0.201	0.198
	No children	0.206	0.413**	0.414**
		0.193	0.177	0.176
	Risk index	-3.365***	-3.340***	-3.387***
		0.322	0.302	0.288
$\mathbb{1}\{seen{=}1\}\cdot\{soc\ dem \neq 0\}$	Year of birth	0.00989	0.00776	0.00623
		0.00794	0.0077	0.00767
	Uni degree	-0.0261	-0.00661	-0.0164
		0.246	0.231	0.224
	Partner	-0.269	-0.188	-0.185
		0.216	0.207	0.208
	High income	1.409***	1.429***	1.458***
		0.240	0.237	0.231
	Female	-1.118***	-1.133***	-1.158***
		0.218	0.218	0.217
	Children	-0.654***	-0.748***	-0.766***
		0.251	0.246	0.243
	Risk index	0.885***	0.887***	0.878***
		0.113	0.104	0.101
Risk pref.	Self		0.183***	0.186***
			0.0352	0.0495
	Self · junior			-0.142**
				0.0696
	Self · senior			0.103
				0.0905
Junior		-0.667**	-0.422**	0.146
		0.189	0.176	0.295
Senior		-0.653**	-0.265	-0.587*
		0.282	0.241	0.317
Rank		-0.0709	-0.0885	-0.0886
		0.0982	0.0971	0.0970
Constant		3.781***	2.756***	2.742***
		0.351	0.333	0.341
N		1,336	1,336	1,336
R^2		0.43	0.474	0.483
Adjusted R^2		0.419	0.464	0.472
Advisee FE		yes	yes	yes

* p<0.1; ** p<0.05; *** p<0.01, robust standard errors clustered at advisors' level. Dependent variable: advisor's belief in €100,000 question. $\mathbb{1}\{seen = 1\}$ indicates a characteristic is visible. *{soc dem}* indicates the realization of the characteristic. The left-out category is $\mathbb{1}\{seen{=}0\}$.

Table 5.4: Regression results: Belief formation

Model	*(1)*	*(2)*	*(3)*
$H_0 : \{socdem = 0\} + \{socdem \neq 0\}$=0			
Year of Birth	0.4207	0.3155	0.4207
Education	0.3891	0.3461	0.3891
Family status	0.2277	0.2350	0.2277
Income	0.0000	0.0000	0.0000
Gender	0.0022	0.0046	0.0022
Parenthood	0.1400	0.1692	0.1400
Risk index	0.0000	0.0000	0.0000

Table 5.5: Wald test on joint significance (p-values) for table 5.4

We run an OLS regression in which the dependent variable is the belief on the eight advisees.[13] However, how much and which information is available to each advisor when forming the belief depends on the ranking and the random number (RANK) or on how many categories are bought (PAY). The empirical models have to incorporate different states of available information of the advisor when making the prediction. Therefore, we include two major sets of variables. The estimated models thereby allow evaluating how advisors adopt their beliefs when information on different categories is available.

The dummy variables in the upper part ($\mathbb{1}$*{seen=1}*) bear a value of one if the corresponding characteristic is visible. The variables in the part below ($\mathbb{1}$*{seen=1}* · *{soc dem ≠0}*) are interaction terms carrying the value of the variable itself and are interacted with the upper dummy variables. Thus the value of the characteristic shows up only if it is observable.[14] The omitted category in this specification is 'not seen' ($\mathbb{1}$*{seen=0}*). Hence, this allows us to interpret the results as the marginal effects of the specific characteristics if it is observed. In this specification the coefficients of the upper set of dummy

[13]Remember that for a better readability, in the analyses, we present the belief in the €100,000 question in '€10,000 invested' such that the beliefs are scaled from 0 to 10.

[14]Note that the value of the sociodemographic information on 'income', 'education' and 'family status' is converted into a dummy variable to ease the interpretation. 'Income' is divided into high income (value=1) and low income (value=0), 'education' into advisees with (value=1) or without (value=0) university degree and 'family status' into having a partner (value=1) and not having a partner (value=0).

variables reflect the effect if the actual value of the variable is zero (e.g., the effect on male, as the gender dummy variable has a value of zero for male and one for female).

Additionally, by including dummy variables for the junior and senior professionals respectively, we disentangle deviations in the behavior of the groups being familiar with giving advice. Since the unit of observation is the advisor, the errors are clustered on the level of the advisors.

Given the econometric specification, we compute the scope of adjustment of the advisors' forecast dependent on the observable information. Generally, we expect the signs to be coherent with recent literature such as Dohmen et al. (2011), who use the same risk measure; we expect an advisor's belief to be more risk averse if an advisee is female instead of male. In chapter 4 we show that especially males, younger people, singles and non-parents are on average associated with a higher degree of risk taking. Advisors are thus expected to form their beliefs according to the known correlations. While model (1) serves as the baseline specification, model (2) and (3) include advisors' risk preferences in addition.

The regression results show that the risk index and gender variable are highly significant for both sets of controls in all models. By evaluating the gender variable in model (1) we find that advisors increase their forecast for the €100,000 question by €6,660 on average if a male is assessed. The investment decreases by €4,520 if a female is indicated.[15] In effect, males are expected to invest €4,520 more in the lottery than females. A Wald test on the joint significance over both sets of controls ($H_0 : \{socdem = 0\} + \{socdem \neq 0\} = 0$) reveals joint significance at the 1%-level (table 5.5). The correlation between gender and risk preferences, as suggested by the literature, is thus incorporated into

[15] To calculate the total effect, we have to sum both the male and female coefficient; the total effect turns out to be negative.

the advisor's belief.

A similar statement can be made for the variable risk index. The variable risk index in the upper part has the value of one if the advisee's risk index is zero and visible to the advisor. The fact that it shows up to be significant decreases the investment by approximately €33,650.[16] We find that on average the advisors increase their investment forecast by €8,850 for each point the advisee's risk index variable increases. Both coefficients are jointly significant.

Regarding the income variable, we find that advisors adjust their belief only for advisees with high income.[17] The interaction variable for high income is highly significant. Therefore, the amount invested in the lottery increases by €14,090.[18]

In addition to the advisee fixed effects we incorporate advisor attributes in model (2). The 'self' variable contains the advisor's personal risk attitude. This variable turns out to be highly significant. This is an interesting finding since the forecast is not only made on the grounds of the provided information about the advisees but is also related to the advisor's personal risk attitude. Especially the size of the coefficient shows the considerable influence of the advisor's preferences. Together with the dependent variable, this variable is located on the same domain. For every €1,000 an advisor invests into the lottery, he or she expects the advisee to invest €183 more, on average. This implicates that an advisor's personal risk attitude serves as a reference point for judging others. The inclusion of further advisor's characteristics (e.g., gender, age) shows a stable influence of the advisor's risk preferences (not reported).

[16] The advisees' choices of risk index range from 0 to 5 (table 5.2).

[17] Note: High income refers to a monthly net income of €6,000 and more. Regarding the correlation between income and risk preferences, results in the literature are ambiguous (see section 2).

[18] For the information on parenthood, we can observe that the effect is significant if the advisor observes that the advisee has children. Nevertheless, the Wald test on joint significance in table 5.5 proves that this is not significant.

In model (3) we are interested in whether professional experience changes the extent to which advisors base their belief on their own risk preferences. Similarly to the 'Self' variable we include two more interaction variables: 'Self · junior' and 'Self · senior'.[19] These variables interact the advisor's risk preferences with a dummy variable of the respective advisor's type. This specification allows analyzing systematic differences of the influence of the advisors' own risk attitude on the beliefs in the different advisor groups. The coefficient of 'Self' stays largely unchanged when comparing model (2) and model (3). Hence, the non-professional advisor expects, on average and ceteris paribus, an advisee to invest €186 more into the lottery for every €1,000 the advisor himself invests. The junior professionals' advice decisions are not based on their own risk preferences because the coefficients 'Self · junior' and 'Self' are jointly not significant as proven by a Wald test. In contrast to that, senior professionals show no significantly different behavior compared to the omitted category 'non-professionals'. The false consensus bias is thus driven by senior professionals and non-professionals, while junior professionals seem to abstain from using their own decision as reference point.

As suggested above, pooling the data of RANK and PAY is not an issue since 'Rank' is insignificant in all models. The variables controlling for the advisor's type indicate that professionals compared to the non-professional advisors generally believe that advisees invest a lower amount in the €100,000 question.

In conclusion, this analysis demonstrates that advisors adjust their beliefs according to the available information. In particular, the significant variables show the presumed signs. Furthermore we conclude that they use their own risk attitude as a reference point. Hence, this matches the findings of Chakravarty et al. (2011) who report a correlation between advisors' and advisees' preferences.

[19] The omitted category is 'non-professional'.

4.3 Prediction error

One of the research questions raised in the introduction is whether the advisors' beliefs coincide with the advisees' actual risk preferences. In other words, we analyze if the advisors' beliefs are correct. Furthermore, we inspect whether and which information is a prerequisite for forming precise beliefs. In order to answer this question we combine our experimental data with the large-scale heterogeneous data from the SOEP. This allows us to generalize our results and to make statements on a representative level.

Derivation of Prediction Errors In a similar manner as described in section 3.1, we compute the risk preferences of 'representative counterparts' of the advisees in order to make use of the higher predictive power of the SOEP data. However, in contrast to section 3.1 we have to take into account that not all characteristics are visible to the advisor when making the prediction. Hence, the subsample on which the conditional average of the answer to the €100,000 question is based has to be adjusted to the available information for every single assessment. Take for example the advisee in the second row of table 5.2. If the advisor sees all seven characteristics, this could be due to the fact that the random number is seven in RANK or the advisor buys all seven categories in PAY. In this case, the conditional mean is computed as described in section 3.1 and would amount to an investment of €8,300. However, if the advisor buys only gender, or alternatively, ranks gender first and the random number is one, the subset contains all female observations. On average, panel participants of the SOEP with this characteristic invest €6,878 in the lottery.

By the above procedure we obtain a value for every observation which proxies the advisee's actual decision. In order to analyze if the advisor's belief is correct, we compute the advisor's prediction error. For this we take the squared difference of the advisor's belief and the computed average choice from above. This difference serves as the dependent variable for the analyses below.

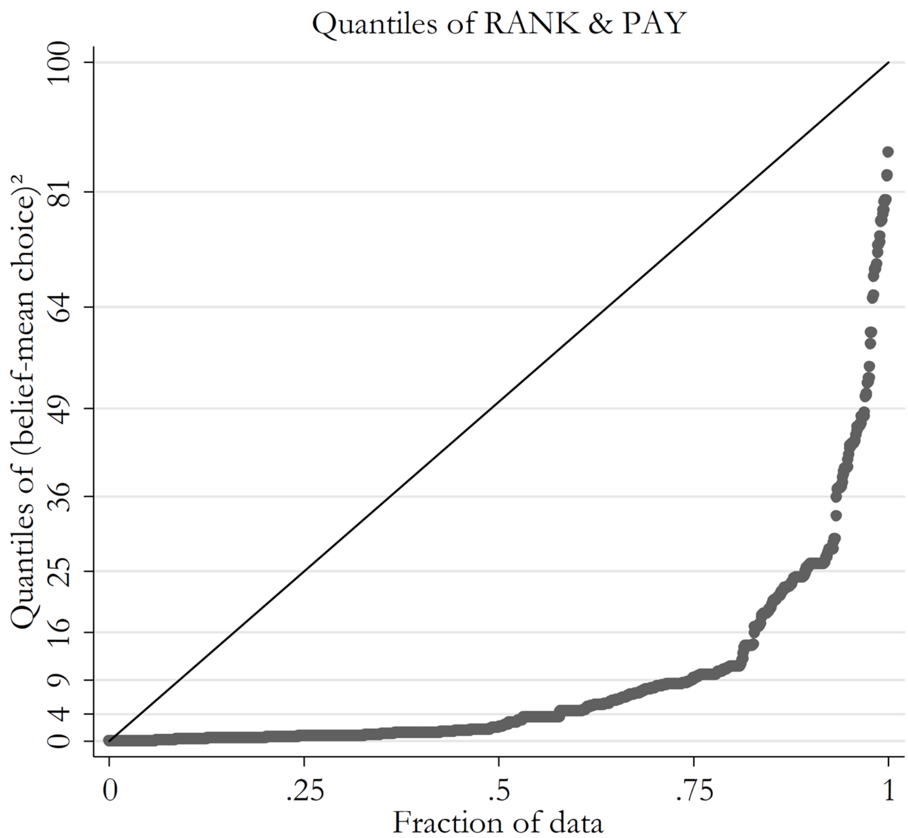


Figure 5.4: Quantiles: Prediction errors

Results In figure 5.4 we show a quantile plot of the prediction errors for the pooled prediction errors for the RANK and PAY treatment. The 45°-line represents the benchmark case of a uniform distribution of the prediction errors over the quantiles. About 20% of advisors exhibit a squared prediction error of 16 and larger, which indicates the advisors' predictions to be fairly accurate. Approximately 60% of the observations exhibit a squared prediction error below four. In other words: As the scale on the y-axis is squared, in 60% of the cases the belief deviates from the actual average choice by €20,000 or less.

To analyze the prediction errors in more detail, in table 5.6 we present two regression models to investigate if more and which information helps to decrease the advisor's prediction error. The dependent variable is the squared difference between the advisor's belief and the conditional average for the respective advisee is employed. In model (5) and model (6) we include two different types of explanatory variables. In model (5) the variable 'sum seen' measures the number of sociodemographic characteristics that is visible to the advisor when making the prediction. In model (6) the sum of visible characteristics is split up into the different categories. For each category a dummy variable is included which indicates a one if the category is uncovered. As a second set of variables in both models we include controls for the treatment and the advisor's type where the omitted category is 'non-professional'. Furthermore, both models correct for advisee fixed effects and employ robust standard errors clustered on advisors.

In model (5) we find the variable 'sum seen' to be significant at the 1%-level. The negative sign indicates that if more categories are available, the precision of the prediction increases. The marginal effect of -0.652 is economically relevant as the mean of the squared prediction error amounts to approximately 8.7. Hence, we find that indeed the amount of information plays a significant role for giving precise advice.

When considering model (6) we find a negative coefficient for the category risk index, significant at the 1%-level. This indicates that if the advisee's self-assessed risk preference is visible to the advisor, the squared prediction error decreases by approximately nine units. This confirms that the risk index variable possesses a significant predictive power. This is also true for the family status variable as it decreases the squared prediction error by 2.1 units on average.

Model		*(5)*	*(6)*
dependent variable		$(\text{belief-choice})^2$	$(\text{belief-choice})^2$
	sum seen	-0.652***	
		0.224	
$\mathbb{1}\{seen=1\}$	Year of birth		-0.945
			0.990
	Education		1.823
			1.173
	Family status		-2.105**
			1.037
	Income		0.970
			1.009
	Gender		0.322
			1.124
	Children		-0.101
			1.274
	Risk index		-8.943***
			1.826
	Junior prof.	-4.599***	-4.011***
		1.253	1.118
	Senior prof.	-2.197	-3.009*
		1.819	1.747
	Rank	0.433	-0.652
		0.671	0.640
	Constant	11.18***	16.92***
		1.680	2.383
N		1,336	1,336
R^2		0.163	0.222
Adjusted R^2		0.156	0.211
Advisee FE		yes	yes

Results of OLS regression, * p<0.1; ** p<0.05; *** p<0.01, robust standard errors clustered at advisors' level, dependent variable: squared difference between advisors belief and actual choice of representative advisee calculated from SOEP. $\mathbb{1}\{seen=1\}$ indicates if a characteristic is seen.

Table 5.6: Regression results: Prediction errors

A further considerable result of this analysis is obtained with respect to the types of advisors. The prediction error of the junior professionals shows up to be significantly lower compared to the reference group of (omitted) non-professionals. In model (5) this coefficient has a relevant impact with a value of -4.6. When comparing the two groups of professionals we find the junior professionals to have significantly lower prediction errors compared to the senior professionals. The coefficient of the senior professionals is not significantly different from the reference category of non-professionals. Both groups of professional advisors perform significantly better in model (6) compared to the non-professionals. In addition to junior professionals, also senior professionals have a significantly lower prediction error at a significance level of 10%.

A further observation in these models is that they explain 16% to 21% of the variation in the prediction errors. Compared to other studies analyzing risk preferences and their determinants, this is remarkably high.

In summary, these models demonstrate that if more information is available, the prediction quality of advice increases. The variables risk index and parenthood improve the prediction of risk preferences. A major result is that professionals outperform non-professionals in making precise predictions. Interestingly, young professionals' beliefs are even more precise than the beliefs of the senior professionals.

5 Robustness checks and further results

As outlined in section 3, the whole experiment is executed with the risk measure of Holt and Laury (2002), which serves as robustness check (see chapter 2 for details). In the following paragraphs we reproduce the previous analyses to back the arguments made in the sections 4.1 and 4.2. For section 4.3 we cannot provide a robustness check since the alternative risk measure is not available for the SOEP dataset. All mentioned tables and figures can be found in the appendix.

5.1 Self-assessment and beliefs

Figure 7.2 shows the distributions of the advisor's beliefs and the advisor's own risk preferences as in section 4.1. In contrast to the €100,000 measure, the HL-task allows to reveal risk-loving preferences. Approximately 12.6% of the advisors switch from lottery A to lottery B before row 5 and therefore exhibit risk-loving behavior. These results are comparable in size with the results reported by Holt and Laury (2002).

In general, we find a significant relationship between the beliefs in the HL-task and the €100,000 question. The rank correlation coefficient of the beliefs in the two measures amounts to 0.52 and is statistically significant at 0.1%. Hence, the observed distribution of the beliefs in the HL-task (figure 7.2) is comparable to the distribution of the beliefs in the €100,000 question (figure 5.3).

In figure 5.3 we find that advisors judge the advisees to be less risk tolerant compared to their own risk attitude in the RANK and PAY treatment. This result is detected in the robustness check as well since the dashed lines lie above the solid black line, as can be observed in figure 7.2. A sign-test approves this result at a significance level of 1%. 72% of advisors' beliefs are less risky or equally risky compared to the advisors' own risk preferences. Furthermore a Wilcoxon test does not detect any difference between SELF and PICT. Therefore the statistical findings of the robustness check are in line with the results of section 4.1.

5.2 How do advisors form beliefs?

In the following section we present the robustness checks for the question of section 4.2. For this we replicate the analysis above with the HL-task and re-estimate the empirical models (1) to (3) and refer to them as (1a) to (3a) in table 7.3 and 7.4. If we find coefficients to exhibit an opposite sign compared to section 4.2, our results are similar, as for the HL-task, a higher number indicates that the advisee is supposed to switch later and thus reveals a higher risk aversion. Aside from the sign, the dependent variables of both risk measures range on a scale from 0 to 10.

For model (1a), which analyzes the specification of (1), we find similar effects. Again the risk index, gender and income variables are significant at the 1%-level. All mentioned coefficients are jointly significant at the 1%-level as well.[20]
In model (2a) we incorporate advisors' own risk preferences ('all advisors self') in addition to the advisee-fixed effects. In line with model (2a) the coefficient is significant and of relevant magnitude.
Model (3a) includes indicator variables for the different groups of advisors. In model (3) we find no false consensus effect for the junior advisors. In contrast to that, in model (3a) these advisors exhibit a false consensus. However it is not statistically different from the non-professionals. The same is true for the senior professionals.
These robustness checks largely confirm the results of chapter 4.2. We find differences in the magnitude of the false consensus for the junior professionals.

6 Conclusion

This study investigates how advisors form beliefs about the risk preferences of advisees. Advice, especially in the financial sector, is important as people increasingly make their investment decisions after consulting a professional advisor. Hence, an accurate prediction of an advisee's risk preferences is vital for good advice. The results of this study contribute to the existing literature in several ways.
We find that the risk tolerance an advisor assigns to an advisee significantly depends on the advisee's self-assessment of risk preferences. Besides, the self-assessment, gender and income have a significant impact on the advisors' assessment of the advisees' risk preferences. A salient finding is that advisors employ

[20] See table 7.4 in the appendix for details.

their own risk preferences as a reference point when giving advice.

Interestingly, the beliefs show a higher risk aversion than the advisors' own risk preferences. For the process of giving advice this indicates that - abstracting from any incentive problems arising in the advice process - advisors in general do not assess people to be more risky than they are themselves.

When analyzing the prediction errors we find that more available information reduces prediction errors. Especially the visibility of the risk index and family status improves the prediction. By using the large-scale data of the SOEP to construct choices of representative advisees, we provide further robustness for this result. Sociodemographic information is helpful for advice to become more precise. Good advice is thus not cheap, it needs sociodemographic information. Information about family status and the advisees' self-assessment of risk preferences, however, can be obtained easily in a counseling interview.

The fact that professional advisors are able to predict the risk preference with higher precision is good news for costumers of financial advisors. Furthermore, theoretical studies that solely focus on agency problems and incentives that arise in the counseling interview often take as given that the advisor is aware of the risk preferences of the advisee. Given our study, this assumption should be viewed with some caution.

A major asset of this study is the rich dataset. We investigate whether the financial professionals' behavior differs from non-professionals. Interestingly, junior professionals emerge as a group that stands out for two reasons. First, their advice is less dependent on their own risk preferences, and second, the prediction is more precise than in any other group. Hence, extensive counseling experience does not necessarily lead to a better outcome in terms of prediction accuracy.

Chapter 6

Does Meeting Make a Difference? - How Personal Interaction Affects the Assessment of Risk Preferences

1 Introduction

Advice is important for decision making, particularly in the financial domain. Two important features characterize recent developments in financial markets and are closely related to our study.

First, financial products are becoming more and more complex. Financial literacy is required, but knowledge about even basic financial principles is not necessarily given among the population (Rooij et al. 2007, Lusardi and Mitchell 2005). Thus advice by professionals is increasingly important (Shiller 2008). Furthermore, recent research suggests that subjects have a preference for advice when making a decision. People ask for advice even if it is common knowledge that the advisor does not have any information advantage in the field of the decision (Nyarko et al. 2006, Schotter and Sopher 2007). When making risky decisions subjects strongly react to advice (Allen 2001, Schotter 2003). However, for giving good advice, the consultant has to know the risk preferences of the client to recommend products that match the client's preferences.

Second, the development of web-based technologies has induced that people are able to buy financial products online and do not necessarily visit a bank. Online trading accounts for a major share of the trading activity and influences the performance of investors (Barber and Odean 2001, 2002). Also, communication via the internet has become easy and cheap. However, when communicating via the internet, the social distance[1] between the financial advisor and the advisee is increasing. These two developments raise the question whether, for giving good advice, personal interaction between consultant and client is necessary. For example, for many online services a client transmits all relevant information over the web. Based on this information, and without a face-to-face meeting, the consultant recommends products. Recent research suggests that personal involvement, empathy and the social distance between subjects affect the decisions made on behalf of others (e.g., Faro and Rottenstreich 2006, Güth et al. 2007).

The central question of this paper is whether personal interaction is necessary for assessing the risk preferences of others. In our setup, subjects have to assess the risk preferences of others in a within-subject-design. In our baseline treatment, subjects base their decisions only on demographic information. In our two main treatments we manipulate the social distance between the subjects: In the INFORMATION treatment we provide the demographic information by chat protocols between two persons. In the INTERACTION treatment subjects predict the other's risk preferences after gathering the information by a face-to-

[1] In our understanding of social distance we follow Bohnet and Frey (1999): "When social distance decreases, the "other" is no longer some unknown individual from some anonymous crowd".

face conversation.

In our setup, advisors are rewarded for exactly meeting the preferences of the advisee. We thus abstain from explicitly modeling payoff responsibility; advisors know that there are no payoff consequences for the advisee. The main asset of our study is that we manipulate the social distance between subjects when predicting the risk preferences of others in a within-subject design. Our results show that social distance has an ambiguous effect on the prediction of risk preferences. While we find mild evidence that chat protocols help to avoid misjudgments, interestingly, personal interaction does not have a positive effect on prediction errors.

In the subsequent analysis, we will proceed as follows. While section 2 gives an overview of the literature, in section 3 the experimental design is described. In section 4 we derive our hypothesis and present the results in section 5. Finally, section 6 concludes. In the appendix, the experimental instructions can be found.

2 Literature

Our investigation adds to the four following strands of the literature. First, several studies investigate the assessment of another person's risk preferences given their sociodemographic information. With this respect, Eckel and Grossman (2008) study gender stereotypes in a setup in which the subject to be judged is fully visible. The authors find that subjects believe that women are less risk tolerant than men. Indeed, in their data females are less willing to take risks. In a similar manner, Siegrist et al. (2002) find that if groups of males or females are assessed, the risk tolerance of the male group is overestimated, while the female group is correctly assessed. In terms of cultural stereotypes, people perceive Chinese to be less risk tolerant than Americans (Hsee and Weber 1999). Interestingly, the actual experimental data show an opposite correlation. Roth and Voskort (2012b) study the assessment of others' risk preferences based on several sociodemographics and find that indeed the amount of sociodemographic information increases the precision of advice. Our paper adds to this literature as we let people interact face-to-face with the assessed person.

In a second strand of literature, subjects take risky decisions referring to others. In this setup, no particular sociodemographic information is transmitted, but the degree to which people have an (emotional) relationship differs. According to Loewenstein et al. (2001) decisions might change if people are emotionally involved. The results by Hsee and Weber (1997) are twofold. First, they show that subjects predict others to be more risk seeking than themselves in risky choices. In addition, the authors find that this self-other discrepancy vanishes if the assessed person is vivid and shown to the subject. The concept of an empathy gap (Loewenstein 1996) between advisee and advisor is also investigated by Faro and Rottenstreich (2006). The authors study whether the self-reported ability to empathize with someone else influences the ability to assess others' risk preferences. The authors compare risky decisions made on behalf of a close friend and an unknown person (on whom the decision maker has no further information). Faro and Rottenstreich (2006) find that the greater the self-reported ability to empathize with others' emotional reactions, the less regressive are the predictions of others' risk preferences.

A third strand of literature introduces payoff externalities for the judged subject. The baseline result is provided by Chakravarty et al. (2011) and Eriksen and Kvaloy (2009), who find opposite effects. First, Chakravarty et al. (2011) inspect risk taking in delegated decisions by using lottery gambles. Judging and judged subject are placed in different rooms, no further information on the judged subject is provided and the identities are not revealed to each other. As a result, the decision maker assigns more risk to others than to himself. However, Eriksen and Kvaloy (2009) show that subjects take less risk with clients' money than with their own. In a study by Pahlke et al. (2012) risky decisions are made on behalf of others, but the decision maker has to justify his decision in front of the judged subjects. The results deliver evidence that the decisions on behalf of others bear less risk under responsibility, which is in line with Eriksen and Kvaloy (2009).

Finally, Charness and Jackson (2009) investigate risk taking in a setting with a dictator and a recipient. They compare dictators investing for themselves with a setting where the investment is made on behalf of the recipient. As a restriction, communication between the two players is not possible. The results show the dictator's investments to be less risky when the investments are made for the recipients than for themselves. Güth et al. (2007) investigate the effect of social distance on risk taking on behalf of others. They compare a situation in which a speechless video clip of the judged subject is shown to a situation in which the judged subject is unknown in order to investigate the relationship between risk attitudes and social preferences. The authors do not detect significant differences between their treatments.

In our design, we manipulate the social distance differently as we introduce the information treatment in which only text-based communication is observable as well as face-to-face communication (interaction treatment). The next paragraph explains the experimental setup in more detail.

3 Experimental design

As outlined above, the experiment investigates the effect of social distance on the assessment of risk preferences of others. The experimental design we use is a within-subject design. Subjects play one treatment after another. Therefore we consider each subject to be an independent observation. The experiment is computerized and programmed in zTree (Fischbacher 2007). In total we conduct thirteen sessions. Each experimental session consists of eight subjects. Overall, 104 subjects participate in the experiment. The subjects are recruited via ORSEE (Greiner 2004) at the AWI-lab at Heidelberg University. Descriptive statistics can be found in table 6.1.

For the remainder of the experiment we introduce two roles: a subject is denominated to be an *advisor* if he or she forms beliefs about somebody else; a subject is called *advisee* if an advisor forms beliefs about him or her. All subjects play both roles subsequently.

Variable	Obs	Mean	Std. Dev.	Min	Max
Female	104	0.48	0.5	0	1
Year of birth	104	1989	2.65	1979	1994
Partner	104	0.35	0.48	0	1
Height (in cm)	104	175	8.85	157	198
Uni education	104	1	0	1	1
High income**	104	0	0	0	0
Profit	104	13.46	2.65	8.6	19,2
€100,000***	103*	4.58	3.08	0	10
sMPL****	99*	6.02	1.89	1	10

* Outliers excluded
** refers to an income above €6,000
*** Decision in €100,000 question, amount not invested in €10,000.
**** row of switching to option B in sMPL

Table 6.1: Descriptive statistics of subjects in the experiment

The experimental setup comprises the following treatments: In the first treatment, we elicit the advisor's own characteristics and risk preferences (SELF). In

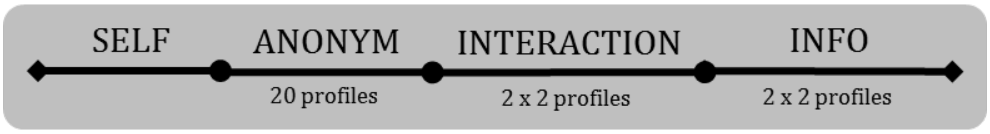


Figure 6.1: Course of actions

the second treatment (ANONYM) advisors have to predict the risk preferences of 20 advisee profiles given their sociodemographic characteristics. In the third treatment (INTERACTION), advisors take part in a one-to-one conversation with four of the advisees presented in ANONYM and have to forecast their risk preferences. In the fourth treatment (INFO) advisors judge the risk preferences of four co-players already assessed in ANONYM. In contrast to INTERACTION, the information is provided by a transcribed conversation. Hence, in the INFO treatment the informational structure is as in INTERACTION, but the advisees' appearance and voice cannot be observed. The following sections explain the experiment in detail.[2]

Since the experiment includes treatments in which anonymity cannot be ensured, all participants have to sign a disclosure agreement at the beginning.

Measures of risk aversion Throughout the whole experiment two distinct risk measures are employed. The first measure is borrowed from Dohmen et al. (2011) while the second mechanism is a multiple price list design taken from Holt and Laury (2002). In chapter 2 we provide a detailed discussion of both measures. In order to make sure that subjects understand these mechanisms we include a test questions for both risk tasks.

[2]After INTERACTION we elicit second-order beliefs. We do not expect any interference as no feedback is given.

3.1 Treatments

The experiment is separated into four main treatments (SELF, ANONYM, INTERACTION, INFO). When entering the lab, the subjects have to draw a lot which randomly assigns them to a computer workspace.

SELF In the first treatment SELF, we elicit the subject's demographics and risk preferences. Therefore, subjects have to play the two risk tasks as described above. The preference elicitation is incentivized. In the €100,000 question, the value of €100,000 is paid off by €2.50. The subjects' payoffs range between €1.25 and €5. For the sMPL the payoffs range from €0.10 to €3.85.

ANONYM After finishing the SELF treatment advisors enter the second treatment (ANONYM) in which they assess the risk attitudes of others. It serves as a baseline treatment. The advisors' task is to predict exactly the advisee's decision in the two elicitation mechanisms. Therefore we ask the advisors *"How do you think the advisee, whose characteristics are displayed in the box above, decided?"* in the respective risk measure. In all treatments, when the advisor's prediction meets the choice of the advisee we pay €0.50 per risk elicitation mechanism. As we reward only for an exactly correct prediction, this payoff structure is incentive compatible.

Level of education	university, technical college, apprenticeship, currently a student, currently a student with an economics major, currently in an apprenticeship, no vocational training or education
Age	0-25 years, 26-40 years, 40-65 years, over 65 years
Monthly net inc.	Up to €1000, €1000-3000, €3001-6000, over €6000
Marital status	single/single parent, divorced, in a relationship, living separately, married, widowed
Gender	male, female
Children	children, no children
Body height	in cm

Table 6.2: Information provided in the profiles

In this treatment advisors have to predict the risk preferences of 20 profiles. For each profile we provide the advisor with seven sociodemographic characteristics on the computer screen. The possible realizations of the characteristics are presented in table 6.2. These characteristics are considered to be significant correlates with risk taking (Dohmen et al. 2011, Gaudecker et al. 2011, Roth and Voskort 2012b). An example of a profile presented is: *gender: female, family status: single, parental status: without children, age: 33 years, education: university degree, monthly net income: €1001 - €3000, body height: 158 cm.* Hence, in this treatment, an advisor has only demographic information at hand when making the judgment. The profiles presented are composed as follows: we include the seven profiles of the co-players in INTERACTION and INFO. In addition to the seven co-player profiles, we include further profiles from chapter 5. In total we elicit the beliefs over twenty profiles in order to achieve a higher degree of heterogeneity in the profiles' demographics. The profiles are presented to the subjects one after another in a random order.

INTERACTION In this treatment subjects come together for four personal one-to-one conversations in groups of two. Compared to the previous treatment, subjects experience a lower social distance through the personal interaction.
At the beginning of the experiment, subjects are randomly matched to four co-players. In the INTERACTION treatment, the subjects meet these co-players successively in person for a conversation. Each conversation takes place at a separated table. At first, one subject interviews the other and vice versa. By this we gain observations for every pair. After the last of the four conversations, subjects return to their computer workplaces and their task is to predict each partner's risk preferences in both risk measures. To make sure the advisors remember their advisee correctly, they fill out a questionnaire which they keep

after the interview. Thus both partners of the one-to-one conversation take the role of advisor and advisee: in the same conversation, they have to assess their interview partner and are assessed themselves.

To make sure they actually do not collude and simply tell their partner their decisions in the risk measures, several control instruments are employed. The sessions consist of eight subjects and therefore only four groups are chatting simultaneously. In all sessions, two or three experimenters are present in the lab and the conversations are audio recorded. Finally, subjects are told in the instructions that they would be excluded from the experiment when mentioning the risk measures. Throughout the whole experiment, we have not detected a single attempt of non-compliance.

The four personal meetings differ in the questions that subjects are allowed to ask: two meetings are of TYPE A and two meetings are of TYPE B. In TYPE A subjects are equipped with a questionnaire containing demographic questions they are expected to ask their partners during the conversation (see table 6.2). These questions are designed to ask exactly for the demographic information according to the profiles. The subjects are told that they strictly have to follow the questionnaire. By asking questions about the sociodemographics we ensure that the advisor has at least as much information available as in ANONYM. However, it could easily happen that advisors gain more sociodemographic information "between the lines" in this treatment compared to the ANONYM treatment. Moreover, in TYPE B conversations, in addition to the demographic questions, subjects can ask whatever they want except for the risk measures. In contrast to the ANONYM treatment, the social distance is substantially decreased in this treatment as in the face-to-face conversation subjects will recognize appearance, voice, etc.

INFO In this treatment, we equip subjects with transcripts of a chat of the INTERACTION treatment. We use audio recordings of previous sessions to transcribe an exact chat protocol of a conversation. By this, the advisor has exactly the same amount of information available as in INTERACTION, but does not meet with the advisee. Hence, the content of the communication is kept constant but the social distance is larger compared to INTERACTION. The transcripts are taken from conversations of earlier sessions. The drawback of this treatment is that we cannot establish a within-advisor effect as the transcribed conversations are transferred to later sessions. For further details see figure 6.2.

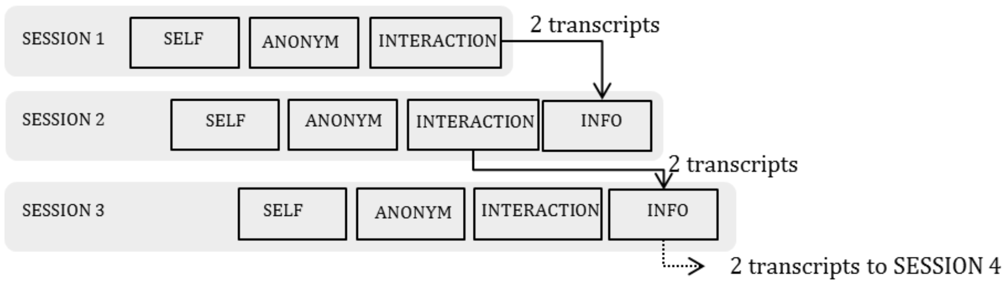


Figure 6.2: Allocation of transcripts

Over all thirteen sessions advisors judge 35 transcripts.[3] As in INTERACTION the transcripts are of two types: one of TYPE A and one of TYPE B. One advisee presented in transcript TYPE A is also present in the transcript of TYPE B. Thus every subject judges the profiles of three different advisees. For each transcript we gain eight observations.

[3]One transcript coming from session 1 is used twice.

4 Hypotheses and data

4.1 Hypotheses

The key aspect of this study is to relate social distance to the prediction of risk preferences. We use three treatments that implement different levels of social distance between advisor and advisee to evaluate this effect. The underlying assumption is that information on another person affects the social distance. In the INFO treatment the advisor gathers additional information on the advisee by a transcribed conversation. By this feature of our design, the advisor receives the same demographic information as in the ANONYM treatment but is possibly able to extract more information "between the lines". Hence, in INFO the social distance should be lower compared to the ANONYM treatment in which the information is presented in a list.

In the INTERACTION treatment, the advisor acquires information in an authentic face-to-face conversation. Again, when making the decision the same amount of demographic information as in ANONYM is available. In the conversation the advisor will receive information "between the lines" in a similar fashion as in INFO and additionally experience the personal interaction. As a consequence, we expect the lowest social distance in this treatment.

The variable of interest in this experiment is the prediction error of the advisor. This is measured by the squared difference δ between the advisor's prediction and the advisee's choice of the risk measure.[4] As outlined above, both risk measures are scaled from 0 (choice with the highest risk tolerance) to 10 (the most risk averse choice). Therefore the squared difference ranges from 0 to 100.

[4] δ=(advisor's belief-advisee's choice)^2

Hypothesis 1. (Information)

In treatment *INFO*, the advisor possesses more information on the advisee compared to *ANONYM*. Hence, we expect that the availability of the additional information decreases the prediction errors: $\delta_{ANONYM} > \delta_{INFO}$

Hypothesis 2. (Interaction)

The personal interaction in treatment *INTERACTION* allows the advisor to gather additional information such as gesture, appearance, behavior or reactions compared to INFO. This should help the advisor to evaluate the advisee's risk preference and lower the prediction errors: $\delta_{INTERACTION} < \delta_{INFO}$

Hypothesis 3. (Total effect: Interaction and information)

As a consequence of H1 and H2, when analyzing the total effect, we expect lower prediction errors in *INTERACTION* than in *ANONYM*: $\delta_{ANONYM} > \delta_{INTERACTION}$

Before turning to the statistical analysis of our hypothesis in chapter 5, we discuss the structure of the dataset in the following.

4.2 Data structure and outliers

In total, we have eight advisor observations in each of the 13 sessions. In total this amounts to 104 observations for treatment ANONYM and INTERACTION. For treatment INFO, only twelve sessions with eight advisors can be analyzed, since in session 1 the transcripts for session 2 are generated. In table 6.3 we present the structure of the observations from the experiment.

In order to make sure that subjects have understood the sMPL measure we control whether subjects have understood the risk measures and in case of non-understanding, exclude them as outliers. We exclude subjects case-by-case if the control questions are not answered correctly either for the €100,000 question or the sMPL mechanism. Additionally, in the sMPL in row ten the payoff of

Hypothesis	H1		H2		H3	
Treatments	ANONYM	INFO	INFO	INTER*	ANONYM	INTER
Sessions	12	12	12	12	13	13
Advisors/session	8	8	8	4	8	8
Advisees/treatment	4	4	4	3	4	4
Total observations	384	384	384	140	416	416
Effect: advisors	within		between		within	
Effect: advisees	within		within		within	

*Note: (12 sessions · 3 advisees -1 [one profile is used twice]) · 4 advisors = 140 obs

Table 6.3: Observations in treatments

option A is strictly lower than the payoff of option B. Subjects that do not choose the option with the higher payoff are classified as an outlier for the sMPL mechanism. For the sMPL we classify five subjects and for the €100,000 question a single subject as an outlier.[5] For all results presented, there is no significant effect on the results if the outliers are included. Table 6.1 shows the risk preferences of the subjects without outliers. Table 6.3 summarizes our dataset and the number of observations available for the analysis of the treatment effects.

As outlined above, we consider each subject to be an independent observation because there is no strategic interaction between the subjects. To control for the multiple observations for each subject econometrically we prefer random effect models over non-parametric statistics.

5 Results

After describing the dataset in the section above, in the following we present the econometric analysis. In section 5.1 we test the hypotheses raised in section 4.1. We show robustness checks in 5.2 and 5.3 where we argue that subjects do not answer the risk tasks randomly and that the treatments do not induce any

[5]Also, Holt and Laury (2002) report that 8 to 10 % of the subjects exhibit non-monotonic or non-rational preferences in the sMPL, which might be due to difficulties in understanding.

Model	*(1)*	*(1a)*	*(2)*	*(2a)*	*(3)*	*(3a)*
Hypothesis	Hypothesis 1 INFORMATION		Hypothesis 2 INTERACTION		Hypothesis 3 TOTAL EFFECT	
Measure	100,000	sMPL	100,000	sMPL	100,000	sMPL
ANONYM	3.937**	-0.0467			0.0583	-1.293
	1.91	0.717			1.987	1.048
INFO			-3.585**	-1.465*		
			1.726	0.81		
Type A	-0.316	-0.797	-3.416*	-1.994**	0.485	-0.419
	1.91	0.717	1.779	0.834	1.987	1.048
Order	1.874	0.313	-0.905	-1.252	-1.534	-2.268**
	1.91	0.717	1.769	0.837	1.987	1.048
Constant	18.14***	5.445***	5.604	5.423**	17.02***	6.927***
	1.385	0.514	5.252	2.386	1.191	0.599
RE: Advisors	95	91	102	98	103	99
Advisees dummy	no	no	35	35	no	no
Observations	760	728	520	497	824	792

Random effects models, Significance * p<0.1; ** p<0.05; *** p<0.01; Outliers excluded

Table 6.4: Regressions: Treatment effects

structural biases.

5.1 Treatment effects

In order to tackle our hypotheses we set up three regression models as presented in table 6.4. We choose a regression analysis over non-parametric tests to control for the dependencies within the multiple observations for each subject. Thus, we use random effects models which include an individual effect for each advisor. For each of the three specifications we present the results of the €100,000 question in the first model and the results for the sMPL in a model denominated with "a".

For all models the dependent variable is the prediction error as defined above. The set of independent variables contains a dummy variable indicating the respective treatment. Furthermore we include binary variables capturing the different types of conversation (Type A) and potential order effects (Order), which result from the order in which advisees are presented to advisors.

As described in hypothesis 1, model (1) and (1a) capture the effect of information as the treatments ANONYM and INFO are compared. In ANONYM advisors have only demographic information available (cf. table 6.2) while in INFO, advisors make their prediction given a protocol of a chat. A difference between these treatments indicates that information provided by the transcribed conversation has an impact on the precision of the prediction error. As the results in table 6.4 show, only for the €100,000 task a treatment effect can be observed. The variable "ANONYM" carrying the treatment effect is only statistically significant in model (1) at 5%. The availability of the transcript decreases the prediction error by 3.937 on average. This effect is of economically relevant magnitude. If we take the square root we find that the availability of the transcript increases the prediction accuracy by €19,842 on average. Hence, we find mild evidence in favor of hypothesis H1 saying that information lowers the prediction error of risk preferences.

In a second step, we consider the hypothesis H2 to evaluate the effect of a personal interaction. For this we compare the prediction errors δ in the INFO and the INTERACTION treatment in model (2) and (2a). In both treatments we have additional information compared to ANONYM, but only in the INTERACTION treatment a face-to-face communication takes place. Consequently, a difference in the prediction errors is caused by the personal interaction. The results of the regressions show a significant treatment effect for the personal interaction in both risk elicitation tasks. For the €100,000 question we find the effect to be significant at the 5%-level. The sign of the coefficient INFO indicates that the availability of the transcript compared to a personal meeting decreases the prediction error by 3.585. By taking the square root this translates into a higher accuracy of €18,934 on average in the INFO treatment compared to the INTERACTION treatment. Hence, the size of the coefficient is economically relevant in its magnitude. When considering the sMPL we find a coefficient which is significant only at the 10%-level. The sign is also coherent to the €100,000 question. Interestingly, for hypothesis H2 we expected the effect to be in the opposite direction. Hence, the advisors are not able to extract useful information (with respect to the accuracy of the prediction) from a personal meeting. In contrast, meeting the advisee in person apparently biases the advisor. Therefore, H2 cannot be confirmed.

In all models, the effects in the sMPL are less pronounced, compared to the €100,000 question. This could be due to the higher sophistication of the sMPL as described above.

Model (3) and (3a) investigate the total effect of personal interaction and information as we compare the treatment effect between ANONYM and INTERACTION (Hypothesis H3). In INTERACTION demographic information is transmitted and personal interaction take place whereas in ANONYM only demographic information is available. Within our treatments, these two conditions exhibit the largest possible social distance and therefore difference between these two treatments measures a total effect of information and interaction. However, as the results in table 6.4 show, there is no statistically significant treatment effect. The variable "ANONYM" carrying the treatment effect is not statistically significant at conventional levels. Hence, for the accuracy of the prediction of risk preferences we do not detect an effect. Hence, we reject hypothesis 3.

No significant effect can be observed for the type of questionnaire (Type A or B) in the regression models comparing ANONYM with INTERACTION and INFO, as the coefficient on 'Type A' indicates. Only a mild effect can be observed if comparing INFO and INTERACTION. We can thus conclude that the additional information asked by subjects themselves apart from the provided questions on sociodemographics has no strong effect on the prediction accuracy.

Finally, considering all models, we do not observe any systematic order effect as we detect only in model (3a) a significant coefficient.
Summarizing the results, we find no significant effect of personal interaction on the prediction of risk preferences. This is due to the fact that two opposite forces work in countervailing directions. On the one hand, we find mild evidence that information improves the prediction of risk preferences. On the other hand, a personal interaction decreases the quality of the forecast. From that we conclude that the driving force for a good prediction is the information in a counseling interview but not the information extracted from the appearance of a person. Moreover, the appearance of a person even seems to bias an advisor's prediction negatively.

5.2 Prediction errors are not random

In order to demonstrate that subjects give non-random answers, in figure 6.3 we present quantile plots of the prediction error for the three treatments ANONYM, INFO and INTERACTION. On the y-axis the quantiles of the prediction errors are displayed whereas the x-axis denotes the fraction of observations that exhibits the respective error. About 20% of the observations are able to meet the advisee's actual choice in the €100,000 question. Approximately 25% deviate only one notch from the advisee's decision, e.g., the advisor predicts €60,000 while the advisee actually chooses €40,000. In the sMPL around 15% are able to predict the advisee's choice correctly. Even approximately 70% of the predictions deviate two or less rows from the advisee's actual choice. If the advisors predicted the risk preferences of their advisees randomly, one would expect an even distribution of the prediction errors over the quantiles. Hence, the prediction errors would coincide with the 45°-degree line. According to figure 6.3 this is not evident in our data. We can confirm this result by non-parametric tests.

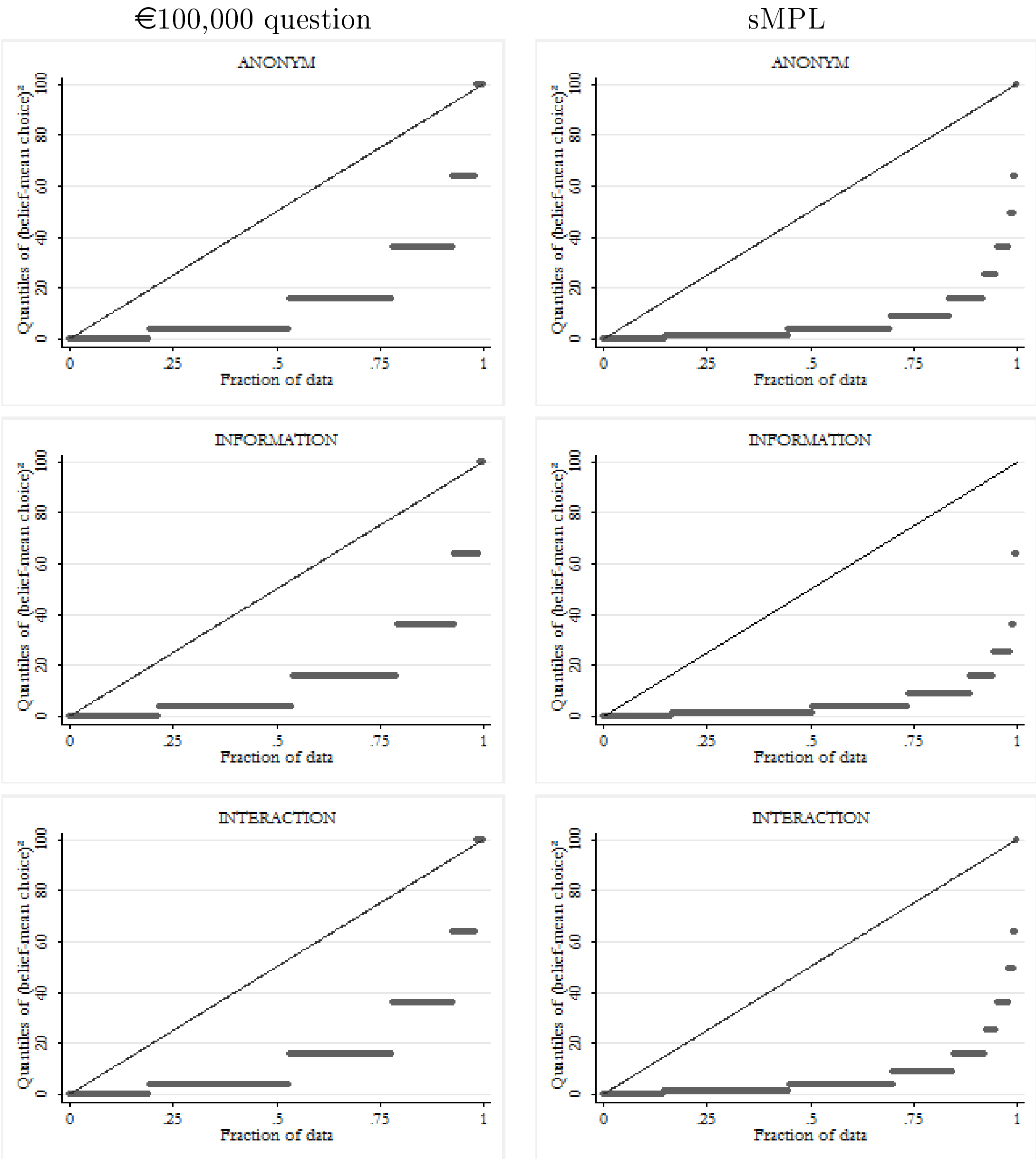


Figure 6.3: Quantiles of prediction error (δ)

Dependent variable: advisor's belief

Model	*(4)*	*(4a)*	*(5)*	*(5a)*	*(6)*	*(6a)*
Hypothesis	ANONYM-INFO		INFO-INTER		ANONYM-INTER	
Measure	100,000	sMPL	100,000	sMPL	100,000	sMPL
ANONYM	-0.147	-0.217			-0.126	-0.0909
	0.229	0.16			0.22	0.154
INFO			0.293	0.131		
			0.241	0.195		
Type A	0.116	-0.192	0.206	0.0366	0.194	0.141
	0.229	0.16	0.226	0.187	0.22	0.154
Order	0.116	0.324**	0.344	0.509***	0.33	0.222
	0.229	0.16	0.224	0.187	0.22	0.154
Constant	5.100***	6.082***	5.540***	6.888***	5.019***	6.162***
	0.194	0.137	0.678	0.573	0.205	0.153
RE: Advisors	95	91	102	98	103	99
Advisees dummy	no	no	35	35	no	no
Observations	760	728	520	497	824	792

Random effects models, Significance * p<0.1; ** p<0.05; *** p<0.01; Outliers excluded

Table 6.5: Regressions: Treatment effect beliefs

χ^2-goodness-of-fit tests reject that prediction errors are uniformly distributed for all three treatments and for both risk tasks ($p < 0.001$ for all tests). In general, we find that advisors are fairly precise in their predictions.

5.3 Beliefs

Beside the analysis of the accuracy of the prediction of risk preference it is of interest to analyze the advisors' beliefs about the advisees. In other words, we have a look at the advisors' predictions instead of the prediction errors. This analysis provides an insight whether the beliefs are biased in a systematic way when personal interaction takes place. Given the results of Loewenstein (1996) there could be effects that advisors exhibit a biased prediction of risk preference when they are in an empathetic relationship such as in the INTERACTION treatment. If there are structural biases over the treatments at work it would contaminate our above treatment effects.

The models in table 6.5 are set up similar to the models in table 6.4. Again, the data is pooled over all treatments and the outliers are omitted. The only difference is that we include the advisor's belief about the risk preferences of the advisee as a dependent variable instead of the prediction error. Again, the set of independent variables contains a dummy variable that identifies the effect coming from the ANONYM respectively INFO treatment. Additionally, we include dummy variables capturing order effects as well as the different types of the transcripts. Econometrically, we control for the multiple observations per subject by assigning a random effect to every subject which is the independent unit of observation.

The main finding from these regression models is that we do not find a significant treatment effect in the beliefs. In none of the models (4) to (6a) we do find a significant impact of the treatment dummy. Mild order effects can be observed in model (4a) and (5a), however, without exhibiting a general pattern.

For the results found in section 5 this is good news as table 6.5 proves that there is no systematic bias on the beliefs caused by the treatments.

Hence, the treatment effects of the prediction errors are solely induced by individual predictions but not by systematically biased beliefs of the treatment itself.

6 Conclusion

The idea of this paper is to explore the effect of a personal meeting on the prediction of risk preferences of others instead of having demographic information only. We compare the advisors' prediction error of advisees' risk preferences in two treatments. In our baseline treatment, only sociodemographic information is available, while in the subsequent treatments we decrease the social distance by increasing the available information. By construction of the treatments, we make sure that the advisors receive at least as much sociodemographic information in the main treatments as in the baseline.

The experiment reveals two countervailing effects. First, in our information treatment advisors have a protocol of a chat of the advisee at hand to predict the risk preferences. We find that in this treatment the predictions of the advisee's risk preferences are more accurate than in the baseline. Therefore we conclude that the information gathered "between the lines" in a conversation helps to forecast risk preferences.

Second, in the interaction treatment, the advisor meets the advisee in a face-to-face conversation. Interestingly, when having the personal interaction the advisors show higher prediction errors than in the information treatment. This result is statistically significant for both risk measures. Apparently, the personal interaction does not help to "read" another person's risk attitudes. Combining both effects answers the question raised in the title of the paper: Does meeting make a difference? If we compare the interaction treatment with the baseline treatment we do not detect a statistically relevant treatment effect. This means that a subject's prediction of a person's risk preference is not improved by a personal conversation.

Despite the mild experimental evidence, there is also a policy perspective coming from our analysis as we find that a good prediction of a person's risk attitude is necessarily coming from a face-to-face meeting.

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Chapter 7

Appendices

1 Appendix for chapter 3

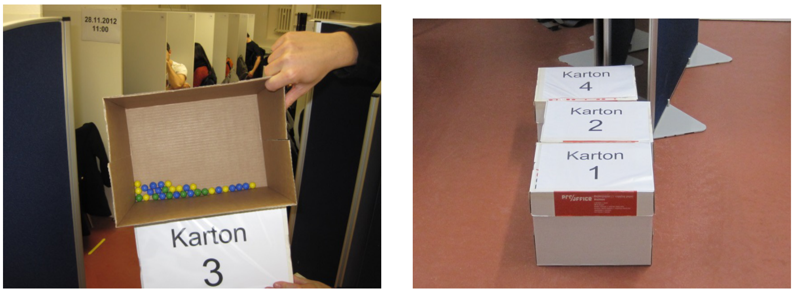
1.1 Tables

P-values for Wald tests for joint significance for models in table 3.1

H_0:	(1)	(2)	(3)	(4)	(5)	(6)
samecndtn=PF-F	0.000	0.000	0.000	0.000	0.0001	0.000
samecndtn=P-PF	0.002	0.0017	0.045	0.034	0.17	0.12
PF-F=P-PF	0.000	0.000	0.000	0.000	0.000	0.000
P-P'=PF-F	0.003	0.007	0.0017	0.0047		
P-P'=P-PF	0.57	0.63	0.72	0.87		
P-P'=samecndtn	0.62	0.59	0.54	0.4		
recall P-F=recall P-PF					0.69	0.73
recall P-F=recall PF-F					0.15	0.087
recall P-F=recall samesit					0.57	0.56
recall P-F=recall P-PF					0.16	0.12
recall PF-F=recall samecndtn					0.88	0.099
recall P-PF=recall samecndtn					0.000	0.8
P_ PF=recall P-PF					0.86	0.73
PF_ F=recall PF-F					0.000	0.000
samecndtn=recall samecndtn					0.6	0.64

Table 7.1: Consistency: Wald tests on joint significance

1.2 Pictures for credibility



Urn content with time identifier

Presentation of urns

Figure 7.1: Pictures of urns

1.3 Instructions

Please note: The experiment is a paper-and-pencil type experiment. The page numbers in this section are referring to the actual page numbers of the instructions.

Instructions – First experimental session

Dear participant,

Welcome to our experiment. Your participation in this experiment supports our scientific work. At the same time, your actions allow you to earn money.
The scientific coordinators for this experiment are Peter Dürsch, Daniel Römer, and Benjamin Roth (Alfred-Weber-Institute for Economics, Heidelberg University).

Course of the Experiment

Firstly, please turn off your mobile phone, and keep it off during the entire experiment. Do not talk to other participants. If you have any questions, please stay calm and raise your hand. Someone of our experimental staff will answer your question.

Your payoff depends on the choices you make during the experiment.

The experiment consists of two experimental sessions. The first session is taking place today. The second session is going to take place in January 2013. For the experiment it is essential that you participate in both sessions.

Today's session consists of five parts. These five parts are labeled in the instructions as "A", "B", "C", "D", and "E". The instructions at hand explain today's entire experimental session, and they are identical for all participants. The experiment starts with part A, then part B, and part C, followed by part D. E is the last part. You can keep the instructions and read them during the experiment, at any time.

Part A

In part A, you have to make choices for two different boxes („Box 1“ and „Box 2“). Both boxes are situated in this room, and each of them contains 30 marbles. Each box contains **10 yellow marbles**. The remaining **20 marbles are either blue, or green**, in an arbitrary combination.

We will hand out decision sheets A. On decision sheet A you have to make two choices for each of the boxes. Each choice determines your payoff depending on the color of the marble that will be drawn from the corresponding box.

You make your choices for **both boxes**. You are paid-off for the choices you made for **one box**. At the end of this experimental session, a coin flip decides which of the two boxes will be selected for today's session's payoff. Afterwards, two independent draws (the marble is put back into the box after each draw) determine your individual payoff according to the choices you have made on decision sheet A. To do so, one marble will be drawn from the box. The color will be recorded. Then the marble will be put back into the box. The procedure will be repeated for the second draw. The other box will be used in part B.

Part B

Again, you have to make your choices for two boxes (“Box 3” and “Box 4”). **Box 3 is the identical box from part A which was not selected for the payoffs**. Box 4 is a new box. Both boxes are situated in this room, and each of them contains 30 marbles. Each box contains **10 yellow marbles**. The remaining **20 marbles are either blue, or green**, in an arbitrary combination.

We will hand out decision sheet B. On decision sheet B you have to make two choices for each of the boxes. Each choice determines your payoff depending on the color of the marble that will be drawn from the corresponding box.

You make your choices for **both boxes**. You are paid-off for the choices you have made for **one box**. At the end of this experimental session, a coin flip decides which of the two boxes will be selected for today’s session’s payoff. **Please be aware of that, contrary to part A, the draws from this box, as well as the corresponding payoff will take place in the second experimental session in January 2013**. In the second experimental session in January 2013, two independent draws (the marble is put back into the box after each draw) determine your individual payoff according to the choices you have made on decision sheet B. To do so, in January, one marble will be drawn from the box. The color will be recorded. Then the marble will be put back into the box. The procedure will be repeated for the second draw. The other box will be used in part B.

Note: The box from which will be drawn in January will remain unchanged. Therefore, we will take a picture of the box’s content, together with an identifier for this session, in this room, directly before the draw. This picture will be sent to you via e-mail after the second session in January. In the January session we will take a picture of the content of the box again, such that you will be able to check that the content has not been changed.

Part C

We will hand out decision sheet C. On decision sheet C you will find the following table. In this table, we ask you for ten choices. In each row you have two options: Option A and Option B. You have to choose one option in each row (**Option A or Option B**).

Example: In the first row you can decide between two options.

- If you choose **Option A**, you will receive with a probability of 10% a payoff of 2.00€ and with a probability of 90% a payoff of 1.60€.
- If you choose **Option B**, you will receive with a probability of 10% a payoff of 3.85€ and with a probability of 90% a payoff of 0.10€.

(This is just an example table. You do not need to tick anything!)

Option A							Option B		
Row	Payoff	Probability	Payoff	A	or	B	Payoff	Probability	Payoff
1	2 €	10% / 90%	1,60 €	O		O	3,85 €	10% / 90%	0,10 €
2	2 €	20% / 80%	1,60 €	O		O	3,85 €	20% / 80%	0,10 €
3	2 €	30% / 70%	1,60 €	O		O	3,85 €	30% / 70%	0,10 €
4	2 €	40% / 60%	1,60 €	O		O	3,85 €	40% / 60%	0,10 €
5	2 €	50% / 50%	1,60 €	O		O	3,85 €	50% / 50%	0,10 €
6	2 €	60% / 40%	1,60 €	O		O	3,85 €	60% / 40%	0,10 €
7	2 €	70% / 30%	1,60 €	O		O	3,85 €	70% / 30%	0,10 €
8	2 €	80% / 20%	1,60 €	O		O	3,85 €	80% / 20%	0,10 €
9	2 €	90% / 10%	1,60 €	O		O	3,85 €	90% / 10%	0,10 €
10	2 €	100%	1,60 €	O		O	3,85 €	100%	0,10 €

Your actual payoff in part C will be determined at the end of this experiment. One out of the ten rows (by rolling a **ten-sided** dice) is chosen by chance for payoff. For this row, the option you have marked (Option A or Option B) is paid off. Another cast of the dice determines whether the amount highlighted in gray, or the amount highlighted in white, is paid off.

Example: If the dice indicates a 1 after the first cast, row 1 is selected. Consider the **first row** in the table. If the dice indicates again a 1 after the second cast, the amount highlighted in gray (not the white area) is paid out. Hence, you will receive 2€ if you have marked Option A, and 3.85€ if you have marked Option B. If the dice had indicated a number between 2 and 10 after the second cast, you would have received 1.60€ for Option A and 0.10€ for Option B.

Part D

We will hand out decision sheet D. On decision sheet D you will find the following table. In this table, we ask you for ten choices. In each row you have two options: Option A and Option B. You have to decide for one option in each row (**Option A or Option B**).

Example: In the second row you can decide between the following two options.

- If you choose **Option A**, you will receive a payoff of 2.00€ in today's session.
- If you choose **Option B**, you will receive a payoff of 2.05€ in the next session in January.

(This is an example table. You do not need to cross anything!)

	Option A				**Option B**
Row	Payoff today	A	or	B	Payoff in January
1	2,00 €	o		o	2,00 €
2	2,00 €	o		o	2,05 €
3	2,00 €	o		o	2,10 €
4	2,00 €	o		o	2,15 €
5	2,00 €	o		o	2,20 €
6	2,00 €	o		o	2,30 €
7	2,00 €	o		o	2,40 €
8	2,00 €	o		o	2,60 €
9	2,00 €	o		o	2,80 €
10	2,00 €	o		o	3,00 €

Your actual payoff in part D will be determined at the end of the experiment. Which one of the ten rows determines the payoff will be determined by chance (rolling a **ten-sided** dice). For this row, only the option you have chosen by crossing will be of relevance (Option A or Option B).

Example: If the dice indicates a 2, row 2 is selected. Consider the **second row** in the table. You will receive 2€ today if you have marked option A, or 2.05€ in January if you have marked option B.

Part E

We will hand out a questionnaire. Please state some general information on this questionnaire.

Total Payment

At the end of today's session, you will receive the sum of your payoffs from part A, C, and potentially from part D. You will receive your payoff in cash and in private. Please remain patient. The distribution of the payoffs can take some time.

Please wait until we call your number and then step forward. Please remain calm and do not talk to other participants.

The drawings and payoff of part B will take place in the second experimental session in January 2013.

Decision sheet A **Seat number: ________**

BOX 1

<u>Choice 1.1:</u> What do you prefer? (Please mark with a cross)

○ You will receive 4€ if the drawn marble is yellow. or
○ You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above?
(Please mark with an „X“ the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

<u>Choice 1.2:</u> What do you prefer? (Please mark with a cross)

○ You will receive 4€ if the drawn marble is yellow or green. or
○ You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above?
(Please mark with an „X“ the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

BOX 2

Choice 2.1: What do you prefer? (Please mark with a cross)

- O You will receive 4€ if the drawn marble is yellow. or
- O You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above?
(Please mark with an „X“ the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Choice 2.2: What do you prefer? (Please mark with a cross)

- O You will receive 4€ if the drawn marble is yellow or green. or
- O You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above?
(Please mark with an „X“ the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Decision sheet B **Seat number: ________**

BOX 3

Choice 3.1: What do you prefer? (Please mark with a cross)

- O You will receive 4€ if the drawn marble is yellow. or
- O You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X" the amount in the following scale)

```
|----+----|----+----|----+----|----+----|
0€        1€        2€        3€        4€
```

Choice 3.2: What do you prefer? (Please mark with a cross)

- O You will receive 4€ if the drawn marble is yellow or green. or
- O You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X" the amount in the following scale)

```
|----+----|----+----|----+----|----+----|
0€        1€        2€        3€        4€
```

BOX 4

<u>Choice 4.1:</u> What do you prefer? (Please mark with a cross)

○ You will receive 4€ if the drawn marble is yellow. or
○ You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X" the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

<u>Choice 4.2:</u> What do you prefer? (Please mark with a cross)

○ You will receive 4€ if the drawn marble is yellow or green. or
○ You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X" the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Decision sheet C   Seat number: ________

Below, you will find a table. We ask you for ten choices in this table. In each row of this table you have to decide between two options: Option A and Option B. You have to decide for one option in each row (**Option A or Option B**).

TABLE (Please choose now for each row <u>either A or B</u>!)

Option A						Option B			
Row	Payoff	Probability	Payoff	A	or	B	Payoff	Probability	Payoff
1	2 €	10% / 90%	1,60 €	O		O	3,85 €	10% / 90%	0,10 €
2	2 €	20% / 80%	1,60 €	O		O	3,85 €	20% / 80%	0,10 €
3	2 €	30% / 70%	1,60 €	O		O	3,85 €	30% / 70%	0,10 €
4	2 €	40% / 60%	1,60 €	O		O	3,85 €	40% / 60%	0,10 €
5	2 €	50% / 50%	1,60 €	O		O	3,85 €	50% / 50%	0,10 €
6	2 €	60% / 40%	1,60 €	O		O	3,85 €	60% / 40%	0,10 €
7	2 €	70% / 30%	1,60 €	O		O	3,85 €	70% / 30%	0,10 €
8	2 €	80% / 20%	1,60 €	O		O	3,85 €	80% / 20%	0,10 €
9	2 €	90% / 10%	1,60 €	O		O	3,85 €	90% / 10%	0,10 €
10	2 €	100%	1,60 €	O		O	3,85 €	100%	0,10 €

Decision sheet D Seat number: ________

Below, you will find a table. We ask you for ten choices in this table. In each row of this table you have to decide between two options: Option A and Option B. You have to decide for one alternative in each row (**Option A or Option B**).

TABLE (Please choose now for each row either A or B!)

	Option A				**Option B**
Row	Payoff today	A	or	B	Payoff in January
1	2,00 €	o		o	2,00 €
2	2,00 €	o		o	2,05 €
3	2,00 €	o		o	2,10 €
4	2,00 €	o		o	2,15 €
5	2,00 €	o		o	2,20 €
6	2,00 €	o		o	2,30 €
7	2,00 €	o		o	2,40 €
8	2,00 €	o		o	2,60 €
9	2,00 €	o		o	2,80 €
10	2,00 €	o		o	3,00 €

Questionnaire E **Seat number:** ________

Year of birth: __________

Gender: ○ female ○ male

Studies

○ currently not studying

○ currently studying

Field of study: __________

Semester: __________

Specific subjects

I took part in lectures in the following subjects:

○ Game Theory

○ Statistics

○ Econometrics

Height:

Height in cm: __________

Instructions – Second experimental session

Dear participant,

Welcome to our experiment. Your participation in this experiment supports our scientific work. At the same time, your actions allow you to earn money.
The scientific coordinators of this experiment are Peter Dürsch, Daniel Römer, and Benjamin Roth (Alfred-Weber-Institute for Economics, Heidelberg University).

Course of the experiment

Please turn off your mobile phone, and keep it off during the entire experiment. Do not talk to other participants. If you have any questions, please stay calm and raise your hand. Someone of our experimental staff will answer your question.

Your payoff depends on the choices you make during the experiment.

The experiment consists of two experimental sessions. The first session took place in November 2012. Today the second session takes place.

Today’s session consists of five parts. These five parts are labeled in the instructions as “A”, “B”, “C”, “D”, and “E”. The instructions at hand explain today’s entire experimental session, and they are identical for all participants. The experiment starts with part A, then part B, and part C, followed by part D. E is the last part. You can keep the instructions and read them during the experiment, at any time.

Part A

In part A, you have to make choices for two different boxes („Box 5“ and „Box 6“). Both boxes are situated in this room, and each of them contains 30 marbles. Each box contains **10 yellow marbles**. The remaining **20 marbles are either blue, or green**, in an arbitrary combination.

Please note: Box 5 is the box for which you have already made a decision in the first session but was not chosen for payment. Box 6 is new.

We will hand out decision sheet A. On decision sheet A you have to make two choices for each of the boxes. Each choice determines your payoff depending on the color of the marble that will be drawn from the corresponding box.

You make your choices for **both boxes**. You are paid-off for the choices you have made for **one box**. At the end of this experimental session, a coin flip decides which of the two boxes will be selected for today's session's payoff. Afterwards, two independent draws (the marble is put back into the box after each draw) determine your individual payoff according to your choices you have made on the decision sheet. To do so, one marble will be drawn from the box. The color will be recorded. Then the marble will be put back into the box. The procedure will be repeated for the second draw.

Note: The content of box 5 from the last session remained unchanged. Again, we will take a picture of the box's content, together with an identifier for this session, in this room, right before the draw. This picture will be sent to you via e-mail after the last session (presumably on 25.02.2013) such that you will be able to check that the content has not been changed.

Part B

Please answer all questions on the questionnaire. For each correct answer we pay €0.25

Part C

Please answer all questions on the questionnaire. For each correct answer we pay €0.25

Part D

We will hand out a questionnaire. Please state some general information on this questionnaire.

Part E

We will hand out decision sheet C. On decision sheet C you will find the following table. In this table, we ask you for ten choices. In each row you have two options: Option A and Option B. You have to choose one option in each row (**Option A or Option B**).

Example: In the first row you can decide between two options.

- If you choose **Option A**, you will receive with a probability of 10% a payoff of 2.00€ and with a probability of 90% a payoff of 1.60€.

- If you choose **Option B**, you will receive with a probability of 10% a payoff of 3.85€ and with a probability of 90% a payoff of 0.10€.

(This is just an example table. You do not need to tick anything!)

Option A							Option B			
Row	Payoff	Probability	Payoff	A	or	B	Payoff	Probability		Payoff
1	2 €	10% / 90%	1,60 €	O		O	3,85 €	10% / 90%		0,10 €
2	2 €	20% / 80%	1,60 €	O		O	3,85 €	20% / 80%		0,10 €
3	2 €	30% / 70%	1,60 €	O		O	3,85 €	30% / 70%		0,10 €
4	2 €	40% / 60%	1,60 €	O		O	3,85 €	40% / 60%		0,10 €
5	2 €	50% / 50%	1,60 €	O		O	3,85 €	50% / 50%		0,10 €
6	2 €	60% / 40%	1,60 €	O		O	3,85 €	60% / 40%		0,10 €
7	2 €	70% / 30%	1,60 €	O		O	3,85 €	70% / 30%		0,10 €
8	2 €	80% / 20%	1,60 €	O		O	3,85 €	80% / 20%		0,10 €
9	2 €	90% / 10%	1,60 €	O		O	3,85 €	90% / 10%		0,10 €
10	2 €	100%	1,60 €	O		O	3,85 €	100%		0,10 €

Your actual payoff in part C will be determined at the end of this experiment. Which one of the ten rows determines the payoff will be determined by chance (rolling a **ten-sided** dice). For this row, only the option you have chosen by crossing will be of relevance (Option A or Option B). The ten-sided dice will be rolled one further time in order to determine whether the amount highlighted in gray will be paid out, or the amount in the white area.

Example: If the dice indicates a 1 after the first rolling, this means that row 1 is determined. Consider therefore the **first row** in the table. If the dice indicates again a 1 after the second rolling, this means that the amount highlighted in gray (not the white area) will be paid out. Hence, you will receive 2€ if you have marked Option A, and 3.85€ if you have marked Option B. If the dice had indicated a number between 2 and 10 after the second rolling, you would have received 1.60€ for Option A and 0.10€ for Option B.

Total payment

At the end of today's session, you will receive the sum of your payoffs from part A, B C, D, E and, if applicable, from the first part of the experiment. We also pay you a show-up fee of € 4 for today's session. The payment will be cash and in private. Please remain patient since payment can take some time.

Please wait until we call your number and then step forward. Please remain calm and do not talk to other participants.

Decision sheet A **Seat number: ________**

BOX 5

Choice 5.1: What do you prefer? (Please mark with a cross)

O You will receive 4€ if the drawn marble is yellow. or
O You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above?
(Please mark with an „X" the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Choice 5.2: What do you prefer? (Please mark with a cross)

O You will receive 4€ if the drawn marble is yellow or green. or
O You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above?
(Please mark with an „X" the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

BOX 6

<u>Choice 6.1:</u> What do you prefer? (Please mark with a cross)

- O You will receive 4€ if the drawn marble is yellow. or
- O You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X“ the amount in the following scale)

```
|----+----|----+----|----+----|----+----|
0€        1€        2€        3€        4€
```

<u>Choice 6.2:</u> What do you prefer? (Please mark with a cross)

- O You will receive 4€ if the drawn marble is yellow or green. or
- O You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X“ the amount in the following scale)

```
|----+----|----+----|----+----|----+----|
0€        1€        2€        3€        4€
```

Questionnaire B **Seat number: ________**

In this part you will receive 0.25€ for each correct answer.

Assume that a participant has made the following choices for a box:

<u>Choice 1:</u> What do you prefer? (Please mark with a cross)

X You will receive 4€ if the drawn marble is yellow. or
○ You will receive 4€ if the drawn marble is blue.

<u>Choice 2:</u> What do you prefer? (Please mark with a cross)

X You will receive 4€ if the drawn marble is yellow or green. or
○ You will receive 4€ if the drawn marble is blue or green.

Assume that in the corresponding box there are exactly **10 yellow marbles, 5 blue marbles, and 15 green marbles.**

Please state how many marbles have to be in the box such that the participant's payoff is 4€.

<u>For the draw for choice 1:</u>

There are ______ marbles in the box such that the payoff is 4€.
There are ______ marbles in the box such that the payoff is not 4€.

<u>For the draw for choice 2:</u>

There are ______ marbles in the box such that the payoff is 4€.
There are ______ marbles in the box such that the payoff is not 4€.

Questionnaire C   Seat number: ________

The following questions refer to the first experimental session in November. During the first session you have made decisions on two boxes, one of which is paid out today. The other was not chosen for payment. For this box you have made a decision today (box 5).

The following questionnaire will evaluate whether you are able to recall your decisions on these two boxes.

Every correct answer pays €0.25.

A. The box that was chosen for payment today in the first session.

Choice A.1: What do you prefer? (Please mark with a cross)

- ○ You will receive 4€ if the drawn marble is yellow. or
- ○ You will receive 4€ if the drawn marble is blue.

Choice A.2: What do you prefer? (Please mark with a cross)

- ○ You will receive 4€ if the drawn marble is yellow or green. or
- ○ You will receive 4€ if the drawn marble is blue or green.

Hoe confident are you with your recall in the above decisions?

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

B. The box that was not chosen for payment. (Box 5 of today's session)

Choice B.1: What do you prefer? (Please mark with a cross)

- ○ You will receive 4€ if the drawn marble is yellow. or
- ○ You will receive 4€ if the drawn marble is blue.

Choice B.2: What do you prefer? (Please mark with a cross)

- ○ You will receive 4€ if the drawn marble is yellow or green. or
- ○ You will receive 4€ if the drawn marble is blue or green.

Hoe confident are you with your recall in the above decisions?

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

Questionnaire D **Seat number: ________**

Additional questions on the boxes

Remember: All boxes contain 30 marbles. 10 are yellow; the remaining 20 are either blue or green, in an arbitrary mix.

1. Have you made the same decisions on box 5 and 6?

O Yes O No

2. Why did you make different decisions?

____

____

____

3. Do you think box 5 and 6 are filled the same?

O Yes O No

4. What do you think is the share of blue and green marbles in box 5?

O There are more blue than green marbles in box 5.
O There are more green than blue marbles in box 5.
O There are equally many blue and green marbles in box 5.

5. What do you think is the share of blue and green marbles in box 6?

O There are more blue than green marbles in box 6.
O There are more green than blue marbles in box 6.
O There are equally many blue and green marbles in box 6.

6. You neither know the content of box 5 nor of box 6. Have you treated the boxes differently?

○ Yes ○ No

Explain why:

---

7. Remember: In the first session you had to make decisions for boxes that were paid out in the future but also for boxes which were paid out immediately. For none of the boxes did you know the exact content. Did you treat the boxes differently?

○ Yes ○ No

Explain why:

---

8. Remember: Today and in the first session you decided on boxes that were paid out in the same session. For none of the boxes did you know the exact content. Did you treat the boxes differently?

○ Yes ○ No

Explain why:

Decision sheet E Seat number: ________

Below, you will find a table. We ask you for ten choices in this table. In each row of this table you have to decide between two options: Option A and Option B. You have to decide for one option in each row (**Option A or Option B**).

TABLE (Please choose now for each row either A or B!)

Option A						Option B			
Row	Payoff	Probability	Payoff	A	or	B	Payoff	Probability	Payoff
1	2 €	10% 90%	1,60 €	O		O	3,85 €	10% 90%	0,10 €
2	2 €	20% 80%	1,60 €	O		O	3,85 €	20% 80%	0,10 €
3	2 €	30% 70%	1,60 €	O		O	3,85 €	30% 70%	0,10 €
4	2 €	40% 60%	1,60 €	O		O	3,85 €	40% 60%	0,10 €
5	2 €	50% 50%	1,60 €	O		O	3,85 €	50% 50%	0,10 €
6	2 €	60% 40%	1,60 €	O		O	3,85 €	60% 40%	0,10 €
7	2 €	70% 30%	1,60 €	O		O	3,85 €	70% 30%	0,10 €
8	2 €	80% 20%	1,60 €	O		O	3,85 €	80% 20%	0,10 €
9	2 €	90% 10%	1,60 €	O		O	3,85 €	90% 10%	0,10 €
10	2 €	100%	1,60 €	O		O	3,85 €	100%	0,10 €

Instructions –*Single Session*

Instructions

Dear participant,

Welcome to our experiment. Your participation in this experiment supports our scientific work. At the same time, your actions allow you to earn money.
The scientific coordinators of this experiment are Peter Dürsch, Daniel Römer, and Benjamin Roth (Alfred-Weber-Institute for Economics, Heidelberg University).

Course of the Experiment

Please turn off your mobile phone, and keep it off during the entire experiment. Do not talk to other participants. If you have any questions, please stay calm and raise your hand. Someone of our experimental staff will answer your question.

Your payoff depends on the choices you make during the experiment.

Today's session consists of five parts. These five parts are labeled in the instructions as "A", "B", "C", "D", and "E". The instructions at hand explain today's entire experimental session and they are identical for all participants. The experiment starts with part A, then part B, and part C, followed by part D. E is the last part. You can keep the instructions and read them during the experiment at any time.

In the following, we will start with part A.

Part A

In part A, you have to make choices for two different linen bags ("Bag 1" and "Bag 2"). Both bags are situated here in this room, and each of them contains 30 marbles. Each bag contains **10 yellow marbles**. The remaining **20 marbles are either blue or green**, in an arbitrary combination.

We will hand out decision sheets A. On decision sheet A you have to make two choices for each of the bags. Each choice determines your payoff depending on the color of the marble that will be drawn from the corresponding bag.

You make your choices for **both bags**. You are paid-off for the choices you made for **one bag**. At the end of this experimental session, a coin flip decides which of the two bags will be selected for today's session's payoff. Afterwards, two independent draws (the marble is put back into the bag after each draw) determine your individual payoff according to the choices you have made on decision sheet A. To do so, one marble will be drawn from the bag. The color will be recorded. Then the marble will be put back into the bag. The procedure will be repeated for the second draw. The other bag will be used in part B.

Part B

Again, you have to make your choices for two linen bags ("Bag 3" and "Bag 4"). **Bag 3 is that bag from part A that was not selected for payoff**. Bag 4 is a new bag. Both bags are situated in this room, and each of them contains 30 marbles. Each bag contains **10 yellow marbles**. The remaining **20 marbles are either blue or green**, in an arbitrary combination.

We will hand out decision sheet B. On decision sheet B you have to make two choices for each of the bags. Each choice determines your payoff and depends on the color of the marble that will be drawn from the corresponding bag.

After collecting the decision sheets, a coin flip decides which of the two bags is selected for the payoff. At the end of the experiment, two independent draws from this bag (the marble is put back into the bag after each draw) determine your individual payoff according to the choices you have made on decision sheet B. The other bag will not be used.

Part C

We will hand out decision sheet C. On decision sheet C you will find the following table twice. In each of the tables, you have two options: Option A and Option B. You have to choose one option in each row (**Option A or Option B**).

Example: In the first row you can decide between two options.

- If you choose **Option A**, you will receive with a probability of 10% a payoff of 2.00€ and with a probability of 90% a payoff of 1.60€.
- If you choose **Option B**, you will receive with a probability of 10% a payoff of 3.85€ and with a probability of 90% a payoff of 0.10€.

(This is an example table. You do not need to tick anything!)

Option A							Option B			
Row	Payoff	Probability	Payoff	A	or	B	Payoff	Probability	Payoff
1	2 €	10% 90%	1,60 €	O		O	3,85 €	10% 90%	0,10 €
2	2 €	20% 80%	1,60 €	O		O	3,85 €	20% 80%	0,10 €
3	2 €	30% 70%	1,60 €	O		O	3,85 €	30% 70%	0,10 €
4	2 €	40% 60%	1,60 €	O		O	3,85 €	40% 60%	0,10 €
5	2 €	50% 50%	1,60 €	O		O	3,85 €	50% 50%	0,10 €
6	2 €	60% 40%	1,60 €	O		O	3,85 €	60% 40%	0,10 €
7	2 €	70% 30%	1,60 €	O		O	3,85 €	70% 30%	0,10 €
8	2 €	80% 20%	1,60 €	O		O	3,85 €	80% 20%	0,10 €
9	2 €	90% 10%	1,60 €	O		O	3,85 €	90% 10%	0,10 €
10	2 €	100%	1,60 €	O		O	3,85 €	100%	0,10 €

Your actual payoff in part C is determined at the end of this experiment. The payoff is either for **Table 1 *or* Table 2**. At the end of this experiment, a coin flip decides which table is selected for the payoff. For the selected table, one out of the ten rows (by rolling a **ten-sided** dice) is chosen by chance for payoff. For this row, the option you have marked (Option A or Option B) is paid off. Another cast of the dice determines whether the amount highlighted in gray or the amount highlighted in white is paid off.

Example: If the dice indicates a 1 after the first cast, row 1 is selected. Consider the **first row** in the table. If the dice indicates again a 1 after the second cast, the amount highlighted in gray (not the white area) is paid out. Hence, you will receive 2€ if you have marked Option A and 3.85€ if you have marked Option B. If the dice had indicated a number between 2 and 10 after the second cast, you would have received 1.60€ for Option A and 0.10€ for Option B.

Part D

We will hand out a questionnaire. Please answer the questions on this questionnaire. For each correct answer you receive 0.25€.

Part E

We will hand out a questionnaire. Please state some general information on this questionnaire.

Total Payment

At the end of the experiment, you will receive the sum of your payoffs from parts A, B, C, and D. You will receive your payoff in cash and in private. Please remain patient since distributing the payoffs can take some time.

Please wait until we call your number and then step forward. Please remain calm and do not talk to other participants.

After the experiment, each participant has the opportunity to examine the bags.

Decision sheet A **Seat number: ________**

BAG 1

Choice 1.1: What do you prefer? (Please mark with a cross)

○ You will receive 4€ if the drawn marble is yellow. or
○ You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above?
(Please mark with an „X" the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Choice 1.2: What do you prefer? (Please mark with a cross)

○ You will receive 4€ if the drawn marble is yellow or green. or
○ You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above?
(Please mark with an „X" the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

BAG 2

Choice 2.1: What do you prefer? (Please mark with a cross)

O You will receive 4€ if the drawn marble is yellow. or
O You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X" the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Choice 2.2: What do you prefer? (Please mark with a cross)

O You will receive 4€ if the drawn marble is yellow or green. or
O You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X" the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Decision sheet B **Seat number: ________**

BAG 3

<u>Choice 3.1:</u> What do you prefer? (Please mark with a cross)

O You will receive 4€ if the drawn marble is yellow. or
O You will receive 4€ if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X“ the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

<u>Choice 3.2:</u> What do you prefer? (Please mark with a cross)

O You will receive 4€ if the drawn marble is yellow or green. or
O You will receive 4€ if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all O O O O O *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X“ the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

BAG 4

Choice 4.1: What do you prefer? (Please mark with a cross)

○ You will receive 4€, if the drawn marble is yellow. or
○ You will receive 4€, if the drawn marble is blue.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X“ the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Choice 4.2: What do you prefer? (Please mark with a cross)

○ You will receive 4€, if the drawn marble is yellow or green. or
○ You will receive 4€, if the drawn marble is blue or green.

How confident (from not confident at all to very confident) are you about this decision?

not confident at all ○ ○ ○ ○ ○ *very confident*

You will be paid-off according to your decision above. But, hypothetically asked, how much would we need to pay you such that you would change your decision above? (Please mark with an „X“ the amount in the following scale)

|----+----|----+----|----+----|----+----|
0€ 1€ 2€ 3€ 4€

Decision sheet C **Seat number: ________**

Below, you will find Table 1 and Table 2. We ask you for ten choices in each table. In each row of this table you have to decide between two options: Option A and Option B. You have to decide for one option in each row (**Option A or Option B**).

TABLE 1(Please choose now for each row <u>either A or B</u>!)

Option A						Option B			
Row	Payoff	Probability	Payoff	A	or	B	Payoff	Probability	Payoff
1	2 €	10% / 90%	1,60 €	O		O	3,85 €	10% / 90%	0,10 €
2	2 €	20% / 80%	1,60 €	O		O	3,85 €	20% / 80%	0,10 €
3	2 €	30% / 70%	1,60 €	O		O	3,85 €	30% / 70%	0,10 €
4	2 €	40% / 60%	1,60 €	O		O	3,85 €	40% / 60%	0,10 €
5	2 €	50% / 50%	1,60 €	O		O	3,85 €	50% / 50%	0,10 €
6	2 €	60% / 40%	1,60 €	O		O	3,85 €	60% / 40%	0,10 €
7	2 €	70% / 30%	1,60 €	O		O	3,85 €	70% / 30%	0,10 €
8	2 €	80% / 20%	1,60 €	O		O	3,85 €	80% / 20%	0,10 €
9	2 €	90% / 10%	1,60 €	O		O	3,85 €	90% / 10%	0,10 €
10	2 €	100%	1,60 €	O		O	3,85 €	100%	0,10 €

TABLE 2(Please choose now for each row <u>either A or B</u>!)

Option A						Option B			
Row	Payoff	Probability	Payoff	A	or	B	Payoff	Probability	Payoff
1	2 €	10% / 90%	1,60 €	O		O	3,85 €	10% / 90%	0,10 €
2	2 €	20% / 80%	1,60 €	O		O	3,85 €	20% / 80%	0,10 €
3	2 €	30% / 70%	1,60 €	O		O	3,85 €	30% / 70%	0,10 €
4	2 €	40% / 60%	1,60 €	O		O	3,85 €	40% / 60%	0,10 €
5	2 €	50% / 50%	1,60 €	O		O	3,85 €	50% / 50%	0,10 €
6	2 €	60% / 40%	1,60 €	O		O	3,85 €	60% / 40%	0,10 €
7	2 €	70% / 30%	1,60 €	O		O	3,85 €	70% / 30%	0,10 €
8	2 €	80% / 20%	1,60 €	O		O	3,85 €	80% / 20%	0,10 €
9	2 €	90% / 10%	1,60 €	O		O	3,85 €	90% / 10%	0,10 €
10	2 €	100%	1,60 €	O		O	3,85 €	100%	0,10 €

Questionnaire D **Seat number: ________**

Additional assessment of the bag

In this part you will receive 0.25€ for each correct answer.

Assume that a participant has made the following choices for a bag:

<u>Choice 1:</u> What do you prefer? (Please mark with a cross)

X You will receive 4€ if the drawn marble is yellow. or
O You will receive 4€ if the drawn marble is blue.

<u>Choice 2:</u> What do you prefer? (Please mark with a cross)

X You will receive 4€ if the drawn marble is yellow or green. or
O You will receive 4€ if the drawn marble is blue or green.

Assume that in the corresponding bag there are exactly **10 yellow marbles, 5 blue marbles, and 15 green marbles.**

Please state how many marbles have to be in the bag such that the participant's payoff is 4€.

For the draw for choice 1:

There are ______ marbles in the bag such that the payoff is 4€.
There are ______ marbles in the bag such that the payoff is not 4€.

For the draw for choice 2:

There are ______ marbles in the bag such that the payoff is 4€.
There are ______ marbles in the bag such that the payoff is not 4€.

Questionnaire E **Seat number: _________**

Year of birth: __________

Gender: ○ female ○ male

Studies

○ currently not studying

○ currently studying

Field of study: __________

Semester: __________

Specific subjects

I took part in lectures in the following subjects:

○ Game Theory

○ Statistics

○ Econometrics

Height:

Height in cm: __________

2 Appendix for chapter 4 and chapter 5

2.1 Robustness check for section 4.2

In order to test for differences between the subject groups in the self-assessment relative to the population mean we run four regression models including demographic covariates. In all models the dependent variable is a binary variable which is one if the prediction is correct. For the independent variables, we include the same set of variables as for the regressions in section 4.3. While models 1 and 3 are logit models to account for the binary structure for the dependent variable, models 2 and 4 are OLS estimations which serve as a robustness check.

As the results show, a significant effect between the subject groups can be detected for the €100,000 question in model 4. Here, we find the senior professionals to be less successful in locating themselves in the distribution of risk attitudes than the omitted non-professionals. This seems to be in line with the findings in figure 4.3. There we find the largest differences in the unconditional means between these subject groups too. When testing the senior against the junior professionals a Wald test does not reveal any significant effect for the HL-task. For the €100.000 question we find that junior professionals show up to be significantly more accurate (model 3: p-value=0.029, model 4: p-value=0.089). Overall, we find only mild significant structural effects between the subject groups. Only for the €100.000 question we find a significant effect between the subject groups.

Model	1	2	3	4
Method	Logit	OLS	Logit	OLS
Dep. Var.	HL correct		100,000 correct	
senior	0.4	0.095	-1.85	-0.30*
	0.75	0.17	1.11	0.13
junior	-0.25	-0.057	-0.0082	0.0027
	0.39	0.089	0.44	0.083
female	0.67	0.15	0.1	0.019
	0.36	0.081	0.39	0.075
lowinc	1.23	0.29	-0.79	-0.076
	0.68	0.15	1.1	0.12
yob	-0.013	-0.0029	-0.021	-0.0039
	0.028	0.0058	0.032	0.0052
single	0.069	0.014	-0.11	-0.026
	0.43	0.096	0.43	0.088
children	1.12	0.26	0.69	0.14
	0.72	0.16	0.77	0.15
Constant	25.5	6	44.3	8.64
	55.8	11.5	62.9	10.3
Observations	167	167	167	167
R-squared		0.057		0.036

Robust standard errors, *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 7.2: STEREOTYPE: Self-assessment

2.2 Robustness check and further results of chapter 5

2.2.1 Self-assessment and beliefs

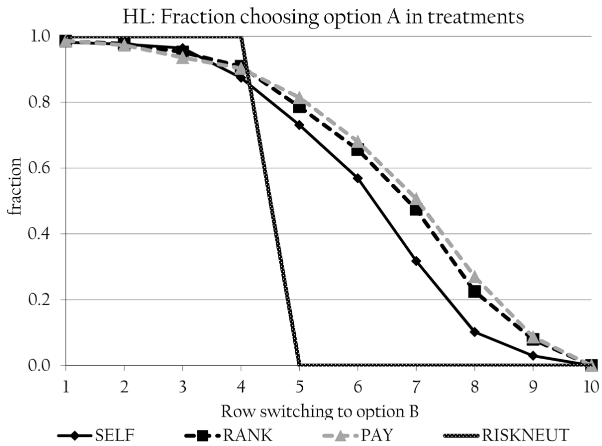


Figure 7.2: Advisors' choices in treatments (HL-task)

2.2.2 Belief formation

	Model	*(1a)*	*(2a)*	*(3a)*
	dependent variable	HL	HL	HL
$\mathbb{1}\{seen=1\}$	Year of birth$_0$	13.95	15.22	15.22
		13.79	13.35	13.09
	No uni degree	-0.12	-0.272*	-0.267*
		0.187	0.164	0.161
	Single	-0.16	-0.179	-0.197
		0.192	0.164	0.165
	Low income	0.0865	0.047	0.0399
		0.149	0.143	0.142
	Male	-0.246	-0.232	-0.203
		0.164	0.142	0.142
	No children	-0.177	-0.155	-0.12
		0.161	0.144	0.145
	Risk index$_0$	1.563***	1.666***	1.666***
		0.216	0.2	0.202
$\mathbb{1}\{seen=1\}\cdot\{soc\ dem \neq 0\}$	Year of birth	-0.00725	-0.00785	-0.00785
		-0.00697	-0.00676	-0.00662
	Uni degree	0.123	0.27	0.262
		-0.196	-0.182	-0.178
	Partner	0.24	0.253	0.275
		-0.199	-0.18	-0.176
	Female	0.706***	0.643***	0.644***
		-0.131	-0.12	-0.12
	High income	-0.636***	-0.613***	-0.636***
		-0.215	-0.212	-0.206
	Parenthood	0.291	0.297	0.286
		-0.204	-0.195	-0.197
	Risk index	-0.406***	-0.426***	-0.427***
		-0.073	-0.0654	-0.0652
Risk prefs self	Self		0.397***	0.349***
			0.0558	0.066
	Self· junior			-0.0324
				0.126
	Self· senior			0.183
				0.127
	Junior prof.	0.0235	0.198	0.384
		0.203	0.181	0.920
	Senior prof.	-0.661**	-0.467*	-1.647*
		0.324	0.267	0.947
	Rank	0.02	0.0395	0.0326
		0.0863	0.0838	0.083
	Constant	6.916***	4.082***	4.404***
		0.264	0.454	0.529
	N	1,336	1,336	1,336
	R^2	0.23	0.353	0.36
	Adjusted R^2	0.216	0.341	0.347
	Advisee FE	yes	yes	yes

* p<0.1; ** p<0.05; *** p<0.01, robust standard errors clustered at advisors' level. Dependent variable: advisor's belief in HL-task. $\mathbb{1}\{seen = 1\}$ indicates a characteristic is visible. *{soc dem}* indicates the realization of the characteristic. The left-out category is $\mathbb{1}\{seen = 0\}$.

Table 7.3: Regression results: Belief formation in HL-task

Model	*(1)*	*(2)*	*(3)*
$H_0 : \{socdem = 0\} + \{socdem \neq 0\}$=0			
Year of Birth	0.256	0.256	0.247
Education	0.988	0.988	0.971
Family status	0.647	0.647	0.625
Income	0.014	0.014	0.009
Gender	0.003	0.003	0.002
Parenthood	0.460	0.460	0.378
Risk index	0.000	0.000	0.000

Table 7.4: Wald test on joint significance (p-values) for models in table 7.3

2.3 Instructions of the web survey for chapter 4 and 5

Regarding this survey:[1] Please try to answer all questions. If you do not know an answer or if you prefer not to answer a question please skip it.

General Questions

- Please state: Year of birth, Federal state of birth, Gender, Mother tongue, Nationality, Religion
- Please state: Do you speak other languages? If so, which?
- Family status: (Please choose: single, divorced, partnership, live separated, married, widowed)
- Number of children: (Please choose: 1, 2, 3, 4, 5 or more, none)

Education

- Highest school degree: (Please choose: Abitur, Realschule, Hauptschule, Sonderschule, no school graduation)
- Please state: How many years have been in school till your highest degree?
- Education: (Please choose: University, Advanced training, Training, in training, no training)
- State the name/title of your last training:
- Job: (Please choose: Worker, Employee, Employee in public sector, Civil Servant, in education/training, self-employed, working at my own household, unemployed, disabled, other)
- Working time: (Please choose: full-time, half-time, part-time but less than half-time, not working)

[1] The experiment was executed in German language and by using an experimental software based on a PHP framework. Here, we present a transcribed and translated version of the German instructions.

- Last executed job (Please state):
- Monthly net income: (Please choose: up to €1,000, €1,001-€3,000, €3,001-€6,000, over €6,001)
- Do you own: (Please choose: Bonds, Properties, Security funds, Stocks or derivatives)

Lotteries

Lottery 1
You will have to make ten decisions in the table below. In every row of the table you can choose either Option A or Option B. Option A and Option B are two lotteries. Your job is to decide on one lottery (either Option A or Option B). Consider the first row for example: In Option A you receive a payment of €2 with a probability of 10% and a payment of €1.60 with a probability of 90%. If you imagine a ten-sided-dice this would mean that you receive €2 if you rolled a 10 and €1.60 for rolling any number between 1 and 9. If you choose Option B you will receive €3.85 with a probability of 10% and €0.10 with a probability of 90%. If you again imagine the ten-sided-dice, this would indicate that you receive €3.85 if you roll a 10 and €0.10 if you roll a number between 1 and 9.
Please decide whether you would choose Option A or Option B in each of the 10 rows:

Your Choice			Option A				Option B			
A	B	Nr.	Probabiliy	Payment	Probabiliy	Probabiliy	Probabiliy	Probabiliy	Probabiliy	Probabiliy
○	○	1	10%	2 €	90%	1,60 €	10%	3,85 €	90%	0,10 €
○	○	2	20%	2 €	80%	1,60 €	20%	3,85 €	80%	0,10 €
○	○	3	30%	2 €	70%	1,60 €	30%	3,85 €	70%	0,10 €
○	○	4	40%	2 €	60%	1,60 €	40%	3,85 €	60%	0,10 €
○	○	5	50%	2 €	50%	1,60 €	50%	3,85 €	50%	0,10 €
○	○	6	60%	2 €	40%	1,60 €	60%	3,85 €	40%	0,10 €
○	○	7	70%	2 €	30%	1,60 €	70%	3,85 €	30%	0,10 €
○	○	8	80%	2 €	20%	1,60 €	80%	3,85 €	20%	0,10 €
○	○	9	90%	2 €	10%	1,60 €	90%	3,85 €	10%	0,10 €
○	○	10	100%	2 €	0%	1,60 €	100%	3,85 €	0%	0,10 €

Lottery 2
Please now consider that it is not possible for you to answer the lottery. You ask a close confidant to make the following decision for you. On your behalf, the close confidant is asked to name the preferred option in every row. Please remind yourself of the person's image and name. You are not able to communicate with your close confident, you are not able to inform him/her about your decision. What do you think, how would this close confident take the decisions in the following lottery?
Again you find the same table as before in which we ask you for 10 decisions. As before, you can either choose Option A or Option B. You make your decision by crossing the option in the column "Your choice".
Which relationship do you have with the person (e.g., partner, friend, relative etc.)?

Other Questions

People can behave differently in different situations.
How would you describe yourself? Are you a risk-loving person or do you try to avoid

Your Choice			Option A				Option B			
A	B	Nr.	Probabiliy	Payment	Probabiliy	Probabiliy	Probabiliy	Probabiliy	Probabiliy	Probabiliy
○	○	1	10%	2 €	90%	1,60 €	10%	3,85 €	90%	0,10 €
○	○	2	20%	2 €	80%	1,60 €	20%	3,85 €	80%	0,10 €
○	○	3	30%	2 €	70%	1,60 €	30%	3,85 €	70%	0,10 €
○	○	4	40%	2 €	60%	1,60 €	40%	3,85 €	60%	0,10 €
○	○	5	50%	2 €	50%	1,60 €	50%	3,85 €	50%	0,10 €
○	○	6	60%	2 €	40%	1,60 €	60%	3,85 €	40%	0,10 €
○	○	7	70%	2 €	30%	1,60 €	70%	3,85 €	30%	0,10 €
○	○	8	80%	2 €	20%	1,60 €	80%	3,85 €	20%	0,10 €
○	○	9	90%	2 €	10%	1,60 €	90%	3,85 €	10%	0,10 €
○	○	10	100%	2 €	0%	1,60 €	100%	3,85 €	0%	0,10 €

risks? People behave differently in different areas. How would you assess your own risk tolerance in the following areas? Please choose a number on a scale between 0 and 10. A 0 denotes "no willingness to take risks" and 10 indicates "very high risk-tolerance". You can gradate you assessment with the values in between. Your risk tolerance?

- When driving? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- In leisure and sports? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- In your career? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- Concerning your health? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- In your trust in unfamiliar people? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- In financial investments? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)

Another question regarding your risk preferences:

Please consider what you would do in the following situation:
Imagine that you had won €100,000 in the lottery. Almost immediately after you collect the winnings, you receive the following financial offer, the conditions of which are as follows: There is the chance to double the money. It is equally possible that you could lose half of the amount invested. You have the opportunity to invest the full amount, part of the amount or reject the offer. What share of your lottery winnings would you be prepared to invest in this financially risky, yet lucrative investment?
What fraction of your winnings do you want to invest in the risky but also profit-promising lottery?
(Please choose: €100,000; €80,000; €60,000; €40,000; €20,000; nothing, I would decline the offer)

What is your opinion on the following three statements?

- On the whole one can trust people (Please choose: Totally agree, agree slightly, slightly disagree, disagree totally)
- Nowadays one can't rely on anyone (Please choose: Totally agree, agree slightly, slightly disagree, disagree totally)

- If one is dealing with strangers, it is better to be careful before one can trust them (Please choose: Totally agree, agree slightly, slightly disagree, disagree totally)

Would you say that for most of the time, people *(Please choose one of the two possibilities)*

- attempt to be helpful?
- or only act in their own interests?

Do you believe that most people *(Please choose on of the two possibilities)*

- would exploit you if they had the opportunity
- or would attempt to be fair towards you?

What would you say: How many close friends do you have?

How often does it occur that,

- you lend your friends your personal belongings (e.g., CDs, books, car, bicycle)? (Please choose: Very Often, Often, Sometime, Seldom, Never)
- you lend your friends money? (Please choose: Very Often, Often, Sometime, Seldom, Never)
- you leave the door to your apartment unlocked? (Please choose: Very Often, Often, Sometime, Seldom, Never)

2.4 Instructions of the lab experiment for chapter 4 and 5

Please note:

- Comments to the instructions are printed in italic and were not presented to the subjects.
- A horizontal line indicates whenever a new window was presented to advisors.
- To ease orientation, treatments as mentioned in the paper are identified by TREATMENT X.

Instructions of the Lab Experiment:

Goal and Process of the Experiment

The experiment consists of a total of two phases, in each of which you will have to make decisions. In the first phase we will ask you a number of questions and you will make two decisions. In the second phase of the experiment you will make the same set of decisions for other people and your payment will depend on the accuracy of your decisions.
The €2.65 that you receive for you participation can be used during the experiment - more on that later. You can make money with every decision you make. We will inform you about your compensation in every round as well as your total compensation for the entire experiment only **after the completion of the experiment**.

TREATMENT SELF

Basic Information

Please answer the following general questions. The success of the experiment depends on you answering the questions carefully.

General Information

- Year of Birth:
- Height in cm:
- Gender: (please choose: male/ female)
- Marital Status: (please choose: Single, Divorced, In a relationship, Living separately, Married, Widowed)

- How many children do you have?: (please choose: no children, one child, two children, three children, four children, five or more children)
- Enter your highest level of education: (please choose: University, Technical College, Apprenticeship, Currently a student, Completed Economics Major, Currently an Economics Major, No vocational education)
- What is your current occupation?: (please choose: white-collar employee, white-collar civil servant, blue-collar employee, blue-collar civil servant, civil servant with tenure, student, self-employed, working at home, unable to work, unemployed, other)
- What are your current working hours?: (please choose: full-time, half-time, part-time (less than halftime), not employed)
- What is your monthly net income in Euro?: (please choose: Up to €1,000, €1,001 - €3,000, €3,001 - €6,000, over €6,000)

How would you describe yourself?

Are you a risk-loving person or do you try to avoid risks?
People behave differently in different areas. How would you assess your own risk tolerance in the following areas?
Please choose a number on a scale between 0 and 10. A 0 denotes "risk averse" and 10 indicates "fully prepared to take risks". You can gradate you assessment with the values in between.
Your risk tolerance?

- In general? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- When driving? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- In leisure and sports? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- In your career? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- Concerning your health? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- In your trust in unfamiliar people? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)
- In financial investments? (Please choose: 0,1,2,3,4,5,6,7,8,9,10)

Game Decision I

We will now begin with the first game decision. Please read the instructions carefully; it is very important that you understand the question.

Game Decision I
Please consider what you would do in the following situation:
Imagine that you had won €100,000 in the lottery. Almost immediately after you collect the winnings, you receive the following financial offer, the conditions of which are as follows: There is the chance to double the money. It is equally possible that you could lose half of the amount invested. You have the opportunity to invest the full amount, part of the amount or reject the offer. What share of your lottery winnings would you be prepared to invest in this financially risky, yet lucrative investment?

Your Compensation
In terms of your actual compensation, the €100,000 are equivalent to €2.50 (€80,000 correspond to €2 , etc.). Your chosen amount will be entered into the lottery; the computer draws lots to see if you double or half your invested amount.

Your Decision
What fraction of your winnings do you want to invest in the risky but also profit-promising lottery?
(Please choose: €100,000; €80,000; €60,000; €40,000; €20,000; nothing, I would decline the offer)

By clicking on NEXT your choices are saved. You cannot change your choices afterwards. Your compensation will be revealed at the end of the experiment.

Game Decision II

The second game decision is up next. Please read the instructions carefully. Take your time. It is very important that you thoroughly understand the question, since this question will be repeated in different variations throughout the rest of the experiment.

Game decision II
You will have to make ten decisions in the table below. In every row of the table you can choose either Option A or Option B. Option A and Option B are two lotteries. Your job is to decide on one lottery (either Option A or Option B). Consider the first row for example: In Option A you will receive a payment of €2 with a probability of 10% and a payment of €1.60 with a probability of 90%. If you imagine a ten-sided-dice this would mean that you receive €2 if you roll a 10 and €1.60 for rolling any number between 1 and 9. If you choose Option B you will receive €3.85 with a probability of 10% and €0.10 with a probability of 90%. If you again imagine the ten-sided-dice, this would indicate that you will receive €3.85 if you roll a 10 and €0.10 if you roll a number between 1 and 9.
There are two rational strategies in this game:

- you choose Option A at the beginning before switching to Option B for the rest of the rows,
- you choose Option B for all of the rows.

We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B below the table. If you only choose Option B, please enter a 1.

Your Compensation
A random row will be chosen for your actual Euro-payment. Your chosen option will be applied to this row. The realization of either the higher or the lower payment for a certain option will be chosen randomly. If the seventh row is chosen for example and you have decided on option A, you will receive €2 with a 70% probability and €1.60 with a 30% probability.

Option A				Option B		
Nr.	Payoff	Probability	Payoff	Payoff	Probability	Payoff
1	2 Euro	10% 90%	1,60 Euro	3,85 Euro	10% 90%	0,10 Euro
2	2 Euro	20% 80%	1,60 Euro	3,85 Euro	20% 80%	0,10 Euro
3	2 Euro	30% 70%	1,60 Euro	3,85 Euro	30% 70%	0,10 Euro
4	2 Euro	40% 60%	1,60 Euro	3,85 Euro	40% 60%	0,10 Euro
5	2 Euro	50% 50%	1,60 Euro	3,85 Euro	50% 50%	0,10 Euro
6	2 Euro	60% 40%	1,60 Euro	3,85 Euro	60% 40%	0,10 Euro
7	2 Euro	70% 30%	1,60 Euro	3,85 Euro	70% 30%	0,10 Euro
8	2 Euro	80% 20%	1,60 Euro	3,85 Euro	80% 20%	0,10 Euro
9	2 Euro	90% 10%	1,60 Euro	3,85 Euro	90% 10%	0,10 Euro
10	2 Euro	100%	1,60 Euro	3,85 Euro	100%	0,10 Euro

I choose option B the first time in row: Pls choose

Your Decision
I choose option B the first time in row: (Please choose: 1,2,3,4,5,6,7,8,9,10)

By clicking on NEXT your choices are saved. You cannot change your choices afterwards. Your profit and your compensation will be revealed at the end of the experiment.

TREATMENT STEREOTYPE

How do other people decide?

In the rest of the experiment you will have to estimate how other people made the game decisions that you just made.

Game Decision 1

Ca. 22,000 participants answered the Game Decision I in a preliminary survey.
Remember, the wording of Game Decision 1 was:

To shorten the experimental instructions, we will subsequently refer to this description of Game Decision 1 as "DESCRIPTION GAME DECISION 1".

Please consider what you would do in the following situation: Imagine that you had won €100,000 in the lottery. Almost immediately after you collect the winnings, you receive the following financial offer, the conditions of which are as follows: There is the chance to double the money. It is equally possible that you could lose half of the amount invested. You have the opportunity to invest the full amount, part of the amount or reject the offer. What share of your lottery winnings would you be prepared to invest in this financially risky, yet lucrative investment?

- €100,000
- €80,000
- €60,000
- €40,000
- €20,000
- Nothing, I would decline the offer

Your Compensation
You will receive €0.25 for every correct assessment.

Do you think the average participant of the preliminary survey invested more, less, or the same amount of money as you did in the first game decision?

Your Decision
I think that the average participant of the preliminary survey invested
(Please Choose: More, less, the same amount of)
money as I did in the first game decision.

How do you think certain groups within the preliminary survey decided?

Your Decision
Who invested more money in the lottery?

- Gender: (please choose: men, women, both groups invested the same amount)
- Age: (please choose: older (40 and up), younger (below 40), both groups invested the same amount)
- Marital Status: (please choose: single, married or in a relationship, both groups invested the same amount)
- Level of Education: (please choose: participants with a university degree, participants without a university degree, both groups invested the same amount)
- Number of Children: (please choose: participants with children, participants without children, both groups invested the same amount)
- Income Category: (please choose: participants with a net monthly income up to €1,000, participants with a net monthly income above €1,000, both groups invested the same amount)

By clicking on NEXT your choices are saved. You cannot change your choices afterwards. Your compensation will be revealed at the end of the experiment.

How do other people decide?

Game Decision II

In another survey 190 people responded to Game Decision II. The characteristics of the participants were also documented.

Remember, the wording of Game Decision 2 was:

To shorten the experimental instructions, we will subsequently refer to this description of Game Decision 1 as "DESCRIPTION GAME DECISION 2".

You will have to make ten decisions in the table below. In every row of the table you can choose either Option A or Option B. Option A and Option B are two lotteries. Your job is to decide on one lottery (either Option A or Option B). Consider the first row for example: In Option A you receive a payment of €2 with a probability of 10% and a payment of €1.60 with a probability of 90%. If you imagine a ten-sided-dice this would mean that you receive €2 if you rolled a 10 and €1.60 for rolling any number between 1 and 9. If you choose Option B you will receive €3.85 with a probability of 10% and €0.10 with a probability of 90%. If you again imagine the ten-sided-dice, this would indicate that you receive €3.85 if you roll a 10 and €0.10 if you roll a number between 1 and 9. We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B below the table. If you only choose Option B, please enter a 1.

Option A				Option B			
Nr.	Payoff	Probability	Payoff	Payoff	Probability	Payoff	
1	2 Euro	10% 90%	1,60 Euro	3,85 Euro	10% 90%	0,10 Euro	
2	2 Euro	20% 80%	1,60 Euro	3,85 Euro	20% 80%	0,10 Euro	
3	2 Euro	30% 70%	1,60 Euro	3,85 Euro	30% 70%	0,10 Euro	
4	2 Euro	40% 60%	1,60 Euro	3,85 Euro	40% 60%	0,10 Euro	
5	2 Euro	50% 50%	1,60 Euro	3,85 Euro	50% 50%	0,10 Euro	
6	2 Euro	60% 40%	1,60 Euro	3,85 Euro	60% 40%	0,10 Euro	
7	2 Euro	70% 30%	1,60 Euro	3,85 Euro	70% 30%	0,10 Euro	
8	2 Euro	80% 20%	1,60 Euro	3,85 Euro	80% 20%	0,10 Euro	
9	2 Euro	90% 10%	1,60 Euro	3,85 Euro	90% 10%	0,10 Euro	
10	2 Euro	100%	1,60 Euro	3,85 Euro	100%	0,10 Euro	

I choose option B the first time in row: Pls choose

Your Compensation
You will receive €0.25 for every correct assessment.

Do you think the participants in the preliminary survey switched to Option B earlier (so in a row with a smaller row number), later, or at the same time as you did?

Your decision

I think that on average, the participants in the preliminary survey switched to option B Please Choose (earlier, later, at the same place) as I did.

How do you think certain groups within the preliminary survey decided?

Your decision

Which group switched to option B earlier (so in a row with a smaller row number)?

- Gender: (please choose: men, women, both in the same row)
- Age: (please choose: older (40 and up), younger (below 40), both in the same row)

- Marital Status: (please choose: single, married or in a relationship, both in the same row)
- Level of Education: (please choose: participants with a university degree, participants without a university degree, both in the same row)
- Number of Children: (please choose: participants with children, participants without children, both in the same row)
- Income Category: (please choose: participants with a net monthly income up to €1,000, participants with a net monthly income above €1,000, both in the same row)

TREATMENT RANK

In this section you are supposed to estimate how other people decided in the Game Decisions that you have just made. The better your estimation, the higher your compensation will be. You will receive some information about the persons whose decision behavior you are trying to predict.
It is important to understand what information is subsumed in certain characteristics. Please carefully read the characteristics and the possible manifestations of these characteristics.

The following characteristics are available:

1. Age
2. Level of Education
    - University
    - Technical College
    - Apprenticeship
    - Still in Apprenticeship
    - Currently an Economics Major
    - No vocational education
3. Income (current monthly net income)
    - Up to €1,000
    - €1,001-€3,000
    - €3,001-€6,000
    - over €6,000
4. Marital Status
    - Single
    - Divorced
    - In a relationship
    - Living separately
    - Married
    - Widowed
5. Gender
    - Male
    - Female
6. Children

- Has children
- Has no children

7. Risk disposition concerning financial investments

    - Answer to the question: Are you risk-loving when it comes to financial investments or do you try to avoid financial risks? Please choose a number on a scale between 0 and 10. A 0 denotes "risk averse" and a 10 indicates "fully prepared to take risks".

You will only have to assess how a single person decided in the two Game Decisions, so you will have to evaluate a specific person. You are paid according to the accuracy of your assessment. If you correctly assess how the presented person acted in both decisions, you will receive €0.50 for every correct prediction. In order to make your assessment, you will make the decisions you previously made for yourself for the specific person instead.
The information available for assessing the person will consist of a selection of the seven characteristics presented above. You will not receive all seven of the person's characteristics. Instead, we will generate a random number between 1 and 7 that corresponds with the number of revealed characteristics. If the randomly generated number is a 3, for example, you will receive the first three characteristics of the person that you are assessing.
You can now decide which characteristic you want to assign to the first position, the second position, all the way to the seventh position. Make you decisions carefully; characteristics with a higher position are revealed with a higher probability.

Your Decision
Sort the characteristics by clicking and dragging the characteristics to the positions you want them in.
The characteristic at the top of the list has the highest prioritization; the second characteristic has the second-highest characterization etc.
Note: The characteristics are presented in alphabetic order

- Level of Education
- Income category
- Marital Status
- Year of Birth
- Gender
- Has Children
- Risk disposition concerning financial investments

This window appeared 4 times with differing number of characteristics shown

How do you assess other people?

The person has the following characteristics: Since x was drawn as the random number you receive the first x of the characteristics that you had chosen for the person that you are assessing.

- ...
- ...

Game Decision I
What decision do you think the person above made in the game's first round? Remember, the wording of Game Decision I was:

DESCRIPTION GAME DECISION 1

Your Compensation
If you make exactly the same decision as the described person, you will receive €0.50. If your decision does not correspond with the described person's decision, you will not receive any money.

Your Decision
What fraction of your winnings do you want to invest in the risky but also profit-promising lottery?
(Please choose: €100,000; €80,000; €60,000; €40,000; €20,000; nothing, I would decline the offer)

Game Decision II
What decision do you think the person described above made in the game's second round? Remember, the wording of Game Decision 2 was:

DESCRIPTION GAME DECISION 2

Your Compensation
If you make exactly the same decision as the described person, you will receive €0.50. If your decision does not correspond with the described person's decision, you will not receive any money.

Your Decision
Please try to make the same decision as the person described above made. We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B.
The person chooses Option B for the first time in row: (Please choose: 1,2,3,4,5,6,7,8,9,10)

By clicking on NEXT your choices are saved. You cannot change your choices afterwards. Your compensation will be revealed at the end of the experiment.

TREATMENT PAY

This and the following window appeared 4 times.

How do you assess other people?

In this round you will have to assess four other people again. As in the previous round, you will be given a selection of the seven characteristics shown above to help facilitate your decision-making process. This time, however, you can choose which of the characteristics of the person you are assessing you want to have revealed. You have to pay for every revealed characteristic.
As you can garner from the table below, the costs of the characteristics vary. The first characteristic costs €0.01, the second €0.02 etc. The seventh characteristic costs €0.50. The right-hand column of the table displays the total costs. If you want to see all seven characteristics of the person you are assessing, for example, you will be charged €0.99.

	Cost of Characteristic	Total cost
1. Characteristic	€0.01	€0.01
2. Characteristic	€0.02	€0.03
3. Characteristic	€0.03	€0.06
4. Characteristic	€0.06	€0.12
5. Characteristic	€0.12	€0.24
6. Characteristic	€0.25	€0.49
7. Characteristic	€0.50	€0.99

Your compensation is as follows:

Compensation for Game Decision I + Compensation for Game Decision II - Payment for Characteristics

As in the previous round you will receive €0.50 for Game Decision 1 and €0.50 for Game Decision 2 if your assessment proves to be correct.
The costs of buying certain characteristics will be subtracted from your compensation. If, for example, your assessment for Game Decision I is correct and your evaluation for Game Decision II is not and you have bought three characteristics, you will receive (€0.50 + €0 -€0.06 =€0.44).
Please note: Since you have winnings from previous rounds and the €2.65 that we put at your disposal at the beginning of the game, your total compensation cannot be negative.
Please decide on the characteristics that you want to buy now:

- Age
- Level of Education

- Income
- Marital Status
- Gender
- Children
- Risk disposition concerning financial investments

By clicking on NEXT your choices are saved. You cannot change your choices afterwards. Your compensation will be revealed at the end of the experiment.

How do you assess other people?

The person has the following characteristics:
You have bought x characteristics. The person you are supposed to assess has the following characteristics:

- ...
- ...

Game Decision I
What decision do you think the person above made in the game's first round?
Remember, the wording of Game Decision I was:

DESCRIPTION GAME DECISION 1

Your compensation
If you make exactly the same decision as the described person, you will receive €0.50. If your decision does not correspond with the described person's decision, you will not receive any money.

Your Decision
What fraction of your winnings do you want to invest in the risky but also profit-promising lottery?
(Please choose: €100,000; €80,000; €60,000; €40,000; €20,000; nothing, I would decline the offer)

Game Decision II
What decision do you think the person described above made in the game's second round?
Remember, the wording of Game Decision 2 was:

DESCRIPTION GAME DECISION 2

Your Compensation
If you make exactly the same decision as the described person, you will receive €0.50. If your decision does not correspond with the described person's decision, you will not receive any money.

Your Decision
Please try to make the same decision as the person described above made. We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B.
The person chooses Option B for the first time in row:
(Please choose: 1,2,3,4,5,6,7,8,9,10)

By clicking on NEXT your choices are saved. You cannot change your choices afterwards. Your compensation will be revealed at the end of the experiment.

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3 Appendix for chapter 6

3.1 Instructions

Please note: A horizontal line indicates whenever a new window was presented to the subjects

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Welcome to the experiment!
Dear participants,
Welcome to our experiment. You support our academic work through your participation in our experiment. At the same time, you have the opportunity to earn money by participating. The game administrators are Andrea Leuermann and Benjamin Roth (Department of Economics at Heidelberg University).
Please remain quiet and do not communicate with the other participants. Please turn off your cell phones. Raise your hand if you have any questions.

Goal and Design of the Experiment
The experiment consists of a total of three phases. Your task in each phase will be to assess the risk preferences of other people. You can earn money with every decision you make during the experiment. Your compensation depends on how successful your choices are. Therefore, you should consider every choice carefully.
Both your payment for every round and your total compensation will be revealed only after all rounds have been completed. You can earn up to 20 Euros.
Please note: All the information you supply us with within the experiment will be treated in a confidential and anonymous manner and will only be used for research purposes.

Nondisclosure Agreement
You will receive personal information about the other participants during the experiment.
You hereby commit to treat all information you receive confidentially. In particular, the information can under no circumstances be given to a third party in any form whatsoever and is only to be used within the experiment. A declaration containing the statement above can be found on the desk in front of you. Please sign the declaration.
By clicking on the OK-button, you confirm that you have signed the nondisclosure agreement.

Basic Information
We need some basic information about you before we can proceed with the experiment. The successful completion of the experiment depends on you answering the

following questions carefully.
What is your gender? m/f
What is your year of birth?
Marital Status: Single or single parent/ divorced /In a relationship/ Living separately/ Married/ Widowed
Do you have children? No children/ have children
If you have children, how many do you have?
What is your highest level of schooling? Abitur/ no Abitur
What is your highest level of education? University/ Technical College/ Apprenticeship/ Currently a student/ Currently a student with an Economics Major/ Currently in an apprenticeship/ No vocational training or education
What is your monthly net income? Up to 1000 Euro/ 1001 Euro- 3000 Euro/3001 Euro- 6000 Euro/ over 6000 Euro
Click OK to confirm that you have answered all the questions.

We need some further information:
Do you have a side job? Yes/No
How many hours a week do you spend at your side job (if you have one)? Up to 10/ 11 to 20/ 21 to 30/ more than 31
What is your monthly net income from your side job (if you have one)? Up to 200/ 201 to 400/ 401 to 800/ more than 801
What is the main reason why you have a side job (if you have one)? to earn a living/to gain professional experience/the side job is a fun pastime/ other reasons
How would you describe yourself? Are you a risk-loving person or do you try to avoid risks? Please tick a box on the 10-notch scale. A value of 0 corresponds to "not at all willing to take risks" and value of 10 corresponds to "very willing to take risks." You can gradate your choice by choosing a value between these two extremes. How risk-loving are you...
In general?
When driving?
When participating in leisure activities of sports?
When it comes to your career?
When your health is at stake?
When trusting strangers?
When investing money?

Game Decision I
We are now coming to the first game decision. It is very important that you understand exactly what you are doing, so please read the instructions carefully.

Game Decision I
Imagine that you have just won 100,00 Euros in a lottery. Immediately after receiving the 100,000 Euro you obtain the following proposal for a new lottery: On the one

hand you have the chance of doubling your money. On the other hand, you could lose half of the money you have invested with the same probability. What fraction of your winnings do you want to invest in the risky but also profit-promising lottery? The total amount of €100,000; the amount of €80,000; the amount of €60000; the amount of €40000; the amount of €20000; nothing, I would not take part in the lottery Please answer the following question before you decide what to do: Consider two individuals. Individual A invests €80,000 and individual B invests €40,000.
Which individual made the less risky decision?
Individual A/ Individual B

Game Decision I
Let's return to your choice in Game Decision I. Please answer the following question: Consider what you would do in the following situation: Imagine that you have just won 100,000 Euros in a lottery. Immediately after receiving the 100,000 Euros you obtain the following proposal for a new lottery: On the one hand you have the chance of doubling your money. On the other hand, you could lose half of the money you have invested with the same probability.
Your Compensation
In terms of your actual compensation, the 100,000 Euro are equivalent to 2.50 Euro (80,000 Euro correspond to 2 Euro, etc.).
Your chosen amount will be entered into the lottery; the computer draws lots to see if you double or half your invested amount.
What fraction of your winnings do you want to invest in the risky but also profit-promising lottery? The total amount of €100,000; the amount of €80,000; the amount of €60,000; the amount of €40,000; the amount of €20,000; nothing, I would not take part in the lottery

---

Game Decision II
We are now coming to the second game decision. Please read the instructions very carefully. Take your time. It is very important that you understand the question, since it will be repeated in different variations throughout the rest of the experiment.

Game decision II
You will have to make ten decisions in the Table below. In every row of the Table you can choose either Option A or Option B. Option A and Option B are two lotteries. Your job is to decide on one lottery (either Option A or Option B).
Consider the first row for example: In Option A you receive a payment of 2 Euro with a probability of 10.
There are two rational strategies in this game:

- you choose Option A at the beginning before switching to Option B for the rest of the rows.
- you choose Option B for all of the rows.

We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B below the Table. If you only choose Option B, please enter a 1. If you choose only Option A, please enter 11. Please answer the following question before you decide what to do: Consider two individuals. Individual A first chooses Option B in row 4. Individual B first chooses Option B in row 8.
Which individual made the less risky decision?
Individual A/ Individual B

Game decision II
You can now make your decision of the second game decision. The lottery was explained on the prior slide. Please note how your compensation is calculated. We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B below the Table. If you only choose Option B, please enter a 1. If you choose only Option A, please enter 11.
Your Compensation
A random row will be chosen for your actual Euro-payment. Your chosen option will be applied to this row. The realization of either the higher or the lower payment for a certain option will be chosen randomly. If the seventh row is chosen for example and you have decided on option A, you will receive 2 Euro with a 70% probability and 1.60 Euro with a 30% probability. Please make your decision now! What row would you choose in the lottery? You choose Option B for the first time in row:
Enter a number between 1 and 11.

We need some additional information.
Please indicate the likelihood of engaging in each activity for each of the following statements. Provide a rating from 1 to 7 (1= extremely unlikely, 2=unlikely, 3=somewhat unlikely, 4= not sure, 5= somewhat likely, 6= likely, 7= extremely likely).
Here the 30 item questionnaire of Weber et al. (2002) are asked.

In this section you have to assess how other people decided in the game decisions that you have already faced. You will evaluate the profiles of multiple individuals. A better evaluation will lead to a higher payoff. A number of characteristics of the individuals that you are assessing may help facilitate your decision.
It is therefore important to know what information can be contained within a certain characteristic category. Please read the categories and the possible characteristics carefully. The following characteristics are available (in alphabetical order):

1. Level of Education: University, Technical College, Apprenticeship, Currently a student, Currently a student with an Economics Major, Currently in an apprenticeship, No vocational training or education

2. Age of the person you are assessing: 0-25 years, 26-40 years, 40-65 years, over 65 years of age

3. Income (monthly net income): Up to 1000 Euro, 1001 Euro- 3000 Euro, 3001 Euro- 6000 Euro, over 6000 Euro
4. Marital Status: Single/single parent, divorced, In a relationship, Living separately, Married, Widowed
5. Gender: male, female
6. Children: children, no children
7. Height: in cm

The following 3 screens are repeated 19 times with different profiles.
Profile 1: Characteristics of the assessed individual

- Level or Education: University
- Age category: under 25
- Income: under 1000
- Marital Status: single/ single parent
- Gender: male
- Children: has no children
- Height: 180 cm

As a reminder, the wording of game decision I was:
Imagine that you have just won 100,000 Euro in a lottery. Immediately after receiving the 100,000 Euro you obtain the following proposal for a new lottery: On the one hand you have the chance of doubling your money. On the other hand, you could lose half of the money you have invested with the same probability. If you assess the described individual's choice correctly, you will receive 0.50 Euro. Profile 1: Characteristics of the assessed individual

- Level or Education: University
- Age category: under 25
- Income: under 1000
- Marital Status: single/ single parent
- Gender: male
- Children: has no children
- Height: 180 cm

How do you think the individual, whose characteristics are displayed in the box above, decided? What fraction of his or her winnings did the described individual invest in the risky but also profit-promising lottery? The total amount of 100,000 Euro; the amount of 80,000 Euro; the amount of 60,000 Euro; the amount of 40,000 Euro; the amount of 20,000 Euro; nothing, I would not take part in the lottery

---

As a reminder, the wording of game decision II was:
In every row of the Table below you can choose either Option A or Option B. We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B below the Table. If you only choose Option B, please enter a 1. If you choose only Option A, please enter 11. Please consider how the individual whose characteristics are displayed in the box to the right decided. If you assess the described individual's choice correctly, you will receive 0.50 Euro. Characteristics of evaluated individual: Profile 1: Characteristics of the assessed individual

- Level or Education: University
- Age category: under 25
- Income: under 1000
- Marital Status: single/ single parent
- Gender: male
- Children: has no children
- Height: 180 cm

Please make your decision now! How do you think the individual, whose characteristics are displayed in the box above, decided?
The individual described above first chooses Option B in row: Enter a number between 1 and 11.
Please await further instructions from the game administrators

---

Phase 2: Conversation
In the following section of the experiment you will work together with other participants. The participant that you will work with has been determined randomly. In order to identify participants, you will receive a player number for the remainder of the experiment. Your player number is XXX.
The sequence of events for the following section is as follows: You will successively meet with four other experiment participants. You will receive the player number of the partner you are to meet with before the meeting. A game administrator will direct you to your partner.
You will then ask your partner questions and your partner will ask you questions. You will receive a questionnaire before the meeting. Please return to your seat as

soon as you have answered all the questions from the questionnaire. Wait until the game administrators distribute the next questionnaire and take you to meet your next partner. Your task is to find out information about your partner during the interview. You will have to assess the risk preferences of your playing partners later in the experiment.

Phase 2: Conversation
There will be two different types of questionnaires. For the first two interview partners you will use questionnaire A. For the final two interview partners you will employ questionnaire B. Questionnaire A: Begin by writing down your own player number and your partner's player number on the questionnaire. Then ask the questions from the questionnaire and make sure to write down the answers on the questionnaire. The participant with the lower player number begins asking the questions. Do not deviate from the questions. Only ask questions from the questionnaire. Questionnaire B: You will have the opportunity to think of further questions before the start of the interview. Write these additional questions on the back of the questionnaire. Begin by writing down your own player number and your partner's player number on the questionnaire. Ask both the questions from the questionnaire and the questions that you have thought of yourself. Write down the answers to all the questions on the questionnaire. The participant with the lower player number begins asking the questions. You can answer all questions that you deem to be important as long as you do not directly ask your partner how he or she answered game decisions I and II. Asking for the answers to game decisions I and II will lead to your exclusion from the experiment.
Please note that the conversations are recorded.
Please click OK to see the player number of your first partner.

Your player number is X1, your first partner's player number is X2.
Please wait until you receive a questionnaire and a game administrator directs you to your partner.
Please wait for further instructions.
(These instructions are repeated for all four partners (X2, X3, X4, X5)

Your player number is X1, your third partner's player number is X4.
Please wait until you receive a questionnaire and a game administrator directs you to your partner.
Please consider if and which questions you want to ask your partner. You have 5 minutes to write down your questions on the questionnaire.

The following 3 screens are repeated 4 times.
Please read the questionnaire from the conversation with player B. Recall player X2. Confirm by clicking OK.

As a reminder, the wording of game decision I was:
Imagine that you have just won 100,000 Euro in a lottery. Immediately after receiving the 100,000 Euro you obtain the following proposal for a new lottery: On the one hand you have the chance of doubling your money. On the other hand, you could lose half of the money you have invested with the same probability. If you assess the choice of the individual you have met correctly, you will receive 0.50 Euro.
Evaluated individual: Assess your first partner with the player number X2. How do you think the individual who you met earlier decided? What fraction of his or her winnings did the described individual invest in the risky but also profit-promising lottery? The total amount of 100,000Euro; the amount of 80000 Euro; the amount of 60000 Euro; the amount of 40000 Euro; the amount of 20000 Euro; nothing, I would not take part in the lottery

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As a reminder, the wording of game decision II was:
In every row of the Table below you can choose either Option A or Option B. We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B below the Table. If you only choose Option B, please enter a 1. If you choose only Option A, please enter 11.
Please consider how the individual whose characteristics are displayed in the box to the right decided. If you assess the described individual's choice correctly, you will receive 0.50 Euro.
Evaluated individual: Assess your first partner with the player number X2. Please make your decision now! How do you think the individual, whose characteristics are displayed in the box above, decided? The individual described above first chooses Option B in row: Enter a number between 1 and 11.

You will now receive the transcript of a conversation from a previous experiment. Please read the conversation. Confirm that you have finished reading the conversation transcript by pressing OK.

The following two screens are repeated four times
Please begin by evaluating the individual *XX* from the recorded conversation.
As a reminder, the wording of game decision I was: Imagine that you have just won 100,000 Euro in a lottery. Immediately after receiving the 100,000 Euro you obtain the following proposal for a new lottery: On the one hand you have the chance of doubling your money. On the other hand, you could lose half of the money you have invested with the same probability. If you assess the choice of the individual *XX* correctly, you will receive 0.50 Euro.
Evaluated individual: Assess individual *XX* from the recorded conversation. How do you think the individual *XX* from the recorded conversation decided? What fraction of his or her winnings did the described individual invest in the risky but also profit-promising lottery?

The total amount of €100,000; the amount of €80,000; the amount of €60,000; the amount of €40,000; the amount of €20,000; nothing, I would not take part in the lottery

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As a reminder, the wording of game decision II was:
In every row of the Table below you can choose either Option A or Option B. We are interested in finding out in which row you first choose Option B. Please specify the row in which you will first choose Option B below the Table. If you only choose Option B, please enter a 1. If you choose only Option A, please enter 11. Please consider how the individual whose characteristics are displayed in the box to the right decided.
If you assess the described individual's choice correctly, you will receive 0.50 Euro. Evaluated individual: Assess individual *XX* Please make your decision now! How do you think the individual *XX* decided? Individual *XX* first chooses Option B in row: Enter a number between 1 and 11.

Your Compensation
Your total compensation: x Euro
Your player number: XXX
Payment Procedure
We will prepare the payment for player number 1. Please answer the questionnaire that will appear presently while you wait. Please bring the nondisclosure agreement with you when you are called.
Thank you for your participation
Andrea Leuermann and Benjamin Roth
Please wait. You will be redirected to the final questionnaire in a moment.