Essays on Risk Preferences and Behavioral Finance

Inaugural-Dissertation zur Erlangung der Würde eines Doktors der Wirtschaftswissenschaften an der Fakultät für Wirtschafts- und Sozialwissenschaften der Ruprecht-Karls-Universität Heidelberg

Vorgelegt von:
Andrea Leuermann

Heidelberg im August 2012

Acknowledgements

Preparing a thesis is like a long journey: sometimes it is a hard way and you cannot see the light at the end of the tunnel or it feels like an endless circuit. It is thanks to many people that the journey resulted in this thesis.

First and foremost, I would like to thank Andreas Roider. He gave me the time and freedom to discover and pursue my fields of interest. He has been open and supportive for any idea I came up with. I profited enormously from his guidance, support and advice during the various questions and challenges I faced.

I want to thank Jörg Oechssler for immediately agreeing to join the thesis committee and for always being ready to discuss any research questions.

I am indebted to the fruitful and friendly environment I experienced at Heidelberg University. All the open, interesting and critical comments I received in seminars and discussions have contributed greatly to my research and understanding of economics.

I am grateful to have met my co-authors Sarah Necker and Benjamin Roth. We celebrated the achievements, had enthusiastic moments as well as heated debates. Enjoying the ups and surviving the downs of research and life as a doctoral student together made it an incredible time and so much easier.

I owe thanks to Christine Binzel, Johannes Diederich, Alessandra Donini, Isadora Dorn, Johanna Kühnel, Andreas Lindenblatt, Karin Loch, Julia Müller and Jan Schrader, for being great colleagues, becoming good friends and making Heidelberg much more than a place to work. Freya Schadt and Gabi Rauscher are responsible for introducing me into the secrets of Poker and many unforgettable evenings (and nights) of play.

I am deeply grateful to my friends and family outside university. In particular, my parents always believed in me and I always felt certain about their unconditional support in every respect.

Finally, I want to thank Heinz-Georg for his trust, love, care and never-ending patience and understanding. For everything.

Contents

List of Tables **V**

List of Figures **VII**

1 Introduction **1**

1.1 Risk Preferences . . . 1

1.2 Behavioral Finance . . . 4

2 Intergenerational Transmission of Risk Aversion - A Revealed Preference Approach **10**

2.1 Introduction . . . 10

2.2 Literature Review . . . 12

2.3 Measuring Risk Preferences . . . 14

2.3.1 Stated Versus Revealed Preferences . . . 14

2.3.2 Revealing Risk Attitudes by Occupational Choice . . . 15

2.3.3 Construction of the Risk Measure . . . 17

2.4 Empirical Analysis . . . 21

2.4.1 Merging Children and Parents . . . 21

2.4.2 Regression Analysis . . . 24

2.5 Discussion . . . 33

2.6 Conclusion . . . 35

3 Stereotypes and Risk Attitudes: Evidence from the Lab and the Field **36**

3.1 Introduction . . . 36

3.2 Literature . . . 38

3.3 Experimental Design . . . 40

3.3.1 Measures of Risk Aversion . . . 41

3.3.2 Part 1: Surveys . . . 42

3.3.3 Part 2: Lab Experiment . . . 43

3.4 Description and Results 44
3.4.1 SELF: Advisors' Risk Preferences 45
3.4.2 SINGLE: Variation of a Single Characteristic 46
3.4.3 SIMULT: Which Characteristics are Important? 50
3.5 Conclusion 58

4 Does Good Advice Come Cheap? - On the Assessment of Risk Preferences in the Lab and the Field 59
4.1 Introduction 59
4.2 Literature 61
4.3 Experimental Design 63
4.3.1 Measures of Risk Aversion 64
4.3.2 Part 1: Surveys 65
4.3.3 Part 2: Lab Experiment 68
4.4 Results 72
4.4.1 Self-Assessment and Beliefs 72
4.4.2 How Do Advisors Form Beliefs? 73
4.4.3 Does Social Distance Matter? 77
4.4.4 Prediction Error 79
4.5 Robustness Checks 83
4.5.1 Risk Measure of Holt and Laury (2002) 83
4.5.2 HL-lottery: Self-Assessment and Beliefs 84
4.5.3 HL-lottery: How Do Advisors Form Beliefs? 85
4.5.4 HL-lottery: Does Social Distance Matter? 86
4.6 Conclusion 86
4.7 Appendix: Additional Material for Robustness Check 88
4.7.1 Risk Measure: HL-lottery 88
4.7.2 HL-lottery: Self-Assessment and Beliefs 88
4.7.3 HL-lottery: How Do Advisors Form Beliefs? 88
4.7.4 HL-lottery: Does Social Distance Matter? 90

5 Reputational Herding in Financial Markets: A Laboratory Experiment 91
5.1 Introduction 91
5.2 Related Literature 95
5.3 Theoretical Predictions 96
5.3.1 Basic Structure 96
5.3.2 No Reputational Concerns of Investors 97

5.3.3 Investors with Reputational Concerns 98
5.4 Experimental Design 101
5.5 Results 104
5.6 Conclusion 114
5.7 Appendix: Theoretical Predictions with Market Prices and Experimental Parameters 116

Bibliography **122**

A Appendix to Chapter 3 and 4 **135**
A.1 Instructions of Web Survey 135
A.2 Instructions of Lab Experiment 140

B Appendix to Chapter 5 **160**
B.1 Instructions of Lab Experiment 160

List of Tables

2.1 Mincer Regression 19
2.2 Mincer Jobrisk 20
2.3 Income Variance by Actual Vocational Education 21
2.4 Descriptive Statistics Transmission Regression 23
2.5 Intergenerational Transmission: Baseline Results 26
2.6 Intergenerational Transmission: "Life Cycle Effects" 28
2.7 Intergenerational Transmission: Stability of Risk Measure over Time . 30
2.8 Intergenerational Transmission: Ability and Individual Income Variance 32

3.1 Descriptive Statistics of Advisees and Advisors 43
3.2 SINGLE: Average Choices of Subsamples 47
3.3 RANK and PAY: Categories Provided 51
3.4 RANK: Joanes Rank Sum Test of Differences in Decision on Ranking 53
3.5 RANK: Informational Content and Decision on Ranking 54
3.6 PAY: Test of Differences in Categories Bought 56
3.7 PAY: Informational Content and Categories Bought 57

4.1 Descriptive Statistics of the Subjects in Surveys and Lab Experiment 66
4.2 Profiles of Advisees Selected for Presentation in RANK and PAY . . 66
4.3 Risk Attitudes of Advisees in Treatment PICT 68
4.4 Information/Categories Provided in RANK and PAY 69
4.5 Regression Results: Belief Formation 74
4.6 Wald Test on Joint Significance (P-values) of Coefficients in Table 4.5 76
4.7 Regression Results: Social Distance 78
4.8 Regression Results: Prediction Errors 82
4.9 Regression Results: Belief Formation in HL-lottery 89
4.10 HL-lottery: Wald Test on Joint Significance (P-values) of Coefficients in Table 4.9 90
4.11 Regression Results: Social Distance in HL-lottery 90

5.1 Prices for Assets A and B 98
5.2 Percentage of Subjects Behaving in Line with the Theoretical Prediction 105
5.3 Assets Bought at Information Set XXy 107
5.4 Evidence on Imitative Behavior 108
5.5 Average Wages Offered to Investor 3 110
5.6 Wage Offered to Investor 3 if Investors 1 and 2 Act Alike 111
5.7 Actual Wages r^{all} Offered to Investor 3 by Imitators and Non-Imitators 113
5.8 Payoff Differences for Investor 3 from Not Following Respectively Following His Own Signal under Various Beliefs 114
5.9 Prices for Assets A and B Given a History of Trades by Predecessors 117
5.10 Payoff Differences from Investment if Following Respectively Not Following the Own Signal 117
5.11 Total Payoff from Reputation and Investment if Following Respectively Not Following the Own Signal 120

List of Figures

2.1 Income Variance by ISCO Occupation Group 21
2.2 Income Variance: Sons Versus Fathers 22

3.1 Experimental Design: Course of Action 41
3.2 HL-lottery as Presented to Subjects 42
3.3 SELF: Advisors' Risk Attitudes in €100,000 Question and HL-lottery 46
3.4 SINGLE: Advisors' Self-Assessment Compared to Reference Group . 48
3.5 SINGLE: Distribution of Correct Answers 49
3.6 SINGLE: Distribution of Answer "Both Equal" in €100,000 Question and HL-lottery 50
3.7 Course of Action in RANK and PAY 52
3.8 Decisions in RANK & PAY 53
3.9 RANK and PAY: Fraction that Buys Category Dependent on Rank of Category 58

4.1 Experimental Design: Course of Action 64
4.2 Treatment PICT: Pictures Presented 68
4.3 Course of Action in Treatments RANK, PAY and PICT 70
4.4 Advisors' Own Risk Preferences and Beliefs in Treatments (€100,000 Question) 73
4.5 Quantiles: Prediction Error in RANK, PAY and PICT 81
4.6 sMPL Mechanism (HL-lottery) 88
4.7 Advisors' Own Risk Preferences and Beliefs in Treatments (HL-lottery) 88

5.1 Sequence of Events without Reputational Concerns 97
5.2 Sequence of Events with Reputational Concerns 99
5.3 Percentage of Investors 3 Behaving in Line with Theoretical Predictions 106
5.4 Percentage of Investors 2 Behaving in Line with Theoretical Predictions 107

Chapter 1

Introduction

Over 30 years of research in the field of *behavioral economics* have widened the knowledge about human behavior and decision making. Research in behavioral economics investigates whether predictions of theoretical models and their underlying assumptions hold. It thereby enhances the predictive power of economics. All chapters of this thesis contribute to this research. While the second and third chapter take a look at the origin of and subjects' knowledge about *risk preferences*, Chapter 4 and 5 analyze aspects of *behavioral finance*. Chapter 4 deals with financial advice and Chapter 5 investigates the roots of the herd behavior of financial investors. Survey data are employed for the analysis in Chapter 2; in Chapters 3 to 5, experimental methods are applied. All chapters have an empirical focus.

1.1 Risk Preferences

People face risky decisions every day: some are unconscious (crossing the street on a red light) and some involve long-term and major financial consequences (pension savings, medical treatments). Risk preferences are an integral part of decision making. Since the first formalization by Bernoulli (1738), many theoretical models incorporate assumptions about the subjects' risk preferences which have a significant impact on the outcome of the models. Consider, for example, first price auction models as surveyed by Kagel (1995). To study risk preferences of individuals in real world situations, several measures to elicit risk preferences have been developed. Responses to these risk questions have been found to predict behavior such as smoking, holding stocks, and occupational choices (Dohmen et al. 2011, Bonin et al. 2007) or geographic mobility (Jaeger et al. 2010) in large panel datasets. Furthermore, risk preferences can also explain behavior in economic experiments, such as the trust game (Lönnqvist et al. 2011).

However, many questions regarding risk preferences remain. Stigler and Becker (1977) proposed that preferences are exogenous and stable. This view has been put into question in recent years and the determinants of individual risk preferences have been intensely studied. For example, the environment and experiences of people are found to have an influence on the formation of risk preferences (Dang 2012, Malmendier and Nagel 2011).

A decisive environment for children is formed by their parents. Intergenerational links are relevant to understand the correlations of outcomes between parents and children (Björklund 2007, Lochner 2008) and the persistent differences in behavior across social groups (Doepke and Zilibotti 2005, Glaeser et al. 2002, Kling et al. 2007, De Paola forthcoming). Furthermore, parent-child relationships can have an impact on the stability of an individual's risk aversion over time and the dynamics of risk preferences in a population (Bisin and Verdier 2011).

Recent evidence suggests that risk preferences are partly passed on from parents to their children. The findings regarding the intergenerational transmission of risk preferences are mainly based on an individual's self-assessment of risk aversion, i.e., parents and children reporting similar risk attitudes in surveys (Charles and Hurst 2003, Arrondel 2009, Kimball et al. 2009, Hryshko et al. 2011, and Dohmen et al. 2012). The elicitation and measurement of risk attitudes in surveys and experiments have been subject to a broad discussion (e.g., Harrison and Rutström 2008, Deck et al. 2008), and all measures have been found to have merits and drawbacks. It is thus important to study whether the intergenerational transmission of risk preferences can also be established in a revealed preference approach. So far, evidence showing that parents and children exhibit the same willingness to take risk in real life situations is limited to Shore (2011), who finds that there exists an intergenerational transmission of income volatility.

Chapter 2 of this thesis studies the intergenerational transmission of risk preferences revealed by an individual's actual job choice. The riskiness of the job is measured by the variation of cross-sectional earnings unexplained by human capital. According to the theory of compensating wage differentials, individuals are compensated for non-pecuniary features of alternative occupations, inter alia the risk that arises from pursuing the job (Rosen 1987). The theory predicts that workers opt for the occupation that maximizes their utility. Since the costs of bearing occupational uncertainty are lower for more risk tolerant individuals, their disutility of working in a risky job is lower. By employing this sorting effect, it is studied whether an intergenerational transmission of risk preferences revealed by occupational choice from parents to children can be observed. The data of the SOEP

(German Socio-Economic Panel) survey allows for linking parents and children and observing their actual choice of job.

The analysis reveals that different male generations of a family indeed exhibit similar risky behavior. Earnings variations of fathers and sons are correlated positively and significantly. This effect holds even after excluding child-parent pairs that work in exactly the same occupation. The magnitude of the effect is similar to the one found for approaches using self-reported risk preferences. Hence, considering risky behavior in exactly the same situation yields a similar intergenerational link as approaches considering stated risk preferences.

The magnitude of the intergenerational link is rather weak, which is also in line with approaches employing stated preferences. This implies that, while part of the son's job choice is potentially influenced by his parents' riskiness of job, many other factors also have an effect on the decision. Regarding the impact on intergenerational mobility and stability of risk preferences across generations, it is not necessarily the case that parents strongly determine - either genetically or through their behavior - their children's preferences. The variation in stated and revealed preferences cannot be fully explained by parents. There remains substantial room for influence by other factors, such as sociodemographic characteristics.

The correlation between risk preferences and sociodemographic characteristics has been actively studied in recent years in several large panel studies (Dohmen et al. 2011 for Germany, von Gaudecker et al. 2011 for the Netherlands), as well as in experiments (e.g., Eckel and Grossman 2008). For example, previous studies show that women are more risk averse than men, older or smaller people are more risk averse than younger or taller ones.

Given these empirical results about the correlation between risk preferences and sociodemographics, it is of importance whether the correlations found have a causal interpretation as well. Chapter 3 answers the question of whether subjects are aware of the correlation between risk preferences and sociodemographic characteristics and attach informational value to sociodemographics when assessing the risk attitudes of others. If this is the case, this is an indication that the relationship between risk preferences and sociodemographics exceeds mere correlations.

The research question raised is particularly interesting if people who take decisions on behalf of others are considered - e.g., in the financial sector or doctors. They have to know the risk preferences of the assessed person in order to take an adequate decision. A major asset is that our sample, besides student subjects, includes individuals that professionally make those decisions: senior and junior advisors with differing years of counseling experience in the financial sector. It is of interest whether their extensive counseling experience increases their knowledge about decision making, or at least changes it. Secondly, sorting effects into employment in the financial sector (Bonin et al. 2007, Dohmen and Falk 2011, Haigh and List 2005) can be studied by comparing junior financial professionals and student subjects.

As the aim of the study is to analyze how advisors judge the risk preferences of subgroups of the population, an experiment consisting of two main parts is employed. In the first part, based on survey data, risk preferences of certain subgroups of the population are estimated (e.g., older versus younger, female versus male). A computerized lab experiment is used in the second part. In the first treatment of the lab experiment, the subjects' perceived correlations on the risk preferences of the subgroups derived in part one are elicited (e.g., whether females or males are perceived as more risk averse). In a second treatment, it is studied to which sociodemographic information subjects attach informational content.

The results of the experiment show that subjects recognize the correlation between the sociodemographic variables age, gender, parenthood and family status and risk preferences. People are not aware how income and education correlate with risk preferences. When forming beliefs about another person's risk attitude, subjects are willing to pay for sociodemographic information about the assessed person. Subjects thus expect informational value coming from sociodemographics. These findings imply that the link between risk preferences and sociodemographics goes beyond pure correlations. Furthermore, it shows that risk preferences are indeed considered to be heterogeneous among people and influenced by sociodemographics.

In particular, the advisor considers an advisee's self-assessment of risk preferences to be informative when judging another person. Regarding the differences in subgroups, senior financial professionals attach less informational content to the advisees' self-assessment of risk preferences than the junior professionals or non-professionals. This is interesting from a regulatory perspective as well, as in previous years German regulators included the elicitation of the customer's risk preferences as a mandatory question into the counseling interview. Especially senior financial professionals - being well familiar with giving advice and using this question in real life - trust less in the advisees' self-assessment of risk preference.

1.2 Behavioral Finance

Chapter 4 and Chapter 5 experimentally study the behavior of individuals in financial markets. The recent financial crisis has been a major event that concerns and challenges economists. When the housing bubble began to burst in 2008 and thus initiated the global financial crisis, the financial sector with its mechanisms and incentive structures came under criticism. Excessive risk taking on behalf of financial investors, the securitization in the mortgage market or the failure of the rating agencies (Hellwig 2009) are just some examples. Despite the massive deficits of banks and companies during the crisis and the following recession, also private investors incurred financial losses (Bucher-Koenen and Ziegelmeier 2011). To a large extent, their asset holdings were not in line with their risk preferences. Remuneration schemes of financial advisors were partly made responsible for that as they provided incentives to promote equity-based portfolios (Jansen et al. 2008). In recent years, regulators have also become concerned about the quality of financial advice and the incentives for financial advisors. In this context, Inderst and Ottaviani (2012a) contrast several policy interventions that can enhance the efficiency of financial advice.

Furthermore, financial instruments are becoming more complex which entails that financial literacy is required. Knowledge about even basic financial principles is not necessarily given among the population (van Rooij et al. 2007, Lusardi and Mitchell 2006). Thus advice by professionals is increasingly important (Shiller 2008). A further aspect is that advice is recognized as helpful by customers and they strongly demand advice (Schotter 2003). Results yet show that people follow advice too often, and even for random events, such as a fair coin-flip, they ask for advice (Powdthavee and Riyanto 2012). These findings suggest that the process of giving advice and in particular the quality of advice should be of major concern and analyzed in detail. In order to give good advice and to choose the product that best fits the advisee's preferences, the advisor needs to know the preferences of the advised person.

Chapter 4 analyzes the process of the assessment of risk preferences of others in detail. The main question asked is whether an advisor is able to give "good" advice. In particular, it is studied whether advisors are capable of correctly assessing the risk preferences of a specific advisee given sociodemographic information. Of course, agency problems, which have been discussed in the theoretical literature (Ottaviani and Soerensen 2006, Inderst and Ottaviani 2012b, or Bhattacharya and Pfleiderer 1985), are of major influence in the counseling interview. However, these models assume that the advisor is aware of the risk preferences of the advisees or at least knows about the distribution of risk preferences. The research of this chapter starts by tackling this assumption. If the advisor's only goal is to correctly gauge the risk preferences of the advisee, is the advisor able to do so?

Chapter 4 builds on further treatments of the experiment employed in Chapter

3. In Chapter 3, the subjects' perceived correlations on risk preferences of certain sociodemographic subgroups and the sociodemographics that are considered to carry informational value are studied. This chapter proceeds a step further as the process of *how* advisors assess the risk preferences of individual advisees is analyzed in detail. Advisors are provided with a *set* of different sociodemographic information and furthermore, advisors are able to manipulate which sociodemographic information is available to them.

Several aspects are studied: First, it is investigated how advisors form beliefs about the risk preferences of specific advisees. It is analyzed how advisors incorporate sociodemographic information into their beliefs and whether the advisors' beliefs are subject to false consensus regarding their own risk preferences. This would indicate that they overestimate the extent to which other people are similar to themselves (Hsee and Weber 1997, Hadar and Fischer 2008). Furthermore, it is of interest whether the social distance between advisor and advisee, namely the similarity of advisor and advisee in sociodemographic characteristics, influences advice. A major question is how precise the advisors' beliefs are, namely whether the stated beliefs coincide with the advisees' actual decision and which information helps to give precise advice. Again, it is a major asset of our dataset that financial professionals with varying counseling experience can be observed.

The results of the experiment show, first, that advisors perceive advisees to be less risk tolerant compared to themselves. When forming beliefs about the risk preferences of others, a false consensus bias of the advisors is present; the advisors' own risk preferences positively correlate with their beliefs about the advisees' ones. For experienced financial advisors and non-professionals this bias is especially pronounced. Besides the advisors' own risk preferences, the advisees' gender and the self-assessment of risk preference have a major influence on the formation of the beliefs. The precision of advice increases if more information is available. Professionals outperform non-professionals significantly when forecasting the risk attitudes of others. Information on family status and the advisee's self-assessment on risk improve predictions of risk preferences.

The German regulatory requirement to elicit the advisees' risk preferences in the counseling interview is indeed found useful. Advisors use the advisees' stated risk preferences in the process of giving advice and the precision of their advice increases. Although senior professionals trust least in the advisees' self-assessment compared to non- and junior professionals as found in Chapter 3, the precision of their advice is higher than that of non-professionals. Senior professionals are, however, outperformed by junior professionals. This could be driven by the fact that senior and non-professional advisors incorporate their own risk preferences into the assessment of others. This finding should trouble advisees as well as regulators.

Another interesting aspect - in particular in the context of the current, but also any other financial crises - is how the behavior of financial investors can lead to the formation of bubbles (Bikhchandani et al. 1992). From a theoretical perspective, one reason why bubbles in financial markets can emerge is herd behavior. If investors follow their predecessors irrespective of their own information, this can be subsumed by intentional herd behavior. This is found to be inefficient as, e.g., asset prices fail to reflect fundamental values (Kremer 2008). Explanations for herd behavior are, e.g., the gain of information (Banerjee 1992, Bikhchandani et al. 1992, Welch 1992), investigative herding or fads (for an extensive survey on sources of herd behavior see Hirshleifer and Teoh 2003). A prominent reason for herd behavior - also extensively studied and referred to in the empirical literature (e.g., Ehrbeck and Waldmann 1996, Chevallier and Ellison 1999) - is attributed to reputational concerns or career concerns.

Chapter 5 of this thesis analyses whether herding out of reputational concerns exists in financial markets. Whereas there are already some experimental studies which test whether and when informational cascades in laboratory financial markets arise (Drehmann et al. 2005, Cipriani and Guarino 2005), this study is the first to experimentally investigate whether evidence for herding out of career concerns can be found. In particular, it is tested whether the predictions of the model by Dasgupta and Prat (2008) hold. This model concludes that herd behavior by investors can be detected if career concerns (à la Scharfstein and Stein 1990) are incorporated into a sequential financial market model.

While the popular press alludes to herd behavior in financial markets, the empirical literature has difficulties to assign observed herd behavior to the differing reasons (e.g., Welch 2000, Sias 2004). The lab experiment allows disentangling the underlying motives for herd behavior by employing differing incentive schemes. Therefore, the subjects' behavior is studied in two treatments. First, in the role of financial investors, subjects take the decision which of two assets to buy without career concerns. For their investment choice, they observe investment decisions of predecessors and an informative signal about which asset is the successful one. Their profit consists of the final payoff of the asset bought minus the price paid for it. In a second treatment, career concerns are incorporated. In addition to subjects in the role of investors, principals who set wages for the investors based on the observed investment choices and the actual outcome of the asset are introduced. Investors thus receive wages set by the principals besides earning profits from investing in the asset. In the first treatment, according to the theory, investors should always follow their own signal and buy the respective asset. However, in the second treatment with career concerns, investors should engage in herd behavior and neglect their own signal if sufficient predecessors bought the same asset and prices are becoming precise.

The experimental results indicate that herd behavior can be observed in the treatment with reputational concerns. About half of the investors engages in herd behavior when theoretically expected by Dasgupta and Prat (2008). Surprisingly, this imitation can also be observed in the treatment without reputational concerns to a similar extent. Due to the within-subject design it can be concluded that investors do not significantly change their behavior between the two treatments. Moreover, we provide further evidence for investors (irrationally) imitating predecessors. To understand the underlying mechanisms, wages set by principals are studied. Interestingly, wages are remarkably close to the theoretically derived wages. In addition, imitative behavior seems to be understood by the principals who adjust wages accordingly. Nevertheless, the recalculation of the theoretical model with the wages offered in the experiment reveals that incentives to engage in herd behavior disappear once taking imitative behavior of preceding investors into account.

Regardless of whether incentives for herding are provided, a substantial fraction of agents engages in herd behavior. From a policy perspective this would indicate that, no matter which incentives are provided from a reputational perspective, agents still tend to herd. Furthermore, our results indicate that in order to combat herd behavior, other underlying mechanisms and incentives than reputation have to be studied.

Overall, this dissertation contributes to the research of behavioral economics in several ways. It is shown that the occupational risk a son bears is partly inherited from the father. Intergenerational transmission can thus explain outcome correlations across generations to some extent. However, as the magnitude of the effect is low, intergenerational transmission is not sufficient to describe individual risk preferences. As previous evidence shows, sociodemographics are correlated with risk preferences. This dissertation builds on this research. It is shown that the link between risk preferences and sociodemographics exceeds mere correlations and sociodemographics are regarded to carry informational value.

Analyzing advisors' behavior in financial markets reveals that, when judging the risk preferences of others, financial professionals are more successful in giving an accurate prediction compared to non-professionals. The fact that advisors use their own risk preferences as a reference point when giving advice can lead to severe biases and should be of concern to regulators and customers. Regarding investors' behavior in financial markets, this dissertation shows that the empirically observed herd behavior cannot necessarily be attributed to reputational concerns.

The dissertation is organized in such a way that the chapters can be read independently of each other. All references are collected in the bibliography. Except for the experimental instructions, any supplementary materials - if any - can be found immediately after each chapter.

Chapter 2

Intergenerational Transmission of Risk Aversion - A Revealed Preference Approach

2.1 Introduction

A crucial determinant of almost any decision in life is an individual's risk tolerance. In their analyses, economists long proceeded on the assumption of exogenously given and stable risk preferences. In recent years the traditional view has been challenged. Attention shifted to the stability of risk aversion over time and across contexts. An important issue is the source of risk preferences, in particular the role of intergenerational transmission. If risk preferences are inherited from parents to children, this should have an effect on the stability of an individual's risk aversion over time and the dynamics of risk preferences in a population (Bisin and Verdier 2011).[1]

Previous analyses agree that parents' *risk attitudes* are positively related to their child's one (Charles and Hurst 2003, Arrondel 2009, Kimball et al. 2009, Hryshko et al. 2011, and Dohmen et al. 2012). The evidence is based on individual's self-assessments of their risk aversion, i.e., parents and children reporting similar risk attitudes in surveys. Evidence showing that parents and children also exhibit the same willingness to take risk in real life situations is limited. An exception is the study by Shore (2011) who provides evidence for intergenerational transmission of income volatility and discusses the importance of similar volatility tolerance for the link.

A key requirement in the empirical analysis of risk preferences is the validity of the measure. Every method of quantifying risk aversion has merits and drawbacks.

[1] This chapter is based on Leuermann and Necker (2011).

While survey data offer an easy way to learn about individual's attitudes, responses suffer from a number of biases (e.g., Bertrand and Mullainathan 2001). Inferring risk aversion from behavior has the advantage that risk preferences are based on actual decisions. Constraints on individual's decisions are taken into account and assumptions that statements are not just cheap talk rendered unnecessary. However, revealed preference measures may also present a biased approximation of normative preferences if decision-making errors are of importance (e.g., Beshears et al. 2008).

The lively debate regarding the appropriate measurement of risk attitudes suggests that it is important to study whether an intergenerational transmission of risk preferences can also be established in a *revealed preference approach*. Comparing results from different methods allows assessing the sensitivity of the effect to the use of different approaches. A revealed preference analysis gives an insight whether the link is different when risk tolerance in exactly the same situation is considered.

The present study aims to investigate whether children and parents not only report similar risk aversion but also behave accordingly. We focus on the willingness to take risk revealed by an individual's actual job choice. According to the theory of compensating wage differentials, individuals are compensated for non-pecuniary features of alternative occupations, inter alia the risk that arises from pursuing the job (Rosen 1987). Occupations vary by health risk, risk of fatality, or unemployment and earnings risk. The theory predicts that workers opt for the occupation that maximizes their utility. Since the costs of bearing occupational uncertainty are lower for more risk tolerant individuals, their disutility of working in a risky job is lower. Assuming that individuals sort into jobs accordingly, their choice reveals information regarding their risk aversion (controlling for other relevant factors).

This sorting effect allows us to investigate whether the intergenerational transmission of risk preferences is indeed reflected in children's and parents' occupation being similarly risky. We use the cross-sectional variation in income that is not explained by human capital differences as our main measure of job risk (as proposed by McGoldrick 1995). Employing data from the 1990 to 2009 waves of the German Socio-Economic Panel (SOEP), we calculate the unexplained earnings volatility per occupation on a 3-digit-level of the International Standard Classification of Occupations (ISCO) for West German men. The resulting values are assigned to fathers and sons, whose information we are able to merge. By excluding child-parent pairs that work in exactly the same occupation, we rule out the possibility that the link is due to inherited preferences for a certain job instead of similarity in risk aversion.

The analysis shows that different generations of a family indeed exhibit similar risk behavior in exactly the same situation. We observe a significantly positive relationship between fathers' and son's earnings variation. In line with the literature on occupational sorting (Bonin et al. 2007) and on intergenerational mobility of earnings (e.g., Dahl and DeLeire 2008), the correlation is stronger for older children. With more experience in the labor market, individuals increasingly sort into occupations representing the risk they are willing to bear and which is similar to their parents' one. The result holds in a number of robustness checks, including a test that takes into account a(n albeit crude) measure of ability. Calculating earnings volatility per individual, i.e., over time irrespective of the occupation pursued, also does not change the results.

The magnitude of the effect strongly resembles the one found in studies using self-reported risk attitudes, i.e., a correlation of 0.1-0.2. Considering risk behavior in exactly the same situation does not yield a stronger intergenerational link. While it is possible that in all studies the link is underestimated due to attenuation bias (due to the limitations which apply to every quantification of risk aversion), a conclusion indicated by all studies is that the intergenerational correlation in risk aversion is rather weak.[2] With respect to our study, the link might even be overestimated when other factors than risk aversion drive the similarity in earnings volatility. According to Cohen (1988), a correlation of 0.1-0.3 is small in terms of effect size (0.3-0.5 is moderate, >0.5 is large). In the literature on intergenerational earnings mobility, a correlation of this magnitude is taken as weak transmission (or a "highly mobile" society). Intergenerational analyses hence explain only a small fraction of where risk preferences come from.

The remainder is organized as follows. In Section 2.2, we review the literature on intergenerational transmission of risk preferences. The measurement of risk preferences is discussed in Section 2.3. The procedure and results of the empirical analysis are reported in Section 2.4, followed by a discussion of our results in Section 2.5. Section 2.6 concludes.

2.2 Literature Review

Bisin and Verdier (2005) emphasize that "preferences, beliefs, and norms that govern human behavior are formed partly as the result of genetic evolution, and partly they are transmitted through generations and acquired by learning and other forms of

[2]Decades of studying the intergenerational earnings elasticity have shown that the more attention is paid to attenuation bias, the higher the link that is found (e.g., Solon 2002, Dahl and DeLeire 2008).

social interactions."[3] Following this idea, several studies investigate the issue of intergenerational transmission of risk preferences.

Based on data from the US Panel Study of Income Dynamics (PSID), Charles and Hurst (2003) find a high similarity in parents and children's stated risk tolerance (according to a hypothetical gamble question). Children reporting "high" risk tolerance are almost 16 percentage points more likely to have parents whose risk tolerance is also "high" (highest value of four distinct categories).[4] Kimball et al. (2009), using the same data, account for measurement error in survey responses and find an intergenerational correlation of 0.14 for fathers and 0.23 for mothers. Hryshko et al. (2011) find, however, only a significant effect for children and parents that belong to an extremely risk tolerant or averse group. Children that are "very risk averse" are 14% less likely to have parents that are "very risk tolerant". An explanation for the difference to the first study is that Hryshko and co-authors take into account the parents' schooling which seems to have a direct effect on children's risk aversion.

Arrondel (2009) studies intergenerational transmission using a measure of risk aversion created from 27 questions covering different life dimensions (seemingly superficial (e.g., whether the respondents take precautions when weather turns out nasty), serious (e.g., health) as well as traditional lottery questions) of the DELTA-TNS-Sofres Survey in France. Regressions of the child's preference score on the parents' one (mothers and fathers are not distinguished as it is a household panel) reveal an elasticity of roughly 0.2.

A closely related study is the one by Dohmen et al. (2012). The authors provide evidence based on self-reported evaluations of risk attitudes from the SOEP in which respondents are assessed on an 11-point scale: "How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" The authors find that the responses of parents and children have a significantly positive relationship. This result is observed with respect to the general willingness to take risks as well as specific domains, i.e., financial matters, health, car driving, sports and leisure and career. They obtain an intergenerational correlation of about 0.1-0.2 depending on the specification and risk measure used.

Two studies relate parents' risky behavior to children's risk attitudes. Hryshko et al. (2011) show that parents' risky behavior in the respondent's childhood, revealed

[3]In the following, we refrain from a distinction between genetic and cultural inheritance. Our interest is in whether intergenerational transmission takes place at all and not via which channel it occurs.

[4]In this analysis and other subsequently cited, the magnitude of the effect varies to some extent with the specification and the variable employed as a measure of risk.

via family business ownership, has a weakly negative effect on a child's stated risk aversion. Based on a sample of Italian students, De Paola (forthcoming) also finds that the riskiness of the father's but not of the mother's job (self-employment/public sector) matters for the child's stated risk aversion.

To our knowledge, only one study exists analyzing similarity of *risk behavior* more thoroughly. Similar to our approach, Shore (2011) investigates intergenerational correlation of income volatility. He employs the variance of year-to-year income changes that are unexplained by a regression of wages on a set of sociodemographic variables. Using data from the PSID, he shows that the correlation between father's and son's earnings volatility is 0.266 (using 4-year changes). Modeling income dynamics, he also distinguishes between permanent and transitory income volatility. The relationship between fathers' and sons' permanent income volatility is 17.5% while that of transitory income volatility is 11.7%.[5] As also stated financial risk tolerance and self-employment are correlated across generations in his sample, he concludes that inherited preferences account at least partly for the established link.

2.3 Measuring Risk Preferences

2.3.1 Stated Versus Revealed Preferences

The above analyses provide valuable insights into the question whether risk attitudes are transmitted between generations. An advantage of self-reported risk measures is that they offer an easy way to study people's attitudes. They suffer from different drawbacks, however. Common objections to stated measures are that low effort is exerted on answering questions accurately, the desire of an individual to convey a certain impression, the absence of having an attitude, etc., bias the preferences reported by surveyed individuals (Bertrand and Mullainathan 2001). Furthermore, the framing of questions matters (Kahneman and Tversky 1981, Kimball et al. 2009).

To gain confidence with respect to their validity, responses have been compared with experimental or real world behavior. However, analyses dealing with the consistency of individual's risk attitude across experimentally elicited measures and survey based ones yield contradictory results (e.g., Deck et al. 2008, Anderson and Mellor 2009). Dohmen et al. (2011) test the behavioral relevance of self-assessed risk preferences of the SOEP in a complementary field experiment. The responses

[5] Assuming that permanent and transitory income volatility are uncorrelated. The results are higher if perfect correlation is assumed. Shin and Solon (2011), however, discuss the difficulty of separating the components, see Section 2.4.2.

to a questionnaire are found to be a significant predictor of the riskiness of choices with real money at stake. Ding et al. (2010) replicate their study with a sample of Chinese students and conclude that stated risk attitudes only explain 10% of the variation in the real money situation. Similarly, while stated risk preferences have been found to be a significant determinant of actual risk taking behavior (such as smoking or investments), they only explain a small fraction of the variation in real world decisions (Barsky et al. 1997, Sahm 2007). Another problem associated with risk attitudes reported on a qualitative scale - as requested in the SOEP - is that it is not ideal for comparisons of the degree of risk aversion across individuals.

Another approach is directly inferring risk aversion from behavior on real markets. Economists long insisted that only actual choices represent actor's true interests and allow inferences on people's preferences (e.g., Samuelson 1938, 1948). Behavior is not just cheap talk but has real consequences. Assumptions that individuals behave as stated are unnecessary. Revealed preferences imply that the constraints that individuals face when deciding are taken into account. A challenge is, however, that other determinants of choice have to be separated to provide a valid measure of risk aversion. Like responses to surveys, choices might present a biased measure of preferences if analytic errors, myopic impulses, inattention, passivity, and misinformation influence behavior (Beshears et al. 2008).

Revealed risk preferences - as any other measurement of risk aversion - might thus be subject to noise. Studying the intergenerational link using revealed risk preferences allows us to check whether parents and children not only state similar attitudes but also behave accordingly. A confirmation of previous results would give some confidence regarding the effect. Another advantage of studying risk behavior is that the possibility of domain-specific risk preferences can be taken into account. Recent research suggests that risk preferences differ to some extent in different situations (e.g., Weber et al. 2002, Barseghyan et al. 2011, Einav et al. forthcoming). The intergenerational link might be underestimated if different generations of a family have different scenarios in mind when responding to survey questions even if the questions refer to the same domains (Vlaev et al. 2010, Nosić and Weber 2010). Observing risk behavior in the same situation allows us to check whether the link is stronger when exactly the same context is considered.

2.3.2 Revealing Risk Attitudes by Occupational Choice

With respect to their willingness to take risks, an individual's behavior on financial markets, the choice of sports, taking out insurances, or occupational choice is informative. In this study, we focus on the willingness to take risk associated with the choice of job.

According to standard economic theory, an individual chooses an occupation that maximizes his or her expected utility (Becker 1962). Utility from a certain job is assumed to be a function of wage, personal traits such as education and experience, as well as occupational features like working conditions or the exposure to different types of risk. The theory of compensating (or equalizing) wage differentials postulates that in a competitive labor market, unfavorable working conditions have to be compensated in order to attract workers (Rosen 1987). Higher risks of future income growth, unemployment, or health are thus reflected in a wage premium. Since the costs of bearing occupational uncertainty are lower for less risk averse individuals, the expectation of monetary compensation makes them more likely to opt for jobs connected to higher risk.[6]

A rich body of empirical literature provides evidence for the existence of a wage premium for income risk (e.g., King 1974, Johnson 1977, Feinberg 1981). McGoldrick (1995) proposes a way of approximating earnings volatility that dominates in the subsequent literature. The present study is based on this measure. First, a standard Mincer wage regression including education, experience and other characteristics (Mincer 1958, 1974) is estimated. The residual from that regression is exploited to calculate the variation in income within an occupation that is unexplained by observable differences in the individual's human capital stock. The measure is supposed to reflect the income uncertainty of an occupation from an *ex ante* perspective. It can therefore be taken as given when making the job decision. Using this measure, McGoldrick (1995), McGoldrick and Robst (1996), Hartog et al. (2003), Hartog and Vijverberg (2007) and other studies provide evidence that compensation of earnings risk, in fact, takes place.

Another requirement for occupational choice being informative regarding an individual's risk aversion is that individuals sort into jobs accordingly. A large number of studies provide the respective evidence. To only cite a few, agents with low (stated) risk aversion are more likely to be self-employed (Ekelund et al. 2005) while those with high risk aversion tend to sort into public sector employment (Guiso and Paiella 2004, Pfeifer 2011). Risk averse workers prefer fixed payments and are less likely to sort into variable pay schemes (Dohmen and Falk 2011). In contrast, workers of a real firm with incentive contracts and daily income risk are highly risk tolerant (Bellemare and Shearer 2010). DeLeire and Levy (2004) show that the risk of injuries has a considerable effect on an individual's choice of job.

[6] This is an application of the standard model of risk compensation, e.g., Gollier (2001). An occupational choice model is provided in Jacobs et al. (2009). Levhari and Weiss (1974) more broadly study the effect of risk aversion on investment in human capital.

In a study closely related to ours, Bonin et al. (2007) investigate whether the income risk an individual is willing to take matches his or her stated risk attitudes. As the dependent variable, the authors employ the risk measure proposed by McGoldrick (1995). Based on data from the SOEP, their analysis establishes a significantly positive relationship between a higher stated willingness to take risks and working in an occupations with a higher unexplained variation of income. The result is confirmed by Hryshko et al. (2011) and Fouarge et al. (2011).

2.3.3 Construction of the Risk Measure

In constructing a measure of earnings risk, we follow the approach established in the literature. We first estimate a Mincer regression and calculate a measure of risk from the resulting residual. We use the 1990 to 2009 waves of the SOEP to generate a measure that allows for variation across observed years within an occupation. The SOEP is an annual panel of German households which was first conducted in 1984 and has been expanded to East Germany in 1990.[7] We only include all waves from 1990 onwards (i.e., the year after full unification) to ensure that differences between the pre- and post-reunification period do not bias the results.

For categorizing occupations, we use the International Standard Classification of Occupations 88 (ISCO88) provided by the International Labor Organisation.[8] This classification groups jobs by similarity of tasks and required skills. Of the ten "major groups" of the ISCO88-code, eight refer to one of four skill levels. Major group 2 relates to tertiary education with university degree, major group 3 to tertiary education without university degree, major groups 4-8 to secondary education and major group 9 to primary education. For the managerial major group 1 the range of tasks was deemed too large to link directly with a particular skill level. For armed forces (0), information required to categorize occupations was not available for many countries (Elias 1997). An advantage of occupations grouped according to skills is that it allows us to check whether individuals with a certain education can choose between jobs with different wage uncertainty.

We employ the 3-digit-level of the code which is the second-most detailed level, sorting occupations into 116 groups.[9] The unexplained variation of income by occupational group is calculated for the total period considered. While it would be interesting to also analyze earnings volatility due to unemployment, our data does not provide for that. Information on the occupation is only available for individu-

[7] See [www.diw.de/soep] for further information.

[8] Documented at [http://www.ilo.org/public/english/bureau/stat/isco].

[9] Employing the 4-digit level of the code would imply a substantial reduction of occupations and sample size.

als that are actually employed. All occupations for which our dataset contains at least 100 observations are included in the analysis. This leaves us with 74 different occupation groups.[10]

In line with much of the literature dealing with earnings, the sample is restricted to men (e.g., Solon 2002, Bonin et al. 2007). McGoldrick (1995) finds that women have a lower percentage of earnings uncertainty attributable to systematic factors. A women's choice of job is more likely to be driven by factors that cannot be captured by the Mincer regression. Besides, female employment opportunities changed substantially over the last decades.

Since the historical and economic environment varies between the two parts of Germany, we drop all individuals that lived in the eastern part of Germany prior to 1989. Riskiness of job was much less an issue and politics severely influenced the choice of job. Fuchs-Schündeln and Schündeln (2005) argue that self-selection due to risk aversion was absent in the German Democratic Republic. Due to path-dependency, the current job of East Germans might not reflect the riskiness that they are willing to bear.

The sample is restricted to adults between age 25 and 59 to avoid biases that may occur in the age-related tails. We only include employees that are full-time employed and exclude individuals working in compulsory paid community service and self-employed individuals. The determination of earnings in this sector is typically not comparable to the earnings of employees. We drop all observations for which income has been imputed. Finally, we exclude implausible earnings information at the bottom of the distribution of net earnings by dropping the lowest 1-percentile in every year.

In our Mincer regression, the dependent variable is the logarithm of the net monthly income of the individual. Employing the net income has the advantage that income smoothing due to the tax system is taken into account. Our set of explanatory variables includes the usual human capital variables (education in years, professional experience in years (^{2}), and tenure in years of employment at the current employer (^{2})). In Germany, working in the public sector is usually connected to a more stable development of income as the conditions of employment are regulated by federal and state laws. We thus include a dummy indicating whether the individual is employed in the public sector.[11] We include dummies for each occupation per 3 digit-ISCO code, thus controlling for the average payment level in that group. Fur-

[10]The reduction in occupations is not reflected in an equivalent reduction in observations. We lose less than 2% of the sample.

[11]It is also possible to split the sample into employees that are employed in the private and public sector and re-estimate separate Mincer regressions. Results are unchanged.

thermore, indicator variables for the German states in which the individual resides and the year of observation are included.[12]

Column (1) of Table 2.1 shows the results of the OLS regressions. The variables explain a large fraction of net monthly earnings. Coefficients are highly significant with signs as expected. We use these estimates to calculate residuals and compute the measure of earnings risk as the standard deviation of the residuals in each occupational group.

Table 2.1: Mincer Regression

Variable	(1) Basis b/se	(2) Incl. Ability b/se
EXPB	0.034***	0.046***
	(0.001)	(0.001)
EXPB2BY100	-0.066***	-0.084***
	(0.001)	(0.003)
TEN	0.010***	0.007***
	(0.000)	(0.001)
TEN2BY100	-0.012***	-0.011***
	(0.001)	(0.003)
EDUC	0.045***	0.054***
	(0.001)	(0.002)
PUBSEC	-0.068***	-0.101
	(0.004)	(0.009)
Average School Grade (Math/German)		-0.026***
		(0.004)
Intercept	6.077***	6.092***
	(0.058)	(0.125)
3 digit-ISCO dummies?	YES	YES
STATE dummies?	YES	YES
TIME dummies?	YES	YES
N	51327	11666
F	588.53	205.74
Adj. R2	0.561	0.574

Significance levels : $*$: 10% $**$: 5% $***$: 1%. Dependent variable: log monthly income of the respondent.

The variation of the resulting risk measure ranges from 0.16 and 0.48 with a mean of 0.28 and standard deviation of 0.068, as shown in the first row of Table 2.2. The occupational category with the highest earnings risk is ship and aircraft controllers and technicians (ISCO Code 314) and the one with the lowest encompasses police

[12]Being interested in the wage uncertainty from an ex ante point of view, we refrain from including individual-specific fixed effects. Individual specific effects represent or remove time-invariant effects which may include risk aversion. We also do not know whether the individual acted on the information captured by fixed effects. We address the issue of a bias due to missing controls for ability in Section 2.4.2.

inspectors and detectives (345), as can be seen in Figure 2.1. The earnings risk found by Bonin et al. (2007) ranges from 0.2 to 0.8. An obvious explanation for those differences is that we employ a dataset spanning several years and thus containing many more observations than the single cross-section by Bonin and co-authors. Estimating a pooled cross-section allows us to control for year-specific effects which lowers the unexplained variance. Hartog and Vijverberg (2007) show that annual measures are noisier than those based on several years.

Table 2.2: Mincer Jobrisk

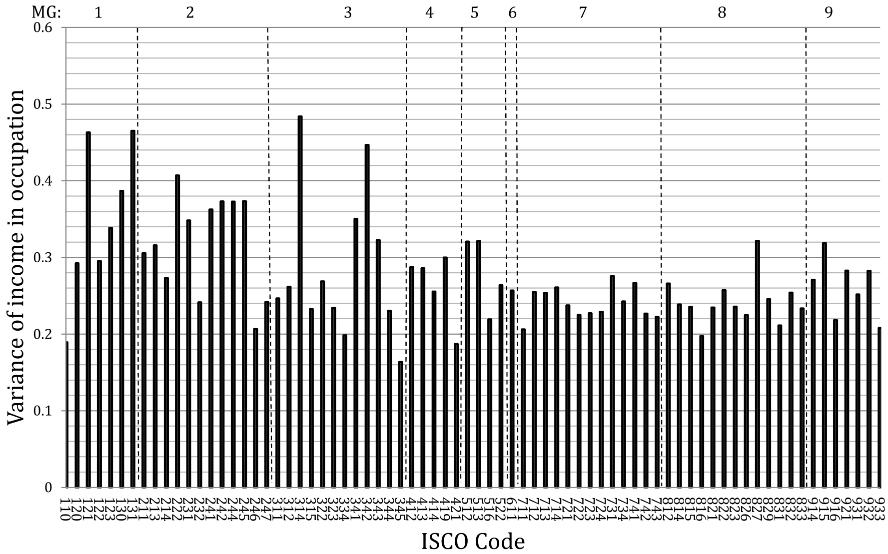
Period	# of Occ.	Mean	sd	min	max
Baseline Mincer 1990-2009	74	0.2771	0.0685	0.1635	0.4838
1990-1999	50	0.2478	0.0549	0.1314	0.4396
2000-2009	61	0.2840	0.0642	0.1653	0.4813
2005-2009	45	0.2822	0.0640	0.1607	0.4877
Including Ability 1990-2009	42	0.2902	0.0677	0.1616	0.5122

The relationship between income risk and skill-level of the occupation does not seem to follow a clear pattern. As can be seen in Figure 2.1, for each level of required skills (according to major groups (MG) of the ISCO code) occupations with different income volatility are available. The occupations with the largest income variance are in major group 1 (no specific skill level), 2 (tertiary education with university degree) and 3 (tertiary education without university degree). These groups also contain occupations that range among the least volatile. While the gap between largest and lowest income risk occupations is lower for major groups 4-9 which require a skill level of secondary education (MG:4-8) or primary education (MG:9), there is still a menu of occupations with different volatility available. A similar result is found if earnings risk by the actual education of respondents is considered, as can be seen in Table 2.3. While the mean and standard deviation is slightly higher for individuals with university degree, all "degrees" of earnings volatility are available for the different actual educational levels.[13]

We investigate whether workers are actually compensated for bearing earnings uncertainty by adding the calculated risk measure in the Mincer regression. The results show that the unexplained earnings variation has a large and significantly positive effect (not reported). We also study the relationship between income volatility and stated risk attitudes. The risk preference revealed by occupational choice is more closely related to the self-reported risk attitude with respect to career than to general risk attitude, in line with the hypothesis of domain specific risk attitudes.

[13]The empirical literature on the relationship between education and wage variance is ambiguous, see e.g., Chen 2008.

Figure 2.1: Income Variance by ISCO Occupation Group



Note: MG = Major group classification of ISCO88.

We refrain from a rigorous analysis of the relationship already performed by Bonin et al. (2007).

Table 2.3: Income Variance by Actual Vocational Education

Education	Mean	sd	min	max
No formal training	0.2523	0.0379	0.1635	0.4838
Training	0.2623	0.0473	0.1635	0.4838
University	0.2990	0.0624	0.1635	0.4838

2.4 Empirical Analysis

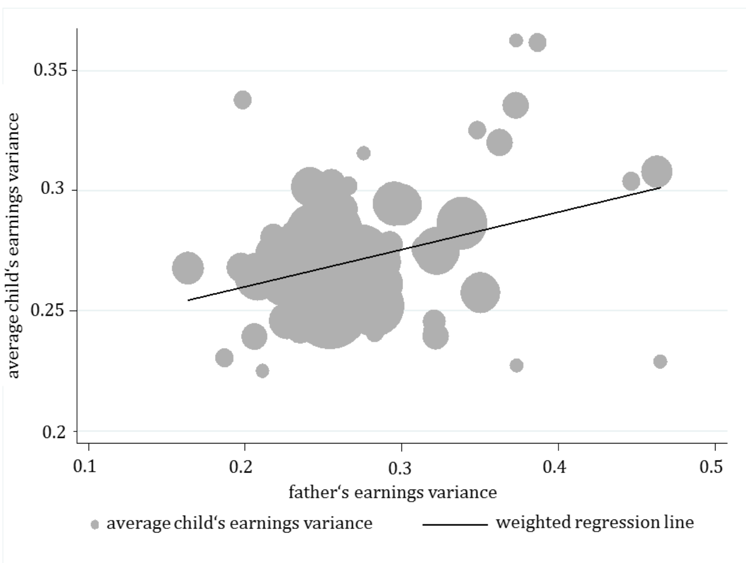
2.4.1 Merging Children and Parents

For investigating the intergenerational transmission of the willingness to take earnings risks, we construct a dataset from the SOEP waves of 2001 to 2009. The findings by Bonin et al. (2007) suggest that occupational sorting according to risk attitudes is weaker for labor market entrants. Individuals seem to require some time to collect enough information about their talents and the labor market until sorting adequately according to risk attitudes. We observe each child-parent pair only once and, in case of multiple observations in different years, keep the most recent observation. This has the advantage that children are older and occupational decisions presumably more in line with actual willingness to bear risk.

An important restriction is that we drop children and parents working in exactly the same occupation. The intention is to rule out the possibility that tastes for a certain job rather than similarities in risk tolerance determine the decision.[14] Like in the Mincer regressions, we restrict the sample to West German men that are full-time employed, and exclude individuals that are self-employed.

This leaves us with 539 children for which we also have information for fathers (descriptives are shown in Table 2.4). We merge the information obtained from Mincer regressions to sons and fathers according to the 3-digit ISCO code of their occupation. The income volatility of parents as well as that of children contains the lowest and highest values; means (0.26) and variance (0.05) are stable across generations. Figure 2.2 provides a first look at the intergenerational relationship between income volatility of fathers and sons. The figure shows children's average earnings risk, for given income volatility of their father without controls for any observable characteristics. The size of the circles indicates the frequency of children. The son's willingness to take risks is clearly increasing in the father's willingness to take risks, the simple correlation is 0.157.

Figure 2.2: Income Variance: Sons Versus Fathers



Note: Average earnings variance of child for a given level of father's earnings volatility. Size of circles indicates weighting with the number of children.

[14]We obtain similar results if we keep these observations or drop parent-child pairs with the same occupations at higher levels of ISCO-code aggregation.

Table 2.4: Descriptive Statistics Transmission Regression

Variable	Description	Obs	Mean	SD	Min	Max
Son's Jobrisk	Generated risk measure son	539	0.2699	0.0473	0.1635	0.4651
Father's Jobrisk	Generated risk measure father	539	0.2637	0.0463	0.1635	0.4651
Controls for Sons:						
Age	In years	539	25.2004	5.5098	17	44
Year of Birth	Year	539	1980.64	6.0995	1961	1991
Married	1=yes, 0=no	539	0.1484	0.3558	0	1
Health	Health status	539	2.0278	0.7375	1	4
Education	In years	539	11.4499	2.3900	7	18
Tenure	In years	539	3.5353	3.9068	0	25.4
Works in Public Sector	1=yes, 0=no	539	0.1132	0.3171	0	1
log net income	Logged monthly income in €	539	6.8496	0.6712	4.6052	8.8537
Religion: Catholic	1=yes, 0=no	539	0.3024	0.4597	0	1
Religion: Protestant	1=yes, 0=no	539	0.2301	0.4213	0	1
Religion: other	1=yes, 0=no	539	0.0631	0.2433	0	1
Religion: none	1=yes, 0=no	539	0.0575	0.2330	0	1
Religion: missing	1=yes, 0=no	539	0.3469	0.4764	0	1
Obs. from 2001	1=yes, 0=no	539	0.1095	0.3125	0	1
Obs. from 2002	1=yes, 0=no	539	0.1058	0.3078	0	1
Obs. from 2003	1=yes, 0=no	539	0.0724	0.2593	0	1
Obs. from 2004	1=yes, 0=no	539	0.0686	0.2531	0	1
Obs. from 2005	1=yes, 0=no	539	0.0872	0.2824	0	1
Obs. from 2006	1=yes, 0=no	539	0.0631	0.2433	0	1
Obs. from 2007	1=yes, 0=no	539	0.0705	0.2562	0	1
Obs. from 2008	1=yes, 0=no	539	0.0835	0.2769	0	1
Obs. from 2009	1=yes, 0=no	539	0.3395	0.4740	0	1
Controls for Fathers:						
Fathers' Age	In years	539	53.5399	6.0127	36	72
Fathers' Year of Birth	Year	539	1952.42	6.4294	1932	1968
Fathers' Education	In years	539	11.3701	2.1515	7	18
Father married	1=yes, 0=no	539	0.9351	0.2466	0	1
Father in public sector	1=yes, 0=no	539	0.2152	0.4114	0	1
Father log net HH income	Logged monthly HH income in €	539	8.1471	0.4150	6.3969	9.3057
Father grew up in:						
Large City	1=yes, 0=no	539	0.0835	0.2769	0	1
Medium City	1=yes, 0=no	539	0.0353	0.1846	0	1
Small city	1=yes, 0=no	539	0.1095	0.3125	0	1
Countryside	1=yes, 0=no	539	0.1892	0.3921	0	1
Information Missing	1=yes, 0=no	539	0.5826	0.4936	0	1

2.4.2 Regression Analysis

Regression Approach

We are interested in whether the correlation between children's and parent's risk behavior can be confirmed when controlling for other determinants. We regress the child's risk variable on the parent's one using four different specifications. Equation 2.1 shows the (comprehensive) model of our transmission regressions:

$$Child\_risk_i = \alpha + \beta_1 Father\_risk_i + \beta_2 X_i + \beta_3 Father\_X_i + \varepsilon_i \tag{2.1}$$

The dependent variable is the earnings risk associated with the child i's current occupation. Our main (independent) variable of interest is the earnings risk of the father's current occupation. Model 1 is a bivariate regression. We estimate the model using ordinary least squares (OLS) and include dummies for the wave from which the observation is drawn in all regressions. To take into account the possibility that errors are correlated within occupations, all hypothesis tests are calculated using standard errors clustered at the occupation-level of the child.

Model 2 adds several personal and labor-market-related variables of the child (X_i). In various studies, risk preferences have been found to be related to socioeconomic characteristics (e.g., Barsky et al. 1997, Sahm 2007, Dohmen et al. 2011). Furthermore, we aim to control for other factors that determine occupational sorting. We take into account the age of the child, being married, and a set of dummies for the individual's religion. Since healthy individuals have been found be more inclined to take risks, we include an individual's self assessment of his health status measured on a 5-point-scale. The (riskiness of the) occupational choice should be influenced by the individual's years of schooling and the duration at an employer. We also include a dummy indicating whether the individual is employed in the public sector.

In model 3, we add the individual's net monthly income in logs. We do so in an extra step as the variable is potentially endogenous.[15] A relationship between risk aversion and income and wealth is assumed by standard microeconomic theory. The empirical evidence is, however, mixed. While some studies find a negative relationship (e.g., Hartog et al. 2002), Barksy et al. (1997) show that the willingness to take risks increases in income and wealth until the middle of the distributions, and then decreases.

[15] One might argue that, if only compensation is sufficient, all workers are willing to accept a risky job. An alternative is to consider income when calculating the risk measure. We obtain the same results if we divide the variation of the residual by the mean of log income in the respective occupation to account for the relative nature of income risk.

In the fourth specification, we include fathers' characteristics ($Father\_X$). King (1974) points out that children from wealthy family choose occupations involving higher occupational risk. The net household income of the parental household is included as a proxy for the wealth of a family. In addition, we control for the father's years of education, his age, whether he is married and works in the public sector and the residence during the first 15 years of life of the parents to take into account risk-related effects that stem from growing up in a certain environment.[16] Summary statistics are given in Table 2.4.

Baseline Results

The results of the OLS estimates can be found in Table 2.5. In all models, the effect of fathers' risk measure is significant at the 1% level and positive as expected. The magnitude of the effect drops from 0.156 to 0.12 once we include children's characteristics and does not change after adding further controls. It is striking that the coefficient obtained by Dohmen et al. (2012) in the regressions of the child's stated risk attitude on their parents' one (mother and father) also using SOEP data is of almost equal magnitude.

In line with Bonin et al. (2007), we find that education has a positive effect on occupational risk tolerance. Tenure at an employer has a weakly negative effect. Individuals that change their jobs less frequently seem to be less willing to take income risks. The material endowment does not seem to have an effect. Neither the individual's income nor the parent's one has an effect on the income volatility of the occupation. We find weak evidence that individuals without church affiliation are more inclined to take income risk.

To interpret the size of the fathers' effect, we multiply the coefficient from the fourth model with the standard deviation of the fathers' risk measure. An increase in the father's income risk by one standard deviation increases the child's earnings volatility by 0.006. It implies that an increase in father's income volatility by one standard deviation increases the child's earnings volatility by 0.13 standard deviations for the child. It is similar to the results by Dohmen et al. (2012) who report that a one standard deviation increase in self-reported risk aversion for both parents is associated with a total increase of about 0.32 standard deviations for the child.

[16]While it would be interesting to also include this information for the child, the data is largely unavailable. The parent's residence of youth might yet serve as a proxy if the family lived or moved to the same type of region when the child was young.

Table 2.5: Intergenerational Transmission: Baseline Results

	model 1 b/se	model 2 b/se	model 3 b/se	model 4 b/se
Father's jobrisk	0.156***	0.127***	0.126***	0.122***
	(0.040)	(0.039)	(0.039)	(0.044)
Age		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
Married(d)		-0.004	-0.004	-0.006
		(0.007)	(0.008)	(0.009)
Subj health (1-5)		-0.000	-0.000	-0.000
		(0.003)	(0.003)	(0.003)
Education(yrs)		0.005**	0.005**	0.004**
		(0.002)	(0.002)	(0.002)
Tenure(yrs)		-0.001*	-0.001	-0.001*
		(0.001)	(0.001)	(0.001)
Works in public sector(d)		-0.002	-0.002	-0.003
		(0.011)	(0.011)	(0.011)
log net income			-0.002	-0.002
			(0.006)	(0.006)
Father age (yrs)				-0.000
				(0.000)
Father education (yrs)				0.001
				(0.001)
Father married (d)				-0.001
				(0.008)
Father in public sector (d)				0.003
				(0.004)
Father log net HH income				-0.002
				(0.007)
Other controls	NO	YES	YES	YES
N	539	539	539	539
F	3.277	2.295	2.206	2.283
Adj. R2	0.036	0.097	0.095	0.089

OLS estimation. Robust standard errors clustered at the occupation-level of the child in parentheses. Significance levels : $*$: 10% $**$: 5% $***$: 1%. Dependent variable is the variation of the residuals obtained from the regressions shown in Table 2.1 (the earnings risk of the child's current occupation). All regressions contain year dummies. Additional controls are for model (2-3): indicator variables for religion (catholic, protestant, other religion, no religion, missing). For model (4): as in model (2-3) plus dummies for parent's location of residence at the age of 16.

"Life Cycle Effects"

An important question is whether children of all age groups are equally influenced by their parents' willingness to take income risks. As suggested by Bonin et al. (2007), younger children might work in an occupation which is only one step of the career path necessary to proceed to the occupation in which they actually aim to work in - and which represents the riskiness they are willing to take. Beshears et al. (2008) point out that personal experience with a decision decreases possible deviations between revealed and normative preferences. The literature on intergenerational earnings elasticity furthermore suggests that a "life cycle bias" exists. The intergenerational link is found to be stronger if earnings are observed at similar ages (Gouskova et al. 2010) or for older children (Haider and Solon 2006, Dahl and DeLeire 2008).

For this reason, we estimate the transmission regressions using different subsamples. First of all, we split the sample at the age of 25, i.e., the mean age in our sample. Results are shown in Table 2.6. As can be seen, for children that are 25 years old or older the coefficient on the fathers' riskiness of the job choice is significant and with a value of 0.2 larger than in the baseline regressions. In contrast, the effect is smaller (0.07) and insignificant for children younger than 25. In line with the literature on intergenerational earnings mobility, the correlation seems to increase with the age of the child. For instance, Dahl and DeLeire (2008) find that the intergenerational correlation is 0.04 for 20-year-old, 0.17 for 24-year-old and 0.33 for 30-year-old children suggesting some similarity with our findings.

In the above regressions, we observe the current choice of job of parents and children. It would be interesting to study whether parents' and children's risk behavior is alike at a similar stage in their life, i.e., when they are of the same age, have the same family status etc. Unfortunately, the only occupational information available for fathers and sons is their job at an early stage of their career. A regression of the children's current on the father's first job (an information requested in the SOEP) indicate that there is no relationship, as can be seen in Table 2.6. This result is hardly surprising, several explanations have already been provided above.

Another possibility is to include an historical average of father's job risk as an explanatory variable. In the literature on intergenerational earnings elasticity, historical averages of father's earnings have been shown to reduce the attenuation bias; the correlation increases when more years of father's earnings are taken into account (Solon 2002, Dahl and DeLeire 2008). We follow that approach and calculate averages of fathers' earnings risk over the last five years using all observations available for that period. As can be seen in Table 2.6, the magnitude of the effect is unchanged compared to baseline regressions. The significance of the effect drops to the 5%-level once we include further control variables. While we cannot confirm that using averages increases the link, we also do not find evidence for the contrary.

Table 2.6: Intergenerational Transmission: "Life Cycle Effects"

	model 1 b/se	model 2 b/se	model 3 b/se	model 4 b/se
Only children<25				
Father's jobrisk	0.097	0.081	0.075	0.073
	(0.058)	(0.063)	(0.060)	(0.059)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls	NO	NO	NO	YES
N	281	281	281	281
F	1.925	2.565	2.594	2.359
Adj. R2	0.022	0.068	0.085	0.082
Only children>24				
Father's jobrisk	0.207***	0.177***	0.187***	0.197***
	(0.062)	(0.060)	(0.061)	(0.066)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls	NO	NO	NO	YES
N	258	258	258	258
F	2.434	2.535	2.338	3.933
Adj. R2	0.031	0.087	0.097	0.100
Father's first job				
Father's first jobrisk	0.070	0.010	0.010	0.000
	(0.058)	(0.045)	(0.044)	(0.044)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls*	NO	NO	NO	YES
N	594	594	594	594
F	2.513	2.012	1.961	2.229
Adj. R2	0.008	0.117	0.116	0.123
History of father's jobrisk				
Father's history of jobrisk	0.148***	0.128**	0.122**	0.124**
	(0.052)	(0.053)	(0.052)	(0.060)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls	NO	NO	NO	YES
N	350	350	350	350
F	4.854	3.351	3.052	6.441
Adj. R2	0.049	0.087	0.092	0.087

OLS estimation. Robust standard errors clustered at the occupation-level of the child in parentheses. Significance levels : $*$: 10% $**$: 5% $***$: 1%. Dependent variable is the variation of the residuals obtained from the regressions shown in Table 2.1 (the earnings risk of the child's current occupation). Controls as in Table 2.5.

Stability of the Risk Measure over Time

A problem is that we cannot observe the distribution of earnings risk when the individual chose his occupation. As a global measure of income risk perceived from an ex ante point of view, the measure calculated using the full period thus seems to be the most representative. However, it is possible that earnings risk changes over time (for example due to shocks or structural changes in the economy) and individuals are constrained in continuous optimization (for example due to incomplete information, cognitive limitations or transaction costs). Given path-dependencies, individuals from the parent generation might work in an occupation that is connected to another risk today then it was when they decided. The income variation from an earlier period might be a better proxy for the risk they are willing to take.

For this reason, we calculate two separate risk measures, one for each decade that our sample for the Mincer regressions covers. A comparison of the mean of income risk in the period from 1990 to 1999 compared to the variance calculated for the years from 2000 to 2009 shows an increase in unexplained variation of income over time from an average of 0.24 to 0.28, the change is significant at the 1%-level (see also Table 2.2, row 2 and 3). This is in line with the literature reporting that men's income volatility increased over time (e.g., Bartels and Bönke (2010) for Germany).

We attach the risk measure calculated using the subsample from 1990 to 1999 to parents and assign the earnings volatility based on the years 2000 to 2009 to children. We thereby try to account for parents and children making their job choices at different times. Results are largely unchanged; while the coefficient is the same as in the baseline regression, the significance drops to 5%, as can be seen in Table 2.7. It is of course a crude approach to address the issue raised above.

Since children observe the current job choice and income variation, it is also possible that the risk distribution based on the sample from recent years is more appropriate. Regression with the earnings volatility from 2000-2009 assigned to parents and children show slightly larger and more significant coefficients; the correlation between fathers' and sons' income risk is 0.14, as can be seen in Table 2.7. While the difference is rather negligible, the result weakly suggests that children observe the current income volatility of their fathers when making their own choice.

Another objection with respect to earnings variance calculated over one or two decades is that substantial labor market reforms were introduced in Germany in the early 2000s. Between 2003 and 2005 several changes came into effect which had the aim to increase efficiency and decrease the unemployment rate (so called "Hartz concept"). To increase incentives to participate in the labor market, this inter alia included cutting unemployment benefits. It is possible that these changes had an effect on the income volatility. Therefore, we calculate the earnings variance over the period 2005-2009 (descriptive statistics can be found in Table 2.2) and assign the measures to parents and children. Results are shown in Table 2.7. As can be seen, baseline results are confirmed, the intergenerational correlation is 0.14.

The analyses reported in this section suggest that the period used for calculating earnings volatility does not have an effect on the magnitude of the intergenerational link.

Table 2.7: Intergenerational Transmission: Stability of Risk Measure over Time

	model 1 b/se	model 2 b/se	model 3 b/se	model 4 b/se
Variance of 1990s=parents, 2000s=children				
Father's jobrisk	0.148***	0.131**	0.129**	0.124**
	(0.051)	(0.052)	(0.052)	(0.055)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls	NO	NO	NO	YES
N	480	480	480	480
F	8.404	2.738	2.713	1.983
Adj. R2	0.015	0.064	0.067	0.056
Variance of 2000s=parents+children				
Father's jobrisk	0.143***	0.139***	0.136***	0.136***
	(0.043)	(0.043)	(0.042)	(0.045)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls	NO	NO	NO	YES
N	506	506	506	506
F	11.092	3.515	3.499	2.581
Adj. R2	0.020	0.086	0.090	0.083
Variance since 2005=parents+children				
Father's jobrisk	0.158***	0.158***	0.149***	0.135***
	(0.039)	(0.041)	(0.040)	(0.043)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls	NO	NO	NO	YES
N	432	432	432	432
F	3.378	2.293	2.307	4.041
Adj. R2	0.038	0.090	0.102	0.095

OLS estimation. Robust standard errors clustered at the occupation-level of the child in parentheses. Significance levels : $*$: 10% $**$: 5% $***$: 1%. Dependent variable as explained in the text. Controls as in Table 2.5.

Taking into Account Ability

A possible objection to occupational earnings variance as a measure of risk aversion is that the residual captures a variety of unobservable factors besides compensation for income risk. In particular, ability is presumed to be an important determinant of earnings that can hardly be observed. If earnings heterogeneity is to some extent due to information known to and acted on by the individual when making decisions - while unknown to the researcher - the observed variance in wages is the sum of the variance of random income components and of ability (as well as the covariance of the two, see Jacobs et al. 2009).

Cunha et al. (2005) show that earnings variability is a largely reliable measure of the unpredictable earnings component if the individual only has knowledge about his cognitive ability (e.g., from cognitive tests). To take such knowledge into account, we include a proxy for an individual's ability into the Mincer regression. The only measure that is available at a larger scale (though still only for a quarter of the observations used in the baseline Mincer regressions), are grades received during school. Grades have been requested in the biography questionnaire for persons entering the SOEP since 2001.[17] We include the mean of the individuals' grades in mathematics and German lessons in the baseline Mincer regressions. As expected, the results indicate that better grades in high school have a positive impact on an individual's income as can be observed in column (2) of Table 2.1. The number of occupations for which we are able to calculate the variation of unexplained income drops (from 74 categories to 42 categories) which also does the sample size for analyzing the intergenerational link. Nevertheless, the mean, standard deviation and minimum and maximum value remain similar to the risk measure employed for the baseline results, as can be seen in Table 2.2.

Results on the intergenerational transmission regressions are shown in Table 2.8. The positive relationship between fathers' and sons' earnings risk is largely unchanged; the coefficient is 0.11 in the comprehensive model and still significant at the 5%-level. If the sample is restricted to individuals older than 24, we again find a coefficient of 0.2 that is significant at the 1%-level (not reported). Removing unobserved variance due to ability reflected in grades thus does not change previous results. While we hope to remove some doubts that earnings variance is (partly) due to ability, we have to acknowledge that grades may not represent all knowledge that individuals have regarding their ability. The issue is further discussed in Section 2.5.

Income Volatility per Individual

The results might be challenged by a general skepticism regarding our risk measure. The above approach is grounded on the assumption that an individual contemplating to opt for a certain occupation considers the wage distribution of that job. When

[17] "What grade or points did you get in your last report card?" The highest achievable school grade in Germany is a 1, while a 6 denotes the lowest grade.

Table 2.8: Intergenerational Transmission: Ability and Individual Income Variance

	model 1 b/se	model 2 b/se	model 3 b/se	model 4 b/se
Including ability				
Father's jobrisk	0.125***	0.130***	0.120***	0.111**
	(0.045)	(0.045)	(0.044)	(0.051)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls	NO	NO	NO	YES
N	383	383	383	383
F	2.529	2.032	1.946	4.984
Adj. R2	0.037	0.079	0.100	0.093
Individual income volatility(*)				
Father's jobrisk	0.200***	0.184***	0.183***	0.163**
	(0.066)	(0.066)	(0.067)	(0.073)
Child controls	NO	YES	YES	YES
Child income	NO	NO	YES	YES
Father controls	NO	NO	NO	YES
N	305	305	305	305
Adj. R2	0.021	0.039	0.045	0.028

OLS estimation. Dependent variable as explained in the text. Controls as in Table 2.5. Significance levels : $*$: 10% $**$: 5% $***$: 1%. (*) Bootstrapped standard errors in parentheses to take into account that regressors have been generated in a previous stage (1000 repetitions). Child controls: cohort dummies, religion dummies, education (yrs); Child income: mean log income in observed period; Father controls: cohort dummies, education (yrs), mean log HH income in observed period, parent's location of residence at the age of 16.

making the decision, the individual cannot predict where in the relevant earnings distribution he will end up. He thus chooses according to the uncertainty he is willing to accept with respect to his future wages. Income volatility calculated per occupation over several years seems to be a good proxy for this.[18]

Another possibility is to employ the realized income path of an individual. The literature concerned with trends in earnings volatility provides alternative approaches to calculate individual earnings variation. Many analyses use complicated models to decompose earnings inequality into permanent and transitory components (e.g., Moffitt and Gottschalk 1995, 2008, Haider 2001, Baker and Solon 2003, or also Shore 2011). These approaches have been criticized for being sensitive to variations in model specification which makes results to some extent arbitrary (Shin and Solon 2011). As a consequence, many researchers have focused on simple variances of year-to-year changes of the (residual) income (e.g., Dahl et al. 2008, Dynan et al. 2007, Shin and Solon 2011). Moffitt and Gottschalk (2008) find that simpler meth-

[18]Ex ante variability is proxied by ex post income, as pointed out by Cunha et al. (2005).

ods produce approximately the same patterns as more sophisticated methods which consider autocorrelation. We check whether our results hold using such measure of income volatility.

First of all, we estimate a Mincer regression as described above (see Shore 2011). The residual from that regression is used to calculate the difference of the unexplained component between two subsequent years. We then calculate the standard deviation of residual income changes per individual. The same sample selection outlined in Section 2.3.3 applies. Furthermore, we restrict the sample to all individuals for which we have more than two income differences. Calculating the variance for children of which many only started working recently requires us to set these numbers as low as possible. The sample for which we are able to obtain individual income variance slightly differs; the most important difference is that children are on average older (average birth year: 1971, above: 1980).[19] Given the life-cycle effects described above, this has to be taken into account when interpreting results.

We regress the son's income volatility on father's income volatility. Some adjustments apply to the control variables as income volatility now refers to a period instead of an occupation pursued in a specific year. We include all controls that are (largely) time-invariant (cohort, education, religion) or can be included as an average (income).

Table 2.8 shows the results. As can be seen, we find a significantly positive relationship, the coefficient drops once we include control variables. The correlation between fathers' and sons' individual income volatility in the most comprehensive model is 0.16. The effect is more similar to the one obtained with the subsample of individuals older than 24. This can easily be explained by average years of birth being more similar. Using individual or occupational earnings variance hence does not seem to have an effect on the result, albeit limitations of comparability due to differing samples have to be taken into account.

2.5 Discussion

Intergenerational transmission of risk aversion has been established using stated preferences. The comparison of those studies to our findings shows large similarity of results. In ours and most of the other analyses, the correlation between children's

[19]Differences in the sample are inevitable due to two different restrictions. In the above analysis, a requirement is availability of information on ISCO-codes which is relaxed here. In the regressions reported in this section, we require the individual to be observed in at least 3 years. The overlap of the two samples is too small to impose the restriction that individuals are included in both samples. This of course limits comparability of results.

and parents' risk preferences ranges between 0.1 and 0.2 (Charles and Hurst 2003, Dohmen et al. 2012, Arrondel 2009, Kimball et al. 2009, Shore 2011). Hryshko et al. (2011) only find an intergenerational link for persons that belong to an extreme category.

A conclusion indicated by all studies is that the intergenerational correlation in risk aversion is rather weak. According to Cohen (1988), a correlation of 0.1-0.3 is small in terms of effect size (0.3-0.5 is moderate, >0.5 is large). In the literature on intergenerational earnings mobility, a correlation of this magnitude is taken as weak transmission (or a "highly mobile" society). Intergenerational analyses hence explain only a small fraction of where risk preferences come from.

However, decades of studying the intergenerational earnings elasticity have shown that the more attention is paid to attenuation bias, the higher the link that is found (e.g., Solon 2002, Dahl and DeLeire 2008). As has been pointed out above, all quantifications of risk aversion are potentially subject to noise. If attenuation bias is also of importance for estimating intergenerational transmission of risk aversion, the results might provide an underestimation. Uncertainty remains regarding the existence and magnitude of such effect.

A possible concern specific to our revealed preferences approach is that parents determine their child's human capital acquisition. While the literature trying to identify a causal link between parents' and children's education does not provide clear-cut evidence (e.g., Black et al. 2005), it is reasonable to assume that parents' to some extent influence the educational track of the child. Due to path-dependency of the educational system, the correlation might simply reflect parents' educational decisions. Our analysis shows that for each skill level differently risky occupations are available. Even if the educational choice by parents determines the menu of occupations available to the child, we would expect that parents choose an education in line with their own risk preferences. This might represent one mechanism of inheritance of risk preferences. However, to the extent that parents influence their children's occupational choice for other reasons, the link would be overestimated.

The analysis is based on the assumption that measured earnings risk is the unforecastable component of earnings an individual expects and accepts from an ex ante point of view. Taking into account ability by including school grades in Mincer regressions does not change the results. A bias might, however, exist if the individual has further information on his ability and acts on it when making decisions. The theoretical analysis by Jacobs et al. (2009) shows that the sign of the selectivity bias due to ability is ambiguous. Cunha et al. (2005) claim that about half of the variability in returns to schooling (high school versus college graduation) can be forecasted by agents at age 19. Equating earnings variability with uncertainty hence overstates earnings risk. If the forecastable component increases the earnings variance equally in all occupations, this should not provide a problem. Another possibility is that the forecastable component differs, e.g., is lower for occupations which require lower ability, but is similar for parents and children (e.g., due to similar ability). This would also imply an overestimation of the link.

We cannot be sure whether the limitations apply, whether they are crucial and would change our results. The fact that evidence based on different approaches produces very similar results is, however, reassuring. The joint evidence suggests that intergenerational transmission of risk aversion is weak.

2.6 Conclusion

The controversy regarding the appropriate measurement of risk aversion suggests that it is important to study whether children and parents not only report similar risk attitudes but also show a similar willingness to take risks in their behavior. The present chapter provides evidence based on a real and major economic decision: the choice of occupation.

We find that risk behavior, revealed by sons' and fathers' willingness to accept earnings volatility, is significantly correlated across generations. Our study thus confirms the hypothesis of intergenerational transmission of risk aversion. It is reassuring that results are not sensitive to the use of different approaches; even the magnitude of the effect found in different studies is largely similar. Ours and previous evidence, however, suggests that the intergenerational correlation is rather weak. Intergenerational analyses hence explain only a small fraction of where risk preferences come from.

Chapter 3

Stereotypes and Risk Attitudes: Evidence from the Lab and the Field

3.1 Introduction

The correlation between risk attitudes and sociodemographic characteristics has been actively studied in recent years (Dohmen et al. 2011, von Gaudecker et al. 2011). However, the studies so far only report correlations between risk preferences and sociodemographics. These findings give rise to the question of whether subjects are aware of the correlation between risk preferences and sociodemographic information. It is of interest whether and to which sociodemographic attributes subjects assign value, i.e., attach informational content. Therefore, our study allows to proceed a step further than previous studies by studying how subjects assess the risk preferences of others. If subjects rely on sociodemographics when forming beliefs about others' risk preferences - in particular if this information is costly - this allows concluding that the relationship goes beyond pure correlations.[1]

Previous evidence suggests that risk attitudes are important for decision making, for example for buying stocks or becoming self-employed (e.g., Dohmen et al. 2011). When making their decisions, however, individuals are increasingly relying on professionals - such as doctors in the health domain, insurance agents, and in particular financial consultants (cf. Allen 2001, Bhattacharya et al. 2012). In recent years, regulators have become concerned about the quality of financial advice.[2] In order

[1]This chapter is based on Leuermann and Roth (2012a).

[2]A result of these concerns is e.g., the "Markets in Financial Instruments Directive" of the European Union, which is - besides other objectives - set up to protect consumers in investment services. In the US, the "Restoring American Financial Stability Act of 2010" accommodates these

to improve financial advice, some countries, e.g., Germany[3], introduced a standardized questionnaire in the course of the counseling interview in which advisees are asked to self-assess their risk attitudes. Our research thus focuses on regulations as well; we investigate whether this self-assessment it recognized as helpful by advisors, especially if they are working in the financial sector.

To study these concerns, we conduct an artefactual field experiment[4] in which three types of subjects participate: senior financial advisors, junior financial advisors and non-professionals. In particular, we assess professionals' knowledge about decision making and seek to ascertain if they attach importance to other characteristics than subjects without advice experience. Studying these groups in particular allows us to explore potential sorting effects into employment in the financial sector (cf. Bonin et al. 2007, Dohmen and Falk 2011, Haigh and List 2005), especially as the junior professionals and non-professionals are similar in age and educational status.

The experiment consists of two main parts. The first part is based on a survey conducted on the Web and a large-scale survey (SOEP) of Germany. In them, 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 main stages. In the first stage, we elicit subjects' stereotypes (perceived correlations) of risk preferences of sociodemographic groups (such as gender). Secondly, we inspect which sociodemographic characteristics subjects use in the process of giving advice, namely assessing the risk preferences of others. By augmenting the subject pool with financial professionals we are able to study behavioral differences between financial advisors and non-professionals.

The results of the experiment show that subjects recognize the correlation between particular sociodemographic variables and risk preferences. The subjects are able to assess how their own risk attitude relates to the mean risk attitude of a representative population with a high precision. Professionals in general are slightly more risk averse than the observed non-professionals.

When forming beliefs over another person's risk attitude, subjects are willing to pay for sociodemographic information about the assessed person. Subjects thus expect informational value coming from the sociodemographic information. This finding provides external validity for studies that find pure correlations between risk

matters.

[3] The exact wording of the regulations defined by German regulators can be found under §31,4-5 WPHG (Security Trading Act).

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

preferences and sociodemographics.

In particular an advisee's self-assessment of risk preferences and the advisee's gender are considered to be informative when judging another person. However, senior financial professionals attach less informational content to the self-assessment of risk preferences than the other subject groups. Surprisingly, the subject group with the highest counseling experience trusts less in the information requested by regulators. Our findings are consistent across the treatments and mechanisms to elicit risk preferences.

The remainder of this chapter is structured as follows: In the next section (Section 3.2), we discuss the literature on risk preferences and advice. Section 3.3 explains the experimental design of the study. Section 3.4 presents the treatments in detail and the results, the conclusions follow in Section 3.5. The experimental instructions can be found in Appendix A.

3.2 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) in addition find that individuals are more risk averse if older, married, or with children. 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 (cf. Belzil and Leonardi 2007, Barsky et al. 1997, Hartog et al. 2002). In addition, Dohmen et al. (2011) report that actual behavior is related to answers to risk questions asked; a significant correlation between stated risk preferences and e.g., holding risky financial assets such as stocks, smoking, and being self-employed becomes evident. Nevertheless, these findings report mere correlations.

One strategy to figure out others' preferences is subsumed by "stereotyping", namely subjects' intuition regarding the variation of a single piece of sociodemographic information. 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[5] over gender are consistent since women are perceived to be less risk tolerant. In this setup the judged

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

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).

One of the most obvious situations in which advice is of major interest is in financial decision making. Previous studies suggest that 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). Furthermore, there is contradictory evidence regarding the degree of myopic loss aversion of financial professionals compared to student subjects (Eriksen and Kvaløy 2009, Haigh and List 2005). Financial professionals 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 rare.

One reason why financial professionals could systematically exhibit different risk preferences than other employees is occupational sorting. It is argued that individuals who are willing to take more risk sort into occupations with a higher variance in income (Bonin et al. 2007, Fuchs-Schündeln and Schündeln 2005, Grund and Sliwka 2010) or even with a higher mortality risk (DeLeire and Levy 2004). Typically, financial advisors are paid with highly premium dependent incentive schemes, which might attract particularly risk tolerant individuals (Dohmen and Falk 2011, Masclet et al. 2009).

This study contributes to the existing literature by analyzing subjects' stereotypes of risk preferences by varying *several* sociodemographic characteristics. We investigate to which characteristics subjects attach *informational content* when assessing others. We are thus able to extend research on the relationship between risk preferences and sociodemographics beyond pure correlations. This is the first study that takes up these questions by an *artefactual field experiment* as the subject pool is augmented by junior as well as senior financial professionals. This setup allows exploring differences in behavior between the subject groups.

3.3 Experimental Design

Since the objective of this analysis is to investigate how subjects predict the risk preferences of others, it is vital to prepare the exposition of the given sociodemographic characteristics thoughtfully. Therefore, the experiment consists of two parts (cf. Figure 3.1). In the first part we use survey data and evaluate risk attitudes of subsamples identified by certain sociodemographic variables (e.g., parents vs. non-parents). In the second part, initiated six months afterwards, a computerized lab experiment is employed. The lab experiment consists of the treatments SELF, SINGLE and SIMULT.[6] Subjects participating in the first part are denominated as *advisees* whereas the subjects of the lab experiment are called *advisors*. In the lab, advisors perform one treatment after another. During the experiment there is no interaction and no feedback about the payoff. Each treatment is performed with two different risk measures which will be described in Section 3.3.1.

The SELF treatment is the first step in the experiment. When coming to the lab, advisors are randomly allocated to sit at the computers. After logging into the experimental software advisors answer questions about their sociodemographics and their risk attitudes are elicited.

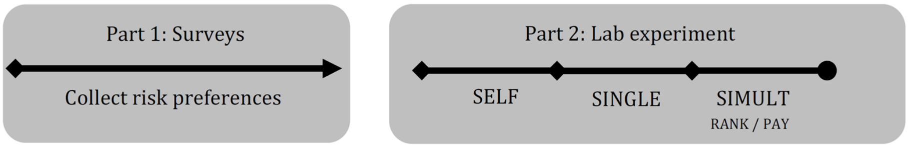
In the second treatment (SINGLE), we study advisors' knowledge about the correlation between a single sociodemographic variable and risk tolerance. The different subsamples from part one are presented to the advisors. Their task is to decide which subsample makes the riskier choice *on average* within each subgroup (e.g., whether they think that parents show a riskier behavior than non-parents). By this we are able to investigate the advisors' stereotypes on the effect of the variation of a single sociodemographic property on risk preferences. With the data from the surveys (see Section 3.3.2), we compare the risk attitudes of different subsamples (e.g., whether non-parents are more risk tolerant than parents) and construct the correct answer.

In the third treatment (SIMULT), we investigate if advisors attach informational value to the different sociodemographic properties. To accomplish this we choose eight profiles from the survey-data of part one, which we show to the advisors successively. The advisor's task is to predict the risk attitude for each single advisee presented. The profiles are presented in different modes - RANK and PAY - which are explained in Section 3.4.3. In contrast to the SINGLE treatment, the advisors have to judge the risk preferences of an *individual* advisee instead of assessing the average decision of certain subgroups. Finally, the payoffs are shown to the advisors

[6]The instructions of both parts of the experiment can be found in Appendix A.

and the session is finished.[7]

Figure 3.1: Experimental Design: Course of Action



3.3.1 Measures of Risk Aversion

Before the treatments are described in detail, we introduce two mechanisms to elicit risk preferences.

The first measure employed is a variation of the multiple price list design (MPL) of Holt and Laury (2002) (hereafter: "HL-lottery"). 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) as depicted in Figure 3.2. In this mechanism a subject is confronted with ten 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 amount of the first state is paid for sure. Hence, a rational individual switches from option A to option B once - at least at 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 option A to option B, the higher the subject's risk tolerance. For the subject's payoff in the lab experiment, one row is randomly chosen. In this row, the lottery is played according to the subject's choice.[8] For the analysis, we will use the first row the subject opts for option B as the measure of risk attitudes.

The second mechanism (hereafter: "€100,000 question") applied is taken from the German Socio-Economic Panel (SOEP) survey. It provides the opportunity to cross-check our experimental data with the large-scale data of the survey. The exact wording is as follows:

[7]Before the payoffs are presented a further treatment is played. A companion paper explains this treatment in detail (Leuermann and Roth (2012b) or see Chapter 4). Subjects are not informed about the content of this last treatment before entering it. We are thus confident that it does not bias our results.

[8]Although this elicitation mechanism is widely used in the literature it has its weaknesses - it is prone to framing effects and intellectually sophisticated (Harrison and Rutström 2008). Nevertheless, the mechanism measures risk attitudes outside the lab consistently (Harrison and List 2004, Harrison et al. 2007).

Figure 3.2: HL-lottery as Presented to Subjects

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

€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 HL-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 the 0 means that €100,000 are invested into the lottery. Hence, in both measures a higher value indicates a higher willingness to take risk on a comparable numerical scale.

3.3.2 Part 1: Surveys

Our main goal is to study subjects' stereotypes of the risk preferences of certain sociodemographic groups and individuals. Before we are able to elicit these beliefs we have to collect profiles of individuals containing their risk attitudes and their sociodemographic information. In order to elicit the mean decision of representative subgroups in SINGLE and to present advisees with heterogeneous sociodemographics in SIMULT it is necessary to obtain sufficient variation within the advisees' profiles. To collect this data we use two surveys.

First, for the HL-measure we employ a web-based survey which can be easily distributed to different people via e-mail.[9] This is necessary because for the HL-measure no large-scale data sources are publicly available. The survey collects risk preferences (in the HL-lottery as well as the €100,000 question) and sociodemographic information and it ran from November to December 2010.[10]

Secondly, concerning the collection of decisions for the €100,000 question, we can make use of a large-scale panel. The SOEP provides representative data on 20,750 individuals containing the relevant sociodemographic information and the €100,000 question.[11]

The second and the third column in Table 3.1 show the descriptives of the surveys. The data show heterogeneity within the surveys especially in the categories age, parenthood and university education. Nevertheless, the subjects in the SOEP survey are significantly older and thus more often have a partner and children.

Table 3.1: Descriptive Statistics of Advisees and Advisors

	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
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
Parenthood (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. (years)	-	-	-	-	-	-	1.02	1.07	10.97	8.27
Risk index$^{\Upsilon}$	3.54	1.81	1.90	2.13	5.26	1.39	5.08	1.52	4.68	1.71
HL$^{\Delta}$	5.30	1.78	-	-	6.81	1.56	6.33	1.78	6.32	2.08
100,000$^{\psi}$	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. $8,460) .
$^{\Upsilon}$ Self-stated risk (0=risk averse to 10= fully prepared to take risks) regarding financial matters.
$^{\Delta}$ refers to the row in which option B was chosen for the first time in the HL-lottery.
$^{\psi}$ refers to the the amount not invested into the lottery in the €100,000 question.

3.3.3 Part 2: Lab Experiment

The experimental sessions took place from April 2011 to January 2012. In total 167 subjects in the role of advisors participated.[12] In the subject pool of the lab experi-

[9] See Appendix A.1 for details.

[10] 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.

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

[12] The experiment involves no interaction among the advisors, each advisor is therefore considered to be an independent observation.

ment we have three types of advisors: 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.[13] The senior professional advisors were recruited from a German financial advisory agency and from local banks. The junior advisors come from a banking specific advanced training institution.[14] 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 education. Since these advisors are currently students, their age and educational level are comparable to the non-professional advisors.

An experimental session lasted approximately 50 minutes, on average advisors earned €11.92. Detailed information on the subject pool is shown in Table 3.1 in columns four through six. A first observation of relevance is that, while the gender division between junior professionals is nearly half-half, there are significantly less female advisors among the senior professionals. This could either be a result of women leaving their job for family reasons. On the other hand this could also indicate that women, being more risk averse than males on average, avoid the premium dependent financial sector and sort into other occupations.

A detailed description of all treatments will be given along with the results in the next section.

3.4 Description and Results

This chapter describes the different treatments in detail and presents the results. In Section 3.4.1 we report the advisors' risk preferences (SELF). Then we discuss the treatment SINGLE. In this treatment advisors were called to predict the effect of a variation of a single sociodemographic variable on others' risk preferences (stereotypes). In Section 3.4.3 we present the treatment SIMULT that investigates which characteristics (out of a given set of characteristics) are important to the advisors. Finally, we check whether choices in the SIMULT treatment are consistent with the knowledge exhibited in the SINGLE treatment.

[13]The experiment is programmed on a PHP-platform.

[14]We ran seven sessions with professionals - three in the lab and four on-site - under identical conditions.

3.4.1 SELF: Advisors' Risk Preferences

Procedure The SELF treatment elicits the advisors' own sociodemographics and their risk tolerance. First, advisors answer the questions about their sociodemographics. Then they play the €100,000 question and the HL-lottery. Both measures are incentivized as described in Section 3.3.1.

Results The distributions of the advisors' choices in both risk elicitation mechanisms are presented in Figure 3.3, separately for each advisor group.[15] The two-sample Kolmogorov-Smirnov test for distribution equality reveals that we cannot observe a statistically significant difference between choices of senior and junior professionals for the €100,000 question. On the contrary, non-professionals exhibit a significantly different distribution compared to both groups of professionals. This is also backed by the means of the choices in every subgroup. The amount not invested is significantly lower for non-professional advisors (around €47,000) than for professionals. Again, no difference between senior and junior professionals can be observed; junior professionals do not invest €60,000, senior professionals around €69,000 (cf. Table 3.1) on average. Compared to the mean choice of the SOEP survey population (cf. Table 3.1), we find that all advisor groups are less risk averse on average.

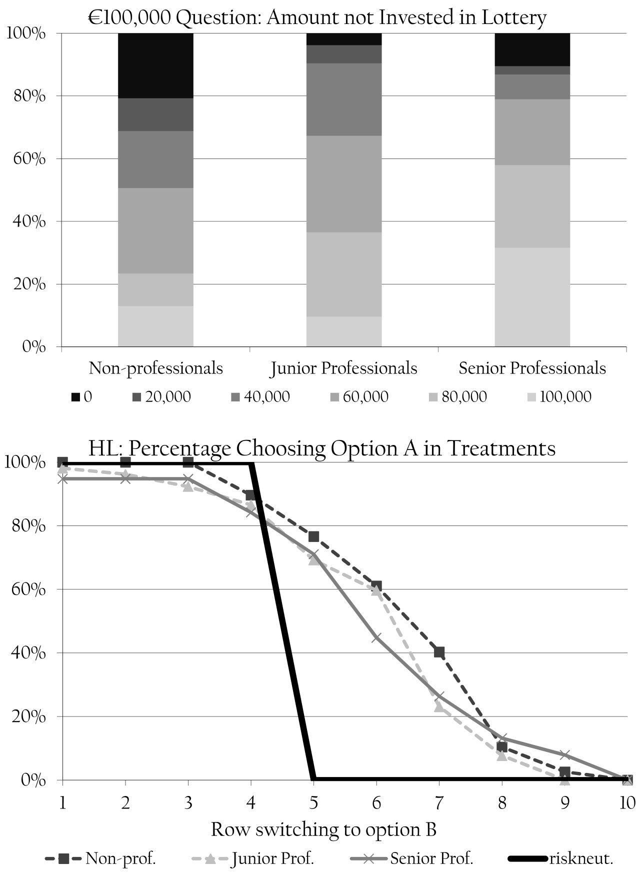
No obvious pattern of advisors' risk attitudes in the HL-lottery for the different types exists, neither for the distribution of choices nor for the means as presented in Table 3.1. The intersection of the risk neutral prediction (black solid line) with the actual distribution of subjects' choices in Figure 3.3 indicates that up to 13% of the advisors exhibit risk loving choices.[16] On average, however, the advisors exhibit risk averse preferences.

Apparently, the relative payoffs - namely the earnings in the experiment compared to the actual income - of advisors in the experiment could matter. In particular senior professionals with a significantly higher income could be affected. However, previous evidence suggests that even unincentivized lottery choices correlate with actual behavior or behavior in incentivized choices (Dohmen et al. 2011). If the actual income matters, junior professionals should exhibit preferences similar to those of non-professionals, as their income is similar. However, we observe that junior and senior professionals exhibit similar choices, which underlines the occupational sorting argument.

[15] Recall that for the €100,000 question we present the amount not invested in the lottery. For the HL-lottery, the row in which option B is chosen for the first time is presented. An increasing row number indicates a higher degree of risk aversion.

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

Figure 3.3: SELF: Advisors' Risk Attitudes in €100,000 Question and HL-lottery



3.4.2 SINGLE: Variation of a Single Characteristic

Procedure At first, after finishing the SELF treatment, advisors move on to SINGLE. In the first task, we are interested in finding out whether advisors are able to locate their own risk attitudes in the (representative) distribution of risk preferences. We ask the advisors 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. Advisors are informed that in a pretest, subjects answered the €100,000 question and the HL-lottery.[17]

Secondly, we study stereotypes of risk preferences of different subsamples. The exact wording and the different subsamples are presented in Table 3.2. The advisors' task is to predict correctly the subsample that makes the riskier decision. To determine whether the advisors' stereotypes are correct, we use the data from the surveys of part 1. The average decisions of different subsamples formed in the

[17]For the HL-lottery 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. As mentioned above, no large representative surveys are available for the HL-lottery.

categories 'age', 'gender', 'family status', 'education', 'parenthood' and 'income' are computed. Two subsamples are formed per category, i.e., characteristic. For these 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. The averages are computed for both risk measures separately.

In Table 3.2 an asterisk (triangle) indicates the subgroup that makes the decision that embodies more risk for the HL-lottery (the €100,000 question).[18]

In total, there are fourteen questions to answer: One regarding the assessment of the advisor's own risk preferences compared to the mean decision of the reference group and six about the specific subgroups, each for both risk measures. Each question pays €0.25 if answered correctly and zero otherwise.

Table 3.2: SINGLE: Average Choices of Subsamples

€100,000 question: Which group invested more money in the lottery?
HL-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 (= the correct answer) as computed from the web survey (HL-lottery) and the SOEP survey (€100,000 question) is denoted by an asterisk (*) for HL and by a triangle ($^{\Delta}$) for the €100,000 question.

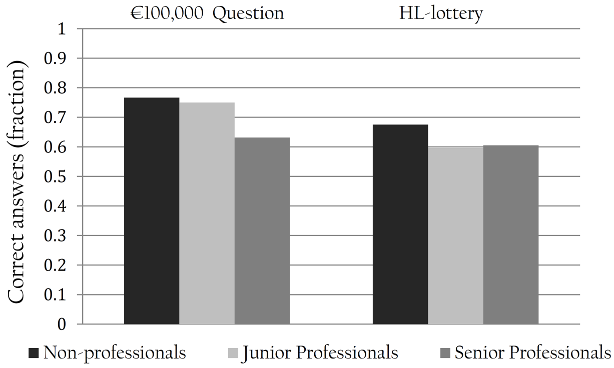
Results: Risk Preferences Relative to the Population Mean Figure 3.4 shows the percentage of advisors which are able to locate themselves correctly in the distribution of risk preferences. The figure is split up into the different subject groups and the two elicitation instruments. On the left, the fractions of correct answers in the €100,000 question are presented. 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.[19] For senior professionals this value is lower but still amounts to 63%. Decisions in the HL-lottery in the right part show a similar pattern. Approximately

[18]The decisions of two 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 in income and wealth. In contrast to that, Barsky et al. (1997) identify an inverse U-shape relation of risk aversion and income.

[19]As there are three possible answers, random answering would result in 33% of correct answers.

60% of the professionals and 67% of non-professionals assess their risk tolerance correctly. However, no statistically significant difference can be observed between the subgroups.

Figure 3.4: SINGLE: Advisors' Self-Assessment Compared to Reference Group



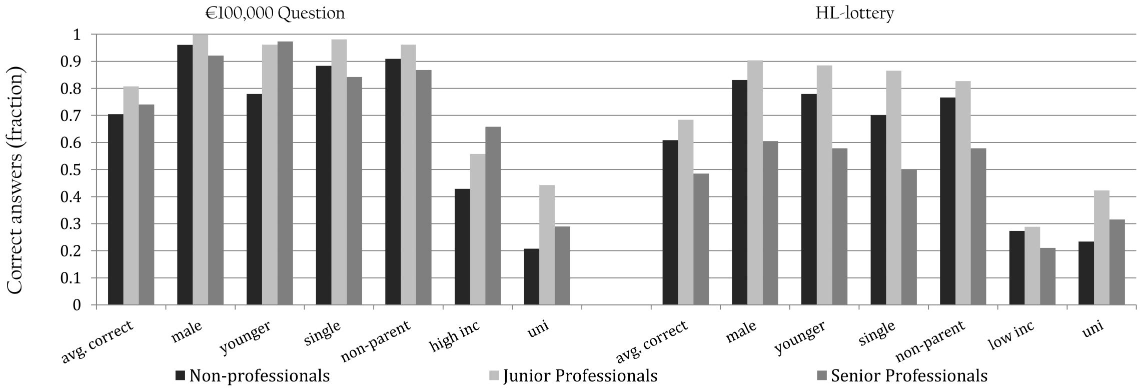
Note: The columns denote the percentage of advisors that are able to correctly answer the question *"What do you think, did people in the pretest invest more, less or the same amount respectively switch earlier, later or at the same point as you?"* split by the mechanism of elicitation. Answers of the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

Results: Risk Preferences and Stereotypes Table 3.2 outlines the different subsamples and their attitudes towards risk. In Figure 3.5 we present the fraction of advisors who are able to identify this correlation correctly in the experiment. The column labeled '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.

On average, for the €100,000 question, the stereotypes of the junior professionals coincide significantly more often with the correlations in the subsamples studied in part one than for the other subject groups; the stereotypes of the non-professionals significantly coincide more often than the stereotypes of senior-professionals. Regarding the HL-lottery, 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 significantly higher precision than non-professionals or senior professionals.

Considering the category 'gender' in Figure 3.5, nearly all advisors are aware of the fact that men tolerate more risk than women; in the €100,000 question even 100% of junior professionals judge this correctly. On the other hand, in the HL-lottery mechanism 61% of the senior professionals correctly believe that males, on

Figure 3.5: SINGLE: Distribution of Correct Answers



Note: The columns denote the percentage of advisors 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 categories below the columns denote the correct answers, namely the subgroups that are found to take riskier decisions in the SOEP and web survey. The column "avg. correct" averages the correct answers over the six characteristics per risk elicitation mechanism.

average, tolerate more risk. Considering the categories 'age', 'family status' or 'parenthood', around 70% to nearly 100% of advisors assess the statistical relationship in the €100,000 question correctly. The percentage of correct answers is lower for the HL-lottery 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.[20] Approximately 20% of the non-professionals and 30 - 40% of the professional groups identify the effect of a university degree correctly.[21] While in the €100,000 question 50% to 65% are aware of the correct correlation with 'income', for the HL-lottery 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-lottery. Our study finds that only 7% recognize this pattern correctly and answer that a different subgroup exhibits the riskier choice.

By choosing the answer "both groups switch at the same time/invest the same

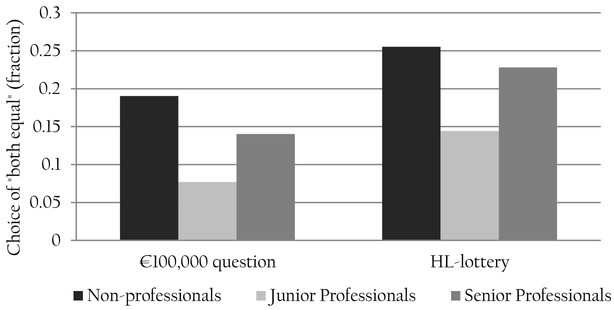
[20] If advisors chose their answers randomly from the three possible answers, the percentage of correct answers (in expectation) would amount to 33%. In both mechanisms beside for income and education a t-test rejects the null-hypothesis that the presented fractions equal 33% at reasonable levels of significance. If we consider that people randomly answer except for the answer "both equal", this would amount to a 50:50 chance of answering. In all categories, the fractions of correct answers of junior and non-professionals are significantly different from 50% except for income and education.

[21] 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.

amount" advisors indicate that they do not or cannot attach any informational value to this sociodemographic information. Figure 3.6 shows the percentage of advisors per subgroup and preference elicitation mechanism averaged over all categories choosing this option. The results indicate, first, that junior professionals significantly pick this option less frequently, namely on average in 7% (€100,000 question) and 14% of cases (HL-lottery). The other groups choose this option nearly twice as often. Second, in the HL-lottery, the option "both groups switch at the same time/invest the same amount" is employed significantly more often than in the €100,000 question.

In summary, we find that advisors are able to identify their own risk attitude relative to the risk preferences of the average choices in the surveys. The stereotypes regarding gender, age, partner and parenthood widely coincide with the correlations of the surveys, while this is not the case for income and education. Overall, junior professionals appear to have the highest degree of coherence in the stereotypes.

Figure 3.6: SINGLE: Distribution of Answer "Both Equal" in €100,000 Question and HL-lottery



Note: 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?"* with "both groups switch at the same time/invest the same amount", averaged over all categories and split by advisors' type and elicitation mechanism.

3.4.3 SIMULT: Which Characteristics are Important?

In this section we analyze the sociodemographic characteristics to which (if at all) advisors attach informational value when assessing the risk attitude of an advisee.

Procedure In contrast to the SINGLE treatment, in SIMULT the advisors have to assess *individual profiles* of advisees. We chose eight profiles from the web survey data of part one to use them as advisee profiles. Each profile contains data on seven sociodemographic characteristics as shown in Table 3.3. The advisors are informed which menu of information is provided for each category. The advisor's task is to assess the advisee's choice in the two risk measures correctly. If the advisor's prediction is correct, it pays off €0.50 for each risk measure. Each advisor has to assess all eight advisee profiles. An example for such a profile would be a married man with children and university degree, aged 64, and with an income over €6,000.

However, to the advisor not the whole set of sociodemographic characteristics is necessarily available when making the prediction. We used two modes (RANK, PAY) in order to present the advisees' information to the advisors. Each advisor has to assess four advisee profiles in RANK and four advisee profiles in PAY. The order of the eight profiles is randomly assigned.

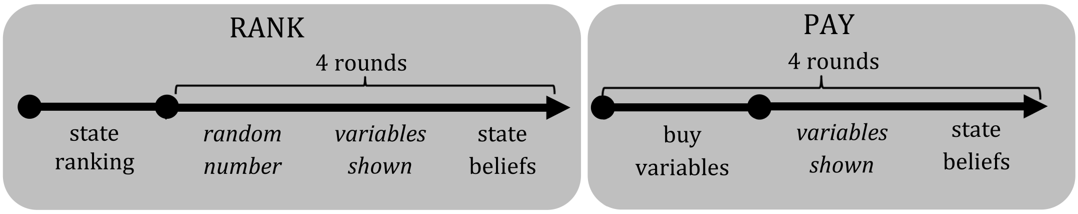
Table 3.3: RANK and PAY: Categories Provided

Age	age in years
Education	university, advanced training, training, studying economics, in training, no formal training
Family status	single, partner, married, divorced, living separated, widowed
Gender	male, female
Net income	up to €1,000, €1,001-€3,000, €3,001-€6,000, more than €6,000
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)*

RANK We are interested in the informational value advisors attach to the different sociodemographic characteristics. In this mode, advisors can influence the probability with which characteristics are shown to them. We ask the advisors to rank the seven characteristics of Table 3.3. The ranking has to be stated at the beginning of the treatment. For example, an advisor states: 1. age, 2. gender, 3. income, 4. risk index,.... In the following the computer draws a random number between 1 and 7. If, for example, the number is two and the ranking is as in the example above, the advisor would see the following information about the advisee: age: *64 years old*, gender: *male*.

As presented in the timeline in Figure 3.7, each advisor states the ranking once before assessing the four advisees. The same advisor's ranking is applied to all four advisees. However, for each advisee we draw a separate random number that determines how many characteristics are seen. This means that advisors could see the 'age' and 'gender' of the first advisee but 'age', 'gender' and 'income' for the second advisee. The probability that a category is visible is strictly higher if ranked higher. The category ranked first is definitely seen.

Figure 3.7: Course of Action in RANK and PAY



PAY In the second mode PAY advisors can freely choose which characteristics are presented to them. In contrast to RANK, the advisors have to pay for each category in each profile (cf. Figure 3.7) separately. The characteristics are priced according to a convex pricing rule. While the first characteristic costs €0.01 buying all seven characteristics amounts to a total price of €0.99.[22] This means, for example, that an advisor pays €0.06 if he or she wants to see 'age', 'gender' and 'income'. For each new profile advisors can make their payment decision, which amounts to four decisions. Advisors can win a maximum of €1 per profile by assessing both risk questions correctly. The total price of the characteristics therefore never exceeds the maximum earnings. In contrast to the RANK treatment, it is not possible to obtain a ranking over the bought characteristics in this treatment. The advisor's observed decisions to buy a characteristic indicate the informational value coming from this sociodemographic characteristic.

Results: RANK As outlined above, in the RANK treatment advisors state a ranking to affect the probability that a category is visible. Figure 3.8 displays the average rank of these categories assessed by the three groups of advisors separately.[23] Table 3.4 shows the significance of differences between ranks according to the Joanes's rank sum test[24] and displays the average position of the ranked category.

For the highest average rank, we observe agreement among the groups that 'risk index', the self-assessment of risk preferences regarding financial matters, is on average the most important category. While 64% of the non-professionals and 58% of the junior professional choose 'risk index' on the first position, only 32% of senior

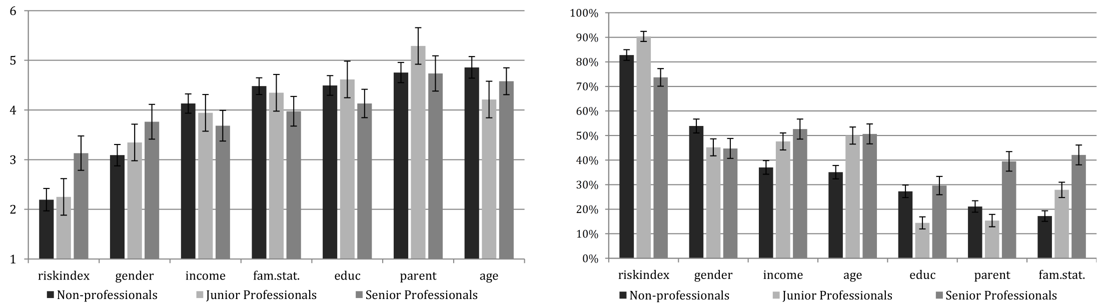
[22]Price for the second characteristic: €0.02, the third: €0.03, the fourth: €0.06, the fifth: €0.12, the sixth: €0.24, the seventh: €0.50. Since advisors earn at least €4 before entering the treatments in SIMULT, we insure that there are non-negative net earnings. Advisors are informed about this.

[23]For the interpretation, a "higher" average rank indicates that the respective variable is ranked at a position that is revealed more often. A rank of 2 is thus "higher" than a rank of 3.

[24]This test takes the difference in the total rank sum of the categories as an indicator of significant differences in ranks (Joanes 1985).

professionals do so. In addition, the average rank of the risk index is significantly lower for senior professionals than for the other two groups. All advisors on average agree that ‘gender’ and ‘income’ are ranked on the second or third position, while for ‘family status’, ‘education’, ‘parenthood’ and ‘age’, no clear pattern can be observed.

Figure 3.8: Decisions in RANK & PAY



RANK: Average Rank of Category PAY: Bought Category

Table 3.4: RANK: Joanes Rank Sum Test of Differences in Decision on Ranking

	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen
aver. rank	1	1	1	2	2	3	3	3	2	4	5	4	5	6	5	6	7	7	7	4	6
	riskindex			gender			income			fam.stat.			educ			parenthood			age		
age	***	***	***	***	*	*	**		*								***				
parenthood	***	***	***	***	***	**	*	***	**		***										
educ	***	***	**	***	***																
fam. stat.	***	***	*	***	*																
income	***	***		**																	
gender		***																			

*** indicate a significance level of 1%, ** of 5% and * of 10% (cf. Christensen et al. 2006)

The rank sum test in Table 3.4 confirms these findings. It indicates that the average rank of the risk index is significantly different from the rank of ‘age’, ‘parenthood’, ‘education’, ’family status’ and ’income’ at the 1%-level for non-professionals and junior professionals. However, the average rank sum is not significantly different from ‘gender’ for non-professionals. The rank of gender is significantly different from ‘age’, ‘parenthood’, ‘education’ and ‘family status’ at least at the 10%-level for non-professionals and junior professionals. Junior professionals consider the information regarding the correlation between risk preferences and parenthood as less valuable, because this category significantly ranks at the last position. Regarding senior professionals, the significance of the differences in the ranks is lower, although ‘risk index’, ‘income’ and ‘gender’ are significantly different from several other categories, especially, ‘age’ and ‘parenthood’.

We check whether the fact that advisors do not or cannot attach informational content to a variable in the SINGLE treatment, i.e., choosing “both groups switch at the same time/invest the same amount" as an answer, has an influence on the ranking decision. Table 3.5 shows the results of an OLS regression. As a dependent variable we include the rank of a certain category. The independent variables carry a value of one if in the treatment SINGLE, the advisor's answer is "both equal" for the specific category.[25] Standard errors are clustered at the advisors level and separate regression for the answers in the HL-lottery and the €100,000 question of the SINGLE treatment are executed. Furthermore, we control for the advisors' type by including dummy variables for junior and senior professionals. The positive sign of the coefficient 'SINGLE' indicates that if the informational content of a sociodemographic variable is not clear to the advisor, indeed, the variable ranks lower. In other words, if an individual attaches informational content to a category, the category is likely to rank at a higher position. The results thereby confirm consistency of behavior across treatments. The coefficients are remarkably close in both regressions, consistency across mechanisms is thus confirmed as well.

Table 3.5: RANK: Informational Content and Decision on Ranking

Risk measure	100,000	HL
SINGLE	0.644***	0.654***
	(0.155)	(0.123)
Constant	4.178***	4.134***
	(0.049)	(0.053)
Observations	1,002	1,002
R^2	0.016	0.021
Controls for advisors' type	YES	YES

Note: OLS regression. *** indicate significance at the 1%-level. Dependent variable: Rank of sociodemographic variable in treatment RANK. Six choices (the effect of the risk index has not been asked in the SINGLE treatment) in the SINGLE treatment per risk elicitation mechanism and 167 advisors in total sum up to 1002 decisions. SINGLE takes a value of one if the decision in the SINGLE treatment is "both equal" for the respective category. Clustered standard errors on advisors are employed. Category left out when controlling for advisors type: Non-professional.

Optimal Ranking Given the design of the experiment, the optimal ranking decision is of interest. A prerequisite to answer this from a theoretical standpoint would be information on the subject's perceived correlations between the ranked characteristics. However, this information can not be observed. Therefore, we provide an empirical explanation to this. An advisor expects to see four (3.5 which is rounded to the next integer) categories. Given the SOEP data, we run regressions for any

[25]Note that in the SINGLE treatment, the effect of the variable 'risk index' has not been answered.

combination of four variables to explain the €100,000 question. The combination of 'risk index', 'gender', 'age' and 'education' jointly explain most of the variation of the answer in the €100,000 question. Hence, from an empirical perspective, it would be an optimal strategy to place these four variables on the first four ranks. Figure 3.8 shows that 'risk index' and 'gender' are - on average - on the first two ranks. 'Education' and 'age', however, are not allocated optimally.

Overall, the results of the RANK treatment show that the 'risk index' ranks at the first position, and is observed as the most important characteristic on average. 'Gender' and 'income' rank with lower significance at the second or third position by all groups of participants. For all other categories no clear-cut and statistically significant distinction between ranks can be identified. Although especially for 'income' and 'education' the knowledge about the correlation with risk preferences as shown in the SINGLE treatment is less pronounced as for the other categories, 'income' is chosen at a high ranks. The senior professionals' choices indicate a less obvious ranking among the categories. Results from the SINGLE treatment and the RANK treatment are consistent as categories with unknown informational content in the SINGLE treatment (i.e., choosing the answer 'both equal') rank lower in the RANK treatment.

Results: PAY Since the advisor is free to buy each sociodemographic variable for every advisee profile separately, in total, four payment decisions have to be made. On average, 2.93 categories per profile are bought. The average number of categories seen in the RANK treatment is 3.88. Thus advisors in the PAY treatment have significantly less variables at hand than in the RANK treatment. Non-professionals buy 2.74 categories, junior professionals 2.91. In contrast, senior professionals purchase significantly more categories, on average 3.33. Over the four decisions, the number of categories bought does not differ significantly. The percentage of advisors buying certain categories is similar over the four purchase decisions of the treatment. This indicates that advisors are confident in their choice of categories. It is also reasonable since the advisors do not get any feedback about their success in the assessment, so learning effects from being informed about the correct belief cannot occur. However, subjects might discover which characteristics are more helpful than others when forming their belief, but given the results, this is obviously not the case.

Averaged over all four rounds, Figure 3.8 shows the fraction of subjects that buy a certain category for every subject group. Table 3.6 shows the significance levels of a paired t-test on the purchase differences in the bought categories. The row named 'position' indicates the position of the characteristic according to the percentage

Table 3.6: PAY: Test of Differences in Categories Bought

	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen	Non	Jun	Sen
position	1	1	1	2	4	4	3	3	2	4	2	3	5	7	7	6	6	6	7	5	5
	riskindex			gender			income			age			educ			parenthood			fam.stat.		
fam.stat.	***	***	***	***	**		***	**		***	**		*	*							
parenthood	***	***	***	***	***		*	***		**	***										
educ	***	***	***	***	***	*		***	***		***	***									
age	***	***	**	***																	
income	***	***	**	**																	
gender	***	***	***																		

*** indicate a significance level of 1%, ** of 5% and * of 10% of a paired t-test.

of advisors buying it. In line with the RANK treatment, 'risk index' is the most important category, bought significantly more often than any other category (in 83% of the cases). While most of the advisors choose the 'risk index', the second largest group of advisors buys 'gender'. For non-professionals, the distribution of the categories in the PAY treatment is similar to the distribution in the RANK treatment. 'Gender' ranges at the second position and is bought significantly more often than the 'income' category. For 'education', 'family status', and 'parenthood' no clear-cut statements can be made.

For the junior professionals, the categories can be divided into two subgroups in which no significant purchase differences can be observed. The categories 'gender', 'income' and 'age' are bought in more than 45% of cases. In contrast 'education', 'family status' and 'parenthood' are less valuable to this advisor group and bought significantly less often (each less than 27%). For the senior professionals, as observed in the RANK treatment, the distribution of choices is rather uniform apart from the risk index. 'Gender', 'income', 'age', 'parenthood' and 'family status' are bought in 40% to 53% of the cases, and only 'education' is bought significantly less often (30%) than 'age' and 'income'. Consistent with the RANK treatment, senior professionals buy the 'risk index' significantly less often than advisors of the other two groups.

Most important, the fact that on average three categories are bought demonstrates that advisors attach informational value to sociodemographic information. Our results suggest that advisors perceive a causal relationship between the categories, i.e., characteristics, they buy and the risk measure. This finding generates external validity for the empirical literature that finds correlations between sociodemographic information and risk attitudes, but so far cannot report a causal interpretation (cf. Dohmen et al. 2011, von Gaudecker et al. 2011).

As in the RANK treatment, we check whether the fact that advisors do not attach informational content to a variable in the SINGLE treatment has an effect on the purchase decision. Table 3.7 shows the results of a probit regression. Here, as the dependent variable we include the investor's choice to buy a certain category for the first profile of treatment PAY.[26] In line with previous findings, the results indicate that if the informational content is not clear to the advisor, indeed, the variable is bought up to 16.3% less often.

Table 3.7: PAY: Informational Content and Categories Bought

Risk measure	100,000	HL
SINGLE	-0.161***	-0.103***
	(0.036)	(0.037)
Observations	1,002	1,002
Pseudo R^2	0.019	0.013
Controls for advisors' type	YES	YES

Note: Probit regression, results are marginal effect. *** indicate significance at the 1%-level. Dependent variable: Choice to buy a category in the first round of treatment PAY. SINGLE takes a value of one if the decision in the SINGLE treatment is "both equal" for the respective category. Clustered standard errors on advisors level. Category left out when controling for advisors type: Non-professional.

To strengthen our results and to verify that behavior in the overall experiment is consistent, we investigate whether choices in the RANK and PAY treatments coincide. Figure 3.9 presents the fraction of advisors in PAY that buys a category given its rank in the RANK treatment.[27] The figure indicates, e.g., that 88% of advisors in the PAY treatment buy the category which they rank on the first position in the RANK treatment. The higher a category ranks, the higher is the probability that it is bought. Characteristics at the seventh rank are bought by less than 15% of advisors. The differences between the purchase decisions of rank one to six are significantly different at least at the 10% level. No significant difference can be observed for the last two ranks.

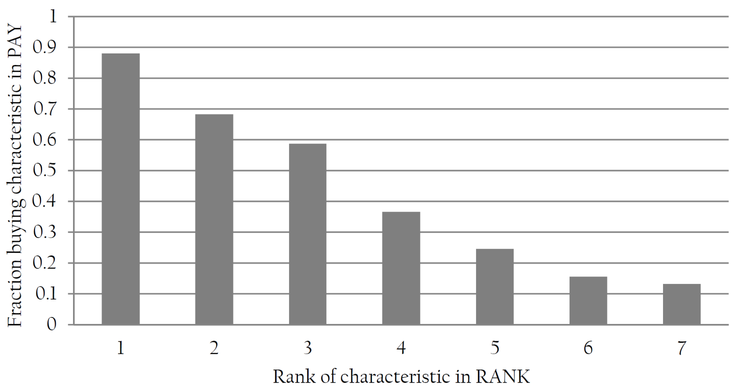
The results from the PAY treatment are threefold. First, they back the findings from the RANK treatment. 'Risk index' carries the highest informational value for the subjects as it is bought most often. 'Gender' (48%), 'income' (43%) and 'age' (43%) are bought more often than the categories 'education' (24%), 'parenthood' (23%) and the 'family status' (26%). Second, while non-professionals exhibit a clear pattern similar to the RANK treatment, no clear distribution can be found for junior and senior professionals.

Finally, we find a consistent behavior across treatments. Categories for which advisors choose "both equal" in SINGLE are bought significantly less often. Categories that are ranked at higher positions in RANK are bought significantly more often in PAY.

[26] Regressions with the purchase decisions in round 2 to 4 reveal similar results.

[27] We display the choice for the purchase decision of the first profile. Figures for purchase decisions 2 to 4 are similar.

Figure 3.9: RANK and PAY: Fraction that Buys Category Dependent on Rank of Category



3.5 Conclusion

The results of this study contribute to the existing literature in several ways. A major advantage of our data is that we observe decisions of three relevant groups of subjects: non-professionals, junior financial professionals and senior financial professionals.

All subject groups show stereotypes of sociodemographics on risk preferences that largely coincide with the true correlations. Subjects are able to identify the relationship of risk attitudes and gender, age, family status and parenthood correctly. Interestingly, subjects are aware of how their own risk preferences rank compared to the mean of a representative sample of the population.

Our design allows to investigate to which sociodemographic characteristics subjects attach informational value when assessing the risk attitude of another person. Especially, gender and a person's self-assessment of risk preferences turns out to be a major source of information. We find that subjects pay to gain information on sociodemographics of the person evaluated. This clearly demonstrates that subjects attach an informational value to the characteristics they buy. Hence, such a behavior provides external validity to the strand of literature that finds only correlations between risk preferences and sociodemographic characteristics.

We find significant differences in the behavior of different subject groups. Professionals are slightly more risk averse than non-professionals. Junior professionals exhibit the most accurate stereotypes. With respect to regulatory issues, a person's self-assessment can be a useful tool. However, we find that especially experienced professionals are less willing to make use of it. The fact that the group with the highest counseling experience trusts less in the self-reported risk measure is interesting from a regulatory perspective as well.

Chapter 4

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

4.1 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 (van Rooij et al. 2011). Thus, individuals are increasingly relying on professionals - such as financial consultants, insurance agents, but also doctors in the health domain - when making their decisions (cf. Allen 2001, Bhattacharya et al. 2012).[1]

An integral determinant of individuals' decision making are 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 (cf. Ottaviani and Soerensen 2006, Inderst and Ottaviani 2012b, or Bhattacharya and Pfleiderer 1985). Our objective is to start a step earlier. If the advisor's only goal is to correctly gauge the risk preferences of

[1] This chapter is based on Leuermann and Roth (2012b).

the advisee, is the advisor able to do so?

Advice is usually given by professional advisors. Therefore, we employ an artefactual field experiment[2] 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 (cf. 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 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. In the last treatment, the advisor is provided with the advisee's picture instead of sociodemographic information.

The results of the experiment show that a false consensus bias of the advisors is present. 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

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

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 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 analysis 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 chapter is structured as follows: In the next section (Section 4.2), we discuss the literature on risk preferences and advice. Section 4.3 explains the experimental design, while Section 4.4 presents the results. In Section 4.5 we provide several robustness checks with an alternative risk measure followed by concluding remarks in Section 4.6. The experimental instructions can be found in Appendix A.

4.2 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 with risk tolerance the findings in the literature are ambiguous (cf. 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 as found previously. 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. 1999). 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 the subject pool consisting of financial professionals and non-professionals. This allows us to study behavioral differences of subjects familiar and unfamiliar with giving advice.

4.3 Experimental Design

The experiment investigates beliefs about the risk preferences of others.[3] 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 (cf. Figure 4.1).[4] In a first part, we collect data on risk preferences of advisees in a web-based survey as described in Section 4.3.2. 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 Socio-Economic Panel (SOEP) to control for representativity as discussed in Section 4.3.3.

In the second part, we run an experiment consisting of four 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

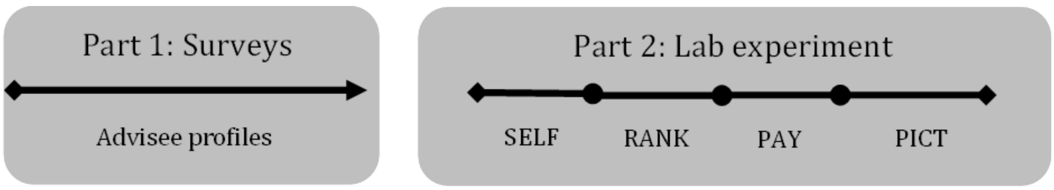
[3] In the literature 'prediction', 'forecast' and 'belief' are used interchangeably.

[4] The instructions of both parts of the experiment can be found in Appendix A.

observation. The payoffs of the whole experiment are shown after 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.[5] These two risk tasks are described in Section 4.3.1. 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 4.3.3. The last treatment (PICT) is similar to RANK and PAY. However, advisors are provided only with four pictures of advisees instead of sociodemographic information.

Before we describe the experiment in detail, we introduce the used risk measures in the following section.

Figure 4.1: Experimental Design: Course of Action



4.3.1 Measures of Risk Aversion

The experiment uses a well-studied, easily understandable lottery question to measure risk preferences. The exact wording 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.*

[5]SELF is followed by a further treatment that is discussed in a companion paper (Leuermann and Roth (2012a) or see Chapter 3). We do not expect interference for the presented results as the advisors do not receive any feedback from this further treatment.

The elicitation mechanism is an ordered lottery selection design in which subjects can invest up to €100,000 into a lottery that doubles or halves the amount invested with equal probabilities.[6] It is called "€100,000 question" in the following and is borrowed from the SOEP panel. This provides the opportunity to cross-check our experimental data with the large-scale data of the survey. The reliability of this measure has been validated via a lab experiment with real money at stake (Dohmen et al. 2011).

Beside this risk measure, all treatments are played with the measure of Holt and Laury (2002) (in the following: HL-lottery) in addition. The results serve as robustness checks and allow to generalize our results with respect to the risk measure employed. A detailed description of the HL-lottery and the results are presented in Section 4.5.

4.3.2 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.[7] This allows us to generate a heterogeneous sample in several sociodemographic characteristics. Furthermore, we ask the participants about their sociodemographics and elicit their choices in the HL-lottery and 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 Socio-Economic Panel (SOEP) survey to generalize our results.[8] 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 4.4.4 we analyze whether the advisors' beliefs coincide with the advisees' actual choices. To assess whether advisors' beliefs are correct, the mean

[6]In order to provide incentives to take the decision in the lab experiment thoroughly, for the actual payoff we convert the €100,000 into €2.50, €80,000 into €2 etc. Scale: To improve readability, in the analyses, we present the data in '€10,000 invested' such that the data is scaled from 0 to 10.

[7]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.

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

risk preferences of a subsample of the SOEP population comparable in sociodemographics to the actual advisee is taken as a benchmark. This allows us to conclude whether advisors are able to assess average advisees.

Restrictively, 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 4.1, column two and three. However, the heterogeneity of sociodemographic characteristics within these two pools is large compared with a sample that mainly consists of students as Table 4.1 (compare column 'non-professionals', which mainly consists of students) shows.

Table 4.1: Descriptive Statistics of the Subjects in Surveys and Lab Experiment

	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
HL$^{\Delta}$	5.30	1.78	-	-	6.81	1.56	6.33	1.78	6.32	2.08
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).
$^{\Delta}$ refers to the row in which option B was chosen for the first time in the HL-lottery (for details see Section 4.5).
$^{\psi}$ refers to the the amount invested into the €100,000 question in €10,000.

Selection of Advisees for RANK and PAY 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 4.2.

Table 4.2: Profiles of Advisees Selected for Presentation in RANK and PAY

Age	Education	Family status	Net income (in €)	Gender	Child.	Risk index$^{\theta}$	100, 000$^{\psi}$	SOEP mean$^{\psi}$	HL$^{\Delta}$
64	university	married	>6,000	male	yes	1	2	2.55	5
38	training	single	1,001-3,000	female	no	2	0	0.83	6
25	econ student	partner	<1,000	male	no	5	4	1.29	6
30	training	married	1,001-3,000	male	yes	1	4	1.01	8
36	adv. training	single	3,001-6,000	male	no	1	2	3.24	5
57	university	married	3,001-6,000	female	yes	0	4	0.62	7
41	university	divorced	>6,000	female	no	1	2	2.50	5
21	econ student	single	<1,000	female	no	4	0	1.59	4

$^{\theta}$ Advisees chose on a scale from 0 (=risk averse) to 10 (=fully prepared to take risks)
$^{\Delta}$ refers to the row in which option B was chosen for the first time in the HL-lottery (for details see Section 4.5).
$^{\psi}$ refers to the the amount invested into the €100,000 question in €10,000.

The sequence in which these eight profiles are shown to the advisors is random. This means 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 4.2. The column '100,000' depicts the individual choices in the €100,000 question whereas the column 'HL' refers to the actual choices of the advisees for the HL-lottery.

Furthermore, we have to assure that our advisee sample is approximately coherent with the population. We thereby ensure that the advisee is not exceptional in his or her risk preferences and correctly assessing the advisee is a feasible task for the advisor. 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 4.2. 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 4.2. 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 that characteristics.[9] This subsample contains all females, aged between 32 and 43, who are single, have an income between €1,000 and €3,000 and as education a training. On average, people with these characteristics invest €8,300 in the lottery.

In our opinion the described procedure minimizes the advisees' deviations from the population mean as we only choose advisees who are similar to the population mean. This can be observed when comparing the column '100,000' and 'SOEP mean'. We thereby assure that the subjects to be judged are not exceptional and it is therefore not impossible to assess their risk preferences. At the same time it provides the opportunity to let advisors judge real individuals.

Advisees for PICT In contrast to the preceding treatments, advisors exclusively receive visual information on the advisees in treatment PICT. Figure 4.2 displays an anonymized version of the advisees' pictures presented in the PICT treatment. Table 4.3 shows the advisees' gender and choices in both lotteries. As above, the column '100,000' denotes the actual choice in the €100,000 question, whereas 'HL' displays the choice for the HL-lottery. Again, we compute the average answer in the €100,000 question based on a subsample of the SOEP data. Therefore, we assume

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

gender and age to be observable to the advisors. In order to determine the 'SOEP mean' variable, we consider all SOEP panel participants which are born between 1976 and 1988 and have the respective gender.[10] In the experiment, advisors either have to assess four male advisees or four female advisees, which will be randomly determined per session.

Figure 4.2: Treatment PICT: Pictures Presented

Table 4.3: Risk Attitudes of Advisees in Treatment PICT

Gender	100,000$^{\psi}$	SOEP mean$^{\psi}$	HL$^{\Delta}$
female	2	1.13	4
female	6	1.13	5
female	4	1.13	4
female	4	1.13	7
male	6	1.69	4
male	0	1.69	3
male	6	1.69	6
male	6	1.69	8

$^{\psi}$ refers to the the amount invested into the €100,000 question in €10,000.
$^{\Delta}$ refers to the row in which Option B was chosen for the first time in the HL-lottery.

4.3.3 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.[11] In the subject pool we

[10]The actual advisees in PICT are born between 1978 and 1985; this information is not transmitted to the advisors.

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

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.[12] The senior professional advisors were recruited from a large German financial advisory agency and from local banks. The junior advisors were recruited from a banking specific advanced training institution.[13] 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 4.1. The experiment lasted approximately 50 minutes. The average payoff was €11.92.

In the following we present the four treatments (SELF, RANK, PAY, PICT). RANK, PAY and PICT 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 4.4. In PICT only visual information is provided.

Table 4.4: Information/Categories Provided in RANK and PAY

Age	age in years
Education	university, advanced training, training, studying economics, 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)*

Treatments

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

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

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

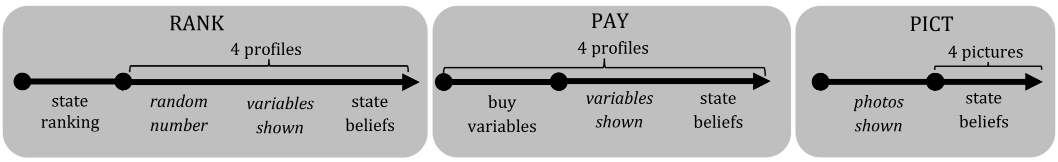
questions on their sociodemographics. Subsequently, first they play the €100,000 question followed by the HL-lottery.

Procedure Treatment RANK The task in this treatment is to assess correctly the risk preferences of an advisee. As discussed above, for this purpose we chose eight advisee profiles providing sociodemographics as shown in Table 4.4. Out of the eight profiles, four are randomly selected to be presented to the advisors in RANK. However, in RANK (as well as in PAY) the advisors are able to influence with which probability the respective sociodemographic information about the advisee is provided to them. At the beginning of the RANK treatment, as depicted in Figure 4.3, advisors are asked to state a ranking over the seven sociodemographic characteristics (e.g., 1. age , 2. gender, 3. income, 4. risk index,...) and advisors are informed that based on the revealed sociodemographic information they have to assess certain advisees. In the following the computer draws a random number that determines how many categories are disclosed.[14] If, for example, the random number is two and we are dealing with the advisee of the last row of Table 4.2, the computer displays the following information: age: *21 years old* and gender: *female*.

After the presentation of the advisee's characteristics, the advisor has to assess how this specific advisee has decided in the €100,000 question and the HL-lottery. For this advisee the correct answers would be *0* for the €100,000 question and *4* for the HL-lottery (see Table 4.2). 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.

Figure 4.3: Course of Action in Treatments RANK, PAY and PICT



Procedure Treatment PAY In the PAY treatment, advisors can freely choose which and if characteristics out of the available seven are presented to them. In contrast to RANK, the advisors have to pay for each category they want to see in

[14] The random number is drawn from a uniform distribution on the interval [1,7]. Hence, the category on the first rank is observed for sure.

each round separately (cf. Figure 4.3). The characteristics are priced according to a convex pricing rule. The first characteristic costs €0.01 while buying all seven characteristics amounts to €0.99 in total.[15] When entering the PAY treatment, the advisor is asked which categories he or she wants 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. Out of the eight profiles of Table 4.2, the remaining four after the RANK treatment are presented to the advisors. However, the advisor is able buy different categories for different profiles.

Procedure Treatment PICT As mentioned above, in the PICT treatment solely visual information is the basis for the advisor's prediction. After finishing the PAY treatment, advisors enter the PICT treatment. First, advisors open an envelope containing a sheet of paper showing four pictures. The task is then the same as in the treatment before. The advisors are asked to assess the risk preferences of the depicted advisees one after another. Again for every correct prediction €0.50 are paid off.

The advisors exclusively have the information provided on the photo available. In each session either four males or four female photos are used. Which gender is presented is randomly assigned. Although we do not explicitly provide any further sociodemographic information, at least gender and possibly age can be inferred from the pictures. The photos show individuals who are of similar appearance and are dressed alike. By holding the age, gender and the style of clothing constant we force the advisors to form their beliefs given the characteristics of the face only. In Figure 4.2 the anonymized pictures can be found. Overall, out of the 167 advisors there are 91 advisors judging the pictures of women and 76 advisors judging the pictures of men.

[15] 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.

4.4 Results

After introducing the different treatments, in this section we present the results. We contribute to four questions. Section 4.4.1 studies differences in the belief formation in the different treatments and sheds a light on self-other discrepancies. Secondly, in Section 4.4.2 we investigate how information on the advisee's sociodemographic characteristics affects the advisor's belief. Section 4.4.3 studies how differences in sociodemographic characteristics between advisor and advisee influence the advisor's deviation from his own risk preferences when forming his belief. Finally, in Section 4.4.4 we inspect if the advisors' beliefs are correct. For this we combine representative survey data with lab data.

4.4.1 Self-Assessment and Beliefs

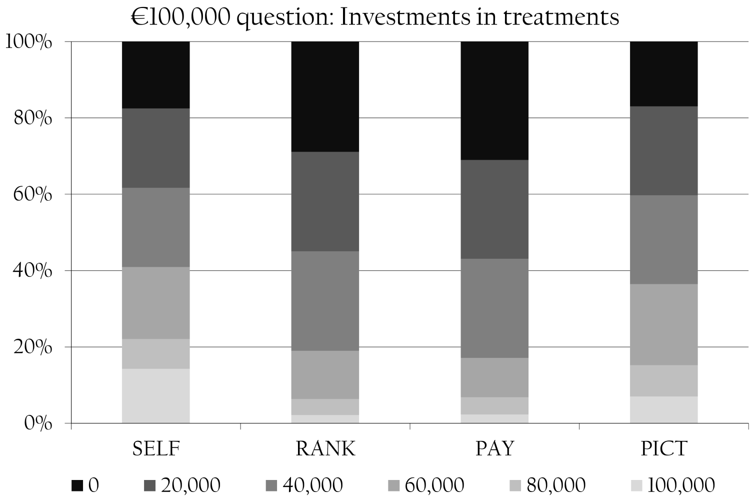
In this section, we analyze how the advisors' own risk preferences relate to their beliefs. The term self-other discrepancy refers to a systematic misperception between the advisor's own risk tolerance and the *perceived* risk tolerance of the advisee. This effect is found by Hsee and Weber (1997) but also discussed by Eckel and Grossman (2008), Faro and Rottenstreich (2006) and Eriksen and Kvaløy (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 three treatments RANK, PAY and PICT in Figure 4.4. 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 and the fourth and last stands for the beliefs in the PICT treatment. A Wilcoxon signed-rank test does not detect a statistical difference between the beliefs in RANK and PAY at the 1%-level. 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 all other pairs, e.g., SELF vs. RANK and PAY as well as PICT 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 indeed exists.

Interestingly, the choices of PICT are not statistically different from the choices in SELF. This could be due to the fact that in PICT less information is provided. As a proxy, advisors use their own risk preferences in these cases.

Figure 4.4: Advisors' Own Risk Preferences and Beliefs in Treatments (€100,000 Question)



4.4.2 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 4.5. The data of RANK and PAY are pooled in the regressions since we do not find statistically significant differences in the beliefs.[16] As the 167 advisors have to judge four randomly chosen advisees in each treatment, the pooled decisions sum up to 1,336 observations.

We run an OLS regression in which the dependent variable is the belief on the eight advisees.[17] 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 to evaluate how advisors adopt their beliefs when information on different categories is available.

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

[17]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 is scaled from 0 to 10.

Table 4.5: Regression Results: Belief Formation

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 $\mathbb{1}\{seen{=}0\}$.

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 ($\mathbb{1}\{seen{=}1\}\cdot\{soc\ dem \neq 0\}$) 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.[18] 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 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 0 for male and 1 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 used the same risk measure; we expect an advisor's belief to be more risk averse if an advisee is female instead of male. A companion paper (Leuermann and Roth 2012a) that uses the same subjects reports 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 the gender coefficients 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.[19] 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 ($\{socdem = 0\} + \{socdem \neq 0\} = 0$) reveals joint significance at the 1%-level (see Table 4.6). The correlation between gender and risk preferences

[18] 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).

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

as suggested by the literature is thus incorporated into the advisor's belief.

Table 4.6: Wald Test on Joint Significance (P-values) of Coefficients in Table 4.5

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

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.[20] 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 (see Table 4.6).

Regarding the income variable, we observe that advisors adjust their belief only if an advisee with high income is observed.[21] The interaction dummy variable indicating high income reports that the amount invested in the lottery increases by €14,090 and is jointly significant with the variable indicating low income (see Table 4.6).[22]

In addition to the advisee fixed effects we incorporate advisor attributes in model (2). The 'Self' variable contains the advisor's own 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 own 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 own risk attitude serves as a reference point for judging others. The inclusion of further advisor's characteristics

[20]The advisees' choices of risk index range from 0 to 5 (Table 4.2).

[21]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 4.2).

[22]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 4.6 proves that this is not significant.

(e.g., gender, age) shows a stable influence of the advisor's risk preferences (not reported).

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'.[23] These variables interact the advisor's risk preferences with a dummy variable of the respective advisor's type. This specification allows to analyze 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 invests himself.

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) and others who report a correlation between advisors' and advisees' preferences.

4.4.3 Does Social Distance Matter?

In this section we trace a question raised by Hsee and Weber (1997). Arguably, the self-other discrepancy described in Section 4.4.1 could be caused by the *social distance* of advisee and advisor. The reasoning can be summarized as follows: If an advisor recognizes an advisee to be similar in observable characteristics, the advisor alleges the advisee to have similar preferences. Hence, the deviation between the advisor's preferences and the advisor's belief should depend in the sociodemographic

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

Table 4.7: Regression Results: Social Distance

Model		*(4)*
dependent variable		|belief-own choice|
|advisor - advisee| · $\mathbb{1}\{seen=1\}$	Year of birth	0.00992
		0.00861
	Education	0.103
		0.233
	Family status	-0.0524
		0.222
	Income	0.0821
		0.229
	Gender	0.292
		0.179
	Parenthood	0.597**
		0.250
	Risk index	0.412***
		0.0354
Junior prof.		-0.946***
		0.163
Senior prof.		-1.118***
		0.18
Rank		0.112
		0.146
Constant		3.143***
		0.208
Observations		1,336
R^2		0.131
Dummy if char. seen		yes
Advisee FE		yes

Results of Random effects model, * p<0.1; ** p<0.05; *** p<0.01, dependent variable: absolute difference between advisor's belief and advisor's own risk preferences. $\mathbb{1}\{seen=1\}$ indicates if a characteristic is seen.

similarities - or social distance. We interpret the social distance as the absolute difference between the advisor's and the advisee's sociodemographic characteristics. Following this argument, the belief and the advisor's own lottery choice should coincide if both, advisor and advisee, share the same gender or family status, for example.

In order to evaluate this hypothesis, we estimate a regression shown in Table 4.7. The dependent variable is the absolute difference between an advisor's self-assessment and the belief on the advisee. As independent variables we include the absolute differences between the advisor's and the advisee's sociodemographic characteristics, derived for each category separately. To account for the experimental design, these variables are interacted with a dummy variable which is equal to one if the specific category is visible in the experiment (cf. Section 4.3.3). In a similar manner as in the models (1) to (3), additionally we include a set of dummy variables that indicates if the particular variable is seen by the advisee.[24] Furthermore, we control for differences between the treatments and the different advisor groups.

Considering the results of model (4) in Table 4.7, we find significant effects for the variables risk index and children. Hence, the absolute difference in the risk index between advisor and advisee positively correlates (ceteris paribus) with the absolute difference between the self-assessment and the belief. These results indicate that advisors perceive the risk index as a reliable measure and adjust their beliefs and their behavior according to this variable. With respect to the variable children, the positive sign of the significant coefficient can be interpreted as follows: If advisors recognize that they do not share the parenthood status with the advisee, they update their belief as they deviate from their own preferences. In the analyses above, gender turned out to be a major predictor for the risk preferences of others. Interestingly, there is no significant gender effect in model (4).

Similarly to the findings in Section 4.4.2, there is a significantly different behavior of the professionals compared to the non-professional advisors, as the respective control variables show. The self-other discrepancy is found to be smaller for professionals than for non-professionals. Junior and senior professionals deviate from their risk preferences to a smaller extent than non-professionals. This does not contradict our findings regarding the false consensus bias derived in the previous section. There, our interest is in the correlation between advisors' risk preferences and beliefs, while in this part we analyze the absolute difference.

4.4.4 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 4.3.2, 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 4.3.2 we have to take into account that not all characteristics are visible to the advisor when making the prediction. Hence, the subsample on

[24] In contrast to the former models, these dummy variables are not displayed and interpreted.

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 4.2. 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 4.3.2 and would amount to an investment of €8,300. However, if the advisor buys only gender, or alternatively, ranked 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. In the PICT treatment, only the gender and potentially the age is observable. By studying all males or females being 25 to 35 years old, the 'representative counterparts' are constructed for the PICT treatment. Hence, for every single observation, we have to compute this average, given the observed characteristics.[25]

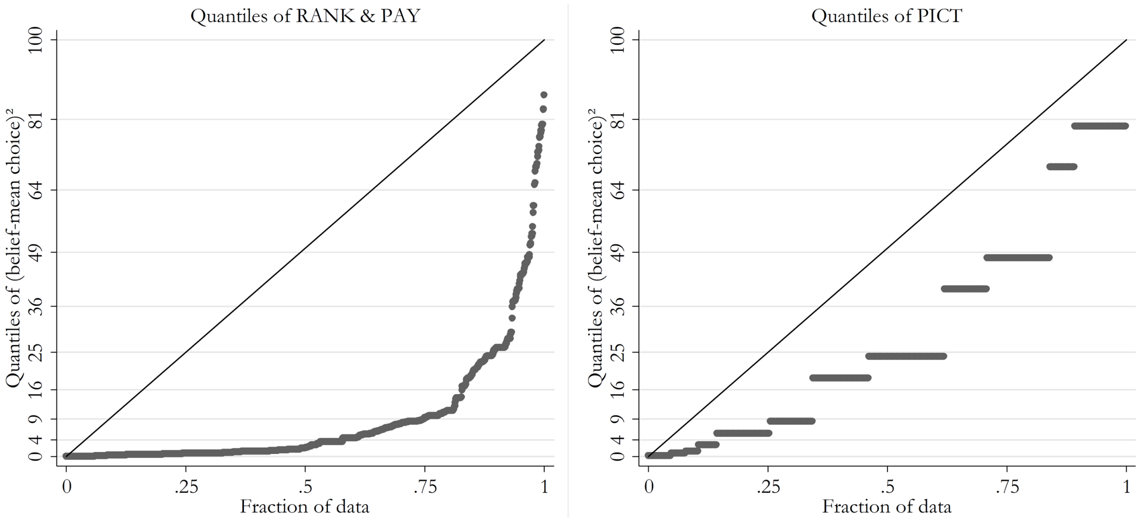
By the above procedure we obtain a value for every observation which proxies the advisee's actual decision. In order to analyze if the advisor's belief is correct, we compute the advisor's prediction error. For this we take the squared difference of the advisor's belief and the computed average choice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

Results In Figure 4.5 we show a quantile plot of the prediction errors by treatment. The pooled prediction errors for the RANK and PAY treatment are displayed in the left figure, while the right figure shows the prediction errors for the PICT treatment. The 45°-line represents the benchmark case of a uniform distribution of the prediction errors over the quantiles. Several aspects are noteworthy: First, the quantiles derived for the PICT treatment are closer to the 45°-line compared to the RANK and PAY treatment. While only about 20% of advisors exhibit a squared prediction error of 20 and larger in RANK and PAY, in PICT this amounts to over 50%. Hence, for the treatments RANK and PAY, the precision of the advisors' assessment is found to be higher. Second, in the RANK and PAY treatment the advisors' predictions are 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.

Given the strong differences in RANK and PAY compared to PICT, indeed either the amount of sociodemographic information provided or which categories are revealed might enhance precision. The visual appearance turns out not to be a major

[25] In order to ensure representativity we employ a dataset-specific weighting function which considers cross-sectional personal weights of each subject.

Figure 4.5: Quantiles: Prediction Error in RANK, PAY and PICT



source of information when predicting the risk preferences. We thus expect that if the advisor has more or particular information available this leads to lower prediction errors.[26] As the information available is varied in the treatments RANK and PAY, consequently, we analyze these treatments in detail. In Table 4.8 we present the results of two regression models. In these models we investigate if more and which categories help to decrease the advisor's prediction error.

As discussed above, as dependent variable 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.[27] 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, a finding is that indeed the amount of information plays a significant role for giving precise advice.

[26] A companion paper (Leuermann and Roth 2012a) reports that advisors largely interpret the information in line with the correlations found in the data.

[27] Note: For the advisor's type the omitted category is 'non-professional'.

Table 4.8: Regression Results: Prediction Errors

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
	Parenthood		-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.

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. The results indicate why the prediction error is found to be larger in PICT. None of the sociodemographic categories provided in PICT - age and gender - significantly reduce the prediction error in RANK and PAY.

A further considerable result of this analysis is obtained with respect to the the advisors' types. 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 results 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.

4.5 Robustness Checks

As outlined in Section 4.3.1, the whole experiment is executed with a second risk measure (the HL-lottery) which serves as robustness check. In the following paragraphs we reproduce the previous analyses to back the arguments made in the Sections 4.4.1 to 4.4.3. For Section 4.4.4 we can not 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 following immediately after this chapter in Section 4.7.[28]

4.5.1 Risk Measure of Holt and Laury (2002)

The alternative method we employ is the multiple price list design (MPL) of Holt and Laury (2002). In this risk task the subject has to decide in ten rows between two lotteries (option A and option B) as depicted in Figure 4.6. In each row, except for the last row, option B has a higher payoff variance than option A. The expected payoffs are increasing with the row number. Therefore, an individual with monotone preferences either chooses option B in every row or switches from A to B. The more

[28]The results are robust for using a structural maximum likelihood estimation (Harrison and Rutstöm 2008) of a utility function ($U(x) = x^r$) with constant relative risk aversion (CRRA).

rows a subject opts for option B, the higher is the subject's implied risk tolerance. A risk neutral individual would choose option A in row one to four and switch to option B for row 5 to 10. 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). That is, a subject does not state ten separate decisions but has to announce in which row he or she chooses option B for the first time. For the subject's payoff in the lab experiment one row out of the ten is chosen randomly with equal probability. For this row, the lottery chosen by the subject (either option A or B) determines the payoff. The computer draws a lot according to the winning probabilities and determines the money won by the subject.

Although this elicitation mechanism is widely used in the literature it has its weaknesses - it is prone to framing effects and intellectually sophisticated (Harrison and Rutström 2008). Nevertheless, it is well-studied in many different contexts and is extensively used in previous studies, which allows comparability to previous results. Recent research shows that risk preferences are not stable across mechanisms (e.g., Anderson and Mellor 2009), a second mechanism thus allows a broader generalizability of our results. Furthermore, it is documented that the mechanism measures risk attitudes outside the lab consistently (Harrison and List 2004, Harrison et al. 2007). Yet another drawback of the €100,000 question is that it captures only preferences on the risk averse domain.

Regarding the procedure in the lab experiment, directly after stating the belief in the €100,000 question, the advisor's belief in the HL-lottery is elicited. Advisors have to answer in which exact row the presented advisee first chose option B. Both questions of risk elicitation have to be answered directly after the sociodemographic information or the picture is presented to the advisor. The beliefs formed in both measures are comparable as they are formed on the same advisees.

4.5.2 HL-lottery: Self-Assessment and Beliefs

Figure 4.7 shows the distributions of the advisor's beliefs and the advisor's own risk preferences as in Section 4.4.1. In contrast to the €100,000 measure, the HL-measure allows to reveal risk-loving preferences. Approximately 12.6% of the advisors switch from option A to option 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-lottery 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 the 0.1%-level. Hence, the observed distribution of the beliefs in the HL-lottery (Figure 4.7) is comparable to the distribution of the beliefs in the €100,000 question (Figure 4.4).

In Figure 4.4 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 4.7. 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 4.4.1.

4.5.3 HL-lottery: How Do Advisors Form Beliefs?

In the following section we present the robustness checks for the question of Section 4.4.2. For this we replicate the analysis above with the HL-lottery and re-estimate the empirical models (1) to (3) and refer to them as (1a) to (3a) in Table 4.9 and 4.10. If we find coefficients to exhibit an opposite sign compared to Section 4.4.2, our results are similar, as for the HL-lottery, 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.

In model (2a) we incorporate advisors' own risk preferences ('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 advisors' groups. 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 Section 4.4.2. We find differences in the magnitude of the false consensus for the junior professionals.

4.5.4 HL-lottery: Does Social Distance Matter?

As a final validation, in Table 4.11 we provide the robustness check for Section 4.4.3. In general, model (4a) shows comparable results as model (4). Especially, for the variables of interest - the interaction terms - we find the same pattern as in the baseline model as risk index and parenthood turn out to be significant and comparable in size. The same result can be identified for the dummy variables of the advisors' groups, although the signs of the coefficients of these variables differ.

Consistently, the baseline model and the robustness check show that sociodemographic differences between advisor and advisee cause a deviation of the advisors' beliefs from their own risk attitudes.

4.6 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 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.

As a result of our analysis we find that advisors update their beliefs on the advisee's risk preferences according to their social distance to the advisee. If advisors' and avisees exhibit a different parenthood status or risk index, the advisor' beliefs deviate significantly from their own risk attitude which we interpret as an updating process.

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 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.

The presented results are fairly robust as the additional analysis with the measure of Holt and Laury (2002) shows.

4.7 Appendix: Additional Material for Robustness Check

4.7.1 Risk Measure: HL-lottery

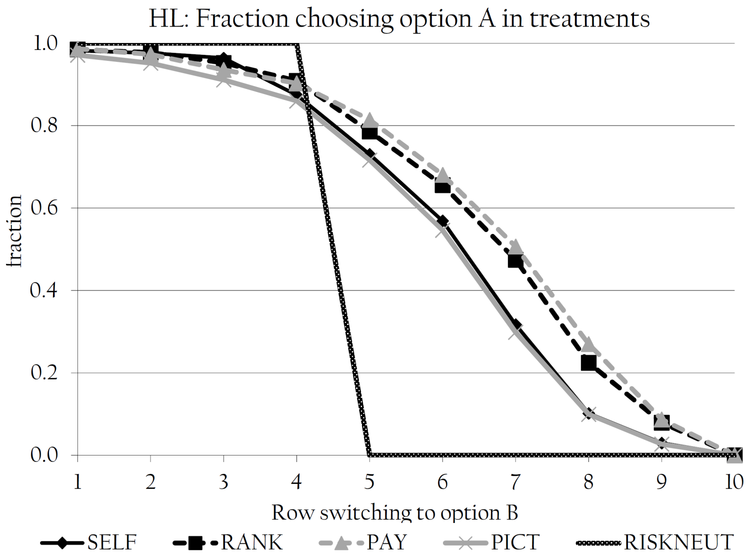
Figure 4.6: sMPL Mechanism (HL-lottery)

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

4.7.2 HL-lottery: Self-Assessment and Beliefs

Figure 4.7: Advisors' Own Risk Preferences and Beliefs in Treatments (HL-lottery)



4.7.3 HL-lottery: How Do Advisors Form Beliefs?

Table 4.9: Regression Results: Belief Formation in HL-lottery

	Model	*(1a)*	*(2a)*	*(3a)*
	dependent variable	belief HL	belief HL	belief HL
$\mathbb{1}\{seen{=}1\}$	Year of birth	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	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-lottery. $\mathbb{1}\{seen = 1\}$ indicates a characteristic is visible. $\{soc\ dem\}$ indicates the realization of the characteristic. The left-out category is $\mathbb{1}\{seen = 0\}$.

Table 4.10: HL-lottery: Wald Test on Joint Significance (P-values) of Coefficients in Table 4.9

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

4.7.4 HL-lottery: Does Social Distance Matter?

Table 4.11: Regression Results: Social Distance in HL-lottery

Model		*(4a)*
dependent variable		HL: |belief -self|
$\lvert$advisor - advisee$\rvert \cdot \mathbb{1}\{seen{=}1\}$	Year of birth	0.00631
		0.00484
	Education	-0.071
		0.131
	Partner	0.0772
		0.131
	Income	-0.122
		0.129
	Gender	0.0769
		0.101
	Parenthood	0.260*
		0.140
	Risk index	0.169***
		0.0199
Junior prof.		0.221**
		0.0919
Senior prof.		0.500***
		0.101
Rank		-0.0626
		0.082
Constant		1.302***
		0.117
Observations		1,336
R^2		0.110
Seen dummy		yes
Advisee FE		yes

Results of Random effects model, * p<0.1; ** p<0.05; *** p<0.01, dependent variable: absolute difference between advisor's belief and advisor's own risk preferences. $\mathbb{1}\{seen{=}1\}$ indicates if a characteristic is seen.

Chapter 5

Reputational Herding in Financial Markets: A Laboratory Experiment

"They [equity investors] are not paid to make money, or even to beat the market. Rather, they are paid not to do worse than their peers. Going down with the market would not be so bad for them; missing out on a rally like in 2009, when stocks doubled in barely two years, would be catastrophic for their career. That is the logic of the way they are paid - usually, as a proportion of their assets under management - and of the way they are judged - against their peers and public stock indices."(Financial Times, Comment by J. Authers, "Dangers of market herd stampedes", 30.11.2011.)

5.1 Introduction

Motivation The popular press frequently alludes to herd behavior as a potential source of mispricing in financial markets.[1] Also, there is a substantial academic literature (both theoretical and empirical) on this phenomenon. Perhaps surprisingly, even under full rationality, herding might arise in financial markets, and market prices might fail to converge to true values even in the long-run. One strand of the literature suggests that this might be due to "social learning" on part of individual investors (see e.g., Park and Sabourian 2011, Avery and Zemsky 1998). In particular, these authors introduce information cascade models (in the spirit of Bikhchandani, Hirshleifer, and Welch 1992, Banerjee 1992, Welch 1992) into a Glosten and Milgrom (1985) style sequential asset market, and they show that, despite a flexible market

[1]This chapter is based on Leuermann and Roider (2012).

price, rational herd behavior might occur.[2]

As the introductory citation above suggests, another potential source of rational herd behavior are reputational concerns of individual investors vis-a-vis outside observers (e.g., potential future employers). In particular, Dasgupta and Prat (2008) introduce career concerns (in the spirit of Scharfstein and Stein 1990) into the Glosten and Milgrom (1985) model. There, investors are of various (unobservable) ability types. Dasgupta and Prat (2008) show that, following a number of trades in the same direction, the profit from acting on one's own information becomes smaller and smaller as prices get precise. At the same time, if one's own information runs counter to the behavior of previous investors, acting on the own signal implies a reputational loss, which might make it rational to herd. Intuitively, if several predecessors have bought the same asset, with a high probability, a trade contrarian to predecessors decisions and according to the own signal turns out to be worthless and the investor incurs a reputational loss as he is observed as an investor with low ability. He thus considers following predecessors and neglects his own information to not harm his reputation. From that moment onwards, prices remain constant and all subsequent investors follow the crowd.[3] Of course, besides payoff externalities from information-based or reputation-based herd behavior, there might be still other explanations for herding. For example, herding might also be driven by irrational investors following their "animal spirits" as Akerlof and Shiller (2010) have put it.

From an empirical perspective, there is by now a large literature on potential herd behavior and its likely causes in financial markets (for surveys, see e.g., Bikhchandani and Sharma 2000, Daniel, Hirshleifer, and Teoh 2002, or Hirshleifer and Teoh 2003). In particular, various authors have investigated whether there is reputational herding (due to career concerns) by investment newsletters (see e.g., Graham 1999), macroeconomic forecasters (see e.g., Lamont 2002, Ehrbeck and Waldmann 1996), security analysts (see e.g., Hong and Kubik 2003, Hong, Kubik, and Solomon 2000, Welch 2000), mutual fund managers (see e.g., Massa and Patgiri 2005, Chevalier and Ellison 1999), or institutional investors (see e.g., Sias 2004). So far, the empiri-

[2] Avery and Zemsky (1998) consider a setup with two dimensions of uncertainty and two states of the world. A trader has private information not only about the assets' value, but also about event uncertainty that might change the value of the asset substantially. With these two dimensions, prices might fail to reflect all privately observed information and herding might arise. Park and Sabourian (2011) show that, even with one-dimensional uncertainty, herding may arise if there are more than two states of the world.

[3] In another approach, Dasgupta and Prat (2006) consider career concerns in a static asset market with two periods and focus on the effect on the trading volume. Trueman (1994) studies the incentives of analysts to herd in their earnings forecasts and finds herding on the sequential forecasts as well. For further theoretical models consider Zwiebel (1995), Huddart (1999), Prendergast and Stole (1996), and Villatoro (2009).

cal evidence seems to be mixed.[4] Moreover, while in the theoretical models private information plays a crucial role, in empirical studies it is, in general, impossible to control for private information of individual actors. Also, it is frequently difficult to observe the performance incentive, which, in general, will also motivate behavior. Consequently, Hirshleifer, and Teoh (2003) point out that, with empirical studies, it will always be difficult to disentangle the mixture of reputational effects, informational effects, direct payoff externalities, and imperfect rationality. As a consequence, we turn to the laboratory to test Dasgupta and Prat's (2008) theory of reputational herding experimentally. This way we can also control for the information and incentives faced by decision makers.

Experimental Setup In this chapter, we experimentally test whether herd behavior occurs out of reputational concerns. We therefore design an experimental setup similar to the theoretical model of Dasgupta and Prat (2008). Their theory suggests that investors engage in herd behavior[5] if they face reputational concerns and asset prices get precise.

In the experiment, subjects in the role of financial investors take the decision which of two assets to buy. The subjects' investment behavior in two treatments is studied via the strategy method. While in a treatment *investment*, subjects take their decision in the absence of career concerns, in a treatment *reputation*, career concerns are incorporated endogenously. For their investment choice, investors observe investment decisions of predecessors and a signal about which asset is the successful one. Investors can be of two types. Either they are of good type and receive an informative signal about the assets' value or they are of bad type and receive an uninformative signal. Subjects are not aware of their type.

In the first treatment *investment*, the investor's profit consists of the final payoff of the asset bought minus the price paid for it. In this setup, according to the theory, investors should always follow their own signal and buy the respective asset (i.e., there should be sincere trading). The second treatment *reputation* additionally introduces principals who set wages for the investors based on the observed investment choices and the actual outcome of the asset. Investors thus receive wages set by the principals besides earning profits from investing in the asset. In this second treatment with career concerns, investors should engage in herd behavior and ne-

[4]For example, Sias (2004) and Ehrbeck and Waldmann (1996) fail to find evidence for reputation-driven herd behavior, while in Welch (2000) clustering of behavior might be due to informational or reputational reasons.

[5]Herd behavior, in our setup, refers to the case in which investors follow the investment decisions of predecessors regardless of their own signal. The investors' behavior thus does not carry informational value and asset prices do not converge to the true liquidation value.

glect their own signal if a sufficient number of predecessors bought the same asset (and hence, prices are becoming sufficiently precise).

In particular, our experiment focuses on the following questions: First, do investors exhibit herd behavior out of reputational concerns? And second, is wage setting in line with theory? Do principals recognize herd behavior out of reputational concerns and incorporate this into the assessment of investors' trading qualities? By employing differing incentive schemes - with and without (endogenous) reputational concerns - we thus aim at disentangling the underlying motives for herd behavior.

Results The experimental results show that, as suggested by Dasgupta and Prat (2008), herd behavior can be observed in treatment *reputation*. About half of the investors engages in herd behavior when theoretically expected. Surprisingly, even in treatment *investment*, herd behavior occurs to a similar extent. We find evidence that an (irrational) imitation of predecessors is present on behalf of investors.

In a second step, wages set by principals are studied to understand the underlying motives of investors. Interestingly, wages are remarkably close to the theoretically derived wages. In addition, imitative behavior seems to be understood by the principals who adjust wages accordingly. Recalculating the theoretical model with the wages set by the principals in the experiment reveals that these wages offer incentives to engage in herd behavior. However, when calculating the underlying incentives while additionally taking earlier investors' imitative behavior into account, incentives to herd disappear. Thus, the lack of reputational incentives might rather be attributed to noisy behavior on the part of earlier investors.

Moreover, regardless of whether incentives for engaging in herd behavior are provided, a substantial fraction of agents exhibits herd behavior. This contradicts previous experimental findings which show that in a setup with flexible market prices (similar to e.g., Avery and Zemsky 1998), herd behavior does not occur.

Outline The remainder of the chapter is structured as follows. The related literature is discussed in Section 5.2. In Section 5.3, we introduce Dasgupta and Prat's (2008) model and present the theoretical predictions. In Section 5.4, we outline the experimental design, and the experiment's results are presented in Section 5.5. Section 5.6 contains concluding remarks. In the subsequent appendix in Section 5.7, the theoretical predictions are recalculated for the prices and parameters set in the experiment. The experimental instructions can be found in Appendix B at the end of this thesis.

5.2 Related Literature

The present analysis contributes to three strands of the literature.

First, our study is related to various experiments that investigate the incentive effects of career concerns (i.e., concerns for one's reputation). However, in contrast to the present study, this literature has focused on career concerns in labor markets. In particular, Irlenbusch and Sliwka (2006) and Koch, Morgenstern, and Raab (2009) experimentally investigate Holmstrom's (1999) seminal model, where through providing effort an agent tries to influence the perception of potential employers regarding his unknown ability, which has an impact on his future wages ("signal jamming").[6]

Second, there is a recent experimental literature on herd behavior in financial markets with flexible prices. However, so far this literature has mainly focused on purely information-based explanations for rational herding.[7] For example, Drehmann, Oechssler, and Roider (2005) and Cipriani and Guarino (2005) confirm Avery and Zemsky's (1998) prediction of no herding in a simple financial market with (one-dimensional) uncertainty over two potential states of the world (but they also find evidence for (irrational) contrarian behavior). Park and Sgroi (2009) find support for Park and Sabourian's (2011) prediction of rational herding and contrarian behavior in financial markets with more than two possible states of the world. We differ from this literature by considering Dasgupta and Prat's (2008) model where rational herding is not driven by informational externalities, but by reputational considerations of investors.

Third, there is the empirical literature on reputational herding in financial markets. As discussed above, it will always be difficult to disentangle various explanations for herd behavior with empirical data. This is especially true as most of the leading theories rely on the presence of asymmetric information (or certain probability distributions over states of the world), which is hard to observe empirically. We complement this literature by testing Dasgupta and Prat's (2008) theory of reputational herding under controlled conditions in a lab experiment.

[6] While in Irlenbusch and Sliwka (2006) experiment gift-exchange might also play a role, Koch, Morgenstern, and Raab (2009) focus on career concerns and provide support for the theoretical predictions.

[7] Beginning with Anderson and Holt (1997), there is a vast experimental literature on information-based herding in settings with *fixed* prices (which, however, does not directly apply to financial markets where prices are flexible). For an overview, see e.g., Drehmann, Oechssler, and Roider (2007).

5.3 Theoretical Predictions

5.3.1 Basic Structure

We consider a simplified version of Dasgupta and Prat (2008) to make it suitable for a laboratory experiment. The sequence of events is illustrated in Figure 5.1 below.[8] There are three risk-neutral investors $i \in \{1, 2, 3\}$ and four dates $t \in \{1, 2, 3, 4\}$. Investors have to decide sequentially which of two assets A or B to buy, and at date $t = i$ it is investor i's turn to buy either one unit of asset A or one unit of asset B.[9]

Only one of the assets will turn out to have a value of 10 points[10] at date $t = 4$, while the other will have a value of zero points. Both states $v \in \{A, B\}$ (i.e., which asset has a value of 10 points) occur with equal probability, and this is known to investors. The state of the world is the same for all three investors. As additional information, each investor receives a private signal $s^i \in \{a, b\}$. The signal's precision depends on the respective investor's type, where each investor has an equal probability of being either "good" or "bad". In the case of a good investor, we have $\sigma_g = Prob(s^i = a|v = A) = Prob(s^i = b|v = B) = 0.9$, while in the case of a bad investor we have $\sigma_b = Prob(s^i = a|v = A) = Prob(s^i = b|v = B) = 0.5$. For each investor, the signal is drawn independently conditional on the state and the investor's type. That is, while a good investor receives additional information by observing the signal, a bad investor's signal is uninformative. Denote the asset bought by investor i by $V^i \in \{A, B\}$.[11]

The state of the world, as well as the investors' types, is determined at the beginning of the game. Investors do not learn their type throughout the game, and the state of the world (and hence, investors' payoffs) is only revealed after all investment decisions have been made. When making his investment decision, each investor can rely on three pieces of information: (i) his privately observed signal, (ii) the current market prices for assets A and B, and (iii) the investment decisions of earlier investors (if there are any) as well as the history of market prices these earlier investors have faced. How market prices for the assets are determined is explained

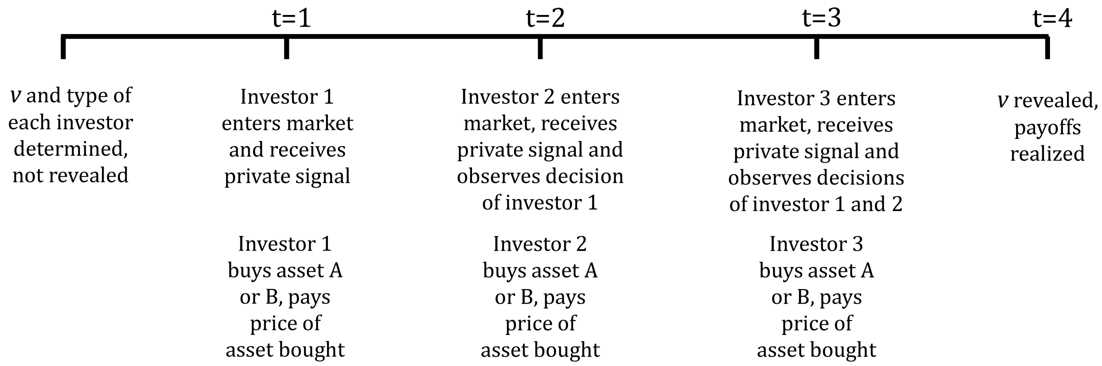
[8]The basic structure of the model, as well as the informational environment, is common knowledge. All instructions of the experiment can be found in Appendix B.

[9]Dasgupta and Prat (2008) consider the choice between buying or (short) selling a single asset. In line with other experiments on herding in financial markets (see e.g., Drehmann, Oechssler, and Roider 2005, Cipriani and Guarino 2005) we consider the strategically equivalent choice between buying either A or B, which seems to be easier to explain to experimental subjects.

[10]The presentation of the theoretical model incorporates the currency used in the experiment - points.

[11]Note that we do not introduce uninformed (noise) traders. This simplification does not affect the theoretical predictions but makes it easier to explain the setting to experimental subjects. Market break-down is not an issue as in the experiment subjects have to buy one of the two assets.

Figure 5.1: Sequence of Events without Reputational Concerns



in more detail below.

5.3.2 No Reputational Concerns of Investors

In a first step, we consider a benchmark setting where the investors do not have reputational concerns because they only derive a profit from buying one of the assets. That is, in this benchmark setting, the overall payoff of investor i is given by

$$\pi_I^i(V^i, p_{V^i}^i, v) \equiv \begin{cases} 10 - p_{V^i}^i & \text{if } V^i = v \\ -p_{V^i}^i & \text{if } V^i \neq v \end{cases} \tag{5.1}$$

for $V^i, v \in \{A, B\}$ and $i \in \{1, 2, 3\}$.

Market prices are set by a risk-neutral, competitive market maker who efficiently incorporates all publicly available information (i.e., the history of trades) as well as the investor's decision to buy the respective asset. Hence, the market price of asset A at time i is given by

$$p_A^i = 10 \cdot Prob(A|H^i, \text{buy } A) \tag{5.2}$$

where H^i denotes the history of observable decisions of all earlier investors up to time i. Likewise, the price of asset B is equal to $p_B^i = 10 \cdot Prob(B|H^i, \text{buy } B)$.[12]

In line with earlier results by Glosten and Milgrom (1985) and Avery and Zemsky (1998), if investors are only motivated by profits from trading, all trading will be sincere (i.e., all investors will act according to their signal), and hence investors

[12]Other experiments (such as Drehmann, Oechssler, and Roider 2005, Cipriani and Guarino 2005) have assumed that the market maker does not condition the price on the kind of order he receives (and hence, is not fully profit-maximizing). We deviate from this and assume the price setting rule (5.2) because it facilitates more "extreme" prices earlier on in a given sequence of investors. From a theoretical perspective, this will lead to the emergence of reputational herding even in a sequence of only three investors (see Section 5.3.3 below).

reveal their private signal through their investment decision to the market maker, who will adjust prices accordingly. To see this, suppose that the market maker believes that trading is sincere and that investor i has received signal $s^i = a$. In this case, the price of A will equal the investor's expected value of A, and hence buying A yields him an expected profit of zero. However, buying B would yield a loss because the market maker would assume that the investor has received signal b and set a price that exceeds the investor's expected value of B. Consequently, it is optimal for the investor to trade sincerely, i.e., to buy asset A (recall that the investors do not have the option not to trade). Likewise, after a signal $s^i = b$ only an investment in asset $V^i = B$ is optimal. To summarize:

Proposition 1 (Dasgupta and Prat 2008, Section 3) *In the absence of reputational concerns, investors always follow their signal and trade sincerely, i.e., $V^i = A$ if $s^i = a$ and $V^i = B$ if $s^i = b$ for all i. That is, there is no rational herding. Prices are as in Table 5.1.*

Table 5.1: Prices for Assets A and B

i	H^i	p^i_A	p^i_B
1	—	7.0	7.0
2	A	8.4	5.0
2	B	5.0	8.4
3	AB or BA	7.0	7.0
3	AA	9.3	3.0
3	BB	3.0	9.3

5.3.3 Investors with Reputational Concerns

Dasgupta and Prat (2008) augment the model as outlined in Sections 5.3.1 and 5.3.2 by reputational concerns of investors. More precisely, in addition to the payoff from buying a certain asset, at date $t = 4$ each investor i receives some wage r^i that is determined at the end of the game, i.e.,

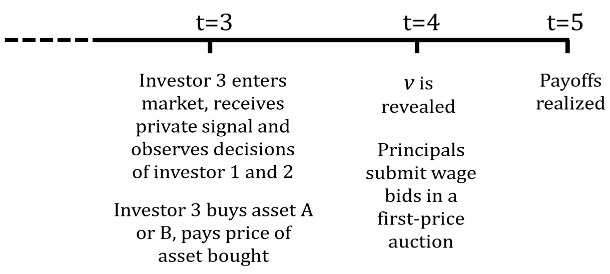
$$\pi^i_R \equiv \pi^i_I + r^i. \tag{5.3}$$

Dasgupta and Prat (2008) assume that the investors are fund managers and the wage r^i is given by an outside market's posterior belief that investor i is a good type (i.e., an investor whose signals have informational content). The outside market (i.e., potential future employers) observes the entire history H^T of trades and prices as well as the realized true state of the world v (i.e., which of the two assets is successful). Consequently, in contrast to Section 5.3.2 investors have an incentive to be perceived as a good type, and for investor 3 it will be optimal to disregard his private signal and to herd whenever both predecessors have bought the same asset.

The intuition is as follows: If early investors follow their signal, the price incorporates their private information and moves towards the true liquidation value. Over time, however, price movements become smaller. In particular, profits from trading according to one's signal stay zero, and profits from trading against one's signal stay negative, but decrease in absolute terms. At the same time, a trader who observes a signal contrarian to earlier price movements (and hence the most likely outcome of the asset) faces endogenous reputational costs: if he would follow his signal, with a high probability the asset he buys would turn out to be worthless and he would be perceived as a bad investor who has received an uninformative signal. Thus, as prices become sufficiently precise (and profits from trading sufficiently small), investors start to follow predecessors out of reputational concerns.

Wage Setting Process by Principals In practice, whether reputational herding indeed emerges depends not only on the behavior of investors, but potentially also on the wage setting behavior by the outside market. Consequently, in contrast to Dasgupta and Prat (2008) we consider an explicit wage setting process where investor i's wage is determined in a sealed-bid, first-price auction among six risk-neutral "principals", where investor i's wage r^i is determined by the highest bid. The sequence of events is identical to Section 5.3.1 up to date $t = 3$, as can be observed in Figure 5.2. It only differs from $t = 4$ onwards.

Figure 5.2: Sequence of Events with Reputational Concerns



As in Dasgupta and Prat (2008), principals can observe the entire history of trades and prices as well as the realized true state of the world v. The winning principal has to pay his bid and additionally gets 20 points if and only if investor

i happens to be good (otherwise he gets 0 points).[13] The remaining five principals get a payoff of zero each. In the appendix in Section 5.7, we show that if, at date 4, principals hold a (common) belief r that investor i is of good type, the principals' bidding strategies in symmetric equilibrium are $20 \cdot r$ (i.e., bids are equal to the respective investor's "expected value").[14] Hence, in analogy to Dasgupta and Prat (2008), in equilibrium investor i receives a reputational payoff of $r^i = 20 \cdot r$.[15]

Dasgupta and Prat (2008) show that the belief r that principals hold about a given investor only depends on this investor's equilibrium strategy and the realized true state of the world (but not on the behavior of other investors). Intuitively, this is the case because principals can observe which of the assets turns out to be successful, and investors' signals are mutually independent given the true state of the world v (see Dasgupta and Prat 2008, Proof of Proposition 1). Consequently, (with one notable exception to be discussed below) equilibrium wage bids take on only two values: they are equal to 12.86 points if the respective investor chose the successful asset, and they are equal to 3.33 points if the respective investor chose the unsuccessful asset. The exceptions are the wage bids for an investor 3 who invests in the same asset as both of his predecessors (i.e., if $H^4 \in \{AAA, BBB\}$). Such an investor engages in rational herding, and hence his behavior does not reveal his signal. As, from an ex-ante perspective, both types of the investor are equally likely, such an investor 3 receives a wage offer of $0.5 \cdot 20 = 10$ points.

Market Prices Set by the Market Maker The possibility of rational herding raises an issue with respect to price setting by the market maker in the experiment. From a theoretical perspective, it will turn out that, even in the presence of reputational concerns, in equilibrium both investor 1 and 2 trade sincerely. Consequently, for them a profit-maximizing market maker will set asset prices as spelt out in Table 5.1. However, for the case of investor 3 a profit-maximizing market maker might suspect herd behavior (if $H^3 \in \{AA, BB\}$) and confront investor 3 with market prices that deviate from Table 5.1. In the experiment, this would be problematic as earlier studies have shown that price levels per se influence subjects inclination to follow their own signal (see e.g., Cipriani and Guarino 2005, Drehmann, Oechssler, and Roider 2005). In particular, there is evidence for contrarian behavior, where

[13] In case of a tie, each of the highest bidding principals wins with equal probability.

[14] In addition, there is an asymmetric equilibrium, where at least two principals bid $20 \cdot r$, while the remaining principals bid less than that. However, the investor's reputational payoff is not affected and again given by $r^i = 20 \cdot r$.

[15] Note that in Dasgupta and Prat (2008) the weight of reputational concerns in an investor's payoff function is determined by the parameter $(1 - \beta)$, where β constitutes the payoff fraction from investment in the asset. By fixing the value of the good investor to 20 and the successful asset's payoff to 10, $(1 - \beta)$ equals $\frac{2}{3}$ in our setup.

subjects are more likely to act against their signal and a preexisting trend, if prices are higher. This price effect would make it difficult to compare our treatments with and without reputational concerns. To rule out this confounding effect, we assume that even if investors' payoffs are given by (5.3), the market maker sets market prices according to Table 5.1.[16] In the appendix in Section 5.7, we show that theoretical predictions with respect to the behavior of investors (and hence with respect to wage setting by principals) remain unchanged.[17]

In particular, as a theoretical benchmark in the presence of reputational concerns we focus on the "most revealing equilibrium" as derived by Dasgupta and Prat (2008), in which investors maximally condition their trades on their private information (see Dasgupta and Prat, 2008, Section 4.1):

Proposition 2 (Dasgupta and Prat 2008, Proposition 4) *Assume that market prices are given by Table 5.1 and that investors have reputational concerns. Then, in the most revealing equilibrium, investors 1 and 2 trade sincerely. Investor 3 trades sincerely unless both of his predecessors have invested in the same asset, in which case he herds. The wage bid that a principal submits for investor* $i = 1, 2$ *is equal to 12.86 (3.33) if the respective investor has bought the successful (unsuccessful) asset. The wage bid that a principal submits for investor* $i = 3$ *is equal to 10 if* $H^4 \in \{AAA, BBB\}$. *Otherwise, investor 3 receives wage bids equal to 12.86 (3.33) if he has bought the successful (unsuccessful) asset.*

5.4 Experimental Design

Recruitment and Subject Pool The experiment was conducted in five sessions, which ran in May and June 2011 in the AWI Lab at the University of Heidelberg. Participants were recruited via Orsee (Greiner 2004). In total 90 subjects participated; 18 in each session. The entire experiment was paper and pencil based. Each session lasted approximately 120 minutes. Participants earned 13.95 Euro on average. Altogether, 44 females (48.89%) and 46 males participated. The average age was 21.68 years, and the average number of semesters studied 3.75. Of the participants, 35.6% were economics majors, while the second largest group consisted of

[16] Recall that the role of market maker is played by the experimenter, and hence potential losses are not an issue.

[17] Intuitively, as argued above, equilibrium wage bids by principals for a given investor do only depend on this investor's equilibrium strategy as well as on the realized true state of the world. In the appendix (Section 5.7), we show that, given equilibrium wage bidding strategies of principals, equilibrium investment strategies of investors are the same independent of whether one sets market prices according to Table 5.1 or whether market prices take potential herd behavior by investor 3 into account.

law students (12.22%).

Implementation Upon entering the laboratory, all 18 participants of a given session were informed that investment decisions in two completely independent rounds had to be taken. A translation of the experimental instructions can be found in the Appendix B.[18]

In the first round subjects played a treatment *investment*, and in the second round subjects played a treatment *reputation*. The (benchmark) treatment *investment* corresponds to the setting without reputational concerns described in Section 5.3.2. That is, all subjects acted as investors, their payoff function was given by (5.1), and this was common knowledge among participants. Treatment *reputation* corresponds to the setting with reputational concerns of investors described in Section 5.3.3. Subjects learned about the details of treatment *reputation* only after they had completed the first round. In each session of treatment *reputation*, six randomly selected subjects acted as principals, while the remaining 12 subjects acted as investors. Investors' payoff function was given by (5.3), principals made wage offers for investors as described in Section 5.3.3, and again this was common knowledge among participants.[19] As discussed in Sections 5.3.2 and 5.3.3, in both treatments market prices for the two assets were set according to Table 5.1.[20]

Both rounds of a session had the same basic structure. First, the instructions for the respective round were handed to subjects and read out aloud by the experimenter. Afterwards, the experimenter additionally explained the main features of the respective round via a flip chart to subjects. Subsequently, to check whether the experimental setup was clear, a questionnaire regarding details of the setup had to be answered (see the Appendix B). Only after all subjects filled out the questionnaire correctly, decision sheets were distributed and filled out by the subjects, after which the respective round ended. Only after the second round, payments were calculated, subjects answered a post-experimental questionnaire requesting demographic infor-

[18]Throughout the whole experiment, we abstain from using the term "reputation" to ensure a neutral framing. We asked subjects about the purpose of the experiment in the post-experimental questionnaire. In their answers, none of the subjects mentioned "reputation", and only three explicitly speak of "herd behavior".

[19]In order to ensure that both investors and principals were informed about the entire (information) structure of the game, all subjects received identical instruction sheets. To achieve comparability, investors received decision sheets identical to the decision sheets of the first round. Subjects were allowed to keep a copy of their first round decision sheet as a reference for the second round.

[20]Drehmann, Oechssler, and Roider (2005) conduct an experiment on information-based herding in financial markets, and document behavior that is quite robust across pricing rules that make different assumptions on the behavior of investors (e.g., full rationality or different forms of "mistakes").

mation as well as asking questions about the experiment. Finally, payments were privately handed out to subjects, after which the experiment ended.

To elicit subjects' decisions, the strategy method was used. In particular, when acting as an investor, the respective subject was asked to state decisions V^i for all $i \in \{1, 2, 3\}$, for all possible histories of prices and predecessors' decisions, and all possible own signal realizations he might observe (i.e., the respective subject was asked to state a decision for every *information set* at which an investor might have to make a decision). For example, when acting as an investor the subject was asked to imagine he were investor 1 and to state his decision for both the cases that he received the signal $s^1 = a$ and $s^1 = b$. Likewise, the subject was asked to imagine he were investor 2 and state his (in total, four) decisions depending on whether his predecessor had chosen A or B and depending on whether his own signal was a or b. In a similar vein, as investor 3 he had to state 8 decisions. Similarly, subjects who acted as principals in treatment *reputation* were asked to submit a bid for each investor $i \in \{1, 2, 3\}$ for each possible history of decisions and prices the respective investor might have observed and for each possible realization of the state of the world.[21]

Payments Subjects received a show-up fee of 4 Euro about which they were informed at the beginning of the experiment. Subjects were furthermore told that, depending on their success in the experiment, they could earn additional money, where each additional point (the experimental currency throughout the experiment) paid out 0.20 Euro. In each of the two rounds each subject (investors in treatment *investment* and investors and principals in treatment *reputation*) received an initial endowment of 20 points. Except for the show-up fee, the exact amount earned was revealed at the end of the experiment only (and subjects were aware of this).

As we employ the strategy method, in each of the two rounds each subject's payoff depended on one randomly chosen decision, and we took care to explain in detail to subjects how individual payoffs were to be calculated (see the experimental instructions in the Appendix B). In particular, at the end of the experiment and independently for each of the two rounds, payments were determined as follows: By making draws from urns, (i) we randomly allocated investors into groups of three subjects and randomly assigned the role of investor 1, 2, and 3, and (ii) according to the probabilities described above, for each of the investor groups, we randomly determined the successful asset and each investor's type and signal.[22] Given this

[21]The maximal possible bid per investor was limited to 20 points.

[22]That is, in all of the sessions there were six investor groups in treatment *investment* and four investor groups in treatment *reputation*.

information, for each of the investor groups, we then were able to obtain the decision of investor 1 from the respective subject's decision sheet and to calculate his payoff from his investment decision (see (5.1) above). In a second and third step, we then obtained the decisions (and calculate the payoffs) of investors 2 and 3 in an analogous way (given the decisions of investor 1 and of investors 1 and 2, respectively). This concluded the determination of payoffs in treatment *investment*.

As out of the 18 participants in each session, 6 randomly became principals in treatment *reputation*, we had 12 investors in four investor groups. The above procedure left us with a decision history and a successful asset for each of the four investor groups in treatment *reputation*. Based on this information, principals had to take their decisions in the experiment (for every possible combination of V^1, V^2, V^3 and v). By looking at the decision sheets of principals, we were, hence, able to determine the highest bid for a given investor in treatment *reputation* (which determines his wage). In total, there were 12 auctions, one for each of the 12 investors remaining. Given the respective investor's type, we were also able to determine a principal's payoff from the auction for the respective investor: only the winning principal had to pay the bid, and, if the investor was a good type, the winning principal earned 20 points. All other principals earned zero from the respective auction.[23]

5.5 Results

In this section, we present and discuss the results of our experiment.

Overview Table 5.2 provides a first overview of our results. For both treatment *investment* and *reputation*, Table 5.2 depicts the fraction of subject that behave in line with the theoretical prediction for all information sets of the game (i.e., combinations of predecessors' choices and own signal) at which investors have to make a decision. Note that we pool information sets that differ in labeling only, and hence are symmetric. For example, in Table 5.2 *AAb* and *BBa* are both subsumed

[23] In both rounds, by experimental design, investors could never lose more money than the initial endowment of 20 points. If, in treatment *reputation*, a principal won many auctions and hired only investors of bad type, he or she may, in principle, accumulated losses that exceeded the initial endowment of 20 points. We excluded this possibility by informing principals that the minimum they could earn were zero points (including the initial endowment). While this limited liability constraint might, in principle, have given principals an incentive to overbid, we do not find evidence for this. In fact, looking at all principals, there is even evidence for some underbidding as the average actual wage bid is equal to 6.28, while Proposition 2 would predict an average wage bid of 8.25.

under XXy.[24] More formally, in the following we describe information sets by combination of capital letters and small letters, where capital letters refer to the observed decisions of predecessors (i.e., $X, Y \in \{A, B\}$, where $X \neq Y$), and small letters indicate the own signal (i.e., $x, y \in \{a, b\}$, where $x = a$ if $X = A$, $x = b$ if $X = B$, $y = a$ if $X = B$, and $y = b$ if $X = A$).

Table 5.2: Percentage of Subjects Behaving in Line with the Theoretical Prediction

		treatment	
investor	information set	investment	reputation
1	x	91.66 %	95.83 %
2	Xx	85.00 %	89.17 %
2	Xy	79.45 %	80.00 %
3	XXx	81.11 %	86.67 %
3	XXy	56.33 %	41.67 %
3	XYy	86.67 %	90.00 %
3	XYx	94.45 %	95.00 %

Note: $N = 90$ ($N = 60$) in treatment investment (reputation). With respect to the information available to subjects, capital letters refer to the observed decisions of predecessors (i.e., $X, Y \in \{A, B\}$, where $X \neq Y$), and small letters indicate the own signal (i.e., $x, y \in \{a, b\}$, where $x = a$ if $X = A$, $x = b$ if $X = B$, $y = a$ if $X = B$, and $y = b$ if $X = A$).

A first inspection of Table 5.2 reveals that at all information sets except XXy behavior is remarkably close to the theoretical prediction of subjects following their own signal independent of the investment decisions of predecessors. Indeed, Figure 5.3 below shows that in both treatments over 85% of subjects act in line with theory if one averages over all information sets except XXy.[25]

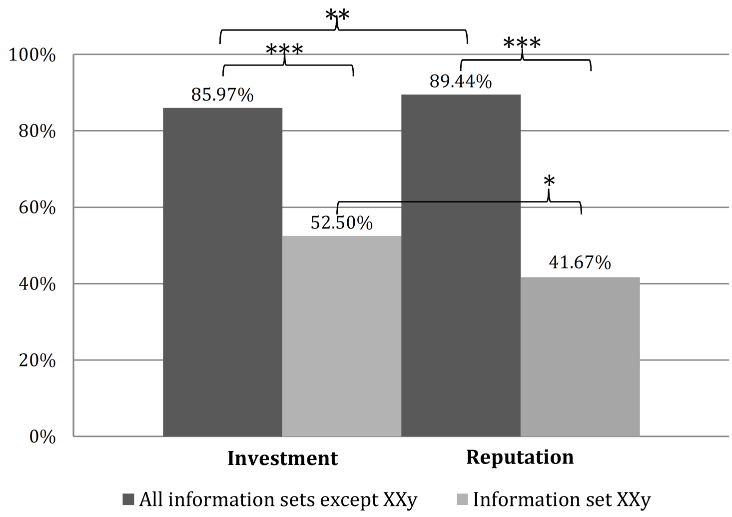
In treatment *reputation*, investor 3 should rationally herd at information set XXy (if the decisions of his predecessors conform). And indeed, Table 5.2 and Figure 5.3 show that a substantial fraction of subjects disregards its own signal and follows the lead of predecessors' decisions instead. Two observations with respect to behavior at information set XXy are, however, surprising. First, even in treatment *reputation*, a majority of subjects still follows its own signal. Second, even in treatment *investment* (where, according to theory, acting against one's signal is never rational) a similar fraction of subjects disregards its own information. A t-test reveals that in treatment *reputation* as well as in treatment *investment*, behavior differs significantly at the 1%-level at information set XXy compared to all other information sets. Furthermore, if one pools behavior at all information sets except XXy (i.e., situations where subjects should follow their signal independent of the treat-

[24] A paired t-test confirms that the decisions of the investors in the pairwise symmetric information sets do not differ significantly.

[25] In Figure 5.3, Figure 5.4, and Table 5.3 we restrict attention to the subset of 60 subjects who serve as investors in both treatments.

ment), significantly more subjects (at the 5%-level) follow theoretical predictions in treatment *reputation* than in treatment *investment*. On the contrary, at XXy the opposite is true at the 10%-level.

Figure 5.3: Percentage of Investors 3 Behaving in Line with Theoretical Predictions



Note: ***, **, * indicate significant differences of decisions at the 1%, 5%, 10%-level, respectively.

Consequently, Table 5.3 investigates the behavior at information set XXy in more detail. As Table 5.3 indicates, substantial fractions of subjects either follow their own signal in both treatments (i.e., in both treatments choose Y) or follow the lead of their predecessors in both treatments (i.e., always choose X). At information set AAb (BBa) only 4 (3) out of 60 subjects act rationally in both treatments. Behavior at XXy does not differ across treatments according to a McNemar-Change-test, which does not reject the null-hypothesis that no behavioral change occurs (Chi-squared of 2.33, critical value for $p<0.05$ is 3.84.).[26]

Evidence on Imitative Behavior by Investors The finding that even in treatment *investment* a substantial fraction of subjects (nearly 50%) disregards its own signal at information set XXy is indicative of (irrational) imitative behavior on the part of investors. If such imitative behavior is prevalent and if it is anticipated by principals in treatment *reputation*, it might affect principals' wage offers (and hence the reputational incentives faced by investors in treatment *reputation*). This, in turn, might help to explain the apparent lack of evidence for reputational herding in

[26]In order to guarantee independence of observations, we apply the McNemar-Change-test separately to both information set AAb and BBa. The Chi-squared are 0.82 and 1.60, respectively.

Table 5.3: Assets Bought at Information Set XXy

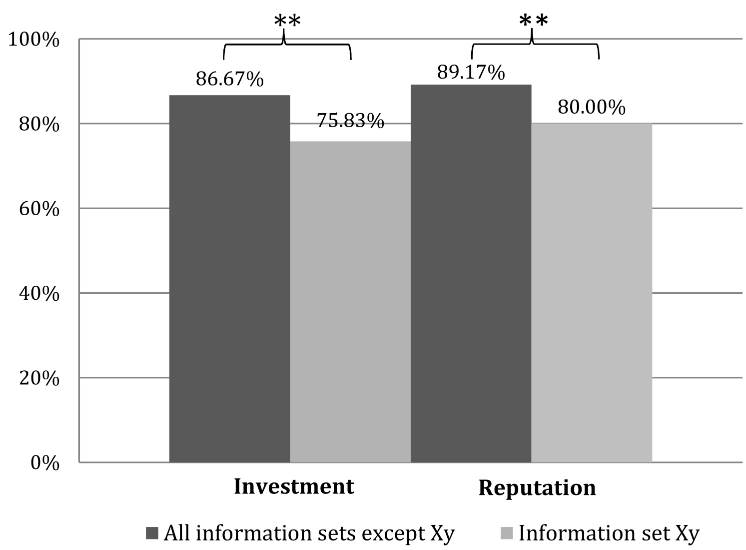
		reputation		
		X	Y	sum
investment	X	43	14	57
	Y	7	56	63
	sum	50	70	120

Note: $N = 60$ (i.e., all subjects except principals) in both treatments. For example, the table shows that at information set XXy (i.e., AAb and BBa) 43 investors buy asset X in both treatments. A McNemar-Change-test reveals no statistical significant changes between treatments.

treatment *reputation*. Consequently, in a next step, we provide evidence on imitative behavior among our subjects.

To do so, in a first step, we look at the behavior of investor 2, who, independent of the treatment, should always follow his own signal. However, it becomes clear from Table 5.2 and Figure 5.4 that investor 2 is less likely to trust his own information at information set Xy than at information set Xx. That is, if the predecessor's decision contradicts the own information some investors indeed seem to imitate the respective predecessor. According to t-tests, the differences in behavior at information sets Xx and Xy are statistically significant in both treatment *investment* and *reputation* (with p-values of 0.0316 and 0.0495, respectively).

Figure 5.4: Percentage of Investors 2 Behaving in Line with Theoretical Predictions



Note: ***, **, * indicate significant differences of decisions at the 1%, 5%, 10%-level, respectively.

Further evidence for imitative behavior is provided by a regression analysis in Table 5.4. There, we report on a probit estimation, where the dependent variable is equal to one if A is chosen and equal to zero if B is chosen. We consider the following explanatory variables: *signal* is an indicator variable that is equal to 1 if the signal observed by the respective investor was A, and that is 0 otherwise. The variable *history* captures the net number of A-decisions by predecessors (i.e., it may take on the values 2, 1, 0, -1, -2). The variable *decision*1 (*decision*2) is an indicator that is equal to 1 if investor 1's (investor 2's) decision was A, and that is 0 otherwise.

Table 5.4: Evidence on Imitative Behavior

	(1)	(2)	(3)	(4)	(5)
signal	0.833***	0.644***	0.592***	0.623***	0.614***
	(0.040)	(0.044)	(0.032)	(0.032)	(0.033)
history				0.077***	
				(0.025)	
*decision*1					0.229***
					(0.058)
*decision*2					0.109*
					(0.057)
Observations	180	360	720	1080	720
Log − Likelihood	−50.71	−168.44	−364.41	−516.56	−346.02
$PseudoR^2$	0.5927	0.3249	0.2698	0.3100	0.3067

Note: Probit estimates, where all regressions include a constant, and where coefficients represent marginal effects. Dependent variable: Investor's choice of asset (equal to 1 (0) if asset A (B) chosen). The regression analysis studies all subjects that serve as investors in treatment *investment* ($N = 90$). Robust standard errors (clustered at the subject-level) are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Columns (1), (2), and (3) consider behavior of investor 1, investor 2, and investor 3, respectively. Column (4) pools observations from investors 2 and 3, and column (5) considers investor 3 only.

In the regression analysis, we restrict attention to investors in treatment *investment*, where, from a theoretical perspective subjects should always follow their own signal.[27] Consequently, in column (1) of Table 5.4 we regress the decision of investor 1 on his signal (columns (2) and (3) repeat the same exercise for investor 2 and investor 3, respectively). In these regressions, we find a highly significant effect of the own private information (where standard errors are clustered at the subject-level). Nevertheless, coefficients are declining in the position of the investor, which is indicative of the fact that subjects follow other information than their own signal. In column (4), we pool observations from investors 2 and 3, who might potentially engage in imitative behavior. There, we again find a highly significant effect of the own signal. However, also *history* has a highly significant, positive effect that demonstrates that, contrary to what theory would predict, these investors tend to

[27]The exclusion of investors that serve as principals in treatment *reputation* from the regression for treatment *investment* does not affect results qualitatively. Regression results are similar in magnitude and significance for investors in treatment *reputation*, where investors follow their own signal even slightly more often. Details are available upon request.

imitate their predecessors. In column (5), we focus on investor 3 only in order to investigate whether investor 1 or investor 2 has a stronger influence on investor 3's behavior. In this regression, we find a highly significant influence of investor 1 and a marginally significant influence of investor 2. Thus, investor 3 seems to be more influenced by earlier decisions and is following direct predecessors less often. Taken together, the findings of Table 5.4 provide strong evidence for (irrational) imitation. This finding is quite surprising given the earlier experimental literature. For example, experiments studying informational cascades in markets with flexible prices show that herding or imitative behavior rarely occurs (e.g., Cipriano and Guarini 2005, Drehmann, Oechssler, and Roider 2005).

Wage Setting by Principals: Two Benchmarks Having documented (irrational) imitative behavior on the part of investors, we now turn to the wage setting of principals. Is their wage setting in line with theory? Given the actual behavior of investors, do principals anticipate imitation? And if yes, does this lead to reduced incentives for (rational) reputational herding in treatment *reputation*?

In order to assess the wages offered by principals, in a first step, we consider two theoretical benchmarks: On the one hand, we consider the equilibrium wages r^{theo} as proposed by Dasgupta and Prat (2008) (see Proposition 2 and the surrounding discussion). On the other hand, as a second benchmark, we construct (behavioral) wages r^{beh} that should have been optimally set by principals if they would have correctly anticipated the actual behavior of investors in treatment *reputation.* To derive the benchmark wages r^{beh}, we use the actual frequencies with which investors 1, 2 and 3 follow their own signal in treatment *reputation* in order to derive the empirical frequencies of facing a good investor given a certain combination of history of trades and realized value of the asset. Multiplying this empirical frequency with the good investor's value of 20 points, we arrive at r^{beh}.

In Table 5.5, we compare the benchmark wages r^{theo} and r^{beh} to the actual wages offered to investor 3 in order to assess the reputational incentives he faces. With respect to actual wages, we consider the average wage r^{all} offered by all principals participating in the auction, as well as the average r^{max} of the actual winning wages, i.e., the maximum wages per session. In Table 5.5, we differentiate situations that, from a theoretical perspective, would be indicative of herding (i.e., investor 3 makes the same decision as investors 1 and 2) from all other situations. Moreover, we separately consider the cases that investor 3 buys the successful respectively the unsuccessful asset.

Looking first at settings where the history of trades is not given by XXX, Table

Table 5.5: Average Wages Offered to Investor 3

History of trades	Average wage if asset is	r^{theo}	r^{beh}	r^{all}	r^{max}
$\neq XXX$	successful	12.86	11.43	10.31	16.53
	unsuccessful	3.33	4.76	2.37	6.80
$= XXX$	successful	10.00	10.37	9.42	16.10
	unsuccessful	10.00	5.83	3.40	10.10

5.5 reveals that average behavioral wages r^{beh} are remarkably close to theoretical wages r^{theo}, but that average behavioral wages if the successful (unsuccessful) asset is bought are lower (higher) than the theoretical wage, i.e., behavioral wages are less extreme. Given that the partially irrational behavior of investors makes it more difficult to gauge the investor's type from the outcome of the game, this does not seem to be surprising. Looking at situations that from a theoretical perspective would be indicative of herding (XXX), Table 5.5 shows that, in contrast to theoretical wages, behavioral wages vary in the success of the investment (driven by the fact that in these situations some investors in fact trade according to their signal and do not herd).

Averaging over actual wages set by *all* principals, Table 5.5 documents that r^{all} are again relatively close to the benchmark wages r^{theo} and r^{beh}, albeit lower than expected relative to both benchmarks. From a qualitative perspective, the (average) actual wage setting by principals thus seems reasonable. The actual winning wages r^{max} on the other hand overshoot both benchmarks.

Wage Setting by Principals: Do they Anticipate Herd Behavior by Investor 3? In the following, we look more closely at the question whether principals in fact anticipate herd behavior by investor 3. Herding by investor 3 may arise if both of his predecessors bought the same asset (XX). Four cases may emerge from the principal's point of view. Either it turns out that investor 3 buys the same asset as both of his predecessors or he deviates from the behavior of his predecessors. Furthermore, the decision of investor 3 may ex-post turn out to be successful or unsuccessful.

To investigate whether principals anticipate herding by investor 3, as a benchmark, in Table 5.6 we first display behavioral wages r^{beh} that principals should optimally have set in the four cases described above.[28] The column labeled "difference" states the average difference of the (hypothetical) behavioral wage investor 3 receives if he chooses X and the (hypothetical) behavioral wage if he chooses Y. Put

[28]Note that for the history of trade XXX Table 5.6 replicates the information from Table 5.5.

Table 5.6: Wage Offered to Investor 3 if Investors 1 and 2 Act Alike

Average behavioral wage r^{beh}			
	History of trades		
Average wage if asset is	$= XXX$	$= XXY$	difference
successful	10.37	11.78	-1.41
unsuccessful	5.83	4.41	1.41

Average actual wage r^{all}			
	History of trades		
Average wage if asset is	$= XXX$	$= XXY$	difference
successful	9.42	9.98	-0.57
unsuccessful	3.40	1.68	1.72***

Average actual wage r^{max}			
	History of trades		
Average wage if asset is	$= XXX$	$= XXY$	difference
successful	16.10	16.50	-0.40
unsuccessful	10.10	6.00	4.10

Note: *** indicates that differences between wages offered given history XXX versus XXY are significant at the 1%-level.

differently, if principals would have set wages optimal relative to actual behavior of investors, principals should have "rewarded" investor 3 for not following the herd if he bought the successful asset, while they should have "punished" investor 3 for not following the herd if he bought the unsuccessful asset.

But why should a principal reward an investor who does not conform to earlier investors and purchases the successful asset? The intuition is as follows: If the investor conforms, his decision can stem either from following an x-signal or engaging in herd behavior after a y-signal. The principal does not observe the signal and thus it is not clear-cut to him which case occurred. On the other hand, if the investor does not conform, this could result from an investor following a y-signal or buying asset Y after an x-signal (contrarian behavior). In this case, it is more likely that the investor followed his own, correct signal y. In the latter situation he is thus more likely to be of good type (see also Table 5.2 for the respective empirical frequencies).

Next, why should an investor be rewarded by a higher wage if he conforms to earlier investors and purchases the unsuccessful asset? In this case, the situation is reversed to the case described above. If the investor does not conform and buys the wrong asset Y, it seems more likely to the principal that the investor acted on his own, wrong signal y. On the other hand, if the investor conforms, it is unclear to the principal on which informational basis this decision is taken.

"Hiding" in the herd is thus rewarded in case of purchasing the unsuccessful asset.

In a next step, we compare actual average wage setting behavior of principals (i.e., r^{all} respectively r^{max}) to the wages principals should optimally have set (i.e., r^{beh}). Table 5.6 reveals that investors' behavior seems to be anticipated by principals: in a similar vein as r^{beh}, actual wages vary with investor 3's decision (and its success).[29] The signs of the differences (column "difference" in Table 5.6) between actual wages given history XXX versus history XXY are the same as in the case of r^{beh} (for both r^{all} and r^{max}). However, the magnitudes of the differences are not the same. With respect to r^{all}, a deviation from the herd is rewarded in case of the purchase of the successful asset only modestly by 0.57 points compared to 1.41 points in the case of r^{beh}. On the other hand, the punishment in terms of r^{all} for deviating from the herd if the investor buys the unsuccessful asset even exceeds the punishment by 0.31 points in terms of r^{beh}. An analogous picture emerges with respect to r^{max}. Investors thus seem to anticipate behavior of investors and seem to incorporate this into their setting of wages in the presumed direction.

Wage Setting by Principals: Are there Different Behavioral Types? One might suspect that principals who are prone to imitative behavior themselves might set wages differently from other principals. We can investigate this issue by using data from treatment *investment* where the principals of treatment *reputation* acted as investors. Therefore, we label a principal as an *imitator* if, in treatment *investment*, he bought asset A at information set AAb and bought asset B at information set BBa (i.e., if he engaged in (irrational) imitative behavior). All 22 remaining principals (out of 30) are labeled *non-imitators*.

In Table 5.7 we display the actual wages r^{all} offered to investor 3 in treatment *reputation* by *imitators* respectively *non-imitators*. Interestingly, *imitators* reward investor 3 more strongly for not following the herd in case the successful asset is purchased. For principals who are *non-imitators*, the relationship is even reversed. *Non-imitators* in fact always reward herd behavior on average. At the same time, *imitators* (more strongly than *non-imitators*) punish investor 3 if he does not conform to earlier investors and this decision turns out to be unsuccessful. This might be interpreted as follows: Given that *imitators* are inclined towards imitation themselves, they are more likely to react to it when setting wages. Their own tendency of imitating predecessors makes it more likely that they also react to imitation by investors more strongly.

[29] Similar to Table 5.5, wages r^{all} are lower than r^{beh}, while r^{max} overshoot the behavioral benchmark.

Table 5.7: Actual Wages r^{all} Offered to Investor 3 by Imitators and Non-Imitators

Imitator in treatment *investment*	Average wage if asset is	History of trades $= XXX$	History of trades $= XXY$	difference
Yes	successful	8.81	11.03	-2.22
Yes	unsuccessful	3.50	1.36	2.14
No	successful	9.63	9.27	0.36
No	unsuccessful	3.36	1.80	1.56

Note: A principal is labeled an *imitator* if in treatment investment he bought asset A at information set AAb and bought asset B at information set BBa. Out of a total of 30 principals, 8 can be classified as *imitators*, while the remaining 22 are *non-imitators*.

Wage Setting by Principals: Reputational Incentives for Investor 3 A key question is whether the actual wage setting behavior of principals generates incentives for investor 3 to engage in reputational herding. In order to investigate this issue, we consider all information sets investor 3 might face (i.e., XXy, XXx, XYx, and XYy), and for each of these four cases we derive the difference between his payoff when he does not follow his signal and his payoff when he follows his signal (i.e., when he trades sincerely). We calculate these payoff differences under various assumptions on what investor 3 believes about the behavior of investors 1 and 2 and the behavior of the principals.

In column (1) of Table 5.8, we report the (benchmark) payoff differences predicted by Proposition 2, which indicate that, from a theoretical perspective, investor 3 should engage in reputational herding at information set XXy (yielding him a payoff that is 1.51 points higher than if he would trade sincerely), but should trade sincerely otherwise (as indicated by the negative payoff difference).[30]

In columns (2) and (3) of Table 5.8 we assume that investor 3 holds the belief that investors 1 and 2 always act in line with theory (i.e., always trade sincerely). However, with respect to the wage offers he will receive, we assume that investor 3 correctly anticipates the actual wage setting behavior by principals and counts on a wage of r^{all} (column (2)) respectively r^{max} (column (3)). Interestingly, in both cases reputational incentives (as predicted by theory) remain intact, and an investor 3 holding these beliefs should still herd at information set XXy (although his monetary payoff from doing so is weaker than in column (1)).

In column (4) and (5) of Table 5.8 we assume that investor 3 not only anticipates actual wage setting by principals (as in columns (2) and (3)), but that he also has correct beliefs about the actual (potentially irrational) behavior of investors 1 and

[30]Note that the history of trades XXY is off the equilibrium path. In order to calculate the respective payoff difference, in line with Dasgutpa and Prat (2008) we assume that in this case principals hold the off-equilibrium belief that investor 3 traded sincerely and they set their wage offers accordingly.

Table 5.8: Payoff Differences for Investor 3 from Not Following Respectively Following His Own Signal under Various Beliefs

	Investor 3 assumes sincere trading by investors 1 and 2			Investor 3 correctly anticipates actual behavior by investors 1 and 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Information set	r^{theo}	r^{all}	r^{max}	r^{all}	r^{max}	r^{beh}
XXy	1.51	0.45	0.85	-1.89	-0.38	-2.76
XXx	-10.50	-8.93	-11.14	-7.14	-9.23	-3.30
XYx	-7.81	-6.31	-6.81	-7.59	-8.12	-6.88
XYy	-7.81	-6.14	-6.91	-5.68	-6.35	-4.75

Note: The table displays the difference in expected payoff from disregarding the own signal minus following the own signal under various beliefs on the behavior of investors 1 and 2 and principals.

2. That is, investor 3 anticipates the actual frequencies with which investors 1 and 2 do not trade sincerely, and hence, given a certain history of investor 1's and investor 2's decisions, investor 3 draws correct inference with respect to the success probabilities of the two assets. Columns (4) and (5) of Table 5.8 indeed reveal that, given these assumptions on investor 3' beliefs (i.e., that he perfectly foresees the behavior of investors 1 and 2 and of principals), reputational incentives to herd indeed disappear.

Finally, in column (6) we conduct a thought experiment. We ask whether incentives for reputational herding would re-emerge if investor 3 holds correct beliefs with respect to the behavior of the other investors and if he expects optimal wage setting by principals (i.e., wage offers r^{beh}). As indicated by column (6) this is not the case as following his own signal would always yield a higher payoff in this case. Hence, the lack of reputational incentives for investor 3 does not seem to be driven by (defective) wage setting by principals, but rather by noisy behavior of earlier investors (where observing history XX is less indicative for the success of investment X than the theory would suggest).

5.6 Conclusion

While herd behavior is studied in various empirical studies, it is difficult to disentangle the investors' underlying incentives and to assign the observed herd behavior to the different motives mentioned in the theoretical literature. Therefore, we turn to a laboratory test to study one particular reason for herd behavior, reputational concerns, in a similar setup as outlined in a theoretical model by Dasgupta and Prat (2008). Explicitly, it allows analyzing the incentives faced by investors.

The model by Dasgupta and Prat (2008) predicts that it is an equilibrium strategy of investors to engage in herd behavior if faced with reputational concerns and if asset prices are close to the liquidation value. If prices are getting precise, gains from trading the asset decrease. At the same time, not following predecessors induces a reputational loss, as it becomes more likely that the asset bought turns out to be the worthless one. The investor then appears as having observed a bad signal. The experiment presented in this study explores in a similar, but simplified setup whether herd behavior out of reputational concerns occurs.

The experimental results indeed show that herd behavior as predicted by Dasgupta and Prat (2008) occurs. About half of the subjects engages in herd behavior in treatment *reputation*. Surprisingly, we find that investors also imitate predecessors in treatment *investment* without reputational concerns, although the theoretical prediction of Dasgupta and Prat (2008) and other papers (e.g., Avery and Zemsky 1998) are clear-cut and herding should not occur. Furthermore, we find investors to (irrationally) imitate predecessors even if prices are not precise.

By analyzing wages offered by principals, we are able to study the underlying incentives to exhibit herd behavior in the experiment. We find that principals, being in charge of creating reputational incentives by offering wages, do this in a surprisingly precise way. Wages set by principals are close to the wages derived on the basis of actual behavior in the experiment. Furthermore, if investors correctly anticipated the actual wage setting behavior of principals, this would provide incentives to engage in herd behavior. However, assuming that investors do not only anticipate the wage setting of principals, but also the imitative behavior of other, earlier investors, this entails that the incentives to engage in herd behavior disappear. The lack of incentives to engage in herd behavior might thus rather be attributed to noisy behavior of earlier investors than to principals' wage setting.

Although reputational concerns account for a major share of the investors' payoffs in our experiment (reputational incentives are twice as large as investment incentives), additional herd behavior compared to the treatment without reputational concerns cannot be observed. Moreover, in line with the previous literature, investors do not always follow their signal when expected. However, if this is anticipated by investors and principals, wages (and also prices if a market maker anticipates this behavior) will hardly become as extreme as necessary to induce herd behavior. Observing whether herd behavior out of reputational concerns occurs would require earlier investors to follow their signal to a larger extent than it is found so far.

While previous empirical studies refer to reputational concerns if herd behavior is observed, our findings suggest that even without reputational concerns, herd behavior arises.

5.7 Appendix: Theoretical Predictions with Market Prices and Experimental Parameters

In the following, it will be shown that given the market prices for asset A and asset B and the parameters assumed in the experiment, trade is sincere in treatment *investment*. Similarly, if reputational concerns are introduced in treatment *reputation*, herd behavior arises if prices get precise.

Treatment Investment Table 5.9 displays the prices set in the experiment for asset A and B, respectively, given all possible histories of trades of predecessors H^i. When setting prices, the market maker[31] assumes that trade is sincere (e.g., that the investor buys the asset $V^i = A$ if observing signal $s^i = a$) and incorporates the investor's decision to buy the respective asset into his price setting.

If trading sincerely, the price of the asset reflects the investor's expected value of the asset (compare, e.g., column (1) with column (3) in Table 5.9). Thus, the investor's payoff from trading sincerely is 0 as shown in Table 5.10. If not trading sincerely, the investor incurs a loss (consider column (2), Table 5.10). The market price of the respective asset exceeds the investors' expected value of the asset (compare, e.g., column (1) with column (5) in Table 5.9).

As displayed in column (3) of Table 5.10, the profits from trading sincerely versus not trading sincerely $\Delta\pi_I$ are positive for every H^i. Thus, if investors only receive payoffs from trading the asset, all trading will be sincere as outlined in Section 5.3.2.[32]

If the decisions of the predecessors coincide for the third investor (row 4 of Table 5.10), payoffs from trading the assets become smallest. This is a key mechanism for the results in treatment *reputation*.

Treatment Reputation In treatment *reputation*, in addition to the payoffs from investing in asset A or B, payoffs from the investors' reputation r^i arise. We derive the wages set by the principals according to Dasgupta and Prat (2008) in a first step. Secondly, payoffs from trading sincerely versus not trading sincerely are determined assuming concrete asset prices and experimental parameters.[33]

[31] Played by the experimenter in the experiment.

[32] This is also shown in, e.g., Glosten and Milgrom (1985) or Avery and Zemsky (1998).

[33] In the original paper by Dasgupta and Prat (2008) mixed strategies - namely investors only partly engaging in herd behavior - are possible in the most revealing equilibrium. We rule out this possibility and derive clear-cut predictions by adjusting parameters. Investors should either exhibit herd behavior or not.

Table 5.9: Prices for Assets A and B Given a History of Trades by Predecessors

i	H^i	p_A^i (1)	p_B^i (2)	$Pr(A\|a,H^i)$ (3)	$Pr(B\|b,H^i)$ (4)	$Pr(A\|b,H^i)$ (5)	$Pr(B\|a,H^i)$ (6)
1	—	7	7	0.7	0.7	0.3	0.3
2	A	8.4	5	0.84	0.5	0.5	0.16
2	B	5	8.4	0.5	0.84	0.16	0.5
3	AB or BA	7	7	0.7	0.7	0.3	0.3
3	AA	9.3	3	0.93	0.3	0.7	0.07
3	BB	3	9.3	0.3	0.93	0.07	0.7

Note: For example, $Pr(A|a, H^i)$ denotes the probability that asset A is the successful one, given a history of trades H^i and investor i has observed the signal a. Asset prices are rounded to the first decimal.

Table 5.10: Payoff Differences from Investment if Following Respectively Not Following the Own Signal

i	H^i	Profit if trading sincerely (1)	Profit if not trading sincerely (2)	$\Delta\pi_I$ (3)
1	—	0	-4	4
2	A or B	0	-3.4	3.4
3	AB or BA	0	-4	4
3	AA or BB	0	-2.3	2.3

The reputational payoff in Dasgupta and Prat (2008) is derived from the probability that the investor is of good type as outlined in Section 5.3.3. The principal takes the state of the world v and the investor's purchase decision V^i to arrive at his wage offer.[34] There are two wages that emerge in equilibrium without herding, the wage in which the investor buys the successful asset, respectively the unsuccessful asset.

In the first case in which $v = V^i$, the principal calculates the probability that the investor is of good type as $r(v = V^i) = \frac{\alpha_V \sigma_g + \alpha_{-V}(1-\sigma_g)}{\alpha_V \sigma + \alpha_{-V}(1-\sigma)}\gamma$. Herein α_V denotes the probability that after, e.g., an a-signal asset A is bought, α_{-V} that the asset B is bought after the same a-signal. γ denotes the ex-ante probability that the investor is of good type, and σ describes the average probability that a signal according to the assets' value is observed: $\sigma = 0.5\sigma_b + 0.5\sigma_g = 0.7$. If trade is sincere ($\alpha_V = 1$ and $\alpha_{-V} = 0$), $r(v = V^i)$ equals 0.6428. Thus, with a probability of 64.28 percent the investor is assumed to be of good type.

In the second case in which $v \neq V^i$, the investor's reputation formed by the principal is denoted as $r(v \neq V^i) = \frac{\alpha_V(1-\sigma_g) + \alpha_{-V}\sigma_g}{\alpha_V(1-\sigma) + \alpha_{-V}\sigma}\gamma$, which equals 0.1667 if trade

[34]As outlined in Section 5.3.3, it is irrelevant whether the principal observes behavior of the other investors in the model by Dasgupta and Prat (2008).

is sincere. Obviously, the principal concludes that the investor is of good type with a higher probability if the investor bought the successful asset ($r(v = V^i) > r(v \neq V^i)$).

In case the principals assumes the investor engages in herd behavior ($\alpha_V = 1$ and $\alpha_{-V} = 1$), the investor's trade does not reveal any information about his type. The probability the principal derives equals the ex-ante probability that the investor is of good type $r(v = V^i) = 0.5$, which is independent of the purchase decision V^i.

The reputational payoff is denoted by $r^i = 20 \cdot r$. Thus, wages set by the principals amount to 12.86 (3.33) points if the successful (unsuccessful) asset is bought and no herding occurs. Only if the principal anticipates herd behavior by investor 3 (if $H^4 \in \{AAA, BBB\}$) the wage amounts to $0.5 \cdot 20 = 10$ points.

Again, the model by Dasgupta and Prat takes the difference in expected payoffs from investors investing sincerely and not investing sincerely denoted as $\Delta\pi_R = \Delta\pi_I + \Delta r$ to derive the theoretical prediction. The derivation of $\Delta\pi_I$ has been outlined in the previous paragraph.

Δr denotes the difference in expected reputational payoff from following the own signal versus not following the own signal. In case of an a-signal, this is derived as $\Delta r = Pr(A|a, H^i)(r(v = V^i = A) - r(v \neq V^i = B)) + Pr(B|a, H^i)(r(v \neq V^i = A) - r(v = V^i = B))$. The first part of the equation assumes that asset A is the successful asset ($v = A$) with the respective probability, while in the second part $v = B$ is assumed. Both parts are multiplied by the reputational payoff difference from buying asset A instead of B. All possible information sets and the respective payoffs can be found in Table 5.11.

Whenever both predecessors buy the same asset and investor 3 observes a contrarian signal, reputational losses from trading sincerely versus not trading sincerely add up to $\Delta r = \frac{3}{10}(12.86 - 10) + \frac{7}{10}(3.33 - 10) = -3.81$. For example, suppose investor 3 receives an a-signal and both predecessors buy asset B. Not trading sincerely ($V^i = B$) reveals no information about the investors' type to the principal, thus $r = 10$. In case the investor purchases asset A, the wages remain informative and will amount to 12.86 and 3.33 points.[35] The probability that asset A is the unsuccessful one is $\frac{7}{10}$. Thus, as prices get precise, the second, negative part of the equation receives a higher weight. In this situation, investment gains from trading sincerely are $\Delta\pi_I = 2.3$ as presented in the previous section. In total, the reputational losses therefore exceed the gains from the assets' payoff if the investor trades sincerely. Thereby, in the model with three periods, prices in period three become

[35] Dasgupta and Prat (2008) assume that in an off-equilibrium path principals believe that trades are sincere. Thus wages remain informative.

sufficiently precise such that investors engage in herd behavior.

As outlined in Section 5.3.3, the asset prices presented to subjects are calculated under the assumption that trade is sincere in both treatments. In the model of Dasgupta and Prat (2008), the market maker anticipates non-sincere trading of investor 3 and sets market prices accordingly. However, the theoretical predictions remain similar even with these prices, as the last two rows of Table 5.11 reveal.

Wage Setting Behavior in the First-Price Auction Among the Principals
As discussed in Section 5.3.3, we assume an explicit wage setting process through a sealed-bid, first-price auction among six risk-neutral "principals", where investor i's wage r^i is determined by the highest bid. As in Dasgupta and Prat (2008), principals can observe the entire history of trades and prices as well as the realized true state of the world v. The winning principal has to pay his bid and additionally gets 20 points if and only if investor i happens to be good (otherwise he gets 0 points). In case of a tie, each of the highest bidding principals wins with equal probability. The remaining five principals get a payoff of zero each.

Suppose that, at date 4, principals hold a (common) belief r that investor i is of good type. In the following, we show that there are two types of equilibria. On the one hand, there is a symmetric equilibrium where all principals' bidding strategies are given by $20 \cdot r$ (i.e., bids are equal to the respective investor's "expected value"). On the other hand, there is a continuum of asymmetric equilibria where at least two principals bid $20 \cdot r$, while the remaining principals bid less than that. In both cases, the investor's reputational payoff (i.e., the winning bid) is the same and given by $r^i = 20 \cdot r$.

To prove this claim, we proceed as follows. Let b_j be the bid made by principal $j = 1, ..., 6$.

First, we show in equilibrium no bid can be strictly larger than r. To the contrary, assume that the highest bid is above r. In this case, the winning principal would make a loss and would have a profitable deviation to some bid below r (in which case he would either lose the auction and earn zero, or win the auction and achieve a positive payoff). Hence, in equilibrium bids satisfy $b_j \leq r$ for all j. In a next step, we verify which bids can emerge in equilibrium.

Second, we show that the highest bid cannot be strictly below r. If this were the case, one of principals could make a deviating bid that slightly exceeds this highest bid. Thereby, he would win the auction with certainty and earn a strictly positive profit. Hence, in equilibrium the highest bid(s) have to be equal to r.

Third, suppose that one of the principals submits a bid equal to r, while all of

Table 5.11: Total Payoff from Reputation and Investment if Following Respectively Not Following the Own Signal

Investor	H^i and s^i	$\Delta\pi_I$	$Pr(A\|s^i, H^i)$	$Pr(B\|s^i, H^i)$	$(r(v = V))$	$(r(v \neq V))$	Δr	$\Delta\pi_R$
1	a	4	0.7	0.3	12.86	3.33	3.81	7.81
1	b	4	0.3	0.7	12.86	3.33	3.81	7.81
2	Aa	3.4	0.84	0.16	12.86	3.33	6.48	10.88
2	Bb	3.4	0.16	0.84	12.86	3.33	6.48	10.88
2	Ab or Ba	3.4	0.5	0.5	12.86	3.33	0	3.4
3	ABa or BAa	4	0.7	0.3	12.86	3.33	3.81	7.81
3	ABb or BAb	4	0.3	0.7	12.86	3.33	3.81	7.81
3	AAa	2.3	0.93	0.07	12.86	3.33	8.20	10.5
3	BBb	2.3	0.07	0.93	12.86	3.33	8.20	10.5
Fixed asset prices as presented in experiment								
3	AAb	2.3	0.7	0.3	10/12.86	10/3.33	-3.81	-1.51
3	BBa	2.3	0.3	0.7	10/12.86	10/3.33	-3.81	-1.51
Asset prices of market maker suspecting herd behavior (Dasgupta and Prat 2008)								
3	AAb	1.4	0.7	0.3	10/12.86	10/3.33	-3.81	-2.41
3	BBa	1.4	0.3	0.7	10/12.86	10/3.33	-3.81	-2.41

the remaining principals bid strictly less. In this case, the winning principal (who bids r) would have an incentive to slightly lower his bid. Thereby, he would still win the auction with certainty, but earn a strictly higher profit.

Finally, suppose that two principals bid r, while the remaining principals bid weakly less. In this case, all principals obtain an expected payoff of zero, and there are no incentives to deviate: bids above r can never be optimal. A winning bidder could bid less, but thereby we would still earn zero. The same is true of a losing bidder who deviates to a higher bid. This proves the claim.

Bibliography

Akerlof, G.A., Shiller, R.J. (2010). *Animal spirits: How Human Psychology Drives the Economy, and why it Matters for Global Capitalism*, Princeton University Press, Princeton NJ

Alevy, J.E., Haigh, M.S., List, J.A. (2007). Information Cascades: Evidence from a Field Experiment with Financial Market Professionals, *Journal of Finance*, 62, 151-180

Allen, F. (2001). Do Financial Institutions Matter?, *Journal of Finance*, 56, 1165-1175

Andersen, S., Harrison, G.W., Lau, M.I., Rutström, E. (2006). Elicitation Using Multiple Price List Formats, *Experimental Economics*, 9, 383-405

Anderson, L., Holt, C. (1997). Information Cascades in the Laboratory, *American Economic Review*, 87, 847-862

Anderson, L., Mellor, J. (2009). Are Risk Preferences Stable? Comparing an Experimental Measure with a Validated Survey-Based Measure, *Journal of Risk and Uncertainty*, 39, 137-160

Arrondel, L. (2009). "My Father was Right": The Transmission of Values between Generations, *HAL-PSE Working Papers*, 2009-12

Avery, C., Zemsky, P. (1998). Multidimensional Uncertainty and Herd Behavior in Financial Markets, *American Economic Review*, 88, 724-748

Baker, M., Solon, G. (2003). Earnings Dynamics and Inequality among Canadian Men, 1976-1992: Evidence from Longitudinal Income Tax Records, *Journal of Labor Economics*, 21, 289-321

Banerjee, A. (1992). A Simple Model of Herd Behavior, *Quarterly Journal of Economics*, 107, 797-818

Barseghyan, L., Prince, J., Teitelbaum, J.C. (2011). Are Risk Preferences Stable across Contexts? Evidence from Insurance Data, *American Economic Review*, 101, 591-631

Barsky, R.B., Juster, F.T., Kimball, M.S., Shapiro, M.D. (1997). Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study, *Quarterly Journal of Economics*, 112, 537-579

Bartels, C., Bönke, T. (2010). German Male Income Volatility 1984 to 2008: Trends in Permanent and Transitory Income Components and the Role of the Welfare State, *SOEPpapers, DIW Berlin*, 325

Becker, G.S. (1962). Investment in Human Capital: A Theoretical Analysis, *Journal of Political Economy*, 70, 9-49

Bellemare, C., Shearer, B. (2010). Sorting, Incentives and Risk Preferences: Evidence from a Field Experiment, *Economics Letters*, 108, 345-348

Belzil, C., Leonardi, M. (2007). Can Risk Aversion Explain Schooling Attainments? Evidence from Italy, *Labour Economics*, 14, 957-970

Bernoulli, D. (1738). "Specimen Theoriae Novae de Mensura Sortis." Comentarii Academiae Scientiarum Imperialis Petropolitanae, 5, 175-92 [translated by Sommer, L. (1954). *Econometrica*, 22, 23-36]

Bertrand, M., Mullainathan, S. (2001). Do People Mean What They Say? Implications for Subjective Survey Data, *American Economic Review*, 91, 67-72

Beshears, J., Choi, J.J., Laibson, D., Madrian, B.C. (2008). How are Preferences Revealed?, *Journal of Public Economics*, 92, 1787-1794

Bhattacharya, S., Pfleiderer, P. (1985). Delegated Portfolio Management, *Journal of Economic Theory*, 36, 1-25

Bhattacharya, U., Hackethal, A., Kaesler, S., Loos, B., Meyer, S. (2012). Is Unbiased Financial Advice to Retail Investors Sufficient? Answers from a Large Field Study, *Review of Financial Studies*, 25, 975-1032

Bikhchandani, S., Hirshleifer, D., Welch, I. (1992). A Theory of Fads, Fashion, Custom and Cultural Change as Informational Cascades, *Journal of Political Economy*, 100, 992-1026

Bikhchandani, S., Sharma, S. (2000). Herd Behavior in Financial Markets, *IMF Staff papers*, 47, 279-310

Bisin, A., Verdier, T. (2005). Cultural Transmission. In: *The New Palgrave Dictionary of Economics*, S. N. Durlauf, L. E. Blume (eds.), 2nd Edition, Palgrave Macmillan

Bisin, A., Verdier, T. (2011). The Economics of Cultural Transmission and Socialization. In: *Handbook of Social Economics, Volume 1B*, Benhabib, J., Bisin, A., Jackson, M. (eds.), North Holland

Björklund, A., Jäntti, M., Solon, G. (2007). Nature and Nurture in the Intergenerational Transmission of Socioeconomic Status: Evidence from Swedish Children and Their Biological and Rearing Parents, *BE Journal of Economic Analysis and Policy*, 7(2)

Black, S., Devereux, P., Salvanes, K. (2005). Why the Apple Doesn't Fall Far: Understanding the Intergenerational Transmission of Education, *American Economic Review*, 95, 437-449

Bonin, H., Dohmen, T., Falk, A., Huffman, D., Sunde, U. (2007). Cross-Sectional Earnings Risk and Occupational Sorting: The Role of Risk Attitudes, *Labour Economics*, 14, 926-937

Bucher-Koenen, T., Ziegelmeyer, M. (2011). Who Lost the Most? Financial Literacy, Cognitive Abilities, and the Financial Crisis, *MEA Discussion Paper*, 234-11

Byrnes, J.P., Miller, D.C., Schafer, W.D. (1999). Gender Differences in Risk Taking: A Meta-Analysis, *Psychological Bulletin*, 125, 367-383

Chakravarty, S., Harrison, G.W., Haruvy, E., Rutström, R. (2011). Are You Risk Averse Over Other People's Money?, *Southern Economic Journal*, 77, 901-913

Charles, K.K., Hurst, E. (2003). The Correlation of Wealth Across Generations, *Journal of Political Economy*, 111, 1155-1182

Chen, S.H. (2008). Estimating the Variance of Wages in the Presence of Selection and Unobserved Heterogeneity, *Review of Economics and Statistics*, 90, 275-289

Chevalier, J., Ellison, G. (1999). Career Concerns of Mutual Fund Managers, *Quarterly Journal of Economics*, 114, 389–432

Christensen, Z.T., Ogden, L.V., Dunn, M.L., Eggett, D.L. (2006). Multiple Comparison Procedures for Analysis of Ranked Data, *Journal of Food Science*, 71, 132-143

Cipriani, M., Guarino, A. (2005). Herd Behavior in a Laboratory Financial Market, *American Economic Review*, 95, 1427–1443

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences (2nd ed.)*, New Jersey: Lawrence Erlbaum

Croson, R., Gneezy, U. (2009). Gender Differences in Preferences, *Journal of Economic Literature*, 47, 448-474

Cunha, F., Heckman, J., Navarro, S. (2005). Separating Uncertainty from Heterogeneity in Life Cycle Earnings, *Oxford Economic Papers*, 57, 191-261

Dahl, M., DeLeire, T. (2008). The Association between Children's Earnings and Fathers' Lifetime Earnings: Estimates Using Administrative Data, *Institute for Research on Poverty, University of Wisconsin-Madison, Discussion Paper*, 1342-08

Dahl, M., DeLeire, T., Schwabisch (2008). Recent Trends in the Variability of Individual Earnings and Household Income, *CBO Paper*, 2996

Dang, D.A. (2012). On the Sources of Risk Preferences in Rural Vietnam, *MPRA Paper*, 38738

Daniel, K., Hirshleifer, D., Teoh, S.H. (2002). Investor Psychology in Capital Markets: Evidence and Policy Implications, *Journal of Monetary Economics*, 49, 139-209

Daruvala, D. (2007). Gender, Risk and Stereotypes, *Journal of Risk and Uncertainty*, 35, 265-283

Dasgupta, A., Prat, A. (2006). Financial Equilibrium with Career Concerns, *Theoretical Economics*, 1, 67-93

Dasgupta, A., Prat, A. (2008). Information Aggregation in Financial Markets with Career Concerns, *Journal of Economic Theory*, 143, 83-113

Deck, C., Lee, J., Reyes, J., Rosen, C. (2008). Measuring Risk Attitudes Controlling for Personality Traits, *University of Arkansas, Florida International University*, mimeo

DeLeire, T., Levy, H. (2004). Worker Sorting and the Risk of Death on the Job, *Journal of Labor Economics*, 22, 925-954

De Paola, M.. The Determinants of Risk Aversion: The Role of Intergenerational Transmission, *Universitá della Calabria, Dipartimento di Economia e Statistica, Working Paper*, 16 - 2010, (*forthcoming in: German Economic Review)*

Ding X., Hartog, J., Sun, K. (2010). Can We Measure Individual Risk Attitudes in a Survey?, *IZA Discussion Paper*, 4807

Doepke, M., Zilibotti, F. (2005). Social Class and the Spirit of Capitalism, *Journal of the European Economic Association*, 3, 516–524

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G. (2011). Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences, *Journal of the European Economic Association*, 9, 522-550

Dohmen, T., Falk, A. (2011). Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender, *American Economic Review*, 101, 556-590

Dohmen, T., Falk, A., Huffman, D., Sunde U. (2012). Intergenerational Transmission of Risk and Trust Attitudes, *Review of Economic Studies)*, 79, 645-677

Drehmann, M., Oechssler, J., Roider, A. (2005). Herding and Contrarian Behavior in Financial Markets - An Internet Experiment, *American Economic Review*, 95, 1403–1426

Drehmann, M., Oechssler, J., Roider, A. (2007). Herding with and without Payoff Externalities: An Internet Experiment, *International Journal of Industrial Organization*, 25, 391-415

Dynan, K.E., Elmendorf, D.W., Sichel, D.E. (2007). The Evolution of Household Income Volatility, *Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System (US)*, 61

Eckel, C.C., Grossman, P.J. (2008). Forecasting Risk Attitudes: An Experimental Study Using Actual and Forecast Gamble Choices, *Journal of Economic Behavior and Organization*, 68, 1-17

Ehrbeck, T., Waldmann, R. (1996). Why are Professional Forecasters Biased? Agency Versus Behavioral Explanations, *Quarterly Journal of Economics*, 111, 21-40

Einav, L., Finkelstein, A., Pascu, I., Cullen, M.R.. How General are Risk Preferences? Choices under Uncertainty in Different Domains, *NBER Working Paper*, 15686, (*forthcoming in: American Economic Review*)

Ekelund, J., Johansson, E., Järvelin, M.-R., Lichtermann, D. (2005). Self-Employment and Risk Aversion: Evidence from Psychological Test Data, *Labour Economics*, 12, 649-659

Elias, P. (1997). Occupational Classification (ISCO-88): Concepts, Methods, Reliability, Validity and Cross-National Comparability, *OECD Labour Market and Social Policy Occasional Papers*, OECD Publishing, 20

Eriksen, K.W., Kvaløy, O. (2009). Myopic Investment Management, *Review of Finance*, 14, 521-542

Faro, D., Rottenstreich, Y. (2006). Affect, Empathy, and Regressive Mispredictions of Others' Preferences under Risk, *Management Science*, 52, 529-541

Feinberg, R. (1981). Earnings-Risk as a Compensating Differential, *Southern Economic Journal*, 48, 156-163

Fouarge, D., Kriechel, B., Dohmen, T. (2011). Occupational Sorting of School Leavers: The Role of Economic Preferences, *mimeo*

Fuchs-Schündeln, N., Schündeln, M. (2005). Precautionary Savings and Self-Selection: Evidence from the German Reunification "Experiment", *Quarterly Journal of Economics*, 120, 1085-1120

von Gaudecker, H.M., van Soest, A., Wengström, E. (2011). Heterogeneity in Risky Choice Behavior in a Broad Population, *American Economic Review*, 101, 664-694

Glaeser, E.L., Laibson, D.I., Sacerdote, B. (2002). The Economic Approach to Social Capital, *Economic Journal*, 112, 437–458

Glosten, L., Milgrom, P. (1985). Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders, *Journal of Financial Economics*, 14, 71-100

Gollier, C. (2001). *Economics of Risk and Time*, MIT Press, Cambridge, MA(USA)

Gouskova, E., Chiteji, N., Stafford, F. (2010). Pension Participation: Do Parents Transmit Time Preference?, *Journal of Family and Economic Issues*, 31, 138-150

Graham, J. (1999). Herding Among Investment Newsletters: Theory and Evidence, *Journal of Finance*, 54, 237-268

Greiner, B. (2004). An Online Recruitment System for Economic Experiments. In: *Forschung und Wissenschaftliches Rechnen*, Kremer, K., Macho, V. (eds.), GWDG Bericht 63. Göttingen: Gesellschaft für Wissenschaftliche Datenverarbeitung

Grund, C., Sliwka, D. (2010). Evidence on Performance Pay and Risk Aversion, *Economics Letters*, 106, 8-11

Guiso, L., Paiella, M. (2004). The Role of Risk Aversion in Predicting Individual Behavior, *CEPR Discussion Paper*, 4591

Hadar, L., Fischer, I. (2008). Giving Advice under Uncertainty: What you do, what you should do, and what others think you do, *Journal of Economic Psychology*, 29, 667-683

Haider, S.J. (2001). Earnings Instability and Earnings Inequality of Males in the United States: 1967-1991, *Journal of Labor Economics*, 19, 799-836

Haider, S.J., Solon, G. (2006). Life-Cycle Variation in the Association between Current and Lifetime Earning, *American Economic Review*, 96, 1308-1320

Haigh, M.S., List, J.A. (2005). Do Professional Traders Exhibit Myopic Loss Aversion? An Experimental Analysis, *Journal of Finance*, 60, 523-534

Harrison, G.W., List, J.A. (2004). Field Experiments, *Journal of Economic Literature*, 42, 1009-1055

Harrison, G.W., List, J.A., Towe, C. (2007). Naturally Occurring Preferences and Exogenous Laboratory Experiments: A Case Study of Risk Aversion, *Econometrica*, 75, 433-458

Harrison, G.W., Rutström, E. (2008). Risk Aversion in the Laboratory. In: *Risk Aversion in Experiments*, Cox, G., Harrison, G.W., (eds.), Bingley, UK, Emerald, Research in Experimental Economics, 12

Hartog, J., Ferrer-i-Carbonell, A., Jonker, N. (2002). Linking Measured Risk Aversion to Individual Characteristics, *Kyklos*, 55, 3-26

Hartog, J., Plug, E., Diaz-Serrano, L., Vieira, J. (2003). Risk Compensation in Wages - A Replication, *Empirical Economics*, 28, 639-647

Hartog, J., Vijverberg, W.P.M. (2007). On Compensation for Risk Aversion and Skewness Affection in Wages, *Labour Economics*, 14, 938-956

Hellwig, M. (2009). Systemic Risk in the Financial Sector: An Analysis of the Subprime-Mortgage Financial Crisis, *De Economist*, 157, 129-207

Hirshleifer, D., Teoh, S.H. (2003). Herd Behaviour and Cascading in Capital Markets: A Review and Synthesis, *European Financial Management*, 9, 25-66

Holmstrom, B. (1999). Managerial Incentive Problems: A Dynamic Perspective, *Review of Economic Studies*, 66, 169-182

Holt, C., Laury, S.K. (2002). Risk Aversion and Incentive Effects, *American Economic Review*, 92, 1644-1655

Hong, H., Kubik, J. (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts, *Journal of Finance*, 58, 313-351

Hong, H., Kubik, J., Solomon, A. (2000). Security Analysts' Career Concerns and Herding of Earnings Forecasts, *RAND Journal of Economics*, 31, 121-144

Hryshko, D., Luengo-Prado, M.J., Sørensen, B.E. (2011). Childhood Determinants of Risk Aversion: The Long Shadow of Compulsory Education, *Quantitative Economics*, 2, 37-72

Hsee, C.K., Weber, E.U. (1997). A Fundamental Prediction Error: Self-Others Discrepancies in Risk Preference, *Journal of Experimental Psychology*, 126, 45-53

Hsee, C.K., Weber, E.U. (1999). Cross-National Differences in Risk Preference and Lay Predictions, *Journal of Behavioral Decision Making*, 12, 165-179

Huddart, S. (1999). Reputation and Performance Fee Effects on Portfolio Choice by Investment Advisers, *Journal of Financial Markets*, 2, 227-271

Inderst, R., Ottaviani, M. (2012a). Financial Advice, *Journal of Economic Literature*, 50, 494-512

Inderst, R., Ottaviani, M. (2012b). Competition through Commissions and Kickbacks, *American Economic Review*, 102, 780–809

Irlenbusch, B., Sliwka, D. (2006). Career Concerns in a Simple Experimental Labour Market, *European Economic Review*, 50, 147-170

Jacobs, B., Hartog, J., Vijverberg, W.P.M. (2009). Self-Selection Bias in Estimated Wage Premiums for Earnings Risk, *Empirical Economics*, 37, 271-286

Jaeger, D., Bonin, H., Dohmen, T., Falk, A., Huffman, D., Sunde, U. (2010). Direct Evidence on Risk Attitudes and Migration, *Review of Economics and Statistics*, 92, 684–689

Jansen, C., Fischer, R., Hackethal, A. (2008). The Influence of Financial Advice on the Asset Allocation of Individual Investors, *Working Paper, European Business School*

Joanes, D.N. (1985). On a Rank Sum Test Due to Kramer, *Journal of Food Science*, 50, 1442-1444

Johnson, W. (1977). Uncertainty and the Distribution of Earnings. In: *The Distribution of Economic Well-Being*, F.T. Juster (ed.), Ballinger, Cambridge, MA, 379-396

Kagel, J.H. (1995). Auctions: A Survey of Experimental Research. In: *Handbook of Experimental Economics*, Kagel, J.H., Roth, A.E. (eds.), Princeton University Press, 501-585

Kahnemann, D., Tversky, A. (1981). The Framing of Decisions and the Psychology of Choice, *Science*, 211(4481), 453-458

Kaustia, M., Alho, E., Puttonen, V. (2008). How Much Does Expertise Reduce Behavioral Biases? The Case of Anchoring Effects in Stock Return Estimates, *Financial Management*, 37, 391-412

Kimball, M.S., Sahm, C.R., Shapiro, M.D. (2009). Risk Preferences in the PSID: Individual Imputations and Family Covariation, *American Economic Review*, 99, 363-68

King, A.G. (1974). Occupational Choice, Risk Aversion, and Wealth, *Industrial and Labor Relations Review*, 27, 586-596

Kling, J., Liebman, J., Katz, L. (2007). Experimental Analysis of Neighborhood Effects, *Econometrica*, 74, 83–119

Koch, A., Morgenstern, A., Raab, P. (2009). Career Concerns Incentives: An Experimental Test, *Journal of Economic Behavior and Organization*, 72, 571-588

Kremer, S. (2010). Herding of Institutional Traders, *SFB 649 Discussion Papers*, 2010-025

Lamont, O. (2002). Macroeconomic Forecasts and Microeconomic Forecasters, *Journal of Economic Behavior and Organization*, 48, 265-280

Leuermann, A., Necker, S. (2011). Intergenerational Transmission of Risk Attitudes: A Revealed Preference Approach, *SOEP Papers, DIW Berlin*, 412

Leuermann A., Roider, A. (2012). Reputational Herding in Financial Markets: A Laboratory Experiment, *Heidelberg University*, mimeo

Leuermann A., Roth, B. (2012a). Stereotypes and Risk Preferences: Evidence from the Lab and the Field, *AWI Discussion Paper, Heidelberg University*, 533

Leuermann, A., Roth, B. (2012b). Does Good Advice Come Cheap? On the Assessment of Risk Preferences in the Lab and in the Field, *AWI Discussion Paper, Heidelberg University*, 534

Levhari, D., Weiss, Y. (1974). The Effect of Risk on the Investment in Human Capital, *American Economic Review*, 64, 950-963

Lochner L. (2008). Intergenerational Transmission. In: *The New Palgrave Dictionary of Economics*, S. N. Durlauf, L. E. Blume (eds.), 2nd Edition, Palgrave Macmillan

Lönnqvist, J.-E., Verkasalo, M., Walkowitz, G., Wichardt, P.C. (2011). Measuring Individual Risk Attitudes in the Lab: Task or Ask? An Empirical Cmparison, *SOEPpapers, DIW Berlin*, 370

Lusardi, A., Mitchell, O. (2006). Financial Literacy and Planning: Implications for Retirement Wellbeing, *PRC Working Paper*, 1/2006

Malmendier, U., Nagel, S. (2011). Depression Babies: Do Macroeconomic Experiences Affect Risk-Taking?, *Quarterly Journal of Economics*, 126, 373-416

Masclet, D., Colombier, N., Denant-Boemont, L., Loheac, Y. (2009). Group and Individual Risk Preferences: A Lottery-Choice Experiment with Self-Employed and Salaried Workers, *Journal of Economic Behavior and Organization*, 70, 470-484

Massa, M., Patgiri, R. (2005). Compensation and Managerial Herding: Evidence from the Mutual Fund Industry, *Working Paper, INSEAD*

McGoldrick, K. (1995). Do Women Receive Compensating Wages For Earnings Risk?, *Southern Economic Journal*, 62, 210-222

McGoldrick, K., Robst, J. (1996). The Effect of Worker Mobility on Compensating Wages for Earnings Risk, *Applied Economics*, 28, 221-232

Mincer, J. (1958). Investment in Human Capital and Personal Income Distribution, *Journal of Political Economy*, 66, 281-302

Mincer, J. (1974). Schooling, Experience and Earnings, *NBER*, New York

Moffitt, R., Gottschalk, P. (1995). Trends in the Covariance Structure of Earnings in the United States: 1969-1987, *The John Hopkins University, Baltimore, Working Papers in Economics*, 355

Moffitt, R., Gottschalk, P. (2008). Trends in the Transitory Variance of Male Earnings in the US, 1991-2003: Preliminary Evidence from LEHD Data, *Boston College Manuscript*

Nofsinger, J.R., Varma, A. (2007). How Analytical is Your Financial Advisor?, *Financial Services Review*, 16, 245-260

Nosić, A., Weber, M. (2010). How Riskily do I Invest? The Role of Risk Attitudes, Risk Perceptions, and Overconfidence, *Decision Analysis*, 7, 282-301

Nyarko, Y., Schotter, A., Sopher, B. (2006). On the Informational Content of Advice: A Theoretical and Experimental Study, *Economic Theory*, 29, 433-452

Ottaviani, M., Soerensen, P.N. (2006). Professional Advice, *Journal of Economic Theory*, 126, 120-142

Park, A., Sabourian, H. (2011). Herding and Contrarian Behavior in Financial Markets, *Econometrica*, 79, 973-1026

Park, A., Sgroi, D. (2009). Herding and Contrarian Behavior in Financial Markets: An Experimental Analysis, *Cambridge Working Papers in Economics*, 0938

Pfeifer, C. (2011). Risk Aversion and Sorting into Public Sector Employment, *German Economic Review*, 12, 85-99

Powdthavee, N., Riyanto, Y. (2012). Why Do People Pay for Useless Advice? Implications of Gambler's and Hot-Hand Fallacies in False-Expert Setting, *IZA Discussion Paper*, 6557

Prendergast, C., Stole, L. (1996). Impetuous Youngsters and Jaded Old-Timers: Acquiring a Reputation for Learning, *Journal of Political Economy*, 104, 1105-1134

van Rooij, M., Lusardi, A., Alessie, R. (2011). Financial Literacy and Stock Market Participation, *Journal of Financial Economics*, 101, 449-472

Rosen, S. (1987). The Theory of Equalizing Differences. In: *Handbook of Labor Economics*, Ashenfelter, O., Layard, R. (eds.), 1, 641-688

Sahm, C.R. (2007). How Much Does Risk Tolerance Change?, *Finance and Economics Discussion Series, Federal Reserve Board, Washington, D.C.*, 2007-66

Samuelson, P.A. (1938). A Note on the Pure Theory of Consumer's Behaviour, *Economica*, 5, 61-71

Samuelson, P.A. (1948). International Trade and the Equalisation of Factor Prices, *Economic Journal*, 58, 163-184

Scharfstein, D., Stein, J. (1990). Herd Behavior and Investment, *American Economic Review*, 80, 465-479

Schotter, A. (2003). Decision Making with Naive Advice, *American Economic Review*, 93, 196-201

Schotter, A., Sopher, B. (2007). Advice and Behavior in Intergenerational Ultimatum Games: An Experimental Approach, *Games and Economic Behavior*, 58, 365-393

Siegrist, M., Cvetkovich, G., Gutscher, H. (2002). Risk Preference Predictions and Gender Stereotypes, *Organizational Behavior and Human Decision Processes*, 87, 91-102

Shiller, R.J. (2008). *The Subprime Solution: How Today's Global Financial Crisis Happened, and What to Do about it*, Princeton University Press, Princeton NJ

Shin, D., Solon, G. (2011). Trends in Men's Earnings Volatility: What does the Panel Study of Income Dynamics show?, *Journal of Public Economics*, 95, 973-982

Shore, S.H. (2011). The Intergenerational Transmission of Income Volatility: Is Riskiness Inherited?, *Journal of Business and Economic Statistics*, 29, 372-381

Sias, R.W. (2004). Institutional Herding, *Review of Financial Studies*, 17, 165–206

Slovic, P., Finucane, M.L., Peters, E., MacGregor, D.G. (1999). Risk as Analysis and Risk as Feelings: Some Thoughts about Affect, Reason, Risk, and Rationality, *Risk Analysis: An Official Publication of the Society for Risk Analysis*, 24, 311-322

Solon, G. (2002). Cross-Country Differences in Intergenerational Earnings Mobility, *Journal of Economic Perspectives*, 16, 59-66

Stigler, G.J., Becker, G.S. (1977). De Gustibus Non Est Disputandum, *American Economic Review*, 67, 76–90

Trueman, B. (1994). Analyst Forecasts and Herding Behavior, *Review of Financial Studies*, 7, 97-124

Villatoro, F. (2009). The Delegated Portfolio Management Problem: Reputation and Herding, *Journal of Banking and Finance*, 33, 2062-2069

Vlaev, I., Kusev, P., Stewart, N., Aldrovandi, S., Chater, N. (2010). Domain Effects and Financial Risk Attitudes, *Risk Analysis*, 30, 9

Weber, E.U., Blais, A.-R., Betz, N.E. (2002). A Domain-Specific Risk-Attitude Scale: Measuring Risk Perceptions and Risk Behaviors, *Journal of Behavioral Decision Making*, 15, 1-28

Welch, I. (1992). Sequential Sales, Learning, and Cascades, *Journal of Finance*, 47, 695–732

Welch, I. (2000). Herding Among Security Analysts, *Journal of Financial Economics*, 58, 369-396

Zwiebel, J. (1995). Corporate Conservatism and Relative Compensation, *Journal of Political Economy*, 103, 1-25

Appendix A

Appendix to Chapter 3 and 4

A.1 Instructions of Web Survey

Regarding this survey: Please try to answer all questions. If you do not know an answer or if you prefer not 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, in a relationship, living separately, 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)
- 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 persons 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".

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 €

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 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 you winnings do you want to wager on 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 one 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 (i.e. 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)

A.2 Instructions of Lab Experiment

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 chapters 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 €?: (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 wagered amount.

Your Decision
What fraction of you winnings do you want to wager on 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 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.
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 €-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 SINGLE

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 wagered 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 wagered
(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 wagered more money in the lottery?

- Gender: (Please choose: men, women, both groups wagered the same amount)
- Age: (Please choose: older (40 and up), younger (below 40), both groups wagered the same amount)
- Marital Status: (Please choose: single, married or in a relationship, both groups wagered the same amount)
- Level of Education: (Please choose: participants with a university degree, participants without a university degree, both groups wagered the same amount)
- Number of Children: (Please choose: participants with children, participants without children, both groups wagered 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 wagered 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 SIMULT 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 your 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 you winnings do you want to wager on the risky but also profit-promising lottery?

(Please choose: €100,000; €80,000; €60,000; €40,000; €20,000; nothing, 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 SIMULT 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 you winnings do you want to wager on the risky but also profit-promising lottery?
(Please choose: €100,000; €80,000; €60,000; €40,000; €20,000; nothing, 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 PICT

This window appeared 4 times for picture number 1,2,3,4.

How do you assess other people?

In this round you will assess four different persons. You will receive a picture of the person you are assessing in order to help you make your decision.

We have placed a brown envelope (C4 format) on your seat. The envelope contains a sheet with four pictures. Please consider picture number X.

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 you winnings do you want to wager on the risky but also profit-promising lottery?
(Please choose: €100,000; €80,000; €60,000; €40,000; €20,000; nothing, would decline the offer)

Game Decision II
What decision do you think the person above 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 person above, you will receive €0.50. If your decision does not correspond with the person above decision, you will not

receive any money.

Your Decision

Please try to make the same decision as the person 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.

Questions

Please answer the following questions.
Note: The questions refer to the entire experiment.

1. Do you know one of the persons on the pictures? If yes, which one(s)?
2. Which of the people on the pictures would you trust most with you money? Please indicate a picture number.
3. Do you think that the provided information was sufficient? What additional information about the individuals you assessed would you have liked to have had?
4. Do you generally believe that it is possible to evaluate the decisions of other people?
5. Were you more confident making you assessments on the basis of the picture or of the profile (with the characteristics)?
6. Did you have a certain strategy in making your assessments? If yes, please describe briefly.
7. When you think back to your last counseling session at your bank, did you have the feeling that you counselor could assess your preferences/wishes well? (*Professionals*: How many years of counseling experience do you have?)

By clicking on NEXT your choices are saved. You cannot edit your answers afterwards.

Your compensation

Calculation of your compensation

You total payment comprises the compensation for every single round.

Basic amount		€x
Part 1		
Game Decision 1		€x
Game Decision 2		€x
Part 2		
Pre-survey Assessment	Game Decision I	€x
	Game Decision II	€x
Part 3		
Ordering Characteristics	Round 1:	€x
	Round 2:	€x
	Round 3:	€x
	Round 4:	€x
Buying	Round 1:	€x
	Purchase Price:	€x
	Round 2:	€x
	Purchase Price:	€x
	Round 3:	€x
	Purchase Price:	€x
	Round 4:	€x
	Purchase Price:	€x
Pictures	Round 1:	€x
	Round 2:	€x
	Round 3:	€x
	Round 4:	€x
Total Compensation		€x

Payment Procedure

We will make the payments according to your ID (identification number)

You will find a receipt among the documents in front of you. Please enter your total compensation, your ID, and selected other information in the acknowledgment form.

Important: Do not close the browser window. Raise your hand as soon as you are finished.

Thank you for your participation

Appendix B

Appendix to Chapter 5

B.1 Instructions of Lab Experiment

In the following we present an English translation of the German instructions.

Please note: Text written in italic was not part of the experiment, but offers additional information for the reader.

Participants enter the lab and draw a random number that determines their winning number throughout the experiment. Participants are then seated in cabins.
The whole experiment has been "paper and pencil"-based. The instruction (except for the questionnaire and the decision sheets) is read out by the conductor of the experiment.

Welcome

Welcome
Welcome to our experiment. The laboratory for experimental economics at the University of Heidelberg's Department of Economics – AWI Lab (game administrator: Professor Roider) wants to test different scientific theories with this experiment.

Payment
You support our academic work with your participation in our experiment. By participating in the experiment, you are guaranteed to receive €4. You will have the possibility to receive additional compensation for the decisions you make during the experiment. The more considered your decisions are, the higher your potential payment. A more detailed explanation of your payment will be provided later. Each point earned in our experiment corresponds to €0.20. The experiment will take approximately 120 minutes.

The Experiment
The experiment consists of two rounds that are independent of each other. In each round the players are randomly assigned to an investor group (which will change from round to round) and must make investment decisions – as well as the other participants in the investor group. In order to facilitate your decision, you will receive information about the prospect for success of the investment decision as well as information about how previous players in your group decided.

Enough explanation, on to the game!

Round 1

The investment decision

One group of investors includes 3 investors, who make their investment decisions one after another. Every investor must choose between two stocks (A and B). Only **one** of the stocks will ultimately be successful and have a value of 10 points at the end, the other stock will close with a value of 0 points. Which of the two stocks will be successful will be determined before the first investor of the investor group decides. The successful stock is therefore **the same for all** of the investors in your investor group. **Without additional information** you can therefore assume that **stock A** will be successful 50% of the time and **stock B** will be successful 50% of the time.

Additional Information

Every investor can observe **the investment decisions of the other investors** in his investor group that have decided **before him**.
Moreover, every investor receives an additional clue about whether stock A or B is successful prior to making his decision. The accuracy of the clue depends on which of two possible sources of information the investor draws on: a **good source of information** or a **bad source of information**. Which information source an investor draws on is determined randomly and can differ from investor to investor within an investor group: The probability of drawing on a good source of information is 50% and is the same for every investor. The probability of drawing on a bad source of information is 50% for every investor as well.
No investor knows the quality of his information source or the quality of the information source that any other investor is drawing on.

Bad source of information: Investors who "draw on a bad source of information" will privately be shown a randomly drawn ball from an urn with 5 "A-Balls" and 5 "B-Balls." A new ball will be drawn from the 5:5 urn for every investor, so that the investors might be receiving different clues. The balls are returned to the urn after they have been shown to the investor.

Good source of information: Investors who "draw on a good source of information" will privately be shown a randomly drawn ball from an urn in which the number of "A-Balls" and "B-Balls" depends on which stock is successful. If stock A is successful, the urn will contain 9 "A-Balls" and 1 "B-Ball." If stock B is successful, however, the urn will include 9 "B-Balls" and 1 "A-Ball." Every investor with a good source of information will be shown a new ball from such a 9:1 urn, so that the investors might be receiving different clues here as well. The balls are returned to the urn after they have been shown to the investor.

Only the investor who receives the clue knows the clue; the other investors do not have access to other players' clues.

Summary: Every investor in your investor groups is facing the same problem that you are. He has to decide whether to buy stock A or stock B. Every investor receives a clue in form of an "A-Ball" or a "B-Ball" that only that investor can observe. None of the investors know the quality of their information source or the quality of the information sources that the other investors are drawing from. Every investor does see the decisions that the other investors in his investor group have made before him (if applicable) and the prices (or price development) of the stocks.

Prices

Every investor that has decided on buying a certain stock must pay the valid current purchase price. The experiment program adjusts the current purchase price of the stocks upwards or downwards on the basis of the observed investment decisions. Every investor receives a starting budget of 20 points for the first round.

.

We request the decision for every possible decision situation

In the following we will ask you for your decision for every possible decision situation that can occur. That means we will ask you to put yourself in the position of investor 1 and make a decision for the case that you see an A-Ball as well as for the case that you see a B-Ball. Afterwards we will ask you to put yourself in the position of investor 2 and make a decision for every possible combination of investor 1 decision and possible clue that you might receive. Finally we will ask you to put yourself in the place of investor 3 and again make a decision for every possible decision situation.

Calculation of your payment

How do we calculate the payment that you receive at the end of the game? **After** the end of the experiment and **after** all investment decisions have been made, the conductor of the experiment will randomly choose who will occupy the role of investor 1, investor 2, and investor 3 in every investor group. Afterwards, by drawing lots in the manner described above, a) the successful stock will be determined, b) the urn from which the clue for the respective investor is picked, and c) the clue itself will be drawn from the respective urn.

Assume, for example, that you have been assigned the role of investor 1 and that the A-Ball has been picked for investor 1. In that case, the decision you made for investor 1 given that he has received an A-Ball would determine your payment.

Assume that you have been assigned the role of investor 2. Furthermore, suppose that investor 1 in you investor group has bought stock B (given the random draws specified above), and you as an investor have received an A-Ball. In this case, the decision you made for Investor 2 in the case of (Investor 1: Bought B, your clue: A-Ball) would determine your payment. Your payment for the case that you are investor 3 will be determined by the decision that you made for the situation that you received a certain ball and the two players that went before you bought a certain stock.

That is how the decision that determines your compensation is determined. The number of points that result from this decision depends on the actual value of the bought stock and the price you paid for the stock. The purchase price of the stock that you decided to buy will be subtracted from you starting budget. That is the payout for the round if your stock is not successful. If the stock you have purchased is successful, you will receive 10 additional points. Thereby, in this round one of your decisions made will be payoff relevant.

The composition of your investor group will ensue anonymously; you will not get to know your fellow players by name.

The experimenter again explained the main information of the first round to the participants. Afterwards participants had to fill out the following questionnaire.

Have you understood everything?

Please answer the following questions before you continue so that we can ensure that you have understood everything:

1. Before you receive a ball: With what probability is stock A the successful stock?
   - 50%
   - 90%
2. Assume that you have access to the good source of information. With what probability do you receive a ball that shows the correct value?
   - 50%
   - 90%
3. With what probability do you receive a ball from the good source of information?
   - 50%
   - 90%
4. What information does player 1 receive before he makes his decision?
   - His clue in form of a ball and the price of the stocks
   - His clue in form of a ball and the quality of his clue's source of information
   - His clue in form of a ball, the quality of his clue's source of information, and information on which stock has a value of 10
5. What information does player 2 receive before he makes his decision?
   - His clue in form of a ball and the price development
   - His clue in form of a ball and the quality of his clue's information source
   - His clue in form of a ball, the price development, and the decision of player 1
   - His clue in form of a ball, the quality of his clue's source of information, and information on which stock has a value of 10

6. What information does player 2 receive before he makes his decision?
    - His clue in form of a ball, the quality of his clue's source of information, and information on which stock has a value of 10
    - His clue in form of a ball and the quality of his clue's source of information
    - His clue in form of a ball and the price development
    - His clue in form of a ball, the price development, and the decisions made by players 1 and 2
7. Assume player 1 receives the A-Ball as a clue. What clue does player 2 receive?
    - Player 2 also receives an A-Ball
    - A new ball is drawn for player 2
8. Assume players 1 and 2 receive the A-Ball as a clue. What clue does player 3 receive?
    - Player 3 also receives an A-Ball
    - A new ball is drawn for player 3
9. Suppose that you have bought stock A and stock A has a value of 10. The purchase price amounts to 7. Your starting budget is 20 points. How high is your total compensation for this round?
    - 10-7+3
    - 20+7-10=17
    - 20+10-7=23
    - 20-7=13
10. Suppose that you have bought stock A and stock A has a value of 0. The purchase price amounts to 4. Your starting budget is 20 points. How high is your total compensation for this round?
    - 20-4=16
    - 20+10-4=26
    - -4
    - 10-4=6

Participants have to answer all questions. Answers are checked. After all participants answer all questions correctly, the following decision sheets are distributed.

Decision Situations Round 1

Your Task

Put yourself in investor 1's shoes:

Suppose you receive a certain ball as a clue and must then decide whether to buy stock A or stock B for the indicated price. The price **in bold print** is the price that you have to pay for stock A or stock B. Please indicate if you want to buy stock A or stock B in the decision situations described below:

Decision Situation 1

Price stock A	**7,0**
Price stock B	**7,0**

You receive an **A-Ball.** I buy o Stock A o Stock B

....

Two decisions in total, available upon request.

Put yourself in investor 2's shoes now:

Suppose you observe both investor 1's decision and the price development in addition to a certain ball you receive as a clue. Please indicate if you want to buy stock A or stock B for the indicated price **in bold print** in the respective decision situation. The price **in bold print** is the price that you have to pay for stock A or stock B. The prices to the left are the prices that the investors before you had to pay.

Decision Situation 1

Investor	1	2
Price stock A	7,0	**8,4**
Price stock B	7,0	**5,0**
Decision	A	?

You receive an **A-Ball.** I buy o Stock A o Stock B

....

Four decisions in total, available upon request.

Put yourself in investor 3's shoes now:

Suppose you observe the investment decision of the first two investors, the price development, and certain ball as a clue. Please indicate if you want to buy stock A or stock B for the indicated price **in bold print** in the respective decision situation. The price **in bold print** is the price that you have to pay for stock A or stock B. The prices to the left are the prices that the investors before you had to pay.

Decision Situation 1

Investor	1	2	3
Price stock A	7,0	8,4	**7,0**
Price stock B	7,0	5,0	**7,0**
Decision	A	B	?

You receive an **A-Ball.** I buy o Stock A o Stock B

. . . .

Eight decisions in total, available upon request.

Notes

Participants have the possibility to save their decision of the first round by filling out this sheet after they made their decision. This sheet can be kept.

The decision situations in round 1 and 2 are similar. If you want to, you can take notes on the decisions you made in round 1. You can make the decisions in round 2 without notes from round 1.

Decision Situation Number	A	B
Investor 1/ Decision 1		
Investor 1/ Decision 2		
Investor 2/ Decision 1		
Investor 2/ Decision 2		
Investor 2/ Decision 3		
Investor 2/ Decision 4		
Investor 3/ Decision 1		
Investor 3/ Decision 2		
Investor 3/ Decision 3		
Investor 3/ Decision 4		
Investor 3/ Decision 5		
Investor 3/ Decision 6		
Investor 3/ Decision 7		
Investor 3/ Decision 8		

After all decisions of the first round are made, decision sheets are collected and participants have to draw a slip of paper which indicates whether in the second round they become "observer" or remain "investor". Afterwards, the instructions for the second round are distributed and read out. Except for the questionnaire and the decision sheets, the instructions distributed are identical for investors and observers.

Round 2

The rules of the game are the same in the second round as in the first one, only the calculation of your compensation differs. There will be observers in addition to investors in this round. If you have drawn a card with an **"I"** you are still an **investor**. If you have drawn a card with a **"B"** you are now an **observer**. 6 players have now anonymously and randomly been drawn to assume the role of the observers.

The observers will not invest themselves but will evaluate the investment decision made by the investors. The observers are no longer part of an investor group. The identity of the investors and the observers will not be revealed.

Apart from the calculation of the compensation nothing changes for the investors.

Payment Calculation

This stays the same:

We will ask for you decision in all possible decision situations just like in the first round.

Every investor and every observer will receive a **starting budget of 20 points** for the second round.

After the experiment ends and **after** all investors and observers have made their decisions, the conductor of the experiment will randomly arrange the investors in new groups. Every investor will have different teammates than in round 1.

Afterwards, the roles of investor 1, investor 2, and investor 3 will be assigned randomly. By drawing lots in the manner described above, a) the successful stock, b) the urn from which the clue for the respective investor is picked, and c) the clue that every investor receives, are then picked again.

That is how the decisions that determine your compensation are made. As in round 1, for each investor **only one** of the investment decisions that you will now make will determine your compensation.

This changes:

The value of the stock will continue to affect the investors' compensation. The stock value will no longer affect the observers' compensation, however.

The **additional** compensation that the investors receive will depend on the evaluation by the observer. The observer will no longer have to choose between the 2 stocks. Instead, the observer will have to estimate with what probability the investors had access to a good sources of information when making their decision and will have to offer the individual investors wages.

The observers are willing to pay a wage because they can win points by employing an investor with a good source of information. If the observer hires an investor who has access to a good information source, the investors employment is helpful and the observer will receive 20 additional points. The observer is not rewarded for hiring investors who have access to bad information. An observer who hires an investor who has a bad source of information receives 0 points.

For every possible decision situation and every investor, the 6 observers have to submit a wage offer between 0 and **maximally** 20 points that they would be willing to pay the investors. The observer that submits the highest of the 6 wage offers for a single investor will win the bid and pay the investor the stated wage. The other 5 investors that did not win the bid do not receive points, but also do not have to pay any wages. There are now 4 investor groups with a total of 12 investors.

The observers submit their wage offers at a point in time where the actual value of the stock is already publicly known. On top of that, the observers can only observe the investment decisions of the individual investors and the price development of the stocks. They cannot observe the clue that every investor receives or the quality of an investor's source of information.

Sequence of events

After all investors and observers have made their decisions for all possible decision situations, as in round 1, the decision that determines the compensation within the investor groups and the value of the stock will be established.
The wage offers that the 6 observers have made for the investors in the established decision situation will then be compared and the highest bidding observer will win the bid. That is how the compensation for every investor in every investor group and the paying observer will be determined.

It is important to remember that the observers to not know what clue or what source of information the investors received. The observers only see the investment decision itself, the actual value of the stock, and the price development.

The points you receive are calculated as follows:

Payment Observer

If an observer has submitted the highest bid for an investor, the observer pays the investor a wage commensurate with his bid for the investor. If the particular investor had a good source of information, the observer receives an additional 20 points. If multiple observers submit the same (high) bid for a particular investor, the winning bidder will be determined randomly among the group of the highest bidders by a lot. If an observer has not submitted the highest bid for an investor, the observer does not have to pay a wage and does not receive any additional points. It is therefore possible for a single observer to submit the highest bid for none, one, multiple, or even all 12 of the investor(s). Please note: The observer cannot lose money. Even if an observer ends up losing money in this round, he or she will still be credited for 0 points.

The decisions the observers make influence both their own compensation and the compensation of the investors.

Payment Investor

The starting budget, the value of the stock minus the price paid for the stock, and the wages received from one of the observers add up to the investor's total compensation.

Again, the main parts of the experiment are explained to the participants by the experimenter.

Questions distributed to observers (Observers receive different questions than investors.).

Questions for Observers

Have you understood everything?

Please answer the following questions before you continue so that we can ensure that you have understood everything.

1. Assume that you have submitted a wage offer of 9 points and won the bid. The investor whom you are paying 9 points bought stock A and stock A has a value of 10 points. The investor had a starting budget of 20 points and bought stock A for 6 points. Moreover, the investor had a good source of information.

   (a) How high is the investor's total compensation in this round?

   - 9+10-6+20+20=53
   - 9+20=29
   - 9+10-6+20=33

   (b) How high is your compensation from this investor? (Excluding your starting budget.)

   - 20-9=11
   - 20+10+9-6=33
   - 9+20=29

   (c) How high is your compensation if the investor had a bad source of information and you had won the bid? (Excluding your starting budget.)

   - 0-9=-9
   - 20+10+9-6+0
   - 9+0=9

   (d) Assume that the stock has a value of 0 points. How high is the investor's compensation?

   - 9+0-6+20+20=43
   - 9+20=29
   - 9+0-6+20=23

2. You have bid 14 points for an investor, which is exactly the same amount one other observer's bid for the same investor. Who wins the bid?

- Both of the observers win the bid; the profit is divided
- The winner of the bid is decided by lot
- None of the observers wins the bid

3. What information can you use to decide on your wage offers?

   - The investors' sources of information and the actual value of the stock
   - The investors' clues and the actual value of the stock
   - The investors' decisions and the price development
   - The investors' decisions, the price development, and the actual value of the stock

Participants have to fill out the questions. Answers are checked. After all participants answer all questions correctly, the following decision sheets are distributed.

Questions distributed to investors (Investors receive different questions than observers.).

Questions for Investors

Have you understood everything?
Please answer the following questions before you continue so that we can ensure that you have understood everything.

1. The observers have submitted the following wage offers for the decision that determines the compensation: (10; 4; 7; 14; 5; 13). How high is the winning wage offer?

   - 7
   - 14
   - 5
   - 10

2. Assume that you your wage from the observer equals to 9 points. You have bought stock A and stock A has a value of 10 points. You had a starting budget of 20 points and bought stock A for 6 points. Moreover, you had access to a good source of information.

   (a) How high is your total compensation in this round?

   - 9+10-6+20+20=53
   - 9+20=29
   - 9+10-6+20=33

   (b) How high is the compensation of the observer who has won the bid and is employing you? (Excluding the observer's starting budget.)

   - 20-9=11
   - 20+10+9-6=33
   - 9+20=29

   (c) Assume that the stock has a value of 0 points. How high is your compensation?

   - 9+0-6+20+20=43
   - 9+20=29

- 9+0-6+20=23

(d) How high is the observer's compensation if you had a bad source of information and he won the bid to employ you? (Excluding the observer's starting budget.)

- 0-9=-9
- 20+10+9-6+0
- 9+0=9

3. What information can the observer use to decide on his or her wage offer?

- The investors' sources of information and the actual value of the stock
- The investors' clues and the actual value of the stock
- The investors' decisions and the price development
- The investors' decisions, the price development, and the actual value of the stock

Participants have to fill out the questions. Answers are checked. After all participants answer all questions correctly, the following decision sheets are distributed.

Decision sheets for Investors and Observers are different; each group only observes its own decision sheets.

Decision Situations Round 2 (Investors)

Please note: Your decisions in round 2 are completely independent of round 1.

Decisions taken by Investors are identical to decision in Round 1. See "Decision Situations Round 1"

Decision sheets for Investors and Observers are different; each group only observes its own decision sheets.

Decision Situations Round 2 (Observer)

Your Task:

You can now see all decision situations that occur. Please indicate what wage offer between 0 and 20 you want to make for the respective investor. You can make separate offers between 0 and 20 points for every investor 1, 2, and 3.
Moreover, you can observe the price development, the prices the investors had to pay for the stocks, the stocks that the investors eventually bought and the successful stock.

Decision Situation 1:

Investor	1	2	3	
Price Stock A	7,0	8,4	7,0	
Price Stock B	7,0	5,0	7,0	
Decision	A	B	A	Successful Stock: A

Your wage offer for Investor 1: __
Your wage offer for Investor 2: __
Your wage offer for Investor 3: __

Decision Situation 2-15 are similar, available upon request.

Decision Situation 16:

Investor	1	2	3	
Price Stock A	7,0	5,0	3,0	
Price Stock B	7,0	8,4	9,3	
Decision	B	B	B	Successful Stock: B

Your wage offer for Investor 1: __
Your wage offer for Investor 2: __
Your wage offer for Investor 3: __

After all decisions are taken, decision sheets are collected. The experimenter then randomly draws (by urn draws) the decisions situations of round 1 and 2 that determine the payoffs for all players. Participants are then asked to fill out a final questionnaire while the payoffs are calculated via the actual decisions taken by the participants.

Payment Notification

Thank you for your participation in the experiment. We will now calculate your point total, convert that total into Euros, and then pay you. This can take a few minutes. Please fill out the following questionnaire in the meantime.
Please do not speak with other participants and refrain from using your cell phone until the end of the experiment.
As soon as we have determined your compensation, we will call your number.

Thanks again for your participation!

Personal Data and Questionnaire

Personal Data

Please answer the following questions. The results of the experiment will naturally be anonymized and it will not be possible to connect the information to your personal data. The information you share with us will only be used for scientific analysis.

Age: ___

Gender:

- female
- male

  Are you:

- a student
- a doctoral candidate
- employed
- other: ___

If student or doctoral candidate:
Subject: ________
If student: semester number: ___

Questionnaire

Please take some time to answer the following questions.

1. Please consider what you would do in the following situation: Suppose you have just won €100,000 in a lottery. Immediately after being given the €100,000 you receive the following proposal for a new lottery:
   There is the chance to **double** your money. It is **equally possible** that you could **lose half** of the amount you invested.
   You can wager your entire €100,000, a fraction thereof, or you can choose not to take part in the lottery at all.
   What fraction of you winnings do you want to wager on the risky but also profit-promising lottery?

   - the entire €100,000
   - €80,000

- €60,000
- €40,000
- €20,000
- Nothing, I would not take part in the lottery

2. Do you think that player 1 always acted according to the clue he received in form of a ball?
3. Do you think that player 2 always acted according to the clue he received in form of a ball? If not: When did he not act in accordance with his clue?
4. Do you think that player 3 always acted according to the clue he received in form of a ball? If not: When did he not act in accordance with his clue?
5. What did you base your decisions on while in your role; your own ball or the other players' investment decisions?
6. What do you think was the purpose of this experiment?
7. In the decisions you make daily, you follow
    - Other people's advice
    - My own assessment
    - Other people's advice in some situations and my own assessment in others

Thank you for filling out the questionnaire and for taking part in the experiment. Please wait until your number is called.

Participants wait until they are called to come forward for payment. Participants are asked to remain silent until then. Participants leave the lab.