Social Preferences under Risk

Peer Types and Relationships in Economic Decision Making

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Timm Teubner

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Chapter 1.

Introduction

"Live together like brothers and do business like strangers."

(Arabic proverb)

Virtuality has changed the way commerce is conducted, even how economies work, since "the Internet has influenced the economy in every respect" (Choi and Yi, 2009, p. 39). Where ancient market places were built on personal relationships and in-person transactions, the consumer culture of the 20th century was rather characterized by mass markets and anonymity. E-Commerce on the Internet now comprises both aspects: On the one hand, many online market places yield anonymity among the transaction partners, sometimes even ambiguity about the nature of the other party. On the other hand, however, recent forms of e-commerce are explicitly based on the notion of personal connections and relations. Starting from services like eBay early on, peer-to-peer platforms today allow to market and share spare real estate, commodities, skills, or time. In the "global village," knowledge about identity, history, and accountability potentially decreases economic risk and thus increases potential counterparts' mutual trustworthiness, which is a prerequisite for exchange. Operators of peer-to-peer platforms have recognized this and urge their users to create personal profiles and maintain their online presence, let alone the appearance in online social networks. This puts transactions in e-commerce increasingly into a social context. And it leads to new questions for market engineers, designers and operators of e-commerce platforms, but also with regard to economic decision situations involving social facets in a wider sense.

In particular, the aspects *social context* and *risk* become more explicit in online environments, since people lack the necessary sensing capabilities when there is no physical presence and direct contact. But the factors *social context* and *risk* are neither new nor limited to e-commerce. They do, however, appear in a new light in the context of peer-to-peer economies, in some cases even driving business success. The convergence of "private" and "professional" sphere in many e-commerce applications raises new questions. On the one hand, economic decision making may be distorted when the mere economic outcome is intermingled with personal and relational objectives. The general presence of peers may, on the other hand, be part of an online- and peer-to-peer provider's value proposition, be it the thrill of competing, the "warm-glow" of helping others, or the anticipation of complacent interaction.

This work thus addresses risky decision making in stylized market situations, which are characterized by the presence of a peer. In two major experimental studies, the peer's role is investigated by systematically varying i) the nature of the peer (human or computer), and ii) the relationship to the peer (friend or stranger). The interplay of social context and individual risk preferences should be of interest in view of economic and information systems related matters. By taking a theoretical and practical perspective, this work may inform market design as well as operators and users in the e-commerce business.

1.1. The "Peer-to-Peer Economy"

The advent of the personal computer and the World Wide Web have caused a shift in the structure of who is able to offer products and services to a global pool of potential customers. E-business and e-commerce have almost become the default form of economic exchange and are ubiquitous in today's society. "As computers and the Internet pervade almost every corner of life, the impact of IT on economic behavior is definitive" (Riedl et al., 2011, p. 2). Whereas it was long reserved to large corporations with sufficient resources for development, marketing, and logistics, private persons can now make use of different kinds of information systems and online channels in order to develop and offer their products and services to a global clientele, as well as to purchase and consume from it.

These private entrepreneurs not only satisfy the demand of an anonymous consumer market, but sell to and interact with other private persons. This has led to the development of specialized small size businesses and has also enabled the emergence of a peer-to-peer economy, in which the Internet is utilized for means of exchange. Starting off with traditional market places like eBay, there has been an increasing use of platforms that allow private users to share their spare goods, skills, and resources with other private users at a charge, or even for free. In this peer-to-peer or *sharing economy* people rent out their cars and apartments, share rides, tools, and so forth.[1]

Web- and mobile services have laid the ground for the development of a novel form of market. These “new” tools enable the connection and coordination of widely spread people, their resources and demands at sufficiently low cost and effort (cf. Anderson, 2007). The mediation of supply and demand in peer-to-peer markets has shifted away from bulletin boards, newspaper advertisements, and manually operated card files, and does now exist almost exclusively in the form of online platforms.

In this context, the intermediary, i.e. the operator of such an online platform, and the concept of trust play an important role. Naturally, corporations strive to build a reputation of high quality, good service, and reliability. The mere fact, however, that a company has been in the market for a considerable time can here be interpreted as a signal of sufficient quality, since otherwise the company would have long been out of the market due to competition and the customer’s choice. But this consideration does typically not hold for private product or service providers in a peer-to-peer economy, where the creation of a user profile might only take as few as a couple of clicks. Additionally, and even more than traditional forms of exchange, Internet transactions heavily rely on a sufficient level of trustworthiness and trust[2], since the conditions are very different to real world transactions, where people meet in person, shake hands, and are personally accessible and accountable (Pavlou and Gefen, 2004). The “designers” or “engineers” of a platform (online or offline) for economic exchange—which basically constitutes the definition of a *market*—may thus want to create ways for their users to mutually judge their trustworthiness. Also may it be the task of a *market designer* or *engineer* to set up and explore the rules, terms, and facets of social interaction, aiming at improving the market, may that be in terms of revenue, profit, efficiency, time spent by the users, or whatsoever desired criteria.

[1]Typically, the case is made that a car sits idle for 23 out of 24 hours a day, and a power drill is used only for 6 to 13 minutes during its entire lifetime; cf. www.shareable.net/blog/ how-to-share-your-car-with-a-stranger, www.earthshare.org/ 2012/05/sharing.html, both accessed on 13.05.2013. For this “sharing reinvented through technology,” Botsman and Rogers (2010) have coined the term *collaborative consumption*.

[2]In her 2013 TED talk, Onora O’Neill noted on the unconditional aim to increase trust: “Well frankly, I think that’s a stupid aim. It’s not what I would aim at. I would aim to have more trust in the trustworthy, but not in the untrustworthy. In fact, I aim positively to try not to trust the untrustworthy. [...] More trust is not an intelligent aim in this life. [...] Intelligently placed and intelligently refused trust is the proper aim.” (cf. http://www.ted.com/talks/onora_o_neill_what_we_don_t_understand_about_trust.html).

1.2. The Market Engineering Approach

In both regards, assessment of quality and accountability, business in a peer-to-peer economy thus faces the challenge of overcoming obstacles of lacking trust and to create ways for users to mutually evaluate their trustworthiness. Therefore, among means like reputation systems or personalized recommendations, social online identity and social presence become increasingly important. Particularly, online platform operators in two-sided markets often make use of the social identities and spheres of their users in order to stimulate benevolent behavior and stress reliability. Companies like *Airbnb, Inc.* and *carpooling.com GmbH*, for instance, animate providers and consumers on their platforms—whereat people usually act in both roles—to integrate their facebook account (cf. “facebook connect”) or to maintain a distinguishable profile. In that regard, the main German ride sharing company states: “faces create trust: please complete your profile.”[3]

This, in turn, puts e-commerce transactions progressively into a social context. The transaction partner (or competitor) is not necessarily anonymous anymore, but may appear with a face, a name, a history and reputation, a circle of friends, maybe even with acquaintances in common (cf. facebook’s *“12 of your friends like this”*). This shifts the focus towards new questions. Bidders, buyers, traders, and sellers might ask whether their transaction partners (or competitors) are other humans at all, since fake accounts, sniping bots, and automated trading agents have long become prevalent in e-commerce and online trading. And if so, it occurs possible that the other person’s attributes and the relation to the decision maker may interfere with the underlying economic reasoning. What, for instance, do the sayings “friendship doesn’t extend to money matters,” or, somewhat more subtle, “Live together like brothers and do business like strangers” imply in this context?

Now, for applications in electronic markets involving other persons, i.e. where social preferences potentially take effect, trust plays an important role (see above). Mayer et al. (1995, p. 712) defined trust as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party.” This is often supplemented by the explanation that the trustor faces uncertainty about the trustee’s *ability* and *intention*. Risk and trust are thus strongly linked to each other. Johnson-George and Swap (1982, p. 1306) even stated that the “willingness to take risks may be one of the few characteristics common to all trust situations.” Since it may be particularly difficult to “monitor or control” the other party when interacting online, the users’ risk attitudes may, besides the aforementioned social concerns, be seen

[3] www.mitfahrgelegenheit.de/news/viewNews/464, accessed on 13.05.2013

as one major factor, relevant to the design and operation of online environments and mechanisms.

The recent peer-to-peer economies are rooted online. Technical, design, and privacy related issues are thus vital. From an information systems perspective, this means that the interplay between social presence and economic decisions and outcomes is of high relevance. In fact, the intersection of social facets and risky decisions is key in a series of applications. Social trading, peer-to-peer lending, crowd funding, crowd investing, (online) gambling, and serious gaming are such.

But also in classical economic settings, applications of this type can be found. Both in the private and in the professional context, decision making is inherently linked to the social ties among friends, colleagues, and acquaintances. In contrast to the traditional microeconomic perspective, individuals evidently do not exclusively value their own prospective gains or losses, but may derive utility also from the fortune of beloved ones or from the misfortune of an opponent or rival (Fehr and Schmidt, 2006; Overbeck et al., 2010). The associated notions here may be sympathy and spitefulness, or benevolence, altruism, and malevolence. In the context of the firm, managers decide about the execution of risky projects, deliberately deciding on the level of risk taken. They might be evaluated not only on their individual (project-) results, but also on how these results compare to those of their colleagues. They might compete for bonuses, the future allocation of budget, the next promotion, or—most probably—simply for status. Fairness, envy, and gloating are potential motives in this regard (cf. Bault et al., 2008). Different heads of departments, for instance, might take their rivals' actions into account. Knowing one's competitor in person may fuel the desire to "win," which in turn may distort the quality of the underlying economic decisions. Generally speaking, a principal with certain requirements towards his risk portfolio might want to install adequate mechanisms to avoid undesired dynamics and an escalation of risk propensity or aversion among the decision makers.

In order to capture the players' motivations and create incentives accordingly, the concept of Homo Economicus has long been serving as a main pillar of theoretical and empirical research in social science and, in particular, in economics.[4] The Homo Economicus concept regards humans as fully rational, entirely unchanging and self-interested utility maximizers. Most scholars uniformly agree that these assumptions are very simplistic and highly unrealistic. Kenneth Binmore, an important contributor to the foundations of

[4] Ockenfels (2013). ... über die Grenzen der experimentellen Ökonomie, realitätsferne Verhaltensforscher und seine neue Rolle als "Ingenieur", *Frankfurter Allgemeine Zeitung*, blogs.faz.net/fazit/2012/11/08/ oekonomen-im-gespraech-axel-ockenfels- ueber-die-grenzen-der-experimentellen-oekonomie- realitaetsferne-verhaltensforscher-und-seine-neue-rolle-als-ingenieur-635, accessed on 14.05.2013.

game theory and experimental economics, stated: "Homo economicus is dead, but whose Homo behavioralis will replace him?"[5] The concept is albeit taught in ECON-101 classes around the world. Economists up to the first half of the 20th century regarded their field as a social science, stressing psychological factors in order to understand economic—still human—behavior (Thaler, 2000). It was a "mathematical revolution," which led to a more extensive use of models and formulas, and assumed rationally optimizing agents: "The IQ of Homo Economicus became bounded only by the IQ of the smartest economic theorist" (cf. Thaler, 2000, p. 134). Lately, it is argued that the concept of Homo Economicus is not entirely rejected in most recent approaches. However, the assumption of perfect selfishness is scrapped and substituted by the assumption of other-regarding, so called *social* preferences.[6,7] A very intuitive form of social preferences is referred to as "distributional preferences." Models based on such distributional preferences have found much attention in the literature (Fehr and Schmidt, 2006). These models still use a formal approach. The decision maker is, however, not assumed to be fully selfish, but to consider the allowances of other persons or the relevant peer group in some way. Bolton and Ockenfels (2012, p. 669) stated that "it is now widely acknowledged, including in economics, that some human decision makers care not only about their own material payoff, but also about the distribution of payoffs in the reference group, about how the distribution was generated, and about reciprocity."

Furthermore, the consideration of emotions may contribute to better understand the participants' behavior and its interaction with the institutional design. Emotions, with no doubt, are complex. In order to albeit address the participants' emotions in the analysis, researchers may use psychophysiological measurements. Adam et al. (2011, p. 3), in this context, used the term *physioeconomics* to describe a technique that "builds on this well-established methodology of experimental economics, but additionally incorporates physiological measurements of participants as proxies for their individual emotional processing." In particular, the methods of NeuroIS enable researchers to get an idea of the visceral processes underlying the users' emotions and potentially decision-making (Dimoka et al., 2012; Vom Brocke et al., 2013). Correlates of the activity of the autonomous nervous system (ANS) like heart rate and skin conductance, taken as a starting point, are comparably easy to access in the laboratory, and are "typically much less expensive than the low-cost neuroscience tools (e.g., EEG)" (Riedl et al., 2010, p. 256). The amplitude of a skin conductance response to a certain event, for instance,

[5] Quote by Kenneth Binmore, University College London; from the back cover of *Microeconomics: Behavior, Institutions, and Evolution* by Samuel Bowles, 2003, Princeton University Press.

[6] Pennekamp (2012). Abschied von der Weltformel, *Frankfurter Allgemeine Zeitung*, blogs.faz.net/fazit/2012/11/07/abschied-von-der-weltformel-633, accessed on 14.05.2013.

[7] Pennekamp (2012). Der Homo oeconomicus lebt, *Frankfurter Allgemeine Zeitung*, www.faz.net/aktuell/wirtschaft/wirtschaftswissen/wirtschaftswissenschaften-der-homo-oeconomicus-lebt-11938235.html, accessed on 14.05.2013.

has been identified as a measure of emotional arousal (Lang et al., 1993; Bradley et al., 2008). In particular for experiments involving multiple participants, or even large groups, and real time interaction, methods like functional magnetic resonance imaging (fMRI), where only one subject at a time can be treated under very constrained conditions, may be not applicable. The methods of NeuroIS, in contrast to that, allow researchers to address questions like whether arousal impacts certain patterns of economic behavior and vice versa, and also how inter- and intra-personal differences of arousal (even in groups with interaction) affect decision making. Making use of this information may help to better understand what makes people behave irrational, competitive, benignly, or particularly beneficial or detrimental at certain decisions. Platform operators, in this regard, might be interested in how to explicitly induce or mitigate arousal during the process of interacting with their service.

Many behavioral economists employ the insights about social preferences and increasingly also about the role of emotions in order to think of and to create *markets that work*. Setting up a market becomes an increasingly complex task with the information at hand. Since theoretical models are oftentimes unable to capture this complexity in a reasonable way, the process requires methodological approaches, very much alike the engineering sciences. Bolton and Ockenfels (2012, p. 666) defined *economic engineering* as "the science of designing real-world institutions and mechanisms that align individual incentives and behavior with the underlying goals." Behavioral economic engineering, in addition to that, "aims to discover how actual (social) behavior interacts with the institutional design" (Bolton and Ockenfels, 2012, p. 669).

Like any engineering approach, behavioral economic engineering partly relies on *trial and error*, since not every dynamic in human interaction is foreseeable. For the case of electronic markets, Weinhardt et al. (2003) stated that economists increasingly made use of the tools and methods of the engineering sciences and defined the term *market engineering* as

> "[...] the systematic and theoretically grounded approach for the analysis, design, adoption, quality control, and further development of electronic markets as well as the respective legal frame conditions, based on an integrated view on micro structure, infrastructure, and business structure."

In particular, the authors named simulations and economic experiments as techniques, potentially helping at the design of markets, where "established theories, due to high complexity, come up against borders" (Weinhardt et al., 2003, p. 636). This has not always been the case. As up to the early 2000's, economists like Nobel laureate Alvin Roth and his colleague Axel Ockenfels, who regarded themselves as economic engineers, were considered outsiders. Roth (2002, p. 1341) stated that, in addition to analyzing markets, "economists have lately been called upon [...] to design them." The success of their approach presumably stems from the fact that it does not solely rely on mathematically aesthetic models, but incorporates real-life aspects.[8] Factual human behavior, such as motivated by the desire for fairness or revenge can be rationalized by such models, whereas these factors were hitherto mostly disregarded.

To sum it up: Most electronic markets now increasingly comprise social aspects, e.g., the relation between the actors, identities, etc. Trust and risk are vital for almost any economic decision in this context, be it the uncertainty about exogenous events, or the fact that one relies on others'—ex ante uncertain—capability and benignity. It is thus straightforward to address both concepts within an integrated approach. However, both areas of research, social factors and risk preferences, have mostly been studied separately and, as Bolton and Ockenfels (2010, p. 628) stated, "surprisingly, [...], few contributions investigate risk taking in a social context." The economic literature on this joint topic is rather sparse. Only in the last decade, research on distributional preferences is increasingly accompanied by the question of how these preferences can be expanded to decisions in the presence of risk. Most contributions do so by means of laboratory experiments and behavioral models.

The aim of this work is to gain a deeper understanding on the relevant principles and to derive theoretical and practical implications for economic decision scenarios from a market engineering perspective. The focus thereat is on the aspects relevant to the design and operation of online platforms, since the Internet has become a major pillar of global commerce and even altered the way economies work. In this regard, this work is structured into two main building blocks. The first one is concerned with the question how different types of peers (human or computerized) in online markets affect decision making. The second block then explores the role of different relationships among human peers in greater detail. Common to both blocks is the intersection of social- and risk related aspects. The research questions on that account, as well as the structure of this work are outlined in the following sections.

1.3. Research Questions

Overall, this work is concerned with human decision making in different economic contexts, which are characterized by the presence of i) a social context and ii) risk. Both aspects are relevant from a mere economic perspective. Their junction, however, is only sparsely covered by the existing literature (cf. Yechiam et al., 2008; Bolton and Ockenfels,

[8] Pennekamp (2013). Ökonomische Ingenieurskunst, *Frankfurter Allgemeine Zeitung*, blogs.faz.net/fazit/2013/04/11/okonomische-ingenieurskunst-1398, accessed on 14.05.2013.

2010; Trautmann and Vieider, 2011). Whereas almost all prior studies in experimental economics created an abstract social context, i.e. matching subjects to anonymous, unknown other experiment participants, this approach is challenged and extended in the scope of this work. In order to match people of different types of relationships, lab experiments appear inapplicable, since subject pool as well as invitation process (using e-mail notifications) do not allow to effectively control for that aspect. Therefore, the respective experiment (cf. Chapter 5) is conducted in the field, i.e. on well frequented campus sites such as dining commons and cafeterias. In the scope of this work, the assessment of personal risk preferences is essential. In order to capture the participants' individual risk preferences in such experiments "in the wild," a light-weight risk aversion questionnaire is needed. By developing and evaluating a simplified version of the standard procedure for risk preference elicitation in the lab (Holt and Laury, 2002), Chapter 3 lays the ground for the subsequent work. The associated question here is how well this short version of the test is able to capture and depict personal risk preferences, where the original test serves as benchmark. Research Question 1 thus states:

> **Research Question 1:** *Can a short version of the Holt and Laury (2002) risk aversion task serve as a substitute? How well do the results correlate and which factors are determinant?*

Now, a very intuitive way to conflate social preferences and risk taking are auctions. This format is specifically interesting because Internet auctions are widely used as a particular form of electronic markets and are "one of the greatest success stories of web-based services" (Ariely and Simonson, 2003, p. 113). At that, the nature of the other participants one faces in online environments may differ, and sometimes may not even be clear. Chapter 4 thus presents an experimental study analyzing the economic, behavioral, and emotional aspects of human decision making under risk in a laboratory auction experiment. Auctions are suitable for this purpose since—in first-price sealed-bid auction formats—the other bidders' actions are unknown at the time of bidding. High bids increase the probability of winning the auction and thus the auctioneered commodity. They do however potentially reduce the profit (value of the commodity less the bid) in case the auction is won. Low bids yield high profits. It is then, however, likely that another bidder has submitted a higher bid. This trade-off between potential gain and probability of winning constitutes the risky decision and may be expected to depend on one's risk preferences. But auctions also serve as a suitable environment for the investigation of interpersonal effects. The nature of auctions, the fact that only one player can win, is known to foster competition among the players, which may in turn affect bidding behavior. In order to isolate the effect of social facets in the light of the risks involved in auctions, the nature of the other bidders (human or computerized) is varied in a systematical way. Economically, bidding behavior may be regarded as the most direct expression of a bidder's risk attitude and social preferences. Research Question 2 thus states:

> **Research Question 2:** *Is there a difference in bidding behavior in first-price sealed-bid auctions where the other auction participants are either human or computerized?*

Along with competition, the nature of the auction may lead to competitive arousal (Ku et al., 2005; Malhotra, 2010) and auction fever (Ku et al., 2005; Adam et al., 2011), resulting in excessive bidding. The phenomenon is long known: "Already in ancient Rome, legal scholars debated whether auctions were void if the winner was infected by *bidder's heat* (calor licitantis)" (Malmendier and Lee, 2011, p. 749). For that reason, it is of interest how the market participants' arousal varies, how arousal and auction environment interact, and how this eventually may help to understand bidding behavior. Research Question 3 thus states:

> **Research Question 3:** *Is there a difference in arousal in first-price sealed-bid auctions where the other auction participants are either human or computerized—and how do auction environment, arousal and bidding behavior interact?*

The next building block of this work considers the interaction among humans in greater detail. Building on the results of the literature review and the auction study, an experiment is designed in order to address a yet mostly neglected type of decision: prospect selection with a coincident decision about payoff alignment among the peers. A novel experiment yielding such a scenario is proposed. Again, the intersection of other-regarding and risk preferences is addressed. Using the *type* of the relationship between the decision makers involved, an important aspect is addressed in the analysis. Two decision makers at a time face a risky situation, where the decision makers of the pairs have different types of relationships towards each other (friends or strangers). The overarching research question in this regard addresses the role of the relationship and is formulated as follows:

> **Research Question 4:** *Is there a difference in economic behavior among friends and strangers, regarding risk preference and the desire to align or de-align payoffs ex ante in prospect selection?*

Since the proposed experiment represents a novel approach, the empirical analysis is accompanied by a game-theoretical analysis. This analysis considers the first- and second-mover's perspective and the resulting equilibria. The analysis is based on a simple behavioral model, which incorporates the motives of envy and gloating. The model parameters are estimated using a maximum likelihood estimation on the empirical data. It is then benchmarked against other models of social preferences from the literature. Research Question 5 thus states:

> **Research Question 5:** *Can a model with the emotional motives of envy and gloating explain the observed data? How well does it in comparison to other existing models?*

Taken together, this work addresses economic decisions from different perspectives, whereat it is oriented towards the central idea of conflating risk preferences and social preferences. The subject is regarded from an IS perspective, particularly having in mind the design and operation of peer-to-peer markets. A major working hypothesis throughout this work is that the impact of the reference peer is dependent on the type of, as well as the relationship between the decision maker and the peer, which proves to be valid, as shown in Chapters 4 and 5.

1.4. Structure of the Thesis

This work and the research agenda therein are structured in blocks that build upon another. Chapter 1 introduces and motivates the topic and extrapolates a set of research questions.

In Chapter 2, the foundations of social preferences and risk preferences are illustrated and the intersection of both aspects is examined. This part is divided into the main subsections *Social Preferences*, *Risk Preferences*, and the synthesis *Social Preferences and Risk*. After introducing the basic terms and concepts of social preferences and risk preferences, the recently emerged body of literature on the interplay of both aspects is reviewed. Existing theories, empirical evidence, and conceptual approaches regarding social preferences under risk are considered. In order to differentiate and organize the respective decision scenarios used in the literature, a classification framework is presented.

Chapter 3 proposes and evaluates a short version of the Holt and Laury (2002) risk aversion task and discusses methodological issues on economic experiments "in the field," which are not to be confused with field experiments. This light-weight version of the test is needed for measuring risk preferences in a later-on experiment (Chapter 5), which is conducted at well frequented campus sites but, apart from the location, rather comparable to a standard laboratory experiment.

Chapter 4 presents the design, results, and implications of a study in the context of online auctions, which considers the impact of the type of the other bidders (humans or computer agents), and the bidders' behavior and emotions.[9]

Chapter 5 then focuses on the interaction among humans. Particularly, the impact of different types of relationships between the decision makers (friends or strangers) is considered. As mentioned, the experiment is conducted outside the lab. This is done to get access to different types of relationships in a natural manner. The decision situation and the empirical findings are then analyzed from a theoretical perspective by means of a game-theoretical model.[10]

Concluding this work, Chapter 6 summarizes, provides concluding remarks, and elaborates on limitations, possible extensions, and future research.

[9]Chapter 4 is based on joint research with Marc Adam and Ryan Riordan (Teubner et al., 2013): a previous version was circulated under the working title "Bidding against the Machine: Emotions in Electronic Markets."

[10]Chapter 5 is based on joint research with Marc Adam and Christof Weinhardt (Teubner et al., 2012). A previous version was circulated under the working title "Risky Choices Among Friends and Strangers: How Relationship Types Affect Ex-Ante Payoff Considerations."

Chapter 2.

Foundations

"No man is an island, entire of itself; every man is a piece of the continent, a part of the main."

(John Donne)

This chapter provides the foundations of the the broader fields of *social preferences* and *risk preferences*. In the third part, the conflation of both aspects is discussed. For that purpose, a classification framework is proposed, along which theory, experiments, and results from the literature are reviewed.

2.1. Social Preferences

This section illustrates the concept of social—or other-regarding—preferences. First, the general foundations are introduced, a brief historical outline is given and the main terms and definitions are presented. Second, the notion of reciprocity is explored in some more detail. Third, the role of emotions, particularly interpersonal emotions in economic decision making, is described briefly and a basic framework is proposed. Then, different formal models of social preferences are considered and some well-established experimental methods for the assessment of social preferences are presented. The models presented in this chapter are also used as a benchmark for explaining the experimental observations in Chapter 5. An illustrative example eventually demonstrates an application of such models.

2.1.1. Foundations

"People care about the outcomes of others." Loewenstein et al. (1989, p. 426) argued that the social context is important for beings that live in companionship with others or in a community, rather than in isolation. Thus, preferences and decisions are (to some extent) derived by evaluating social aspects. Preferences of social beings are thus necessarily social preferences, which was common sense from time immemorial: "Man is by nature a social animal" (Aristotle), or as John Donne framed it: "No Man is an Island."

Economic Approaches & Social Comparison Theory

Social preferences were studied systematically starting from the second half of the 20th century by Leon Festinger (Festinger, 1954), and, in a narrower economic sense, among others, by Hochman, Rodgers, and Becker (Hochman and Rodgers, 1969, 1974, 1977; Becker, 1974), who began to interpret functions of social welfare from an individual, rather interpersonally motivated perspective. Until then, economic redistribution was thought of as a sovereign act, imposing a necessary loss on the richer parts of society in order to maximize total welfare. Hochman and Rodgers (1969, p. 542) were concerned:

> "We believe that this line of reasoning is misleading. It implies that redistribution yields no benefits to the parties who finance it, so that from this viewpoint it imposes a simple deadweight loss. [...] If accepted, redistribution carried out by government institutions can only be explained as legalized Robin Hood activity, and redistribution through private institutions would seem to imply individual irrationality."

That is, they rejected the view that "less for oneself and more for some others" is necessarily considered pernicious for oneself, and only a broader social welfare perspective can justify this act of redistribution ("legalized Robin Hood activity"). Instead they proposed a variety of self-interested reasons why non-recipients could support redistribution, including expectations about being reliable on transfers in the future oneself, expecting (higher) profits from supported sections of the population, or the coverage of a private need (Hochman and Rodgers, 1977). They stated, however, that "the basis of nonrecipient support for redistribution programs may extend beyond simple self-interest," but do not become more explicit than saying that "nonrecipients may be concerned, for a variety of reasons, with the well-being of the poor" (Hochman and Rodgers, 1977, p. 74). While the motivational and psychological constructs behind such considerations remained mostly untouched, the ground was laid for the economic conceptual design of fairness, inequality aversion, altruism, efficiency preferences, and the like.

Until then, economists usually spoke of *households* as the atomic building blocks of an economic system. This understanding was gradually extended and shifted towards an individual, i.e. personal, and with that, behavioral perspective. This made it reasonable to think about aspects again, which had, in favor of a cleaner utilitarian approach, been deliberately excluded from the analysis. Becker (1974, p. 2, p. 32) wrote:

> "As greater rigor permeated the theory of consumer demand, variables like distinction, a good name or benevolence were pushed further and further out of sight. Each individual or family generally is assumed to have an utility function that depends directly on the good and services it consumes. This is not to say that interactions between individuals have been completely ignored. Pigou, Fisher and Panteleoni at the turn of the century included attributes of others in utility functions (but did nothing with them) [...]
> The central concept of the analysis is "social income", the sum of a person's own income (his earnings, etc) and the monetary value to him of the relevant characteristics of others, which I call his social environment."

The acknowledgment of this dimension of personality indicates that social psychology is inseparably connected with questions of distributional preferences. Becker explicitly named *charitable behavior*, *envy*, and *hatred* as possible motives. With this at hand, and the thought from above that the direct benefit (or damage) from the material conditions of others should be formally acknowledged in people's utility functions, the birth of (economic) social preferences most certainly falls somewhere into that era.

Festinger (1954) sketched an influential Theory of Social Comparison Processes, mainly building on a set of hypotheses. These were, among others, that humans exhibit a natural tendency to evaluate their opinions and abilities, they use social comparison if no objective measures are available, and that the tendency for comparison with others is stronger if the reference peer is more similar to themselves. Moreover, humans are said to constantly strive to improve their abilities, with no natural upper boundary. Whereas it is hard to change one's abilities on short call for obvious reasons, this does not hold for opinions. Where Festinger (1954) took a perspective of social psychology, the subject has also and increasingly so raised the interest of economists, accompanied by a higher degree of formalization (Loewenstein et al., 1989).

2.1.2. Distributional, Type, and Intention Based Preferences

Economic decisions are typically not made in a sterile environment. Being part of a socio-economic environment, decision makers inevitably compare their decisions with those of others: friends, co-workers—possibly collaborators—or competitors, maybe even strangers. Again, it should be clarified that the terms "social preferences" and "other-regarding preferences" are oftentimes used synonymously in the literature. The concept of social preferences is oftentimes thought of as limited to the incorporation of the economic payoffs of other people into one's utility function. This view, although accurate in many cases, is too narrow. The concept of social preferences, which is closely linked to the fields of psychology, psychological game theory and experimental economics, yields a broader perspective. Depending on the perspective, this may comprise strategic and rational considerations, other-regarding evaluations, intension, beliefs, beliefs about intentions or beliefs, reciprocal interaction, relationship types, and emotions.

The concept of social preferences, as including others' outcomes into the utility function, was used by experimental economists early on. These economists, however, mostly tried to rule out any such factors in experimental investigations. With regard to interpersonal utility criteria Smith (1976, p. 278) stated that "this kind of interdependence is effectively controlled by the experimental condition of 'incomplete' information," where *incomplete information* in this context means that subjects only learned about their own reward.

If one now assumes that another person's payoff in a particular situation *is* relevant to a decision maker for whatever reasons, it is straightforward to include this payoff into his utility function and thus base a model of rational decision making also on this value. When it comes to strategic interaction between two or more decision makers with mutually relevant payoffs, game theoretic approaches may also be extended to such other-regarding aspects by using utility values instead of raw payoffs. Section 2.1.7 provides an example in this regard.

Classical game theory may be seen as the study of strategic decision making. Rationality of the decision makers is one fundamental assumption. But, as Colman (2003, p. 139) stated, "instrumental rationality, conventionally interpreted, fails to explain intuitively obvious features of human interaction." Psychological game theory takes into account, that not only the sheer outcomes are relevant to the actors, but also the beliefs and intentions linked to those payoffs. 100 dollars for the other person may be seen as beneficial, neutral or harmful, depending on what the other person has done—or just on what one believes about the other person's plans, intentions, or prior actions.

Furthermore, people differ with regard to personality characteristics. Often, the interaction and the course of events is as important for behavior than personality. Reciprocal behavior is very common: "[...] the same people who are altruistic to other altruistic people are also motivated to hurt those who hurt them" (Rabin, 1993, p. 1281).

Distributional preferences are defined as a subset of the more general concept of social preferences. At that, decision makers with distributional preferences consider the (economic) payoffs of others besides their own payoff. Anything else, e.g., intentions, path dependence, etc. is not considered, simply the combination of "what I get" and "what you get" is evaluated. This narrow definition is favorable since it allows formalization in a practical way. Several formal approaches are considered in Section 2.1.5. In the last decades, many of such models have been proposed, sometimes giving the impression that the mathematical formulation, instead of the actual problem (which still is a research question of the social sciences), is central. At the outset of this, in the early and mid 20th century, economists used to excuse for the use of mathematical equations in their papers. "Social preferences" were a topic of anthropologists and psychologists: "It may be hard for younger economists to image, but nearly until midcentury it was not unusual for theorist using mathematical techniques to begin a substantial apology, explaining that this approach need not assume that humans are automatons deprived of free will" (Baumol, 2000, p. 23).

Fehr and Schmidt (2006) provided a summary of the development and the status quo of social preferences in economic research. They pointed out that a vast set of experiments and studies provided evidence for the existence of social preferences and that "the real question is no longer whether many people have other-regarding preferences, but under which conditions these preferences have important economic and social effects and what the best way to describe and model these preferences is" (Fehr and Schmidt, 2006, p. 618). The authors regard social preferences mainly as a contrapose to selfish behavior, i.e., subjects showing fair or altruistic behavior are denoted socially motivated, others are selfish. This, of course, omits the negatively connoted side of socially motivated, e.g., envious, spiteful, or sadistic behavior. Fehr and Schmidt (2006) distinguished between three types of social preferences from a formal perspective: *distributional*, *intention based*, and *type based* preferences.

Distributional Preferences are present when a subject cares about how the material resources, e.g. the payoffs, are allocated among him or herself and the other (relevant) subjects of the reference group. It might be important that everyone has the same, or that oneself has the largest share, but anything that cannot be expressed by means of payoff allocation is not in the scope of this type of preferences.

Intention Based Preferences, in contrast, include the fairness, or more general, the benevolence or malevolence, of the other's behavior. Since feelings about another subject's actions or intentions cannot be easily measured or formalized, this type of preferences cannot be modeled by means of standard game theory. The very same action might be regarded differently, depending on the underlying intention of the actor. Intention Based Preferences therefore require the tools of psychological game theory (Geanakoplos, 1989), conceptualizing belief-dependent motives like reciprocity, guilt aversion, regret, or shame.

Type Based Preferences, on the other hand, let subjects behave differently towards different types of counterparts, e.g., kindly towards “good,” and hostilely towards “bad” persons. In this case, not the intention of the other person’s action, which may be ambiguous, but the attributable property of the person self is the relevant factor for the game mechanics.

2.1.3. Reciprocity

As early as Stone Age, humans made use of the advantages of reciprocal good exchange. Trusting other individuals by transferring more or less valuable goods in order to receive an adequate service or good in return subsequently influenced the very organization of economy and the formation of first market forms, as well as social behavior. The rule of reciprocity, in this context, stated that “people should help those who help them” (Fogg and Nass, 1997; Milinski, 1987). In the economic literature, trust and reciprocity are often regarded as the fundamental driving forces for the evolution of cooperative behavior (Falk and Fischbacher, 2006; McCabe et al., 2003). This is in contrast to classical self-interest-theory and many models of social preferences (cf. Bolton and Ockenfels, 2000; Charness and Rabin, 2002; Fehr and Schmidt, 1999).

Table 2.1.: Classification of different channels of reciprocal behavior in groups of $n \geq 4$.

	to			
from	**A**	**B**	**C**	**D**
A	—	×	*(Self-Commitment)*	
B	*Direct*	—	*Forward*	*Forward*
C	*Reward*	*Matthew*	—	*Community*
D	*Reward*	*Matthew*	*Community*	—

A novel approach for classifying the different ways of reciprocal behavior in groups is presented here. Assume a group of $n = 4$ people[1]. These people are denoted player A, B, C, and D. Furthermore, assume that initially, A transfers some money to B or does B a favor in a broader sense. There now occur multiple ways for reciprocal behavior in the group, which can be summarized as follows:

[1]All statements hold for any number $n \geq 4$ likewise, but there occurs no additional class of action, and thus no reason to do so.

- Direct Reciprocity: B directly returns the favor or the contribution to A.
- Rewarding Behavior: Another player than B rewards A for her benevolent behavior.
- The Matthew Effect: *He that has plenty of goods shall have more.* Player B receives contributions also from other players. The initial transfer from A to B might be interpreted as a signal of B's credibility.
- Forwarding Behavior: The movie *Pay It Forward*[2] illustrated this notion: A young boy is granted a favor, and out of this, starts a ponzi-scheme-like movement, in which everyone pays forward (not back) a good deed to three new—random or known—people. B is granted a benefit and forwards this very same or any different benefit to others.
- Community Spirit: Simply observing a (successful) transaction between players A and B leads a third uninvolved player (C) to become active herself and engage a transaction with another, hitherto uninvolved player (D). This behavior can be observed in strongly committed communities and movements. The couchsurfing community (cf. www.couchsurfing.org) can be seen as an example of this community bond or loyalty.
- Self-Commitment: For the sake of completeness of this framework, another form of induced action may be considered, which typically would not be called reciprocal behavior. When initially, A grants a favor to B, and subsequently A also grants favors to an uninvolved party C or D, this behavior could be seen as motivated by self-commitment of A. A might not want to treat C or D less favorable than B and hence feels committed to help out C or D as well. The motivation for the second action might also stem from a positive utility derived from the first action.

The compilation is summarized in Table 2.1, where the × symbol indicates the initial transfer or favor from A to B.

2.1.4. Emotional Motives

> "Economists refer to the desirability of an outcome as its *utility*, and decision making is depicted as a matter of maximizing utility. This does not, however, imply that consequentialist decision makers are devoid of emotion or immune to its influence" (Rick and Loewenstein, 2008, p. 138).

[2]cf. http://www.imdb.com/title/tt0223897/, accessed May 2013.

Emotions were classically not a subject in economics. Elster (1998, p. 47) wrote that the fields of economics and psychology "seem to exist in near-complete isolation from each other." This has changed in recent years. Behavioral economics has increasingly tried to address the role of immediate and anticipatory emotions (cf. Loewenstein and Lerner, 2003) in order to understand human behavior and its effect on markets. By now, there exists a variety of different definitions and terms for emotional motives for decision making in an interpersonal context: spite, envy, similarity seeking, competitiveness, altruism, to name just a few. In order to clarify these terms for the further use in the scope of this work, this section provides a brief classification of the most common terms and relates them to the different economic scenarios. There exists a quantity of different frameworks, some of which shall be briefly presented here.

An early study aiming at decomposing the concerns for own and others' outcomes into basic motives was conducted by Scott (1972). The author distinguished between the three motives *avarice*, *altruism*, and *egalitarianism*. MacCrimmon and Messick (1976) proposed a framework of *Social Value Orientation* (SVO) considering six basic motives, namely *self-interest*, *self-sacrifice*, *altruism*, *aggression*, *cooperation*, and *competition*. Liebrand (1984) used a graphical representation for the SVO framework, which was widely used in following studies. This framework has recently been further extended by Murphy and Ackermann (2012). In particular, the SVO framework contraposes the payoffs for a decision maker and a reference person in a two-dimensional space as depicted in Figure 2.1. The decision maker has to make a (series of) binary choice(s) between different resource distributions of the form (payoff to self, payoff to other). Each of the locations on the circle characterizes a different type of social preference. A choice for the *pro-social* distribution is oftentimes also regarded as expression of an *efficiency concern*, since here the joint outcome is maximized and thus the social optimum is achieved (85, 85). In the logic of this framework, the *individualistic* distribution (100, 50) would be chosen by selfish decision makers, whereas *competitive* subjects would chose (85, 15) in order to maximize the difference between their own and the other's payoff. Despite a rather non-uniform and varying terminology, the SVO framework was widely used in different contexts aiming at expressing the same ideas.

In order to explain an experimental observation, there is a need to identify motives and emotions driving the behavior. Hence, the underlying emotional concepts of decision making in an interpersonal context shall briefly be conceptualized. Rick and Loewenstein (2008) distinguished between expected and immediate emotions, where immediate emotions are experienced as the response to an (external) event (e.g. good or bad news, a payoff, a noise, an odor, even as little as a mere thought, etc.). At the moment of decision making, a subject expects future immediate emotions and takes the set of such expected emotions and the respective probabilities into account when maximizing expected utility.

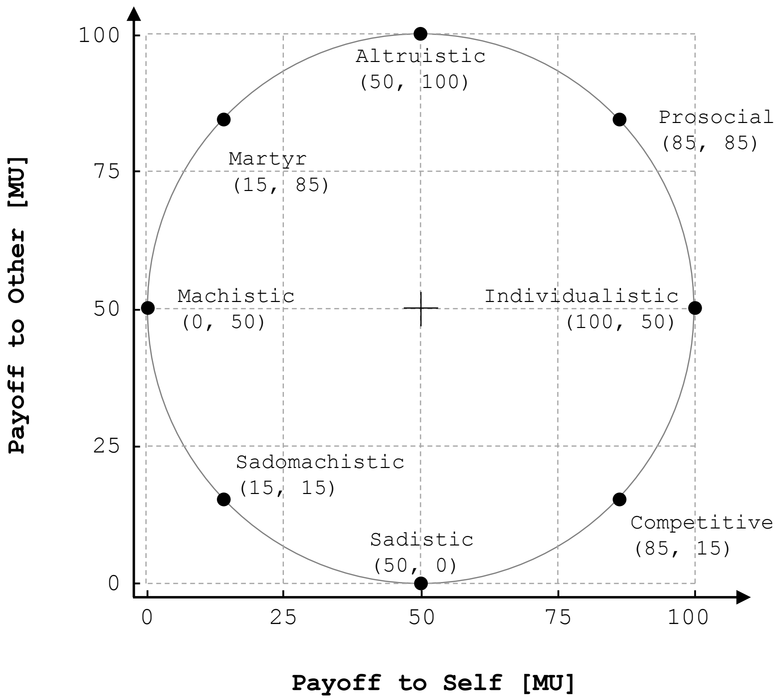


Figure 2.1.: A graphical representation of the SVO framework, based on Murphy and Ackermann (2012).

Models of experienced affect categorize emotions among the two dimensions of arousal (or involvement, or activation) and valence (cf. Russell, 1980; Watson and Tellegen, 1985; Larsen and Diener, 1992). There exist several standard measures, mostly using self-report questionnaires, for emotions and emotional motives in the literature.

With the increasing availability of neuroscience methods and tools, research has also begun to explore the neural basis of emotions and social decision making. Rilling and Sanfey (2011) presented a review on a variety of studies concerning the role of the prefrontal cortex in social decision scenarios.

Envy and Gloating. Envy is a complex but pervasive emotion (Parrott, 1991; Smith et al., 1999). Feeling envy means, that something important is missing, and this lack becomes apparent through social comparison (Smith et al., 1996). “Equity theory in psychology [...] and studies in the field of organizational behaviour all suggest that envy can play an important role in economic behaviour” (Mui, 1995, p. 311). Baumol (1982, p. 640), in the context of the distribution of a fixed bundle of outputs, wrote on envy: "A distribution, i, of n commodities is said to involve envy by individual 2 of the share obtained by individual 1 if 2 would rather have Y_{1i}, the bundle of commodities received by 1 under this distribution, than Y_{2i}, the bundle the distribution assigns to 2," i.e. that envy is only absent when no individual prefers the bundle of any other individual over her own. This is not very probably to ever happen in reality. In the literature, there exist different measures for envy, e.g. the 8-item self-report questionnaire by Smith et al. (1999), asking to indicate agreement or disagreement with statements like *"I feel envy every day."* or *"Frankly, the success of my neighbors makes me resent them."* In economic research, the role of envy has been considered formally for ultimatum games (Kirchsteiger, 1994), for allocation problems (Feldman and Kirman, 1974), for alternating-offer bargaining (Kohler, 2013; Bolton, 1991), for strategic behavior in innovation (Mui, 1995), and for the evaluation of risky prospects and outcomes (Grygolec et al., 2012; Bault et al., 2008; Coricelli and Rustichini, 2010). As a constituent part of their model of inequality aversion, Fehr and Schmidt (1999) constructed a utility function, which explicitly puts a negative weight on a negative difference to someone else's payoff, which can be interpreted as an aversion towards feeling envy. Envy may be seen as a very powerful emotions, also in terms of behavioral consequences. Regarding, material arms races among peers, as a form of such, it has found its way into proverbial usage: "Keeping up with the Joneses" refers to the comparison to one's neighbor (with the common family name "Jones") as a benchmark for social status or the accumulation of material goods.

Gloating, on the other hand, has found much less attraction in the economic literature.[3] Common web dictionaries[4] define gloating as a malicious glee, or as "contemplat[ing] or dwell[ing] on one's own success or another's misfortune with malignant pleasure." One reason for this lower prominence may be the higher ambiguity about the term. It is oftentimes used synonymously with *schadenfreude*, spite, or spitefulness. Morgan et al. (2003, p. 1), for instance, considered the effect of the spite motive in auctions, at which they explored "the consequences of a model for bidder behavior that incorporates, in addition to a utility for one's own surplus, a disutility for the surplus of a rival—interpretable as *spiteful* behavior." In fact, envy and *schadenfreude* are closely related. Smith et al. (1996, p. 167) argued that "*Schadenfreude* will result from a misfortune befalling an envied person because, for one thing, the misfortune can directly benefit the envying person" and also that "by eliminating the very basis for envy, the misfortune should supply a pleasant relief from the pain of envy." The notions are disentangled in this section.

[3] In fact, in contrast to over 89,000 hits on the search term "envy + economics," there were only 2,790 for "gloating + economics" on google scholar in May 2013.

[4] cf. www.thefreedictionary.com, www.merriam-webster.com, en.wiktionary.org/wiki/gloat.

Altruism and Sympathy. Andreoni (1990, p. 473) stated that "when people make donations to privately provided public goods, they may not only gain utility from increasing its total supply, but they may also gain utility from the act of giving." This *warm glow* from the act of giving is often referred to as a rational for altruistic behavior. Another approach to explain altruistic behavior, often pursued by socio-biologists is called "kin selection." It basically states that humans act altruistically towards others who share genes with them, since this helps (part of) their own genes to survive. "Therefore," Becker wrote, "altruism toward siblings, children, grandchildren, or anyone else with common genes could have high survival value, which would explain why altruism toward kin is one of the enduring traits of human and animal *nature*." (Becker, 1976, p. 818).

In order to experimentally measure altruistic attitude, Rushton et al. (1981) proposed a 20-item questionnaire. In this questionnaire, subjects are asked how often they faced situations, in which they altruistically helped others. These questions were formulated like *"I have given directions to a stranger"*, *"I have donated blood,"* or *"I have offered to help a handicapped or elderly stranger across a street."* Subjects indicated the frequency, choosing from *never*, *once*, *more than once*, *often*, and *very often*. Johnson et al. (1989) took a similar approach, extending this scale to 56 items.

Similarity Seeking. Similarity seeking (or inequality aversion) describes preferences, which discount utility for any difference in the payoffs between the decision maker and the reference person. In a way, these preferences thus comprise envy and the notion of having more than the other is also bad (maybe due to *shame*, or *guilt*, maybe because it violates a group harmony preference). Loewenstein et al. (1989) let their subjects evaluate different payoff allocations and found evidence for such preferences. Fehr and Schmidt (1999) proposed an influential model implementing this notion, which is described in more detail later on. With regard to the results of Loewenstein and his colleagues, the latter authors wrote "that subjects exhibit a strong and robust aversion against disadvantageous inequality: for a given own income x_i, subjects rank outcomes, in which a comparison person earns more than x_i substantially lower than an outcome with equal material payoffs. Many subjects also exhibit an aversion to advantageous inequality although this effect seems to be significantly weaker than the aversion to disadvantageous inequality" (Fehr and Schmidt, 1999, p. 821).

Emotional Motives Framework

The framework presented in this work approaches the subject from a slightly different perspective. Whereas previous frameworks considered the shift away from the reference

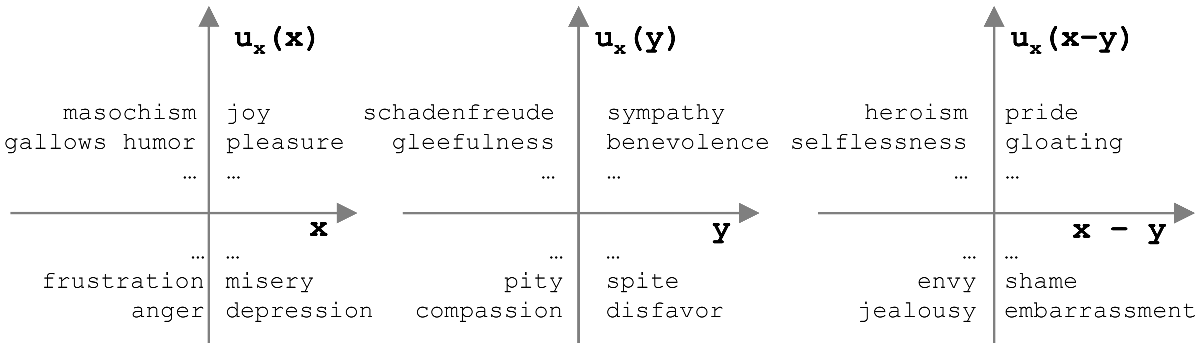


Figure 2.2.: Categorization of self-regarding, other-regarding, and relative emotions.

point of a given payoff allocation, the allocation itself and the associated emotional motives are regarded here. It is important to highlight, that the term *emotional motive* shall explicitly not denote the *emotion* triggered by a particular allocation or outcome, but rather the *underlying psychological concept* that may trigger the desire for a particular allocation in the first place. These terms are usually hard to separate, however.

A categorization of possible emotional motives due to 1) one's own payoff x, 2) another's payoff y and 3) the difference (or ratio) between x and y is formulated. Figure 2.2 attributes possible emotional motives to the sections of the diagrams—where the x-axis denotes the economic payoffs and the y-axis denotes utility or general valence, respectively. Note that this attempt to classify and label emotional motives can of course neither be exhaustive nor consummate. The first coordinate system depicts all possible combinations of own payoff (x) and emotional valence. A typical graph would have a positive slope and show positive values for positive payoffs, and negative values for negative payoffs. It could be considered a standard utility function (cf. Kahneman and Tversky, 1979).

If people derive a positive utility from payoffs, this is denoted *joy* or *pleasure*. A negative payoff is usually associated with negative, or *dis*utility, termed *frustration* or *anger* here. Some people might just be different minded and derive utility from negative payoffs (*masochism* or *gallows humor*). Then again, others may experience disutility from positive payoffs (*misery*, *depression*).

The second coordinate system depicts all possible combinations of the other's payoff (y) and one's own emotional valence. A benevolent person's chart would run from the lower left to the upper right. A positive valuation for the other's fortune is denoted *benevolence* or *sympathy*, a negative valuation for the other's misfortune *pity* or *compassion*. Other people might not be as benevolent, but feel *schadenfreude* or *gleefulness* for someone else's misfortune, or, negatively, *spite* and *disfavor* for someone else's achievement. Note that this does not consider the comparison between oneself and the reference person, but only the absolute view onto the other's payoff.

The third coordinate system depicts all possible combinations of the difference of own and other's payoff ($x - y$) and emotional valence. For positive values of $x - y$, one receives a higher payoff than the other, for negative values, one receives less. It could be assumed that most people's utility is positive for a positive difference (*pride*, *gloating*) and negative for a negative difference (*envy*, *jealousy*). However, depending on the context, it is conceivable that someone is *inequality averse* or *similarity seeking* to such a degree, that even an own surplus is regarded as deleterious. Possible explanations for this could be *shame* or *embarrassment*. Moreover, someone could regard a situation, in which he has less than the other as beneficial, out of *heroism* or *selflessness*, like a grandfather may be proud of his grandchild outperforming him in chess.

As stated before, the set of terms presented in this overview is by no means exhaustive—other traits may be included in a meaningful way. Griffin-Pierson (1990) presented a questionnaire in order to measure subjects' *competitiveness*, on both an individual and goal-directed level. Competitiveness, in contrast to the motives described here, does not constitute an emotional motive in itself, but could, in the context of this framework, rather be interpreted as the slope of an assumed function $u_x(x - y)$, running through the third coordinate system (from the lower left to the upper right) in Figure 2.2.

2.1.5. Models of Social Preferences

> "A number of social preference models have been developed in an effort to explain and organize the evidence from economic experiments. It has been found that people share with others in dictator games, reject offers in ultimatum games, cooperate in public good games, etc., all of which is in direct conflict with traditional microeconomic utility theory" (Daruvala, 2010, p. 199).

There have been quite a lot propositions for different types of social preference models in the literature. Each of these models incorporates and stresses different motives, e.g. inequality aversion, a preference for efficiency (total welfare), or the maximization of the worst off player (maximin). While some models typically perform well at explaining certain types of decisions, they fail to do so for others. Daruvala (2010), in this sense, urged: "Would the right social preference model please stand up!" Wilson (2010, p. 78) quoted three prominent articles in order to clarify what functions and models of social preferences actually are:

- "social preference functions [...] balance a person's desire to have more money with their desire to reciprocate those who have treated them fairly or unfairly, or to achieve equality" (Camerer, 2003, p. 11).
- "formal models of *social preferences* [...] assume people are self-interested, but are also concerned about the payoffs of others" (Charness and Rabin, 2002, p. 817).
- "people exhibit social preferences, which means they are not solely motivated by material self-interest but also care positively or negatively for the material payoffs of relevant reference agents" (Fehr and Fischbacher, 2002, p. C1).

This section introduces the most prevalent tractable models of social preferences with regard to distributional preferences. Such tractable models can be used to fit empirical data, and they may actually explain behavioral patterns. Typically, such models formulate a utility function $u_x(\cdot)$ for a player x, whose perspective is taken. Then by design, player x's utility does not only depend on her own payoff π_x, but also, in some way, on the payoffs of one or more other players, the reference person(s), peer(s), or peer group. Oftentimes, the general n player case is simplified to a generic 2-player scenario with players x and y. The formal utility of player x is hence denoted as $u_x(\pi_x, \pi_y)$.

Fehr and Schmidt (1999, FS) formulated the presumably most successful utility concept in terms of usage, citation[5], and circulation in the subsequent literature in their article *A theory of fairness, competition, and cooperation*. Here, in addition to the value of the own payoff, negative weights are assigned to the differences between own and the other person's payoff. This approach thus implements the concept of inequality aversion. The function is given by

$$u_x(\pi_x, \pi_y) = \pi_x - \alpha \max\{\pi_y - \pi_x, 0\} - \beta \max\{\pi_x - \pi_y, 0\}, \tag{2.1}$$

where $0 \leq \beta \leq \alpha$ and $\beta \leq 1$. An increase of the other player's payoff is only useful for x, if y has less than x: $\partial u_x / \partial \pi_y \geq 0$ if and only if $\pi_x \geq \pi_y$. Also note that having less than the other player is considered more harmful than having more ($\beta \leq \alpha$). Thus, the Fehr and Schmidt (1999) approach implements a concept of differentiated inequality aversion. Having more is different than having less. However, the question remains, why having more than a peer is necessarily considered a bad thing, causing disutility. It can easily be thought of situations, where people strive to receive more than their peers, regardless of how much it is (e.g., in competition, or among rivals). This thought will be followed in more detail in Chapter 5.

[5] Over 5,700 citations on google scholar in July 2013.

Bolton and Ockenfels (2000, BO) take a similar perspective in their influential ERC-paper (*A Theory of Equity, Reciprocity, and Competition*). Here, however, the utility model is not ultimately defined. Instead, the authors presented the principle of such a functional form and several requirements, in order to be implemented by a specific function. Stating x's utility to be given by the "motivation function"

$$u_x(\pi_x, \sigma_x), \tag{2.2}$$

where, loosely speaking, σ_x represents the relative share of x's payoffs compared to the entire reference group[6], the actual characteristic is provided by the formal requirements on u_x: weakly increasing and concave in π_x and strictly concave in σ_x, yielding a maximum at $\sigma_x = 1/N$, where N denotes the number of players. Fehr and Schmidt (2006, p. 641) noted that the utility, or motivational concepts of "Fehr-Schmidt and Bolton-Ockenfels often yield qualitatively similar results for two-player games, while some interesting differences arise with more than two players." One of the main differences between the models of Fehr and Schmidt (1999) and Bolton and Ockenfels (2000) lies in the fact that, in the latter, the player compares her share to the average share of each member of the group, i.e. only the total payoff and the number of players is relevant. In the former model, a player compares her payoff to each of the other players' payoffs. Thus, in the case of more than 2 players, a transfer of money between two other players will alter one's utility in the Fehr and Schmidt (1999) model. It will, however, not do so in the Bolton and Ockenfels (2000) model.

Charness and Rabin (2002, CR) considered a utility function of the form

$$u_x(\pi_x, \pi_y) = (1-\gamma)\pi_x + \gamma(\delta \min\{\pi_x, \pi_y\} + (1-\delta)(\pi_x + \pi_y)), \tag{2.3}$$

where $0 \leq \gamma, \delta \leq 1$. The utility of player x is driven by self-interest, as well as by a measure for social welfare. The measure for social welfare itself consists of a term that determines how much player x cares about the player with the minimum payoff (including herself), known as *maximin* preferences, and how much she cares about the total of outcomes (social welfare concerns). The parameter δ weights these terms. The parameter γ defines to what extent the player is concerned about her own payoff and how important the mentioned social aspects are to her.

In their working paper, Cox and Sadiraj (2005, CS) provided a utility function of the form

$$u_x(\pi_x, \pi_y) = \Big((1 - \theta^- \mathbf{1}_{\pi_x<\pi_y} - \theta^+ \mathbf{1}_{\pi_x \geq \pi_y})\pi_x{}^\alpha + (\theta^- \mathbf{1}_{\pi_x<\pi_y} + \theta^+ \mathbf{1}_{\pi_x \geq \pi_y})\pi_y{}^\alpha\Big)^{1/\alpha}, \tag{2.4}$$

[6] In particular, $\sigma_x = \pi_x / \sum_{i \in P} \pi_i$ if $\sum_{i \in P} \pi_i \neq 0$, and $\sigma_x = 1/N$ otherwise (P representing the set of all N players.)

where $0 < \alpha < 1$, $0 \leq \theta^- \leq \theta^+ < 1$ and $\theta^- + \theta^+ \leq 1$. They refer to the function as a modified CES (constant elasticity of substitution) utility function. The weights on π_x and π_y depend on which player receives the higher payoff.

Tan and Bolle (2006, TB) considered a utility function using a quadratic term in the payoff difference. It takes the form

$$u_x(\pi_x, \pi_y) = \pi_x + a\pi_y - \frac{b}{2}(\pi_x - \pi_y)^2, \tag{2.5}$$

with no further restrictions on the parameters a and b, respectively. The parameter a represents the concern for the other player's outcome in an altruistic or spiteful way. If $b > 0$, the third term refers to a quadratic inequality aversion, whereas $b < 0$ indicates a quadratic desire for inequality, regardless of which player is better or worse off.

Cox et al. (2007, CFG) considered a modified CES function, defined by

$$u_x(\pi_x, \pi_y) = \begin{cases} \frac{1}{\alpha}(\pi_x^\alpha + \theta\pi_y^\alpha), & \text{if } \alpha \in (-\infty, 1] \setminus \{0\} \\ \pi_x \pi_y^\theta, & \text{if } \alpha = 0 \end{cases} \tag{2.6}$$

where $\alpha \in (-\infty, 1]$. Again, the structure of this function is generic: It allows for altruism as well as resentment, depending on the sign of θ. An overview is provided in Table 2.2.

Engelmann and Strobel (2004) presented a general view on different utility models, applying them to the data of one-shot distribution experiments, conducted in the classroom. They considered the role of efficiency concerns, maximin preferences, and inequality aversion. The different allocations to choose among were set up in a way that would lead different theories to different predictions. They found that efficiency concerns and maximin preferences did well at rationalizing their empirical data. Since the Fehr and Schmidt (1999) model is in line with maximin preferences, they concluded, it did better in rationalizing the data than the ERC model by Bolton and Ockenfels (2000). Bolton and Ockenfels (2006) responded that in other experiments—using a vote about the allocation in their case—the willingness to pay for efficiency was low, whereas there was considerable demand for equity. To conclude this section, Bolton and Ockenfels (2006, p. 1910)'s closing remark puts it splendidly:

> "In closing, we would say that the test for social preference theory is not so much whether the model is *true*, but rather whether the model can usefully organize important behavioral patterns and economic phenomena (in the sense of Alvin E. Roth, 1996)[7]."

[7] Roth, Alvin E. 1996. "Individual Rationality as a Useful Approximation: Comments on Tversky's 'Rational Theory and Constructive Choice'." In *The Rational Foundations of Economic Behavior:*

Table 2.2.: Selected models of other-regarding preferences, π_x: own payoff, π_y: other person's payoff.

model	**utility function** $u_x(\pi_x, \pi_y) =$	**parameters**
FS 1999	$\pi_x - \alpha\max\{\pi_y - \pi_x, 0\} - \beta\max\{\pi_x - \pi_y, 0\}$	$0 \leq \beta \leq \alpha$, $\beta \leq 1$
BO 2000	$u_x(\pi_x, \sigma_x)$	$\sigma_x \sim \pi_x / \sum_{i \in P} \pi_i$
CR 2002	$(1-\gamma)\pi_x + \gamma(\delta\min\{\pi_x, \pi_y\} + (1-\delta)(\pi_x + \pi_y))$	$0 \leq \gamma$, $\delta \leq 1$
CS 2005	$((1 - \theta^- \mathbf{1}_{\pi_x < \pi_y} - \theta^+ \mathbf{1}_{\pi_x \geq \pi_y})\pi_x{}^\alpha$ $+(\theta^- \mathbf{1}_{\pi_x < \pi_y} + \theta^+ \mathbf{1}_{\pi_x \geq \pi_y})\pi_y{}^\alpha)^{1/\alpha}$	$0 < \alpha < 1$, $0 \leq \theta^+ < 1$, $0 \leq \theta^- \leq \theta^+$, $\theta^- + \theta^+ \leq 1$
TB 2006	$\pi_x + a\pi_y - \frac{b}{2}(\pi_x - \pi_y)^2$	$a, b \in \mathbb{R}$
CFG 2007	$\begin{cases} \frac{1}{\alpha}(\pi_x^\alpha + \theta\pi_y^\alpha), & \text{if } \alpha \in (-\infty, 1] \setminus \{0\} \\ \pi_x \pi_y^\theta, & \text{if } \alpha = 0 \end{cases}$	$\alpha \in (-\infty, 1]$

2.1.6. Experimental Measurement of Social Preferences

In order to illustrate how existence and effect of social preferences can be measured experimentally, the most common standard games are presented in this section. Two of those games, namely the Ultimatum Game and the Dictator Game, shall be presented in more detail, since they are particularly simple and illustrative.

The Ultimatum Game (UG) was initially presented by Güth et al. (1982). The UG is a 2-player game with two stages. In stage 1, Player A (the proposer) makes an offer about the split of a fixed amount of money M (e.g., $M =$ €10) to Player B (the responder), e.g., €8 for A, €2 for B. Then in stage 2, Player B decides whether to accept or to reject the offer. If B accepts, both players receive the amounts as proposed by A. If B rejects, both players receive nothing.

From a classical economic perspective, A should offer the minimum possible amount, which would be accepted by B, since any $\epsilon > 0$ is still better than nothing. This, however, is not what is found empirically and what would also not be quite consistent

Proceedings of the IEA Conference held in Turin, Italy, ed. Kenneth Arrow, Enrico Colombatto, Mark Perlman, and Christian Schmidt, 198–202. London: Palgrave Macmillan.

with one's intuition. Player B has some control and power in this game—which is to eliminate all payoffs—and this power should typically be paid off. Also do people apparently care about fairness. A and B are equal for the time being. Then why should one receive more than the other, if the roles are assigned purely randomly? For this reason, unfair offers are punished, which in turn is anticipated by the proposer. But this argument also works the other way around. If the roles are not assigned randomly, but the proposer earns his or her position by, for instance, a high performance in a real effort task, he or she feels "entitled" to keep a larger share of the pie, which is also accepted by the responder (e.g., Frey and Bohnet, 1995).

The UG has been played many times and has been varied in almost every possible way since 1982. Hence, the empirical evidence is large and not entirely consistent. There are, however, some overarching trends: Modal and median offers typically lie around 40 to 50 percent of the stake size M. The average offer is typically between 30 to 40 percent of M. Hardly any offers fall into the regions below 10 percent or above 50 percent (hyper-fair) of M. Offers below 30 percent are increasingly rejected; that is to say about half of the time for offers below 20 percent (cf. Camerer, 2003, pp. 48–59). The most important methodological design variables are *repetition*, *stake-size*, *anonymity*, and *experimenter blindness*. For a detailed description of the UG results, also including demographic factors such as *gender*, *race*, *age*, *academic major*, *beauty*, and structural variables such as *identity*, *communication*, *competition*, *outside options*, *information*, *number of players*, etc., as well as *culture*, see Camerer (2003).

The UG is often referred to as an illustrative example of fairness preferences. Player B has the ability to punish unfair offers, which leads A to carefully contemplate how much to offer. The game is often mistaken for revealing fairness preferences on the part of Player A, which is not necessarily true. As outlined above, offering an amount around 50 percent of the stake may be the best strategy for a purely selfish decision maker A, when assuming fairness preferences for B.

A physical version of the Ultimatum Game was conducted by Kaiser et al. (2012), using bonobos and chimpanzees as experimental subjects. The first ape was able to propose a split of 10 grapes by physically moving the grapes with a paper strip. The second ape then was able to pull a bar, which made the grapes (as divided before) accessible for both apes. Kaiser et al. (2012) observed that bonobos and chimpanzees were entirely insensitive to unfairness. The proposer always took as many grapes as possible—and the responder basically always accepted. Even when the proposer took all grapes for himself, the responding ape accepted this zero-offer in about 40 percent of the time.[8]

[8] In other experiments, however, monkeys appear to have distributional preferences and reject what they regard as unfair offers or allocations made by the experimenter (Van Wolkenten et al., 2007). When fed with pieces of cucumber as reward for a simple task (handing over a stone to the experimenter),

The Dictator Game (DG) was initially presented by Kahneman et al. (1986). The DG is a 2-player game with only one stage and only one active player. The active player (the so called dictator) decides about the division of a fixed amount of money M (e.g., $M =$ €10) between herself and the other (passive) player. The passive player does not have any strategic power whatsoever and merely receives the money allocated to her. Forsythe et al. (1994) stated that, in view of the results of Ultimatum Games, fairness cannot fully explain these results, since the amounts offered in the DG are significantly smaller and a much higher share of the participants offers nothing at all. Similar to the UG, DGs have been executed and varied many times. Engel (2011) presented a meta study on Dictator Games and identified overarching positive effects on contribution for conditions, in which the recipient is deserving or has earned the money. Moreover, old age and the presence of multiple recipients has a positive effect, whereas students and children tend to give less. Also repetition and concealment have negative effects on contribution. He found an overall contribution rate of 28.35 percent, where 36.11 percent of all subjects gave nothing, and 16.74 percent gave half of the pie.

Besides Ultimatum and Dictator Game, commonly used standard experiments are the Trust Game, the Gift Exchange Game, and the Public Good Game, or versions of these types. Levitt and List (2007) provided a compact description and overview on these games, which is presented in Table A.1 in the Appendix.

2.1.7. Application Example of Social Preferences

In order to illustrate the thought of social preferences and also the formalization, consider the example of the following game: Two players X and Y are endowed with 100 monetary units (MU) each. They now have to simultaneously decide on whether to keep this endowment for themselves (keep) or to transfer it to the other player (transfer). The amount transferred is multiplied by an efficiency factor $r > 1$ and credited to the other player. Let this factor be $r = 1.4$ for this example. This game represents a prisoners' dilemma (PD). From the game theoretic perspective, the classical PD occurs in many situations such as public goods, syndicates, arms races, climate debates, or mutual gift exchange as outlined here, etc. Each of the players has a dominant strategy, which means that—given the other player's action—it is always best to pursue this strategy. In this case, the dominant strategy is to keep the money. Both players then end up with their

everything is fine until another monkey—the peer—which was rewarded cucumber before as well for the exact same task, receives the more valued grapes instead. The first monkey, which observed the peer and its reward, then refuses the chunks of cucumber and demonstrates its discontent with this unequal treatment. Assuming that cucumber is still valued higher than no food at all, this expression is made even at a cost (http://www.ted.com/talks/frans_de_waal_do_animals_have_morals.html).

initial endowment. This holds for both players symmetrically. The resulting equilibrium is pareto-inferior, meaning that there would be another situation, in which both players would be better off, namely, if they transferred their endowment. They would then both end up with 140 MU. This situation, however, is not stable: then again, both players have an incentive to deviate, i.e. to keep their endowments, and thereby achieve a higher payoff individually. But this thought is followed by the other player, too. So eventually, they end up in the inferior but stable Nash equilibrium (see Figure 2.3(a)).

Player A \ Player B	keep	transfer
keep	$\boxed{100}$ $\boxed{100}$	240 0
transfer	0 240	140 140

(a) Payoff matrix for the initial prisoners' dilemma.

Player A \ Player B	keep	transfer
keep	$\boxed{20}$ $\boxed{20}$	240 -192
transfer	-192 240	$\boxed{252}$ $\boxed{252}$

(b) Utility matrix for the prisoners' dilemma with social preferences.

Figure 2.3.: Game structure of a prisoners' dilemma with and without the consideration of social preferences.

Social preferences come into play when it is acknowledged that not only the own (monetary) payoff might be relevant to a player, but also the payoff of the respective other. On that score, it is necessary to consolidate both own and other's payoff into a single value of utility. Let this function be $u_x(\pi_x, \pi_y) = \pi_x + a_{xy}\pi_y$, where π_x and π_y denote the payoffs of players X and Y. How the other's payoff is evaluated will usually depend on the relationship between A and B, their intentions, the history of actions, personalities, etc. Roughly following the proposition made by Rabin (1993), this aspect is captured by the factor a_{xy}. Assume that a player derives a positive utility from the other player's payoff, if (and only if) this other player decided to transfer her money. The emotion associated could be sympathy for the goodwill of the other player ($a_{xy} > 0$). Analogously, a player derives a negative utility from the other player's payoff, if this other player decides to keep her endowment. This can be interpreted as a disfavor, grudge or spitefulness in response to the other's non-benign action ($a_{xy} < 0$). In particular, let the factors by which the other's payoff is weighted be $a_{xy} = 0.8$ for the positive, and $a_{xy} = -0.8$ for the negative relationship, respectively. Now, the payoff structure of the game is transferred into a utility structure, so that the other player's payoff is taken into account, conditioned by the other player's action.

The new matrix is shown in Figure 2.3(b). There are now two Nash equilibria, which are (keep, keep) and (transfer, transfer). Given what the other player does, it is now always best to act likewise.[9] This example shows in a very simplified manner that the concept of social preferences is able to capture and rationalize actual behavior.

2.2. Risk Preferences

This section illustrates the concept of risk preferences. First, the general foundations are introduced, a brief historical outline is given and the main terms and definitions are presented. At that, first the concepts of risk, expected utility, Prospect Theory, and some characteristics of risk preferences are explained. Second, different methods of experimental risk preference elicitation are presented, with an emphasis on the Holt and Laury (2002) test.

2.2.1. Foundations

> "Most decisions, including decisions of economic importance, entail an element of risk, because the consequences of alternative courses of action are rarely known with certainty. Thus decision making under risk is a central topic in economics" (Rick and Loewenstein, 2008, p. 140).

A risky decision is characterized by the existence of at least one decision alternative, of which the outcome is not determined beforehand. In contrast to ambiguous situations, however, the probabilities of different scenarios are known—or can at least be assumed (cf. Laux et al., 2012). Such a risky choice alternative is usually denoted as *lottery*, or *prospect*. In the context of economics, the results of such prospects are typically expressed in monetary units, the *payoffs*. A decision maker faced with a choice between a prospect and a certain outcome (or several prospects) can—for instance—derive the

[9] This concept is often referred to as *reciprocity*. Teubner et al. (2013) showed within the context of an online gift exchange game (which constitutes a repeated prisoners' dilemma), that people tend to reciprocate, in particular when it is made possible on a 1:1 basis rather than on a group level. A positive action towards oneself or the group is rewarded, whereas negative actions are punished. In reality, not every PD necessarily ends in the inferior situation, as predicted by standard economic theory. Promotive circumstances such as repeated play, adequate framing, communication, outside options, the possibility to punish or reward, or, as was shown here, the provision for social preferences enables deeper insights into the mechanics of interpersonal strategic decision making and provides an explanation for how the dilemma situation can be resolved.

decision by evaluating the expected values of the different prospects and comparing them to the certain payoffs. Consider the following, simple choice problem: A decision has to be made between one of the two options A and B, which are defined as

- Option A: €0,
- Option B: winning €100 with a probability of 50%, losing €100 with a probability of 50%.

In case the risky option B is chosen, the 50% chances are implemented by a flip of a fair coin. The safe option A entails an (expected) value of $EV_A = 0$ (EUR), since this *is* the actual certain payoff. The second, risky option B entails an expected value of $EV_B = 50\% \times 100 + 50\% \times (-100) = 0$ (EUR), too. A risk averse decider will (rationally) choose option A, in order to avoid the risk of losing money. A risk seeking decider, however, will (rationally) choose option B, hoping for the favorable outcome to be realized. A risk neutral decision maker is indifferent between both alternatives.

Utility, Expected Utility, and Prospect Theory

It can be assumed that actual people do evaluate risky alternatives not only by comparing expected values, i.e. completely regardless of any notion of risk. This can be illustrated by a simple example, which is commonly known as the *St. Petersburg paradox*, named after a presentation given by Daniel Bernoulli in St. Petersburg in 1738 (Bernoulli, 1738).[10] Consider the following single player lottery game: A fair coin is tossed again and again until it shows tails. The pot starts at €1 and is doubled in every round (1, 2, 4, 8, 16, ...). The player wins whatever is in the pot when the game ends. So the profit is €1, if the first coin toss is tails, of which the probability is $p_1 = \frac{1}{2}$. The profit is €2, if the first toss is heads and the second toss is tails ($p_2 = (\frac{1}{2})^2 = \frac{1}{4}$), and so on. The expected value of this lottery game is given by

$$\begin{aligned} EV &= \sum_{i=1}^{\infty} 2^{i-1} (\frac{1}{2})^i && (2.7) \\ &= \sum_{i=1}^{\infty} \frac{1}{2} && (2.8) \\ &= \infty. && (2.9) \end{aligned}$$

The expected profit is infinitely high. A rational player would hence be willing to pay any ever so high price to participate in that lottery. This outcome, however, is neither

[10] The problem actually was described earlier by Daniel Bernoulli's cousin Nicolas Bernoulli in a letter to Pierre Raymond de Montmort in 1713 (cf. Bernoulli, 1738).

in line with common intuition, nor does it match any empirical observation—therefore it is called a paradox. As a criterion for the decision, Bernoulli suggested to use the *utility* of the payoff, instead of the payoff itself. Bernoulli actually came back to a thought expressed by Gabriel Cramer[11] in a letter to Bernoulli's cousin Nicolas in 1728, who stated:

> "The paradox consists in the infinite sum which calculation yields as the equivalent which A must pay to B. This seems absurd since no reasonable man would be willing to pay 20 ducats as equivalent. You ask for an explanation of this discrepancy between the mathematical calculation and the vulgar evaluation. I believe that it results from the fact that, *in their theory*, mathematicians evaluate money in proportion to its quantity while, *in practice*, people with common sense evaluate money in proportion to the utility they can obtain from it."

Hence, a decision maker would select the option entailing the highest expected utility. In that sense, already Bernoulli assumed rational behavior. This *Expected Utility Theory* (EUT) was further developed and axiomatically formalized by von Neumann and Morgenstern (1944). Given a decision maker has a utility function of certain properties and acts rational, it would be possible to predict the actual (and optimal) behavior. Note that von Neumann and Morgenstern did not claim that any decision maker would aim at maximizing their utility function consciously, only the general existence of such a function.

Before presenting the basic axioms, the concept of a lottery must be generalized. A lottery in the sense of von Neumann and Morgenstern is a vector of n outcomes v_i ($i \in \{1, ..., n\}$), all of which can be assigned a certain probability of incidence p_i. This vector includes all possible alternatives, i.e. the probabilities sum up to $\sum_{i=1}^{n} p_i = 1$. The outcome of lottery can itself be another lottery. The expected value of a lottery L is thus given by $EV(L) = \sum_{i=1}^{n} p_i v_i$. The main von-Neumann-Morgenstern axioms concern the preference relation among lotteries, where either lottery M is preferred to lottery L ($L \prec M$), lottery L is preferred to lottery M ($L \succ M$), or the decision maker is indifferent between L and M ($L \sim M$). The four main axioms are presented in the following (cf. also Laux et al., 2012, pp. 121ff).

Completeness $L \prec M, L \succ M$, or $L \sim M$. For any two lotteries L and M, exactly one of the relations "is better", "is worse", or is "equal" holds, i.e. the choice alternatives can be ordered completely.

[11] Gabriel Cramer, born in Geneva, Switzerland, mathematician, 1704–1752.

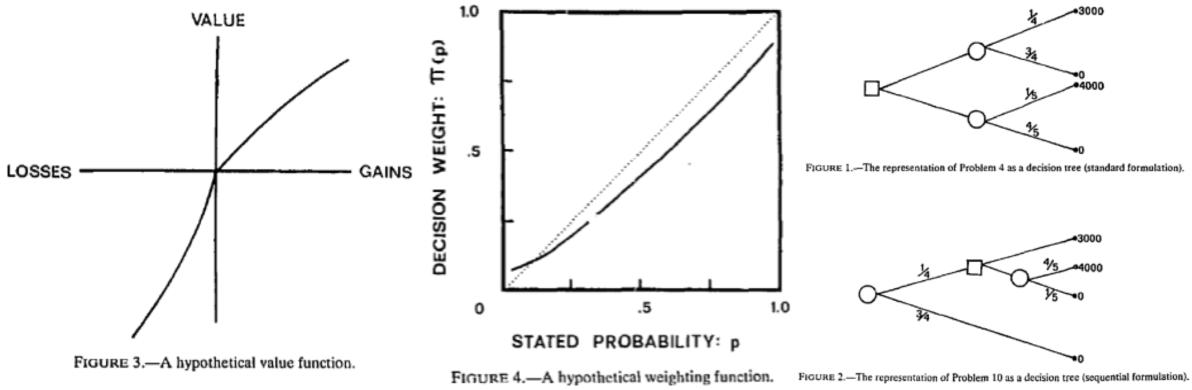


Figure 2.4.: Figures from the Kahneman and Tversky (1979) Prospect Theory paper, illustrating the utility functions for gains and losses, probability weighting, and the isolation effect in multi-stage prospects.

Transitivity $L \prec M$, and $M \prec N \Rightarrow L \prec N$, i.e., if M is preferred over L, and N is preferred over M, then N is necessarily also preferred over L.

Continuity $L \prec M \prec N \Rightarrow \exists p \in [0,1]$ with $M \sim pL + (1-p)N$, i.e., any lottery, in terms of preference, can be replicated by a linear combination of a better and a worse lottery.

Independence $L \prec M \Rightarrow \forall N, p \in (0,1], pL + (1-p)N \prec pM + (1-p)N$, i.e., the preference relation holds independently of the existence of another (irrelevant) outcome.

In the 1970's, psychologists and economists used the concept of (tractable) utility functions to explain real human behavior (in a positivistic way), rather than to derive theoretically optimal decisions (normative approach). Daniel Kahneman and Amos Tversky developed a comprehensive theory of decisions involving risk (Kahneman and Tversky, 1979). Their seminal *Prospect Theory* paper (and later on *Cumulative Prospect Theory* (CPT), Tversky and Kahneman, 1992) extended the classical Expected Utility Theory by the concepts of reference points, probability weighting, path isolation for multi-stage prospects, and a more differentiated view on gains and losses. The authors showed that one of the major heuristics people apply in decisions under risk is to evaluate payoffs as gains or losses, relative to a reference point (cf. Figure 2.4, diagram on the left hand side). Endowing someone with €1000 and then asking to choose among the prospects A_1 (€1,000, 0.50) and B_1 (€500) will result in different choices than endowing someone with €2000 and then asking to choose among the prospects A_2 (€-1,000, 0.50) and

B_2 (€-500). Most subjects, as Kahneman and Tversky showed, chose B_1 in the first problem, and A_2 in the second, exhibiting "risk aversion for positive prospects and risk seeking for negative ones." In summary, the authors proposed that the subjective value function for most individuals is "(i) defined on deviations from the reference point; (ii) generally concave for gains and commonly convex for losses; (iii) steeper for losses than for gains" (Kahneman and Tversky, 1979).

Also it was shown that people tend to handle probabilities in a systematically skewed way. This probability weighting, formalized by a weighting function $\pi(p)$, rationalizes behavior involving probabilities close to 0 or 1, where small probabilities are systematically overestimated ($\pi(p) > p$ for small values of p) and high probabilities are systematically underestimated (cf. Figure 2.4, diagram in the center). In addition, the authors describe a *subcertainty* effect, stating that people tend to assign less than 100 percent of probability in total when evaluating combinations of prospects ($\pi(p) + \pi(1-p) < 1$).

Finally, path isolation shall be outlined here in some more detail. Consider, for this purpose, a two-stage game as given by Kahneman and Tversky (1979). In the first stage, there is a 75 percent chance that the game ends and there is no payoff. Only if the second stage is reached (25 percent), the decision maker has the choice between the two prospects (€4,000, 0.80) and (€3,000), whereat the choice must be made before the game starts. Clearly, in this game, one actually has the choice between the two prospects (€4,000, $0.80 \cdot 0.25 = .20$) and (€3,000, $1.00 \cdot 0.25 = 0.25$). The authors showed that people tend to ignore the first stage of the game and treat the decision problem as if they already reached the second stage.

Utility Functions and Risk Preferences

In order to derive a utility value from a payoff value, a functional relation is constructed. Bernoulli suggested a logarithmic function for discounting excessively high payoffs. As the small example from above shows, a decision maker's individual risk preference is implicitly determined by the curvature of the underlying utility function. Concave functions yield risk aversion, convex functions yield risk seeking behavior. Linear functions represent risk neutrality. Clearly, it is conceivable that a decision maker's utility function is convex in some parts, whereas it is concave in other parts. The risk preference then depends on the stakes involved in the decision situation. Typically, humans are more risk averse for higher stakes (Who would sacrifice a certain gain of €1,000,000 for a 10 percent chance on €10,000,000?). On the other hand, small stakes often support risk seeking behavior: A certain payoff of €1 might just not be seen as useful because the equivalent spending power is limited, while €10, however, would indeed be more useful. As a result, the 90 percent risk of losing the certain €1 is accepted here more often (Holt and Laury, 2002).

The curvature of a function $u(x)$ at x is mathematically defined by the second derivative $u''(x)$. For $u''(x) > 0$, the decision maker is risk seeking at x, for $u''(x) < 0$ the decision maker is risk averse. Thus, the second derivative comes handy to characterize risk attitude, it has, however, a major drawback. The positive linear transformation $v(x) = a \cdot u(x) + b$ will transform the second derivative, yielding $v''(x) = a \cdot u''(x) \neq u''(x)$. This is particularly problematic, since the positive linear transformation of a utility function does *not* alter the preference order as specified by the axioms in Section 2.2.1. Thus, the second derivative as a measure of risk preference does not meet the implications of this characteristic, since it yields different values. In order to ensure comparability, the second derivative can be normalized. Doing so, Pratt (1964) and Arrow (1971) independently developed a measure of absolute risk aversion (ARA), defined as

$$ARA(x) \quad = \quad -\frac{u''(x)}{u'(x)}. \tag{2.10}$$

For positive values of $ARA(x)$, the decision maker is risk averse, negative values indicate risk propensity. The $ARA(x)$ is a measure of the absolute amount of wealth a decision maker is willing to expose to risk as a function of her reference point (e.g., current wealth or credit account). Decreasing absolute risk aversion implies that this amount increases as wealth itself increases. Constant absolute risk aversion remains unchanged as wealth increases or decreases. If the measure of risk aversion is supposed to consider the potential changes in wealth (e.g., the lottery payoffs) relatively to the reference point (the pre-existing credit account), the Arrow-Pratt measure of relative risk aversion (RRA) can be used. It is defined as

$$RRA(x) \quad = \quad -\frac{u''(x)}{u'(x)} \cdot x. \tag{2.11}$$

In order to illustrate the difference between these two measures, consider the following case. There are two decision makers A and B with the exact same utility function $u(x) = \sqrt{x}$ $(x \geq 0)$. Thus, both A and B are risk averse, since the root function is concave at any $x > 0$. The measures of $ARA(x)$ and $RRA(x)$ can easily be derived. The first and second derivative of $u(x)$ are $u'(x) = 0.5 \cdot x^{-0.5}$ and $u''(x) = -0.25 \cdot x^{-1.5}$, respectively. This results in $ARA(x) = \frac{1}{2x}$, and $RRA(x) = 0.5 (= \mathit{const.})$. Note that $RRA(x)$ does not depend on x, i.e., it is constant. This implies Constant Relative Risk Aversion (CRRA), which means that the decision maker shows the same degree of risk aversion, if the ratio of money at risk at wealth is constant. Also note that $ARA(x)$ is strictly decreasing in x, i.e., the decision maker becomes less risk averse for a given

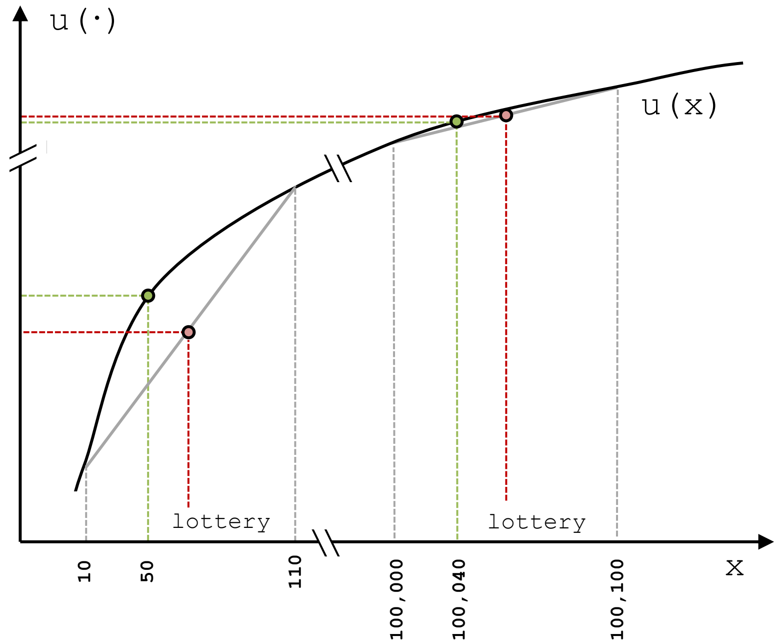


Figure 2.5.: Stylized utility function with decreasing Absolute Risk Aversion.

prospect if the reference level of wealth increases. Now, let A possess a credit balance of €10, while B possesses a credit balance of €100,000, see Figure 2.5 for a stylized illustration. Looking at the measure of Absolute Risk Aversion, A obtains a value of $ARA_A(10) = 0.05$, whereas B obtains a value of $ARA_B(100,000) = 0.00001$, which is much closer to 0, i.e., closer to risk neutrality. Therefore, in terms of absolute risk aversion, A is more risk averse than B towards the same prospect. A concrete decision situation illustrates this. Both decision makers face the choice of either receiving €40 with certainty (safe option S) or playing a 50:50 gamble for €100 or €0 (risky option R). Recall that both players are risk averse. In the case of identical expected values, both players would always prefer the safe option. The risky option, however, yields a higher expected value than the safe option ($EV_R = 50 > 40 = EV_S$). From an outside perspective, decision maker A faces a much "riskier" choice than B since the absolute amount of €40 or €100 is much higher compared to the respective endowments, or in other words, the relative share at risk is larger. The utility function (of both decision makers) does account for this, since it yields decreasing absolute risk aversion. Decision maker A compares a certain payment of €40 with the 50:50 gamble for €100, and because the initial endowment is €10, the respective utility values are $u(40 + 10) = 7.071$, $u(0 + 10) = 3.162$, and $u(100 + 10) = 10.488$. The *expected* utility value of the lottery amounts to $\frac{1}{2}u(10) + \frac{1}{2}u(110) = 6.825$, which is smaller than the utility of the certain payoff. Decision maker A will hence choose the safe payoff. Decision maker

B conducts an analogous calculation and obtains the values $u(100,040) = 316.291$, $u(100,000) = 316.228$, and $u(100,100) = 316.386$. The expected utility of the lottery thus is 316.307, which is (slightly) higher than the utility of the certain payoff. He will thus choose the lottery.

Utility functions with Constant Absolute Risk Aversion (CARA), such as

$$u(x) = 1 - \exp(-\alpha x), \tag{2.12}$$

yield a constant value for $ARA(x) = \alpha$ with respect to x. Any, ever so rich decision maker with this utility function will evaluate a given prospect identically. The concept of Constant Relative Risk Aversion implies decreasing Absolute Risk Aversion and thus implements the thought that the reference point does matter to some extent. The decision problem from the example above would have to be a choice between a certain payoff of €400,000 and a 50 percent chance on €1,000,000 for B, in order to put him into the exact same position as A. Utility functions with Constant Relative Risk Aversion rationalize that millionaires bet €100 chips on single numbers on roulette tables in the casino, whereas ordinary people do not—although the game and the chances are the same for both. Utility functions with Constant Absolute Risk Aversion disregard of this.[12] The concept of CRRA works likewise for risk aversion and risk propensity. This, and the fact that utility functions with CRRA are mathematically comparatively easy to handle, has contributed to a vast proliferation in economic models and in the literature. One of the most simple and adoptable functions satisfying the CRRA property is

$$u(x) = x^{1-r}, \tag{2.13}$$

where the parameter $r \in (-\infty, 1)$ represents risk preference, and $RRA(x) = r$. The decision maker is risk seeking for $r \in (-\infty, 0)$ (convex function), risk neutral for $r = 0$ (linear function), and risk averse for $r \in (0, 1)$ (concave function). In experimental economics, it is often demanded to elicit information about the risk preferences of the decision makers, i.e. to gain information about the individual parameters r. For this purpose, a whole variety of standardized risk preferences tasks has been developed in the last decade, some of which are presented in the following section.

Utility of Facing Risk. There is another, complementary view on risk preferences. People might derive utility, e.g., in form of thrill, fun, or excitement, from participating in

[12]It must be pointed out that betting money in a casino implies risk propensity in the first place, since the expected value of any game is (at best) slightly negative, which is easily proven mathematically, but even more so empirically. Essentially, casinos would simply not exist if the odds were not in their favor.

lotteries or risky decisions per se. This fixed extra utility may overlay the utility derived from the monetary payoffs and expected values of the lottery, which could substantiate the common finding that people show to be generally risk averse, but oftentimes risk seeking if the stakes are sufficiently small. This "attraction to chance" has been shown to be particularly present when the decision about the degree of risk is in the subject's hands (Albers et al., 2000). Adam and Kroll (2012) related the attraction to chance effect to physiological correlates of the decision makers' expected emotions. The latter observed that receiving the low payoff in a standard lottery (with no say in the degree of riskiness) causes negative emotions whereas it does not for lotteries of the form $(0.5, S+X; 0.5, S-X)$, where S represents a fixed amount and X is the decision variable.

2.2.2. Risk Preferences Elicitation

Eliciting subjects' risk aversion is necessary to establish a theoretical benchmark for what could be the "correct" behavior of a subject in a particular decision situation. This notion naturally assumes that subjects actually *have* preferences regarding risk and in particular the trade-off between risk and expected value. Additionally, it is assumed that these preferences are stable at least short term. Eventually, the preferences must be assumed to be transferable from the control situation (e.g. the risk aversion task) to the actual focus decision. The latter can typically not be guaranteed: specifically risk preferences are known to vary among different domains such as health, financial issues, or social behavior (cf. Dohmen et al., 2011).

There are different ways to elicit subjects' risk preferences in the domain of the social sciences, and experimental economics. Sometimes, people are simply asked to describe their risk preference with their own words as, for instance, Dohmen et al. (2011) did for the different domains in a large-scale survey. This method, naturally, is prone to systematic biases. Subjects might just lie and state a wrong preference, simply because there is no reason not to (lack of incentives), or because their actual attitude might not occur socially desirable to them.

Another method is to elicit the willingness to pay for different lotteries by mechanisms such as Vickrey auctions, and thus gain information about the height of the certainty-equivalent (cf. Harrison et al., 2007). Other methods put the decision maker on the spot of choosing one of two or more prospects for themselves. In multiple price list (MPL) designs, this is done repeatedly, whereat the probabilities are held fix and only the related payoffs change (e.g., Binswanger, 1980), or, conversely, the payoffs are held fix and only the probabilities change (e.g., Holt and Laury, 2002). This method is widely-used among experimental economists, and will be discussed in more detail in Chapter 3.

Another class of tests lets the decision maker choose the desired level of risk on a (pseudo) continuous scale. The "bomb" risk elicitation task (BRET) by Crosetto and Filippin (2012) lets the decision maker choose how many (k) of 100 buckets he or she wants to collect. Every bucket pays a certain amount of money γ. One (random) bucket, however, contains a bomb. In case it is among the chosen buckets, the payoff is zero. The probability of not hitting the bomb, when collecting k buckets, is $p(k) = 1 - k/100$. The expected value of choosing k buckets becomes $EV(k) = k\gamma p(k) = \gamma(k - k^2/100)$, which has a maximum at $k^* = 50$. A higher or lower k will decrease the expected payoff, eventually being zero for 0 or 100 buckets. The BRET is similar to the Columbia Card Task (CCT) by Figner et al. (2009).

Another method is presented by Eckel and Grossman (2008). Subjects are asked to chose one of five prospects, whereas each prospect represents a 50:50 gamble between a high (h) and a low (l) payoff. In the no-loss framing, the payoffs (in US$) of the five prospects are $l_1 = 16, h_1 = 16$, $l_2 = 12, h_2 = 24$, $l_3 = 8, h_3 = 32$, $l_4 = 4, h_4 = 40$, and $l_5 = 0, h_5 = 48$. The expected value is increasing linearly from $EV_1 = 16$ to $EV_5 = 24$, and so is the level of risk.

The Holt and Laury (2002) risk aversion task "has been widely implemented in recent laboratory experiments and involves a relatively transparent task," (Harrison et al., 2007, p. 437). It can, from a practical point of view, be regarded as the standard procedure for risk preference elicitation in experimental economics. It is therefore chosen as a reference for grounding risk preferences in the scope of this work and considered in more detail in the following.

The Holt & Laury Risk Aversion Test. In their influential paper, Holt and Laury (2002) presented a risk aversion test using a multiple price list (MPL) design with fixed payoffs and varying probabilities. In this test, subjects face a series of 10 choices between two lotteries (A or B) each. While lottery A represents a gamble with payoffs of either US$ 2.00 or US$ 1.60 in the baseline treatment, lottery B entails payoffs of US$ 3.85 or US$ 0.10. Let p denote the probability for the higher payoff in both lotteries. The low payoff hence has a probability of $1 - p$. The value of p increases over the course of the 10 choices, starting at $p_1 = 0.10$, in steps of $\Delta = 0.10$. Thus, $p_{10} = 1.00$. Note that, the probabilities for the high (and the low) payoff are identical for lottery A and B in every of the 10 choice sets. Apparently, A entails a lower variance, and has a higher expected value for small values of p. Lottery B becomes increasingly attractive for larger values of p. The expected value of B exceeds the expected value of A first in the fifth row. A risk-neutral decision maker would thus make 4 safe choices (A), and then switch to the more risky alternative (B). A summary of all 10 rows, the respective probabilities, values, and differences is provided on the left hand side of Table 3.2.

Table 2.3.: Risk Aversion Classifications based on Holt and Laury (2002). #SC: number of Safe Choices (out of 10). Range of Relative Risk Aversion $(1-r)$ for $U(x) = x^{1-r}/(1-r)$.

#SC	**Range of** $(1-r)$	**Classification**	**Proportion**
0	$2.713 \leq (1-r)$	"highly risk loving"	0.01
1	$1.947 \leq (1-r) < 2.713$		
2	$1.487 \leq (1-r) < 1.947$	"very risk loving"	0.01
3	$1.143 \leq (1-r) < 1.487$	"risk loving"	0.06
4	$0.854 \leq (1-r) < 1.143$	"risk neutral"	0.26
5	$0.588 \leq (1-r) < 0.854$	"slightly risk averse"	0.26
6	$0.324 \leq (1-r) < 0.588$	"risk averse"	0.23
7	$0.001 \leq (1-r) < 0.324$	"very risk averse"	0.13
8		"highly risk averse"	0.03
9	$(1-r) < 0.001$	"stay in bed"	0.01
10			

In addition to this basic specification of their experiment, the authors conducted the test with 20, 50, and 90 times higher, and also with hypothetical payoffs, which is not relevant in the context of this work and thus not further considered. Given that a subject chooses lottery A first, at some point switches over to B, and then strictly chooses B, a personal risk aversion parameter can be estimated. For this purpose, it is necessary to assume a functional relation between (potential) payoff and utility, which is assumed to be $U(x) = x^{1-r}/(1-r)$ in the scope of Holt and Laury's paper. With this, for every subject, the boundaries of an interval for $1-r$ can be estimated. This is done by equating the utility values $p_i\pi_h^{1-r} + (1-p_i)\pi_l^{1-r}$ for A and B and solving for $(1-r)$ for a given row i, where π_h and pi_l denote the high and the low payoffs and p_i the probability for the high payoff in that particular row i. A risky choice (lottery B) in this row i means that the subject's personal risk preference parameter is at least as high as $(1-r)$. A safe choice (lottery A) in this row means that the subject's personal risk preference parameter is at most as high $(1-r)$. Table 2.3 summarizes these values, provides prosaic classifications of the risk preference as given by Holt and Laury and also the proportions of subjects showing the particular behavior.

2.3. Social Preferences and Risk

This section presents research on the joint consideration of other-regarding and risk preferences. Both fields, seen individually, were subject to systematic research for a considerable period of time. However, as it was often stated, "the literature, both at the empirical and theoretical level, has very little to say about how social concerns operate in the presence of risk" (Krawczyk and Le Lec, 2008, p. 3). It can be argued that the literature on decision making under risk has only lately, i.e. in the last years, increasingly acknowledged the relevance of other-regarding preferences. Similarly has the literature on other-regarding preferences for the most time abstracted from the existence of uncertainty and focused on deterministic scenarios. In this context, Bolton and Ockenfels (2010, p. 628) stated that "few contributions investigate risk taking in a social context" and Trautmann and Vieider (2011, p. 1) noted that "economic research on risk attitudes has traditionally focused on individual decision making issues, without any consideration for potential social influences on preferences." An increasing body of theoretical and experimental work, however, was concerned with the interplay of both aspects in the last years. Trautmann (2009), Trautmann and Vieider (2011), as well as Gantner and Kerschbamer (2011) provided reviews thereunto.

Risk preferences were already studied in the early 18th century, allegedly starting with the Bernoulli family (see Section 2.2). Other-regarding preferences in an economic sense were studied starting from the second half of the 20th century by researchers who began to interpret functions of social welfare from an individual, interpersonal perspective (see Section 2.1). It was only until about the turn of the 21st century, when experimental economists began to systematically investigate the interplay of both factors at once, mostly by means of laboratory experiments, sometimes from a theoretical perspective. There has emerged a considerable body of literature in that vein, which is examined in this section. At first, though, some general insights into the foundations of how social and risk preferences may interact and particularly into the concept of *Procedural Justice* are provided.

2.3.1. Foundations

The American philosopher John Rawls, whose *Theory of Justice* (Rawls, 1971) is considered one of the major works of moral philosophy, stated that "if a number of persons engage in a series of fair bets, the distribution of cash after the last bet is fair, or at least not unfair, whatever this distribution is." This means that the procedure, or the law for a society itself may constitute fairness (*ex ante*), regardless of the result (*ex post*). According to the notion of Procedural Fairness, these rules are what should be considered when evaluating whether society is fair or not. A thought experiment made by Rawls constructs an ideal and fair society where all members meet to agree upon the rules and principles they want to live by. However, this meeting is held behind a *Veil of Ignorance*. It is assumed, that at the time these rules are made, "no one knows his place in society, his class position or social status; nor does he know his fortune in the distribution of natural assets and abilities, his intelligence and strength, and the like" (Rawls, 1971, p. 137) and "therefore no one is in a position to tailor principles to his advantage" (Rawls, 1971, p. 139). The agreement upon procedures and principles ex ante occurs to be a way to address questions of fairness and justice for a society. Procedural Justice is indeed preferred over Distributive Justice (i.e., the fairness of the eventual allocation) from a libertarian perspective. An illustrative example of a US prosecution trial in that vein is instanced by Bolton et al. (2005), at which the judges argued in the sense of Rawls.

> "The common rationale for the ex ante desirability of unbiased randomization is uncommonly well articulated in the judicial ruling handed down in US v. Holmes in 1842. The case centred on a leaky and overcrowded lifeboat from which the crew chose to throw fourteen male passengers overboard. The shipmen were ultimately found guilty of homicide, although not for throwing people overboard—this was accepted as necessary to save some lives—rather because the procedure they used to choose the victims, one that exempted the crew, was judged ex ante unacceptable. In ruling, the judge argued that the victims should have been chosen by a lottery in which both crew and passengers participated. He said this would be "the fairest mode" because 'In no other than this or some like way are those having equal rights put upon an equal footing, and in no other way is it possible to guard against partiality and oppression.[13]"'

Another way of looking at the conjunction of risk and social effects is the analysis of group decisions, i.e. if not a single person is the decision maker, but a group has to find a solution by common consent for an alternative. Beginning with the unpublished master thesis by Stoner in 1961 (cf. Mackenzie, 1971), comparing individual and group decisions involving risk, there has emerged quite a substantial body of literature on that subject. Most of the experiments regarding the *risky shift phenomenon* found that the existence of a group yields higher levels of risk, since the individuals mentally transfer the responsibility (partly) to the other group members (Mackenzie, 1971). Group decisions, in contrast to individual decisions in groups, are, however, not in the focus of this work.

Recall the thought experiment of Rawls where the decisions about rules, and thus eventually resource allocation, are made ex ante. Additionally, the role a person obtains in society is assumed to be unknown at that point. One might assume that there are different probabilities to end up as a member of one or the other societal class. A consequent risk seeking would thus agitate for the privileges of the highest caste, hoping to end up just there. It is now straightforward to make the connection between procedural fairness and distributional preferences in the context of risky prospects. The selection of

[13]US v. William Holmes, 1 Wallace Junior, 26 Fed. Cas. 30.

a risky project can be seen as the selection of a rule, or law, which is made in advance, but eventually leads to one or another outcome allocation. The considerations made here are similar to those of a society. They are, however, limited to questions of how economic goods are distributed among the relevant actors. An example may illustrate this.

Illustration. Consider the following simple thought experiment, including 6 players and a regular, six-sided and fair die. The die is used to determine the players' payoffs, corresponding to the result, i.e. €1 through €6. One may now think of four (major) possible procedures to determine the individual payoffs, see Figure 2.6.

a) Each player gets to roll the die individually and receives a payoff corresponding to the result. The payoffs may be very different among the group, but also may be identical for some players.

b) The die is rolled only once and all players receive the corresponding amount. Here, equality among the players is guaranteed, whereas the total payoff may vary considerably.

c) The predefined amounts of €1 through €6 are alloted to the 6 players, i.e. every of the 6 different amounts will be received by exactly one player. Here, the grand total is fixed, but (some degree of) inequality is guaranteed.

d) Every player rolls the die individually, but then the average over all results is taken and paid out to every player equally.

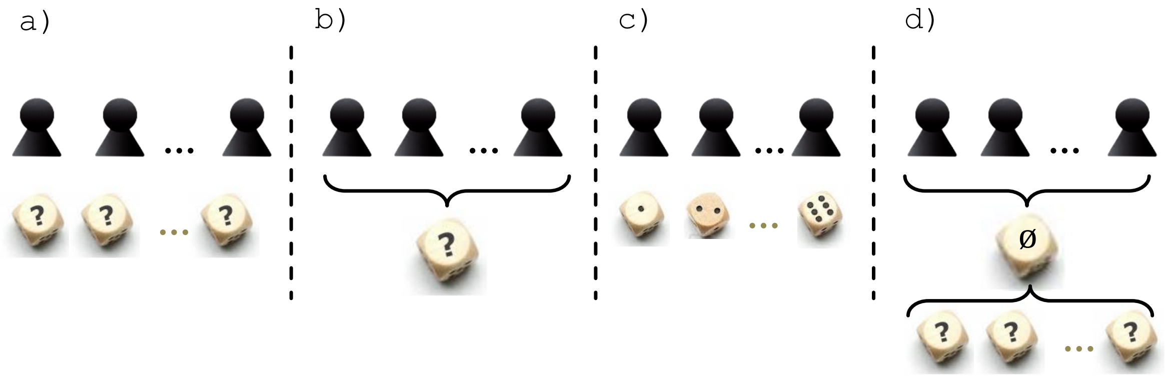


Figure 2.6.: Procedural Fairness: Different Types of Risky Procedures.

Note that the expected grand total is $\hat{X} = 21$ ($\hat{x} = 3.5$ for any player i) in all cases a), b), c), and d). The individual standard error is also identical for a), b), and c), namely $\sigma_{a/b/c} = \sqrt{\frac{1}{6}\sum_{i=1}^{6}(\hat{x}-i)^2} \approx 1.708$, whereas it is lower for d) ($\sigma_d = \sigma_{a/b/c}/\sqrt{6} \approx 0.697$).

The standard error of the group's total payoff, however, varies due to the different procedures. It is $\sigma_t(c) = 0$ for procedure c) since the total sum is always $1+2+3+4+5+6 = 21$. Procedures a) and d) yield $\sigma_t(a/d) = \sqrt{6}\sigma \approx 4.183$, and procedure b) yields $\sigma_t(b) = 6\sigma \approx 10.247$, since the random variables are independent for a), and perfectly correlated for b). Mean and variability of individual and grand total are only one of the aspects to look at when evaluating these different procedures. Variability may be interpreted as a measure of risk the group (or society) is taking. While a completely egalitarian distribution yields the risk of a very low total payoff where everyone obtains a poor result, this risk is mitigated when accepting the possibility of inequality, where also by means of redistribution, the poorest players may be supported by those who are better off. Distribution inequality or equality of opportunities, may thus be the relevant categories for many in that situation. One may think about which procedure the different members of a group would prefer and due to which reasons. In particular, if one's dice-roll does not entirely rely on chance, but also on the capabilities or prerequisites of the players, the different procedures may have different advantages or disadvantages, depending on their respective situation in the group. Ex ante considerations of uncertain events in a social or societal context are hence of high relevance when it comes to questions of how to shape social order. It can be argued this holds both on the micro level (Parental Example provided by Machina (1989)[14]) as well as the macro level (governmental welfare).

2.3.2. Classification Framework

Social preferences and risk preferences may interact in different ways. In order to classify these alternatives systematically, a set of 4 dimensions with 2 parameter values each is proposed. These dimensions (and values) are:

1. decision relevant for oneself (yes, no),
2. decision relevant for the other (yes, no),

[14]Machina (1989) provided the following, illustrative example: "In this case, Mom has a single indivisible item—a *treat*—which she can give to either daughter Abigail or son Benjamin. Assume that she is indifferent between Abigail getting the treat and Benjamin getting the treat, and strongly prefers either of these outcomes to the case where neither child gets it. However, in a violation of the precepts of expected utility theory, Mom *strictly prefers* a coin flip over either of these sure outcomes, and in particular, strictly prefers $1/2 : 1/2$ to any other pair of probabilities. The random allocation procedure would be straightforward, except that Benjie, who cut his teeth on Raiffa's classic *Decision Analysis*, behaves as follows: Before the coin is flipped, he requests a confirmation from Mom that, yes, she does strictly prefer a 50:50 lottery over giving treat to Abigail. He gets her to put this in writing. Had he won the flip, he would have claimed the treat. As it turns out, he loses the flip. But as Mom is about to give the treat to Abigail, he reminds Mom of her preference for flipping a coin over giving it to Abigail (producing her signed statement), and demands that she flip again."

3. risky choice involved (yes, no), and
4. decision about payoff alignment (individual, coupling).

First, the decision may affect one's own chances or payoffs or not. It may, independently, affect a peer's (or a peer group's) chances or payoffs. The decision may comprise a selection between different levels of risk, specified by expected value and standard deviation, or critical r values. Eventually, it might comprise a component of how the payoffs should be coupled from an ex ante perspective.

This yields a total of $2^4 = 16$ cases, which are summarized in Table 2.4. However, not all of these cases are considerable. Most certainly, if the decision involves neither a choice about risk nor about coupling, there is nothing left to decide, neither for oneself, nor for the reference person (or group). The first column therefore is blank.[15] Also, if the decision neither affects oneself nor any other person, there *is* no decision. The lower row therefore is blank. Now, if there is no decision to be made about risk but only about payoff coupling, this decision will inevitably concern both players, since, in the sense of the word, the decision involves coupling. The 2 respective cases are thus obsolete, too. The remaining 7 cases (i) through (vii) are described in the following paragraphs.

Please note: There are, of course, countless other dimensions, along which decision scenarios involving risk and a social context may be structured. For instance, this may be the type of the reference person(s), group size, gains versus losses, height of stakes (~€ 1, ~€ 1,000), area of the decision (financial issues, gambling, health, exams, car driving, smoking, etc.), and so forth. The selection used in the framework presented here attempts to use the most important ones regarding the inherent structure of the decision from the perspective of behavioral economics. For the examples provided in the next paragraphs, a single person as peer reference is assumed.

(i) In this case no risky decision is made, but the choice affects both, oneself and the reference person since the payoffs are coupled. An example would be the choice between the two-players prospects A: [50% (1, 0), 50% (0, 1)] and B: [50% (1, 1), 50% (0, 0)]. In both alternatives A and B, both players face an identical individual lottery. The choice between A and B does thus not constitute a risky choice, since both alternatives are identical regarding expected value ($\mu_A = \mu_B = 0.5$) and standard deviation ($\sigma_A = \sigma_B = 0.5$). But the payoffs are coupled differently. Where in A, only

[15] If both risky and peer-relevant aspects of the decision are absent, there is simply nothing left to decide. The situation might although be interesting, in view of the players' reactions to outcomes. Consider 2 players throwing a die each and being paid off according to their respective results. One might be interested in their evaluation of their respective contentment, which might vary significantly for a dice roll of "4," depending on what the other person rolled.

Table 2.4.: Structure of decision scenarios entailing social and risky aspects

		no risk		risk	
		individual	**coupling**	**individual**	**coupling**
self	**other**	—	(i)	(ii)	(v)
	¬other	—	—	(iii)	(vi)
¬self	**other**	—	—	(iv)	(vii)
	¬other	—	—	—	—

one of both players wins, either both or none of the players win in B. Note that the absence of a real choice between different levels of risk (e.g., the choice between heads or tails, assuming a fair coin, is not a real choice in terms of risk) does not mean that risk is generally absent (it is still a gamble).

(ii) In this case, a risky choice is made and affects both parties, but there is no decision about how the payoffs should be aligned beforehand. The payoffs might be determined independently for both oneself and the reference person. This precludes the possibility of ex ante payoff coupling. The payoffs might, however, be coupled in any way, as long as it is not subject to the decision. An example is the selection of one out of two lotteries, where the one that is chosen for oneself is independently played for the other person. In the sense of the definition, a decision about payoff alignment would not be made even if, in this example, the reference person received the exact same payoff as the decision maker (perfectly coupled payoffs). Pivotal for the categorization is thus not whether the payoffs *are* coupled or not, but whether the coupling (“whether or not, and if, how”) is subject to the decision maker’s choice.

(iii) In this case, the decision does not affect the other person. The peer might just serve as a reference point with a fixed income, or a prior decision. For instance: “The other guy won €4—would you like to get €4 as well, or do you prefer a dice roll instead (€1 to €6)?”

(iv) Here, the decision only affects the other person. An obvious example is a risky choice on behalf of another person.

(v) This might be one of the most interesting cases, because the decision maker affects both her or his own, as well as the other person’s payoff, and also decides about payoff alignment. Probabilistic dictator games as considered by Krawczyk and Le Lec (2010) can be seen as an example for this. The dictator decides on how much of a 100 percent chance to win a fixed amount is transfered to another person. With that, both parties' chances to win are affected. The dictator might as well decide whether the subsequent lottery is played out independently (once for every player), competitively (if A wins, B loses, and vice versa), or (partly) positively correlated. The latter case is not fully intuitive, consider thus the following example: After A transfered 30 percent (in terms of tokens) to B, a random number between 0 and 100 is drawn, and whoever holds a number of tokens higher than the drawn number, receives the amount at stake. With that, the dictator can make sure that the other player wins the amount only if he also wins it: 0-30, both players win; 31-70, only the dictator wins; 71-100, no one wins.

(vi) This case is of particular interest since it occurs in natural situations like the roulette game. In terms of payoff, the decision maker does only affect his own chances and payoffs. In addition to that, however, he can also decide on the way the payoffs are coupled. Say, on a roulette board, the reference person put her money on "13 (black)", the decision now comprises two aspects. First, the level of risk must be chosen. A single number yields a low chance for a very high payoff (36 times the bet), a color (red or black) yields a higher chance ($\sim$ 50 percent) for doubling the money at stake. That is the first thing to decide on. Second, if going with the high-risk alternative, one may put the money on the number "13" as well, so that if a "13" is actually rolled, both players win. In contrast to that, one may deliberately choose a different number. Also one might reason to choose "black", since this yields the lower risk, and ensures at least a small gain in case the other player hits the "13."

(vii) In order to illustrate this last case, consider the following game. The decision maker rolls a die and receives whatever it shows. There is no risky decision for him. He must, however, on behalf of another player choose one of the following alternatives. A: The other player will receive the same amount plus 2 additional monetary units, or B: the other player rolls the die on her own and is paid off accordingly. Thus, the decision on behalf of the other player affects her payoffs. It also is a decision on payoff alignment, which, in the very sense of this notion, affects both players.

Using this structure, most of the experiments and decision situations found in the literature may be classified. Of course there are scenarios outside of or diametric to this framework. For instance, uncertainty may be a structural property of an experiment (e.g., an ultimatum game where the exact pie size is unknown to the responder). The following section reviews a selection of relevant papers, experiments, and results in this context. Using the framework just presented as well as additional other factors, the reviewed literature is also summarized in Table 2.5. As it can be seen from this overview, none of the reviewed contributions investigates a scenario of type (vi). Chapter 5 hence addresses this particular situation.

2.3.3. Related Literature

As outlined above, the literature on other-regarding preferences under risk is often said to be sparse. There have, however, been several contributions, in particular since 2008. This subsection presents an overview, which certainly cannot be exhaustive, and discusses the articles in light of the classification framework developed in the prior section.

Trautmann and Vieider (2011) found that fairness motives and uncertainty may interact if (a) the decision maker is able to observe the payoff of other agents they consider relevant, (b) the outcome of another person serves as a social reference point, and (c) people try to achieve conformity with the behavior of their peers. Creating a social context in a risky choice situation is thus likely to affect the decision, also when subjects are merely affecting their own payoffs or chances. Weigold and Schlenker (1991) found that particularly risk averse subjects become more risk averse when their choices are observed by a passive partner, while risk seeking subjects become more risk seeking. The question of how the presence of a peer affects self-directed decisions in terms of riskiness is of high importance, since it constitutes a common scenario (e.g., stock trading where views, ideas, and investments are exchanged with friends or colleagues, playing roulette). Kroll et al. (2013) thus asked decision makers to express their risk attitude in an individual (i.e., non-social) context using a multiple price list design, based on the task proposed by Holt and Laury (2002). The authors contrasted that to an analogue situation where choices and payoffs of the decision maker and a peer, who was facing an identical task, were mutually transparent, i.e. where a social context did exist. Note that there did not occur any strategic interaction in this setup: neither participant was able to affect the other's payoff in any sense.

Various experiments considered more or less variational scenarios, for instance probabilistic dictator games, where, instead of a fixed pie, a 100%-probability to win the pie is split (e.g., Karni et al. (2008), Krawczyk and Le Lec (2010), Brock et al. (2013), or where uncertainty about the pie size is introduced (e.g., Haisley and Weber (2010), Ockenfels and Werner (2012)). Brennan et al. (2008) and Güth et al. (2008), for instance, analyzed subjects' willingness to pay and -accept for sets of prospects with different combinations of payoffs to oneself and to a peer. Other scholars focused on situations where the decision maker explicitly decided on behalf of a peer (e.g., Chakravarty et al. (2011), Pahlke et al. (2010), or Charness and Jackson (2009)), or where a deliberate departure from one's own preferred level of risk benefits an other player (e.g., Bradler, 2009). Most of the research is based on laboratory experiments. One field experiment, conducted by Ockenfels and Werner (2012), considered a dictator game with hidden pie size. Some contributions developed formal models, e.g. Trautmann (2009); Fudenberg and Levine (2012), representing the decision situation theoretically. Others strove to explain their empirical findings by theoretical model approaches (Bolton et al., 2005; Bault et al., 2008; Karni et al., 2008; Engelmann et al., 2009; Haisley and Weber, 2010; Gantner and Kerschbamer, 2011; Cooper and Rege, 2011; Brock et al., 2013). Trautmann (2009), Trautmann and Vieider (2011), and Gantner and Kerschbamer (2011) provided quite detailed literature overviews.

Most of the experiments confronted the decision maker with a single human peer as their reference person. Some experiments, however, considered the impact of a peer group. Rohde and Rohde (2011, p. 205) investigated individual risky choices in the light of group risks and found that "people prefer risks to be independent across individuals in society rather than correlated."

Cooper and Rege (2011) considered the impact of peer group choices in gambles. The decision maker's choice had no immediate impact on the peers' payoffs. In their experiment, subjects faced gambles with different sets of information about the chances for the respective payoffs, depending on the treatment. The authors theorized about the role of social regret and tastes for conformity. They stated that, among other factors, "social interaction effects driven by social regret can cause peer group effects" (Cooper and Rege, 2011, p. 109), i.e. that observing one's peer taking high-risk (low-risk) action increases the willingness to also take high-risk (low-risk) actions. Social regret as a particular form of regret, the authors argued, explains this behavior since "regret is less intense if others have chosen the same. In other words, misery loves company" (Cooper and Rege, 2011, p. 92).

Reynolds et al. (2009) let their participants take risk for themselves and a reference group. Their results indicated that "subjects take a statistically significant higher level of risk for themselves as individuals than they do when other's payoffs are at stake" (Reynolds et al., 2009, p. 63). Goeree and Yariv (2007) as well as Corazzini and Greiner (2007) conducted experiments investigating group decisions and conformity. The latter do not "observe herding at all: most of our subjects exhibit non-conforming behavior, choosing the alternative which (they believe) the fewest others have chosen" (Corazzini and Greiner, 2007, p. 2).

In most of the experiments, the decision maker decides for both herself and the reference person (or group). A common experimental setup in this context is the probabilistic dictator game. Here, the dictator allocates the chances of winning a pie among the players, rather than the pie itself (e.g., Karni et al., 2008; Haisley and Weber, 2010; Krawczyk and Le Lec, 2010; Brock et al., 2013). The picture, at that, is quite clear. A significant proportion of dictators gives up part of their own probability to win. Typically, this share is smaller in the risky than in the deterministic setting, even smaller when the probabilities are unknown (ambiguity), or when the allocation is exclusive, i.e. the lotteries are not played out independently for each player with the respective chances. Chakravarty et al. (2011) conducted an experiment in which the decision maker either decided for herself, or on behalf of the other person or group and found that “individuals tend to be significantly less risk averse” when deciding on behalf of the other exclusively (Chakravarty et al., 2011, p. 902). Pahlke et al. (2010) considered situations where the decision maker had to make risky choices (also) on behalf of another person. At that, decision maker and reference person simply received the same payoff. The authors, contradictorily, found that “being responsible for somebody else’s payoffs increases risk aversion” when own and the other’s payoff are affected (Pahlke et al., 2010, p. 1).

Brennan et al. (2008) and Güth et al. (2008) elicited subjects’ willingness to pay and accept distributional (risky) prospects. The first-mentioned found that “reservation prices tend to decrease with both one’s own and other’s risk. This indicates that risk-aversion not only refers to individual payoffs, but has also a social dimension” (Brennan et al., 2008, p. 257). Statistically, these results were significant only for the individual, not for the social dimension. Güth et al. (2008) did not find confirmation for a social impact on risk preference. Contrary, Bolton and Ockenfels (2010, p. 632) found that “risk taking is significantly affected by social comparison” in an experiment with safe and risky payoff allocation sets. The authors noted that inequality does decrease attractiveness in safe options, yet not so in risky options.

Linde and Sonnemans (2012) considered whether and how the (non-changeable) payoffs of a peer affect risk preferences and decision making, as constituting a social reference point. They found that “participants are more risk averse when they can earn at most as much as their referent (loss situation) than when they are ensured they will earn at least as much as their referent (gain situation)” (Linde and Sonnemans, 2012, p. 45). Seen absolutely, there were only gain situations in this study since the participants always received a payoff greater than zero. What the authors denoted “gain” and “loss” situations must be understood as *relative* gain or loss, i.e. receiving more or less than the peer. One would, however, assume the opposite result in the light of Prospect Theory. The authors concluded that straightforward extensions of existing theories on risk taking for social comparison may not be accurate.

Fox and Dayan (2004) let participants choose among different options and subsequently asked them to evaluate the outcomes. In line with the general notion of social comparison they stated that "when other significant referents have won much more than we have, we may frame our positive outcomes as a failure [...]. Likewise, when others have lost much more than we have, we might view our loss as gains, since we scored much better than they did" (Fox and Dayan, 2004, p. 302). Other experiments with actual potential losses were presented by Corazzini and Greiner (2007), Yechiam et al. (2008), and Pahlke et al. (2010).

Bault et al. (2008) let their participants pick one of two prospects and contrasted the possible outcomes (winning or losing) with those of a peer. They found that winning, in case the peer player loses ("gloating"), is evaluated more positively than when both players win ("shared relief"). Accordingly, losing is evaluated as less negative when both players lose ("shared regret") compared to when one loses but the other player wins ("envy"). In contrast to Prospect Theory, stating that "losses loom larger than gains" (Kahneman and Tversky, 1979, p. 279), the authors did not find significant difference for the private domain. They did find, however, that "social gains loom larger than social losses" (Bault et al., 2008, p. 2), which refers to the unequal outcome conditions "envy" and "gloating." The outcome evaluation in this study was based on self-report questionnaires as well as on the physiological measures heart rate and skin conductance response.

Another approach presented by Engelmann et al. (2009) employed functional magnetic resonance imaging in order to identify the cognitive processes of humans when evaluating risky prospects. At that, the participants were either supplied with an expert advice or not. Engelmann et al. (2009, p. 1)'s results support "the hypothesis that one effect of expert advice is to *offload* the calculation of value of decision options from the individual's brain."

With respect to payoff alignment, only few experiments put the decision maker in a situation of deliberatively choosing how the payoffs among the players should be coupled. Bault et al. (2008) as well as Bradler (2009) discussed the effects of different ex post payoff constellations. The decision maker, however, has no actual choice at that. Corazzini and Greiner (2007), as stated earlier, did not find indications of payoff alignment ("herding behavior"). Goeree and Yariv (2007) proposed an experiment in which subjects were able to either obtain relevant (and private) information, which helped them to make a more informed risky decision, or to rely on irrelevant ("word of mouth") information, which would enable an active coupling or decoupling with the group payoffs. They found that between one third and half of all participants omitted the chance to obtain helpful statistical information but rather chose to observe their peers' behavior (and possibly by that rely on the information these predecessors gained). The scenarios of Bolton and Ockenfels (2010) and Linde and Sonnemans (2012) constituted situations with implicit decisions on payoff alignment, emerging from the fixed and coupled lottery outcomes.

The focus, however, is on different aspects in these contributions. One of the treatments in Rohde and Rohde (2011) holds the possibility for the decision maker to decide on the payoff alignment among the members of the reference group (but not with respect to her own payoff). At that, the decision maker chose whether everyone should play a lottery individually, or whether the "corresponding allocation" (Rohde and Rohde, 2011, p. 207), similar to the example provided in Figure 2.6 from above, was going to be realized. The probabilistic dictator game experiments conducted by Krawczyk and Le Lec (2010) and Brock et al. (2013) considered the effects of coupled versus independent payoff determination, and particularly, the role of competitive exclusiveness (either A or B wins). In these studies, the decision maker did not choose how to align payoffs. However, Krawczyk and Le Lec (2010) conducted a set of treatments checking up on the differences between coupled and independent payoffs, using a within-subject design. It was found that subjects (in the role of dictators in the DG) tend to share less with recipients where "one's success meant other's failure" (p. 500) than in any other condition. In this competitive condition, the payoffs were thus coupled negatively.

Gantner and Kerschbamer (2011, cf. p. 5), in the experimental part of their paper, explicitly excluded *material externalities* (deciding for the peer), *information on outcomes* (knowing the peer's payoff), and particularly, *stochastic dependence* (coupled outcomes). They found that being exposed to the decisions of a (fictitious) peer in a MPL of risky choices, "subjects on average switch later from the safer to the riskier lottery on the list where the peer switches later from the safer to riskier lottery" (Gantner and Kerschbamer, 2011, p. 19), i.e. that a more risk averse peer actually induces a higher degree of risk aversion.

Bolton and Ockenfels (2010) considered whether models of inequality aversion may rationalize risky choices in a social context. In their experiment, a decision maker had to repeatedly choose between a risky and a safe alternative, whereat the payoff of an anonymous peer was then also either risky or safe. The authors varied the height of and the way the decision maker's and the peer's payoffs were coupled and found that "for decisions with social comparison, there is more risk taking when the safe option yields unequal payoffs" and that this holds (even though not statistically significant) particularly if the distribution is unfavorable for the decision maker (Bolton and Ockenfels, 2010, p. 630).

Theoretical considerations of how to integrate ex ante and ex post preferences over prospects and outcomes were provided by Fudenberg and Levine (2012), Trautmann (2009), and Saito (2013). Fudenberg and Levine (2012, p. 611) recognized that existing outcome-based "models of fairness do not focus on the role of lotteries, and the preferences analyzed in Fehr and Schmidt (1999), Bolton and Ockenfels (2009), Charness and Rabin (2002), Cox and Sadirij (2004) *[sic]* and Andreoni and Miller (2002) are defined for certain outcomes, without specifying how they are to be extended to lotteries." The authors extended the properties of utility functions to the notion of *ex ante fairness* and basically stated that an initial preference order for deterministic allocations may be reversed if the allocations involve a risky component. This, in turn, violates the property of independence (cf. Section 2.2.1). In this regard, also Trautmann (2009), building on the Fehr-Schmidt model, integrated expected values into the player's utility function, whereat only the payoff differences were evaluated using expected values (ex ante). For the own payoff x, the actually occurring value was used (ex post), thus representing a mixed approach. Saito (2013) proposed a model using both ex ante and ex post risk aggregation in a linearly weighted way. For risk aggregation, the plain expected values were used, thus assuming strict risk neutrality. In this *expected inequality-averse (EIA)* model, the decision maker's preference is captured by $\delta U\left(E(x_1), \ldots, E(x_n)\right) + (1-\delta) E\left(U(x_1, \ldots, x_n)\right)$, where $E(\cdot)$ denotes the expected value over all possible outcomes and $U(\cdot)$ represents the Fehr-Schmidt utility function. The parameter $\delta \in [0, 1]$ weights the different approaches. This model is considered in greater detail in Section 5.4.

It is, in this regard, often stated that social preferences violate the independence axiom. This thought may be illustrated by the following example (cf. Saito, 2013). Consider a decision maker who has to choose one of two payoff sets, which determines his own payoff and the payoff of a reference person. The payoff sets are described by $A : (10, 10)$ and $B : (10, -10)$, where in A, both players receive € 10, and in B, the decision maker receives € 10 and the reference person loses € 10. It is commonly acknowledged that most people in the role of the decision maker choose A, since—unless suggested differently—there is no reason for the decision maker to harm the reference person. Most models of social preferences such as inequity aversion, maximin preferences, and efficiency concerns support the choice of A.

Recalling the independence axiom, the preference $A \succ B$ should be invariant against *mixing* both A and B with another constellation X in a linear and similar way. The notion of mixing originally refers to convex combinations of two options, yielding the form $\delta A + (1-\delta)X, 0 \leq \delta \leq 1$. When assuming risk neutrality, this notion can be extended to probabilities (p) instead of proportions (δ).

Let the additional payoff constellation for this example be $X : (-10, 10)$ and probabilities of each outcome $p = 1 - p = 0.5$. The decision maker thus faces the choice between the two prospects $AX : ((10, 10, 0.5), (-10, 10, 0.5))$ and $BX : ((10, -10, 0.5), (-10, 10, 0.5))$[16]. Arguably, BX now might be preferred over AX, since

[16]The notation $((\pi_1^a, \pi_1^b, p), (\pi_2^a, \pi_2^b, 1-p))$ means that in the first case (probability p), player a receives π_1^a and player b receives π_1^b, and in the second case (probability $1-p$) the players receive π_2^a and π_2^b, respectively.

in BX both parties are equally likely to gain or lose, whereas AX favors the reference person over the decision maker. By choosing AX, the decision grants the reference person a certain gain of €10 and puts himself under the risk of either gaining or losing this amount. This empirical observation directly violates the independence axiom. This examples suggests that social preferences under risk—particularly for ex ante decisions—cannot be regarded as a mere extension of standard decision theory, limited to mean and variance (cf. $\mu - \sigma$ preferences), but may need to extend to counter-factual thinking as well as the co-variance between the respective payoffs ($\mu_m - \sigma_m - \mu_y - \sigma_y - \rho(m, y)$ preferences[17]). A such approach, however, is left to future research.

To sum it up, this section described different situations of decisions in the context of both risk *and* a social context. The literature is classified along a framework, which was developed in the context of this work. This framework allows to classify the type of the decision situation in a mutually exclusive and exhaustive way. This does not mean that other factors may not be applied for the decision analysis and classification. From the literature review and particularly from the classification of the specific decision scenarios, a gap in the body of literature—concerning class (vi)—was identified. Chapter 5 thus investigates this type of decision in greater detail, both from an empirical and theoretical perspective. The literature invoked in this section is summarized in Table 2.5. In addition to the classification of the decision situation as proposed in this section, several other factors, such as type of the reference person, gain/ loss framing, physiological assessment, experiment type, etc. are covered. The main Chapters of this work (Chapters 4 and 5) are put into context.

[17] m: "my" payoff, y: "your" payoff.

Table 2.5.: Literature Overview; LE: laboratory experiment; TM: theoretical model; LR: literature overview; EM: emotional motives; CD: coupling/decoupling; PH: physiological measurement; FR: framing (+: gains; −: losses); REF: reference (hyp: hypothetical; H: human peer; H*: human peer matched ex post; G: group); DEC: decision made for (S: for oneself; O: for the other); CL: decision class(es).

Authors (year)	**Focus**	**LE**	**TM**	**LR**	**EM**	**CD**	**PH**	**FR**	**REF**	**DEC**	**CL**
Fox and Dayan (2004)	self-eval. of gains/ losses in hyp. social comp.	×			×			+ −	hyp	S	(iii)
Bolton et al. (2005)	BOS/UG with fair procedure (random) option	×	×					+	H	S+O	(ii)
Corazzini and Greiner (2007)	sequential option (A/B) selection, then DG	×				×		+ −	G	S(+O)	(i)
Goeree and Yariv (2007)	basing decision on social or risky signals	×				×		+	G	S(+O)	(i/v)
Bault et al. (2008)	private vs. social lotteries	×	×		×	×	×	+ −	H/C	S	(iii)
Brennan et al. (2008)	WTP/WTA for prospects with own and others' risk	×						+	H	S+O	(ii)
Güth et al. (2008)	WTA for distributional time and risk preferences	×	×		×			+	H*	S+O	(ii)
Karni et al. (2008)	allocation of prob. in a 3 player DG	×	×					+	2H	S+O	(ii)
Yechiam et al. (2008)	peer decisions & outcomes, rare loss events	×						+ −	H	S	(iii)
Engelmann et al. (2009)	influence of expert advice on decisions under risk	×	×				×	+	(exp)	S	(ii)
Bradler (2009)	shift risk in order to help peer	×				×		+	H	S+O	(ii)
Charness and Jackson (2009)	stag hunt game for oneself and a group	×						+	H	S+O	(ii)
Trautmann (2009)	model of procedural fairness for ultimatum game		×	×					-	-	-
Reynolds et al. (2009)	risk taking for oneself and a reference group	×						+	G	S+O	(ii)
Bolton and Ockenfels (2010)	distributional preferences for safe and risky sets	×				×		+	H	S+O	(v)
Pahlke et al. (2010)	responsible risk choice for peer with equal payoff	×						+ −	H	S+O	(ii)
Haisley and Weber (2010)	self-serving interpretation of ambiguity in a DG	×	×					+	H	S+O	(ii)
Krawczyk and Le Lec (2010)	probabilistic dictator game	×				×		+	H	S+O	(ii)
Harrison et al. (2010)	ind. choice vs. voting for H&L lottery	×						+	2H	S+O	(ii)
Trautmann and Vieider (2011)	literature review, underlying concepts			×					-	-	-
Gantner and Kerschbamer (2011)	social interaction effects on independent lotteries	×	×	×	×			+	H(G)	S	(iii)
Cooper and Rege (2011)	impact of peer group choices in gambles	×	×		×			+	G	S	(iii)
Chakravarty et al. (2011)	risky decisions on behalf of others	×						+	H	S/O	(iii/iv)
Rohde and Rohde (2011)	risky choices in the light of group risks	×				×		+	G	S/O	(iii/vii)
Ockenfels and Werner (2012)	dictator game with hidden pie size	FE						+	H*	S+O	-
Linde and Sonnemans (2012)	risk preferences in gain/loss situations	×				×		+(−)	H	S+O	(v)
Fudenberg and Levine (2012)	axioms for ex ante & ex post preference relations		×			×			-	-	-
Saito (2013)	expected inequality-averse (EIA) model		×						-	-	-
Brock et al. (2013)	probabilistic dictator game	×	×			×		+	H	S+O	(ii)
Teubner et al. (2013, WP, Ch. 4)	Auction experiment, human/ computerized bidders	×			×		×	+	2H/2C	S(+O)	(ii)
Teubner et al. (2012, WP, Ch. 5)	Roulette like dice game, payoff coupling/ decoupling	FE	×		×	×		+	H	S	(vi)

Chapter 3.

Measuring Risk Preferences in Ad-Hoc Experiments

"Things should be made as simple as possible, but not simpler."

(Albert Einstein)

This chapter introduces a short version of the Holt and Laury (2002) risk aversion test, which is designed to serve as a measure of individual risk preferences in economic experiments conducted outside the lab. In this type of experiment, subjects are well aware of the fact that they participate in an experiment, but they are approached by the experimenter in the public sphere and participation is ad-hoc. This type of experiment is thus hereinafter referred to as ad-hoc experiments. The short version of the risk preference elicitation test is evaluated against the original test by means of two online experiments comprising a total of 490 participants. Additionally, differences and design issues of ad-hoc experiments in contrast to in-lab experiments are discussed.

3.1. Methodological Issues in Economic Experiments

Experimental economics applies experimental methods in order to investigate questions in the context of economic decision making. Controlled experiments are used for several purposes. Roth (1995, p. 22) identified four categories of how experiments are motivated by researchers. First, "experiments [can be] designed to test the predictions of well articulated formal theories," i.e. to discriminate between alternating, or to test the predictive power and robustness of existing theories. Second, experiments can study "the effects of variables about which existing theory may have little to say," i.e. exploring and carving out the causes of observed regularities. Third, with a body of facts and results at hand, experiments can contribute to make sense out of it, helping that "theories of the observed behavior can be proposed and then tested." Eventually, Roth (1995, p. 22) named the "dialogue between experimenters and policymakers" as a motivation for experiments, addressing "the kind of question raised by regulatory agencies."

When dealing with experiment participants (in this context often called *subjects*), typically cash money is used as a motivation, to create realistic incentives—and thus: control. "Such control can be achieved by using a reward structure to induce prescribed monetary value on actions" (Smith, 1976, p. 275). Smith's *induced value theory* subsumes this notion. A main assumption is nonsatiation, meaning that an additional payoff yields additional utility. This fact allows experimental economists to replicate real-life markets, auctions, negotiations, or other situations in the laboratory. But it also means that large experiments may be expensive, since the participants have to be paid. So the reason for payoff is both compensation for the time spent in the laboratory, but also the creation of adequate incentives. The interplay of rewards and mechanisms is important, since mechanisms "affect incentives, and decision makers respond to incentives" (Bolton and Ockenfels, 2012, p. 666). Thus, the experimenter usually has to find a trade-off between cost and sample size. As research budget is limited, sample size is limited. Thus, the results have to be regarded in view of economic but also in view of statistical significance, since they are based on a limited number of observations.

Albeit they have much in common, a distinction is made between experimental economics and behavioral economics. Loewenstein (1999) defined this gap by the absence/ presence of the consideration of psychological insights. Where experimental economics aims at understanding the effects of structural characteristics of the environment, behavioral economics rather tries to elicit the underlying principles and motives of human decision making. However, both fields interact in many ways, so that a strict demarcation is often just not sensible. Experimental economics has contributed to the understanding of how markets, and market-like mechanisms work and has shed light on the interactions among the players in and with those environments, both from an economic and behavioral perspective.

At that point, the question arises how valid it is to transfer the findings from controlled lab conditions to real world scenarios. The notion of *external validity* refers to "the ability to generalise from the research context to the settings that the research is intended to approximate" (Loewenstein, 1999, p. 26). It stands in conflict to *internal validity*, which describes "the ability to draw confident causal conclusions from one's research"

(Loewenstein, 1999, p. 26). Abstraction from influencing factors increases control and thus internal validity. It does, however, presumably limit the possibility to draw conclusions for the actual, real application scenario. Allowing for more influencing factors has the opposite effect.

"Would you like to participate in an experiment?" Experiments may be conducted in the classroom (e.g., using pen and paper), in laboratory settings (typically using computer terminals), or in the field. In the latter case, the experiment is conducted in a natural environment, and subjects usually do not know that they participate in an experimental study, i.e. their behavior is assumed to be (more) natural. As one way to address both the issue of high costs of large sample sizes in laboratory experiments and the trade-off between external and internal validity, one can think of *ad-hoc experiments* as a compromise. At that, participants are not invited to the lab, but approached or merely observed by the experimenter(s) in an everyday situation, e.g., in shopping malls, in pedestrian areas, or during waiting times at the bus stop. It may be made clear that the purpose of the approach is a scientific investigation, but the process might also be presented as a survey, a lottery, a sales promotion, or a game.

In order to give a structure to the different types of experimental situations, one can use the dimensions *channel* (laboratory, out-of-lab, impersonal), and the subjects' *awareness of being part of an experiment* (yes or no). In the resulting 2×3 matrix (cf. Table 3.1), the upper left cell represents classical lab experiments, in which subjects are invited to an experiment, and have to come to an on-site lab for the session. The 2 lower right corners represent classical field experiments, in which subjects are observed in a natural environment (offline or online), typically under alternating treatment conditions, and are not aware of the experimental characteristic (e.g., tests of different user interfaces on e-commerce platforms). If subjects come to the lab, they will normally be aware of the fact that they are in an experiment. If this is not supposed to happen (lower left corner), the actual experimental investigation must be a different one than assumed by subjects (e.g., their behavior in the waiting room, see Brauer et al. (2012) for several of such approaches), or may be disguised as a student job for instance. This type thus is denoted "red herring." The upper right corner contains online experiments, as for instance conducted on Amazon Mechanical Turk (AMT, cf. Paolacci et al., 2010). Finally, the upper cell in the center contains the type of ad-hoc experiments.[1]

Here, the experimenter approaches subjects actively, for instance at home on the doorstep, at work, or at public places. The situation is short term, subjects may be

[1]For many target groups such as traders, lab, ad-hoc, and online experiments may not be distinguishable, since the only channel of access is a computer.

Table 3.1.: Classification of different experiment types.

		location		
		laboratory	**out-of-lab**	**impersonal**
awareness	**yes**	lab experiment	ad-hoc experiment	online experiment
	no	“red herring”	field experiment	field experiment

in a hurry, which has implications on how they should be approached in the first place, where they are typically not aware of the fact that their time, effort, cooperativeness or rigidity, or skill will be rewarded. It thus may be necessary to initially lure subjects into participation. There is also a restriction on how long the entire endeavor may take. Where, for instance, 5 minutes might seem as an acceptable sacrifice for most passersby, 50 minutes will probably be considered intolerable. Besides the fact that there is no time for extensive experiments, there is also no time for imparting complex rules, even if the actual task is very short. Participants may not fully understand the rules and mechanics of the experiment, if designed in a too complex manner, or if explained poorly. Scenarios involving interaction between multiple participants might be particularly difficult to realize, since this will usually cause waiting times for the first volunteers.

On the upside, such ad-hoc approaches enable a larger sample size for a given budget. This is of course favorable from a statistical point of view. And also methodologically, it enables the execution of one-shot experiments, ruling out learning- and over-time effects. Where the average expected profit per hour in most student subjects pools presumably varies somewhere between €10.- and €20.-, and even rather short lab experiment take 40 minutes or more, ad-hoc experiments may acquire an individual’s attentiveness for much less.

In the trade-off between internal and external validity, ad-hoc experiments partially give up control for a higher degree of naturalness and sample size. Besides obvious features like gender, age, profession, etc., it may be of interest to the researcher to gain knowledge about the participants’ risk preferences, as a control variable when trying to rationalize their behavior. The peculiar requirements towards a risk preference elicitation task in such ad-hoc experiment situations are considered in greater detail in the next section.

3.2. Ad-Hoc Risk Preference Elicitation

In order to be able to elicit people’s risk aversion in ad-hoc experiments, a questionnaire-like test with real money incentives, comparable to tests used in laboratory settings, is desirable. As it was outlined in Section 2.2.2, there exist several test formats that are used in lab experiments (e.g., Holt and Laury, 2002; Eckel and Grossman, 2008; Figner et al., 2009).

3.2.1. Considerations and Requirements

Ad-hoc experiments, however, require such a test to have different properties compared to lab experiments. In lab experiments, participants are comfortably seated, stay on site for about one hour with usually no time pressure, and are mentally prepared to take part in an experiment. Moreover, many participants are participating at the same time. This makes is feasible to impart complex rules, since larger groups of participants can be instructed at the same time. This all, however, does not necessarily hold for ad-hoc experiments.

Here, situations are short term, subjects rush by and are approached by the experimenter. Sometimes they do not even know that they are part of an experiment, but rather experience the situation like an interview, a survey, or a game. The situation may be rather comparable to the approaches made by product promotion agents in urban pedestrian areas than to typical laboratory experiments—and for this reason may be expected to be more natural and at the same time more chaotic. From a common sense reasoning, one may summarize the peculiar requirements for a risk preference elicitation task in an ad-hoc experiment situation roughly as follows:

- *simplicity, intelligibility*: A risk aversion test designed for an ad-hoc context should be as simple as possible. Subjects should be able to capture what they are supposed to do intuitively, without much explanation. The test itself should be easy to understand and follow.
- *clarity, lucidity, and compactness*: This also holds for the visual presentation of the test. Items should be placed in a structured and logical way. The entire test (excluding instructions) should fit into one single page on a tablet PC or tablet computer so that all information items are available during the entire test.
- *conciseness*: The test should be achievable in a few minutes.
- *segmentation*: The test should discriminate between the subjects' risk attitudes, so that the classification is tolerably even.
- *inherent validity*: The test should by design enable and guide subjects to state their risk preferences in a valid way, not being contradictory from a theoretical point of view.

- *external validity, incentives*: The test should provide real incentives (monetary payoffs of sufficient size) to the subjects in order to create control and external validity.
- *connection, correlation*: The test should be linkable to well established methods from the literature.

A such test is proposed in the next section. Addressing the latter requirement, the test here is designed based on the Holt and Laury (2002) risk aversion test. This means that it implements a multiple price list (MPL) design with binary decisions in every row of the list.

3.2.2. A Proposition based on the Holt and Laury Task

First of all, the number of items in the MPL design is reduced from 10 to 5. The simplified version of the test will thus be referred to as HL5 (5 questions), whereas the original version is referred to as HL10. Since most of the subjects typically switch from A to B in one of the middle rows (3, 4, 5, or 6), it seems plausible to cut off the more extreme rows at the top and the bottom of the list. Most people choose A in the first rows, and B in the last rows, and personal risk aversion seems to be distributed around a rather medium level among subjects. By cutting off questions, of course, the test will become less powerful to distinguish between different degrees of risk attitude, particularly in the range of very strong risk aversion or risk propensity. For these subjects, one can say that their risk preference is at least or at most at a certain level.

As a second step, the complexity of the high-risk lottery (B) is reduced by replacing the low payoff of € 0.10 by a zero payoff. This makes the corresponding probability obsolete and the lottery may be explained in a more concise way: "You receive € 3.85 with a probability of 30%, and nothing, otherwise." Third, the low-risk lottery (A), which represents a payoff of either € 1.60 or € 2.00 for the participant is replaced by an entirely safe payoff (100%). Hereby, the difference of the expected values of alternative A and alternative B from the original test design is retained, so that the choice between the prospects is comparable in that way.

An aggregation of the questions, payoffs, probabilities, and expected payoffs is provided in Table 3.2. In terms of expected value (μ) and standard deviation (σ) of the different prospects in each choice set, the HL10 and HL5 tasks are depicted in Figure 3.1. The safer options (A) are depicted in green, the riskier options (B) are depicted in red. The two corresponding prospects of a particular row are connected with a dotted line. The sequences of prospects pairs are thus displayed like a fan, sorting the rows from the left to the right.

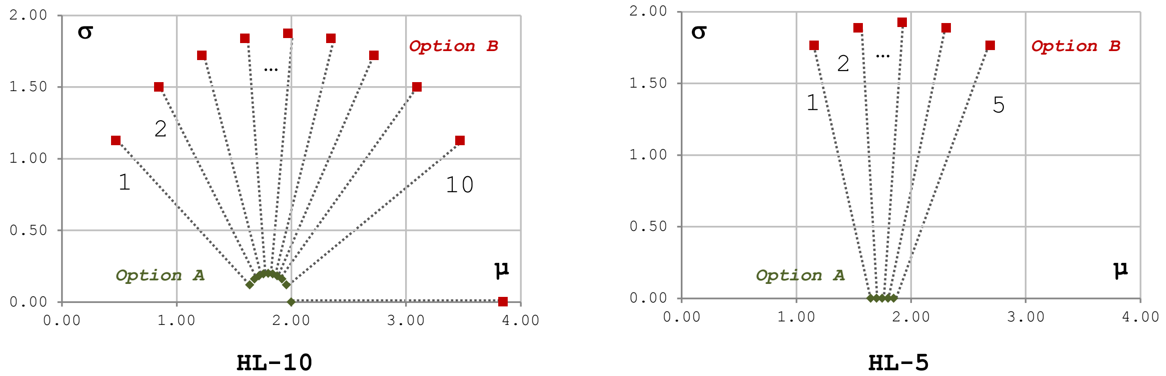


Figure 3.1.: $\mu - \sigma$-structures of the HL10 and HL5 tasks in comparison.

Table 3.2.: HL10 Risk Aversion Test, Derivation of the Short Test.

	Holt & Laury Risk Aversion Test							Short Test		
	Option A			Option B				Option A	Option B	
p	**EUR**	**EUR**	**EV**	**EUR**	**EUR**	**EV**	**Δ(A-B)**	EUR	EV	
0.1	2.00	1.60	**1.640**	3.85	0.1	**0.475**	1.165			
0.2	2.00	1.60	**1.680**	3.85	0.1	**0.850**	0.830			
0.3	2.00	1.60	**1.720**	3.85	0.1	**1.225**	0.495	1.65	1.155	0.3×3.85
0.4	2.00	1.60	**1.760**	3.85	0.1	**1.600**	0.160	1.70	1.540	0.4×3.85
0.5	2.00	1.60	**1.800**	3.85	0.1	**1.975**	-0.175	1.75	1.925	0.5×3.85
0.6	2.00	1.60	**1.840**	3.85	0.1	**2.350**	-0.510	1.80	2.310	0.6×3.85
0.7	2.00	1.60	**1.880**	3.85	0.1	**2.725**	-0.845	1.85	2.695	0.7×3.85
0.8	2.00	1.60	**1.920**	3.85	0.1	**3.100**	-1.180			
0.9	2.00	1.60	**1.960**	3.85	0.1	**3.475**	-1.515			
1.0	2.00	1.60	**2.000**	3.85	0.1	**3.850**	-1.850			

Assuming a utility function with constant relative risk aversion, e.g., $u(x) = x^{1-r}$, every binary decision between risky prospects or between a safe option and a risky prospect yields a risk parameter r^*, which would set the decision maker indifferent between both options. In the third choice set of the HL10 task, for instance, this value r^* may be derived by solving the equation $0.3 \times 2.00^{1-r} + 0.7 \times 1.60^{1-r} = 0.3 \times 3.85^{1-r} + 0.7 \times 0.10^{1-r}$. This equation cannot be solved analytically for r, but must be approached numerically, yielding $r^* \approx 1.4866$. For empirical data gathered with tests using a MPL design, however, a subject's individual parameter r cannot be determined without further ado, since the MPL design merely allows to locate this value between an upper and a lower bound[2]. In particular, the estimation for the highest risk border bin is subject

[2]Making a series of binary decisions, the subjects state their preferences in the form of "my r parameter is at least (or at most) that high."

to vagueness, since there is no finite upper bound. In fact, there exists a lower bound (which is zero) for lowest class, since only values of $1 - r > 0$ are meaningful for utility functions with positive marginal utility. In order to use the risk preference estimations for further computations, exact values are necessary. Let $e = 1 - r$. Hence, for the bounded bins, the arithmetic mean $e^* = (e_{up} + e_{low})/2$ is used. Based on these values, the values for the border bins are estimated by extrapolation. The values for e for $s = 1$ through $s = 4$ safe choices are easily calculated using the arithmetic mean as indicated above. These values are $e_1 = 1.271$, $e_2 = 1.000$, $e_3 = 0.776$, $e_4 = 0.579$. Based on this, the values for e_0 and e_5 are estimated by extrapolation using a second order polynomial: $e_s = 0.0187s^2 - 0.3233s + 1.5747$, $(R^2 = 0.9999)$[3]. Thus, the estimates are $e_0 = 1.5747$ and $e_5 = 0.4257$. An illustration of the fragmentation of both the HL5 and the HL10 test is provided in Figure 3.2.

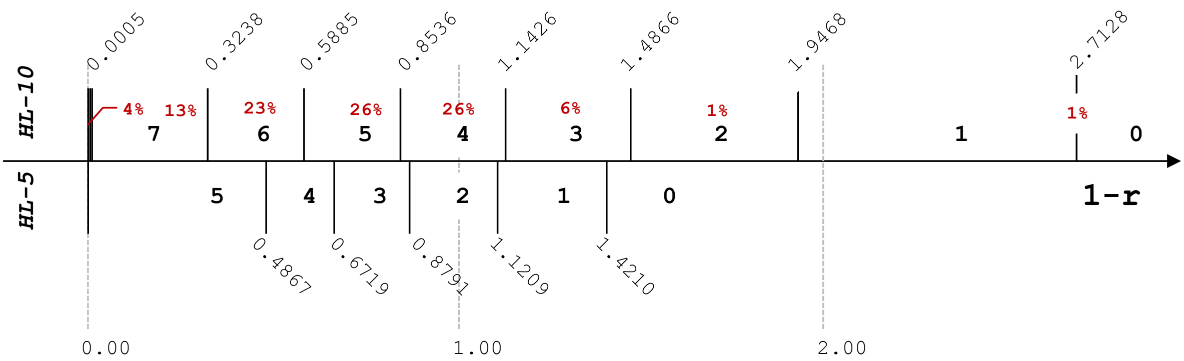


Figure 3.2.: Critical $(1-r)$ values (on x-axis), number of safe choices (option A preferred to option B), and Holt and Laury (2002) empirical distribution (red) for the HL10 and the HL5 risk aversion test.

Structural Properties. The HL5 test has a drawback in contrast to the original test, which, however, is of rather theoretical nature. In the original Holt and Laury risk aversion test, the payoffs in every row for each prospect A and B do not change. Prospect A always pays either €2.00 or €1.60, prospect B always pays either €3.85 or €0.10. Only the associated probabilities differ from row 1 to 10. Note that this makes the theoretical calculus of preferences stable against any characteristics (curvature, discontinuities, etc.) of the underlying utility function $u(\cdot)$, as long as the preference order condition

$$u(3.85) \geq u(2.00) \geq u(1.60) \geq u(0.10) \tag{3.1}$$

[3]The estimation of the polynomial was conducted using the curve fitting function of Microsoft Excel 2010.

is satisfied. Hence, even the most bizarre utility function results in only one single switching point from prospect A to B in the multiple price list. Once B is preferred to A, in every subsequent row B must be preferred over A as well. Thus, any rational decision maker, in disregard of her utility function, be it ever so odd, will only switch from A to B once, and then stick to B (AB-criterion). This property might occur unessential, since one may assume people to have passably well-formed underlying utility functions. Since, however, switching back from B to A is regarded as flawed behavior, it is important to note, that for the simplified 5 question test, it may be a perfectly rational behavior for specific utility functions. One such utility function violating the AB-criterion is depicted in Figure 3.3. The expected values of the risky prospects are indicated by the red horizontal lines. Now, the safe prospect (€ 1.65 with for sure) is preferred to a 30% chance on € 3.85. The additional value of € 0.05 is very small, reflected by a flat section of the utility function, so that the risky prospect "40% chance on € 3.85" is preferred to the safe payoff of € 1.70. Then again, the slope of the utility function is particular steep so that the safe prospect of € 1.75 is preferred to the 50% gamble on € 3.85. The 5 cents from € 1.70 to € 1.75 are thus valued much more than the 5 cents from € 1.65 to € 1.70. In order to rationalize such preferences, one could think of the decision maker in a shop. There are the options to buy a popsicle for € 1.65, or a sandwich for € 1.75, but the additional 5 cents in between are really all useless, since the shop only offers those two products and none at the cost of € 1.70. It may be pointed out, however, that strictly increasing and concave functions do not violate the AB-criterion.

3.3. Experimental Design

In order to evaluate whether the HL5 risk aversion test is applicable for assessing subjects' personal risk preferences, it is benchmarked against the original version of the test. At that, in particular the criteria *conciseness*, *segmentation*, *validity*, and *correlation* are assessed, since the other dimensions as specified in the above section are design related and met by construction. For that matter, two online experiments with a total of $n_{total} = 490$ subjects were conducted. The experiments differed in the height of the stakes that the participants could earn, and are hence denoted LOW and HIGH. This section presents the experimental design.

In both experiments, subjects were recruited from a pool of students at the Karlsruhe Institute of Technology (KIT). The contact data for inviting the participants was drawn from the Online Recruiting System for Experimental Economics (ORSEE, Greiner, 2004). Subjects were invited by email and by announcement in lectures. In both experiments, subjects participated in the HL10 and the HL5 risk aversion test, whereas the

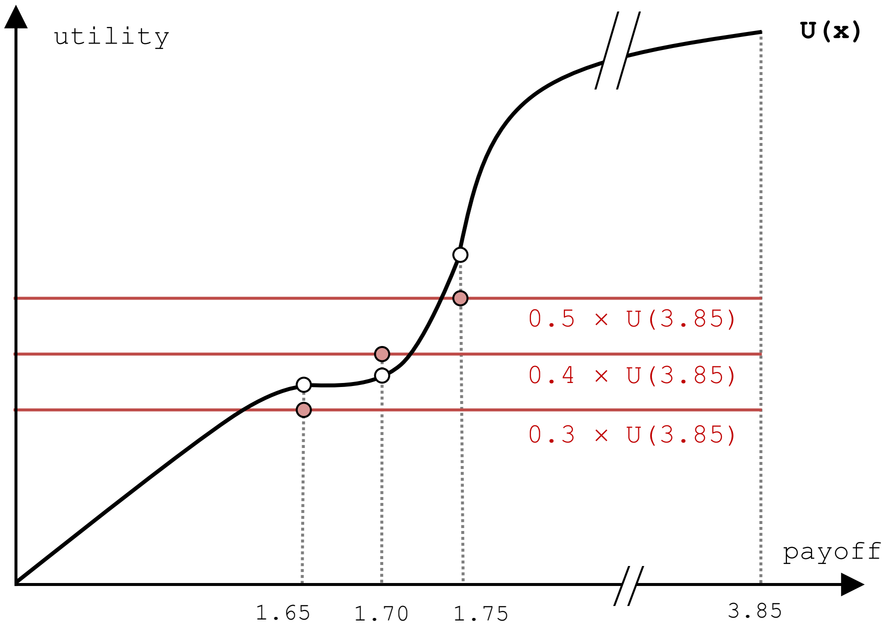


Figure 3.3.: Example of utility function violating the AB-criterion for a risk neutral decision maker.

sequence of these tasks was selected randomly. Both tasks had a probability of 50% to be presented first. There was a monetary compensation offered. It was made clear in the instructions that in either task, participants could earn real money, depending on their decisions, and on chance. It was necessary to register for the experiment (realized using the Lime Survey questionnaire environment), providing one's real name and student ID. This made sure that only those participants who actually engaged in the task could appear and pick up their money, and also that every participant could take the task only once. The payoff could be picked up on campus one week after the experiment was run, and also by appointment any time after this date.

In experiment LOW, the stakes for both tasks were as described in the proceeding section and every participant was paid accordingly, ranging from €0.10 to €3.85. In the second experiment (HIGH), the stakes were multiplied by a factor of 10, however, not every participant was selected for payoff. The probability of being selected was 10%, which was communicated to the participants along with the other instructions. In the high stakes experiments, the information whether one was selected for payoff or not was revealed after completion. Thus, during decision making, all participants only knew the a priori probability of being selected (10%). After completing the two risk preference tasks, subjects provided information on gender, age, field of study, and prior experience with economic experiments. The process is depicted schematically in Figure 3.4.

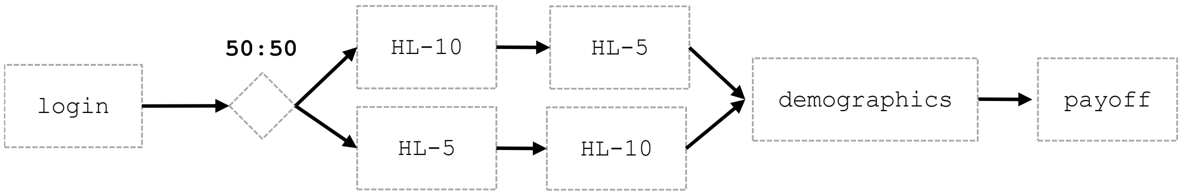


Figure 3.4.: Schematic representation of the 2 online experiments

3.4. Results

This section presents the results of the online study. After reviewing the general statistics, correlation and regression analyses are conducted. The focus lies on the criteria of *inherent validity* ("Do the participants state consistent risk preferences?"), *conciseness* ("How long did it take?"), *correlation* ("Do both test formats correlate?"), and *segmentation* ("Does the test actually discriminate between the risk preferences of the sample population?").

3.4.1. General Statistics

The general statistics about the participants of the online experiments, their decisions and behavior are provided in Table 3.3. There were $n_{low} = 94$ participants in the first (low-stakes) experiment, and $n_{high} = 396$ participants in the second (high-stakes) experiment, yielding a total of $n_{total} = 490$ subjects. Average age was 22.243 years, with a standard deviation of 2.886 years. The majority of subjects had a background in economics and business engineering (65%). Other relevant categories were engineering (10%) and computer science (5%). Roughly 3 out of 4 subjects were male, reflecting the general gender proportions of the fields of study the participants were recruited from. Roughly 2 out of 3 subjects had participated in at least one online or laboratory experiment before.

First, behavior in terms of risk attitude is regarded briefly. In the HL5 test, subjects chose on average 3.233 safe options. The height of the stakes has a markedly effect. Risk aversion is significantly higher (more safe choices) in the HIGH condition (independent samples t-test, p-value < 0.001). In the HL10 test, subjects chose on average 6.035

Table 3.3.: General statistics, number of safe choices, validity of decisions, and time spent on the tasks (s.d.: standard deviation).

	all		**low stakes**		**high stakes**	
	mean	s.d.	mean	s.d.	mean	s.d.
N	490		94		396	
male	370		80		290	
female	120		14		106	
age	22.243	2.886	21.904	1.415	22.323	3.131
HL5 [#SC]	3.233	1.163	2.628	1.067	3.376	1.140
HL5 first	3.128	1.136	2.595	0.989	3.240	1.135
HL10 first	3.335	1.182	2.654	1.136	3.515	1.130
HL10 [#SC]	6.035	1.621	5.362	1.612	6.194	1.583
HL5 first	6.083	1.633	5.357	1.376	6.235	1.644
HL10 first	5.988	1.611	5.365	1.794	6.153	1.521
valid (HL5)	0.992		1.000		0.990	
valid (HL10)	0.988		1.000		0.985	
Time (HL5) [sec]	48.275	43.763	47.904	62.622	48.363	38.048
Time (HL10) [sec]	105.582	136.548	111.000	162.981	104.295	129.692

safe options. Again, the height of the stakes has a markedly effect. Risk aversion is significantly stronger (more safe choices) in the HIGH condition (independent samples t-test, p-value < 0.001).

Regarding the criterion *inherent validity*, it can be said that both the original (HL10) as well as the shortened (HL5) version of the task achieved markedly high values. 484 out of 490 subjects fill out the original test consistently, 486 out of 490 fill out the shortened version consistently. The numbers signify values of 98.8% and 99.2%, respectively, which exceeds what typically is observed in laboratory experiments and also the values Holt and Laury report in their paper ($\sim$ 90%). These high numbers indicate that the experiment instructions were read and understood and that subjects took the task with sufficient seriousness and concentration. A McNemar's test (dichotomous trait, matched pairs of observations) reveals that there is no support for the hypothesis that these proportions are significantly different from another (p-value $= 0.754$). Notice that this does not statistically verify equality of proportions. Given the large sample size and the high p-value, it appears likely, however, that the degree of inherent validity of HL5 and HL10 task are actually equal or at least very similar. The MPL design with only 5 questions instead of 10 thus does not seem to cause arbitrary behavior. At least it does not more so than in the 10 question design.

The criterion *conciseness* is assessed using the execution times associated with the respective tasks. It took the participants roughly half as long to complete the HL5 task compared to the HL10 task ($\sim$48 seconds vs. $\sim$1 minute 46 seconds, paired samples t-test: p-value < 0.001). The effect is consistent for both experiment runs (high and low stakes). Recall that every participant was presented both tasks in random order. It can be assumed that the first of both tasks presented takes longer to be understood and executed, due to inevitable learning effects. Overall, it took the participants 27.088 seconds longer to complete the HL10 task if it was presented first compared to when it was presented second. The HL5 took 17.647 seconds longer when presented first compared to when presented second. Thus, there exist order effects. Their magnitude, however, is smaller than the effect caused by the test itself: the slow execution of the HL5 (when presented first) is still 52 seconds faster on average than the fast execution of the HL10 task (when presented second). The bottom line is that it takes less than half of the time to conduct the HL5, compared to the HL10.

3.4.2. Correlation and Regression Analysis

This section now addresses the correlation between the measures of risk attitude in both tasks. It is of interest to understand how one test explains the results (e.g., number of safe choices) of the other (and vice versa) on an individual subject level. Therefore, first the risk aversion scores are correlated. Additionally, regression analysis for each direction (HL10 explaining HL5 and HL5 explaining HL10), including other relevant factors such as sequence, stakes, and demographic factors, are conducted.

Correlation Analysis In order to assess the correlation between the HL5 and the HL10 test scores, a non-parametric correlation analysis is run. Spearman's rank correlation coefficient (rho) is $\rho = 0.631$, which is statistically different from 0 (two-tailed test) on a significance level of $p < 0.001$. According to Kotrlik and Williams (2003)—who originally refer to Davis (1971), Hinkle et al. (2003), and Hopkins (1997)—the magnitude of the correlation coefficient indicates a "substantial association," a "moderate correlation," and can be interpreted as "large," "high," and "major."

Table 3.4.: Correlation coefficients for different data subsets.

	N	**Spearman's ρ**	**p-value**
All	490	.631	<.001
HIGH	396	.626	<.001
LOW	94	.584	<.001
male	370	.620	<.001
female	120	.661	<.001
HL5 first	242	.618	<.001
HL10 first	248	.648	<.001
both consistent	480	.639	<.001
≥1 inconsistency	10	.236	.511

As it is shown in Table 3.4, the overall correlation is rather robust against dividing the data into subsets along the dimensions stakes (low, high), gender (male, female), sequence (HL10 first, HL5 first), and consistency (both consistent, at least one test inconsistent). With respect to Spearman's rank coefficient, the correlation in the high stakes treatment is 7.2% higher than in the low stakes treatment. Also do women show a 6.6% higher correlation than men. Moreover, starting with the HL10 test results in a 4.9% higher correlation than starting with the HL5 test. In contrast to that, the group of subjects showing inconsistent behavior with regard to the CRRA model in at least one of the tests, has a very low and insignificant correlation. This group is, however, of neglectable small size.

Regression Analysis Next, two linear regressions are conducted, explaining the number of safe choices on an individual level for the HL5 and the HL10 task. As explanatory variables, the respective other measure (safe choices) is used. Additionally, the treatment condition (low stakes or high stakes) and a dummy for sequence (HL5 or HL10 first), as well as the respective execution times, are used. The results, including the adjusted R^2 values, are summarized in Table 3.5.

Confirming the good correlation from above, the number of safe choices in one test, proves to be the strongest explanatory variable for the number of safe choices in the respective other test. When controlling for the mentioned factors, the height of the stakes has a significant impact only on the HL5 test, not so on the HL10. Whichever test is conducted first yields a lower number of safe choices, i.e. the participants act more risk averse in the second task. Time does not affect the number of safe choices significantly.

Table 3.5.: Regression models. Explained variables: number of safe choices in the HL10 and HL5 tasks. The overview list the regression coefficients (coef.), standard errors (s.e.), and significance levels (sig.).

	HL10 (#SC)			**HL5 (#SC)**		
	coef.	s.e.	sig.	coef.	s.e.	sig.
HL5: #SC	.834	.052	$< .001$	—	—	—
HL10: #SC	—	—	—	.413	.026	$< .001$
HIGH stakes	.190	.152	.213	.419	.106	$< .001$
HL10: first	-.241	.117	.040	.235	.083	.005
HL5: time	—	—	—	-.001	.001	.130
HL10: time	-.001	.000	.093	—	—	—
constant	3.384	.202	$< .001$	.355	.188	.060
N		490			490	
$R^2_{adj.}$		.377			.397	

Regarding the criterion *segmentation*, the *number of safe choices* is distributed as follows: 0: 1%, 1: 1%, 2: 30%, 3: 25%, 4: 26%, 5: 17%. It can be said that this distribution is fairly even among the values 2, 3, 4, and 5 safe choices, however, very few subjects showed even stronger risk seeking behavior (0 or 1 safe choice). This is somewhat unexpected in the light of distribution of safe choices as empirically knwon from the standard Holt and Laury task, depicted in Figure 3.2.

To sum it up, the proposed short version of the Holt and Laury task elicits risk preferences in an inherently consistent way. It may be conducted in less than half of the time compared to the original version. The correlation, regarding the number of safe choices made by the subjects, is high. It discriminates between different degrees of risk aversion quite evenly, whereat the two bins of the highest risk seeking behavior seem to be underrepresented[4].

3.5. Discussion and Conclusions

This chapter discussed differences between laboratory and ad-hoc experiments and derived implications for the design of a respective risk preference elicitation task. Clearly, risk preference elicitation in ad-hoc experiments puts the researcher to the challenge of explaining, conducting, processing, and paying out the entire task in much shorter time compared to classical field experiments, if the task is designed comparable to a standard risk preference test as used in laboratory experiments. A short version of the Holt and Laury (2002) risk aversion task was developed and evaluated in reference to the original version by means of two online experiments with a total of 490 subjects, yielding a correlation of 63 percent between the measures (number of safe choices) for both tests. Taken as a whole, the shortened test presented in this chapter can be regarded as an adequate measure, which allows to elicit individual risk preferences within a short amount of time, yielding a very high degree of validity, and is also ascribable to the behavior shown in the established reference task by Holt and Laury (2002). Even though not ruling out switching between alternatives A and B back and forth for peculiar forms of utility models, it does for continuous, monotonic, and concave functions. The within subject correlation for both test measures can be constituted “large,” although not perfect. Possible reasons for different behavior between the tests may stem from a variety of sources, e.g. because

- not all risk preferences of the HL10 test are actually distinctly expressible in the short version,
- the availability of certainty in the short version—compared to ever uncertain prospects in the original task—might alter the way risk is evaluated,
- subjects might try to optimize their overall risk portfolio and thus choose different levels of risk in the different tasks, or

[4]When pooled with the experimental data from Chapter 5, where subjects also conducted the HL5 task, the distribution becomes smoother. A total of 970 subjects (one-shot) exhibits the following distribution over (0, 1, ..., 5) safe choices: (6.4%, 5.4%, 28.2%, 30.3%, 15.3%, 14.4%)

- some subjects might—after all—simply not understand what they are doing.

Of course, subjects also might feel compelled to act similar in both tasks, since they are aware of the fact that they are in an experimental situation and their payoff depends on their action. They might (erroneously) assume that "consistent" behavior is rewarded. A means to address this would be to let subjects participate in the first task, and then, after a considerable amount of time in between (e.g., a week), invite them to conduct the second part of the experiment. This way, it would be rather hard to recall the exact test and one's choices and thus elicit risk preferences in a less biased way.

It is possible to elicit risk preferences in other ways, using for instance the Columbia Card Task (Figner et al., 2009), the Bomb Risk Elicitation Task (Crosetto and Filippin, 2012, BRET), or the Balloon Analogue Risk Task (Lejuez et al., 2002, BART). Clearly, these methods make circumstantial explanations unnecessary and let the decision maker act in a more affective and less deliberate way. They differ, however, markedly from the Holt and Laury (2002) format, which is the most common method in experimental research, using a MPL design. This chapter has approached this conflict by presenting a handy method, which is still comparable to the existing standard. Anticipating the actual execution of the ad-hoc experiment in the field with 480 subjects (cf. Chapter 5), it can be stated that the test proves suitable for risk preference elicitation *in the wild*.

Chapter 4.

Risky Decisions among Humans and Computers

"Instead of racing against the machine, we need to learn to race with the machine. That is our grand challenge."

(Erik Brynjolfsson, 2013)

This chapter examines the impact of the opponents' type (human or computerized) on arousal and bidding behavior in electronic auctions. In an electronic market experiment with human or automated counterparts, skin conductance and heart rate are measured. These measures serve as proxies for emotions and are combined with market results to provide insight into the emotions of participants during first-price sealed-bid (FPSB) auctions and at discrete auction events, such as submitting a bid and winning or losing an auction. It is shown that arousal is stronger in human only markets and when the stakes for the decision maker are higher. Arousal is negatively correlated with the bid price in the human market treatment, but not so in the computer market treatment. It is evident that the process of bidding and competing is more thrilling against other humans, compared to computer bidders. Also, in the human market treatment, bidders place slightly higher (i.e., more risk aversive) bids. This suggests that either higher levels of arousal actually cause riskier bids (arousal is assessed prior to bid submission), or that high arousal is experienced as an effect of risky behavior. Either way, this association holds for the human market treatment exclusively, whereas computerized bidders appear to mitigate the interplay of arousal and behavior in the auction market. These results have important implications for the design of e-commerce platforms and markets that include both humans and automated agents—eBay and stock exchange are the most obvious examples.

4.1. Auctions and Electronic Markets

Information technology has revolutionized markets. While traditionally, a market was a place where people came together to trade, a large portion of today's trading activity in markets is conducted by and with computerized trading agents. A necessary precursor to this development is the ubiquitous adoption of electronic markets in industry and government (Bakos, 1991). Today, electronic markets are pervasive and an integral part of our everyday life. Billions of transactions take place in electronic markets and platforms on a daily basis. They may be small like the purchase of an electronic newspaper or large like in financial and spectrum auctions. In particular, auctions are frequently used in electronic markets (e.g. ebay.com, dubli.com, madbid.com). Regardless of their size, the bidding, search, matching, clearing, and settlement processes are all supported by IT systems. Those systems are designed to reduce transaction costs, increase the probability to find trading partners, and to support complex decision making. Hence, IS research is highly interested in how mechanism and website design affect users' perception and emotions.

For the most part, society has come to accept the fact that humans are no longer actively performing many of these tasks. As markets have automated and increased their operating speeds, so have the participants in these markets. They rely on computerized agents to represent their interests in these markets, such as sniping agents on eBay used "to avoid a bidding war" (Ariely et al., 2005, p. 896). In modern financial markets, the chances are greater to trade with an algorithm than with a human being (Hendershott et al., 2011). It is unclear how accepting market participants are of this trend. However, given the amount of negative public press surrounding algorithmic and high-frequency trading in financial markets, it is safe to say that some participants are unhappy about the current development.[1] This brings up the question how the increasing presence of computerized agents in electronic markets generally affects human decision-making processes. One of the most advanced uses of computerized agents can be found in financial markets. Computerized traders presumably are responsible for over 73% of the volume in US stock markets.[2] Hendershott and colleagues showed that algorithmic traders were responsible for a large increase in liquidity available on the New York Stock Exchange (Hendershott et al., 2011). Previous research showed that a subset of

[1]See: "High-Speed Traders Race To Fend Off Regulators," Wall Street Journal, December 28, 2012.
[2]See "SEC runs eye over high-speed trading," Financial Times, July 29, 2009.

computerized traders, called high frequency traders (HFT), make up more than 50% of the trading volume and that these traders are faster and more informed than non-HFTs (Hendershott et al., 2011). Clearly, computerized traders play an important role in electronic markets today. As part of this development, they have also become *competitors* of human traders. Research regarding their impact is still in its infancy.

To study the impact of computerized agents on the market participants' behavior, emotional responses, and market efficiency, a NeuroIS laboratory experiment, in which participants bid against other human participants in one treatment, and against computerized bidding agents in the other treatment, is conducted and illustrated in this Chapter. The type of the opponent (human or computerized) is the only difference between the treatments whatsoever. During the experiment, the participants' heart rate and skin conductance are measured as proxies for arousal and immediate emotional responses. These measures are combined with market results to provide insights into the participants' emotions during auctions and at discrete auction events, such as submitting a bid and winning or losing an auction. By capturing the participants' arousal in strictly separated scenarios (human opponents/ computer opponents), a better understanding of recent developments in markets is sought. The present study shall take a step towards explaining the source and mode of action of the involved emotional factors. Combining methodologies from neuro- and psychophysiology, experimental economics, and information systems research, the new field of NeuroIS may provide long overdue insights into the decision making process of humans interacting with information technology (Dimoka et al., 2012; Riedl et al., 2010).

In a nutshell, the results show that participants are significantly more aroused when interacting with other human bidders than with computer bidders. Moreover, participants submit lower bids when they experience higher levels of arousal. Lower bids in such an auction setting are necessarily associated with a higher degree of risk. It is striking that the relationship between arousal and risk taking behavior is only present in human opponent markets. In computer opponent markets, by contrast, bids and arousal levels are lower overall—and uncorrelated. Additionally, the participants' immediate emotions in response to auction events, such as the revelation of results, are assessed. Again, participants exhibit stronger reactions in the human market treatment. Thus, this study represents a novel contribution to the literature, since the interplay of arousal, market environment, and economic behavior has not been shown in a competitive, controlled auction environment as yet.

The remainder of this Chapter is structured as follows. In the following section, the theoretical background of the study is outlined. Particularly, the role of emotions in market decision making and how NeuroIS contributes to the understanding of human decision making processes are considered. The next section then outlines the experimental design. In the results section, the interplay of arousal and bidding behavior, the emotional intensity in response to discrete auction events, and market efficiency are investigated. Finally, the scientific and managerial implications of this study are discussed and the main conclusions are presented.

4.2. Theoretical Background and Hypotheses

Over the past decade, the presence of computerized agents has become pervasive in our everyday life. Where, traditionally, humans directly interacted with other human beings, many users interact with computerized agents today. The influence of computerized agents on the users' affective processes and behavior has thus become an important field of IS research (Gefen et al., 2008; Nunamaker et al., 2011; Riedl et al., 2011). While previous research primarily focused on trust and cooperative interaction, the main purpose of this study is to investigate the impact of computerized agents on affective processes and bidding behavior in the competitive environment of electronic auctions. In particular, the case of FPSB auctions is considered. In a FPSB auction, each of the n bidders submits a single sealed bid before the bidder who placed the highest bid obtains the item for the amount of his or her bid (McAfee and McMillan, 1987; Engelbrecht-Wiggans and Katok, 2008).[3]

While classical auction theory assumes that bidding in an auction can essentially be boiled down to a maximization of expected utility, this study starts from the intuition that (i) bidding in an electronic auction is a dynamic process, which also involves affective processes, and that (ii) these processes are influenced by whether a bidder is competing with other human bidders or with computerized agents. Building on the advances in NeuroIS (Riedl et al., 2010; Dimoka et al., 2012; Vom Brocke et al., 2013), skin conductance and heart rate measurements are used to investigate the bidders' affective processes elicited at different stages of the auction process and how they relate to the presence of computerized agents.

[3]The FPSB auction format is particularly well suited for this study, as (i) it belongs to the class of static auctions and thus enables a high level of control with little path dependence, (ii) the impact of computerized agents can be investigated in a scenario with little interaction, and (iii) the FPSB auction format is frequently used in markets world-wide.

4.2.1. Immediate Emotions and Arousal during the Auction

Previous research has shown that interacting with information systems can induce affective processes in users, which may ultimately have an impact on their attitudes, beliefs, and behavior (Deng and Poole, 2010; Riedl et al., 2011). In the context of electronic markets, in particular the design of the user interface, the reputation system, and also the market mechanism play an important role. Affective processes induced by the design of the user interface, for instance, can have an influence on the consumers' fun and enjoyment on the platform, their perception of trustworthiness, as well as their approach tendency and search depth (Stafford and Stern, 2002; Cyr et al., 2009; Deng and Poole, 2010). Even including facial features in product images can increase consumers' perception of trust and enjoyment (Hassanein and Head, 2006; Cyr et al., 2009). This effect is usually explained by the psychological construct of social presence, i.e., the perception of interaction with another human being (Gefen and Straub, 2003; Qiu and Benbasat, 2009).

Psychological research disclosed that humans exhibit an inherent tendency to long for the presence of other humans, giving them a sense of human warmth and sociability. Emphasizing or concealing the presence of other humans, or contrary to that, of computerized agents, is an important design instrument for controlling the perceived level of social presence on a website. This has also ramifications for the design of avatars to represent computerized agents in virtual worlds (Davis et al., 2009). In the context of product recommender agents, for instance, Qiu and Benbasat (2009) found that agents which employ humanoid embodiment can enhance social presence, which in turn positively affects the customers' perceptions and intentions. Nunamaker et al. (2011) created an automated kiosk in order to interview human individuals and let computerized agents actively assess the emotional state of users. The authors showed how the users' perception of information systems can be changed by varying the appearance and demeanor of the computerized interviewers. In this context, one major question is whether trusting or competing with computerized agents induces different neurobiological processes in comparison to trusting or competing with humans. Riedl et al. (2011) found that when subjects think about the trustworthiness of an interaction partner, their mentalizing network shows higher levels of activation if the trustee appears human rather than as an avatar.

While the studies outlined above have provided important contributions to the understanding of how higher levels of social presence can induce stronger affective processes in users, it is important to bear in mind that these studies primarily focused on the *cooperative* interaction of humans with computerized agents. Building on these insights, the increasing number of automated bidding agents in markets raises the question of how the *competitive* interaction with computerized agents affects human traders' emotions and behavior as well as overall market efficiency. The affective processes induced on auction platforms may therefore depend on the website design in terms of type, presence, and immediacy of the competing bidders. Especially, one may assume that the absence of other human bidders in computer markets results in a less emotionally-laden environment and that, hence, the bidders' affective processes are mitigated. Thereby, the bidders' immediate emotions, i.e., short lived subjective experience in response to specific auction events (cf. Rick and Loewenstein, 2008), as well as the bidders' overall *arousal* during the auction process (cf. Ku et al., 2005), are of particular interest.[4]

Ariely and Simonson (2003) and Adam et al. (2011) argued that the bidding process includes salient events that can induce immediate emotions as well as an increase in the bidders' overall arousal, which in turn may have an impact on bidding behavior. This emotional experience contributes to the success of Internet auction platforms as it distinguishes them from fixed-price competitors (Ariely and Simonson, 2003; Stafford and Stern, 2002; Möllenberg, 2004; Lee et al., 2009). One of the major events in this regard is the revelation of the auction outcome. It reveals the winning bidder, the auction price, and the realized profit or loss. The immediate emotions triggered in response to winning or losing an auction are usually referred to as the *joy of winning* and the *frustration of losing*, respectively (Astor et al., 2013; Ding et al., 2005).[5] In the context of auctions, Delgado et al. (2008) found that there is a stronger activation of the right striatum when losing a FPSB auction in comparison to losing a theoretically equivalent lottery. Astor et al. (2013) found that both winning and losing an electronic auction can induce immediate emotions, that increase in relation to the money at stake. Furthermore, also the event of submitting a bid or the suspense of waiting for the auction outcome are possibly able to induce immediate emotions in the bidders (Ku, 2008; Adam et al., 2011).

With respect to the relationship between social presence and the intensities of immediate emotions, Sanfey et al. (2003) found that human subjects exhibit weaker activation in the anterior insula when receiving unfair offers from computer opponents rather than from human opponents. Likewise, Bault et al. (2008) showed that the responses to winning or losing a lottery depend on the presence of a peer. First and foremost, when only one of the players can win, the immediate emotions in response to winning and losing are experienced stronger than when there is no second player at all. The authors

[4]The term *arousal* can be applied to describe both the intensity of *immediate emotions* and the emotional state. In order to avoid such ambiguity, the term *arousal* is used only in reference to the intensity of the emotional state.

[5]In addition, depending on the provided auction mechanism and information, a bidder may also experience winner regret or loser regret in response to the auction outcome (Engelbrecht-Wiggans and Katok, 2008; Astor et al., 2011). These information events are deliberately excluded in our study.

argued that in an interpersonal context, emotions such as envy and gloating serve to "keep track of our social status" by representing relative social gains or losses and thus affect decision making (Bault et al., 2008, p. 1). Hence, being among and competing against other humans might cause stronger immediate emotions than competing against mundane computer bidders, and an electronic market can be viewed as a social competition (Van den Bos et al., 2008). Therefore, it is hypothesized that the presence of computerized opponents mitigates the intensities of immediate emotions in electronic auctions. Against this background, research hypothesis 1 states:

Hypothesis 4.1. *The intensity of the bidders' immediate emotions in response to salient auction events is lower when competing with computer opponents than it is when competing with human opponents.*

In addition, also the bidders' overall level of arousal may be subject to the presence of human or computerized opponents. In particular, the inherent social competition of auctions suggests that the presence of other human bidders is a source of arousal (Malhotra and Bazerman, 2008; Van den Bos et al., 2008). Ku et al. (2005) argued that interpersonal rivalry, social facilitation, and time pressure are the main factors that can induce an intense emotional state in bidders, which the authors referred to as "competitive arousal." Likewise, Adam et al. (2013) found that bidders experience higher levels of arousal when acting under the influence of time pressure. Eventually, competitive arousal can even culminate in head-to-head battles among a subgroup of bidders and has therefore been identified as one of the main reasons for the phenomenon of auction fever (Johns and Zaichkowsky, 2003; Jones, 2011). In this context, it must be highlighted that previous research emphasized that the inherent social competition is a necessary prerequisite for the occurrence of competitive arousal (Ku et al., 2005; Malhotra, 2010). Building on these insights, it is hypothesized that the presence of computerized agents can contribute to mitigate the competitive atmosphere and thus decrease bidders' arousal. This is reflected in research hypothesis 2:

Hypothesis 4.2. *Bidders' levels of arousal are lower when competing with computerized, rather than with human opponents.*

4.2.2. Social Competition and Bidding

Classical economic theory has mostly ignored the impact of emotions on human economic decision making (Sanfey et al., 2003; Adam et al., 2011). In the last two decades, however, a substantial strand of literature has provided robust evidence that emotions play an essential role in market decision making (Ariely and Simonson, 2003; Stafford and Stern, 2002; Ockenfels et al., 2006). Auction theory assumes that bidders are rational in the sense that they maximize their expected utility by taking the interdependencies of the actions of other bidders into account (Vickrey, 1961; McAfee and McMillan, 1987). While these models are undoubtedly an important contribution to the design and understanding of auctions, they seldomly include the influence of emotions on decision making and therefore "idealize the decision-maker as a perfectly rational cognitive machine" (Sanfey et al., 2003, p. 1755). Reality appears to diverge significantly from this assumption, particularly in auctions where competitive arousal plays a role (Ku, 2008).

In contrast to homo economicus, human decision makers may not only be interested in their own individual gains and losses, but also in the payoffs of others (Van den Bos et al., 2008; Bault et al., 2008). More specifically, humans are interested in the relative payoff, e.g., the difference between their payoff and the payoff of others. Such interpersonal comparisons have been identified as a key element in economic behavior. Rewarding emotions in response to winning an auction, in this context, are intuitive. When a bidder wins an auction, the sought-after commodity is acquired and some utility is derived from it.[6] In contrast, bidders may experience frustration when they lose an auction because they did not achieve their goal, even though they *could have*. This notion considers the monetary value that a bidder derives from winning an auction. Due to the "social nature of [the] auctions" (Van den Bos et al., 2008, p. 487), however, an auction has also the component of social competition (Delgado et al., 2008). With regard to the joy of winning, Malhotra and Bazerman (2008, p. 80) argued that "people enjoy winning—especially against their rivals—even at a price." In other words, bidders may derive utility from winning the social competition of an auction "over and beyond any monetary payoffs" (Cooper and Fang, 2008, p. 1580). During the auction process, i.e., prior to the revelation of the auction outcome, this social competition can cause a strong desire to win (Malhotra et al., 2008; Malhotra, 2010). This desire could lead participants to deviate from their typical bidding pattern and place higher bids (Ku, 2008; Van den Bos et al., 2008; Adam et al., 2013). An obvious example from the consumer market, where the emotional experience gained from interacting with other human bidders in second price auctions is seen as an important characteristic, is eBay. In 2007, eBay launched an advertisement campaign called "shop victoriously" with the slogan, "it's better when you win it!" (eBay.com, 2007), stressing the competitive nature of auctions. eBay also sends emails to bidders when some other user has taken over the status of the currently highest bidder from them, prompting them to hit back with an even higher bid. Accordingly, Lee et al. (2009, p. 77) identified "the thrill of bidding,

[6] In this regard, it must be noted that bidders may also derive negative utility when they pay more for an item than it is actually worth. This is referred to as the "winner's curse" (cf. Easley et al., 2010). In this experiment, however, the bidders know the exact value of the item. The "winner's curse" is thus negligible.

the excitement of winning, and the stimulation of beating competitors" as reasons for the popularity of auctions.

Depending on how many other human actors are present and how strong this presence is realized, the social context can become more prevalent. It turns market interaction into a "play-to-win game" (Stafford and Stern, 2002, p. 44). The "uniqueness of being first" (Ku et al., 2005, p. 89), especially among peers, can cause interpersonal emotions (e.g., envy, gloating, and spite (Bault et al., 2008)), which in turn may affect economic behavior. In this sense, Palmer and Forsyth (2006, p. 236) concluded that "auction behavior is, thus, a socially constructed behavior." Human behavior in fact markedly depends on the type of interaction partners, i.e. whether they are human or computerized opponents. In particular, human behavior has proven to be more sensitive to interpersonal factors such as social competition and unfairness. Van den Bos et al. (2008) showed that auction participants submitted significantly higher bids and were prone to the winner's curse when competing against other humans in common value auctions, but not, if the opponents were computers. Sanfey et al. (2003) considered ultimatum bargaining and found that unfair offers by computers were accepted more often than identical unfair offers by humans.

Based on these findngs, this study seeks for a better understanding of how emotions and bidding behavior are affected by the other bidders' types, be it human or computerized. With respect to the fact that a FPSB auction scenario in fact puts participants in a situation of social competition and in view of the state of the literature, it is hypothesized that the presence of human opponents increases the desire to win an auction and thereby outperform the peer bidders, resulting in higher bids (Hassanein and Head, 2006; Van den Bos et al., 2008; Astor et al., 2013). Consequently, the aspect of competition may be mitigated in computer markets, resulting in comparatively lower bids. Research hypothesis 3 captures this relationship:

Hypothesis 4.3. *In FPSB auctions, bidders place lower bids when competing with computerized, rather than with human opponents.*

4.2.3. Arousal and Bidding Behavior

Potentially dangerous, exciting, or simply personally significant situations often bear high levels of risk and stimulate attention, since the potential upsides and downsides are substantial, or as Trimpop (1994, p. 89) put it: "every situation of perceived riskiness is accompanied by arousal." The presence of high risks may cause arousal, but also may arousal cause an increased willingness to take such risks. Either way, "to understand the processes connected to risk taking behavior it is important to incorporate the concept of arousal” (Trimpop, 1994, p. 53). In that sense, Mano (1994, p. 53) investigated the impact of arousal on the willingness-to-pay for lotteries and insurances and found “evidence that higher Arousal is related to risk-seeking and lower Arousal to risk-aversion.” As a consequence, risk seeking behavior may be caused by arousal. Rivers et al. (2008) presented a review on risk taking behavior under the influence of different factors such as age, impulsivity, and arousal, and stated that arousal “is a risk-promoting factor in the short term” (p. 128). Moreover, Ariely et al. (2006) showed that sexual arousal is capable of increasing the subjective willingness to engage in unsafe sexual ventures, thus being exposed to higher degrees of risk (e.g., concerning health, pregnancy, etc.).

In the context of FPSB auctions, a higher level of risk is necessarily associated with submission of lower bids. This strategy increases the potential payoff and leads to a lower probability of winning the auction in the first place, i.e. being the bidder with the highest bid. According to the competitive arousal model (cf. Ku et al., 2005; Malhotra, 2010), a factor like rivalry stimulates physiological arousal, which in turn fuels the desire to win against the opponent. Following this notion, high levels of physiological arousal should be associated with high bids, since high bids are ceteris paribus more likely to win an auction than low bids. Contrary to that, as was pointed out, high levels of arousal are often associated with a high willingness to take risks (Ku et al., 2005; Ariely et al., 2006; Adam et al., 2013). Thus, given the social environment, one may assume that risk taking and arousal are positively correlated, and hence that arousal is associated with comparatively lower bids. It is therefore hypothesized that lower bids are associated with the experience of higher levels of arousal. Research hypothesis 4 states:

Hypothesis 4.4. *Lower bids are related to the experience of higher levels of arousal in FPSB auctions.*

Previous research indicates, however, that the social context may play an important role in the relationship between arousal and behavior. In the context of a power-to-take bargaining scenario, Ben-Shakhar et al. (2007) found that arousal can even cause subjects to destroy a significant proportion of their own payoff in order to harm other participants. Sanfey et al. (2003) investigated ultimatum game bargaining and found that unfair offers by humans induced stronger activation in the anterior insula than did those of computer agents and that unfair offers by humans were rejected more often than identical unfair offers by computerized agents. In a follow-up study, van ’t Wout et al. (2006, p. 565) further investigated this matter to explore whether arousal is related to decisions. Based on skin conductance measurements, the authors found that arousal was higher for unfair offers and that higher arousal levels were also associated with higher rejection rates. Interestingly, however, the authors found that this pattern only existed when humans received “offers proposed by human conspecifics, but not for offers generated by computers” (p. 564). In the context of auctions, previous research argued that interaction with other human bidders is a crucial condition for the influence of arousal on bids (Ku et al., 2005; Adam et al., 2011). In this sense, bidders may not only be less aroused when competing with computer opponents, but their behavior may also be less correlated to arousal. Especially when competing with peers, high risk may be related to high arousal, since the psychological evaluation of economic dimensions (probability of winning, potential payoff) is enriched by the component of social competition. Consequently, it hypothesized that the presence of computer agents in the auctions mitigates the relationship between arousal and bids. H5 thus states:

Hypothesis 4.5. *The relationship between arousal and bids is mitigated when competing with computer opponents.*

Note that this study abstracts from any graphical form of representation, as this might be a potential source of variance, and thus limits the scope of possible causes to the mere matter of fact and the consciousness of interacting with either humans or computers. This market environment (treatment variable) is expected to have an impact on arousal and bidding behavior, and also arousal is hypothesized to affect bidding behavior. It is thus the question whether a mediating effect of arousal exists, partially or fully, and also how this mediation is moderated by the treatment variable itself. The research model linking the research hypotheses (H1 through H5) and the conceptual structure of moderated mediation is depicted in Figure 4.1.

4.3. Experimental Design

This section presents the experimental design of this study. First, the overall treatment and session structure and the auction format itself are illustrated. Second, the experimental procedure in the laboratory is explained and information concerning the physiological measurements is provided.

4.3.1. Treatment and Session Structure

The experiment comprises two treatments. First, in the human market (HM) treatment, the subjects interact with human bidders only. Second, in the computer market (CM) treatment, the subjects interact with computerized agents only. The CM treatment sessions were conducted one week after the HM treatment sessions. The computerized bidders in the CM treatment replicated the bids of the human bidders as collected in the HM treatment one week earlier (see Van den Bos et al. (2008) for a similar approach). By replicating the human bids, influencing the results due to the different bidding of

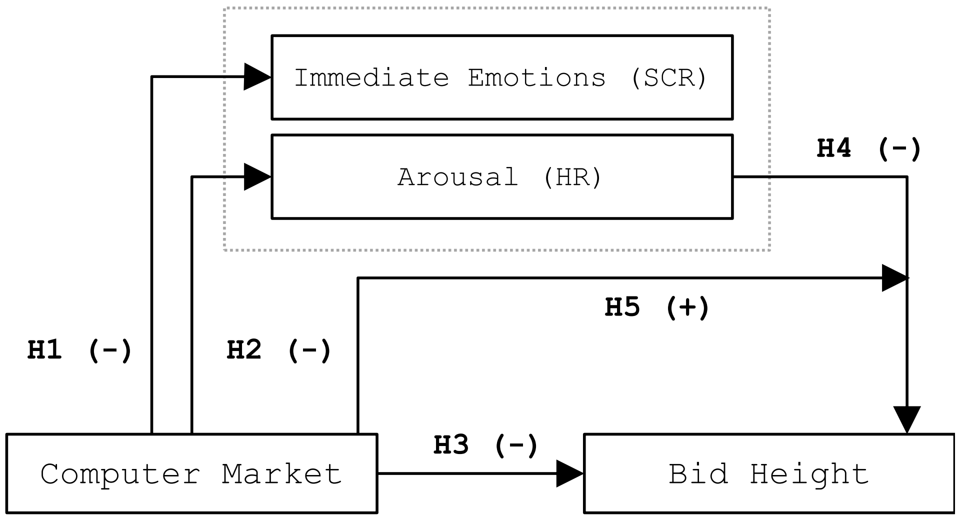


Figure 4.1.: Research Model

agents is avoided. That makes the results comparable across treatments. Subjects in the CM treatment thus faced the exact same bids from their opponents as subjects in the HM treatment. The experiment is based on a between subjects design, i.e., the subjects were randomly assigned to either participate in the HM or CM treatment, but never both (see Van den Bos et al. (2008); Engelbrecht-Wiggans and Katok (2008) for similar approaches). There were 12 sessions in the HM treatment, and 8 sessions in the CM treatment. Each session comprised 6 subjects, yielding a total of 120 subjects ($N_{HM} = 72$, $N_{CM} = 48$). In the HM treatment, the subjects were randomly reassigned to groups of 3 bidders before every single auction period (random stranger matching). Thus, subjects did not know which other subjects were currently participating in the same auction. Each group then played a single FPSB auction independently with three bidders. During the experiment, each bidder took part in a sequence of 30 FPSB auctions with 2 other bidders. After every period, the subjects were re-matched into different groups of 3, so that no learning effects from the interaction with the same opponents was possible. In the CM treatment, every subject was matched with 2 computerized bidding agents, which replicated the human bids from the HM treatment. Again, every subject was re-matched into a different group with 2 computerized bidding agents after each auction period.

4.3.2. Auction Process

In FPSB auctions, all the bidders simultaneously submit single sealed bids (only the auctioneer observes the bids ex post). The bidder who places the highest bid obtains the commodity and has to pay the amount of the bid (Vickrey, 1961). In this experiment, there are 3 bidders in each auction. This is commonly known information. Before an auction starts, each bidder i is informed about his or her independent private value (IPV) v_i for the commodity to be auctioned. The IPV model dates back to the seminal work of Vickrey (1961) (see Katok and Kwasnica (2008); Engelbrecht-Wiggans and Katok (2008); Astor et al. (2013) for similar approaches).

This IPV is independently drawn for each bidder from a uniform distribution with support on the discrete integer interval $\{11, 12, \ldots, 109, 110\}$. It is expressed in monetary units (MU). The bidders only know their own IPV and the general distribution of IPVs, which, in this case, is the same for all bidders. The bid of participant i is denoted by b_i. The winning bidder i receives a payoff equal to the winning bid minus his or her individual valuation for the commodity being auctioned $(v_i - b_i)$. All other bidders receive a payoff of zero. The equilibrium bidding strategy $b^*(v_i)$ for bidder i (cf. Krishna, 2002) in an auction with three risk neutral bidders in total and the common and commonly known distribution of IPVs as denoted above is given by

$$b(v_i)^* = \frac{2}{3}(v_i - 10) + 10. \tag{4.1}$$

In order to exclude missed-opportunity and money-left-on-the-table effects (Filiz-Ozbay and Ozbay, 2007; Engelbrecht-Wiggans and Katok, 2008), a minimal information environment is presented to the bidders. In that setting they are neither informed about the highest nor about the second-highest bid (Armantier, 2004). At the end of an auction, bidders only receive information about whether the auction was won or lost and their payoff. The bidders' identities are not revealed. In order to capture the physiological reactions to specific events, information is provided in timed intervals of at least five seconds (Sanfey et al., 2003; Adam et al., 2011). The auction process is depicted in Figure 4.2.

In order to investigate the intensities of the bidders' immediate emotions throughout the auction process, three specific events in the auction process are considered (E1, E2 and

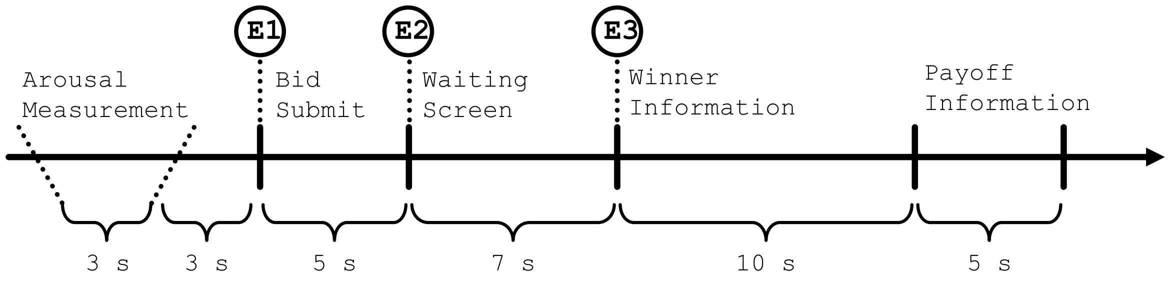


Figure 4.2.: Auction process and timed intervals between different information events.

E3 in Figure 4.2). First, the bidders' physiological response to placing a bid (E1) is analyzed. Subsequently in the auction process, the bidders see an information screen that informs them that the auction outcome will be revealed soon (E2), which constitutes the second monitoring point. Finally, the moment in which bidders find out whether they have won or lost the auction (E3) is considered. Contrary to several studies from recent IS literature (Nunamaker et al., 2011; Cyr et al., 2009; Riedl et al., 2011), there is no graphical representation of opponents (either other humans or computerized bidding agents) at any point before, during, or after the auctions. The subjects, however, *know* about the nature of their opponents. Since this difference is not emphasized any further, the effect of knowing with whom you interact (*awareness*), is isolated from the immediate impression (*affect*), as, for instance, induced by a graphical representation, text messages, or the like. Keep in mind that the type of the opponents (humans or computers) constitutes the only and single difference between the 2 treatments whatsoever. In fact, since the bids are replicated by the computer bidders, this difference is virtually limited to the opponents' designation in the experiment instructions.

4.3.3. Procedure

Before the first auction started, subjects went through a five minute resting period for calibration and benchmarking purposes with respect to the physiological measurements (cf. Sütterlin et al., 2011; Adam et al., 2011). Moreover, in order to ensure comprehension of the rules of the experiment, subjects had to complete a quiz regarding the experimental instructions and then participated in five practice auctions, which were irrelevant for payoff. In order to control for heterogeneities in risk attitude, the subjects' individual risk attitudes were assessed using the Holt and Laury (2002) questionnaire with real monetary payoffs at the end of the experiment.[7] This measure is used to distinguish subjects according to whether or not they are (relatively) risk averse. When comparing the number of safe choices S, the differences in individual risk attitudes between treatments show to be insignificant, although subjects were slightly more risk averse in the HM treatment (independent samples t-test, $S_{CM} = 5.68, S_{HM} = 6.04$, $T = -1.169$, $p = 0.234$, two-tailed).

The experiment was conducted at the laboratory of the Institute of Information Systems and Marketing (IISM) at the Karlsruhe Institute of Technology (KIT). The experimental system was implemented using the z-Tree environment for economic experiments (Fischbacher, 2007). In order to avoid artifacts due to body movements, participant interactions with the experimental system were limited to mouse inputs, i.e., only the dominant hand was needed. Moreover, subjects were equipped with a pair of earmuffs to avoid sensitivity to background noise.

Participants were recruited from a pool of undergraduate students using the ORSEE software environment (Greiner, 2004). Altogether, 27 female and 93 male subjects (6 subjects per session, 120 in total, mean age = 23.16 years) participated in 20 sessions. A total of 12 sessions for the HM treatment ($12 \times 6 = 72$ subjects) and 8 sessions for the CM treatment ($8 \times 6 = 48$ subjects) were conducted. There was no lump sum payment. The experimental currency was monetary units (MU) with 16 MU being equivalent to €1.00. Depending on their individual performance, all gains and losses accumulated during the auctions went to the bidders' individual accounts. The individual accounts were paid out in cash to the participants at the end of the experiment. The average payment was €16.13, with a minimum payment of €5.88 and a maximum payment of €28.44. Subjects were able to earn up to an additional €3.85 in the risk aversion questionnaire.

This study used heart rate as a proxy for the individual degree of arousal before a subject placed a bid. Heart rate is measured in beats per minute (bpm). The heart rate signal was derived from an electrocardiogram (ECG) recording device, using the *lead I* method with single-use electrodes placed on the left and right wrist (Berntson et al., 2007). As proxy for arousal before bidding, the bidders' average heart rate (HR) in the time frame 6 to 3 seconds before bid submission is used hr_{6-3} (cf. Figure 4.2). This HR value is normalized by the bidder's individual HR baseline hr_0, as measured during the initial five minute resting period.

$$\mathrm{hr}_\theta = \frac{\mathrm{hr}_{6-3}}{\mathrm{hr}_0} - 1. \tag{4.2}$$

[7]See Chapters 2 and 3 for more detailed information on experimental risk attitude elicitation in general and this task in particular.

Normalization makes HR comparable across participants and treatments. An arousal parameter of $\mathrm{hr}_\theta > 0$ in this context means that a subject's heart rate in the time frame of 6 to 3 seconds before submitting a bid was higher than in the initial calibration phase.[8]

Additionally, the subjects' skin conductance was recorded throughout the experiment, using a constant current amplifier measurement system and Ag/AgCl (silver/silver chloride) electrodes. The electrodes were attached to the thenar and hypothenar eminences of the palm of the non-dominant hand with standard electrodermal activity (EDA) electrode paste (Boucsein, 1992). As mentioned before, skin conductance can be used as a measure of arousal *in response* to "sudden" events. In order to do so, the amplitudes of such prompt increases (phasic component) must be separated from the general movements of the signal (tonic component, e.g., due to body movements, thoughts, variations of temperature, habituation, etc.). The amplitudes of these skin conductance responses (scr_Δ) are a proxy for the intensity of immediate emotions and reflect short bursts of sympathetic activity. These amplitudes were obtained by decomposing the skin conductance signal with the Ledalab analysis software (Benedek and Kaernbach, 2010). Only amplitudes in the time frame 1 to 3 seconds after an event and with a value greater than or equal to 0.01μS were used (Boucsein, 1992; Fowles et al., 1981). Following the recommendation of Venables and Christie (1980), all raw scr_Δ values x were transformed by $\log(x+1)$.

The physiological measurement results of 17 subjects had to be removed from the data sample. This was because the values of either hr_θ or scr_Δ, or both, were outside the range of the measurement system or because of too much noise on the signal. Thus, the entire analysis is based on a data sample of $120 - 17 = 103$ subjects ($N_{CM} = 39$, $N_{HM} = 64$). The analysis of allocation efficiency is unattached by the physiological measurements, so that all 120 were used.

All sessions were conducted within a period of two weeks (June, 15 to 24, 2011) with an average room temperature of 24.1°C (75.4°F) and a relative humidity of 53.1%. These values comply with the methodological recommendations of the Society for Psychophysiological Research (Fowles et al., 1981). Figure 4.3 displays a photograph of a computer terminal as it was used for the experiment.

[8] It should be noted at this point that this measure for arousal appears somewhat conservative, since it relates the heart rate values to the subject's average heart rate during a five minute resting period. In this resting period, the subjects sit idle, do not experience any stimuli so that a heart rate around the basal (or resting) heart rate of 60 to 80 bpm can be assumed. Designating an increase of 3 bmp on a basis of 60 bpm as an increase of 5 percent ($3/60 = 0.05$) technically assumes a natural null-point of 0 bpm. This, however, is fairly unrealistic, at least for alive beings. Since very low basal heart rates may lie between 30 and 60 bpm, but hardly any lower, the plain percental measure tends to underestimate the effect size.

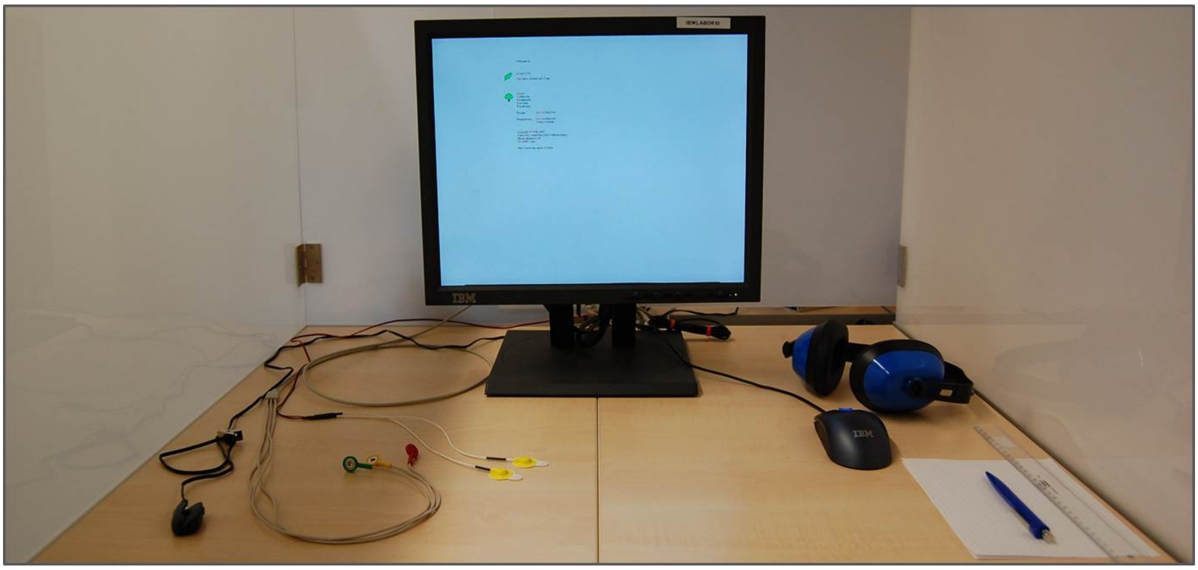


Figure 4.3.: Laboratory Computer Terminal with Physiological Measurement Equipment.

4.3.4. Physiological Measurements

The methods of NeuroIS allow researchers to shed light on the visceral processes underlying users' emotions[9] and decision making (Dimoka et al., 2012; Vom Brocke et al., 2013). NeuroIS uses techniques from cognitive neuroscience to measure objective correlates of human emotional processing while subjects interact with information systems. The two correlates used in this study, heart rate and skin conductance, are proxies for activation of the autonomous nervous system (ANS). The ANS consists of the sympathetic and the parasympathetic nervous system. They typically function in opposition to each other (Cacioppo et al., 2007). The sympathetic branch activates the organisms for fight or flight, while the parasympathetic branch promotes digestion and recreation. Both heart rate and skin conductance response are measures for arousal. In the context of this work, SCR amplitudes as a proxy for the intensities of immediate emotions, i.e. phasic arousal, in response to specific events during the auction process are measured.

[9] There are different types of emotions. This study is concerned with immediate and expected emotions (Loewenstein and Lerner, 2003). An immediate emotion is a direct response to an event, e.g., anger or elation. Immediate emotions are directly experienced by the subject. Within an auction, the joy of winning and the frustration of losing fall into this category (Adam et al., 2011; Astor et al., 2013). In contrast, an expected emotion is not a directly experienced emotional response, but rather an expected emotional reaction in response to a future event. According to Loewenstein and Lerner (2003, p. 620), "expected emotions are not experienced as emotions per se at the time of decision making; [...] they are expectations about emotions that will be experienced in the future."

The subjects' heart rate, i.e. tonic arousal, is used as a proxy for the general level of arousal.

Heart rate is a measure that reflects the activity of both sympathetic and parasympathetic branches of the ANS (Berntson et al., 2007). In contrast, skin conductance is a measure that directly reflects the activity of the sympathetic nervous system only (Boucsein, 1992; Dawson et al., 2011). Skin conductance is measured in microsiemens (μS) and can be broken down into tonic and phasic components. The tonic component reflects the general arousal level of the individual (skin conductance level or SCL), i.e., the ongoing emotional state. The phasic component represents short monophasic bursts of sympathetic activity (skin conductance response or SCR), which are usually elicited by an external or internal stimulation (Wallin, 1981). SCRs typically occur 1 to 3 seconds after a discrete event. The amplitude of an SCR (scr_Δ) has been identified as a valid measure of emotional arousal (Lang et al., 1993; Bradley et al., 2008). In other words, quantifying the amplitude of an SCR in response to an "emotionally competent stimulus" provides a proxy for the intensity of the emotion experienced (Bechara and Damasio, 2005, p. 339). From a psychophysiological perspective, a subjectively experienced feeling is only part of the broader concept of emotion. It also comprises objectively observable changes, e.g., in physiology. Bechara and Damasio (2005, p. 339) defined an emotion as "a collection of changes in the body and brain states triggered by a dedicated brain system [...] relative to a particular object or event." In an auction, this type of stimulus would be for instance the event of being informed about winning or losing the auction, i.e., the auction outcome.

4.4. Results

This section presents the results of the study. In the first part, immediate emotional responses to discrete auction events are considered. The second part analyzes the interplay of market environment, arousal, and bidding behavior. Eventually, the third part briefly deals with allocation efficiency.

4.4.1. Immediate Emotions in Response to Auction Events

This subsection considers the bursts of arousal (i.e., immediate emotions) in response to the discrete auction events *bid submission* (E1), *an intermediate information screen* (informing subjects that the result is about to be displayed) (E2), and the *auction outcome* (E3). This analysis aims at connecting these indicators to treatment, stakes, and the actual outcome (winning or not winning the auction), cf. Figure 4.2. It was hypothesized that such discrete auction events elicit stronger emotional responses when competing with human opponents (H1). For the purpose of this analysis, as stated before, the

Table 4.1.: Value classes.

value class		**value interval** Lower bound	Upper bound
0	very low	11	30
1	low	31	50
2	medium	51	70
3	high	71	90
4	very high	91	110
total range		11	110

subjects' skin conductance response amplitudes are used. This section additionally considers the impact of the IPV as well as the role of the outcome (winning or losing). For the purpose of illustration, the IPV values are grouped into five categories. Table 4.1 reports the ranges for each value class.

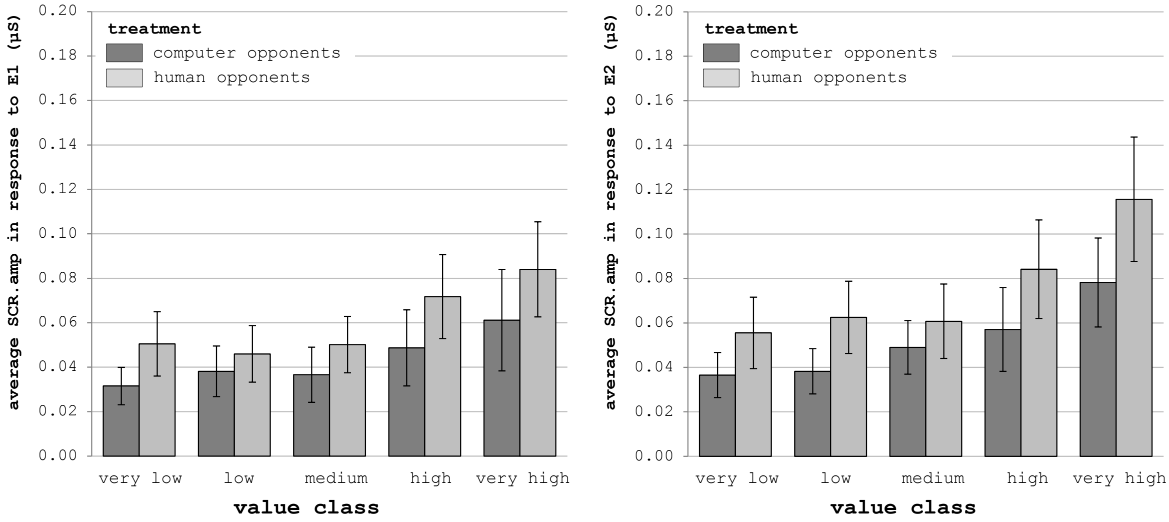
Figures 4.4(a), 4.4(b), and 4.5(a), display the intensity of the participants' immediate emotions in response to the 3 auction events E1, E2, and E3. The results are grouped by value class and treatment. All of the Figures indicate that emotional intensity is generally lower in the CM treatment, and generally higher for higher value classes. The strongest responses are triggered by displaying the auction outcome (E3), whereas E1 and E2 trigger less intense responses. To confirm the graphical evidence, three OLS regressions are conducted, in which each bidder's average scr_{Δ} in response to E1, E2, and E3 is regressed. For all events, treatment (CM: 1, HM: 0), value class (coded as 0 to 4), gender (female: 1, male: 0), and risk aversion (1: above average, 0: below average) are controlled for. For E3(1), a dummy for the auction outcome (winning: 1, losing: 0) is included. In addition to that, the interaction term value class $\times$ auction outcome is included in E3(2).

The results of the regressions are presented in Table 4.2.[10] The differences in the intensities of the emotional responses between the CM and HM treatments are significant and consistent for E1 to E3 (E1: $b = -0.015, p = 0.007$, E2: $b = -0.021, p = 0.001$, E3: $b = -0.029, p < 0.001$), whereat the effect at E3 is stronger than at E2, and stronger

[10] Note that the number of observations for E3(1) and E3(2) could be expected to be $2\times5\times103 = 1030$, since there are 5 value classes, 2 outcome roles (winning and losing), and 103 subjects. Obviously, however, not every combination of outcome role and value class does exist, since for instance, an auction with an IPV from the lowest value class is highly unlikely to be won by the respective bidder.

Table 4.2.: Regression models for SCR amplitudes in response to E1, E2, and E3.

	E1			E2			E3(1)			E3(2)		
	coef.	s.e.	p	coef.	s.e.	p	coef.	s.e.	p	coef.	s.e.	p
Computer Market	-.015	.005	.007	-.021	.006	.001	-.029	.008	$<.001$	-.029	.008	$<.001$
value class	.008	.002	$<.001$	.013	.002	$<.001$	.027	.003	$<.001$	.033	.004	$<.001$
dummy: female	-.025	.006	$<.001$	-.033	.008	$<.001$	-.038	.009	$<.001$	-.038	.009	$<.001$
dummy: risk aversion	.015	.007	.034	.009	.008	.244	.003	.010	.782	.003	.010	.769
dummy: winner							.020	.008	.014	.054	.017	.001
value class $\times$ winner										-.014	.006	.020
constant	.036	.008	$<.001$	.049	.009	$<.001$	.056	.012	$<.001$	.046	.013	$<.001$
N		515			515			846			846	
R^2		.089			.117			.143			.149	



(a) Skin conductance response amplitudes in response to E1.

(b) Skin conductance response amplitudes in response to E2.

Figure 4.4.: Skin conductance response amplitudes in response to E1 and E2.

at E2 than it is at E1. In summary, the null hypothesis can be rejected in favor for hypothesis H1.

> **Result 1:** *The intensity of the bidders' immediate emotions in response to salient auction events is lower when competing with computer opponents than it is when competing with human opponents.*

The general positive relationship between stakes and emotional intensity can also be confirmed in this setting. The coefficient of value class is positive, significant, and consistent for the three regressions E1, E2, and E3(1). Again, the magnitude of the effect is increasing during the course of the auction process (E3 > E2 > E1).

> **Result 2:** *The intensity of the bidders' immediate emotions in response to salient auction events is higher for higher induced IPVs.*

Since the bidders cannot lose money but make a profit if they win the auction, the status quo is maintained when an auction is lost, whereas a gain is realized when an auction is won. One would thus expect a stronger emotional response to winning rather than losing an auction. Regression E3(1) confirms this conjecture. The coefficient on the dummy variable for winning is positive and statistically significant ($b = 0.020, p = 0.014$).

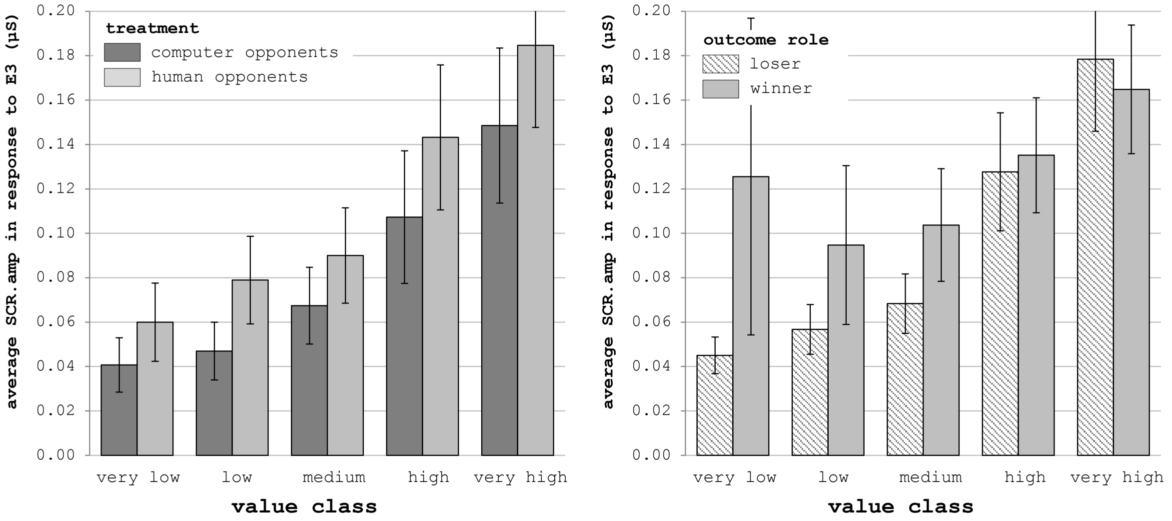
> **Result 3:** *The intensity of the bidders' immediate emotions in response to the auction outcome is higher if the auction is won.*

Additionally, regression E3(2) captures the interaction between outcome role (winning or losing) and value class. The coefficient for the dummy *winner* is positive and significant ($b = 0.054, p = 0.001$), i.e. at the lowest value class (coded as 0), winning causes stronger emotional responses than losing. The coefficient of the variable for *value class* is also positive and significant ($b = 0.033, p = 0.004$), i.e., in case an auction is not won, every increase in *value class* will increase the emotional response significantly. The interaction term *winner* × *value class* is negative and significant ($b = -0.014, p = 0.006$), i.e., the just mentioned increase is lower, but still positive ($0.033 + (-0.014) = 0.019$) if the auction is won. The interaction of *winning* and *value class* captures the notion that the emotional response is stronger when a participant wins an auction unexpectedly, as it is in case of low value classes. Note that the emotional intensity of losing even surpasses the intensity of winning in the highest value class. Intuitively, this makes perfect sense since one would expect to win when the valuation is very high. Losing *despite* a very high valuation appears to evoke strong emotions. This pattern is consistent across treatments. As depicted in Figure 4.6, the general intensity of emotions is higher in the HM treatment and the responses are stronger for winning an auction—both in the CM and the HM treatments. An interaction effect between treatment and auction outcome cannot be observed: winning an auction (compared to losing) causes stronger responses across both treatments. Participants in the HM treatment show stronger responses to both winning and losing the auction than participants in the CM treatment do. The values of scr_{Δ} for winning and losing as well as for each of the 5 value classes are depicted in Figure 4.5(b).

> **Result 4:** *The emotional intensities in response to the auction outcome are higher for higher value classes for both winning and losing the auction (cf. Result 2). This increase is stronger for winning than it is for losing the auction.*

4.4.2. Market Environment, Arousal, and Bidding Behavior

This subsection considers the general level of arousal before bid submission and aims at connecting these values to treatment and bidding behavior. Engelbrecht-Wiggans and Katok (2008) and Katok and Kwasnica (2008) established that when participants think they do not have a realistic chance of winning an auction, as it may be the case for low IPV, they behave aimlessly. Therefore, only auctions with IPV equal to or higher than



(a) Skin conductance response amplitudes in response to treatment and value class (E3).

(b) Skin conductance response amplitudes in response to auction outcome and value class (E3).

Figure 4.5.: Skin conductance response amplitudes after auction result revelation.

60 MU, i.e., the upper 50% of the IPV distribution are used.[11] This means that from the series of 30 auctions, on average roughly 15 auctions are considered in the analysis.

General Statistics. First, the data is analyzed on a subject level. In this experiment, bidders' arousal levels hr_θ are significantly higher in the HM treatment than in the CM treatment (3.92% vs. 1.79%, independent samples, one-tailed t-test, $T = -1.904$, $p = 0.030$). Thus, in line with hypothesis H2, and confirmatory of the results on skin conductance responses, participants appear to be less aroused when they are bidding against computer opponents, cf. Figure 4.7(a). This first result suggests that emotions play a stronger role in markets with human opponents than in markets with computer opponents.

Second, the average height of bids for the different treatments is considered. An independent samples t-test reveals that absolute bids do not significantly differ between treatments ($b_{HM} = 72.36$, $b_{CM} = 71.79$, $T = -0.564$, $p = 0.287$, one-tailed).[12] There

[11] Previous research found that bidding behavior for low valuations is rather different than it is for high valuations (Kagel, 1995; Neugebauer and Selten, 2006; Engelbrecht-Wiggans and Katok, 2008). Bidders seem to realize that their probability of winning the auction in these cases is small and, therefore, they even place bids in excess of their own valuation to prevent another bidder from making a high profit.

[12] Additionally, a regular OLS regression is conducted, using the treatment dummy and average IPV as explanatory variables for the average bid (on subject level). $b_{v_i} = 0.667, p_{v_i} < 0.001, b_{HM} = 0.408, p_{HM} = 0.655, R^2 = 0.200$.

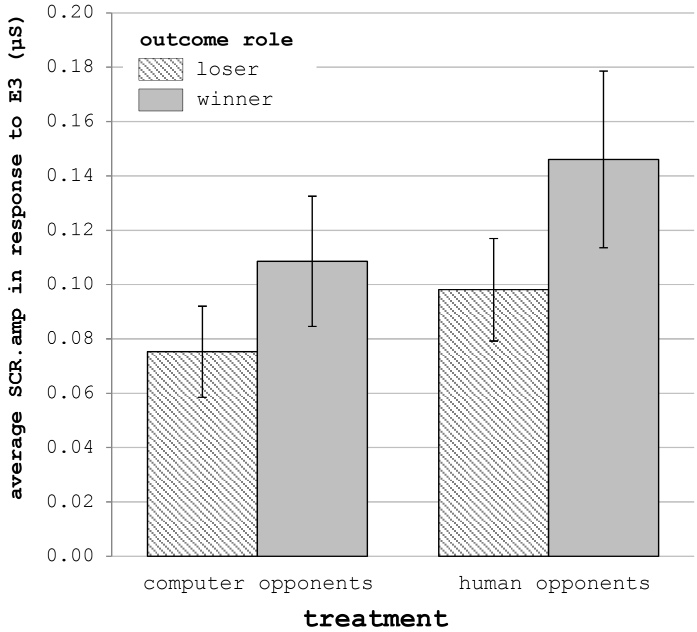
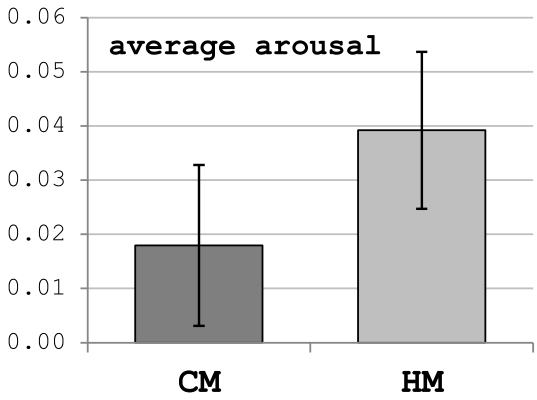


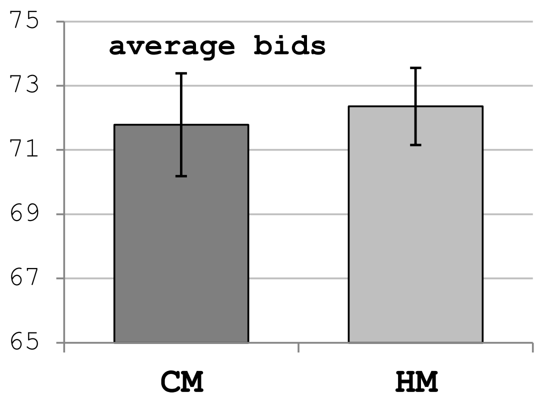
Figure 4.6.: Skin conductance response amplitudes (SCR.amp) in response to winning and losing information and treatment.

is no indication for an immediate, unconditioned effect of treatment on overall bidding behavior—with or without controlling for induced valuation (as hypothesized in H3), cf. also Figure 4.7(b).

The literature suggests that there is a relationship between emotions (specifically arousal) and bidding behavior in auctions. Although not yet definitively established, a link between arousal and bidding behavior seems plausible (H4). A Pearson correlation (on subject level) indicates a negative but insignificant relation of average arousal and average bid height ($r = -0.106, p = 0.144, n = 103$, one-tailed). As outlined above, however, the impact of arousal on behavior (bids) might well be dependent on the market environment (HM or CM). Hypothesis 5 stated that there is a conditional effect of arousal on bids, dependent on whether the bidders face human or computer opponents (cf. Figure 4.1). In order to assess whether such a relationship between arousal and bidding exists, first, the correlations between the bidders' average arousal and average bid, grouped by treatment, are analyzed. The analysis reveals a statistically significant negative correlation between arousal and bids ($n = 64$, $r = -0.232$, $p = 0.033$, one-tailed) in the HM treatment, whereas there is no significant correlation between arousal and bids in the CM treatment ($n = 39$, $r = 0.104$, $p = 0.265$, one-tailed). Both correlations are illustrated in Figure 4.8. In this figure, average bids increase with increases of arousal in the CM treatment. Statistically, however, this effect is neglectable, as confirmed by the



(a) Average level of arousal in the human market (HM) and computer market (CM) treatment (error bars: 95% CI).



(b) Average height of bids in the human market (HM) and computer market (CM) treatment (error bars: 95% CI).

Figure 4.7.: Basic interrelations of treatment, arousal and bid height.

correlation analysis. Participants are more aroused when they are bidding against other humans, and also is their bidding behavior stronger associated with the individual levels of arousal. Bidding lower in FPSB auctions brings about a higher level of risk taking. By lowering their bids, participants reduce the probability of winning the auction, but at the same time increase their payoff in case they win. In compliance with H5, the computer opponents seem to have a mediating influence on the interrelation of arousal and bidding.

It must be added that an entirely reliable conclusion about causality from arousal to bidding behavior is not possible. Even though arousal was measured and averaged in the time frame 6 to 3 seconds *before* the bid was submitted, it might very well be that subjects *intended* to submit a particularly low bid and then—*because* of the thrilling thought about the associated risks and potential gains—became more aroused. Eventually, they might have submitted their bid according to their initial plan. This reflects a general and methodological limitation of experimental approaches such as prosecuted in this study, since it is not generally possible to assess the participants' intentions and thoughts during the experimental process. A noteworthy fact in this context, however, is the non-correlation of (average) induced valuation and (average) arousal. Neither is this correlation significant for the treatments separately ($r_{HM} = 0.137, p_{HM} = 0.140$, $r_{CM} = -0.155, p_{CM} = 0.173$), nor for the total set of subjects ($r = 0.050, p = 0.306$, all p-values one-tailed). Thus, the IPV as a common cause for arousal and bidding behavior does not appear likely.

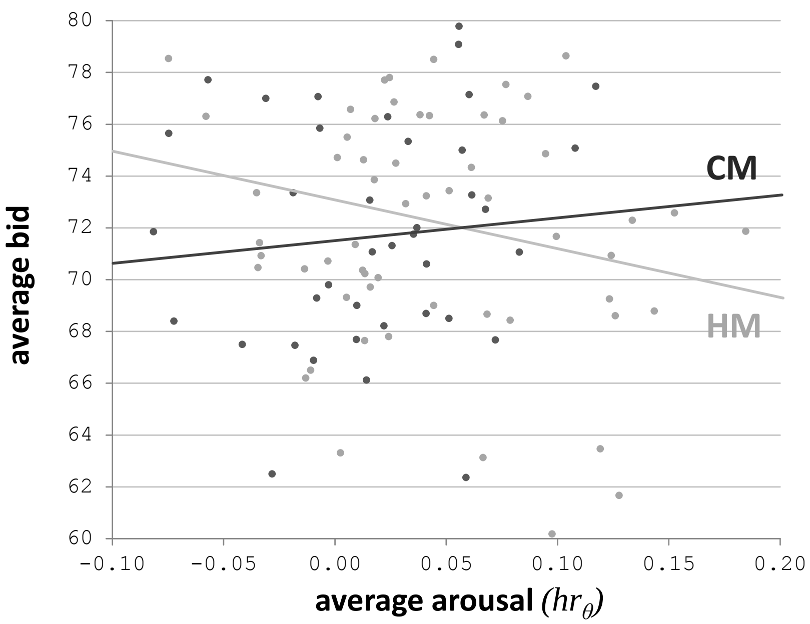


Figure 4.8.: Correlation of arousal and bids in the human market (HM) and computer market (CM) treatment. $R^2_{HM} = 0.052, R^2_{CM} = 0.007$.

The correlations between *treatment*, *average arousal*, *average induced value*, and *average bid* are summarized in Table 4.3 (Pearson correlations, one-tailed significance values, $N = 103$).

Regression Analysis. The previous analysis established a relationship between arousal, bidding behavior, and the market environment on subject level. Though compelling, the previous results may not hold up to more rigorous and differentiated analysis. In particular, the individual differences of single auctions have not been assessed so far. This aspect presumably is of high importance, since people are not generally aroused or bidding in a certain way, but show varying reactions, depending on stimuli such as an IPV. Hereinafter, the empirical data is analyzed on the level of single auctions.

For this reason, 3 different regression specifications are run. First, the level of arousal is explained in specification (1). In specification (2) and (3), the bid height is regressed. Independent variables in all specifications are a treatment dummy (1 in computer opponent markets, 0 in human opponent markets), a gender dummy (1 for female, 0 for male), and a risk aversion dummy (1 for above average risk aversion, 0 otherwise). Risk aversion is measured by using a questionnaire administered after the experiment (Holt and Laury, 2002). It is also controlled for induced valuations and auction sequence. Specifications (2) and (3) include the bidder's level of arousal (hr_θ, mean-centered),

Table 4.3.: Correlation Table: bivariat correlation between average bids, average arousal, average value, and treatment on a subject level. Pearson coefficients, p-values displayed in parentheses (one-tailed), significant correlations ($p < 0.05$) highlighted in bold face type. $N = 110$.

	average bid	average arousal	average value	treatment: HM
average bid	1.000	-.106	**.445**	.056
		(.144)	**(< .001)**	(.287)
average arousal		1.000	.050	**.186**
			(.306)	**(.030)**
average value			1.000	.036
				(.359)
treatment: HM				1.000

whereas specification (3) additionally includes an interaction term between arousal (hr_θ, mean-centered) and treatment (dummy: computer market). Since an interaction effect is tested in the regression, the continuous variable for arousal hr_θ is mean-centered. This basically does not change the analysis but makes the regression coefficients and intercepts interpretable in a sensible way. Following the recommendations of Preacher et al. (2007), Table 4.4 reports the unstandardized regression coefficients.

Consistent with the previous analysis and hypothesis H2, specification (1) (*arousal*) shows that arousal is significantly lower in the CM treatment (by 2.4 percentage points), also when controlling for valuation, sequence, gender, and risk aversion ($b = -0.024$, $SE = 0.011$, $p = 0.026$).

Result 5: *Bidders' levels of arousal are lower when competing with computerized, rather than with human opponents.*

Moreover, the IPV has a positive effect on arousal whereas the auction number has a negative effect. Participants thus seem to be calming down during the experiment.

The results of specification (2) indicate that the market environment has no significant unconditioned effect on bids ($b = -0.689, p = 0.446$), i.e. the working hypotheses ¬H3 cannot be rejected. Female bidders submit significantly higher bids ($b = 2.397, p = 0.017$). Naturally, the IPV affects bid height positively ($b = 0.650, p < 0.001$). The general effect of arousal on bids is negative and shows a trend towards 5% significance ($b = -6.352, p = 0.080$). It is significant on a 10% level.

Result 6: *Lower bids are related to the experience of higher levels of arousal in FPSB auctions.*

Table 4.4.: Regression models (1), (2), and (3) for arousal and bid (CM: dummy for CM treatment, RA: dummy for risk aversion, F: dummy for female.

	(1) Arousal			(2) Bid			(3) Bid		
	coef.	s.e.	p	coef.	s.e.	p	coef.	s.e.	p
CM	-.024	.011	.026	-.689	.901	.446	-.610	.895	.497
RA	-.025	.013	.052	.067	.927	.942	.026	.906	.978
F	-.002	.014	.887	2.397	.989	.017	2.455	.959	.012
IPV	4.E-04	2.E-04	.011	.650	.017	$<.001$	.651	.017	$<.001$
Auction	-.002	3.E-04	$<.001$	-.002	.021	.942	-.003	.022	.908
Arousal				-6.352	3.594	.080	-10.579	4.485	.020
CM × Arousal							12.702	6.901	.069
Constant	.022	.017	.203	16.750	1.481	$<.001$	16.728	1.454	$<.001$
N	1506			1506			1506		
R^2	.053			.729			.732		

The regression in specification (3) confirms the results from above. There exists an interaction effect between arousal and market environment. On an average level of arousal, there is no treatment effect ($b = -0.610, p = 0.497$). In the HM treatment, however, arousal does indeed affect bid height in a negative manner ($b = -10.579, p = 0.020$). In the CM treatment, on the other hand, this effect is superimposed by an opposed, slightly stronger, and marginally significant interaction effect ($b = 12.702, p = 0.069$, significant on the 10% level) and thus abrogated ($-10.579 + 12.702 = 2.123$).

> **Result 7:** *The relationship between arousal and bids is mitigated when competing with computer opponents.*

Moderation-Mediation Analysis. Now, in order to gain an understanding of whether and how bids are indirectly affected by treatment via arousal (depending on the treatment), a moderation mediation analysis—based on the research model (cf. Figure 4.1)—is performed. The analysis is conducted according to the approach of Preacher et al. (2007), using a bootstrapping analysis. Bootstrapping entails the advantage of not requiring any assumptions about the shape of the sampling distribution. Based on $5,000$ bootstrapped samples using bias-corrected and accelerated 95% confidence intervals, the analysis reveals a significant indirect effect of arousal on bids for the HM treatment ($IE_{HM} = 0.252$, $SE = 0.074$, $LL = 0.130$, $UL = 0.434$). This indirect effect (IE) is computed as follows: $IE_{HM} = -0.024 \times -10.579 = 0.252$, i.e. as a product of the direct effect of treatment on arousal (-0.024) and the effect of arousal (in the HM treatment) on bids (-10.579). LL and UL refer to the lower and upper limit of the 95% confidence interval. Since zero is not included in the 95% confidence interval, the indirect effect is significantly different from zero at $p < 0.05$ (two-tailed).

Table 4.5.: Summary of Indirect Effects

	Indirect Effect	Boot SE	LCI95	UCI95
Human Market	0.252	0.074	0.130	0.434
Computer Market	-0.051	0.075	-0.204	0.096

For the CM treatment, the indirect effect is $IE_{CM} = -0.051$. It can be computed as follows: $IE_{CM} = -0.024 \times (-10.579 + 12.702) = -0.051$. In contrast, the corresponding analysis for the CM treatment reveals that the indirect effect is not significant (IE$=-0.051$, $SE = 0.075$, $LL = -0.204$, $UL = 0.096$). Table 4.5 summarizes these numbers. Taken as a whole, there is an indirect effect of market environment on bids, which is transmitted through arousal in one scenario (HM treatment), but not the other. In the traditional context of human markets, bidders are more aroused and this arousal is also directly reflected in their bids. In the CM treatment, bidders are less aroused and the indirect effect of arousal on bids disappears. In other words, the presence of computer opponents reduces both arousal as well as its impact on behavior.

4.4.3. Efficiency

The analysis so far has focused on bidding behavior and arousal and the participants' emotions in response to auction events and outcomes. Another question of interest concerns outcome efficiency and the differences between human and computer opponent markets. Following Vickrey (1961), an auction can be considered efficient if the bidder with the highest valuation for the good wins the auction (and obtains the good). In the case of a tie in terms of IPV, the auction is efficient if any of the highest IPV bidders wins the auction. If bidders submit an identical, highest bid, the winner is determined randomly. This auction is regarded as efficient, with a weight corresponding to the ex ante chances of winning the auction for the bidder with the highest IPV. The experimental results regarding efficiency for the HM and the CM treatment are summarized in Table 4.6.

Table 4.6.: Efficiency of the auction outcomes.

Treatment	# efficient	# total	% efficient	% not efficient
Computer Market	427.0	480	.89	.11
Human Market	647.5	720	.90	.10

Overall, roughly 9 out of 10 of the auctions are efficient. Broken down by CM and HM treatment, the results show little difference. Computer opponent markets are efficient in 89% of all cases. Human opponent markets are efficient in 90% of all cases. The difference is not significant at any conventional level (Chi-squared test, $p = 0.590$). It appears that despite the fact that participants are more aroused in the HM treatment, there is little impact on efficiency. Despite the lack of significance, this is the first investigation that links competition with computer opponents to auction efficiency. While there does not emerge a conclusive answer and efficiency is not the original focus of this study, the interplay of arousal, efficiency, and market type (human opponents, computer opponents, both types) is interesting enough to be addressed in follow-up research.

4.5. Discussion and Conclusions

Taken as a whole, this study shows that the presence of computerized agents reduces participants' arousal and the effect of arousal on bidding behavior. Both electronic market platforms and human traders should be aware of this relationship and consider it in market design and when making economic decisions. Given that some of the world's most important markets contain both human and computerized agents, understanding the interaction and impact of this interaction on bidding behavior and efficiency is not only of academic interest. With respect to technological progress, there is reason to believe that in the future, interaction between humans and computerized agents will become increasingly important in business processes and also in daily life. Certainly, NeuroIS research will contribute to a better understanding of the underlying visceral processes and thereby support the decision making process.

When participants are bidding against humans they are generally more aroused than when they are bidding against computer opponents. Arousal leads participants to submit lower bids, which is often interpreted as increased risk taking, but only when the opponents are human. In computer opponent markets, there is no relationship between arousal and bidding behavior. These results are confirmed by measuring the intensity of emotions experienced by the participants after distinct auction events: the emotional intensities are higher when the opponents are human.

An overarching issue in electronic markets is allocation efficiency. Despite the differences in the emotional state of the participants in a computer versus a human opponent market, there occurs no evidence that this leads to differences in auction efficiency. In most experiments and in reality, participants exhibit risk averse behavior. In FBSB auctions, participants overbid in terms of the risk-neutral rational strategy. In general, overbidding increases the probability of winning an auction, but decreases the payoff. Arousal, presumably due to the social competition in markets with human opponents, leads to more risk taking, i.e. lower bids, and thus a slightly but insignificant more efficient allocation. A commonly as detrimental considered factor here works in favor of overall efficiency.

Most of the important markets in the world have become electronic. This is not a new development but a necessary condition for automating bidding, negotiation, and transaction processes in markets. Computerized agents in these markets support humans and allow them to focus on other value-added tasks by alleviating the attention constraints involved in monitoring market activity continuously. In recent years, however, computer agents have also become competitors of human traders. While traditionally markets have been a place where human traders came together to trade, algorithms now dominate trading (Hendershott et al., 2011). In this work, the interplay of bidding environment, arousal, and actual bidding behavior in FPSB auctions was analyzed in a controlled laboratory experiment. The subjects were facing either other human participants or computerized bidding agents as competing bidders in the auctions. The economic and physiological results show that bidders in the CM treatment bid lower (H1) and are less aroused on average (H2). In addition, treatment and arousal affect bidding behavior in another way: A higher degree of arousal (prior to submitting a bid) is associated with lower bids (i.e., more risk) in the HM treatment (H3). This effect is mostly mitigated in the CM treatment (H4). In other words, there is an indirect effect of arousal on bidding behavior, which is conditional on the opponents' type. The auctions are equally efficient in both treatments. The emotional intensities of the immediate emotions in response to different auction events (submitting a bid, intermediate waiting screen, auction outcome) are lower in the CM treatment than they are in the HM treatment. The analysis shows that emotional intensity depends on the bidders' individual valuations and is particularly strong in response to winning an auction.

4.5.1. Practical Implications

From the practical perspective of electronic market platforms, the study has several implications. First, by letting market participants interact with other humans rather than computer agents, the platform operator is able to induce a higher degree of arousal by highlighting the social presence and hence the perceived competition among more or less equal participants. Analogously, the presence of computer opponents might have a mitigating effect on the emotional intensity in the market and its impact on the market participants' behavior. Depending on the context, market and platform operators are able to manipulate the degree of arousal by emphasizing or concealing the participation of other human peers. For consumer auction platforms, where the thrill of beating competitors is a core element of the shopping experience (Lee et al., 2009), emphasizing the presence of other human bidders may be an important instrument to induce arousal.

Second, the type of the opponents as well as a higher degree of arousal may induce other behavior, which may be exploited by the platform operator. In particular, the bidders behave more emotionally when other human bidders are involved, which is reflected in increased risk taking when arousal is high. In this context, it is important to highlight though, that in FPSB auctions with IPVs, taking more risk translates into lower bids since there is no uncertainty about the valuation. In common value auctions, where the true value of the commodity remains unknown before the end of the auction, more risk taking might also be reflected in higher bids (Van den Bos et al., 2008). Depending on the particular setting, the marketer can thus manipulate the level of emotional behavior, which is mitigated when computerized bidders are involved. The platform operator may wish to conceal the fact that computer agents are present in order to boost arousal and emotional behavior (e.g., avoiding the perception of superhuman behavior by adding response latencies or other human-like behavioral patterns). Hiding or stressing the presence of computerized or other human actors, for instance by presenting profile pictures, rankings etc., can in this light be seen as an important tool of market engineering. Also directly affecting the users' arousal may shift economic outcomes into the desired direction. Stressing the notion of competition, or clock speed (Adam et al., 2013) may serve as means for that purpose.On a more general level, the results give reason to believe that the dominance of algorithmic traders and high frequency traders in financial markets does not only affect market efficiency and liquidity per se (Hendershott et al., 2011), but also has a direct effect on the human traders' arousal and behavior. This should be taken into account by regulatory authorities as well as by the human traders and the organizations they represent.

Third, besides the considerations regarding final prices and auction profit, platform and mechanism design are also important means of attracting and retaining customers (Cronin et al., 2000; Deng and Poole, 2010). In general, emotional experience plays an important role for Internet auction site sponsors as it distinguishes them from fixed-price competitors (Ariely and Simonson, 2003; Lee et al., 2009; Möllenberg, 2004). For bidders in consumer auctions, emotional experience can even be seen as a source of hedonic value (Childers et al., 2001). Single design elements of websites can promote or mitigate affective processes in the user which in turn affect their behavior and general attitude towards the platform (Cronin et al., 2000; Deng and Poole, 2010). Menon and Kahn (2002, p. 39) argued that online marketers can use "very pleasing, enjoyable stimuli to encourage browsing and receptivity to impulse shopping." In this sense, the platform should be designed to be experienced positively, in order to create hedonic value for the customer. Auction format is one way to induce arousal. When comparing the results with other studies, it becomes evident that different auctions formats are associated with different emotional intensities. Adam et al. (2013) found that in Dutch auctions, the frustration of losing is experienced relatively stronger than the respective joy of winning. In contrast to that, and in line with the results of Astor et al. (2013), it is found that the joy of winning in FPSB auctions is experienced particularly strong. By choosing a specific auction mechanism, auctioneers may thus be able to control the set of emotions a user experiences on the platform to some extent. By choosing a FPSB auction over a Dutch auction, for instance, the marketer might particularly seek to promote the rewarding joy of winning and mitigate the experience of negative emotions. In addition to Astor et al. (2013), this study shows that the bidders experience distinctive emotions in response to other, rather mundane auction events, e.g., in response to submitting their bid, and even more so if human bidders are present. Ku (2008, p. 14) argued that, if bidding itself is arousing, this can "feed a vicious cycle of bidding and overbidding." Thus, in dynamic auctions, such emotions may eventually promote higher payoffs for the auctioneer. E-bay, for instance, is practicing this by alerting bidders immediately via email when another bidder has outbid them.

Finally, from the perspective of market participants, the results show that their behavior is affected by arousal. There is reason to believe, that market participants can benefit from an awareness and active consideration of this relationship. Since arousal may be measured early enough before bid submission, it may well be that providing market participants with real-time biofeedback helps them to re-evaluate their decisions (e.g., buy or sell orders, acceptance or rejection of an offer) before making irreversible decisions with undesired consequences for themselves and the organizations they represent. To this end, professional traders and investors have started to use serious games with biofeedback in order to train their emotion regulation capabilities (Fenton-O'Creevy et al., 2010, 2012; Jercic et al., 2012). In this sense, IS design science, and particularly the field of NeuroIS, can provide the methods and tools that help market participants to regulate their emotions during trading in order to make better decisions (Vom Brocke et al., 2013).

4.5.2. Theoretical Implications

One theoretical contribution of this study is the disentangling of competitive arousal and risk taking in auctions with human and computerized bidders. Briefly, humans experience more arousal and systematically bid higher when facing human opponents. Theoretically, this suggests that human behavior is less driven by emotional factors when computerized opponents are involved, which is consistent with previous results on bargaining (van 't Wout et al., 2006). Arousal and its impact on bids may be higher when bidding against human opponents. This is due to the socially competitive nature of auctions (if A wins, B loses, and vice versa) (Ku et al., 2005; Adam et al., 2011), i.e. when one wins the social competition, rather than merely gaining a material surplus. However, more arousal—due to the IPV setting—is associated with lower bids. Yet this is only observed in the HM treatment. Thus, as outlined in the research model, market environment and arousal interact, where automated counterparties seem to mitigate personal arousal per se, as well as the effect of arousal on bidding behavior. On average, bidding behavior is nearly identical for both treatments when arousal is not controlled for, which also explains the fact that efficiency is not significantly impacted in this particular setting. In accordance with the literature and the nature of the auction, it may be concluded that the link between arousal and economic behavior is the willingness to bear risk (Ku et al., 2005; Maule, 2000; Adam et al., 2013).

In this Chapter, it was shown that the intensities of immediate emotions in response to the auction outcome and to other events during the auction process are consistently stronger in the HM environment. The picture is more complex, however, with respect to the impact of the IPV. In general, the joy of winning an auction seems to be stronger than the frustration of losing for most IPV classes, but is reversed for the highest value classes. This provides support for the theories based on “equating the reference point with expectations rather than the status quo” (Kőszegi and Rabin, 2006, p. 1135). Based on their individual IPV, the bidders form expectations about the auction outcome. Winning a bid for a low valuation is unlikely and thus surprisingly positive. Similarly, the frustration of losing is undoubtedly stronger if the own IPV, and thus the chances of winning, were comparatively high ex ante. This notion is confirmed. The frustration of not winning even exceeds the joy of winning for the higher value class slightly. In the regression analysis, this effect is accounted for using the interaction term value class × dummy winner (see Table 4.2). The effect is significant and negative, which reflects the stronger impact of losing a high IPV auction. In this regard, the results are contrary to the assumption of previous research. Van den Bos et al. (2008, p. 488) argued that “winning and losing affect utility independent of the monetary consequences of an auction.” This present results show, however, that higher nominal payoffs yield stronger emotional responses. In particular for the highest values, the frustration of losing can be stronger than the joy of winning, whereas the latter is usually assumed to be the dominating emotion.

Also the emotions elicited in response to submitting a bid and waiting for the auction outcome are experienced more intensely in the HM treatment and are positively correlated with the individual IPV. In both events, however, the bidder does not receive new information. Theoretically, this implies that in those moments the bidders experience immediate emotions in response to thinking about past or future events (Bechara and Damasio, 2005). The immediate emotion in response to placing a bid may, for instance, stem from experiencing a fear of losing, or, putting it in a positive way, a desire to win the auction, which is more intense for high IPV. In any case, the bidders already experience emotions during the auction process even though their information set is not updated in the sense of classical auction theory (Krishna, 2002). This provides a physiological indication for the existence and the intensities of these emotions and yields further insight into the underlying visceral processes of humans interacting with electronic market websites and other information systems. Even seemingly irrelevant information events may trigger affective processes in the user. Such processes may have important ramifications on website perception and success (Cronin et al., 2000; Deng and Poole, 2010).

4.5.3. Limitations and Future Work

There are several limitations to this study. First, and most importantly, the experiment focuses on FPSB auctions, "leaving no opportunity for competitive fire to escalate with the progression of the auction" (Van den Bos et al., 2008, p. 484). The differences in arousal already exist in a static, almost clinical environment, in which bidders are isolated from each other by the use of dividing blinds and earmuffs and only interact very indirectly by exchanging sealed bids. It would thus be interesting to investigate and contrast the differences of physiological arousal and bidding behavior in more dynamic auctions, e.g., Japanese, Dutch, or Dollar auctions (Murnighan, 2002). In particular, the analysis indicated a marginally significant impact of heart rate variability (LFHF ratio) on arousal, but not on bids. Since emotion regulation may be more important in dynamic environments (such as stock trading (Fenton-O'Creevy et al., 2012)), it would be interesting to investigate the affective processes of subjects with different emotion regulation capacities in such settings (comprising time pressure, social facilitation and the like). Moreover, in FPSB auctions, the bidders submit single bids. Future research may therefore also take physiological responses to repeated bidding in the same auction into account. Finally, with the increasing share of automated trading in stock market activity in general, applying this experimental approach to continuous double auctions could yield some promising findings for financial markets.

Another limitation is also related to the type of auction analyzed. Despite the differences in the emotional state of the participants in a computer versus a human opponent market, there is no evidence that this leads to differences in auction efficiency. The HM treatment, which induces greater levels of arousal, seems to be slightly more efficient. However, the difference in efficiency is not significant. This does not mean that there may not exist a systematic difference between human and computer markets with respect to efficiency. It appears promising to apply a treatment differentiation like the present one to more dynamic auction mechanisms, e.g., English or Dutch auctions, where the presence of the other participants is stressed more saliently than in FPSB auctions. The potential impact of arousal might then be stronger since these auction formats leave more room for impulsive decision making. In this context, previous research argued that bidders are more susceptible to the phenomenon of auction fever in dynamic auctions than they are in static auctions (Ockenfels et al., 2006).

The results of this study also give rise to a number of further research questions. In particular, future research may also consider increasing the degree of visibility between the bidders by displaying names, profiles, or photos of the other participants (Van den Bos et al., 2008). This increased level of social facilitation may also fuel competitive arousal (Malhotra and Bazerman, 2008). In addition, the bidders may experience emotions of regret and relief if they get information on the bids of the other and it seems worthwhile to analyze the interpersonal effects of winner and loser regret (Filiz-Ozbay and Ozbay, 2007; Engelbrecht-Wiggans and Katok, 2008). As computer agents become increasingly part of our everyday lives, there is reason to believe that the emotional and behavioral implications of human/ agent interaction are an important area of IS research. In this regard, it seems promising to vary the appearance and other characteristics of the computerized agents (Nunamaker et al., 2011; Riedl et al., 2011). The questions whether humans behave differently when facing different types of opponents, or whether the agents' type and speed matters come to mind in this context. In this setting, there is no dynamic interaction between human and computerized bidding; the bids are submitted and ultimately the result of the auction is revealed. In this regard, competition between humans and computer agents is auspicious, since the respective abilities in the different involved domains, such as rationality, speed, predictability, intuition, or knowledge are fundamentally different.

Given that some of the world's most important markets contain both human and computerized agents, understanding the interaction and impact of this interaction on bidding behavior and efficiency is not only of academic interest. In regard of technological progress, there is reason to believe that in the future, interaction between humans and computerized agents will become increasingly important in business processes and also in daily life. With these agents becoming more intelligent and natural in terms of decision making and "behavior," this will put humans into afore unknown situations. Should you act more or less fair, or polite towards computer agents? Fogg and Nass (1997), for instance, actually found indications of politeness and gratefulness towards computers. This study represents a step towards understanding the cognitive and emotional processes of humans when interacting with other humans and computer agents in economic settings. NeuroIS research and tools will contribute to a better understanding of the underlying visceral processes and to supporting human decision making.

Chapter 5.

Risky Decisions among Friends and Strangers

"If friends make gifts, gifts make friends."

(Sahlins (1972))

Economic decisions are typically not made in isolation. Being part of a socio-economic environment, managers, for instance inevitably compare their decisions with those of others: friends, co-workers—possibly collaborators—or competitors for the next promotion. But the relationship type between decision makers, when distributional preferences are expressed, is typically not considered in the literature. It is typically not even identified as a potentially relevant factor. However, as it is shown in this chapter, other-regarding preferences depend on the actual other.

Consider for instance, two department managers facing the choice between a high-risk project A and a low-risk project B. If a manager successfully completes any of those projects, this success comes along with an increase in prestige, maybe a promotion. On the other hand, even if project B is completed successfully, the manager might feel inferior to the other who succeeded in the high-risk project A. Such considerations could ultimately affect, possibly impair the decisions. Trautmann and Vieider (2011) provided an illustrative example of how relationships may affect the preferences and decisions of individuals. The authors described a situation of two brothers in law. One of the brothers faces the choice between a rather safe job with a sure annual income of €50K and a career as a writer with a risky income between €40 and €65K per year. His decision might very well depend on the financial situation of his brother in law, being an employee with an annual income of either €48K or €52K. This example describes the case of an implicit social linkage between the persons.

This Chapter hence considers a decision situation involving risk and the presence of a peer—either a "friend" or a "stranger." First, in order to assess the subjects' actual behavior, an experimental study is conducted. In this experiment, two individuals at a time participate in a two-stage game, which is presented very much in the style of a standard roulette game as it is known from casinos. In the first stage, each participant picks one of several lotteries of different riskiness individually. In the second stage, the players pick a lottery again, whereas now, the respective other's prior choice is visibly displayed on the game board. From a purely microeconomic perspective, there is no strategic interaction in this game. The players, however, may anticipate feelings of envy, gloating, and sympathy towards the other player when taking their decisions. In this sense, the players face a choice between different levels of risk *and* have to choose on how tightly they want to couple their economic fate to that of a friend or a stranger.

Second, by formally analyzing the decision problem for the first- and the second mover, a rationale for the empirical findings is provided. The best responses and the existence of multiple equilibria are carved out by particularly modeling the emotional motives of envy and gloating, emanating from the prevalent Fehr and Schmidt (1999) model. This approach is then compared to existing models of other-regarding preferences from the literature, by deriving the model parameters and measures of fit using maximum-likelihood estimation.

The results indicate that the behavior among friends differs significantly from that among strangers. Consolidating other-regarding preferences and risk preferences thus appears valid from empirical and anecdotal evidence. Combined formal models of other-regarding preferences and risk, in this regard, represent a consequential step. It can be argued that such models—like, apart from that, any model of other-regarding preferences—may benefit from taking into account the relationship between the decision makers. Market engineering, when designing incentive and payoff schemes, composing teams, or scheduling project decisions may also benefit from considering this notion. In the context of e-commerce applications with peer-to-peer interaction, IS design may consider relationship types when addressing questions like whether or not to include social network data, in which form to allow users to present themselves, what and how to anonymize, or whether to restrict communication at the outset. This chapter thus attempts to make a contribution towards understanding the interplay of risk preference and the social reference from both an empirical and a theoretical point of view.

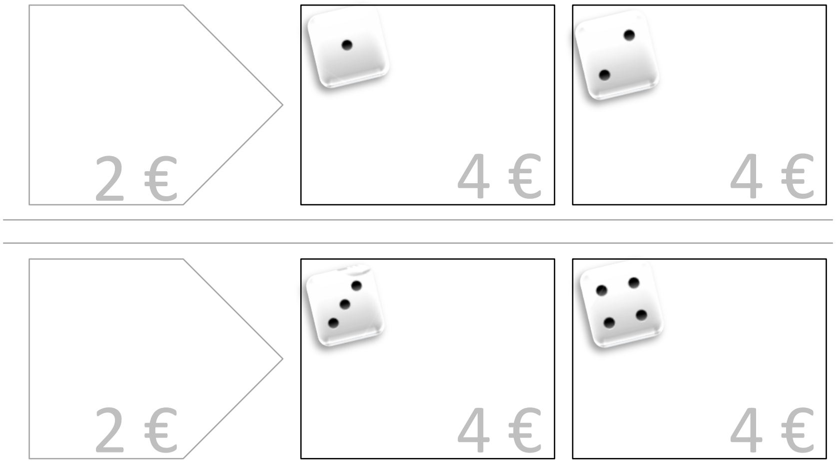


Figure 5.1.: Game board as presented to players in the first stage.

5.1. The 2-Person Risk Game

In order to investigate how relationship types shape preferences under risk, a roulette-like game is proposed, in which each player decides on how tightly to couple their own economic fate to that of another player: the *2-person risk game*. The game comprises two stages. In the first stage of the game, each player individually faces the task to choose between two risky prospects, without knowing the other player's (simultaneous) choice.

- The low-risk option L pays € 2.00 with a probability of 50% and € 0.00 otherwise.
- The high-risk option H pays € 4.00 with a probability of 25% and € 0.00 otherwise.

Both prospects thus entail an expected monetary payoff of € 1.00. Prospect L, however, entails a smaller variance than H ($\sigma_L^2 = 1 < 3 = \sigma_H^2$). The different prospects are presented to each player individually in the form of a six field game board as depicted in Figure 5.1. Each player picks one of the six boxes $\{1, 2, 3, 4, 1\&2, 3\&4\}$, where the four boxes on the right hand side represent the high-risk prospect H and are equivalent. The two boxes on the left hand side, in contrast, represent the low-risk prospects L: these options 1&2 and 3&4 yield a payoff when either a "1" or "2" ("3" or "4", respectively) is rolled. A graphical representation with resemblance of a roulette board is used in order to make the decision task as clear as possible to the participants. The L-boxes can thus be seen as the color bets on a roulette table, which pay for either black or red.

In the second stage of the game, the game boards are exchanged and both players are asked to pick one of the different prospects again. Now, however, the other player's

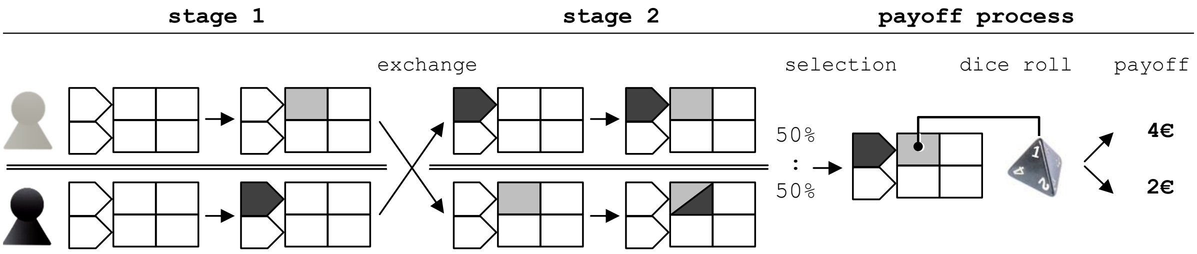


Figure 5.2.: Schematic process of the 2-person risk game.

(prior) choice is visibly displayed on the board. Hence, after the second stage, both players have made an individual first choice on an empty game board *as well as* a second choice, at which there existed a social reference point in form of the other player's selection on the game board. Subsequently, one of the boards is randomly selected with equal probabilities (50%) to be the relevant board for payoff determination. This means that only one of each player's choices is relevant for payoff. It is always the combination of one player's first choice with the second choice of the other player. Like in a roulette game, the actual number is now determined by chance. This is implemented using a fair four-sided die. The payoffs for both players are determined by this single dice roll. The entire process is schematically depicted in Figure 5.2.

Note that player A's payoff is independent of player B's choice, and vice versa. The payoffs of player A and B, however, are coupled since they are determined by the very same dice roll. Picking the same box as the other player will result in identical payoffs for both players in any case. This action is referred to as *perfect duplication*. Chances can be de-coupled in the same manner. Note that, even if a player picks a different level of risk, it is still possible to either couple or de-couple the payoffs partially. Consider, for instance, the case in which player A picks one of the two rows (low-risk) and player B picks one of the pertained single boxes. This case is referred to as *partial duplication*. In the following, both perfect and partial alignment of chances is addressed with the notion *duplicate* (*dup*), and the term *diverge* (*div*) is used otherwise. There are four discrete strategies in response to each observable first mover's action H or L, resulting from the two binary dimensions of choice (level of risk and duplication). In order to capture this, the following notation from the second mover's perspective is used. If a low-risk choice L is observed and the response is a high-risk choice H on the other row (*diverge*), the resulting situation is denoted by LH^{div}, i.e. the first character represents the observed (prior) choice (L or H), the second character represent the second mover's (own) choice. The superscripts *dup* and *div* denote whether the chances are aligned or not. Thus, when faced with a high-risk choice, the second mover decides among the alternatives HH^{dup}, HH^{div}, HL^{dup}, and HL^{div}. Accordingly, when facing a low-risk choice, the

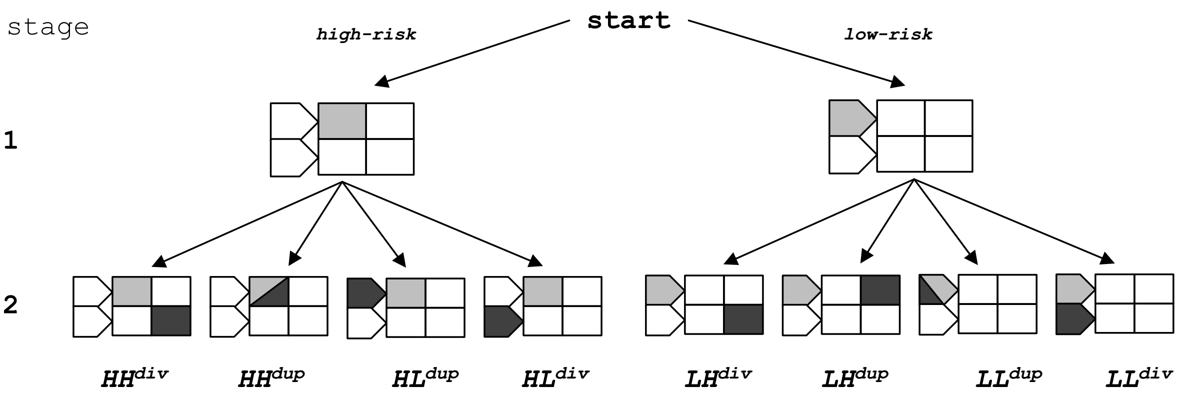


Figure 5.3.: Possible combinations of first and second players' choices.

second mover decides among the alternatives LH^{dup}, LH^{div}, LL^{dup}, and LL^{div}. Figure 5.3 presents all possible combinations of both players' choices—in disregard of effectively equivalent combinations.

Moreover, Table 5.1 shows a full representation of the possible outcome constellations of the 2-person risk game. The first mover selects either high-risk (left 4 columns) or low-risk (right columns). Without loss of generality, number "1" is chosen as representative for a high-risk first move, and row "1&2" is chosen as representative for a low-risk first move. The second mover then selects one of the four strategies H^{dup}, H^{div}, L^{dup}, and L^{div}. The outcomes for every die roll ("1" through "4") are depicted in the form (first mover, second mover).

Table 5.1.: Schematic overview of possible payoff constellations (EUR).

	high-risk ("1")				low-risk ("1&2")			
	"1"	"2"	"3"	"4"	"1"	"2"	"3"	"4"
H^{dup} ("1")	**(4, 4)**	(0, 0)	(0, 0)	(0, 0)	**(2, 4)**	**(2, 0)**	(0, 0)	(0, 0)
H^{div} ("3")	**(4, 0)**	(0, 0)	**(0, 4)**	(0, 0)	**(2, 0)**	**(2, 0)**	**(0, 4)**	(0, 0)
L^{dup} ("1&2")	**(4, 2)**	**(0, 2)**	(0, 0)	(0, 0)	**(2, 2)**	**(2, 2)**	(0, 0)	(0, 0)
L^{div} ("3&4")	**(4, 0)**	(0, 0)	**(0, 2)**	**(0, 2)**	**(2, 0)**	**(2, 0)**	**(0, 2)**	**(0, 2)**

Figure 5.4.: Participant interacting with the experiment tablet computer.

5.2. Experimental Design

Subjects were approached on campus and either knew each other prior to the experiment (friends treatment), or were randomly matched strangers (strangers treatment). Altogether, 244 pairs participated in the experiment. There was no show up fee, and the participants did not put any money at risk. Before the actual experiment started, the rules and procedure were explained to the participants using a three minute video tutorial, which they watched simultaneously on the same screen, wearing headphones connected to the computer with a y-split cable. This way, it was ensured that both participants knew that the respective other was provided with the very same (common) information and that also this fact was commonly known. Communication between participants was not allowed. The element of chance was implemented using a fair four-sided die, which was presented to the subjects prior to the experiment. All decisions were made in the light of actual monetary payoffs: subjects could earn up to €7.85[1] in the experiment. The experiment was one-shot, i.e. every subject participated only once. Effects due to learning or weariness could thus be excluded. If no questions on experiment, procedure, rules, and payoffs remained, the actual experiment (2-person risk game) was started.

After completing the actual experiment, but before determining the payoffs, the participants filled out a short questionnaire, asking for gender, age, field of study, and type of the relation to the other person. Moreover, the participants were asked for the underlying emotional motives of their decision in form of statements to which they expressed

[1]This number comprises the maximum payoff of €4.00 from the actual experiment and the maximum payoff of €3.85 from the risk aversion task.

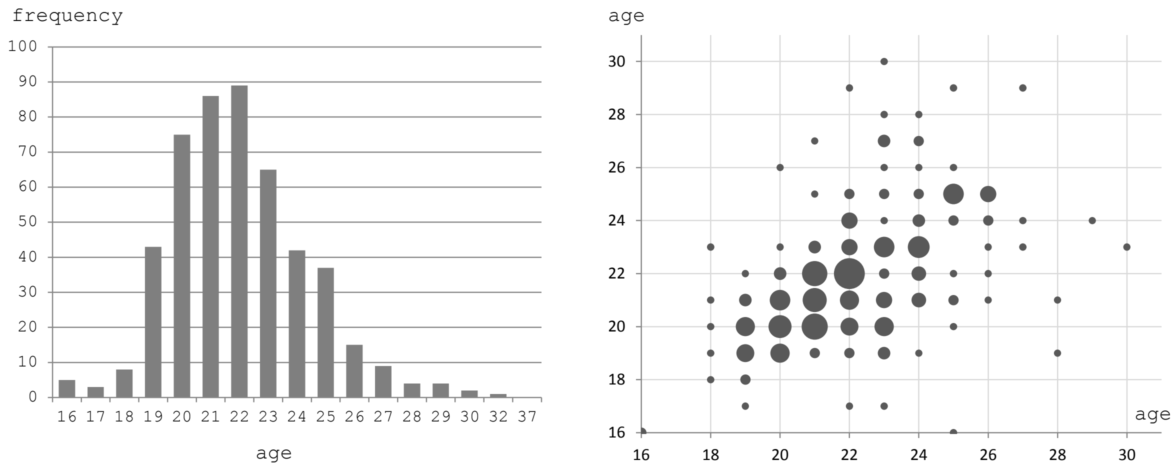
their (dis)agreement on a five-point Likert scale. These statements asked for participants underlying intentions (envy, gloating, sympathy). Additionally, participants were asked whether they anticipated to share the payoffs among each other after the experiment.

- *"I tried to avoid ending up with a lower payoff than the other participant."*
- *"I tried to enforce ending up with a higher payoff than the other participant."*
- *"I tried to optimize the possible payoff constellations for the other participant and me as a whole."*
- *"I expect the other participant and me to share payoffs after the experiment."*

These questions were identical in both treatments. Finally, all participants filled out a 5-question version of the Holt and Laury risk aversion test with real payoffs (ranging from €0.00 to €3.85), as it is presented in Chapter 3. The experiment was conducted on the campus of the Karlsruhe Institute of Technology (KIT) in December 2011 and January 2012. All user interfaces were web-based and accessed by the participants using tablet computers (iPad). Figure 5.4 shows a photograph of the participants' interaction with the game board on the experiment computer.

All subjects indicated what type of relationship they had towards the other person, by choosing one of the options *friend*, *acquaintance*, *stranger*, *couple*, *family*, or *other*. This data is summarized in Table 5.2. Note that in every cell, the number of couples of the particular combination is listed, i.e. the total sum is 244, corresponding to $244 \times 2 = 488$ individuals. Apparently, in most of the cases, both subjects denoted the relationship towards each other with the same term (216 out of 244 cases, 88.5%). The boundaries on campus between friends, fellow students, rather distant acquaintances, etc. may not be drawn as easily as in other contexts. For the sake of manageability, a binary classification into "existing substantial relation" and "no existing substantial relation" is used. The first group contains *friends* and *couples*, since between peers of this designation there arguable exist considerable social ties (→ friends treatment). The second group hence contains *acquaintances* and *strangers* (→ strangers treatment). Naturally, one might be interested in the specific differences between friends, acquaintances, couples, and strangers on a more detailed level. Given the small number of observations in the groups of couples and acquaintances, treating these as independent groups, however, cannot be expected to yield meaningful or resilient results. Note that the classification into one or the other treatment applies on an individual basis: Either subject of a pair is classified according to what he or she stated about the relationship towards the other, i.e., whether he or she considers the other a friend, acquaintance, or stranger. Hence, in some cases, the two individuals of a pair are assigned to different treatments.[2]

[2]2 pairs with friend/ stranger classification, 16 pairs with friend/ acquaintance classification.



(a) General age distribution.

(b) Two-dimensional distribution of age constellations.

Figure 5.5.: General age distribution and two-dimensional distribution of age constellations.

The pairs of two were either male only (118), female only (55), or mixed (71). Average absolute age difference among the pairs was 1.60 years with a standard deviation of 1.70 years, yielding a correlation (Pearson's r) of $r = 0.520$ ($p < .001$).[3] The overall distribution of participants' age and the two-dimensional distribution of age constellations are depicted in Figures 5.5(a) and 5.5(b).

Of the $244 \times 2 = 488$ participants, 480 are either in the friends treatment (314) or in the stranger treatment (166). The remaining 8 participants are discarded from the dataset, since, by choosing "family" or "other," they are assumed to exhibit outright different preferences in terms of monetary distributions or are not relatable to any group in a reasonable way. For these pairs it is indicated in Table 5.2 whether one (^{d1}) or both (^{d2}) of the individuals are discarded. Thus, there remain 480 participants, of which 302 are male and 178 are female. Mean age is 22.00 years with a standard deviation of 2.38 years.

[3]When differentiating for treatment type, the friend/friend pairs' age is correlated with $r_{f/f} = 0.702$, ($p < 0.001, n = 134 + 4 + 9 = 147$), whereas the stranger/stranger pairs' age is correlated with $r_{s/s} = 0.204$, ($p = 0.083, n = 61 + 2 + 10 = 73$).

Table 5.2.: Distribution of paired relationship designation.

	stranger	acquaintance	friend	couple	family	other
stranger	61					
acquaintance	2	10				
friend	2	16	134			
couple			4	9		
family			1^{d1}		1^{d2}	
other	1^{d1}	1^{d1}	1^{d1}			1^{d2}

5.3. Empirical Results

This section elaborates on the empirical results of the 2-person risk game experiment. As stated in the prior section, there were 480 observations in total, partitioned into 314 observations in the friends treatment and 166 observations in the strangers treatment. In line with the general research questions of this work, the following aspects are of particularly interest:

- *treatment effects*: Does the friends' behavior systematically differ to that of strangers? If so, how?
- *risk preferences*: Which levels of risk are selected in the first and in the second stage of the game? Which factors are explanatory? Which factors are explanatory for subjects changing their selected level of risk from the first to the second stage?
- *choice coupling/ decoupling*: Which *strategy* is chosen in the second stage? Which factors are explanatory?
- *emotional motives*: How do the emotional motives of envy and gloating affect the aforementioned characteristics?

First, the general behavioral data is analyzed. Second, a correlation analysis exposes the most direct coherencies of behavior (risk selection in the first and second stage, risk changing, alignment) and explanatory factors (e.g., age, gender, treatment, emotional motives, observed behavior, etc.). This approach is also applied to the sub-datasets for both treatments separately, in order to obtain an idea of how these factors and the relationship type interact. Third, the key binary decision variables are explained by regular logit regressions, for the entire dataset as well as for the subsets separately.

5.3.1. Behavioral Data

The general behavior shall be addressed first. In the first stage, there are only two alternatives (high-risk H and low-risk L). Given this other player's first move, there are four alternatives in the second stage. Table 5.3 presents the particular fractions for both stages and treatments.

Table 5.3.: Fractions of observed behavior in first and second stage; disaggregated for friends and strangers treatment (H: high-risk, L: low-risk).

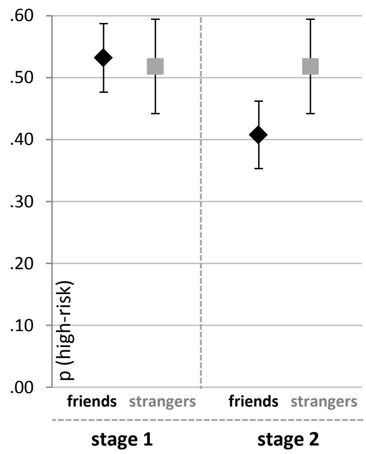
	stage 1		**stage 2**					
	H	L	H	H^{div}	H^{dup}	L	L^{div}	L^{dup}
friends	0.532	0.468	**0.408**	0.303	0.105	**0.592**	0.449	0.143
strangers	0.518	0.482	**0.518**	0.404	0.114	**0.482**	0.259	0.223
all	0.527	0.473	**0.446**	0.338	0.108	**0.554**	0.383	0.171

The overall rate of high-risk choices in the first stage was 52.7%, and 44.6% in the second stage. The percentages of high-risk decisions for the first and second stages for the different treatment conditions are depicted in Figure 5.6(a)[4]. In both treatments roughly half of the participants picked the high-risk prospect H in the first stage (friends: 53.2%, strangers: 51.8%). A test[5] for comparing the proportions confirms that this difference is statistically not significant (two-samples z-test for proportions, $z = 0.288$, $p = 0.774$, two-tailed[6]). This picture changes, however, in the second stage. While the overall share of strangers picking the high-risk prospect remains constant (51.8% in the first stage and also 51.8% in the second stage), the share of participants picking the high-risk prospect in the friends treatment decreases from 53.2% to 40.8%. The difference between these proportions is statistically significant ($z = -2.315$, $p = 0.021$). In other words, there is a systematic shift in the friends treatment towards taking the low-risk prospect in the second stage. The constant overall level of risk in the strangers treatment, however, does not imply a lower switching rate compared to the friends treatment. This effect is considered in more detail in the next paragraph. Thus, there exists an interaction effect of treatment and risk level for the different stages of the game. The key difference

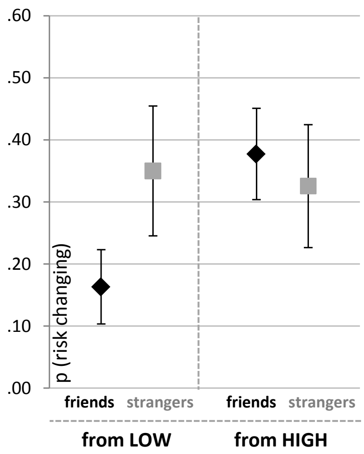
[4]Confidence intervals $\hat{p} \pm z\sqrt{\hat{p}(1-\hat{p})/n}$, where $z = 1.96$, distribution of error approximating as normal.

[5]In order to compare proportions of different samples, a two-samples z-test for proportions may be used. The test statistic z is computed using the respective sample sizes n_1 and n_2, as well as the number of observations showing the characteristic of interest (x_1 and x_2). The test statistic then is $z = (p_1 - p_2)/\sqrt{\hat{p}(1-\hat{p})(1/n_1 + 1/n_2)}$, where $\hat{p} = (x_1 + x_2)/(n_1 + n_2)$ denotes the pooled estimate of the overall proportion, and $p_1 = x_1/n_1$ and $p_2 = x_2/n_2$ the corresponding individual proportions.

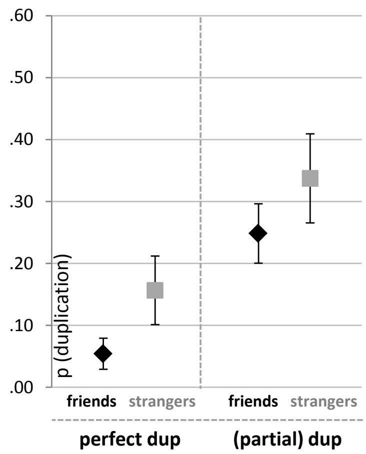
[6]In the following, all z- and p-values refer to two-tailed two-samples z-tests for proportions. This information is thus omitted hereafter.



(a) Frequency of high-risk lottery, depending on treatment and game stage (error bars: 95% CI).



(b) Frequency of risk changing, depending on treatment and initial choice (error bars: 95% CI).



(c) Frequency of perfect and partial duplication, depending on treatment (error bars: 95% CI).

Figure 5.6.: Risk level, risk changing, and coupling/ decoupling behavior.

between the treatment groups here is the reaction to the presence of the peer's choice. Where the strangers' overall risk attitude is not affected, it is so in the friends treatment, namely towards a higher degree of risk aversion. Note that the relationship type was the only variation between the treatments.

> **Result 1:** *Friends and strangers choose about the same fractions of low- and high-risk in the individual step of the game (roughly* 50% *in both groups). When confronted with the peer's choice, friends choose low-risk significantly more often (*$\sim$ 60%*), whereas the ratio remains constant for strangers.*

Second, after looking at the grand total of risk propensity among the treatment groups, it is now regarded, whether subjects individually altered their preferred level of risk from the first stage to the second, and if so, towards which direction. Altogether 29.8% of the participants changed their level of risk from the first to the second stage. In fact, strangers tended to deviate from their initially preferred level of risk *more often* than friends (33.7% versus 27.7%, $z = -1.373$, $p = 0.170$). This figure, however, summarizes the deviation from low- to high-risk as well as the opposite direction. The risk-level changes in the strangers treatment equalize out in sum, so that the overall level of risk is unaffected. This behavior may be disentagled as follows. Roughly one out of three subjects in the strangers treatment changed the risk level from the first stage to the second, see Table 5.4. Figure 5.6(b) clearly shows that in the friends treatment, in contrast to that, a markedly lower proportion of 16.3% of all initial low-risk takers

Table 5.4.: Proportions of subjects choosing the different prospects; specific and overall switching rates for both treatments.

	friends		strangers	
	low-risk	high-risk	low-risk	high-risk
proportion (stage 1)	0.468	0.532	0.482	0.518
of those switch	0.163	0.377	0.350	0.326
overall switch (per treatment)	0.277		0.337	
overall switch (all)	0.298			

switches to high-risk, whereas the fraction of initial high-risk takers changing to low-risk is 37.7%.[7] Thus, the decisive characteristic for the overall risk reduction in the friends treatment is not so much *changing* towards, but rather *staying* with one's low-risk choice.

> **Result 2:** *Overall, friends and strangers seem to change their level of risk between first and second stage to an equal extend. Friends, however, saliently stay with an initially made low-risk choice.*

Third, the degree of alignment between the payoffs is regarded, that is, how often and to which extend subjects chose to duplicate their peer's choice. The overall rate of duplication is 27.9%. The overall rate of perfect duplication is 9.0%. The percentages of perfect and partial duplication for the different treatments are depicted in Figure 5.6(c). With respect to payoff alignment, 15.7% of all strangers chose to perfectly duplicate the other player's choice in the second stage. This is close to the natural benchmark of 1/6 (since there a six boxes on the game board), which would be observed if all choices were made completely randomly. In contrast, only 5.4% of all subjects in the friends treatment perfectly duplicated the other player's choice. The difference in those proportions is significant ($z = -3.740, p < 0.001$). This result is robust towards the more general definition of duplication, including perfect and partial payoff alignment. Here, friends duplicated significantly less often (24.8%) compared to strangers (33.7%) ($z = -2.066$, $p = 0.039$).

> **Result 3:** *Strangers duplicate their peer's choice more often than friends. This holds for partial as well as for perfect duplication.*

[7] The fraction of friends changing from low-risk to high-risk is significantly smaller than the fraction of friends changing from *high-risk to low-risk* ($z = -4.227$, $p < 0.001$). The fraction of friends changing from low-risk to high-risk is also significantly smaller than the fraction of *strangers* changing away from low-risk to high-risk ($z = -3.198$, $p = 0.001$).

Naturally, Result 3 may be framed in the sense that friends tend to *diverge* more often compared to strangers. All numbers from above are summarized in Table 5.5.

After pointing out the most intriguing results, the next sections will take a broader perspective. As it turns out, there may be found several pertinent interrelations in the data. The first step to address these coherences as thorough as possible is a (linear) correlations analysis. Note that not every significant correlation can be worked out as distinguished result as it was done above. The results from above are naturally contained in this analysis. Secondly, a series of logit regressions complements the analysis for the most relevant binary attributes (high-risk/ low-risk, duplicate/ diverge, change/ stay).

Table 5.5.: Frequencies of observed behavior. p-values reported for a two-tailed two-samples z-test for proportions, comparing friends and strangers.

	overall	**friends**	**strangers**	**p-value**
high-risk (stage 1)	.527	.532	.518	.774
high-risk (stage 2)	.446	.408	.518	.021
switch	.298	.277	.337	.170
duplication	.279	.248	.337	.039
perfect duplication	.090	.054	.157	<.001

5.3.2. Correlation Analysis

A correlation analysis is conducted in order to reveal the most direct coherencies in the data. The included variables and their abbreviations used in the correlation table, are: dummy variable for the friends treatment (F), high-risk choice in the first stage (HR1), high-risk choice in the second stage (HR2), risk changing from first to second stage (CHNG), perfect duplication (PRFCT), partial duplication (PRTL), an observed high-risk choice (HR(obs.)), staying with the exact same choice[8] (STAY), and observing a different risk level than the own one (DIF). Additionally, there are series of motives that were each interrogated in the post-experimental questionnaire on a five-point Likert scale: the motive of envy (ENVY), the motive of gloating (GLTG), the motive of sympathy (SMPY), as well as the intention to share gains with other participant (SHRG). Additional variables regarding individual personal aspects are: number of risky choices in the 5-question Holt and Laury test (#RC), the participants' age (AGE), and finally the participants gender (GND, male=0, female=1). All $\frac{1}{2}(16^2 - 16) = 120$ Pearson correlation coefficients are displayed in Table 5.6, p-values in parentheses (two-tailed).

[8] i.e. not only staying with the same level of risk, which is reflected in the variable CHNG, but also choosing the exact same box on the game board (e.g., "1") in both choices.

Significant correlations ($p < 0.05$) are highlighted in bold face type. In the following, selected correlations are described in more detail.

Friends vs. Strangers. Friends choose the high-risk option in the second stage of the game significantly less often than strangers, whereas this difference is not observable for the first stage of the 2-person risk game. Also do friends duplicate (both partially and perfectly) less often than strangers. Moreover, friends express higher agreement to the motives of sympathy (regarding both participants' payoffs as relevant and thus subject to optimization) and are more likely to assume that payoffs will be shared ex post.

Risk Preference. With regard to the participants' choices, the first and second stage risk levels are distinctly correlated ($r = 0.413, p < 0.001$). Moreover, the number of risky choices in the 5-question Holt and Laury risk aversion test is positively correlated with both these measures. This correlation is stronger for the first stage of the game. On the one hand, the emotional motives of envy and sympathy are associated with a tendency to choosing the low-risk option in both stages. The motive of gloating, on the other hand, is associated with a tendency to the high-risk option in both stages. The assumption of sharing the payoffs yields a tendency to the low-risk option, significantly so, however, only in the second stage of the game.

The general risk attitude among the treatment groups is not significantly different. The number of risky choices in the risk aversion task (cf. Chapter 3) may be used as a measure for this purpose. Friends make 2.475 (out of 5) risky choices on average, strangers make 2.488 risky choices on average. An independent samples t-test confirms that the hypotheses "the distribution means are equal" cannot be rejected ($T = 0.100, p = 0.920$, equal variances assumed $F = 0.039, p = 0.843$). In view of the large sample sizes (314 and 166, respectively), and the p-value of 92.0%, it is indeed very likey that the inherent risk preferences are actually similar among friends and strangers.[9]

Risk Changing. There is a general tendency in switching from the high-risk towards the low-risk option: a high-risk choice in the first stage is associated with a higher, a high risk-choice in the second stage with a lower probability of changing the level of risk. Interestingly, the motives of envy and gloating are both associated with a higher probability of switching, i.e. seem to rationalize this behavior to some degree.

[9]Since the distributions of the *number of risky choices* cannot be considered normal, a non-parametric Mann-Whitney-U-Test is used to confirm the results of the t-test. Again, the hypothesis that the distributions of *risky choices* are equal between the treatments friends and strangers, cannot be rejected ($p = 0.781$).

Ex ante Payoff Coupling and Decoupling. When being faced with the other participant's choice, friends tend to diverge from this particular box or row. With other words, strangers are more likely to duplicate. This holds for both perfect and partial duplication. What is striking the eye is that the tendency to stay with one's own choice from the first stage is associated with a higher tendency to duplicate the other participant's choice. In other words, moving away from one's own choice yields a higher probability of diverging from the other's choice. It is hard to say whether one is causal for the other, since the decision about both aspects is made implicitly at the same time. Eventually, the motive of sympathy and the assumption of sharing are associated with a lower probability of duplicating.

Emotional Motives. The motives of envy and gloating are positively, but rather weakly correlated ($r = 0.158, p = 0.001$). Envy is also positively correlated with sympathy, which occurs quite unintuitive ($r = 0.201, p < 0.001$). Gloating is negatively correlated with the assumption of sharing the payoffs ($r = -0.107, p = 0.019$). Finally, the strongest coherence here is found between the motive of sympathy and sharing ($r = 0.507, p < 0.001$).

Other Factors. The demographic characteristics gender and age are mostly uncorrelated with the aforementioned factors. Older participants are less likely to name gloating as a relevant motive. Male participants tend to stay with their (exact) first choice more often. The high-risk option is chosen more frequently if the other participant is female, i.e. participants show riskier behavior towards women, regardless of their own gender.

5.3.3. Logit Regressions

In order to assess the joint impact of an array of explanatory variables on the behavioral characteristics, a set of regular logit regressions is conducted. The dependent variables in the analysis are:

(i) whether in the first (individual) stage, the high-risk option was chosen,

(ii) whether in the second stage the high-risk prospect was chosen,

(iii) whether the other player's choice was duplicated, and

(iv) whether the level of risk was changed from the first to the second choice.

Table 5.6.: Correlation Table: Bivariat Correlation, Pearson Coefficients, p-values displayed in parentheses (two-tailed), $\epsilon = 0.001$. Significant correlations ($p < 0.05$) highlighted in bold face type. $N = 480$.

	F	HR(1)	HR(2)	CHNG	PRFCT	PRTL	HR(obs.)	STAY	DIF	EVVY	GLTG	SMPY	SHRG	#RC	AGE	GND
friends	1.000	.013	**-.106**	-.063	**-.171**	**-.094**	.002	-.075	-.068	.024	.018	**.180**	**.364**	-.005	-.068	-.040
		(.774)	**(.021)**	(.170)	**($<\epsilon$)**	**(.039)**	(.971)	(.103)	(.136)	(.601)	(.690)	**($<\epsilon$)**	**($<\epsilon$)**	(.920)	(.139)	(.379)
high-risk (1)		1.000	**.413**	**.143**	-.010	.022	.030	**-.193**	-.061	**-.262**	**.262**	**-.174**	-.087	**.272**	.032	.062
			($<\epsilon$)	**(.002)**	(.832)	(.630)	(.511)	**($<\epsilon$)**	(.183)	**($<\epsilon$)**	**($<\epsilon$)**	**($<\epsilon$)**	(.056)	**($<\epsilon$)**	(.478)	(.175)
high-risk (2)			1.000	**-.108**	**-.105**	-.072	.053	-.079	.055	**-.261**	**.180**	**-.255**	**-.116**	**.179**	.002	.049
				(.018)	**(.021)**	(.113)	(.246)	(.083)	(.228)	**($<\epsilon$)**	**($<\epsilon$)**	**($<\epsilon$)**	**(.011)**	**($<\epsilon$)**	(.966)	(.284)
change				1.000	-.013	**-.091**	**.092**	**-.458**	.035	**.128**	**.143**	.047	.039	.024	-.022	.066
					(.778)	**(.047)**	**(.045)**	**($<\epsilon$)**	(.439)	**(.005)**	**(.002)**	(.308)	(.390)	(.593)	(.632)	(.150)
perfect dup					1.000	**.504**	**-.159**	**.151**	**-.128**	.033	-.032	-.076	**-.180**	-.087	-.003	.001
						($<\epsilon$)	**($<\epsilon$)**	**(.001)**	**(.005)**	(.475)	(.489)	(.098)	**($<\epsilon$)**	(.057)	(.947)	(.986)
partial dup						1.000	-.076	**.144**	**.179**	-.025	-.009	**-.182**	**-.223**	-.011	-.002	-.026
							(.095)	**(.002)**	**($<\epsilon$)**	(.587)	(.844)	**($<\epsilon$)**	**($<\epsilon$)**	(.815)	(.963)	(.572)
risk (obs.)							1.000	-.049	-.052	.073	.014	**-.094**	-.081	.044	-.003	**.090**
								(.289)	(.254)	(.109)	(.755)	**(.041)**	(.075)	(.331)	(.943)	**(.048)**
stay								1.000	-.070	-.050	**-.206**	**-.098**	**-.091**	.009	.038	**-.100**
									(.128)	(.276)	**($<\epsilon$)**	**(.032)**	**(.046)**	(.845)	(.400)	**(.028)**
observe dif.									1.000	.017	**.094**	**-.150**	**-.216**	-.048	.023	-.035
										(.718)	**(.039)**	**(.001)**	**($<\epsilon$)**	(.290)	(.622)	(.447)
envy										1.000	**.158**	**.201**	.085	**-.125**	-.066	.009
											(.001)	**($<\epsilon$)**	(.063)	**(.006)**	(.149)	(.852)
gloating											1.000	.015	**-.107**	.016	**-.107**	-.025
												(.748)	**(.019)**	(.725)	**(.019)**	(.587)
sympathy												1.000	**.507**	-.082	-.073	-.053
													($<\epsilon$)	(.073)	(.112)	(.248)
sharing													1.000	-.080	.051	.063
														(.081)	(.264)	(.170)
#RC														1.000	.033	-.019
															(.470)	(.670)
age															1.000	-.070
																(.125)
gender																1.000

Note that these variables are subject to being explained, but, if reasonable, also used as explanatory factors. Finally, the values *envy* and *gloating*, which were measured on a five point Likert scale in order to create a link between the expressed intention and actual behavior, are used as explanatory variables. The results of these 4 regular logit regressions are summarized in Table 5.7.

Table 5.7.: Logit regression coefficients and significance levels. Dependent variables are (i) level of risk (1^{st} stage), (ii) level of risk (2^{nd} stage), (iii) duplication, and (iv) risk change from first to second stage. Method: enter. $\epsilon = 0.001$.

	(i) risk (1)		**(ii) risk (2)**		**(iii) duplicate**		**(iv) change**	
	coef.	***p***	**coef.**	***p***	**coef.**	***p***	**coef.**	***p***
high-risk (1)	—	—	1.714	$< \epsilon$	.609	.042	1.098	$< \epsilon$
high-risk (2)	—	—	—	—	-.850	.004	-.971	$< \epsilon$
duplicate	—	—	-.693	.005	—	—	-.643	.010
risk change	—	—	-.950	$< \epsilon$	-.812	.006	—	—
friends	.066	.752	-.758	.001	-.559	.010	-.519	.021
envy	-.606	$< \epsilon$	-.368	$< \epsilon$	-.040	.652	.224	.014
gloating	.606	$< \epsilon$	.301	.001	.030	.727	.180	.037
constant	.113	.589	-.099	.715	-.328	.212	-1.134	$< \epsilon$
Observations	480		480		480		480	
Nagelkerke R^2	.222		.334		.056		.143	
Hosmer-Lemeshow p	.928		<.001		.885		<.001	
0-hitrate	.527		.554		.721		.702	
hitrate	.642		.806		.721		.810	

The logit regression analysis confirms that, first, both treatment groups (friends and strangers) tend to choose about the same level of risk on average in the first (individual) stage of the game, and that the share of risk seeking behavior drops significantly among friends in the second stage. In contrast to that, it remains constant among strangers. Also, the results indicate that the stated motives of envy and gloating seem to affect risk taking. The motive of envy has a significant negative impact on risk taking behavior, the motive of gloating, in contrast, has a significant positive impact. In addition to that, it is found that the actions *duplication* and *risk level changing* are associated with less risky choices in the second stage. Thus, when choosing to duplicate, subjects rather tend to use a low-risk duplication strategy. Also, subjects switched from a high-risk to a low-risk choice more often than contrariwise.

Second, looking at choice alignment, the effect indicated in Figure 5.6(c) is confirmed when controlling for the other factors mentioned before. Friends are more likely to diverge from the observed choice, i.e. choosing a different box or a different row more often. Quite unexpectedly, however, the expressed emotional motives envy and gloating do not have a significant impact on choice alignment, which will be gotten back to in the discussion. Furthermore, diverging is more likely to occur for high-risk choices in the second stage, which seems plausible since there exist simply more combinations to diverge (namely 3) than to duplicate (namely 1) for high-risk/ high-risk. More interestingly, risk changing comes along with significantly less duplicating, i.e. more diverging behavior. Note that risk changing also induces less risky choices as shown in (ii), which should have a positive impact on duplication per se. This strengthens the thought that the level of risk is deliberately changed *in order to* make a low-risk diverging response to the other player's first move.

Finally, whether or not the level of risk (high or low) is changed from the first to the second stage is affected by the entire set of explanatory variables. A high-risk choice in the first stage makes a change to low-risk more likely. Likewise does a low-risk choice in the second stage, which corroborates the thought that subjects are more likely to switch towards low-risk choices than obversely. Friends are less likely (overall) to change their initially chosen level of risk. Note that the changes that are observed in the friends treatment, however, are more systematically (from high- to low-risk). Both the motives of envy and gloating are associated with a higher probability of changing, which seems reasonable, since a socially affected subject might actually have a reason to do so, whereas this is not the case for someone who does not care at all.

As it is reflected by both the Nagelkerke R^2 and the hit rate improvement, the overall regression fit is best for the second stage level of risk (ii), and worst for choice alignment (iii). All R^2 values, 0-hitrates and regression hitrates are listed in Table 5.7. Additionally, the p-values of a Hosmer-Lemeshow test are reported.[10] The regression models (i) and (iii), in this regard, may be seen as well-fitting, whereas (ii) and (iv) are not.

A complementary logit regression analysis on the disjunct data subsets for each treatment group backs these results. Some effects, however, are attributable to one or the other treatment only, other effects are prevalent in both treatments. Some effects are prevalent but weak in both treatments, where only the aggregated dataset provides enough statistical power to flag these effects as significant. The results of the individual

[10]This test divides subjects into 10 ordered groups and compares the actual observed number of subjects in each group to the number predicted by the logistic regression model. The p-value indicates the result of a test for goodness of fit between actual and predicted numbers. For p-values greater than 5 percent, the null hypothesis that there is no difference between actual and observed frequencies, cannot be rejected, indicating a well-fitting regression model.

logit regressions for the friends and the strangers treatment only are reported in Tables C.3 and C.4 in the Appendix. In those regressions, naturally, the explanatory variable for the treatment is not considered.

With regard to the subsets, the impact of the emotional motives envy and gloating on the preferred levels of risk both in the first and in the second stage holds for both treatments. There is thus no interaction effect observable. The same holds for the explanatory variable *high-risk (1)* for estimating *high-risk (2)*. But there are also quite distinct interaction effects indicated by the data: The coherency of *duplication* and *high-risk (2)* is only found in the strangers treatment. The coherency of *risk change* and *duplication*, as well as the coherency of *risk change* and *high-risk (2)* is only prevalent in the friends treatment. Moreover, the envy motive increases the probability of risk changing in the strangers treatment only, whereas the gloating motive does so only for the combined dataset.

Robustness. The logit regressions were checked for robustness by including different sets of additional explanatory variables. The factors *gender*, *age*, and *age difference between the subjects* neither provide any significant explanatory power in the regressions, nor alter the effect directions or magnitudes of the other factors. Additional control variables with some, but not outstanding explanatory power are the number of *risky choices (HL5)*, *sympathy*, and *sharing*. The number of *risky choices (HL5)* was assessed using the HL5 risk aversion test as presented in Chapter 3, ranging from 0 to 5 risky choices at most. The variable *sympathy* addresses the personal sympathy for the other experiment participant (see Section 5.2). Finally, the variable *sharing* addresses the intention/ belief that the players will share the common payoffs after the experiment (see Section 5.2). There is a significant impact of *sympathy* (negative) and the number of *risky choices (HL5)* (positive) on the probability of making a high-risk choice in the first stage of the game; the other factors are unaffected in terms of direction and magnitude. There is also a significant impact of *sympathy* (negative) on the probability of making a high-risk choice in the second stage of the game. Again, the other factors remain unaffected. Both *sympathy* and *sharing* have predictive power for the probability of *duplicating* the other player's choice (both negative). When controlling for those two factors, the treatment variable becomes insignificant, which appears reasonable from a relational point of view, and may indicate an approach to explaining *how* friends actually act differently in comparison to strangers. When using the factors *sympathy* and *sharing* individually, it turns out that the impact of *sympathy* is small compared to *sharing*. Finally, none of the mentioned factors has any significant impact on the probability of risk level changing from the first stage to the second (*risk change*).

5.3.4. Intermediate Summary

The empirical results of the 2-person risk game experiment quarry an array of interesting facts about the differences between friends and strangers in risky decision scenarios. There may be drawn three main conclusions. First, whereas both groups are very similar in terms of risk preferences individually, the respective behavior is saliently affected by the presence of a friend, but not so by a stranger. Being visually confronted with the other person's choice, and by that with the payoff *constellation* for oneself and the other, leads to more risk averse behavior among friends. This effect is mainly driven by the phenomenon that the participants, once settled for a low-risk decision, saliently stick with this decision when confronted with a friend. Second, friends show a strong tendency to diverge from their peer's choice, yielding exclusive payoffs for either one or the other. Where the latter effect may be rationalized by the intention to share and split payoffs subsequent to the experiment ("team play"), the first phenomenon is not. Third, the emotional motives of envy and gloating are reflected exclusively in the way the different levels of risk are selected, and not in the decisions of ex ante payoff coupling and decoupling. This appears somewhat counter-intuitive, since duplicating (diverging) is how to ensure identical (different) payoffs for both players, and thus appears as what would be the most direct way to address the anticipated emotion of envy and gloating. Thereby, envy is associated with risk aversive, gloating with risk seeking behavior. The preferred level of risk thus occurs to be the way participants express their interpersonal preferences. If they seek a higher payoff than their peer, they bluntly risk more, and not explicitly go for the different bet. If they seek not to end up with less, they simply risk less, and not explicitly tie their fate to that of their peer. Taken together, relationship type and risk preferences appear to interact. Experimental economic research, in view of distributional preferences, but also practitioners may profit from considering decision makers' actual relations. The next sections take on this notion and consider the interplay of risk preferences and socially directed motives from a game-theoretical perspective.

5.4. Formal and Strategic Analysis

In this section, the decision scenario of the 2-person risk game is formalized and analyzed from a game theoretic perspective. For this purpose, first, a utility function, comprising socially and risk-related characteristics, based on the Fehr and Schmidt model is suggested. Then, the second mover's decision problem is elucidated and illustrated. With this at hand, a strategic perspective for the first mover can be taken and the game equilibria are derived.

5.4.1. Utility Function and Risk Aggregation

By design, the 2-person risk game involves no strategic interaction between the players whatsoever from the classical economic perspective. In particular, a player's choice in stage 2 should not depend on the other person's choice in stage 1, because the payoffs do not depend on each other either. Including weighted terms for the motives of envy and gloating in the utility function is a way to address the notion that the second mover actually does consider the first mover's action and hence the combination of payoffs. For that reason, a variation of the Fehr and Schmidt (1999) model is used. The Fehr and Schmidt model does not allow for a positive utility from payoff surpluses over the other person. In the Fehr-Schmidt model, people are assumed to be completely inequality averse, even if the payoff difference is in their favor. This assumption is challenged in this section. Having less than the other player is assumed to yield disutility, very much like in the original model. The (linear) weight of this disutility is denoted α. It can be interpreted as *envy*. Now, in contrast to the standard Fehr-Schmidt model, a payoff surplus is assumed to have a positive effect, linearly weighted with the parameter β. This part of the utility function can be interpreted as *gloating*. This means that the players, holding the other's payoff fixed, strictly prefer higher own payoffs and, holding fix their own payoff, strictly prefer lower payoffs for the other. The motive of gloating is thus easily mistaken for spitefulness. Spitefulness, however, should be rather seen as directed towards the other's payoff (regardless of the own payoff). Now, a ceteris paribus decrease of the other's payoff necessarily increases also the payoff difference. A very spiteful player (assuming linear utility) would lower both payoffs to the same extent, whereas a gloating player would not. In the present decision scenario, there is no reason to assume spitefulness since the players cannot manipulate the other player's payoff. The consideration and the decision is limited to one's own payoff and the possible payoff constellations. Additionally, given that both players' payoffs are increased by the same amount, the higher payoff constellation is necessarily preferred. Player x's utility function thus has the form

$$u_x(\pi_x, \pi_y) = \pi_x - \alpha \max\{\pi_y - \pi_x, 0\} + \beta \max\{\pi_x - \pi_y, 0\}, \tag{5.1}$$

where the variables π_x and π_y denote the payoffs to oneself (π_x) and the other player (π_y), and $\alpha, \beta \geq 0$ represent the model parameters. The weight for a player's own payoff is held fixed and normalized to 1. As stated before, the model parameters α and β can be interpreted as measures for *envy* and *gloating*, respectively. Another aspect that easily comes to mind is the incorporation of efficiency concerns, for instance, by adding a term for player y's payoff. See Kohler (2011) for an example. Engelmann (2012), in this regard, pointed out that such approaches are misguided, since the inclusion of an efficiency term to the standard Fehr-Schmidt model yields redundancy. The model in the scope of this work is thus strictly limited to the components own payoff (π_x), positive difference ($\pi_x - \pi_y$), and negative difference ($\pi_y - \pi_x$), very much like the original Fehr-Schmidt model.

Now, the decision situation is not deterministic. Resulting from the nature of the 2-person risk game, there are four possible outcomes, all of which are equally likely to occur. It does now not follow immediately, how the aggregation of these different scenarios should be tackled. One could think of calculating the expected (utility) value for every subject and then applying the social utility function to those values. This does, however, not account for the fact that the respective outcomes might occur in a certain relation towards another, i.e. being coupled. One might, on the other hand, calculate the social utility value for every possible outcome constellation and *then* aggregate using the expected utility function.

In fact, there have been recent considerations of how to integrate functions of social utility and the existence of multiple possible outcomes in the literature. Trautmann (2009), building on the Fehr-Schmidt model, applied expected values for both players to the weighting terms for the (expected) payoff differences. Gantner and Kerschbamer (2011, cf. p. 23), for the case of only three different possible payoffs, proposed a non-functional form, i.e. a lookup table for the transformation from payoff to utility. These values are then evaluated in the social (Fehr-Schmidt) function, whereat also unweighted values are used for the payoff differences. The approach thus appears incomprehensible to some extent. Fudenberg and Levine (2012, p. 608) assumed the Fehr and Schmidt function to be an expected utility function, i.e. that it "socially" aggregates expected values of lotteries. Saito (2013), on the other hand, proposed a model using both ex ante and ex post risk aggregation in a linearly weighted, and risk neutral way. In his approach, the parameter $\delta \in [0, 1]$ assigns weights to the two components. In this *expected inequality-averse (EIA)* model, the decision maker's preference is captured by

$$\delta U\left(E(x_1), \ldots, E(x_n)\right) + (1-\delta) E\left(U(x_1, \ldots, x_n)\right),$$

where $E(\cdot)$ denotes the expected value over all possible outcomes and $U(\cdot)$ represents the Fehr-Schmidt utility function. Note that the risk aggregation function is rudimentary, i.e. implying risk neutrality.

For the experiment considered in this work, the aforementioned approaches do not appear applicable, since the expected payoffs (for both players) are equal to € 1.00 in any case and the consideration of actual risk preferences (other than risk neutrality) is of particular interest. In order to formalize this, let $p = (p_1, p_2, \ldots, p_n)$ denote the probabilities of all possible outcomes. Let then $\pi_x(X, i)$ be the payoff for player x and his or her decision $X \in \{1, 2, 3, 4, 1\&2, 3\&4\}$, in the case of dice roll $i \in \{1, 2, 3, 4\}$. Analogously, $\pi_y(Y, i)$ denotes player y's payoff after choosing alternative Y in case of outcome i. These values are summarized in Table 5.1. Recall that the monetary payoffs for both players are independent of the respective other player's choice (π_x is a function only of X, not of Y). The players individually maximize their expected utility, whereat it is assumed that they have an underlying utility function $v(\cdot)$ with constant relative risk aversion (CRRA). With CRRA, the term $R(\pi_x) = \frac{-\pi_x v''(\pi_x)}{v'(\pi_x)}$ is constant, i.e. independent of π_x (cf. Pratt, 1964). A frequently applied function that satisfies this condition is $v(\pi) = \pi^{1-r}$ where the parameter r represents the player's risk attitude (Holt and Laury, 2002), and π denotes the reference value (e.g., a monetary payoff). A player is said to be risk neutral if $r = 0$ and risk averse (risk seeking) if $r > 0$ ($r < 0$). This parameter is assessed for each participant of the experiment by using a 5-question version of the Holt and Laury (2002) risk aversion test (cf. Chapter 3). Hereafter, this function is used to aggregate the different possible outcomes' social utility values. Thus, a nested utility model is assumed, where the social utility function is applied to the payoffs, and the risk weighting function is applied to the resulting utility values. In doing so, a thought of Güth et al. (2008) is adopted, who applied the risk aggregation function to the entire "inner" argument (distributional and time preferences), yielding an expected overall utility ψ of the form

$$\psi_x(X|Y) = \sum_{i=1}^{4} p_i u_x \left(\pi_x(X, i), \pi_y(Y, i)\right)^{1-r}. \tag{5.2}$$

The optimal decision for a player may now very well depend on the other player's decision, since the payoffs are passively interlinked in the utility function. Naturally, the optimal decision will still depend on the player's own risk attitude, expressed in the single parameter r. Depending on the weights α and β, the preference now, however, may be shifted. This thought is outlined in further detail in the following sections.

5.4.2. Decision Alternatives

In order to understand the decision situation, the 2-person risk game is analyzed starting from the second stage. At this point, the first mover has made a choice—high-risk or low-risk—and the second mover is confronted with the situation. In both cases, there are four different actions available to the second mover: HH^{dup}, HH^{div}, HL^{dup}, and HL^{div} if observing a high-risk choice. Accordingly, when facing a low-risk choice, the second mover decides among the alternatives LH^{dup}, LH^{div}, LL^{dup}, and LL^{div}. The utility value of a specific response to a given first move is defined in (5.2) and piecewise built on the distributional preferences as specified in (5.1). Applied to the concrete payoff and probability values of the 2-person risk game, the expected utility value for every response strategy can be computed. These values are summarized in Table 5.8.

Table 5.8.: Utility values of responses to high-risk and low-risk first moves.

		first move	
second move		**high-risk**	**low-risk**
H^{dup}		$\frac{1}{4}(4)^{1-r}$	$\frac{1}{4}(4+2\beta)^{1-r} - \frac{1}{4}(2\alpha)^{1-r}$
H^{div}		$\frac{1}{4}(4+4\beta)^{1-r} - \frac{1}{4}(4\alpha)^{1-r}$	$-\frac{1}{2}(2\alpha)^{1-r} + \frac{1}{4}(4+4\beta)^{1-r}$
L^{dup}	$\alpha \leq 1$	$\frac{1}{4}(2-2\alpha)^{1-r} + \frac{1}{4}(2+2\beta)^{1-r}$	$\frac{1}{2}(2)^{1-r}$
	$\alpha > 1$	$-\frac{1}{4}(2\alpha-2)^{1-r} + \frac{1}{4}(2+2\beta)^{1-r}$	$\frac{1}{2}(2)^{1-r}$
L^{div}		$-\frac{1}{4}(4\alpha)^{1-r} + \frac{1}{2}(2+2\beta)^{1-r}$	$-\frac{1}{2}(2\alpha)^{1-r} + \frac{1}{2}(2+2\beta)^{1-r}$

Note that the risk weighting function $v(u) = u^{1-r}$ is applied to the aggregated utility value u of a certain outcome alternative (social utility function $u := u_x(\cdot,\cdot)$ for player x) as defined in (5.2). This inner utility value u may be positive or negative. For negative values, the general exponent will not be applicable—as root extraction in the real number domain is mathematically not defined for negative arguments. For this reason, the sign of the argument is factored out, and the absolute value of the argument remains inside the functional evaluation. This technically transformed risk weighting function $v^*(u)$ thus is defined by

$$v^*(u) := \operatorname{sgn}(u) v\left(\operatorname{abs}(u)\right). \tag{5.3}$$

For all but one response value, all summands are either positive or negative, regardless of the parameters α and β. For the low-risk duplication response to a high-risk first move, however, the sign of the argument depends on the envy parameter α. For $0 \leq \alpha < 1$, the argument is positive. If α is sufficiently large ($\alpha > 1$), the argument $2 - 2\alpha$ is negative, which makes a case-by-case analysis necessary. Both cases are listed in Table 5.8. No case-by-case analysis is necessary for the low-risk first move.

5.4.3. Best Responses

As described before, there are four possible (discrete) responses that emerge from the combination of risk level (high-risk or low-risk) and the level of payoff alignment (duplicate or diverge) for both possible first moves (H or L). Equating two of the four expected utility values at a time and solving for β as a function of α yields $\binom{4}{2} = 6$ indifference curves of best responses to an observed action of the other player's choice in stage 1 (for a given and fixed r). These indifference curves $\beta = \beta_r(\alpha)$ are summarized in Tables 5.9 and 5.10. For some of the equations (vii and ix), the implicit curves are solved with respect to α, since the inverse function is mathematically not resolvable in closed form.

Table 5.9.: Indifference curves $\beta_r(\alpha)$ in response to to high-risk first move.

		$\beta = \beta_r(\alpha)$, if $\alpha \leq 1$	$\beta = \beta_r(\alpha)$, if $\alpha > 1$
i	$HH^{dup} = HH^{div}$	$(\alpha^{1-r}+1)^{\frac{1}{1-r}} - 1$	$(\alpha^{1-r}+1)^{\frac{1}{1-r}} - 1$
ii	$HH^{dup} = HL^{dup}$	$\frac{1}{2}\left(4^{1-r} - (2-2\alpha)^{1-r}\right)^{\frac{1}{1-r}} - 1$	$\frac{1}{2}\left(4^{1-r} + (2\alpha-2)^{1-r}\right)^{\frac{1}{1-r}} - 1$
iii	$HH^{dup} = HL^{div}$	$\frac{1}{2}\left(4^{0.5-r}\alpha^{1-r} + 4^{0.5-r}\right)^{\frac{1}{1-r}} - 1$	$\frac{1}{2}\left(4^{0.5-r}\alpha^{1-r} + 4^{0.5-r}\right)^{\frac{1}{1-r}} - 1$
iv	$HH^{div} = HL^{dup}$	$\frac{1}{2}\left(\frac{(2-2\alpha)^{1-r}+(4\alpha)^{1-r}}{2^{1-r}-1}\right)^{\frac{1}{1-r}} - 1$	$\frac{1}{2}\left(\frac{(4\alpha)^{1-r}-(2\alpha-2)^{1-r}}{2^{1-r}-1}\right)^{\frac{1}{1-r}} - 1$
v	$HH^{div} = HL^{div}$	-1	-1
vi	$HL^{dup} = HL^{div}$	$\frac{1}{2}\left((4\alpha)^{1-r} + (2-2\alpha)^{1-r}\right)^{\frac{1}{1-r}} - 1$	$\frac{1}{2}\left((4\alpha)^{1-r} - (2\alpha-2)^{1-r}\right)^{\frac{1}{1-r}} - 1$

Table 5.10.: Indifference curves $\beta_r(\alpha)$ in response to to low-risk first move.

		$\beta = \beta_r(\alpha)$
vii	$LH^{dup} = LH^{div}$	$\alpha_r(\beta) = \left((2+2\beta)^{1-r} - (2+\beta)^{1-r}\right)^{\frac{1}{1-r}}$
viii	$LH^{dup} = LL^{dup}$	$\frac{1}{2}\left((2\alpha)^{1-r} + 2^{2-r}\right)^{\frac{1}{1-r}} - 2$
ix	$LH^{dup} = LL^{div}$	$\alpha_r(\beta) = \left(2(\beta+1)^{1-r} - (\beta+2)^{1-r}\right)^{\frac{1}{1-r}}$
x	$LH^{div} = LL^{dup}$	$\frac{1}{4}\left(2^{2-r}\alpha^{1-r} + 2^{2-r}\right)^{\frac{1}{1-r}} - 1$
xi	$LH^{div} = LL^{div}$	-1
xii	$LL^{dup} = LL^{div}$	$(\alpha^{1-r}+1)^{\frac{1}{1-r}} - 1$

Table 5.11.: Other indifference curves.

		$\alpha_r(\beta) =$
xiii	$LH^{dup} = HL^{div}$	$\alpha_r(\beta) = \left(\frac{2(\beta+1)^{1-r}-(\beta+2)^{1-r}}{2^{1-r}-1}\right)^{\frac{1}{1-r}}$

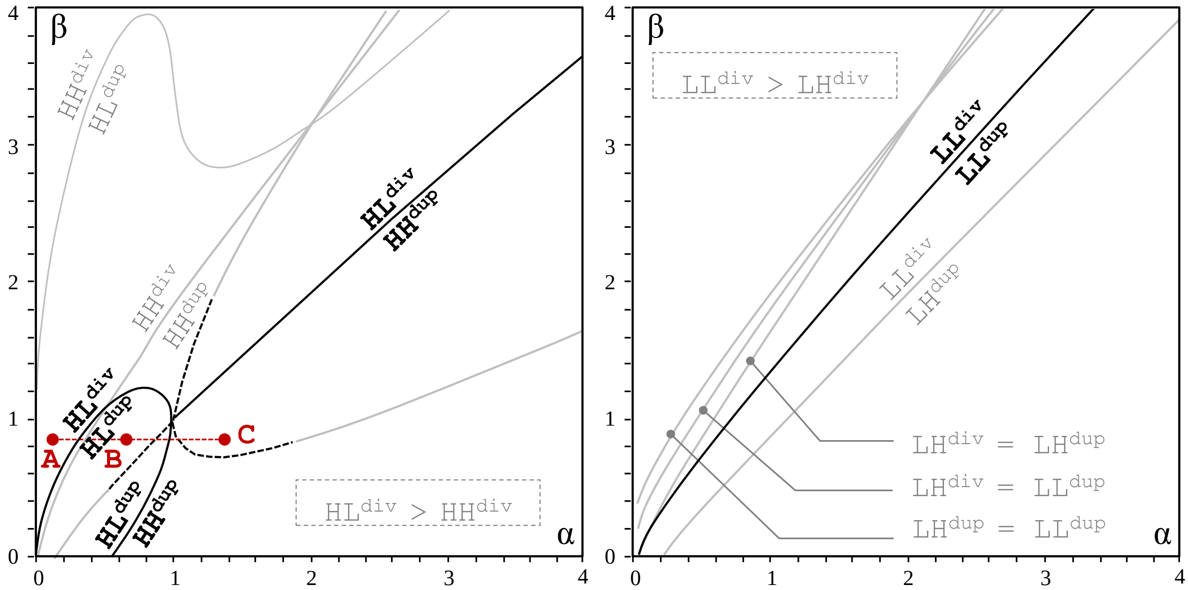
The first player's choice is naturally a choice merely between the two different risk levels, which can be high-risk or low-risk. For both these situations, the second mover's best response can be determined by comparing the respective utility values. In the scope of this analysis, the focus is set on the emotional motives of envy and gloating. It is hence straightforward to evaluate the possible strategies and best responses, depending on the different combinations of the parameters α and β. For this purpose, a two dimensional representation is used: the parameters are plotted on the axis of a simple Cartesian coordinate system. The abscissa represents the parameter α, the ordinate represents β. Both parameters are naturally restricted by $\alpha, \beta \geq 0$, i.e., the constructs of “negative envy” or “negative gloating” are not considered.[11] On the other side, there is no upper bound for α and β. It can be argued that—compared to the reference weight of one's own payoff—values of 2, 3, or more are unrealistically high, since the utility assigned to the payoff differences would in that case exceed the utility for the actual own payoff by these factors. In order to include all structural characteristics of the parameter combinations in the graphical representations, a maximum value of 4 for both axis in the diagrams is chosen.

To obtain the respective best responses for any constellation of α and β, it is feasible to compare the indifference curves and successively discard irrelevant curves. The remaining critical curves indicate which response should be chosen by a fully rational player at a given constellation of the parameters α and β. Figures 5.7(a) and 5.7(b) depict the regions of best responses for a risk averse player ($0 < 1 - r < 1$) to a given first mover action (high-risk or low-risk). Figures 5.8(a) and 5.8(b) depict the regions of best responses for a risk seeking player ($1 - r > 1$) to a given first mover's action. As indicated, some of the indifference curves become obsolete since both responses captured by the curve are dominated by another strategy in that area in any case. These curves are plotted in gray. The effective indifference curves are plotted bold and black. In the following, the best responses of a risk averse and a risk seeking player to a high-risk and a low-risk first move are considered.

Risk Averse Player. As it is shown in Figures 5.7(a) and 5.7(b), a variety of best responses is possible, depending on risk attitude and the constellation of α and β.

The graphical representation of the parameter space and the associated best responses shall now be illustrated by using 3 scenarios as selected examples (cf. to points A, B, and C in Figure 5.7(a)). Assume that the first mover has chosen the high-risk strategy and a fixed parameter $\beta \approx 0.8$ for the second mover, i.e. a surplus over the other player

[11] Negative envy would mean a positive utility from a relatively lower payoff compared to a reference person. This appears somewhat counterintuitive but can be applicable for certain contexts, as is it elaborated on in Chapter 2. A suitable term would be “heroism”. Negative gloating would mean a negative utility from a relatively higher payoff compared to a reference person. This actually seems much more likely to appear in real contexts. Psychological rationales would be “guilt” or “shame”, most of the economic literature has settled for the terms of “inequality aversion” or “similarity seeking,” cf. Fehr and Schmidt (1999).



(a) Best responses of a risk averse player to a high-risk choice ($(1-r) = 2/3$).

(b) Best responses of a risk averse player to a low-risk choice ($(1-r) = 4/5$).

Figure 5.7.: Best responses of a risk averse player.

is assigned about 80% of the weight of the own (absolute) payoff. This player could be called competitive to some extent. There are 3 conceptually different situations with respect to the parameter α:

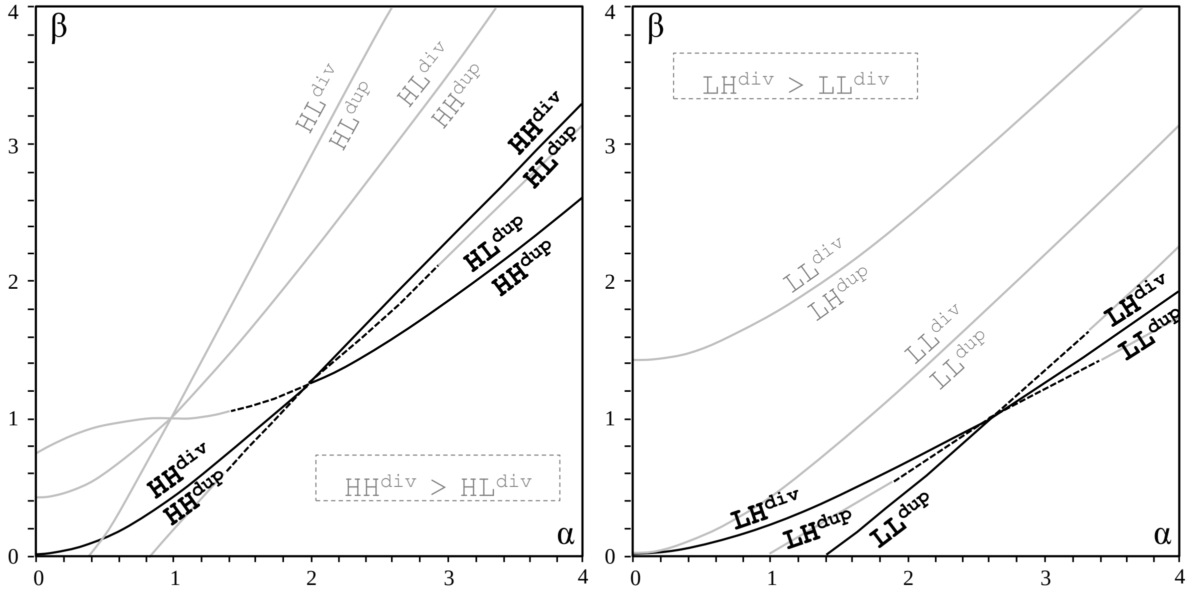
- $\alpha \approx 0.0$: Envy is (almost) not a motive in this case. The best response is the strategy low-risk diverge (HL^{div}). Playing low-risk best meets the original risk preference (risk aversion) and diverging allows a potential surplus over the other player (gloating), cf. point A in Figure 5.7(a).
- $\alpha \gg 1.0$: This is the other extreme. The envy parameter, loosely speaking, the fear of ending up with less than the other player, dominates the consideration. Thus, even though the original risk preference should require a low-risk strategy, the need to make sure not to end up with less is dominant and leads to high-risk duplicate (HH^{dup}). This strategy represents the only way to ensure identical payoffs for both players. The social consideration thus has overwritten the player's inherent risk preference in this case (cf. point C in Figure 5.7(a)).
- $\alpha \approx 0.5$: This case falls in between. Both concepts risk preference and alignment are intermingled here. The resulting best response is a low-risk duplicate strategy (HL^{dup}) (cf. point B in Figure 5.7(a)).

Note that, in the case of a high-risk first move and a risk averse second mover, the strategy high-risk diverge (HH^{div}) is dominated for any combination of the parameters α and β. If either one of the motives (envy or gloating) dominates, the best response will be straightforward determined by this motive. A highly envious player will copy a high-risk move, since it is the only possibility to guarantee not to end up with less than the other player. This holds, even though the player is actually risk averse. A player with a strong motive of gloating will seek to end up with a higher payoff than the other player, which is in consequence effectively equivalent to creating the possibility for different payoffs. In combination with risk aversion, this results in a low-risk diverging strategy. A particular interesting case emerges when both motives are about equally distinctive but rather weak compared to the weight given to the own (absolute) payoff, which is equal to 1. Here, the best response to a high-risk first move is a low-risk duplication strategy. The ambit of this strategy, however, is limited to the *bubble* in the lower left corner of the diagram.

The response to a low-risk first move is less complex, see Figure 5.7(b). The second mover chooses a low-risk strategy in any case, which is in line with the original risk preference. Depending on the constellation of α and β, either a diverging or a duplicating strategy is chosen. A prevalent envy motive will result in a duplicating response, a prevalent gloating motive in a diverging response.

Based on this analysis, it can be concluded that if either the parameter for envy (α) or gloating (β) prevails, and both parameters are high compared to the weight of the own payoff, the best response is distinctly determined. A risk averse player will respond to a high-risk strategy by playing low-risk and concurrently diverging, if gloating is the dominant motive. This holds identically for the response to a low-risk first move. The latter is duplicated perfectly, if the envy motive is predominant. A risk averse player, however, will also perfectly duplicate a high-risk first mover if the envy motive is strong (compared to the other motives), and thus deviate from the inherently preferred level of risk: other-regarding preferences may thus turn milquetoasts into daredevils.

Risk Seeking Player. Now, consider the best responses of a risk seeking player ($1 - r > 1$). The indifference curves for the best responses to high-risk and low-risk first moves are depicted in Figures 5.8(a) and 5.8(b). Again, the best response here depends on the constellation of α and β. A risk seeking player duplicates a high-risk first move with a high-risk move on her part if the envy motive prevails and chooses a high-risk diverging strategy if the gloating motive prevails. If both motives are particularly strong and rather balanced, the best response will be a low-risk duplication strategy. This area of specific parameter composition is figuratively jammed between the other areas of best responses.



(a) Best responses of a risk seeking player to a high-risk choice ($1 - r = 2.0$).

(b) Best responses of a risk seeking player to a low-risk choice ($1 - r = 2.0$).

Figure 5.8.: Best responses of a risk seeking player.

The situation is different for a low-risk first move. The best response is high-risk diverge if the gloating motive prevails and it is low-risk duplicate for a prevailing envy motive. Again and in between, for relatively weak impacts of envy and gloating, the best response is a high-risk duplication strategy.

5.4.4. First Mover Perspective

Now consider the strategic perspective of the first mover, as the 2-person risk game represents a sequential game in its originally form. For this analysis, it is assumed that the first mover knows the second mover's risk preference as well as the parameters α and β with certainty. Furthermore, the players are assumed to be identical with regard to the parameters α and β.

In order to assess a rational first mover's behavior, the following reasoning is used. The first mover anticipates the second mover's actions to any of her own choice alternatives and evaluates her resulting utility values. The second mover responds according to her best response function as developed in the previous section. With respect to the players' risk attitudes, three cases are considered: risk averse players, risk seeking players, and a mixed constellation in which one player is risk averse, and one player is risk seeking.

In the latter case, the sequence, i.e. whether the risk seeking or the risk player is first mover, is of importance, too.

Risk Averse Players. The first move can either be high- or low-risk. A low-risk first move will result either in LL^{dup} or LL^{div}. These values (which are equal for first and second mover, since the players are assumed to be symmetric) are now compared to the corresponding outcomes of a high-risk first move. For this reason, the relevant areas from Figures 5.7(a) and 5.7(a) are superimposed and compared case by case.

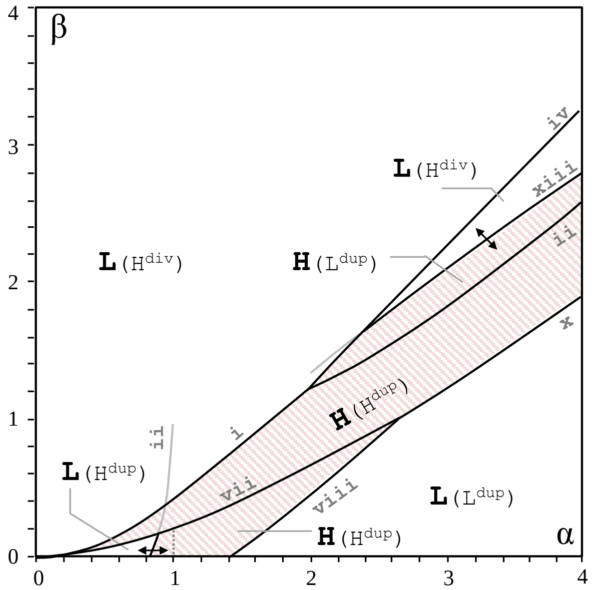
The first mover compares the outcomes LL^{dup} and LL^{div} with HH^{dup}, HL^{div}, and HL^{dup}. Since this notation denotes the utility values from the second mover's perspective, the resulting utility for the first mover can be derived by simply switching the first two letters of the corresponding situation, e.g., the utility value for the second mover in LH^{dup} is equal to the utility value for the first mover in HL^{dup}. The superscripts *dup* or *div* of course remain the same.[12]

For this pairwise comparison, each of the possible outcome constellations as a response to a low-risk first move is compared with each constellation as a response to a high-risk first move. Technically, this process mainly combines different sets of inequations as preconditions for the validity of the best responses. The approach is somewhat extensive but straightforward. The respective sets of inequations—as summarized in Tables 5.9, 5.10, and 5.11—are thus omitted here. In conclusion, the low-risk first move is preferred in any case. Thus, a risk averse player chooses a low-risk strategy, regardless of the parameters α and β in the symmetric case, if the other player is risk averse, too.

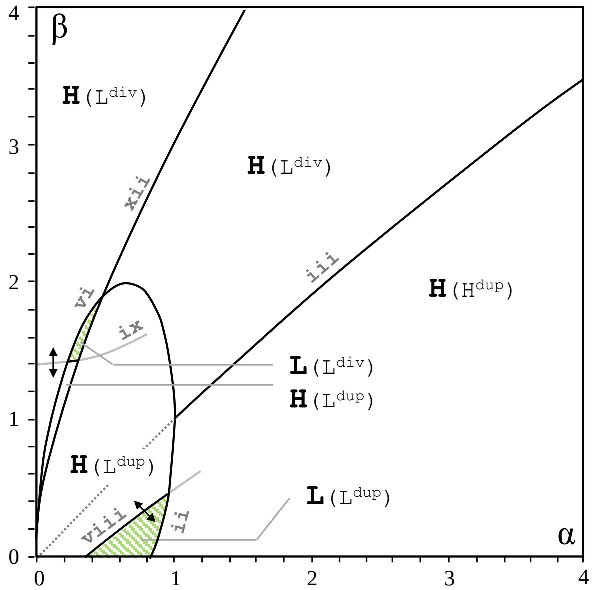
Risk Seeking Players. Again, the first move can either be high- or low-risk. A high-risk first move will result either in HH^{dup}, HH^{div}, or HL^{dup}. The first mover compares these values with the possible outcomes of a low-risk first move, which are LL^{dup}, LH^{dup}, or LH^{div}. In conclusion, the high-risk first move proves to be the preferred choice in any case. Thus, a risk seeking player will choose a high-risk strategy, regardless of the parameters α and β in the symmetric case, if the other player is risk seeking, too.

Mixed Risk Preferences. Eventually, the players can be of different types: one player might be risk seeking, the other risk averse. The analysis for this case is more complex, since now the sequence of decisions (risk averse or risk seeking player first) does play a role for the final outcome. The course of action is similar to that before. It must

[12]The actions of duplicating or diverging inherently involve both players likewise. It is not possible that one player diverges and the other simultaneously duplicates on the same board.



(a) First mover decisions for mixed player types. First mover is risk averse $(1 - r = 0.5)$, second mover is risk seeking $(1 - r = 2.0)$.



(b) First mover decisions for mixed players. First mover is risk seeking $(1 - r = 2.0)$, second mover is risk averse $(1 - r = 0.5)$.

Figure 5.9.: First mover analysis for mixed player types.

be taken into account, however, that the "regions of best responses" (circumscribed by the indifference curves) may cover different, sometimes overlapping areas between the different alternatives (high-risk or low-risk first move, risk averse or risk seeking player). The results, i.e. the respective first moves (first character in bold) and the consecutive responses (in parentheses), are depicted in Figures 5.9(a) and 5.9(b).

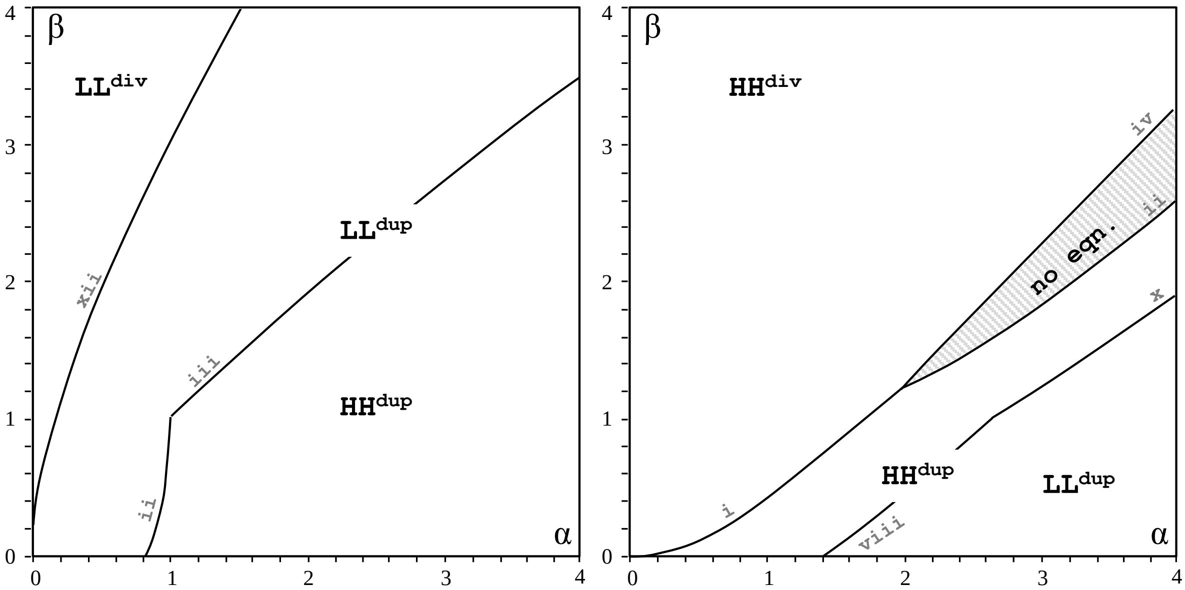
If the risk averse player has the first move, broadly speaking, she chooses low-risk if either the motive of envy *or* gloating is strong, and chooses high-risk in the band between, that is, if both motives are particularly strong (colored red in Figure 5.9(a)). If the risk seeking player has the first move, broadly speaking, she almost always chooses high-risk. Only for very restricted constellations of α and β, the first move will be low-risk (colored green in Figure 5.9(b)).

5.4.5. Equilibria

This section takes a look on possible equilibria in pure strategies, still assuming symmetric players with respect to the parameters α and β. The parameters of risk attitude are not assumed to be symmetric. As a basis for the equilibrium analysis, the preceding analysis of first moves and best responses is employed.

Obviously, if the best response to a low-risk first move is a low-risk second move (diverging or duplicating), no player has an incentive to choose a different strategy, after the other player made her responding choice. The resulting situation is stable and thus represents an equilibrium. The same holds analogously for high-risk first and second moves. Assuming symmetric players, any "same-risk" response thus yields an equilibrium, since the best response to a high-risk (low-risk) first move then is also a high-risk (low-risk) move, which would in turn similarly be responded by the first mover. It becomes obvious, that this also allows for situations with two coexistent equilibria, e.g., in mutually played high-risk or low-risk strategies, or even in a mixed situation, where the players choose different levels of risk. More than two equilibria, however, are not possible. This is due to the fact that the two players may a) mutually prefer to answer a high-risk strategy with a high-risk move (either on the same or on different boxes), they may b) prefer to respond with low-risk to low-risk (either on the same or on different rows), or they may c) mutually prefer to play different risk levels (again, either on different or partially on the same boxes). The two alternatives in a) are mutually exclusive, the players cannot prefer to respond a high-risk move with duplicating and also prefer to diverge, one of the two is simply better. The same holds for b). Each of the two cases in a) and b), however, can be combined with one of the cases of the respective other, which yields 4 different situations with 2 coexisting equilibria. The reasoning for c) is similar. There are two disjunctive alternatives (duplicating and diverging) and two ways to allocate the risk level among the players (player 1: low-risk, player 2: high-risk, and vice versa), which yields another 4 situations with 2 coexisting equilibria. None of the cases in c) can be combined with any case of a) or b), since the assumptions are contradictory. Note that, however, it is also possible that no equilibrium exists for certain parameter constellations. All constellations of equilibria are summarized in Figures 5.10(a) and 5.10(b) and are described in more detail in the next paragraphs.

Risk Averse Players. Minding the argumentation from just above, it can be easily seen from Figure 5.7(b), that for risk averse (and symmetric) players ($0 < 1 - r < 1$), there exists an equilibrium for any combination of the parameters α and β. It is either LL^{div} if the parameter β prevails, or LL^{dup} if α prevails. The line of separation can be derived by equating the respective values of (5.2) for LL^{div} and LL^{dup}, as provided in Table 5.10, cf. curve xii in Figure 5.10(a). There exists, however, another equilibrium for risk averse and symmetric players in the high-risk strategies for certain combinations of α and β, that is, the best response to a high-risk first move, being a high-risk second move. In Figure 5.7(a), this equilibrium area is restricted by the indifference curve between HH^{dup} and HL^{dup} to the left, and the indifference curve between HH^{dup} and HL^{div} to the top, as summarized in Table 5.9 (curves ii and iii). Here, indeed, the motive of envy is of such relative importance that even a originally risk averse player will copy



(a) Equilibria for symmetrical, risk averse players ($1 - r = 0.5$).

(b) Equilibria for symmetrical, risk seeking players ($1 - r = 2.0$).

Figure 5.10.: Equilibria for symmetrical risk preferences.

a high-risk first move of her counterpart, in order to make sure to not fall behind in any case. Hence, there exist two distinct equilibria for these specific parameter constellation. Both (symmetric) players prefer the equilibrium in low-risk strategies, cf. the first mover analysis to this effect.

Risk Seeking Players. The situation is somewhat more complex for risk seeking players. Starting point of this analysis are the diagrams in Figures 5.8(a) and 5.8(b). In total, there arise four different situations. Again, the lines of separation are identical to those of the best response analysis, summarized in Tables 5.9 and 5.10. In the upper left, both players choose a high-risk diverging strategy, since the gloating motive is dominant (above curves i and iv). In the lower right of the diagram, there exists an equilibrium in high-risk duplication strategies, since the envy motive is dominant (below i and ii). In addition to that, if the envy motive is even more distinctive, another, additional equilibrium in low-risk strategies co-exists (below viii and x). Here, the original risk-preference is overruled by the envy motive. Furthermore, for the combination of both strong and balanced envy and gloating parameters, there occurs an area in the parameter space with no equilibrium at all (between ii and iv). Here, the best response to a high-risk first move is HL^{dup}, however, the best response to a low-risk first move is LH^{div}.

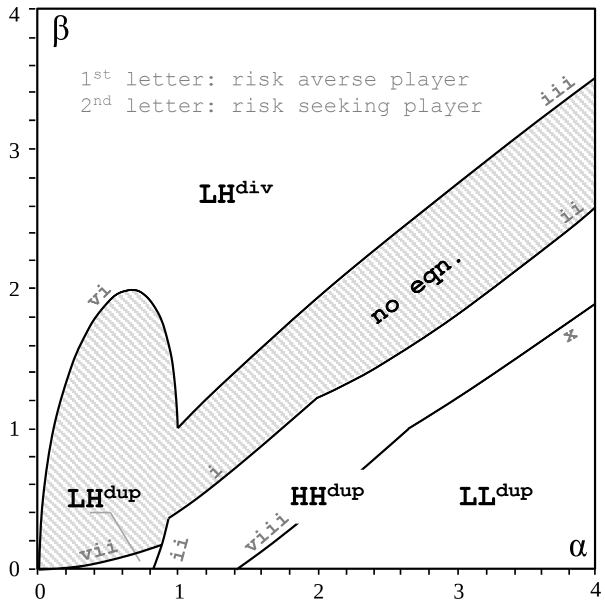


Figure 5.11.: Equilibria for mixed risk preferences. $1 - r_1 = 0.5$, $1 - r_2 = 2.0$.

That means that one player prefers to pick the same box, whereas the other prefers to choose a different one, which is obviously not a stable situation.

Mixed Players. The situation is even more complex for players with different risk preferences. A summary of the resulting equilibria is depicted in Figure 5.11. As it can be seen, high values of α lead to two coexistent equilibria, where both players pick the same box in either high- or low-risk strategies (below viii and x). The first mover coordinates the game according to her risk preferences. Additionally, for rather balanced values of α and β, there exists a band with no equilibrium (below vi and iii, above i , ii, and vii). This also included the area of the "bubble" (see Figure 5.11). Comparatively high values of β yield a unique equilibrium with different risk levels and diverging, at which the risk averse player chooses low-risk, and the risk seeking player chooses high-risk (above vi and iii). Additionally, for rather low values of α and β, there exists an area where this setup is present, but with duplicating instead of diverging (below vii).

Summary. Incorporating the motives of envy and gloating into the decision analysis under risk yields a set of insights.

- Even originally risk averse players may end up taking high-risk actions if accordingly motivated by their believes about the other player's action and a sufficiently high level of anticipated envy.

- This analogously holds for risk seeking players. They might end up taking low-risk actions if accordingly motivated by believes about the other player's action and a high level of envy.
- These counterintuitive equilibria co-exist beside stable constellations in the respective other (expected) risk levels. It is thus a matter of coordination to retrieve the overall desired outcome. From a principal's view, selecting players with suitable individual characteristics (in terms of envy, gloating, risk preference), determining the sequence of actions, and providing information (or creating beliefs) about the other player's action may be a means of doing so.
- For the case of risk seeking players, very strong and balanced occurrences of the motives of envy *and* gloating yield a situation with no equilibrium. One of the players in this case will be motivated to choose a different action.
- For players with opposed risk preferences, the space of parameter combinations, in which no equilibrium emerges, is much larger.
- The resulting degree of risk diversification or clustering depends on the players' motives, at which envy increases the probability of pooling (duplication), and gloating increases the probability of diversification (diverging). This tendency holds universally for both risk seeking and risk averse players.

Taken as a whole, consolidating other-regarding and risk preferences appears valid from empirical and anecdotal evidence. It is suggested that combined formal models of other-regarding preferences and risk are capable of capturing facets of actual human behavior in this regard. This approach assesses the interplay of risk preference and the social reference from a theoretical point of view. It was applied to a simple decision scenario with a coincident choice about the degree of risk and the socially motivated outcome correlation. In the next section, the model is fitted to the experimental data and benchmarked against existing models of other-regarding preferences from the literature.

5.5. Model Fit and Benchmark

Based on the responses made by the second mover in the experiment, the parameters of the presented model are estimated using the maximum likelihood estimation (MLE) method. Thereby, the method of risk aggregation as formally described in 5.2 is used throughout all models. The goodness of fit measures and the parameter estimates are compared to those of the approach based on envy and gloating. The likelihood function is specified based on the different response strategies, $S = \{\mathrm{F}H^{dup}, \mathrm{F}H^{div}, \mathrm{F}L^{dup}, \mathrm{F}L^{div}\}$, where F serves as a place marker for the first mover's choice (either H or L). As specified in 5.2, each of these responses $s \in S$ obtains an expected utility value $\psi_s = EU(s|\mathrm{F})$, which depends on the model parameters and the first mover's decision as specified in the previous section. In order to allow for non-perfect decisions, the absolute (and non-dimensional) utility values ψ_s are converted into probabilities by using a logistic quantal response function (cf. McKelvey and Palfrey, 1995) where the probability $p(s)$ of a strategy $s \in S$ is given by

$$p(s) = \frac{\exp(\lambda\psi_s)}{\sum_{s' \in S} \exp(\lambda\psi_{s'})}. \tag{5.4}$$

Here, the parameter $\lambda \geq 0$ specifies the player's selectivity, or "rationality" in terms of compliance to the model. For the extreme case $\lambda \to \infty$, the best option would always be selected with certainty, even if the second best option has only a slightly lower value. For $\lambda = 0$, all (four) options are equally likely (25%). With that, the following (general) likelihood function for the n observations of a sample is obtained, see Chen et al. (2012) for a similar approach:

$$L(\alpha, \beta, \lambda) = \prod_{i=1}^{n} p(s_i). \tag{5.5}$$

5.5.1. Parameter Estimation

In order to fit the envy & gloating model, $L(\cdot)$ is maximized on the three parameters α, β, and λ simultaneously. The maximum likelihood estimates are the set of values for α, β, and λ, which maximizes the empirical data's likelihood (5.5) of being observed, given that the individual probabilities are determined as in (5.4). The maximum value for $L(\alpha, \beta, \lambda)$ is determined by evaluating the set of possible parameter constellations. All numerical computations were conducted in Java. The MLE is conducted similarly to that described in Gimpel (2007). Separate MLEs on both subgroups are conducted. There are $n_f = 314$ observations in the friends treatment and $n_s = 166$ observations in the strangers treatment, where every subjects represents an observation. A likelihood ratio test assumes that the test statistic $LR_i = -2\log(\frac{L_{MLE\setminus i}}{L_{MLE}})$ follows a χ^2 distribution with one degree of freedom, where L_{MLE} is the likelihood evaluated at the MLE (full model) and $L_{MLE\setminus i}$ is the likelihood of the model when one parameter i is held fix (in this case fixed to zero). It tests whether the model, which is reduced by the tested parameter i, yields the same fit as the full model. With this at hand, a p-value for every estimate can be determined, which denotes the probability of erroneously rejecting the null hypothesis that the estimate is equal to zero. The results of the MLE are summarized in Table 5.12.

In order to evaluate the model regarding its goodness of fit, the following measures may be used. First, the Count R^2 indicates, how often the model predicted the actual behavior, i.e. how often it assigned the highest probability value to the observed choice. This measure, however, is prone to overestimating the model's actual predictive power if one type of observation occurs very frequently. Thus, the Adjusted Count R^2 is adjusted for the most frequent type of observation and yields

$$R^2_{adj.C.} = \frac{n_{correct} - n_{max}}{n_{total} - n_{max}}, \tag{5.6}$$

where $n_{correct}$ denotes the number of correct predictions, n_{max} is the number of the most frequently observed alternative, and n_{total} is the total number of observations. This hit rate can be interpreted as a measure of sensitivity, that is, how often the model makes a correct prediction. This measure, however, is prone to assigning high values to non-specific models. In the extreme case, a null-model would be "correct" in 100 percent of all cases, since it assigns the same (arbitrary) value to all decision alternatives. Therefore, another additional measure to compare the model fits is used. The McFadden R^2 (likelihood-ratio index) is defined as

$$R^2_{McFadden} = 1 - \frac{\ln(L_{model})}{\ln(L_0)} \tag{5.7}$$

and compares the estimated likelihood value for the model without any predictors (L_0) to the likelihood value for the model including the predictors (L_{model}).

Note that the parameter domains are limited. In particular, the restrictions $\alpha \geq 0$, and $\beta \geq 0$ imply that the model is limited to the notions of envy and gloating, rather than similarity seeking or inequality aversion in general. The rationality parameter is limited to $\lambda \geq 0$. As can be seen in Table 5.12, the motive of envy is neglected by the MLE model fit and the motive of gloating is assigned significant weights in both treatments, which is slightly stronger in the friends treatment ($0.789 > 0.697$). This suggests that subjects consider the payoff surplus over the other player as almost as important as their own absolute payoff. For the friends treatment, the value of λ is also higher ($0.873 > 0.754$) indicating a higher degree of "rationality" with respect to the model prediction. The overall fit of the data is better in the friends treatment, which is expressed by Adjusted Count R^2 and McFadden R^2.

5.5.2. Sensitivity Analysis

In order to test the results of the MLE with regard to robustness, a sensitivity analysis is performed. Every parameter is varied around the retrieved optimum while holding

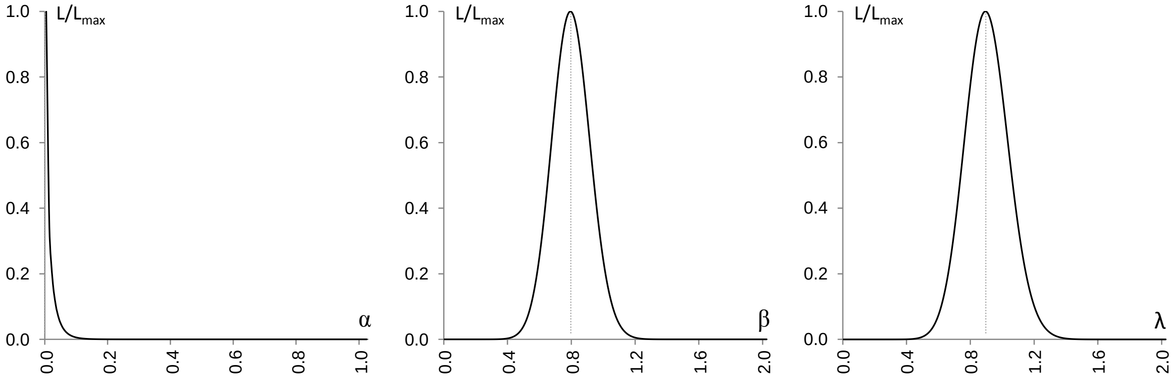
Table 5.12.: MLE results overview for friends and strangers treatment.

	friends		**strangers**	
parameter	estimate	p-value	estimate	p-value
envy (α)	.000	—	.000	—
gloating (β)	.789	<.001	.697	<.001
lambda (λ)	.873	<.001	.754	<.001
n_{total}	314		166	
$n_{correct}$	182		70	
R^2_{Count}	.580		.422	
$R^2_{Adj.C.}$	.237		.030	
$R^2_{McFadden}$	.061		.047	
Log-likelihood	-408.860		-219.421	
L(0)	8.978.E-190		1.143.E-100	
L(model)	2.718.E-178		5.090.E-96	

all other model parameters fixed. This reveals whether the retrieved local optimum is distinctive, i.e. the curve of the $L(\cdot)$ function is smooth, or whether it falls into a noisy range. The latter case would be unfavorable, since it indicates that the retrieved value is less reliable. Depending on the optimal value of the respective parameter, a range from 0 to 1, or 0 to 2 is chosen. The granularity is always 100 steps, i.e. 100 different values are tested. The output value is set in relation to the respective optimum, so that the highest value of L/L_{max} is always 1. The results of the sensitivity analysis for the model of envy and gloating are illustrated in Figures 5.12(a) through 5.13(c). Apparently, the $L(\cdot)$ function curve is smooth in all cases.

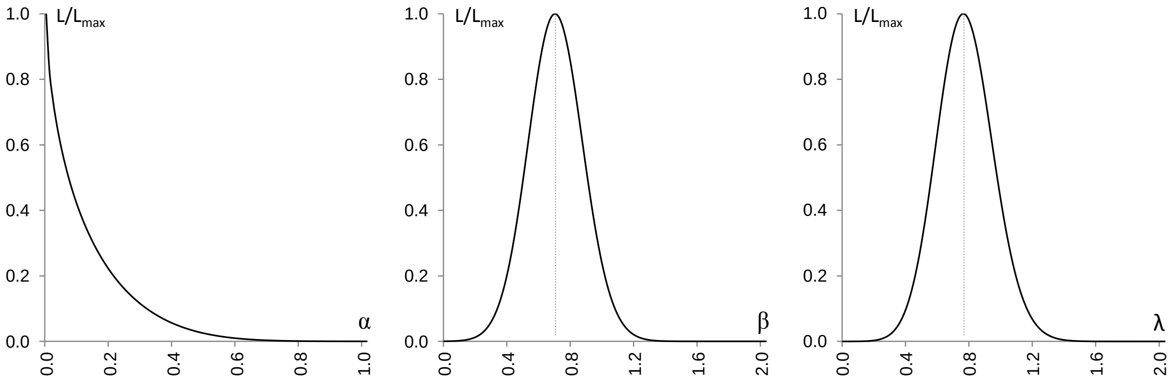
5.5.3. Comparison to Existing Models

The envy & gloating model and its fit of the data is now compared to that of other tractable models of social preferences from the literature. Namely, the models of Fehr and Schmidt (1999, FS), Charness and Rabin (2002, CR), Tan and Bolle (2006, TB), and Cox et al. (2007, CFG) are considered. These models were introduced in Chapter 2, an overview is provided in Table 2.2. Again, separate MLEs for both treatment subgroups are conducted. The results of this comparison are listed in Table 5.13. The results of the sensitivity analysis for the estimates of those reference models are illustrated in Section D in the Appendix.



(a) α, friends treatment. (b) β, friends treatment. (c) λ, friends treatment.

Figure 5.12.: Sensitivity analysis: *envy & gloating* model, friends treatment.



(a) α, strangers treatment. (b) β, strangers treatment. (c) λ, strangers treatment.

Figure 5.13.: Sensitivity analysis: *envy & gloating* model, strangers treatment.

Table 5.13.: MLE summary for selected models of other-regarding preferences for fitting our experimental data sample.

		#pred.	$R^2_{adj.C.}$	$R^2_{McFadden}$	**Log-L.**
envy & gloating	*friends*	182	.237	.061	-408.860
	strangers	70	.030	.047	-219.421
FS 1999	*friends*	241	.578	.006	-432.892
	strangers	119	.525	.013	-227.132
CR 2002	*friends*	199	.335	.008	-431.658
	strangers	81	.141	.014	-227.000
TB 2006	*friends*	131	-.058	.061	-408.750
	strangers	72	.051	.058	-216.790
CFG 2007	*friends*	145	.023	.024	-424.790
	strangers	95	.283	.018	-225.890

The results indicate that, while the highest McFadden R^2 values are obtained by the envy & gloating and TB approaches, the FS model yields the highest hit rates. This, however, is due to the fact that both parameters in the Fehr and Schmidt model are dismissed ($\alpha = \beta = 0$). Consequently, the model has no discriminatory power regarding the data sample. The other models fall in between. There is no clear indication for the dominance of any model regarding both measures and both treatments. The numbers of Table 5.13 are illustrated in Figure 5.14. The estimates and p-values of the referenced models are summarized in Table 5.14.

The results of the MLE show that the envy & gloating model does not fit the data worse than existing models. In the friends subset, the envy & gloating model performs particularly well, where it strictly dominates the model of Cox et al. (2007), and is comparable those of Charness and Rabin (2002) and Tan and Bolle (2006) in one dimension each, but markedly better in the respective other. The single parameter estimates of the reference models are not subject to further discussion in the scope of this work.

5.6. Discussion and Conclusions

This chapter highlighted social interaction effects in risky decision scenarios from 3 perspectives. First, an experimental study demonstrated the impact of peer presence on individual behavior under uncertainty. This impact was shown to depend on the type of the relationship to the peer. Second, using a model of distributional preferences,

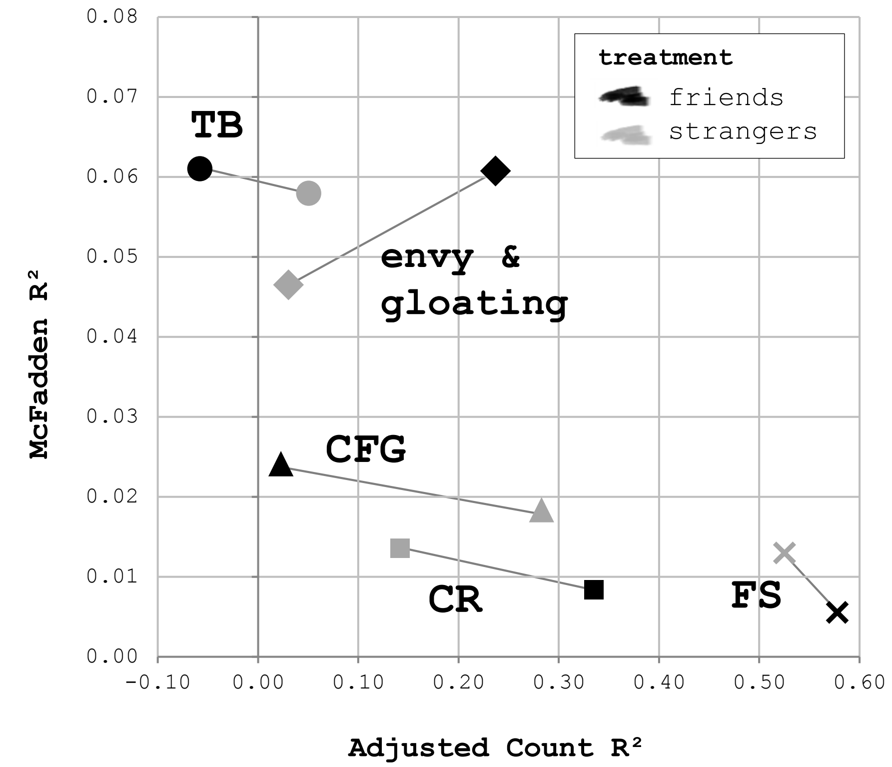


Figure 5.14.: MLE summary for selected models of other-regarding preferences for fitting the experimental data sample.

the interplay of competent interpersonally directed motives and risk attitude was formally analyzed. This established a theoretical baseline for further considerations from a market- and mechanism design perspective. Third, a MLE brought together the empirical data with the theoretical model and located the approach as well as the results in the literature.

5.6.1. Practical Implications

Examples for direct applications of risky decisions in a social context are peer-to-peer lending and social trading platforms. On social trading platforms, users trade shares and other financial products and may be connected to actual friends or simply observe the behavior of other users. Either way, a social context exists. As it was established in this work, social context and risk taking behavior may interact. A social trading platform operator may thus want to manipulate the appearance of a user's surrounding, depending on the actions these users take (e.g., emphasizing the high-volume, high-risk trade of a friend).

Table 5.14.: Model estimates for the reference models.

		friends		strangers	
		estimate	***p*-value**	**estimate**	***p*-value**
FS 1999	λ	.941	.028	1.328	.014
	α	.000	—	.000	—
	β	.000	—	.000	—
CR 2002	λ	1.136	.007	1.360	.012
	γ	.045	.103	.006	.602
	δ	.000	—	.000	—
TB 2006	λ	1.164	$< .001$	.683	$< .001$
	a	.535	.045	.436	.575
	b	-.198	$< .001$	-.304	$< .001$
CFG 2007	λ	2.357	$< .001$	1.364	.004
	α	.735	$< .001$	1.000	—
	θ	.038	.018	-.515	.115

The coherence of relationship type and behavior should be of interest for market and platform operators in the context of social media, too. One fundamental design issue here may be whether to connect users with each other or not. “Connecting” users may be as simple as enabling access to other users’ public profiles, or extend to the possibility of communication. A company may try to maximize social and peer presence in order to create a personal reference to its product or service and to utilize one’s friends as brand ambassadors. In the context of risky decisions, however, it is unclear whether this fosters or hinders the actual desired behavior—as many purchase- or sign-up-or-not decisions can be seen as inherently uncertain—due to unknown product quality, actual necessity and usage, trend development, and so forth. The existence of friends in e-commerce applications may have an impact on economic exchange, if regarded as a signal for trustworthiness. Especially those friends with a credible history themselves may thus constitute “social capital.” As it is practiced by *Airbnb, Inc.* for instance, peer-to-peer intermediaries may animate their users to actively maintain online appearances or even to integrate their facebook profiles. This enables potential transaction partners to conduct “background checks” and may eventually stimulate exchange activity. Lin et al. (2013), in this context, studied the relation between online friendships and transactional outcomes on the peer-to-peer lending platform *Prosper.com* and found that borrowers with online friends were more likely to receive loans. Any peer-to-peer platform operator might hence want to think about ways to stimulate interaction by providing ways for users to signal their credibility. A set of friends might serve as such a signal, in particular when these friends have a history of acting favorably on that platform, not raising the suspicion of fake accounts or detrimental exploitation.

Also in managerial contexts, risky project selection might be affected by a social exposure of outcomes. The relationship type among the decision makers should thus be taken into account. As was suggested by the study in this chapter, this holds particularly when project success can be fully or partly coupled—or deliberately decoupled. Intra-corporate incentive design might profit from considering this idea. In the presented study, stakes were comparatively low and there was no risk of actually losing money. Real scenarios, however, typically involve considerable material and non-material consequences. Personal and interpersonal considerations might be even more important. In the context of managerial decisions, this leads to the questions whether or not companies should enforce the mutual exposure of decisions and outcomes (cf. Ockenfels et al., 2010), and whether acquainted or rather unbeknown, or even anonymous decision makers should be put up for project decisions as illustrated in the introductory example (project A versus project B). From the perspective of a firm's principal, the selection of decision makers might benefit from including individual factors like risk propensity, interpersonally directed emotional motives, and other personality traits. Also the formalized process of decision making (player X or Y first?, simultaneously or sequentially?) should be of interest. Given a particular staffing, the principal might want to make sure that at the time of action, the decision makers' identities are not, or deliberately revealed to one another.

Consider, for instance, an investment company with two traders, one of which is highly risk seeking, the other rather risk averse. A personality test now reveals that both traders are very prone to experiencing envy. In the long run, the company's board desires a rather risky portfolio. Without replacing the risk averse trader, the firm can use the psychological insights and institutional design to drive the firm's overall risk portfolio into the desired direction, e.g. by letting the risk seeker perpetually make first moves—and letting the more risk averse trader know these decisions (for instance by letting the first report his strategy on Tuesdays, and the other on Thursdays). This uses the second mover's anxiety to end up with less without even actively impinging. Of course, this simple example does not capture real life complexity and detailed project scenarios and decisions—it is rather meant to illustrate the general principle.

5.6.2. Theoretical Implications

It is assumed that people consider the possible payoff constellations of a lottery ex ante, and thus evaluate "who gets what" in which cases. The multiplicity of these social outcome constellations is aggregated using a simple isoelastic risk weighting function. This approach particularly differs from the concept proposed by Saito (2013), which assumes risk neutrality and thus does not entail an expression of individual risk preferences. It is, however, conceivable that the evaluation of expected values plays a role when thinking about outcome constellations. This aspect is ruled out in this experiment insofar as both players' expected payoffs are always equal to € 1.00, regardless of their choice.

The results with regard to the model fit are not entirely conclusive. On the one hand, the model does not clearly outperform existing models of social preferences. It does, on the other hand, also not systematically perform worse. Envy as a motive is not corroborated in this formal setup. Gloating, on the other hand, seems to play a significant role—the weight associated with it is only little lower than the weight associated with one's own payoff. This difference is smaller for the friends treatment. This may be thought of as a friendly way of competition among peers—whereas the compared performance is not so important among strangers. This is in line with the findings of Bault et al. (2008) who claimed that "gains loom larger than losses" in the social domain, where it is the other way round in the private domain. There is no support found for the theoretical concept of envy in the MLE. It appears, however, that the emotional motive of envy, as assessed by self-report, *is* associated with subjects' actual behavior.

Given the rather small stakes of the experiment, it is conceivable that the choices are shifted towards risk propensity, whereas subjects in the same situation would act much more risk averse if the stakes were higher. This "peanuts effect" may be due to the low magnitude of the foregone alternative (disappointment or regret) in case the risky choice turns out not to pay off (cf. Weber and Chapman, 2005). For the time being, the risk aggregation function used in this approach does not allow to express risk aversion for high, and risk propensity for low stakes. This extension may not be the most urging since individual risk attitude $(1-r)$ is generally formulated and may extend to any type of risk attitude.

For the most part, experiments have abstracted from the role of personal relations among decision makers. This was not for no reason. Introducing this aspect is problematic in the laboratory environment, since the entire process of experiment execution and participant invitation is laid out for anonymous stranger matching. Taking the experiment into the wild, as was described, introduces a variety of new problems and certainly gives up some degree of control. It was shown that the role of relationships should be taken greater account of, since it was identified as an effective factor. Even though there has not emerged a closed-form theory of how to include the variable yet, modeling behavior may benefit from at least discriminating the data with respect to relationship type. The results indicate that future research should deliberately include the relationship type in some form or the other.

5.6.3. Limitations and Future Work

As it was shown, other-regarding preferences apparently play a role when people decide between risky alternatives, consciously or unconsciously. The approach of using the relationship type as a treatment variable is novel to the literature. Of course, however, the approach followed in this Chapter has several limitations.

Naturally, human relationships comprise a variety of different aspects and are much more complex than being simply “friends” or “strangers.” The classification of the reference person into these groups is admittedly broad. The potential gradations between lose friends, acquaintances, colleagues, fellow students, love-hate relationships, family, or couples could not systematically be considered. Also, the effect of asymmetric relationships could have a much greater effect than was presumed in the scope of this work. However, even when using a highly granular and accurate classification, relationships under the same name tag might still differ substantially from each other. Which factors exactly let people behave in one or another way is hence not entirely allegeable. Putting it positively, there *is* an indication for systematic differences regarding risk taking behavior and distributional preferences *even* at a rather broad level of differentiation. Taking into account relationships in decision scenarios with peers thus appears valid. Further differentiation may further increase the results' quality and significance.

Using the type of the relationship between the decision makers as a treatment variable clearly could benefit from a broader basis of foundational research from the perspective of experimental economics. This would imply to conduct established experiments (e.g., Ultimatum Games, Dictator Games, Prisoners' Dilemmas, Trust Games, etc.) among different groups of subjects with different relationships. It also appears reasonable to test a more differentiated array of relationships in order to identify common and distinctive features that determine the subjects' behavior.

The choices for a certain level of risk in the 2 stages of the game, and especially the notion of changing the level of risk from one stage to the other, may be caused by a variety of reasons. Participants might simply want to play both of the two options, in order to be sure not to miss anything. They might observe that the other player has chosen a different risk level than themselves and simply imitate this behavior without any deeper thought. Moreover, the super-lottery, resulting from a combination of a low-risk (l) and a high-risk (h) choice, might best match the player's risk preferences. Since either stage is selected for payoff with equal probabilities, the $\mu - \sigma-$figures for one's own payoff yield $\mu_{h/h} = \mu_{l/l} = \mu_{h/l} = 1$, and $\sigma_{h/h} = 1.633, \sigma_{l/l} = 0.943$, and $\sigma_{h/l} = 1.333$. Hence, when regarding both stages as a whole, combining high-risk and low-risk yields an intermediate degree of risk ($\sigma_{l/l} < \sigma_{h/l} < \sigma_{h/h}$). Apart from that, both the first and second stage actions might be taken completely at random by some participants, which would cause random risk changing for some of these participants, too.

An additional and complementary way of conducting the experiment, besides as a one-shot game, is the strategy method. This method can arguably be traced back to Selten (1967). In this particular case, the second mover would be asked for a response to all possible first moves by the other player. This bears the advantage that data is collected for any possible state of the game, and not only for the actual reached one. It would enable the indubitable identification of duplication or divergence motives, but also create a huge array of possible intermediate strategies.

Another method would be a dynamic variation in which both subjects are able to follow a common screen in real time and can repeatedly update their decision, until a predefined time is up. This would represent a more realistic model of many situations where it is possible to measure up the intentions of one's counterpart, react to it, and also one's own actions do not remain arcane.

One hypothetical explanation for copying the other's choice is informational guidance. Such effects may be present where, for instance, the other's decision serves as an indication about the quality of the uncertain alternatives. In the present setting, it can be argued that such considerations can mostly be neglected, since there is no ambiguity and complexity is low. Subjects are acquainted with he height of the stakes, the gains are paid off immediately, and the relevant probabilities should be known from any coin flip or game situation (they are neither particularly high or low, nor conditioned). The entire situation can hence be assumed to be assessable intuitively and easily.

The experiment is limited to the notion of gains. Subjects do not put any own money at risk. Many application scenarios do arguably entail the risk of losses, so that an extension in this regard would be intriguing. Generally speaking, the stakes of the experiment were rather small. One could argue that in the magnitude of €2.00 through €4.00, subjects' do not care much about one or the other. On the other hand, expenditure of time and effort for participation was rather low, too.

It is possible that participants in the friends treatment intended or believed that they will pool and share their payoffs after the experiment—as a form of "insurance against not being lucky" among friends. The post-experimental questionnaire actually asked for this intention. Despite that, subjects could share their payoffs no matter what they stated before, and it was out of experimental control whether they did or not.

Another issue in view of the self-reported motivation is social desirability. Subjects might not want to declare motives of envy or gloating, since the societal connotation is negative. This may ultimately distort the measurement. The post-experimental questionnaires, with exception of the risk aversion test, did not entail any monetary incentivization or compensation. Like in most questionnaires, the interpretability of the indications are subject to the participants' honesty and effort to express their characteristics and motives accurately. There is, on the other hand, no compelling reason to assume intentional manipulative behavior.

Admittedly, the post-experimental questionnaire must be seen as a first attempt to raise some data about the participants' motivation in view of the payoff distribution. All constructs comprise a single item only, which is due to the timely restrictions during the experiment. The questionnaires should certainly be further developed and validated.

This Chapter attempted to incorporate the interconnections among decision makers *and* into the notion of economic risks. Thinking of decision making as interpersonally motivated appears reasonable, as has been shown throughout innumerable experiments. But also the type of the relationship matters: real life actions among real life people are not taken anonymously in separate cubicles but with regard to personal attitudes towards the other, be it a friend, an ally, a rival or competitor, or a stranger. Future research may exhibit, whether confounding other-regarding and risk preferences can, after all, be tackled as a combination of the classical economic building blocks, or whether it must be thought of in an entirely different way.

Chapter 6.

Conclusion

"A common mistake that people make when trying to design something completely foolproof is to underestimate the ingenuity of complete fools."

(Douglas Adams)

This chapter concludes this work. First, a brief summary is given, coming back to and answering the research questions as stated in the introductory section in short and thus summarizing the contributions of this work. Second, limitations of this work are discussed and henceforth propositions for future research are made. Lastly, the main conclusions of this work are presented.

6.1. Contributions

This work considered human decision making in different economic scenarios, which are characterized by the presence of a social context and risk. Both aspects are relevant from a mere economic perspective, the junction of them, however, is only sparsely covered in the existing literature (cf. Yechiam et al., 2008; Bolton and Ockenfels, 2010; Trautmann and Vieider, 2011). The subject is particularly relevant in view of the recent development of peer-to-peer platforms and economies, which are mainly rooted online. It was demonstrated that the driving factors, considerations, and insights, however, are not limited to online contexts, but are applicable in economic decision scenarios involving risk and a social context in a more general manner. This may apply to managerial decisions concerning team composition, insurance, or budget allocation. One main conjecture of this work is the differentiated influence of the social context on arousal and behavior. Whereas almost all prior studies in experimental economics created an abstract social context, i.e. matching subjects with anonymous and unknown other experiment participants, this binary concept is challenged and sought to be disentangled in this work. In a first step, the general difference between human and computerized reference players was established. Building on the insight that the presence of human peers causes stronger emotions and also a stronger correlation of arousal and behavior than computerized peers, in a second step, the role of human peers was investigated in greater detail. Specifically, the type of the relationship between the decision makers and their peers was subject to investigation. In fact, not only did the presence of a peer affect economic decision making in general, also did this impact differ for different types of peers (friends or strangers). This speaks in favor of the working assumption, that the established methods of experimental economics may benefit from such an extension.

At the outset of this work, the underlying concepts of risk preferences, social preferences, and emotional motives were considered. Moreover, existing theories and empirical findings were reviewed. In order to give structure to that literature review, a classification framework was proposed. As a first finding, one type of decision had almost not been considered from an economic perspective: ex ante payoff coupling where only one's own chances can effectively be controlled but not the peer's (similar to playing roulette).

Then, in the first instance, a risk preference elicitation task for ad-hoc experiments was developed and evaluated. The task was a methodological prerequisite for the execution of the study involving friend- and stranger relationships between subjects. It was open whether this short test version would be able to capture risk preferences analogously to its established prototype, the Holt and Laury (2002) risk aversion test. The research question in this regard stated:

Can a short version of the Holt and Laury (2002) risk aversion task serve as a substitute? How well do the results correlate and which factors are determinant?

In order to investigate the correlation of both tests, two online experiments with a total of 490 subjects were conducted, in which every subject was facing both tasks (within subject design). The original risk aversion test and the shorter version correlate in a "large," "high," or "major" manner. The correlation is robust among various subgroups such as different height of stakes, sequence, and gender. The new, shorter test was executable by users in less than half of the time on average, compared to the original procedure of Holt and Laury (2002). It has, in addition, proved successful when employed in the experiment presented in Chapter 5.

The next chapter then considered bidding behavior when facing other humans, or in contrast to that, computerized bidding agents in first-price sealed-bid auctions. The emergence of web platforms on which users may interact with both types of counterparts (cf. sniping bots, algorithmic trading, etc.) was addressed. Initially, the relevant theoretical concepts in the light of this scenario were reviewed (competitive arousal, hedonic value, computerized trading, NeuroIS). In order to address the research questions, a laboratory experiment with 120 participants was designed and conducted. The first research question in this context stated:

Is there a difference in bidding behavior in first-price sealed-bid auctions where the other auction participants are either human or computerized?

In a nutshell: it depends on arousal. In auction environments with exclusively human bidders, the bidders' arousal affects their bids in the sense that higher arousal yields lower bids, i.e. a higher degree of risk taking. This effect is not observable when the decision maker faces computerized bidding agents. That is, the impact of arousal is mediated by the presence of computer bidders. Note that, when collapsing the dimension of arousal, the average bid height for both treatment groups is almost identical—the variation, however, differs. This important aspect could only be addressed when controlling for the impact of arousal. The second research question thus concerned the bidders' arousal and stated:

Is there a difference in arousal in first-price sealed-bid auctions where the other auction participants are either human or computerized—and how do auction environment, arousal and bidding behavior interact?

The impact of arousal is definite. Bidders show higher degrees of arousal when facing other humans in the auctions, compared to computerized counterparts. This holds for the general level of arousal prior to submitting a bid (captured by heart rate) as well as for reactions to events such as the presentation of the auction outcome (captured by skin conductance response amplitudes). Moreover, higher induced IPVs for the auctioned commodity yield higher levels of arousal. The difference of the strength of the reaction to winning or losing an auction depends on this value, too: Where from very low to high values, winning causes a stronger SCR amplitude, only for very high valuations, this relation reverses. In the light of these results, practical implications for the design of e-commerce applications were discussed.

In Chapter 5, the impact of different types of relationships among the decision makers was investigated in greater detail. Building on the literature review carried out in Chapter 2, it was revealed that particularly decisions of ex ante payoff coupling under risk had been considered only to some limited extend. This fact was addressed by an accordingly designed experiment, which modeled the relevant aspects in the form of a stylized roulette game. In order to be able to systematically manipulate the type of the relationship between subjects, the laboratory did not appear as the suitable environment for conducting a such experiment. Neither would it have been feasible to invite groups with pre-existing friendships into the lab, nor would it have been promising to artificially create any reliable types of relationships *during* the experiment. Hence, the decision scenario was relocated into a natural environment, which allowed for using the actual, existing relationships between the subjects: the campus. In the course of this experiment, the following research questions were addressed:

Is there a difference in economic behavior among friends and strangers, regarding risk preference and the desire to align or de-align payoffs ex ante in prospect selection?

And indeed, when it comes to risky decisions, there occur distinct differences between the treatment groups. Where socially unexposed, decisions yield the same degree of risk for friends and strangers. The presence of a social context reduces risk taking significantly in the friends condition, whereas it does not so for strangers. Also, friends de-align their choices with those of their peers significantly more often than strangers. It was found that envious players tend to be less risk seeking, and gloating players seek higher degrees of risk, whereas these motive showed no particular connection to the actions of ex ante payoff alignment.

In a second step, a formal model depicting those motives in a linear manner, analogously to the approach of Fehr and Schmidt (1999), was derived and analyzed from a game-theoretic perspective. One of the insights from this analysis was that even risk averse players might end up in equilibria choosing high-risk actions, caused by a mutual motive of envy. Analogously, intrinsically risk seeking players may be caught in low risk actions. From a principal's perspective, aspiring a specific overall portfolio of risk, for instance when staffing workers for a certain task, or arranging payoff rules, this has implications for the design of the scheme of interaction, regarding factors such as sequence, team composition, personality traits, or information availability to the actors.

In a next step, the model was then fitted to the empirical data and evaluated and benchmarked against other, existing models from the literature. The associated research question stated:

Can a model with the emotional motives of envy and gloating explain the observed data? How well does it in comparison to other existing models?

The results here are not entirely conclusive. Whereas the motive of envy is not backed when fitting the model to the data using MLE, the term for gloating does provide explanatory power. The approach using the motives of envy and gloating does not strictly dominate other models in the dimensions of hit rate and McFadden R^2. It is, on the other hand, also not dominated itself. The model's McFadden R^2 values are comparably high, whereas the hit rate is medium for the friends treatment, and comparably low for the strangers treatment. Overall, the theory is supported to some extend, and it performs comparably well with regard to other approaches. In particular does the model of envy and gloating fit the data of the friends treatment well, whereas it does poorer for the strangers treatment. One possible explanation is that these interpersonally directed motives do just not apply sufficiently for strangers. Drastically expressed: a stranger is a stranger, why should one care? This might have fundamental ramifications for experiments investigating social preferences in general, since their design mostly relies on interaction with randomly and anonymously matched strangers.

Chapter 6 summarized objective, research questions and results of this work, indicates limitations, and proposes potential directions for future research. Eventually, the main findings are discussed and conclusions in the context of market engineering and Internet economy are drawn.

6.2. Limitations

In addition to the limitations outlined in sections 3.5, 4.5.3, and 5.6.3, of course, the scope of this work has its limits and the used methodologies have shortcomings. First, a brief summary of the aforementioned limitations is provided for every chapter, which is then extended to the broader context of this work as a whole.

When evaluating a test for **Measuring Risk Preferences in Ad-Hoc Experiments** (Chapter 3), it must be acknowledged that there exists a variety of reasons that could lead subjects to behave differently during the two tasks, which could not be controlled for (e.g., random play, super-lottery, etc.). Also might the erroneous assumption that "consistent" behavior was rewarded, distorts results. Eventually, in the scope of this work, the results could not experimentally be compared to other existing methods and scales for measuring risk preferences in a similar way.

In Chapter 4 (**Risky Decisions among Humans and Computers**) the focus was limited to first-price sealed-bid auctions. Other auction formats might provide valuable insights, particularly since first-price sealed-bid auctions do not allow for dynamic interaction among the decision makers. The individuals' arousal was measured using heart rate and skin conductance response, but it can be argued that the individual capability to regulate one's emotions is another important aspect in this context, which should be incorporated, too (cf. Gross and John, 2003). One can argue that in many realistic settings, the decision maker neither faces exclusively human or exclusively computerized counterparts. One may rather face a mixed population of both types. Also it might often be not clear which type is actually present, so that the ambiguity about the others' nature may have a distinct effect, too. The approach chosen here, strictly separating between human and computerized counterparts and with that leaving no ambiguity about the type, must thus be seen as a first and developable attempt.

With respect to the concept of physiological measurements in economic decision making, a set of methodological issues becomes apparent. First of all, the method has by now proven to be a suitable way of assessing market participants' arousal during economic decision processes and thus may supplement the classical techniques of market design. It must be acknowledged, however, that the actual type of emotion cannot be identified and that arousal may extend to many different feelings, both of positive and negative valence. Neuroimaging (e.g., fMRI, EEG) is arguably a way to address this. Dimoka et al. (2012, p. 682) argued that NeuroIS tools as employed in this work "use various sensors attached to the human body that may themselves induce stress and bias the results." Other potential sources of error and variance are the many factors that cannot entirely be controlled for, such as differences in room temperature, noise, or individual artifacts.[1]

The setting in Chapter 5 (**Risky Decisions among Friends and Strangers**) cannot rule out other reasons for changing or staying with one's level of risk in the different stages of the experiment. Moreover, the classification of the reference person into the groups "friends" and "strangers" is admittedly broad. Also, the stakes of the experiment were rather small. An important issue are the questions that were used to assess the personal motives of action. Each construct was based on a single item, which can typically hardly be regarded as sufficient for a reliable measurement. There were, however, no established questionnaires, suitable for the context of an experiment "in the wild." The development and evaluation of completely new questionnaires from scratch in this regard was not aimed at in the scope of this work.

Even though the empirical data can be explained quite well by using the emotional motives envy and gloating as sampled in the questionnaires, the results of the model fit itself, in contrast to that, are not entirely conclusive. Additional analyses, for instance using the single terms of the utility function piecewise, could lead to a better understanding in this regard.

[1]There are, however, of course technical means to mitigate these potentially detrimental influences, e.g., having experiment participants wear ear muffs, controlling temperature and air moisture by using air condition or heating, and separating participants from each other in cubicles.

Furthermore, the method of experimental economics has its downsides in general. The most important issue, which was briefly discussed in Section 3.1, concerns external validity. The significance of the results depends on their transferability to actual, “real world” contexts. It may well be argued that gambling in the sense of participating in a game, as which an experimental session might be considered by students, is not comparable to “regular” decisions when it comes to financial issues.

Moreover, experimental results can be expected to be biased since participants who volunteer for experiments (even though they are compensated) constitute a distinct subgroup of the entire population of students, which again constitutes a distinct subgroup of the population. This holds for recruiting participants from a subject pool—for which again not every student subscribes—using tools like ORSEE (Greiner, 2004), as well as for recruiting participants “on the fly” in pedestrian areas or frequented spots on campus. Using the latter method, it is clear that different characters will respond differently to being approached by someone who invites them to participate in a “survey,” “study,” or “experiment.” Also will different characters have a different ex ante probability of strolling on campus in the first place. Since spontaneous, curious, open-minded, communicative, and sociable types can be expected to end up participating in the experiment with a higher probability than reluctant, shy, anxious, timid, or hasty types, the sample population is necessarily biased in this regard.

Another issue is that questionnaires (with exception of the risk task) generally do not offer any form of incentives to tell the truth when asking for motives, personality traits, or other information as simple as gender, age, and major. Also might the societal connotation of specific aspects be seen as negative, for instance regarding the admission of feeling envy, which may ultimately distort the measurement. Subjects might simply not feel obliged to provide true or meaningful information, or, due to concerns of social desirability over- or understate specific aspects.

Most of the issues listed, after all, are immanent to the method of experimental economics and the measurement of psychophysiological parameters. Of course, the limitations and imperfections associated with the methods employed in this work should be taken into account when interpreting the results. The aspects mentioned point out several directions for future research.

6.3. Propositions for Future Work

The previous section illustrated several limitations of this work. Following up on that, this section now provides propositions for future research in order to rule out shortcomings and extend the scope of the investigation accordingly.

Other risk elicitation tasks. Besides the widely used Holt and Laury (2002) risk aversion test, there exist other, potentially suitable tests (cf. Section 2.2.2). It would be of interest to systematically analyze execution times, validity, and correlation among those measures in a controlled overarching study. In addition to that, online interfaces would allow to gradually explore personal risk preferences by presenting a sequence of adaptively fitted choice sets to the subject, also ruling out or discovering systematic inconsistencies, and thus providing a higher degree of robustness.

Humans & computers in other experiments. The differences in perceiving and dealing with human and computerized competitors in first-price sealed-bid auctions is evident. It would be interesting to apply this treatment structure to a wider range of other competitive and cooperative situations in a comparable manner. Negotiations represent a scenario in which the collision of human and computerized agents and the access to psychophysiological parameters appears particularly interesting. Negotiations yield an even higher degree of interaction than first-price sealed-bid auctions. Here, feelings for unfair treatment, reciprocity, and revenge might be even more powerful, since the interaction with the counterpart is much more direct. With that, the impact of arousal on behavior might be even more effective, be it harmful or beneficial.

Friends & strangers in other experiments. The same thought holds for the type of the relationship between decision makers. Since this approach is rather novel to the literature, it would be highly interesting to explore this aspect using a set of economic standard experiments with a similar friends/ strangers treatment structure. This would establish an empirical baseline for subsequent experiments and theories to build on. The charming characteristic of this approach is that, rather than hypothesizing and *projecting* laboratory results onto real people with real relationships, it *builds on* actual, existing relationships.

All experiments would potentially benefit from raising additional data about the participants. The aspects of emotion regulation (cf. Gross and John, 2003), competitiveness (cf. Griffin-Pierson, 1990), cognitive reflection (cf. Frederick, 2005), and the Big Five personality traits (*openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*, cf., for instance, McCrae and John (1992)) are particularly noteworthy in this regard.

Realistic field experiments Another way to approach social facets of decision making under risk is to think of situations that naturally provide such a context. The following example of a Karlsruhe based cocktail bar[2] may illustrate that thought. Every Monday between 5 pm and 8 pm this particular cocktail bar makes the following offer to groups of customers, assuming that all members of the group order a cocktail. This offer concerns the ordering and pricing scheme, which is arranged a little different than usually. The customers' choices comprise two aspects. First, a cocktail is picked, yielding a particular price. Second, the consumers individually choose to either pay the fixed price according to the menu (in this case ranging from €2.80 to €5.80), or to alternatively roll a six-sided die and pay whatever the die shows (€1.00, €2.00, ..., or €6.00). The choices are made sequentially, i.e., the i^{th} customer is aware of the choices and outcomes of all $i-1$ antecessors. In particular, the role of group conformity together with the economic and risky aspects of the choice merits further investigation.

Degree of Anonymity. A set of complementary questions between the poles of the presence of humans/ computers and friends/ strangers is related to their appearance. Specifically in e-commerce environments, platform operators set the boundaries for the level of anonymity/ identity, in which users can decide on their profile and appearance. This concerns a variety of relevant questions, regarding the economics of peer-to-peer and other online-based market places. For instance, the trade-off between trustworthiness (much information about your counterpart might be favorable), privacy issues, and effort barriers (less information might be favorable) is of interest for any platform operator reasoning on how much information to demand from its users. In this context, profile pictures might play a particular important role. Where no picture or a meaningless comic might be considered rather untrustworthy but conserves a high level of privacy, a real photo (and maybe also the real name) yields the opposite in both regards. The question is whether, e.g., trusted avatar pictures have the potential to create trust and preserve privacy at the same time (cf. Teubner et al., 2013).

NeuroIS Applications. A way to develop the thought of using physiological measures and feedback in economic decision making scenarios further is described by Gimpel et al. (2013, cf. Figure 6.1). When acknowledging that emotions, and in particular arousal,

[2]http://www.enchilada.de/karlsruhe

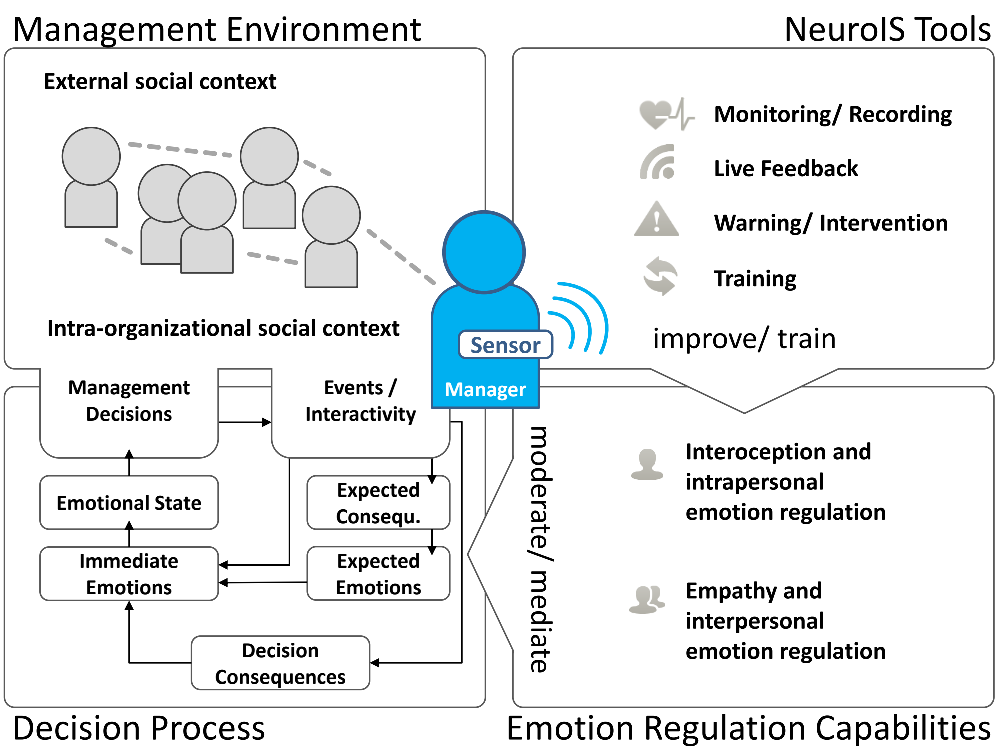


Figure 6.1.: NeuroIS Framework for Emotion Regulation in Management as presented by Gimpel et al. (2013)

may affect decision making, and especially social interactions are able to cause such emotions, economic decisions might benefit from the incorporation of these emotions. Thus, in addition to using physiological measures as explanatory variables ex post, they might be fed into the decision process right away, for instance in the form of real time bio-feedback. For means of supporting management decisions with NeuroIS technology, Gimpel et al. (2013) identified *Monitoring/ Recording*, *Live feedback*, *Warning/ Intervention*, and *Training* as particular relevant. Proxies like heart rate and skin conductance appear feasible since for these measures, "state-of-the-art sensor technology enables IS researchers to conduct continuous physiological measurements in an unobtrusive and unnoticeable way" (Gimpel et al., 2013, p. 4). Overall, this work must be seen as a limited attempt at bringing together the "hard" facets of economic decision making and risk with "soft" notions such as relationship types and arousal in IS contexts.

6.4. Conclusions

This work attempted to demonstrate that the consideration of risk and social facets is relevant to economic decision making, particularly so in online based e-commerce and peer-to-peer applications. Thereby, the aspects of identity versus anonymity, trust, risk attitude, and existing relationships may be regarded as crucial for the success of a particular service. Given that peer-to-peer relations now play an important role in e-commerce, be this a good or bad thing, some findings can punctuated. From anecdotal evidence, it occurs plausible that risk preferences and social preferences may interact. A decision maker that fears to end up with less than his peer may be tempted to bear a greater economic risk than inherently preferred in order to be catching or keeping up "with the Joneses." The interaction of social context and risk attitude may thereby affect decision making in variable ways. Online market contexts appear to be an ideal playing field for this, since they quantify and lay emphasis on otherwise intangible aspects such as the perception of peers and relationships. This notion is confirmed by experimental evidence both from a quite considerable body of literature and the experiments conducted in this work. Additionally, it could be illustrated from a theoretical point of view. From a behavioral market engineering perspective, there may be drawn 3 major conclusions.

First, the actual and perceived *type* of the actors should be considered carefully by market designers, platform operators, and users. Whether one deals with other human users, or rather with or against a script or algorithm may make a difference of how a service is perceived and used. In the context of online auctions, computer opponents appear to induce less arousal and with that less risk seeking behavior. In some sense, computers seem to take emotionality out of the market. Given that many important markets contain both human and computerized agents, understanding the interaction and the impact of this interaction on behavior and efficiency may provide valuable insights for the design and operation of such markets. The actual and perceived type of a platform's actors can, in this sense, be employed as a design factor by market engineering.

This work considered particularly first-price sealed-bid auctions for that matter, but it can be assumed that the general principle applies to other contexts as well, potentially even more so. In regard of technological progress, there is reason to believe that interaction between humans and computerized agents will become increasingly important in business processes and also in daily life. E-commerce naturally "hides" the transaction partner, both timely and spatially. It might thus be desirable to either create or reduce ambiguity about the nature of players on the platform. Repeatedly being outperformed by trading scripts is naturally not a pleasant experience. Competing against deliberately "flawed" algorithms may be simply more fun, making the user believe to encounter a (human) competitor on eye-level, and eventually create higher revenues for the operator. The factor hedonic value is subject to IS research and highly relevant to e-commerce practitioners.

Second, the *relationships* among human decision makers should be considered for market and mechanism design. They blatantly affect economic decisions. Platform operators may want to take the existing relationships among their users into account since the underlying data is available from social networks today. In the context of team composition, this may help principals at staffing (who to assign to a team, in light of personal risk profiles and personality traits), incentivizing, determining the sequence of actions, and also at answering the question of how much information to provide among the workers (anonymity vs. identity).

The shift towards economic peer-to-peer interactions may be seen as the opposite of, but very well as the exact same thing as the economization of civic life. Political philosopher and professor at Harvard University, Michael Sandel[3] stated that many economist believe that markets and commerce were “inert,” i.e. not changing the meaning of the good being exchanged. He doubts that this holds for social goods and practices. Peer-to-peer market places may be seen as the marketization of the social sphere to some extent. Where friends in an online social network serve as a certification of credibility to potential interaction partners, they inevitably become also a commodity, very much in the sense of the notion of “social capital.” This is actually not a new phenomenon, limited to the world of e-commerce. But one wonders, if market thinking and values are not supposed to be applied to civic life, what does it mean if applied vice versa? Applications like social trading, peer-to-peer lending, and other services of the peer economy will prospectively urge this question.

Third, *NeuroIS* may contribute to a better understanding of the underlying visceral processes and to supporting human decision making. In particular, the proponents of the “quantified self”[4] movement use technology to gather data about aspects of their personal daily life. They show a distinct willingness to use such tools to gain knowledge about and improve their routines, physique, reactions, stress levels, etc. Since the tools for measurement and processing are becoming cheaper and less obtrusive, think of Apple’s iWatch, the acceptance and use of such applications can certainly be expected to grow in the future. Once the physiological data has passed the barrier into the IT system, the possibilities are virtually infinite. Only one application one could think of, for instance, are employed are private retail traders that get access to their psychophysiological data using a live bio-feedback device. This device might alarm or

[3] Michael Sandel: “Why we shouldn’t trust markets with our civic life,” TED talk, accessed October 2013.

[4] cf. http://www.economist.com/node/21548493

even deter them from trading if—based on heart rate, skin perspiration, pupil dilation, respiration frequency, or whatever measure is available—their judgment is recognized to be potentially impaired.

In conclusion, e-commerce cannot be considered as the mere transfer of economic processes to the online world. Virtuality, as it was shown, affects several aspects of human interaction considerably. Activity on future market places will presumably shift towards online platforms, incorporate rather more than less computerized agents, maybe involve physiological data, and also the role of peer-to-peer exchange will presumably gain in importance. With that, notions of risk, trust, identity, reciprocity, human/ computer sense, relations, and other social facets become vital. In regard of this trend, market engineering should understand and incorporate the aforementioned aspects into the process of designing mechanisms and market places, where economic reasoning may interfere with social and emotional motives.

Appendix A.

Experimental Measurement of Social Preferences

Table A.1.: Summary of standard experiments, as presented in Levitt and List (2007).

Game	**Summary**	**Typical finding**	**Interpretation**
Ultimatum Game, Güth et al. (1982)	A two-stage game where two people, a proposer and a responder, bargain over a fixed amount of money. In the first stage, the proposer offers a split of the money, and in the second stage, the responder decides to accept or reject the offer. If accepted, each player receives money according to the offer; if rejected, each player receives nothing.	*Proposer*: Majority of offers in the range of 25-50% of fixed amount. Few offers below 5%. *Responder*: requently reject offers below 20% of fixed amount.	*Proposer*: Fairness. *Responder*: Punish unfair offers: negative reciprocity, fairness preferences, such as inequity aversion.
Dictator Game, Kahneman et al. (1986)	A variant of the ultimatum game: strategic concerns are absent as the proposer simply states what the split will be and the proposer has no veto power, rendering the proposed split as effective.	Usually more than 60% of subjects pass a positive amount of money, with the mean transfer roughly 20% of the endowment.	Altruism; fairness preferences, such as inequity aversion.
Trust Game, Berg et al. (1995)	A sequential prisoner's dilemma game wherein the first mover decides how much money to pass to the second mover. All money passed is increased by a factor, $f > 1$, and the second mover then decides how much money to return to the first mover. In this light, the second mover is a dictator who has been given his endowment by the first mover.	*Proposer*: average transfer of roughly 50% of endowment. *Responder*: repayment is increasing in transfer. Average repayment rate is nearly 50% of transfer.	*Proposer*: Trust; foresee positive reciprocity. *Responder*: Trustworthiness, positive reciprocity.
Gift Exchange Game, Fehr et al. (1993)	Similar to the trust game, but the money passed by the first mover (often labeled the "wage" or "price" offer), is not increased by a factor, rather it represents a pure lump-sum transfer. Also, the first mover requests a desired effort, or quality, level in return for the "wage" or "price" offer. The second mover then chooses an effort or quality level that is costly to provide, but increases the first mover's payoff.	*Proposer*: "Wage" or "price" offer is typically greater than the minimum allowed. *Responder*: Effort or quality increases in "wage" or "price" offer.	*Proposer*: Trust; foresee positive reciprocity. *Responder*: Trustworthiness, positive reciprocity.
Public Good Game, –	Generalization of the prisoner's dilemma game in that n group members decide simultaneously how much to invest in the public good. The payoff function is given by $P_i = e - g_i + \beta \sum_n g_j$, where e represents initial endowment; g_i is the level of tokens that subject i places in the group account; β is the marginal payoff of the public good; and $\sum_n g_j$ is the sum of the n individual contributions to the public good. By making $0 < \beta < 1 < n\beta$, the dilemma follows.	Players' contribution to public good is roughly 50% of endowment in one-shot games. Many players' contributions unravel to approach 0% in latter rounds of multi-period games.	Altruism; fairness preferences, conditional reciprocity.

Appendix B.

Participant Instructions

B.1. Instructions for the Risk Aversion Tasks

This section lists the participants instructions of the short version of the Holt & Laury Risk Task presented in Chapter 3. The instructions were translated to English from the original German version.

Welcome and thank you very much for taking the time to participate in this experiment. Ten percent of all participants, who take the entire task completely, will receive a real payoff, cash in Euro. How much money this is, depends on the decisions you take during the experiment.

The payoff session will be held during an entire day at our Institute. You can, if necessary, arrange an individual appointment for the payoff process. You will receive further information on this after completing the experiment. All your data is treated confidentially, i.e. it is securely stored, not forwarded to any third party and processes only for scientific purposes.

Note on the chances to be selected for the real payoff and the payoff amounts: Ten percent of all participants of this experiment will be randomly selected for a real monetary payoff. For the following decision making, please assume that you were selected and receive a real payoff.

In each of the following parts of the experiment, you will fill out a questionnaire-like decision task. For your payoff determination, only one of these questionnaires will be relevant. Which one it is, is determined randomly, both alternatives are equally likely (50% each). Here you see an exemplary questionnaire. How the payoff is determined is now explained in three steps.

1. Every questionnaire-like decision task entails a number of rows, in each of which you have to choose one out of two alternatives (A or B). If in one alternative (of a given row) there is no probability listed next to a payoff amount, this means that this payoff is certain (100%). If there is displayed only one probability next to the payoff amount, the alternative probability will result in a payoff of € 0.-.
2. After having completed the task, one of the rows will be selected randomly and your decision for A or B is looked up. At that, every row is equally likely to be selected. Thus eventually, only one row will be relevant for payoff!
3. The lottery (A or B) you have chosen in the randomly selected row will be played. For this, a ten-sided die is used (more details are provided in the examples below).

B.2. Instructions for the Auction Study

This section lists the participants instructions of the study presented in Chapter 4. The instructions were translated to English from the original German version. The instructions were almost identical for both treatments, with exception of the references to the other bidders (either other human participants or computerized bidding agents). The alternative text snippets for the "computerized opponents" treatment are provided in square brackets.

You are about to participate in an experiment of economic decision making. During the experiment, your skin conductance, pulse, and heart rate are recorded. You can earn real money in this experiment. How much money you earn depends on both your decisions and the decisions of the other participants in this room [the computerized bidding agents]. The experiment consists of 30 consecutive auctions. The experimental software manages a cash account for you that balances gains and losses out of the 30 auctions. A positive cash balance is paid to you at the end of the experiment, a negative one is claimed. During the experiment, gains and losses are calculated in monetary units (MU). 16 MU equal a real amount of € 1.-. 1 MU therefore equals 6.25 Euro cents. Communication between participants is not allowed.

Design of an Auction. In each auction you bid for a fictitious asset. Information about your personal resale value of the asset is given to you prior to an auction. This value is known only to you. Within each auction you and two other participants [computerized bidding agents] compete in an auction. [The computerized bidding agents follow a strategy that you do not know.] The two other bidders also receive their personal resale value prior to the auction and it is known only to them. As soon as the auction starts, you have the possibility to place your bid via a number pad. If you make a mistake you can correct your bid through clicking on the *Correct* button. It deletes the last digit you entered. You finally place your bid by clicking on *Submit Bid*. [The computerized bidding agents bid simultaneously and do not know about other bids.]

If all bidders made their bid, the one with the highest bid is determined. This bidder wins the auction and pays the price he or she bid for the asset. If two or more bidders place the same highest bid, the experimental software selects one of them by equal chances. If you are not the highest bidder you receive a payoff of zero. If you are the highest bidder your payoff is calculated in the following way: Payoff = Personal Resale Value – Price

The Personal Resale Value. Prior to every auction you and the other participants [computerized bidding agents] receive information about your personal resale value but not about the resale value of the others. In each auction, you exactly know the height of your personal resale value for this particular auction.

The personal resale value is drawn independently out of the integer values between 11 and 110 for each bidder. Every value is equally likely to be chosen. This corresponds to an urn with 100 balls, which are labeled with numbers from 11 to 110. A random draw from the urn determines the resale value of the bidder's asset. After the draw the ball is put back into the urn and the resale value for the next bidder is drawn. The winner of an auction obtains her personal resale value minus her bid. This connection should be explained through an example. Assume that you have a personal resale value of 65 MU and you have been the bidder with the highest bid. Then there are the following cases:

1. Bid lies above resale value, e.g. 67 MU $\rightarrow$ Loss of 65 MU $-$ 67 MU $= -2$ MU,
2. Bid equals resale value, i.e. 65 MU $\rightarrow$ Zero payoff: 65 MU $-$ 65 MU $=$ 0 MU,
3. Bid lies below resale value, e.g. 61 MU $\rightarrow$ Gain of 65 MU $-$ 61 MU $=$ 4 MU.

If one of the other participants (computerized bidding agents) is the highest bidder, the auction ends and you receive a payoff of zero.

Course of the Experiment. After the instruction phase there are five practice periods to gain a better understanding of the experiment. Gains and losses out of these practice periods are not considered for the later payoff. After the practice periods there is a five-minute resting period where a fixation cross appears on the computer screen. The resting period is essential for the physiological measurement and later data analysis. Stay calm during this phase and try to move as little as possible. The main course of the experiment consists of 30 consecutive periods where each of the six participants plays against two other participants (computerized bidding agents). In every period you and the other participants [computerized bidding agents] of your group participate in one auction as described above. After every period you are randomly re-matched to a new group of three bidders. Thus, you will play against frequently changing participants [computerized bidding agents]. The result of one auction does not affect following auctions. [Please note that the other five participants in this room do not have any influence on your auction outcome including gains and losses. Six participants are present because this laboratory has six places.]

Payment. At the end of the 30 periods a positive cash balance is paid to you and a negative one is claimed. The cash balance in MU is multiplied with a factor of 1/16 to get the payoff in Euro. I.e. if you have a cash balance of 400 MU you obtain a payment of 25 EUR. 1 MU equals 6.25 Euro cents.

... and finally, some comments. If you have any questions regarding the experiment, please remain seated, raise your hand and wait until the experimenter approaches you. Then, ask your question as quiet as possible. Only use your free hand to interact with the experiment system. The hand linked to the physiological measurement system must remain as calm as possible during the whole experiment. Try to avoid every movement as this can distort the measurement. Upon the end of the experiment, remain seated and wait until the experimenter has removed the electrodes from your arm and wrist. The participant instructions remain at your place. Before the experiment starts, you are going to answer some questions of general understanding about the rules of the experiment on your computer screen. Then, five practice periods are performed as described above. Gains and losses are not considered here. Then the five-minute resting period starts and therewith the actual experiment. Important note: Please click your mouse as quiet as possible and with little effort. You will now be equipped with earmuffs to reduce the influence of background noise.

B.3. Instructions for the 2-Person Risk Game

This section lists the participants instructions of the 2-person risk game experiment presented in Chapter 5. The instructions were translated to English from the original

German version. These instructions presented in form of an audio track and were part of a 3 minute slide show video, which participants watched together on a computer screen.

Welcome. You and the other participant are engaging in an economic experiment, in which you can earn real money in cash. This tutorial video explains the game you will play and the procedure of the experiment.

At the beginning of the experiment you will see this game board in front of you on your tablet computer. You will choose one of the four boxes by touching it on the screen. Each of the boxes represents one of the numbers 1 through 4 of a four-sided die. At that, each of the numbers is equally likely (25 percent). You earn € 4.- if the dice actually shows your number. Furthermore, you can select an entire row, that is, two numbers at once. In this case you win, if either the one, or the other number in shown by the die. The amount you earn then is € 2.-.

Before the winning number is actually determined, you and the other participant exchange your tablet computers.

You now play the game, as described above, and again select a number or row of your choice. However, now, it is visible to you, which box or row was selected by the other player in the first stage of the game. The other participant's choice does not limit your possibilities of choice and does neither impair your chances of winning, nor your payoffs. You can, similar to the first stage, select any of the four boxes, as well as one of the two rows.

After that, one of the two tablet computers is selected at random and the winning number is determined using the four-sided die. Depending on the choices of you and the other participant, both then receive an independent payoff of either € 2.-, € 4.-, or € 0.-. Please note: only one of your two decision will actually be relevant for payoff, either from the first or from the second stage of the game. Which one it will be, is determined randomly.

An example: Player "black" has selected the box number 4, player "green" has selected the lower row, that is, the numbers 3 and 4. Now, the die actually shows a four. Player "black" then receives € 4.-, player "green" accordingly receives € 2.-.

After the experiment, we ask you to fill out a short questionnaire and a receipt for you cash payoff, provided that you win. We are happy to ask any remaining questions regarding the game or the procedure of the experiment, if you have.

Thank you very much for your participation. You can now take off the head phones.

After the 2-person risk game experiment, subjects conducted the short version of the Holt and Laury (2002) risk aversion task. The graphical representation of the task, as presented to subjects (in German language originally) is depicted in Figure B.1. The instructions for this task were as follows:

certain payoff			**lottery**
1,65 EUR	☐	☐	30% Chance for 3,85 EUR
1,70 EUR	☐	☐	40% Chance for 3,85 EUR
1,75 EUR	☐	☐	50% Chance for 3,85 EUR
1,80 EUR	☐	☐	60% Chance for 3,85 EUR
1,85 EUR	☐	☐	70% Chance for 3,85 EUR

Figure B.1.: Graphical representation of the HL5 risk aversion task.

You now choose five times between a safe payoff (on the left hand side) and a lottery (right hand side). Please indicate for each instance, which alternative you prefer. One of the five instances will afterward be selected randomly (equal probabilities of 20 percent each). If you have chosen the safe payoff in the selected instance, this amount of money will be payed out to you right away. If you have chosen the lottery, a die will decide whether you win, or not.

Please note: You can earn real money in this task. Please note also: Only one of your five decisions will actually be relevant for payoff.

Appendix C.

Correlation Tables and Logit Regressions

Table C.1.: Correlation Table for the friends treatment: Bivariat Correlation, Pearson Coefficients, p-values displayed in parentheses (two-tailed), $\epsilon = 0.001$. Significant correlations ($p < 0.05$) highlighted in bold. $N_F = 314$.

	HR(1)	HR(2)	CHNG	PRFCT	PRTL	HR(obs.)	STAY	DIF	ENVY	GLTG	SMPY	SHRG	#RC	AGE	GND
high-risk (1)	1.000	**.467**	**.239**	-.001	.037	.079	**-.236**	-.059	**-.258**	**.301**	**-.180**	**-.141**	**.245**	-.027	**.139**
		($< \epsilon$)	**($< \epsilon$)**	(.984)	(.512)	(.162)	**($< \epsilon$)**	(.299)	**($< \epsilon$)**	**($< \epsilon$)**	**(.001)**	**(.012)**	**($< \epsilon$)**	(.637)	**(.014)**
high-risk (2)		1.000	**-.166**	-.027	.018	.077	-.072	.043	**-.263**	**.194**	**-.264**	**-.125**	**.162**	-.077	.099
			(.003)	(.638)	(.750)	(.174)	(.202)	(.449)	**($< \epsilon$)**	**(.001)**	**($< \epsilon$)**	**(.027)**	**(.004)**	(.173)	(.079)
change			1.000	-.054	-.109	.096	**-.411**	.030	.094	**.161**	.032	-.002	.050	-.075	.059
				(.342)	(.054)	(.090)	**($< \epsilon$)**	(.596)	(.095)	**(.004)**	(.578)	(.968)	(.374)	(.187)	(.298)
perfect dup				1.000	**.416**	-.086	.086	**-.135**	.002	.065	-.068	**-.211**	-.093	.004	-.002
					($< \epsilon$)	(.129)	(.130)	**(.016)**	(.973)	(.250)	(.229)	**($< \epsilon$)**	(.100)	(.951)	(.974)
partial dup					1.000	-.022	.066	**.240**	-.025	.036	**-.260**	**-.249**	.011	-.019	-.043
						(.699)	(.240)	**($< \epsilon$)**	(.664)	(.531)	**($< \epsilon$)**	**($< \epsilon$)**	(.851)	(.741)	(.443)
risk (obs.)						1.000	-.056	-.059	.064	.082	**-.132**	**-.112**	.087	-.024	**.139**
							(.321)	(.299)	(.256)	(.148)	**(.019)**	**(.047)**	(.123)	(.672)	**(.014)**
stay							1.000	-.070	-.008	**-.152**	-.079	-.046	.048	.081	-.061
								(.218)	(.885)	**(.007)**	(.164)	(.420)	(.401)	(.151)	(.280)
observe dif.								1.000	.085	.093	**-.124**	**-.189**	-.039	-.033	-.098
									(.131)	(.100)	**(.027)**	**(.001)**	(.494)	(.564)	(.082)
envy									1.000	**.139**	**.127**	.021	**-.118**	-.035	-.005
										(.014)	**(.025)**	(.710)	**(.036)**	(.537)	(.932)
gloating										1.000	-.076	**-.220**	.005	**-.156**	.011
											(.180)	**($< \epsilon$)**	(.927)	**(.006)**	(.851)
sympathy											1.000	**.487**	-.065	-.071	-.057
												($< \epsilon$)	(.250)	(.209)	(.313)
sharing												1.000	-.098	.087	**.148**
													(.083)	(.125)	**(.008)**
#RC													1.000	.071	.028
														(.211)	(.617)
age														1.000	-.078
															(.171)
gender															1.000

Table C.2.: Correlation Table for the strangers treatment: Bivariat Correlation, Pearson Coefficients, p-values displayed in parentheses (two-tailed), $\epsilon = 0.001$. Significant correlations ($p < 0.05$) highlighted in bold. $N_S = 166$.

	HR(1)	HR(2)	CHNG	PRFCT	PRTL	HR(obs.)	STAY	DIF	ENVY	GLTG	SMPY	SHRG	#RC	AGE	GND
risk (1)	1.000	**.324**	-.026	-.016	.000	-.063	-.115	-.063	**-.273**	**.190**	**-.179**	-.007	**.322**	.140	-.079
		($< \epsilon$)	(.741)	(.842)	(.997)	(.423)	(.139)	(.423)	**(.000)**	**(.014)**	**(.021)**	(.929)	**($< \epsilon$)**	(.071)	(.314)
risk (2)		1.000	-.026	**-.248**	**-.255**	.010	-.115	.058	**-.254**	**.162**	**-.197**	.002	**.212**	.120	-.054
			(.741)	**(.001)**	**(.001)**	(.899)	(.139)	(.456)	**(.001)**	**(.037)**	**(.011)**	(.979)	**(.006)**	(.122)	(.489)
change			1.000	.008	-.078	.085	**-.558**	.034	**.197**	.115	.112	**.210**	-.021	.055	.071
				(.918)	(.318)	(.279)	**($< \epsilon$)**	(.668)	**(.011)**	(.140)	(.151)	**(.007)**	(.790)	(.481)	(.362)
perfect dup				1.000	**.604**	**-.258**	**.209**	**-.159**	.084	-.139	-.023	-.029	-.089	-.036	-.011
					($< \epsilon$)	**(.001)**	**(.007)**	**(.041)**	(.284)	(.073)	(.769)	(.708)	(.252)	(.646)	(.884)
partial dup					1.000	**-.171**	**.256**	.059	-.020	-.080	.000	-.116	-.048	.008	-.007
						(.028)	**(.001)**	(.450)	(.803)	(.305)	(.995)	(.138)	(.543)	(.920)	(.930)
risk (obs.)						1.000	-.035	-.040	.091	-.111	-.021	-.036	-.033	.034	.000
							(.657)	(.610)	(.243)	(.154)	(.789)	(.646)	(.670)	(.666)	(.997)
stay							1.000	-.085	-.123	**-.298**	-.101	-.118	-.059	-.047	**-.179**
								(.279)	(.114)	**($< \epsilon$)**	(.196)	(.128)	(.453)	(.549)	**(.021)**
observe dif.								1.000	-.114	.101	**-.172**	**-.245**	-.067	.108	.074
									(.143)	(.194)	**(.027)**	**(.001)**	(.390)	(.165)	(.342)
envy									1.000	**.193**	**.355**	**.220**	-.138	-.119	.037
										(.013)	**($< \epsilon$)**	**(.004)**	(.076)	(.125)	(.634)
gloating										1.000	**.186**	.088	.036	-.020	-.087
											(.016)	(.259)	(.646)	(.803)	(.263)
sympathy											1.000	**.471**	-.116	-.044	-.025
												($< \epsilon$)	(.136)	(.577)	(.748)
sharing												1.000	-.055	.072	-.055
													(.481)	(.360)	(.480)
#RC													1.000	-.032	-.105
														(.681)	(.177)
age														1.000	-.065
															(.403)
gender															1.000

Table C.3.: Logit regression coefficients and significance levels for the *friends* treatment. Dependent variables are (i) level of risk (1^{st} stage), (ii) level of risk (2^{nd} stage), (iii) duplication, and (iv) risk change from first to second stage. Method: enter. $\epsilon = 0.001$.

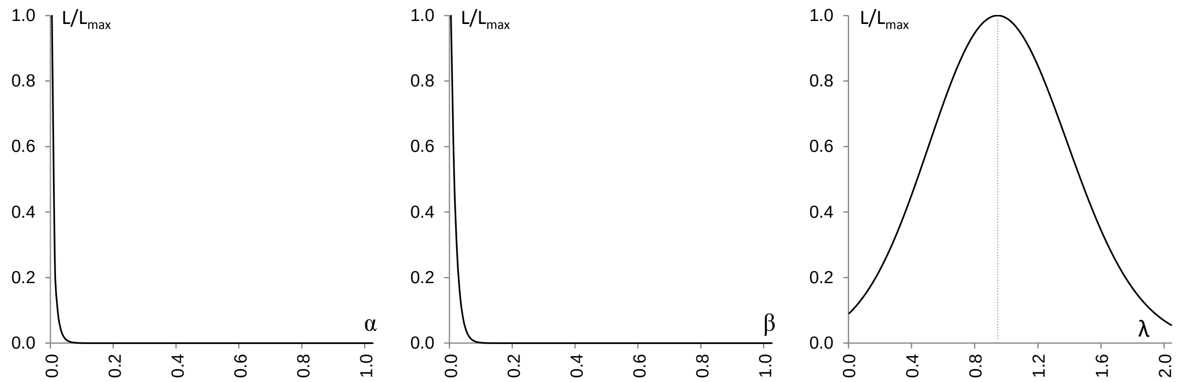
	(i) risk (1)		**(ii) risk (2)**		**(iii) duplicate**		**(iv) risk change**	
	coef.	**sig.**	**coef.**	**sig.**	**coef.**	**sig.**	**coef.**	**sig.**
high-risk (1)	—	—	2.374	$< \epsilon$	.561	.202	1.956	$< \epsilon$
high-risk (2)	—	—	—	—	-.464	.282	-1.719	$< \epsilon$
duplicate	—	—	-.273	.408	—	—	-.721	.041
risk change	—	—	-1.730	$< \epsilon$	-.946	.028	—	—
envy	-.597	$< \epsilon$	-.293	.018	-.021	.853	.170	.155
gloating	.681	$< \epsilon$	.254	.034	.083	.449	.191	.102
constant	.076	.708	-1.166	$< \epsilon$	-1.080	$< \epsilon$	-1.819	$< \epsilon$
Observations	314		314		314		314	
Nagelkerke R^2	.246		.410		.033		.257	
0-hitrate	.532		.592		.752		.723	
hitrate	.653		.911		.752		.901	

Table C.4.: Logit regression coefficients and significance levels for the *strangers* treatment. Dependent variables are (i) level of risk (1^{st} stage), (ii) level of risk (2^{nd} stage), (iii) duplication, and (iv) risk change from first to second stage. Method: enter. $\epsilon = 0.001$.

	(i) risk (1)		**(ii) risk (2)**		**(iii) duplicate**		**(iv) risk change**	
	coef.	**sig.**	**coef.**	**sig.**	**coef.**	**sig.**	**coef.**	**sig.**
high-risk (1)	—	—	1.106	.003	.559	.191	.069	.852
high-risk (2)	—	—	—	—	-1.424	.001	-.067	.860
duplicate	—	—	-1.317	.001	—	—	-.352	.353
risk change	—	—	-.060	.873	-.510	.224	—	—
envy	-.621	$< \epsilon$	-.479	.004	-.092	.555	.321	.033
gloating	.479	.001	.311	.046	-.054	.705	.129	.344
constant	.287	.284	.216	.571	.044	.907	-1.195	.007
Observations	166		166		166		166	
Nagelkerke R^2	.185		.290		.120		.069	
0-hitrate	.518		.518		.663		.663	
hitrate	.633		.669		.663		.663	

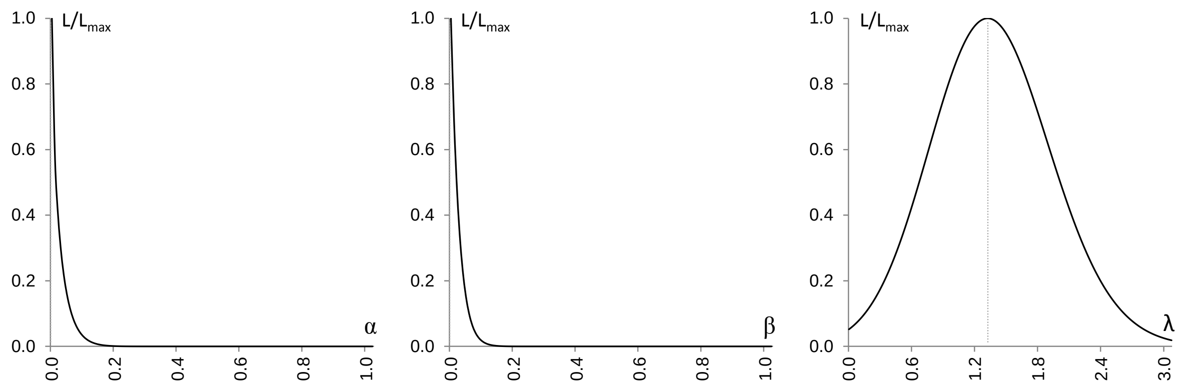
Appendix D.

Sensitivity Analysis



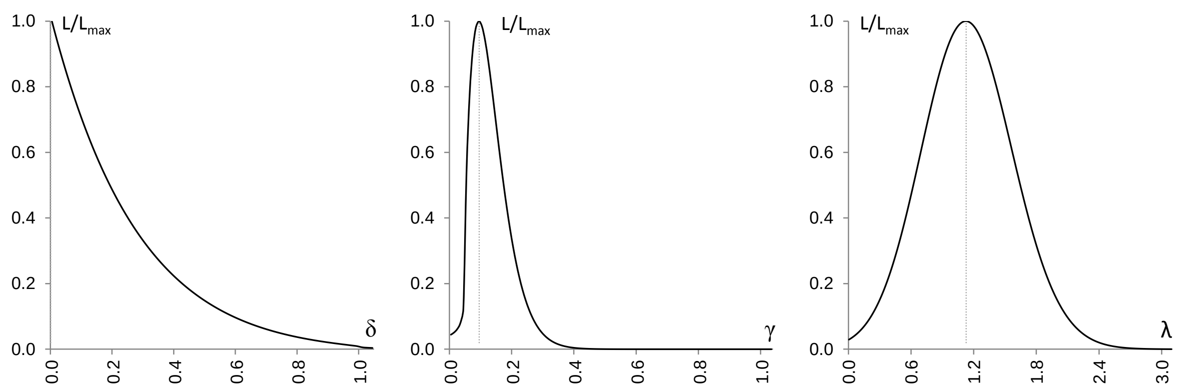
(a) α, friends treatment. (b) β, friends treatment. (c) λ, friends treatment.

Figure D.1.: Fehr and Schmidt (1999) model, friends treatment.



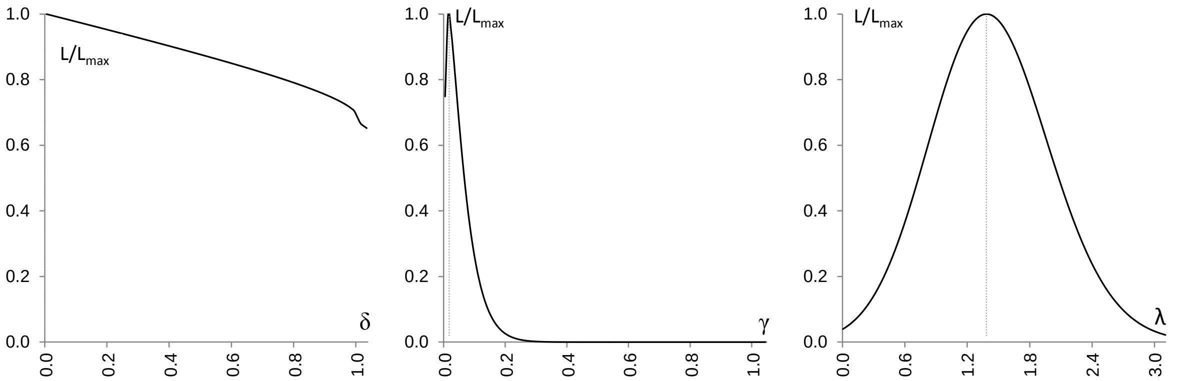
(a) α, strangers treatment. (b) β, strangers treatment. (c) λ, strangers treatment.

Figure D.2.: Fehr and Schmidt (1999) model, strangers treatment.



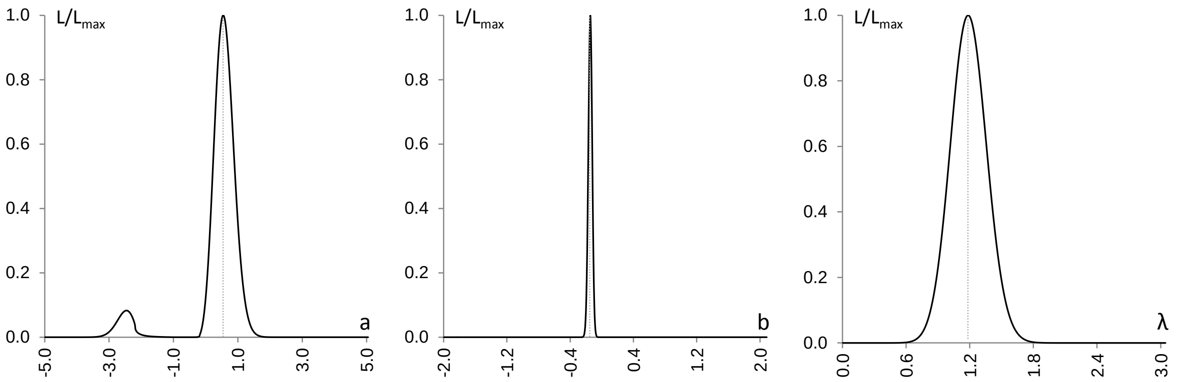
(a) δ, friends treatment. (b) γ, friends treatment. (c) λ, friends treatment.

Figure D.3.: Charness and Rabin (2002) model, friends treatment.



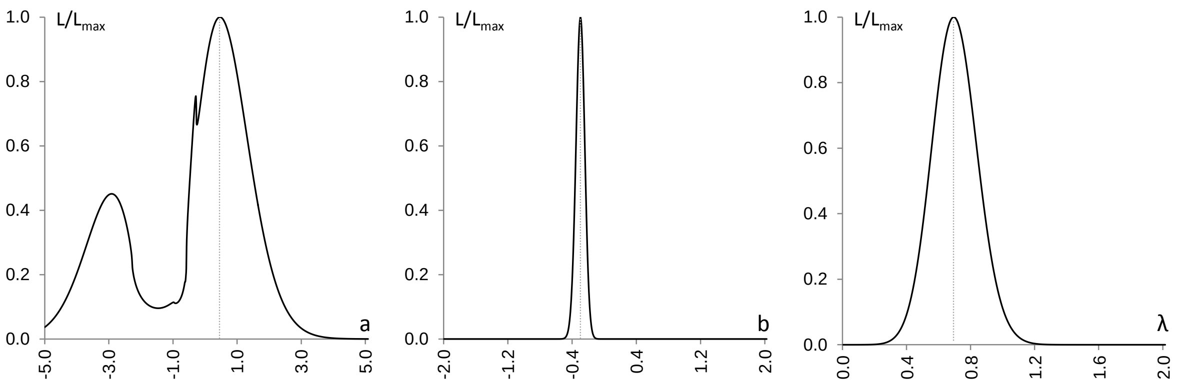
(a) δ, strangers treatment. (b) γ, strangers treatment. (c) λ, strangers treatment.

Figure D.4.: Charness and Rabin (2002) model, strangers treatment.



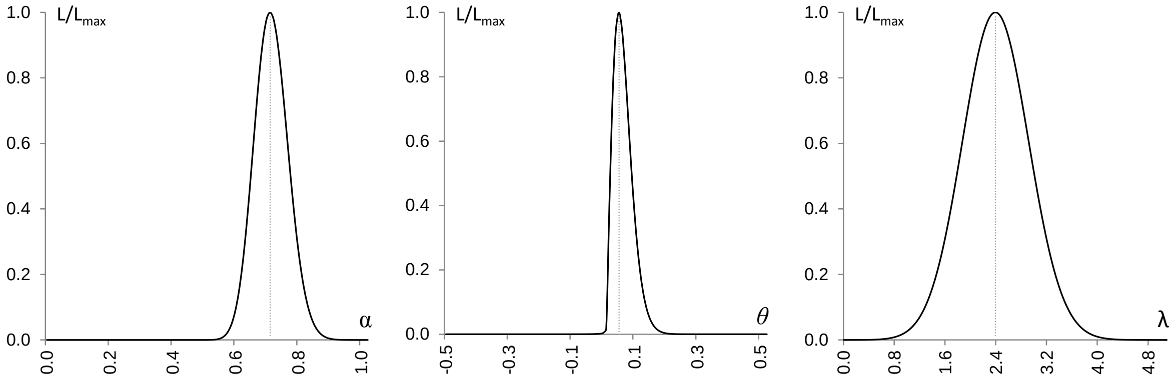
(a) a, friends treatment. (b) b, friends treatment. (c) λ, friends treatment.

Figure D.5.: Tan and Bolle (2006) model, friends treatment.



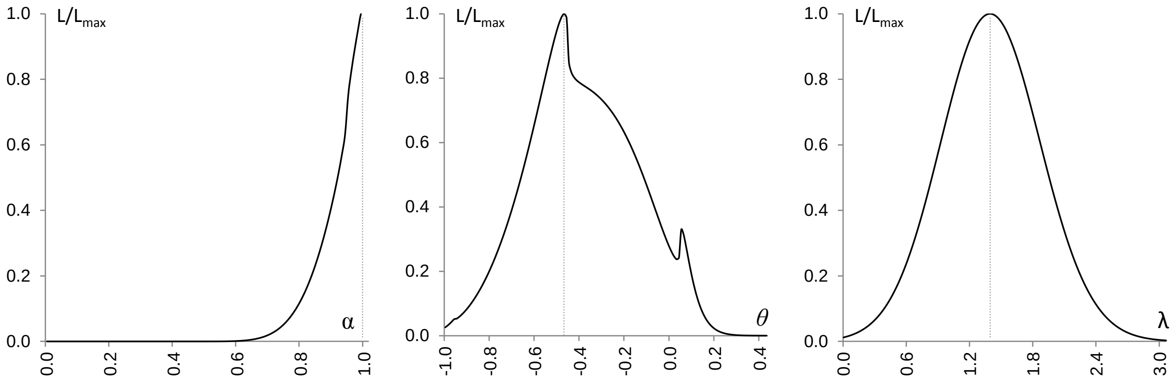
(a) a, strangers treatment. (b) b, strangers treatment. (c) λ, strangers treatment.

Figure D.6.: Tan and Bolle (2006) model, strangers treatment.



(a) α, friends treatment. (b) θ, friends treatment. (c) λ, friends treatment.

Figure D.7.: Cox et al. (2007) model, friends treatment.



(a) α, strangers treatment. (b) θ, strangers treatment. (c) λ, strangers treatment.

Figure D.8.: Cox et al. (2007) model, strangers treatment.

Appendix E.

Formal Representation of Best Response Indifference Curves

Table E.1.: Response to high-risk, $1 - r = 0.5$ (risk averse)

	$\alpha < 1$	$\alpha \geq 1$
$HH^{dup} = HH^{div}$	$\beta = \alpha + 2\sqrt{\alpha}$	$\beta = \alpha + 2\sqrt{\alpha}$
$HH^{dup} = HL^{dup}$	$\beta = -\alpha - 2\sqrt{2}\sqrt{1-\alpha} + 2$	$\beta = \alpha + 2\sqrt{2}\sqrt{\alpha - 1}$
$HH^{dup} = HL^{div}$	$\beta = \frac{1}{2}(\alpha + 2\sqrt{\alpha} - 1)$	$\beta = \frac{1}{2}(\alpha + 2\sqrt{\alpha} - 1)$
$HH^{div} = HL^{dup}$	$\beta = 2\sqrt{2}\alpha + 3\alpha + 6\sqrt{2}\sqrt{1-\alpha}\sqrt{\alpha} + 8\sqrt{1-\alpha}\sqrt{\alpha} + 2\sqrt{2} + 2$	$\beta = 6\sqrt{2} + 9\alpha - 6\sqrt{2}\sqrt{\alpha-1}\sqrt{\alpha} - 8\sqrt{\alpha-1}\sqrt{\alpha} - 2\sqrt{2} - 4$
$HH^{div} = HL^{div}$	$\beta = -1$	$\beta = -1$
$HL^{dup} = HL^{div}$	$\beta = \alpha + 2\sqrt{2}\sqrt{1-\alpha}\sqrt{\alpha}$	$\beta = 3\alpha - 2\sqrt{2}\sqrt{\alpha-1}\sqrt{\alpha} - 2$

Table E.2.: Response to high-risk, $1-r=2.0$ (risk seeking)

	$\alpha < 1$	$\alpha \geq 1$
$HH^{dup} = HH^{div}$	$\beta = \sqrt{\alpha^2+1}-1$	$\beta = \sqrt{\alpha^2+1}-1$
$HH^{dup} = HL^{dup}$	$\beta = \sqrt{-\alpha^2+2\alpha+3}-1$	$\beta = \sqrt{\alpha^2-2\alpha+5}-1$
$HH^{dup} = HL^{div}$	$\beta = \sqrt{2}\sqrt{\alpha^2+1}-1$	$\beta = \sqrt{2}\sqrt{\alpha^2+1}-1$
$HH^{div} = HL^{dup}$	$\beta = \frac{1}{3}(\sqrt{3}\sqrt{5\alpha^2-2\alpha+1}-3)$	$\beta = \frac{1}{3}(\sqrt{3}\sqrt{3\alpha^2+2\alpha-1}-3)$
$HH^{div} = HL^{div}$	$\beta = -1$	$\beta = -1$
$HL^{dup} = HL^{div}$	$\beta = \sqrt{5\alpha^2-2\alpha+1}-1$	$\beta = \sqrt{3\alpha^2+2\alpha-1}-1$

Table E.3.: Response to low-risk, $1-r=0.5$ (risk averse)

$LH^{dup} = LH^{div}$	$\beta = 2\sqrt{2}\sqrt{\alpha^2+\alpha}+3\alpha$
$LH^{dup} = LL^{dup}$	$\beta = \alpha+4\sqrt{\alpha}+2$
$LH^{dup} = LL^{div}$	$\beta = \frac{1}{9}(-4\sqrt{\alpha^2+3\alpha}+5\alpha-6)$
$LH^{div} = LL^{dup}$	$\beta = 2\alpha+4\sqrt{\alpha}+1$
$LH^{div} = LL^{div}$	$\beta = -1$
$LL^{dup} = LL^{div}$	$\beta = \alpha+2\sqrt{\alpha}$

Table E.4.: Response to low-risk, $1-r=2.0$ (risk seeking)

$LH^{dup} = LH^{div}$	$\beta = \frac{1}{3}(\sqrt{3\alpha^2+4}-2)$
$LH^{dup} = LL^{dup}$	$\beta = \sqrt{\alpha^2+2}-2$
$LH^{dup} = LL^{div}$	$\beta = \sqrt{\alpha^2+2}$
$LH^{div} = LL^{dup}$	$\beta = \frac{1}{2}(\sqrt{2}\sqrt{\alpha^2+1}-2)$
$LH^{div} = LL^{div}$	$\beta = -1$
$LL^{dup} = LL^{div}$	$\beta = \sqrt{\alpha^2+1}-1$

References

Adam, M. T. and E. B. Kroll (2012). Physiological evidence of attraction to chance. *Journal of Neuroscience, Psychology, and Economics 5*(3), 152–165.

Adam, M. T. P., M. Gamer, J. Krämer, and C. Weinhardt (2011). Measuring emotions in electronic markets. In *ICIS 2012 Proceedings, Shanghai*.

Adam, M. T. P., J. Krämer, C. Jähnig, S. Seifert, and C. Weinhardt (2011). Understanding auction fever: A framework for emotional bidding. *Electronic Markets 21*(3), 197–207.

Adam, M. T. P., J. Krämer, and C. Weinhardt (2013). Excitement up! Price down! Measuring emotions in Dutch auctions. *International Journal of Electronic Commerce 17*(2), 7–39.

Albers, W., R. Pope, R. Selten, and B. Vogt (2000). Experimental evidence for attractions to chance. *German Economic Review 1*(2), 113–130.

Anderson, C. (2007). *The long tail: How Endless Choice is creating unlimited Demand*. Random House Business Books 2007.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *The Economic Journal 100*(401), 464–477.

Ariely, D., G. Loewenstein, and D. Prelec (2006). Tom sawyer and the construction of value. *Journal of Economic Behavior & Organization 60*(1), 1–10.

Ariely, D., A. Ockenfels, and A. E. Roth (2005). An experimental analysis of ending rules in internet auctions. *The RAND Journal of Economics 36*(4), 890–907.

Ariely, D. and I. Simonson (2003). Buying, bidding, playing, or competing? Value assessment and decision dynamics in online auctions. *Journal of Consumer Psychology 13*(1), 113–123.

Armantier, O. (2004). Does observation influence learning? *Games and Economic Behavior 46*(2), 221–239.

Arrow, J. K. (1971). The theory of risk aversion. In *Essays in the Theory of Risk Bearing*, pp. 90–120. Markham Publ. Co., Chicago.

Astor, P. J., M. T. P. Adam, C. Jähnig, and S. Seifert (2011). Measuring regret: Emotional aspects of auction design. In *Proceedings of the 19th European Conference on Information Systems (ECIS)*.

Astor, P. J., M. T. P. Adam, C. Jähnig, and S. Seifert (2013). The joy of winning and the frustration of losing: A psychophysiological analysis of emotions in first-price sealed-bid auctions. *Journal of Neuroscience, Psychology, and Economics 6*(1), 14–30.

Bakos, J. Y. (1991). A strategic analysis of electronic marketplaces. *MIS Quarterly 15*(3), 295–310.

Bault, N., G. Coricelli, and A. Rustichini (2008). Interdependent utilities: How social ranking affects choice behavior. *PLoS One 3*(10), e3477.

Baumol, W. J. (1982). Applied fairness theory and rationing policy. *American Economic Review 72*(4), 639–651.

Baumol, W. J. (2000). What Marshall didn't know: On the twentieth century's contributions to economics. *The Quarterly Journal of Economics 115*(1), 1–44.

Bechara, A. and A. Damasio (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and Economic Behavior 52*(2), 336–372.

Becker, G. (1974). A theory of social interactions. Working Paper, NBER Working Paper Series, New York.

Becker, G. S. (1976). Altruism, egoism, and genetic fitness: Economics and sociobiology. *Journal of Economic Literature 14*(3), 817–826.

Ben-Shakhar, G., G. Bornstein, A. Hopfensitz, and F. van Winden (2007). Reciprocity and emotions in bargaining using physiological and self-report measures. *Journal of Economic Psychology 28*(3), 314–323.

Benedek, M. and C. Kaernbach (2010). Decomposition of skin conductance data by means of nonnegative deconvolution. *Psychophysiology 47*(4), 647–58.

Berg, J., J. Dickhaut, and K. McCabe (1995). Trust, reciprocity and social history. *Games and Economic Behavior 10*(1), 122–142.

Bernoulli, D. (1738). Theoriae novae de mensura sortis. *Translated to "Exposition of a New Theory on the Measurement of Risk" in Econometrica (1954) 22*(1), 23–36.

Berntson, G. G., K. S. Quigley, and D. Lozano (2007). *Handbook of Psychophysiology.* Cambridge University Press.

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural india. *American Journal of Agricultural Economics 62*(3), 395–407.

Bolton, G. E. (1991). A comparative model of bargaining: Theory and evidence. *American Economic Review 81*(5), 1096–1136.

Bolton, G. E., J. Brandts, and A. Ockenfels (2005). Fair procedures: Evidence from games involving lotteries. *The Economic Journal 115*(506), 1054–1076.

Bolton, G. E. and A. Ockenfels (2000). ERC: A theory of equity, reciprocity, and competition. *American Economic Review 90*(1), 166–193.

Bolton, G. E. and A. Ockenfels (2006). Inequality aversion, efficiency, and maximin preferences in simple distribution experiments: comment. *American Economic Review 96*(5), 1906–1911.

Bolton, G. E. and A. Ockenfels (2010). Betrayal aversion: Evidence from brazil, china, oman, switzerland, turkey, and the united states: Comment. *American Economic Review 100*(1), 628–633.

Bolton, G. E. and A. Ockenfels (2012). Behavioral economic engineering. *Journal of Economic Psychology 33*(3), 665–676.

Botsman, R. and R. Rogers (2010). *What's mine is yours: The rise of collaborative consumption.* HarperCollins e-books.

Boucsein, W. (1992). *Electrodermal Activity* (1st editio ed.). Berlin: Springer.

Bradler, C. (2009). Social preferences under risk: An experimental analysis. Working Paper, Zentrum für Europäische Wirtschaftsforschung.

Bradley, M., L. Miccoli, M. A. Escrig, and P. J. Lang (2008). The pupil as a measure of emotional arousal and autonomic activation. *Psychophysiology 45*(4), 602–607.

Brauer, M., A. Er-rafiy, K. Kawakami, and C. E. Phills (2012). Describing a group in positive terms reduces prejudice less effectively than describing it in positive *and* negative terms. *Journal of Experimental Social Psychology 48*(3), 757–761.

Brennan, G., L. González, W. Güth, and M. Levati (2008). Attitudes toward private and collective risk in individual and strategic choice situations. *Journal of Economic Behavior & Organization 67*(1), 253–262.

Brock, J. M., A. Lange, and E. Y. Ozbay (2013). Dictating the risk: Experimental evidence on giving in risky environments. *American Economic Review 103*(1), 415–437.

Cacioppo, J. T., L. G. Tassinary, and G. G. Berntson (2007). *Handbook of Psychophysiology* (3rd editio ed.). Cambridge: Cambridge University Press.

Camerer, C. (2003). *Behavioral Game Theory*. Princeton University Press.

Chakravarty, S., G. W. Harrison, E. Haruvy, and E. Rutström (2011). Are you risk averse over other people's money? *Southern Economic Journal 77*(4), 901–913.

Charness, G. and M. Jackson (2009). The role of responsibility in strategic risk-taking. *Journal of Economic Behavior & Organization 69*(3), 241–247.

Charness, G. and M. Rabin (2002). Understanding social preferences with simple tests. *The Quarterly Journal of Economics 117*(3), 817–869.

Chen, Y., X. Su, and X. Zhao (2012). Modeling bounded rationality in capacity allocation games with the quantal response equilibrium. *Management Science 58*(10), 1952–1962.

Childers, T. L., C. L. Carr, J. Peck, and S. Carson (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing 77*(4), 511–535.

Choi, C. and H. M. Yi (2009). The effect of the internet on economic growth: Evidence from cross-country panel data. *Economics Letters 105*(1), 39–41.

Colman, A. M. (2003). Cooperation, psychological game theory, and limitations of rationality in social interaction. *The Behavioral and Brain Sciences 26*(2), 139–153.

Cooper, D. J. and H. Fang (2008). Understanding overbidding in second price auctions: An experimental study. *The Economic Journal 118*(532), 1572–1595.

Cooper, D. J. and M. Rege (2011). Misery loves company: Social regret and social interaction effects in choices under risk and uncertainty. *Games and Economic Behavior 73*(1), 91–110.

Corazzini, L. and B. Greiner (2007). Herding, social preferences and (non-) conformity. *Economics Letters 97*(1), 74–80.

Coricelli, G. and A. Rustichini (2010). Counterfactual thinking and emotions: Regret and envy learning. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences 365*(1538), 241–247.

Cox, J., D. Friedman, and S. Gjerstad (2007). A tractable model of reciprocity and fairness. *Games and Economic Behavior 59*(1), 17–45.

Cox, J. C. and K. Sadiraj (2005). Direct tests of models of social preferences and introduction of a new model. Working Paper, University of Arizona.

Cronin, J., M. Brady, and G. Hult (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. *Journal of Retailing 76*(2), 193–218.

Crosetto, P. and A. Filippin (2012). The 'Bomb' Risk Elicitation Task. Working Paper, Jena Economic Research Paper 2012-035.

Cyr, D., M. Head, H. Larios, and B. Pan (2009). Exploring human images in website design: A multi-method approach. *MIS Quarterly 33*(3), 539–566.

Daruvala, D. (2010). Would the right social preference model please stand up! *Journal of Economic Behavior & Organization 73*(2), 199–208.

Davis, A., J. Murphy, D. Owens, D. Khazanchi, and I. Zigurs (2009). Avatars, people, and virtual worlds: Foundations for research in metaverses. *Journal of the Association for Information Systems 10*(2), 90–117.

Davis, J. A. (1971). *Elementary survey analysis*. Prentice-Hall Englewood Cliffs eNJ NJ.

Dawson, M., A. Schell, and C. Courtney (2011). The skin conductance response, anticipation, and decision-making. *Journal of Neuroscience, Psychology, and Economics 4*(2), 111.

Delgado, M., A. Schotter, E. Ozbay, and E. Phelps (2008). Understanding overbidding: Using the neural circuitry of reward to design economic auctions. *Science 321*(5897), 1849–1852.

Deng, L. and M. S. Poole (2010). Affect in web interfaces: A study of the impacts of web page visual complexity and order. *MIS Quarterly 34*(4), 711–730.

Dimoka, A., R. D. Banker, I. Benbasat, F. D. Davis, A. R. Dennis, D. Gefen, A. Gupta, A. Ischebeck, P. H. Kenning, P. A. Pavlou, G. Müller-Putz, R. Riedl, J. vom Brocke, and B. Weber (2012). On the use of neurophysiological tools in IS research: Developing a research agenda for NeuroIS. *MIS Quarterly 36*(3), 679–A19.

Ding, M., J. Eliashberg, J. Huber, and R. Saini (2005). Emotional bidders–an analytical and experimental examination of consumers' behavior in a priceline-like reverse auction. *Management Science 51*(3), 352–364.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association 9*(3), 522–550.

Easley, R. F., C. A. Wood, and S. Barkataki (2010). Bidding patterns, experience, and avoiding the winner's curse in online auctions. *Journal of Management Information Systems 27*(3), 241–268.

Eckel, C. C. and P. J. Grossman (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior & Organization 68*(1), 1–17.

Elster, J. (1998). Emotions and economic theory. *Journal of Economic Literature 36*(1), 47–74.

Engel, C. (2011). Dictator games: A meta study. *Experimental Economics 14*(4), 583–610.

Engelbrecht-Wiggans, R. and E. Katok (2008). Regret and feedback information in first-price sealed-bid auctions. *Management Science 54*(4), 808–819.

Engelmann, D. (2012). How not to extend models of inequality aversion. *Journal of Economic Behavior & Organization 81*(2), 599–605.

Engelmann, D. and M. Strobel (2004). Inequality aversion, efficiency, and maximin preferences in simple distribution experiments. *American Economic Review 94*(4), 857–869.

Engelmann, J., C. Capra, C. Noussair, and G. Berns (2009). Expert financial advice neurobiologically "offloads" financial decision-making under risk. *PLoS One 4*(3), e4957.

Falk, A. and U. Fischbacher (2006). A theory of reciprocity? *Games and Economic Behavior 54*(2), 293–315.

Fehr, E. and U. Fischbacher (2002). Why social preferences matter–the impact of non-selfish motives on competition, cooperation and incentives. *The Economic Journal 112*(478), C1–C33.

Fehr, E., G. Kirchsteiger, and A. Riedl (1993). Does fairness prevent market clearing? An experimental investigation. *The Quarterly Journal of Economics 108*(2), 437–459.

Fehr, E. and K. M. Schmidt (1999). A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics 114*(3), 817–868.

Fehr, E. and K. M. Schmidt (2006). The economics of fairness, reciprocity and altruism - experimental evidence and new theories. In *Handbook of the Economics of Giving, Altruism and Reciprocity, Volume 1*, Chapter 8, pp. 616–689. Elsevier B.V.

Feldman, A. and A. Kirman (1974). Fairness and envy. *American Economic Review 64*(6), 995–1005.

Fenton-O'Creevy, M., J. T. Lins, S. Vohra, D. W. Richards, G. Davies, and K. Schaaff (2012). Emotion regulation and trader expertise: Heart rate variability on the trading floor. *Journal of Neuroscience, Psychology, and Economics 5*(4), 227–237.

Fenton-O'Creevy, M., E. Soane, N. Nicholson, and P. Willman (2010). Thinking, feeling and deciding: The influence of emotions on the decision making and performance of traders. *Journal of Organizational Behavior 32*(8), 1044–1061.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations 7*(2), 117–140.

Figner, B., R. Mackinlay, F. Wilkening, and E. Weber (2009). Affective and deliberative processes in risky choice: Age differences in risk taking in the Columbia Card Task. *Journal of Experimental Psychology: Learning, Memory, and Cognition 35*(3), 709–730.

Filiz-Ozbay, E. and E. Y. Ozbay (2007). Auctions with anticipated regret: Theory and experiment. *American Economic Review 97*(4), 1407–1418.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics 10*(2), 171–178.

Fogg, B. J. and C. Nass (1997). How users reciprocate to computers: An experiment that demonstrates behavior change. In *CHI'97 extended abstracts on Human factors in computing systems: Looking to the future*, pp. 331–332.

Forsythe, R., J. Horowitz, N. Savin, and M. Sefton (1994). Fairness in simple bargaining experiments. *Games and Economic Behavior 6*(3), 347–369.

Fowles, D. C., J. Christie, R. Edelberg, W. Grings, D. Lykken, and P. H. Venables (1981). Publication recommendations for electrodermal measurements. *Psychophysiology 18*(3), 232–239.

Fox, S. and K. Dayan (2004). Framing and risky choice as influenced by comparison of one's achievements with others: The case of investment in the stock exchange. *Journal of Business and Psychology 18*(3), 301–321.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives 19*(4), 25–42.

Frey, B. S. and I. Bohnet (1995). Institutions affect fairness: Experimental investigations. *Journal of Institutional and Theoretical Economics 151*(2), 286–303.

Fudenberg, D. and D. K. Levine (2012). Fairness, risk preferences and independence: Impossibility theorems. *Journal of Economic Behavior & Organization 81*(2), 606–612.

Gantner, A. and R. Kerschbamer (2011). Distributional preferences, risky choices and social interaction effects: Theory and experiment. Working Paper, University of Innsbruck.

Geanakoplos, J. (1989). Psychological games and sequential rationality. *Games and Economic Behavior 1*(1), 60–79.

Gefen, D., I. Benbasat, and P. Pavlou (2008). A research agenda for trust in online environments. *Journal of Management Information Systems 24*(4), 275–286.

Gefen, D. and D. W. Straub (2003). Managing user trust in b2c e-services. *E-service Journal 2*(2), 7–24.

Gimpel, H. (2007). *Preferences in negotiations: The attachment effect.* Springer.

Gimpel, H., M. T. P. Adam, and T. Teubner (2013). Emotion regulation in management: Harnessing the potential of NeuroIS tools. In *ECIS 2013 Proceedings*, pp. 1–7.

Goeree, J. and L. Yariv (2007). Conformity in the lab. Working Paper, California Institute of Technology.

Greiner, B. (2004). An online recruitment system for economic experiments. In *Forschung und wissenschaftliches Rechnen 2003. GWDG Bericht*, Volume 63, pp. 79–93. Gesellschaft für wissenschaftliche Datenverarbeitung mbH, Göttingen.

Griffin-Pierson, S. (1990). The competitiveness questionnaire: A measure of two components of competitiveness. *Measurement and Evaluation in Counseling and Development 23*(3), 108–115.

Gross, J. and O. John (2003). Individual differences in two emotion regulation processes: Implications for affect, relationships, and well-being. *Journal of Personality and Social Psychology 85*(2), 348.

Grygolec, J., G. Coricelli, and A. Rustichini (2012). Positive interaction of social comparison and personal responsibility for outcomes. *Frontiers in Psychology 3*(25), 1–13.

Güth, W., M. Levati, and M. Ploner (2008). On the social dimension of time and risk preferences: An experimental study. *Economic Inquiry 46*(2), 261–272.

Güth, W., R. Schmittberger, and B. Schwarze (1982). An experimental analysis of ultimatum bargaining. *Journal of Economic Behavior & Organization 3*(4), 367–388.

Haisley, E. and R. Weber (2010). Self-serving interpretations of ambiguity in other-regarding behavior. *Games and Economic Behavior 68*(2), 614–625.

Harrison, G. W., M. Lau, E. Rutstrom, and M. Tarazona-Gómez (2010). Preferences over social risk. Working Paper, University of Central Florida.

Harrison, G. W., J. A. List, and C. Towe (2007). Naturally occurring preferences and exogenous laboratory experiments: A case study of risk aversion. *Econometrica 75*(2), 433–458.

Hassanein, K. and M. Head (2006). The impact of infusing social presence in the web interface: An investigation across product types. *International Journal of Electronic Commerce 10*(2), 31–55.

Hendershott, T., C. Jones, and A. Menkveld (2011). Does algorithmic trading improve liquidity? *The Journal of Finance 66*(1), 1–33.

Hinkle, D. E., W. Wiersma, and S. G. Jurs (2003). *Applied statistics for the behavioral sciences*. Houghton Mifflin Boston.

Hochman, H. and J. Rodgers (1969). Pareto optimal redistribution. *American Economic Review 59*(4), 542–557.

Hochman, H. and J. Rodgers (1974). Redistribution and the pareto criterion. *American Economic Review 64*(4), 752–757.

Hochman, H. and J. Rodgers (1977). *Distribution of Economic Well-Being*, Chapter The Simple Politics of Distributional Preferences, pp. 71–114. NBER.

Holt, C. a. and S. K. Laury (2002). Risk aversion and incentive effects. *American Economic Review 92*(5), 1644–1655.

Hopkins, W. G. (1997). *A new view of statistics*. Will G. Hopkins.

Jercic, P., P. J. Astor, M. T. P. Adam, and O. Hilborn (2012). A serious game using physiological interfaces for emotion regulation training in the context of financial decision-making. In *ECIS 2012 Conference Proceedings, Barcelona, Spain*.

Johns, C. L. and J. L. Zaichkowsky (2003). Bidding behavior at the auction. *Psychology and Marketing 20*(4), 303–322.

Johnson, R., G. Danko, T. Darvill, S. Bochner, J. Bowers, Y. Huang, J. Park, V. Pecjak, A. Rahim, and D. Pennington (1989). Cross-cultural assessment of altruism and its correlates. *Personality and Individual Differences 10*(8), 855–868.

Johnson-George, C. and W. C. Swap (1982). Measurement of specific interpersonal trust: Construction and validation of a scale to assess trust in a specific other. *Journal of Personality and Social Psychology 43*(6), 1306.

Jones, M. T. (2011). Bidding fever in eBay auctions of Amazon.com gift certificates. *Economics Letters 113*(1), 5–7.

Kagel, J. H. (1995). Auctions. In J. H. Kagel and A. E. Roth (Eds.), *The Handbook of Experimental Economics*, pp. 501–585. Princeton University Press.

Kahneman, D., J. Knetsch, and R. Thaler (1986). Fairness and the assumptions of economics. *Journal of Business 59*(4), 285–300.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263.

Kaiser, I., K. Jensen, J. Call, and M. Tomasello (2012). Theft in an ultimatum game: Chimpanzees and bonobos are insensitive to unfairness. *Biology Letters 8*(6), 942–945.

Karni, E., T. Salmon, and B. Sopher (2008). Individual sense of fairness: An experimental study. *Experimental Economics 11*(2), 174–189.

Katok, E. and A. M. Kwasnica (2008). Time is money: The effect of clock speed on seller's revenue in Dutch auctions. *Experimental Economics 11*(4), 344–357.

Kirchsteiger, G. (1994). The role of envy in ultimatum games. *Journal of Economic Behavior & Organization 25*(3), 373–389.

Kohler, S. (2011). Altruism and fairness in experimental decisions. *Journal of Economic Behavior & Organization 80*(1), 101–109.

Kohler, S. (2013). Envy can promote more equal division in alternating-offer bargaining. *Journal of Neuroscience, Psychology, and Economics 6*(1), 31–41.

Kőszegi, B. and M. Rabin (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics 121*(4), 1133–1165.

Kotrlik, J. W. and H. A. Williams (2003). The incorporation of effect size in information technology, learning, information technology, learning, and performance research and performance research. *Information Technology, Learning, and Performance Journal 21*(1), 1–7.

Krawczyk, M. and F. Le Lec (2008). Social decisions under risk. evidence from the probabilistic dictator game. Working Paper, University of Amsterdam.

Krawczyk, M. and F. Le Lec (2010). 'give me a chance!' An experiment in social decision under risk. *Experimental Economics 13*(4), 500–511.

Krishna, V. (2002). *Auction Theory.* San Diego, Calafornia: Acad Press.

Kroll, E., M. Adam, and T. Teubner (2013). A note on coupled lotteries. Working Paper, Karlsruhe.

Ku, G. (2008). Learning to de-escalate: The effects of regret in escalation of commitment. *Organizational Behavior and Human Decision Processes 105*(2), 221–232.

Ku, G., D. Malhotra, and J. K. Murnighan (2005). Towards a competitive arousal model of decision-making: A study of auction fever in live and internet auctions. *Organizational Behavior and Human Decision Processes 96*(2), 89–103.

Lang, P., M. Greenwald, M. Bradley, and A. Hamm (1993). Looking at pictures: Affective, facial, visceral, and behavioral reactions. *Psychophysiology 30*(3), 261–273.

Larsen, R. and E. Diener (1992). Promises and problems with the circumplex model emotion. *Review of Personality and Social Psychology 13*, 25–59.

Laux, H., R. M. Gillenkirch, and H. Y. Schenk-Mathes (2012). *Entscheidungstheorie*, Chapter Rationale Entscheidung bei Risiko: Das Bernoulli-Prinzip, pp. 109–143. Springer.

Lee, M., Y. Kim, and a. Fairhurst (2009). Shopping value in online auctions: Their antecedents and outcomes. *Journal of Retailing and Consumer Services 16*(1), 75–82.

Lejuez, C., J. P. Read, C. W. Kahler, J. B. Richards, S. E. Ramsey, G. L. Stuart, D. R. Strong, and R. A. Brown (2002). Evaluation of a behavioral measure of risk taking: The Balloon Analogue Risk Task (BART). *Journal of Experimental Psychology: Applied 8*(2), 75.

Levitt, S. D. and J. A. List (2007). What do laboratory experiments measuring social preferences reveal about the real world? *The Journal of Economic Perspectives 21*(2), 153–174.

Liebrand, W. B. G. (1984). The effect of social motives , communication and group size on behaviour in an n-person multi-stage mixed-motive game. *European Journal of Social Psychology 14*(3), 239–264.

Lin, M., N. R. Prabhala, and S. Viswanathan (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science 59*(1), 17–35.

Linde, J. and J. Sonnemans (2012). Social comparison and risky choices. *Journal of Risk and Uncertainty 44*(1), 45–72.

Loewenstein, G. (1999). Experimental economics from the vantage-point of behavioural economics. *The Economic Journal 109*(453), 25–34.

Loewenstein, G. and J. S. Lerner (2003). The role of affect in decision making. In *Handbook of Affective Sciences*. Oxford, England: Oxford University Press.

Loewenstein, G., L. Thompson, and M. H. Bazerman (1989). Social utility and decision making in interpersonal contexts. *Journal of Personality and Social Psychology 57*(3), 426–441.

MacCrimmon, K. R. and D. M. Messick (1976). A framework for social motives. *Behavioral Science 2*(21), 86–100.

Machina, M. J. (1989). Dynamic consistency and non-expected utility models of choice under uncertainty. *Journal of Economic Literature 27*(4), 1622–1668.

Mackenzie, K. D. (1971). An analysis of risky shift experiments. *Organizational Behavior and Human Performance 6*(3), 283–303.

Malhotra, D. (2010). The desire to win: The effects of competitive arousal on motivation and behavior. *Organizational Behavior and Human Decision Processes 111*(2), 139–146.

Malhotra, D. and M. Bazerman (2008). Psychological influence in negotiation: An introduction long overdue. *Journal of Management 34*(3), 509–531.

Malhotra, D., G. Ku, and J. K. Murnighan (2008). When winning is everything. *Harvard Business Review 86*(5), 78–86.

Malmendier, U. and Y. H. Lee (2011). The bidder's curse. *American Economic Review 101*(2), 749–787.

Mano, H. (1994). Risk-taking, framing effects, and affect. *Organizational Behavior and Human Decision Processes 57*(1), 38–58.

Maule, A. (2000). Effects of time-pressure on decision-making under uncertainty: Changes in affective state and information processing strategy. *Acta Psychologica 104*(3), 283–301.

Mayer, R. C., J. H. Davis, and F. D. Schoorman (1995). An integrative model of organizational trust. *Academy of Management Review 20*(3), 709–734.

McAfee, R. P. and J. McMillan (1987). Auctions and bidding. *Journal of Economic Literature 25*(2), 699–738.

McCabe, K., M. Rigdon, and V. Smith (2003). Positive reciprocity and intentions in trust games. *Journal of Economic Behavior & Organization 52*(2), 267–275.

McCrae, R. R. and O. P. John (1992). An introduction to the five-factor model and its applications. *Journal of Personality 60*(2), 175–215.

McKelvey, R. and T. Palfrey (1995). Quantal response equilibria for normal form games. *Games and Economic Behavior 10*(1), 6–38.

Menon, S. and B. Kahn (2002). Cross-category effects of induced arousal and pleasure on the internet shopping experience. *Journal of Retailing 78*(1), 31–40.

Milinski, M. (1987). Tit for tat in sticklebacks and the evolution of cooperation. *Nature 325*(6103), 433–435.

Möllenberg, A. (2004). Internet auctions in marketing: The consumer perspective. *Electronic Markets 14*(4), 360–371.

Morgan, J., K. Steiglitz, and G. Reis (2003). The spite motive and equilibrium behavior in auctions. *Contributions in Economic Analysis & Policy 2*(1), 1–25.

Mui, V.-L. (1995). The economics of envy. *Journal of Economic Behavior & Organization 26*(3), 311–336.

Murnighan, J. K. (2002). A very extreme case of the dollar auction. *Journal of Management Education 26*(1), 56–69.

Murphy, R. and K. Ackermann (2012). A review of measurement methods for social preferences. Working Paper, ETH Zürich.

Neugebauer, T. and R. Selten (2006). Individual behavior of first-price auctions: The importance of information feedback in computerized experimental markets. *Games and Economic Behavior 54*(1), 183–204.

Nunamaker, J., D. Derrick, A. Elkins, J. Burgoon, and M. Patton (2011). Embodied conversational agent-based kiosk for automated interviewing. *Journal of Management Information Systems 28*(1), 17–48.

Ockenfels, A., D. Reiley, and A. Sadrieh (2006). Online auctions. Working Paper, National Bureau of Economic Research (12785).

Ockenfels, A., D. Sliwka, and P. Werner (2010). Bonus payments and reference point violations. Working Paper, IZA Discussion Papers (4795).

Ockenfels, A. and P. Werner (2012). 'Hiding behind a small cake' in a newspaper dictator game. *Journal of Economic Behavior & Organization 82*(1), 82–85.

Overbeck, J. R., M. A. Neale, and C. L. Govan (2010). I feel, therefore you act: Intrapersonal and interpersonal effects of emotion on negotiation as a function of social power. *Organizational Behavior and Human Decision Processes 112*(2), 126–139.

Pahlke, J., S. Strasser, and F. Vieider (2010). Responsibility effects in decision making under risk. Working Paper, Münchener Wirtschaftswissenschaftliche Beiträge.

Palmer, C. E. and C. J. Forsyth (2006). Antiques, auctions, and action: Interpreting and creating economic value. *The Journal of Popular Culture 39*(2), 234–259.

Paolacci, G., J. Chandler, and P. Ipeirotis (2010). Running experiments on amazon mechanical turk. *Judgment and Decision Making 5*(5), 411–419.

Parrott, W. (1991). The emotional experiences of envy and jealousy. In *The Psychology of Jealousy and Envy*, pp. 3–30. The Guilford Press, New York.

Pavlou, P. A. and D. Gefen (2004). Building effective online marketplaces with institution-based trust. *Information Systems Research 15*(1), 37–59.

Pratt, J. (1964). Risk aversion in the small and in the large. *Econometrica 32*(1–2), 122–136.

Preacher, K., D. Rucker, and A. Hayes (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research 42*(1), 185–227.

Qiu, L. and I. Benbasat (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems 25*(4), 145–182.

Rabin, M. (1993). Incorporating fairness into game theory and economics. *American Economic Review 83*(5), 1281–1302.

Rawls, J. (1971). *A Theory of Justice*. Belknap Harvard Press, Cambridge, MA.

Reynolds, D., J. Joseph, and R. Sherwood (2009). Risky shift versus cautious shift: Determining differences in risk taking between private and public management decision-making. *Journal of Business & Economics Research 7*(1), 63–78.

Rick, S. and G. Loewenstein (2008). The role of emotion in economic behavior. In *The Role of Emotion in Economic Behavior. From Handbook of Emotions*, Chapter 9, pp. 138–156. The Guilford Press.

Riedl, R., R. D. Banker, I. Benbasat, F. D. Davis, A. R. Dennis, A. Dimoka, D. Gefen, A. Gupta, A. Ischebeck, P. Kenning, et al. (2010). On the foundations of NeuroIS: Reflections on the gmunden retreat 2009. *Communication of the Association for Information Systems 27*(15), 243–264.

Riedl, R., M. Hubert, and P. Kenning (2010). Are there neural gender differences in online trust? An fMRI study on the perceived trustworthiness of ebay offers. *MIS Quarterly 34*(2), 397–428.

Riedl, R., P. Mohr, P. Kenning, F. Davis, and H. Heekeren (2011). Trusting humans and avatars: Behavioral and neural evidence. In *ICIS 2011 Proceedings, Shanghai, China, (2011).*

Rilling, J. K. and A. G. Sanfey (2011). The neuroscience of social decision-making. *Annual Review of Psychology 62*(1), 23–48.

Rivers, S. E., V. F. Reyna, and B. Mills (2008). Risk taking under the influence: A fuzzy-trace theory of emotion in adolescence. *Developmental Review 28*(1), 107–144.

Rohde, I. and K. Rohde (2011). Risk attitudes in a social context. *Journal of Risk and Uncertainty 43*(3), 205–225.

Roth, A. E. (1995). Introduction to experimental economics. In J. H. Kagel and A. E. Roth (Eds.), *The Handbook of Experimental Economics*, pp. 3–109. Princeton University Press.

Roth, A. E. (2002). The economist as engineer: Game theory, experimentation, and computation as tools for design economics. *Econometrica 70*(4), 1341–1378.

Rushton, J., R. Chrisjohn, and G. Cynthia Fekken (1981). The altruistic personality and the self-report altruism scale. *Personality and Individual Differences 2*(4), 293–302.

Russell, J. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology 39*, 1161–1178.

Sahlins, M. (1972). *Stone Age Economics*. Aldine de Gruyter.

Saito, K. (2013). Social preferences under risk: Equality of opportunity versus equality of outcome. *American Economic Review 103*(7), 3084–3101.

Sanfey, A. G., J. K. Rilling, and J. A. Aronson (2003). The neural basis of economic decision-making in the Ultimatum Game. *Science 300*(5626), 1755–1758.

Scott, R. (1972). Avarice, altruism, and second party preferences. *The Quarterly Journal of Economics 86*(1), 1–18.

Selten, R. (1967). Die strategiemethode zur erforschung des eingeschränkt rationalen verhaltens im rahmen eines oligopolexperimentes. In *Beiträge zur experimentellen Wirtschaftsforschung, Heinz Sauermann (ed.), Tübingen*, pp. 136–168.

Smith, R., W. Parrott, E. Diener, R. Hoyle, and S. Kim (1999). Dispositional envy. *Personality and Social Psychology Bulletin 25*(8), 1007–1020.

Smith, R., T. Turner, R. Garonzik, C. Leach, V. Urch-Druskat, and C. Weston (1996). Envy and schadenfreude. *Personality and Social Psychology Bulletin 22*(2), 158–168.

Smith, V. (1976). Experimental economics: Induced value theory. *American Economic Review 66*(2), 274–279.

Stafford, M. R. and B. Stern (2002). Consumer bidding behavior on internet auction sites. *International Journal of Electronic Commerce 7*(1), 135–150.

Sütterlin, S., C. Herbert, M. Schmitt, A. Kübler, and C. Vögele (2011). Frames, decisions, and cardiac-autonomic control. *Social Neuroscience 6*(2), 169–177.

Tan, J. and F. Bolle (2006). On the relative strengths of altruism and fairness. *Theory and Decision 60*(1), 35–67.

Teubner, T., M. T. P. Adam, and R. Riordan (2013). The impact of computerized agents on arousal and bidding behavior in electronic auctions. Working Paper, Karlsruhe.

Teubner, T., M. T. P. Adam, and C. Weinhardt (2012). Risky choices among friends and strangers: How relationship types affect ex-ante payoff considerations. Working Paper, Karlsruhe.

Teubner, T., F. Hawlitschek, M. T. P. Adam, and C. Weinhardt (2013). Social identity and reciprocity in online gift giving networks. In *Proceedings of the Hawaii International Conference on System Sciences (HICSS)*, Volume 46, pp. 708–717.

Thaler, R. H. (2000). From homo economicus to homo sapiens. *Journal of Economic Perspectives 14*(1), 133–141.

Trautmann, S. (2009). A tractable model of process fairness under risk. *Journal of Economic Psychology 30*(5), 803–813.

Trautmann, S. and F. M. Vieider (2011). Social influences on risk attitudes: Applications in economics. In S. Roeser (Ed.), *Handbook of Risk Theory*, Chapter 29, pp. 1–28. Springer.

Trimpop, R. M. (1994). *The Psychology of Risk Taking Behavior.* North-Holland.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323.

Van den Bos, W., J. Li, T. Lau, E. Maskin, J. D. Cohen, P. R. Montague, and S. M. McClure (2008). The value of victory: Social origins of the winner's curse in common value auctions. *Judgment and Decision Making 3*(7), 483–492.

van 't Wout, M., R. Kahn, A. Sanfey, and A. Aleman (2006). Affective state and decision-making in the ultimatum game. *Experimental Brain Research 169*(4), 564–8.

Van Wolkenten, M., S. Brosnan, and F. de Waal (2007). Inequity responses of monkeys modified by effort. *Proceedings of the National Academy of Sciences 104*(47), 18854–18859.

Venables, P. H. and M. J. Christie (1980). *Electrodermal activity. In I. Martin (Ed.), Techniques in Psychophysiology.* Wiley.

Vickrey, W. (1961). Counterspeculation, auctions, and competitive sealed tenders. *The Journal of Finance 16*(1), 8–37.

Vom Brocke, J., R. Riedl, and P.-M. Léger (2013). Application strategies for neuroscience in information systems design science research. *Journal of Computer Information Systems 53*(3), 1–13.

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

Wallin, B. (1981). Sympathetic nerve activity underlying electrodermal and cardiovascular reactions in man. *Psychophysiology 18*(4), 470–476.

Watson, D. and A. Tellegen (1985). Toward a consensual structure of mood. *Psychological Bulletin 98*(2), 219–235.

Weber, B. J. and G. B. Chapman (2005). Playing for peanuts: Why is risk seeking more common for low-stakes gambles? *Organizational Behavior and Human Decision Processes 97*(1), 31–46.

Weigold, M. F. and B. R. Schlenker (1991). Accountability and risk taking. *Personality and Social Psychology Bulletin 17*(1), 25–29.

Weinhardt, C., C. Holtmann, and D. Neumann (2003). Market-engineering. *Wirtschaftsinformatik 45*(6), 635–640.

Wilson, B. J. (2010). Social preferences aren't preferences. *Journal of Economic Behavior & Organization 73*(1), 77–82.

Yechiam, E., M. Druyan, and E. Ert (2008). Observing others' behavior and risk taking in decisions from experience. *Judgment and Decision Making 3*(7), 493–500.

List of Abbreviations

AMT	Amazon Mechanical Turk
ANOVA	Analysis of Variance
ANS	Autonomous Nervous System
ARA	Absolute Risk Aversion
BO	Bolton & Ockenfels
BOS	Battle of Sexes
bpm	Beats per Minute
C/D	Coupling/ Decoupling
C	Computer
CARA	Constant Absolute Risk Aversion
CES	Constant Elasticity of Substitution
CFG	Cox, Friedman, and Gjerstad
CM	Computer Market (Treatment)
CPT	Comulative Prospect Theory
CR	Charness & Rabin
CRRA	Constant Relative Risk Aversion
CRT	Cognitive Reflection Test
CS	Cox & Sadiraj
CV	Common Value
DEC	Decision (made for)
DG	Dictator Game
ECG	Electrocardiogram
EDA	Electrodermal Activity
EEG	Electroencephalography
EIA	Expected Inequality-Averse
EM	Emotional Motives
ERQ	Emotion Regulation Questionnaire
EUT	Expected Utility Theory
EV	Expected Value
fMRI	functional Magnetic Resonance Imaging
FPSB	First-Price Sealed-Bid
FS	Fehr & Schmidt
G	Group
H	Human
HF	High Frequency
HFT	High Frequency Trading

HL	Holt & Laury
HM	Human Market (Treatment)
HR	Heart Rate
HRV	Heart Rate Variability
Hyp	Hypothetical
IE	Indirect Effect
IISM	Institute of Information Systems and Marketing
IMC	Instructional Manipulation Check
IME	Information and Market Engineering
IPV	Independent Private Value
IS	Information Systems
IT	Information Technology
KIT	Karlsruhe Institute of Technology
LE	Laboratory Experiment
LF	Low Frequency
LFHF	Low Frequency (to) High Frequency
LL	Lower Level
LR	Literature Review
MLE	Maximum Likelihood Estimation
MPL	Multiple Price List
MU	Monetary Unit
O	(for) other
ORSEE	Online Recruitment System for Economic Experiments
PD	Prisenors' Dilemma
PHY	Physiological Parameters
REF	Reference Player
RRA	Relative Risk Aversion
S	(for) oneself
SC	Skin Conductance
SCL	Skin Conductance Level
SCR.amp	Skin Conductance Response Amplitude
SCR	Skin Conductance Response
SD	Standard Deviation
SE	Standard Error
Sig.	Significance
SV	Survey
SVO	Social Value Orientation
TB	Tan & Bolle
TM	Theoretical Model
UG	Ultimatum Game
UL	Upper Level
WTA	Willingness to Accept
WTP	Willingness to Pay

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List of Symbols

v_i	independent private value of bidder i
$b_i(v_i)$	bidding function
hr_{6-3}	average heart rate 6 to 3 seconds before bid submission
hr_0	average heart rate in the calibration phase
hr_θ	heart rate ratio
scr_Δ	skin conductance response amplitude
H^{div}	strategy: high-risk diverge
H^{dup}	strategy: high-risk duplicate
L^{div}	strategy: low-risk diverge
L^{dup}	strategy: low-risk duplicate
π_x	payoff for player x (perspective player)
π_y	payoff for player y (peer player)
α	envy parameter
β	gloating parameter
$u_x(\cdot,\cdot)$	social utility function of player x
r	risk preference parameter
$v(\cdot)$	risk preference function
ψ	expected overall utility
$p(\cdot)$	probability
$L(\cdot,\cdot,\cdot)$	Likelihood function
λ	rationality parameter

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