Game against the machine
Interacting with artificial economic agents

Dissertation

zur Erlangung des akademischen Grades
doctor rerum politicarum
(Dr. rer. pol.)

vorgelegt dem Rat der Wirtschaftswissenschaftliche Fakultät
der Friedrich-Schiller-Universität Jena
am 13.04.2016

von M.Sc. Mike Farjam

geboren am: 30.11.1986 in: Aachen, Deutschland

Gutachter: ....

Gutachter: ....

Gutachter: ....

Datum der Verteidigung: ...., Jena

Acknowledgements

This research work would not be accomplished without people who were around me during the last three years of my doctoral studies, ready to help me overcoming the obstacles that I faced during this enriching time. I would like to thank:

- Oliver Kirchkamp for taking the risk of accepting me in the IMPRS program and as his "child", supervising me during the last three years, and setting an example in scientific rigor and accuracy.
- Pim Haselager, who was there from the beginning of my study and supported me from the first scientific steps to this dissertation (and hopefully beyond).
- Society, for providing me with education and financing my curiosity.
- Ariel Kanfo, for hosting me during my 4-month stay in Jerusalem.
- Judith Banse, my wife, giving me unconditional support in pursuing my academic goals.
- My colleagues and friends, for mutual support and stimulating research discussions: Susanne Büchner, Alexia Gaudeul, Anna Merkel, Wladislaw Mill, Olexandr Nikolaychuk, Ayu Okvitawanali, Marian Panganiban, Benedikt Werner, and all the other participants of summer schools, workshops and conferences where I got feedback.

Finally, I would like to thank my family and all those little and big helpers that were always around for constant support and care.

Deutsche Zusammenfassung

Wir leben in einer Hybridgesellschaft, in der Menschen und Maschinen co-existieren, voneinander abhängig sind und häufig nicht einmal wissen ob sie gerade mit einer Maschine oder einem Menschen interagieren. Diese Behauptung mag zunächst nach Science-Fiction klingen, doch schauen wir uns beispielsweise Diskussionen in Internetforen oder Handel an modernen Aktienmärkten an, sehen wir, dass Künstliche Intelligenzen (KIs) bereits heute Teil unseres Alltags sind. So werden z.B. an Aktienmärkten algorithmische Trader in ihrer Interaktion mit Menschen als eine der Hauptursachen für sogenannte Blitzcrashs gesehen. KIs haben also bereits heute einen enormen ökonomischen Einfluss. Obwohl Menschen auch zukünftig zentrale Akteure in Hybridgesellschaften bleiben, wird die Hybridisierung sich auf neue Gebiete ausweiten. In unmittelbarer Zukunft werden KIs mit uns am Straßenverkehr teilnehmen und haben es zunehmend leichter in einer digitalen und vernetzten Welt mit uns zu interagieren.

Die zentrale Fragestellung dieser Dissertation ist, inwiefern sich Menschen anders verhalten wenn sie mit einem anderen Menschen oder einer KI interagieren. Eine Frage, die – trotz ihrer ökonomischen Bedeutung (siehe Blitzcrashs) und dem Interesse von Ökonomen an strategischer Interaktion – bisher kaum von Ökonomen untersucht wird. Im Gegenteil, die meisten ökonomischen Modelle und Paradigmen nehmen stur an, dass einzig Menschen relevante ökonomische Akteure sind. In Kapitel 2–4 beschreiben wir 3 Experimente, die verschiedene Teilaspekte unserer Fragestellung beleuchten. Kapitel 2 ist in Zusammenarbeit mit Prof. Oliver Kirchkamp entstanden, die restlichen Kapitel in Alleinautorenschaft.

In Kapitel 2 gehen wir der Frage nach, inwiefern Menschen an Aktienmärkten anders handeln, wenn sie annehmen, dass ein algorithmischer Trader am Markt mithandelt, als wenn sie annehmen, dass nur Menschen handeln. Zu diesem Zweck benutzen wir das Standard-Design von Smith, Suchanek und Williams (1988), in dem typischerweise die Bildung von Marktblasen untersucht wird. In unserem Experiment weiß eine Gruppe, dass sie nur mit anderen Menschen in einem Aktienmarkt handelt und eine andere Gruppe weiß, dass die Möglichkeit besteht, dass ein algorithmischer Trader am Markt handelt. Entscheidend in unserem Design ist, dass es Märkte gibt, in denen die Versuchspersonen unsicher sind ob sie mit algorithmischen Tradern oder nur mit Menschen handeln, tatsächlich aber kein algorithmischer Trader am Markt handelt. Indem wir diese Märkte mit Märkten vergleichen in denen die Versuchspersonen wissen, dass sie nur mit Menschen handeln, können wir den Einfluss der Unsicherheit der Versuchspersonen bezüglich der Teilnahme algorithmischer Trader messen, ohne dass die tatsächliche Einflussnahme der algorithmischen Trader in dem Vergleich eine Rolle spielen kann. Wir untersuchen die Märkte mit Blick auf die Entwicklung des Preises pro Aktie, Volatilität und Handelsfrequenz und finden, dass Aktien näher am Fundamental Wert gehandelt werden, Märkte eine höhere Volatilität aufweisen und die Handelsfrequenz zunimmt, wenn Menschen unsicher sind ob algorithmische Trader am Markt partizipieren.

Kapitel 3 untersucht, ob Menschen es kontextunabhängig bevorzugen von Menschen oder einem auf Zufall basierenden Mechanismus abhängig zu sein. Im Experiment, das wir in diesem Kapitel präsentieren, geben Versuchspersonen an ob sie lieber an Lotterien teilnehmen wollen, in denen der Zufall entscheidet ob sie die Lotterie gewinnen oder an Lotterien teilnehmen wollen, in denen die Wahrscheinlichkeit zu gewinnen von der Entscheidung eines anderen Menschen abhängt. Um einen sauberen Vergleich zwischen Präferenzen in beiden Lotterien zu gewährleisten, wurde die Lotterie, in der eine menschliche Entscheidung über das Gewinnen der Lotterie entscheidet, so konzipiert, dass keine strategische Abhängigkeit zwischen dem Entscheider für/gegen die Lotterie (Entscheider A) und dem Entscheider (B) über das Gewinnen/Verlieren der Lotterie besteht. Entscheider B wusste nicht, dass jemand von seiner Wahl abhängig sein würde und es wurde sichergestellt, dass die Entscheidung von Spieler B moralisch neutral ist. Des Weiteren wurden die Lotterien so beschrieben, dass sie sich möglichst ähneln (z.B. in Bezug auf Komplexität). Wir vergleichen Präferenzen zu der Lotterie mit menschlicher Unsicherheit mit Standardlotterien mit natürlicher Unsicherheit und finden, dass Versuchspersonen Lotterien mit natürlicher Unsicherheit bevorzugen.

Einem Sprichwort nach ist Vertrauen der Klebstoff der Gesellschaft. Da wir uns für Hybridgesellschaften interessieren, ist es naheliegend zu untersuchen wie sich die Art des Agenten, mit dem man interagiert, auf die Bereitschaft zu vertrauen auswirkt. Kapitel 4 geht dieser Frage nach und baut zu diesem Zweck auf einer Studie von Bohnet und Zeckhauser (2004) auf, in der die Autoren finden, dass Menschen betrugsavers sind. In ihrem Experiment verlangen Versuchspersonen in der Rolle von Spieler 1 in einem Vertrauensspiel eine höhere Risikoprämie um einem anderen Spieler zu vertrauen, wenn der andere Spieler selbst entscheiden darf wie Ressourcen verteilt werden, als wenn die Entscheidung des anderen Spieler zufällig bestimmt wird. Unser Experiment geht der Frage nach warum bei Vertrauensspielen, in denen man abhängig von einem menschlichen Spieler ist, eine höhere Risikoprämie verlangt wird. Ist es die vorweggenommene Kompensation für das schlechte Gefühl zu wissen, dass man betrogen wurde oder mögen wir die Möglichkeit nicht, dass die Person sich aufgrund einer bewussten Entscheidung auf unsere Kosten bereichern könnte? Zu diesem Zweck stellen wir das Konzept einer spielbezogenen Lotterie vor. Diese gleicht einer gewöhnlichen Lotterie, allerdings hängt die Wahrscheinlichkeit zu gewinnen von den Entscheidungen anderer in einem Vertrauensspiel ab. Wir finden, dass verlangte Risikoprämien um an den spielbezogenen Lotterien teilzunehmen gleich sind, egal ob in dem Vertrauenspiel von dem die spielbezogene Lotterie abhängt die Entscheidungen von Spieler 2 selbst getroffen oder zufällig bestimmt wurden. Von einer Betrugsabsicht abhängig zu sein scheint also nicht ausreichend für Betrugsaversion zu sein, sondern es bedarf auch des tatsächlichen Nutzen für den Betrüger. Überraschenderweise finden wir jedoch auch, dass Versuchspersonen in unserem Experiment eine höhere Risikoprämie verlangen, wenn Spieler 1 ein Vertrauensspiel spielt, in dem die Entscheidung von Spieler 2 zufällig bestimmt wird, als wenn Spieler 2 die Entscheidung selbst treffen darf. Im Gegensatz zu Bohnet und Zeckhauser finden wir also, dass Menschen lieber auf Menschen vertrauen als auf den Zufall. Wir entschieden uns daher eine möglichst genaue Replikation der Studie von Bohnet und Zeckhauser durchzuführen, kommen jedoch wieder zu Ergebnissen die ihnen widersprechen.

In Kapitel 5 fassen wir die Ergebnisse der Experimente zusammen und setzen sie in Kontext zueinander. Gemeinsam zeichnen sie das klare Bild, dass Menschen in ökonomisch relevanten Situationen abhängig davon entscheiden, ob sie mit Menschen oder künstlichen Agenten interagieren. Obwohl wir in jedem Experiment klar zeigen, dass unsere Versuchspersonen sich künstlichen Agenten gegenüber anders verhalten, zeigen die Ergebnisse keine einfache Faustregel auf wie genau sich Verhalten gegenüber Menschen von Verhalten gegenüber künstlichen Agenten unterscheidet. Zukünftige Experimenten müssen erforschen, welche situativen Umstände beispielsweise zu höherer/niedriger Riskioaversion im Umgang mit Maschinen und anderen künstlichen Agenten führen und wie man diese Erkenntnisse zum Wohle der Gesellschaft instrumentalisieren kann. In Anbetracht des eingangs skizzierten gesellschaftlichen und technologischen Wandels im 21. Jahrhundert und der ökonomischen Tragweite dieses Wandels, wäre es jedoch fahrlässig einfach anzunehmen, dass sich menschliche Entscheidungen während der Interaktion mit künstliche Agenten nicht von den Entscheidungen gegenüber Menschen unterscheiden.

Contents

List of Figures

List of Tables

Chapter 1

General Introduction

1.1 Welcome to hybrid societies!

Nowadays artificial agents (robots, artificial intelligences, etc.) are part of our societies; we interact with them daily, they appear in many different situations, and sometimes we cannot even distinguish between interacting with a human or an artificial agent. This may sound like the beginning of a science fiction novel, but these *hybrid societies*, in which human and artificial agents interact are already reality and may become the norm not the exception (Brynjolfsson and McAfee, 2014). The basic thought that led to the research presented in this dissertation, is that economics (and social sciences in general) are in danger of loosing touch with reality by assuming in their theories, experiments and models that humans are only interacting with each other.

Adam Smith defines a society as something that "may subsist among different men, as among different merchants, from a sense of its utility without any mutual love or affection, if only they refrain from doing injury to each other." (Smith, 1759). His assumption that only human interaction is relevant makes sense given that he was living in the 18th century. During his time humans were the only relevant decision makers on the planet. Nowadays this is no longer true. A growing number of decision makers in social and especially in economic life consists of artificial intelligence agents (AIs).

One reason why hybrid societies have so far been studied so little by economists and other social scientists may be that we are all used to thinking about ourselves as agents that only live in physical space. However, a significant amount of interaction nowadays is taking space in virtual space (e.g. in social networks like Facebook). In physical space, hybrid societies may not seem such an urgent issue. If a robot enters the room, this is obvious and it did not (yet) happen very often to most of us. In virtual space however, it is much easier for an artificial agent to blend in with human agents and an AI may be much harder to spot for humans. The world of the 21st century however is becoming more and more digital and virtual. Besides our social life taking place in virtual space, the battlefields of the future will be (at least to some extent) digital, entire companies are built around digital goods, and modern markets are digital markets.

Given the speed with which the societies we live in are changing to hybrid societies and the all-pervasing changes this could bring to all of us, very little research has been done in general with regard to hybrid societies and even less so by economists. With the help of the experimental method we try to shed light on one aspect that could make hybrid societies different from human-only societies: The expectations that humans have with regard to the different types of agents (human or artificial) they may interact with. The experiments presented in this dissertation all compare the behaviour of humans in treatments where they expect to be relying on other humans, with treatments where they rely on "non-human" mechanisms. All experiments indicate that humans condition their behaviour on the type of agent they rely on and that behaviour differs.

1.2 Why should an economist research hybrid societies?

The fundamental changes that are happening during the transition from a human-only to a hybrid society just started to draw the attention of economists. The book *The second machine age: work, progress, and prosperity in a time of brilliant technologies* (Brynjolfsson and McAfee, 2014) addressing this issue just received the "Deutscher Wirtschaftsbuchpreis" of 2015 from the Handelsblatt.

Why should economists be more than just interested in this change and not just let others do the research for them and then apply the knowledge gathered by the experts? At least two reasons apply: First, if economists want their research to be externally valid they need to predict behaviour of humans and/or (on an aggregate level) groups of them. However, the question of how human behaviour is affected by the growing number of artificial agents is discussed only rarely within the economic literature. The economy is the economists object of research, so it is probably them who can anticipate and hypothesize best how and where certain properties of artificial agents are relevant for the economy. Second, compared to other social sciences, economists - based on the traditional assumption of the homo oeconomicus - have clear normative predictions of human behaviour. This assumption has allowed economists to develop unique experimental methods (e.g. games (in a game theoretical sense), lottery choice experiments, etc.) which allows viewing hybrid societies from a unique point of view.

On the philosophical side one may argue that AIs do not and never will have something like a free will and therefore cannot be considered agents in a metaphysical sense[1]. Furthermore, in the end there is always a human that programs the algorithms running on the AI. However, on a practical side we already see that AIs take decisions autonomously. The speed at which they can react and the quantity of data they can process often makes their behaviour uncontrollable for humans. Because of the complexity of the environments in which the artificial agents are intended to act and the cascade effects which can emerge from that artificial agent interacting with other artificial or human agents, it is impossible for the programmer to anticipate the effect of his work. Hence artificial agents form autonomous factors in our economic exchanges.

To illustrate how artificial agents affect our economy, let us take a look at modern stock markets. On May 6, 2010 the S&P 500 lost within 6 minutes almost 6% of its value and the Wall Street Journal estimated that one trillion Dollar in market value disappeared temporarily because of this crash (Kirilenko et al., 2014). To date it remains unclear whether this "Flash Crash" was intended (by humans) or not, but the U.S. Commodity Futures Trading Commission writes in their 2014 report that High Frequency Traders (HFTs) "did not cause the Flash Crash, but contributed to it by demanding immediacy ahead of other market participants." (Kirilenko et al., 2014). HFTs are computer programs that sell and buy assets autonomously on modern stock markets. Other market participants cannot distinguish between an offer made

[1]This remark points at the philosophical debate on agency (Juarrero, 2002). Though extremely interesting, discussing it would go beyond the scope of this chapter.

by a HFT or e.g. a human trader. Although these HFTs were programmed by humans, they can lead to unpredicted behaviour especially when interacting with other HFTs and human traders as happened on May 6 2010. Modern stock markets are thus hybrid markets which can differ substantially in behaviour from human-only markets. Not understanding how these hybrid markets are different from human-only markets leads to enormous financial risks and misguided legislation of these markets.

One may think that the example of modern stock markets is a very special case, but there are also many others. In the case of plane traffic, modern planes are only partly controlled by humans and there are many cases when the on-board computer overrules decisions of the human pilot. A similar case can be made for car traffic in a few years from now. When driving a vintage car in a few years from now, considering to cross a crossroad, one will not know whether that other car on the other side is driven by a computer or a human. Would humans change behaviour if they knew? Strategic interactions in game-like settings like these (in this case the hawk-dove/chicken game (Smith and Price, 1973)) are at the heart of what interests experimental economists.

1.3 An interdisciplinary view on artificial economic agents

In 2002, Daniel Kahnemann – a psychologist – received the Nobel Prize in economics for "for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty." (Sent, 2005). Kahnemann helped economists to understand the special properties that humans as agents in economies have, emphasizing the difference between real humans and the idealized idea of the homo oeconomicus. The new insight helped economists develop more realistic models and new fields of research within economics evolved since. A similar dynamic might be achieved by studying artificial economic agents and their interaction with humans in hybrid societies.

For this purpose, economics and other social sciences have to strengthen and develop their links with the field of Artificial Intelligence. Because of the growing number of artificial agents in our society, these disciplines span a research space full of highly relevant research questions. This collaboration will be useful as a joint venture in understanding hybrid societies and will generate new insight within each of the disciplines. Economics and Artificial Intelligence for example, have a common view on the agents they study. Both rely on a formal representation of agents' behaviour and assume (some kind of) rationality of the agents they model. Economics and Artificial Intelligence can learn a lot from each other's struggles in understanding and modeling human behaviour and emotions. Although the homo oeconomicus assumption may be an unrealistic assumption of economists, the paradigms developed by them may help in designing a "machina economicus" (Parkes and Wellman, 2015). Social sciences (especially economics) see the field of Artificial Intelligence too often as just a "toolmaker" providing them with the stuff they need to study their research questions (e.g. agent-based computational economics). Instead, social sciences should also view the field of Artificial Intelligence as part of their team and the subject they study.

1.4 Important concepts

Technically, depending on an artificial intelligence (AI) is a special case of depending on Nature (in the form of a *mechanistic process*). Throughout the dissertation we will compare human behaviour towards other humans with the behaviour towards relatively simple mechanistic processes. This comparison is much cleaner than the comparison of differences in behaviour towards humans and AIs because it is not confounded by factors such as the uncertainty about the sophistication of the AI or intentions of the programmer. For sure, real AIs are far more sophisticated than a simple mechanism like e.g. the toss of a coin. Nevertheless, we expect that on a fundamental level we can learn something about human interaction with AIs, by comparing behaviour in situations where one depends on another human, with depending on the outcome of the toss of a coin. Furthermore, it is exactly at this fundamental level, where the research presented in this dissertation has its comparative advantage compared to more applied research in e.g. Human-Robot Interaction with a far higher external validity.

Our chapters also differ in the focus of the research question. While chapter 2 looks at *interaction* between human and artificial agents, chapters 3 and 4 look at *dependence* of humans on either humans or mechanistic processes. Although depending and interacting are certainly not the same, interaction usually involves some kind of dependence between agents. However, interaction is much more complex because it also often contains features like a common fate, moral externalities of actions and intentions, strategic considerations, etc. So chapters 3 and 4 strike off these confounding factors involved when comparing interaction with both types of agents, and look at only one special feature of strategic interaction, while chapter 2 includes these factors for the sake of external validity.

1.5 Overview of dissertation

Chapters 2–4 present 3 experiments. All have in common that they compare the behaviour of subjects in a condition where they depend on other humans, with a condition where they depend on some *mechanistic process*.

The experiment presented in chapter 3 makes the cleanest comparison between depending on machines versus humans. The intent was to exclude any possible explanations for why someone would prefer the treatment where they depend on another human to the treatment where they depend on a mechanistic process, except for "I just prefer to depend on humans/mechanistic processes". For this purpose we had to get rid of all the context usually involved in interaction between agents, and create a very artificial setting. Chapter 2 on the other hand, looks at behaviour while one interacts with either humans or artificial agents in a very specific context (Asset markets), as close to the real world as experimental economics usually gets. As a consequence, the design in chapter 2 allows for many possible explanations of why behaviour would be different while interacting with different types of agents. Chapter 4 is positioned somewhere between these two chapters regarding generalizatability to the real world. It looks at preferences with regard to depending on a mechanistic process or a human in a Trust Game. We chose to focus on trust because according to sociologists it is "the glue of society" (Castelfranchi and Falcone, 2010). Hence, a proper understanding of the differences in trust in hybrid and human-only societies is essential.

Chapter 2 is based on a collaboration with Oliver Kirchkamp. It was presented by the author of this dissertation at the Annual Congress of the European Economic Association (2015) and the Experimental Finance (2015) conference. The initial idea, the literature review, programming of the experiment, and the collection of the data was done entirely by the author of this dissertation. Analysis of the data was mainly done by Oliver Kirchkamp; the rest of the workload was shared equally by the authors. Chapters 3 and 4 are single-author projects and led to two working papers, currently reviewed for conferences. To keep style coherent, as is common in scientific writing, all chapters are written in the first person plural.

1.5.1 Chapter 2: Bubbles in hybrid markets

Bubbles are omnipresent in lab experiments with asset markets. Most of these experiments are based on the experimental paradigm of Smith, Suchanek, and Williams (1988) and were conducted in environments with only human traders. However, a substantial portion of markets in the 21st century are determined by algorithmic traders interacting with human and other algorithmic traders. While there is some literature on how algorithmic traders change properties of the market by engaging in them, there seems to be no systematic attempt to answer the question of how the expected presence of an algorithmic trader would affect human trading on markets. To disentangle the direct effect of algorithmic traders we use a design where we manipulate only the expectations of human traders, without algorithmic traders actively engaging on the market and thereby affecting human traders. We analyze markets with respect to mispricing, volatility and frequency of trades.

1.5.2 Chapter 3: Depending on humans vs nature

We experimentally investigate whether humans prefer to depend on the decisions of other humans (social uncertainty) or states of nature (environmental uncertainty). For both social and environmental uncertainty we either control for the probabilities (risk) or let subjects form their own expectations regarding the probabilities (ambiguity). Different from previous research, we designed the social uncertainty treatments such that the uncertainty does not derive from strategic interaction. Instead, the uncertainty in the social uncertainty treatments derives from decisions of others that were made in ignorance of their consequences to someone else. Furthermore, the decisions were made within a context where the options were not morally loaded. We argue that this is crucial for a ceteris paribus comparison between social and environmental uncertainty and to the best of our knowledge this experimental design is the first achieving this.

1.5.3 Chapter 4: Betrayal aversion

A growing body of literature indicates that humans are betrayal averse, i.e. they prefer an unfortunate outcome when it is the result of a mechanistic process, compared to it being the intended consequence of someone's decision. We use the basic design of Bohnet and Zeckhauser (2004) where they compare preferences of subjects to engage in two versions of the Trust Game. In the standard Trust Game, Trustees decide whether to exploit the trust of a Trustor or not. In the Risky Dictator Game the "decision" of the Trustee is determined by the computer. Our research question is whether the mere possibility that one's trust may get exploited is sufficient to create disutility, even without the intended benefits on the Trustee's side. For this purpose we introduce the concept of a game-related lottery, a lottery where the chance of winning is taken from the Trust Game/Risky Dictator Game played earlier by the decision maker. By comparing preferences in game-related lotteries, we can see whether having ones payoff depending on a Trustee's choice is already sufficient to create disutility, irrespective of the Trustee's payoff.

Chapter 2

Bubbles in hybrid markets – How expectations about algorithmic trading affect human trading

2.1 Introduction

Experimental research on assets markets began in the mid 20th century using a stable design which has hardly changed since (see section 2.2 below). However, if we look at real world asset markets in the 21st century, we see great differences compared to asset markets in the 20th century. Instead of humans bargaining with and shouting at each other, today traders interact via computers. The use of computers on asset markets comes in many forms. It includes simple support of human traders in e.g. the scheduling of sales of assets without influencing the asset price in the market. It also includes sophisticated algorithmic traders which can learn and autonomously decide which assets they sell or buy (Kirilenko and Lo, 2013).

This chapter is co-authored with Oliver Kirchkamp from the Friedrich Schiller University Jena, Germany.

While the markets of the 20th century were human-only markets, modern markets are hybrid markets where computers and humans trade and where neither party gets information whether they sold to or bought from humans or algorithmic traders. De Luca and Cliff (2011) estimate that algorithmic traders are involved in up to 70% of the total trading volume in major European and US equity exchanges. In this chapter we ask how human trading is different in hybrid and human-only markets and whether these differences call for a revision of the classical experimental results from the 20th century.

We will discuss the literature on hybrid markets in more detail in section 2.2.2. Most of this literature deals with optimization of algorithms in hybrid markets or compares hybrid markets per se with human markets. Differences between human-only markets and hybrid markets are attributed to the trading activity of algorithmic traders and not to changes in human trading patterns. Algorithmic traders are seen as more able than humans to discover arbitrage possibilities than human traders. As a result we should see fewer bubbles in hybrid than in human-only markets. In this chapter we argue that differences between the two market types could already result only from changes in human behaviour and without any active participation of algorithmic traders in hybrid markets.

Expectations crucially determine the behaviour of human traders. Cheung, Hedegaard, and Palan (2014) relate bubbles in asset markets to the expectation that other market participants are less rational. Expecting more rationality in hybrid markets could discipline human traders and could cause a different performance in the two types of markets.

In section 2.2 below we will review the literature. We will see that the presence of algorithmic traders could change the behaviour of human traders in different ways. Do human traders trade less because algorithmic traders leave fewer opportunities to exploit the irrationality of other traders? Or do human traders trade more because prices are perhaps more informative in hybrid markets?

In section 2.3 we will present the design of our laboratory experiment. We explicitly do not focus on the properties of specific algorithmic traders used in the real world. Instead we exploit that most humans have an intuition when it comes to the differences between algorithmic traders and human traders. In a first experiment we aggregate the intuition subjects have about algorithmic traders. In a second experiment we use this information as a stimulus to control expectations of participants. In the second experiment we also manipulate expectations about the presence of algorithmic traders. In sections 2.4 and 2.5 we present our results. Section 2.6 concludes by looking at the experimental results in a broader context.

2.2 Literature

2.2.1 Experimental asset markets

Smith, Suchanek, and Williams (1988) (SSW) study a laboratory situation where subjects trade assets which pay a random dividend per round in an anonymized continuous double action. Subjects start with an endowment of assets and some cash. Assets can be sold for cash and cash can be used to buy assets offered by other subjects. Subjects know the average dividend an asset pays per round and the number of rounds. Hence, subjects could work out the fundamental value of an asset in SSW markets.

With common knowledge of rationality and risk neutrality one would expect no trade in these markets. Assets should be bought (and hence sold) only at the fundamental value and since supply and demand of assets is generated only by subjects, no transactions should take place. However, SSW find that asset prices in the experimental markets follow a "bubble and crash" pattern which is similar to speculative bubbles observed in real world markets. In their experiments the price per assets starts below the fundamental value, but then quickly exceeds it (often even above the sum of maximum possible dividends). Towards the end the price drops again quickly, approaching the fundamental value.

The baseline condition of our experiment (presented in section 2.3) is a close replication of the SSW design. Since 1988 many modifications of the SSW design have been studied to understand why people trade in these markets and to generally test theory on market bubbles. A full survey of this literature goes beyond the scope of this section (for a recent survey see Palan, 2013) but the following paragraphs discuss the literature that is most relevant for our experimental design and hypotheses.

Common knowledge of rationality: If traders have identical preferences, access to the same information, if they are perfectly rational and if they have common knowledge about all this then they should trade neither in hybrid nor in human-only markets. Akerlof (1970), Bhattacharya and Spiegel (1991) and Morris (1994) point out conditions under which differences in prior beliefs or information should not lead to a relaxation of the no-trade-theorem in SSW markets.

Common knowledge of rationality is a crucial assumption. Cheung, Hedegaard, and Palan (2014) manipulate the expectations subjects have about the rationality of other market participants. They ask all their subjects a large number of control questions on how a SSW market works and which trading strategies are rational. Subjects in one group are reminded explicitly that the other market participants have to answer the same control questions, subjects in the other group do not get this reminder. Cheung, Hedegaard, and Palan (2014) find that markets in which subjects get an explicit reminder produce smaller bubbles and that subjects trade less in these markets.

If subjects assume algorithmic traders to trade in a more rational way then we should expect smaller bubbles in hybrid markets.

Risk-aversion and Overconfidence: Risk-aversion and overconfidence could very well have an impact on trading in asset markets. In our experiment we measure these traits per subjects before trading starts.

Robin, Straznicka, and Villeval (2012) and Fellner and Maciejovsky (2007) find that risk-aversion leads to smaller bubbles and less trade in asset markets. They follow an approach used by Holt and Laury (2002) (which we will also use) to measure risk aversion. Keller and Siegrist (2006) use a mail survey and find that financial risk tolerance is a predictor for the willingness to engage in asset markets.

Odean (1999) assumes that overconfidence of traders is the reason that there is more trade than one would expect from rational traders. Michailova and Schmidt (2011), Michailova (2010), Fellner and Krügel (2012), and Oechssler, Schmidt, and Schnedler (2011) find that the size of bubbles and trading activity in SSW markets are, indeed, strongly correlated with overconfidence. Glaser and Weber (2007) and Biais et al. (2005) find no or only very weak correlations with overconfidence. One reason for the different results might be that the different studies operationalize overconfidence in different ways. Fellner and Krügel (2014) point out that well established measures of overconfidence from cognitive psychology—such as the miscalibration measure—differs considerably from the usage of the term in economics. Also Moore and Healy (2008) and Hilton et al. (2011) describe different ways to measure overconfidence. In this chapter we operationalize overconfidence specifically in the context of asset market (see section 2.3.4).

2.2.2 Human computer interaction

Since a hybrid market is characterized by human computer interaction we will discuss some non economic aspects of human computer interaction in the following paragraphs.

Arousal: Mandryk, Inkpen, and Calvert (2006) and Weibel et al. (2008) study computer games and find that gamers are more aroused when they know that they are playing with or against humans than when they know their counterpart is a computer program. Andrade, Odean, and Lin (2012) induce emotions with the help of short videos before the SSW market. Breaban and Noussair (2013) measure emotions based on facial expressions. Both studies find that market bubbles increase in magnitude and amplitude when subjects are aroused or excited. If arousal is, as in computer games, also lower in hybrid asset markets, then we should find smaller bubbles in hybrid markets than in human only markets.

Evidence from neuroscience: Humans use different brain areas for the interaction with computers than for the interaction with humans. Krach et al. (2008) find that especially areas associated with social interaction and motor regulation are less active when subjects interact with computers. These findings are robust across different types of games like Rock-Paper-Scissors (Chaminade et al., 2012), prisoners' dilemma games (Krach et al., 2008; Rilling et al., 2004) and Trust Games (McCabe et al., 2001). These experiments also show that humans invest more effort when their counterpart is human.

Nass and Moon (2000) show that humans mindlessly apply to computers social responses in environments where they would usually interact with humans. Subjects do behave in a reciprocal or polite way towards computers although the same subjects explicitly state that this kind of behaviour is senseless. The findings of Nass and Moon (2000) suggests that humans should trade in the same way in hybrid and human only markets.

2.2.3 Hybrid markets

As pointed out in section 3.1 real-world asset markets have changed considerably since the experiments of Smith, Suchanek, and Williams (1988). In particular hybrid markets, i.e. markets with human and algorithmic traders, have become more prominent. The major part of studies on hybrid markets focuses on the computer side of hybrid markets. On the one hand, experiments like Das et al. (2001) and De Luca and Cliff (2011) show that in SSW markets where human and algorithmic traders are active some of their algorithms outperform human traders in terms of payoff. Other studies identify properties in which hybrid markets differ from human-only markets: Walsh et al. (2012) find that liquidity is higher in simulated hybrid markets than in simulated human-only markets. Hendershott, Jones, and Menkveld (2011) find in an empirical analysis of the NYSE since 2003 that liquidity increased in the market as the use of algorithmic traders increased. Gsell (2008) shows with the help of simulations that the presence of algorithmic traders in hybrid markets reduces volatility of prices and speeds up price discovery.

We have found only two studies which are closer to our research question and which study the human side of hybrid markets.

Akiyama, Hanaki, and Ishikawa (2013) investigate the impact of strategic uncertainty on bubbles. They study experimental asset markets with 6 traders. In their treatment 6H six human subjects are trading, in 1H5C 1 subject trades with 5 computer traders. Subjects in 1H5C are informed that the computer traders are strictly selling and buying assets at the fundamental value. In 6H subjects knew they are trading with only humans and got no information on the others' strategy. Hence, in the 6H treatment there is substantial strategic uncertainty while in 1H5C there is no such uncertainty at all. Akiyama, Hanaki, and Ishikawa find that there are no bubbles in 1H5C. Their design allows to better understand the impact of strategic uncertainty on prices.

In this chapter we want to find out whether expectations about the mere presence of algorithmic traders affect trading behaviour. In that respect Akiyama, Hanaki, and Ishikawa can not distinguish whether differences in trading between treatments are the result of different trading behaviour of the algorithmic traders in the 1H5C treatment, or due to the knowledge that algorithmic traders are present in that treatment, or due to the information that all other traders trade only at fundamental value. Furthermore, their study looks at an extreme kind of hybrid market, where the human trader is actually a minority in a market populated by mostly computers. Since the subject gets full information on the computers' strategy the prices in the market can be predicted correctly. The kind of hybrid markets we are interested in are different since we want to allow for human-human interaction, while human-computer interaction is also possible.

Grossklags and Schmidt (2006) study experimental asset markets in which humans trade in hybrid markets. In one of their treatments subjects are ignorant of the presence of algorithmic traders while in the other the presence of algorithmic traders is common knowledge. In line with our findings below Grossklags and Schmidt find that market prices follow more closely the fundamental value when the presence of algorithmic traders is known. They also find that markets in which humans are aware of the (then hybrid) market type are more efficient. Grossklags and Schmidt find slightly (but not significantly) less trading when subjects are aware of the presence of algorithmic traders.

In contrast to Grossklags and Schmidt we give participants in the two treatments exactly the same information, except for one small (but crucial) bit: Are algorithmic traders potentially present or are they not? All remaining information, in particular information about the concept of algorithmic traders in general, is kept constant. Grossklags and Schmidt give information about algorithmic traders only in the hybrid market, not in the human-only market. As a result they cannot disentangle the effect of giving information about algorithmic traders in general from giving information about a specific market. From Cheung, Hedegaard, and Palan (2014) we know that general information may very well matter. In our experiment we can cleanly isolate the effect of the presence of algorithmic traders.

2.3 Methods

2.3.1 Market

The experiment was implemented with the help of z-Tree (Fischbacher, 2007). Participants were recruited with ORSEE (Greiner, 2004). Markets used in this experiment are very similar to those used by Smith, Suchanek, and Williams (1988). A screenshot is shown in Appendix 2.7.6. As in SSW subjects trade in a continuous double auction during 15 rounds and receive a random dividend

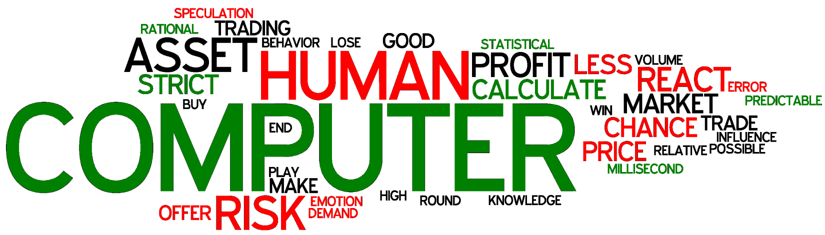


Figure 2.1: Wordle of most frequent words

per round. The possible dividends are with equal probabilities 0, 8, 28, or 60 ECU. The average dividend per round is, thus, 24 ECU. The fundamental value of an asset in round 1 is $15 \times 24 = 360$ ECU, decreasing by 24 ECU at the end of each round. Each round lasts for 60 seconds, so that one market period in total takes 15 minutes. Each subject owns in round 1 an endowment of 4 assets which the subject can offer on the market for cash. Each subject also initially owns 720 ECU in cash which can be used to buy assets. Kirchler, Huber, and Stockl (2012) find that higher amounts of initial cash relative to the fundamental value of assets lead to larger bubbles on SSW markets. The ratio of cash to value we use is at the lower boundary of what seems to be necessary to induce bubbles. Each market consists of 6 anonymous traders.

Subjects got instructions in form of a video tutorial (11 minutes)[1] and had a printed table with the fundamental value of an asset in each round at their disposal. Control questions were asked to make sure they understood the dynamics of the SSW market and the trading interface.

2.3.2 Algorithmic traders

We ran two sessions of a first (preparatory) experiment. In that experiment 6 subjects per session were trading in a SSW market as described in the previous section. After trading subjects had to fill in a questionnaire in which they were asked to write down their expectations how an algorithmic trader would trade in a SSW market and what its impact on the market would be. The most common words were then used to create a wordle (`www.wordle.net`). In this wordle the frequency of words is represented by font size. Figure 2.1 shows the resulting wordle (translated into English) in which words describing how

[1]the video can be found on `http://www.mikefarjam.de/video2`

algorithmic traders work that were used with a negation while are shown in red while positively used words are shown in green (black if mixed or unclear).[2] The exact questions asked to subjects in the pilot sessions and the algorithm that produces the wordle can be found in Appendix 2.7.2.

In a second (main) experiment the wordle was shown to all (new) subjects before they were informed about their treatment condition. Furthermore, subjects were told how the wordle was created and they were told that the algorithmic trader was programmed according to the wordle.

Providing information about the character of algorithmic traders in this way serves two purposes: First, we want to have rather homogeneous beliefs of subjects with respect to algorithmic traders. This allows us (as experimenters) to restrict ex ante the number of alternative explanations for our findings which might otherwise be based on different beliefs subjects may or may not have. Second, we do not want to impose our own expectations with respect to algorithmic traders. Since subjects in the pilot sessions and the actual experiment are drawn from the same population, we can assume that both groups had on average the same beliefs about algorithmic traders. Hence, the wordle should match on average the expectations of subjects.

Of course, subjects still can interpret the wordle in different ways. Hence, beliefs are still not perfectly homogeneous. Also, by writing the algorithm that generated the wordle we still might have introduced a demand effect into the experiment. However, for us this seemed the best possible compromise to make at the same time the beliefs of subjects more homogeneous without introducing a systematic demand effect.

One can also argue that the way we present information about the algorithmic trader is similar to how human traders get information about algorithmic traders in the real world. Information about the exact implementation and behaviour of algorithmic traders in real world asset markets is usually kept secret by their owners. The only information available to human traders are more or less vague concepts of what algorithmic traders are capable of, leaving much room for interpretation.

[2]The original German wordle is shown in Appendix 2.7.3.

2.3.3 Treatments

Subjects were divided randomly and with equal probability into one of the treatments A, B, or C, as specified by Table 2.1.

subjects are in treatment...	type of market	subjects get information that they are in...
A	only human traders	A
B	only human traders	B or C
C	hybrid	B or C

Table 2.1: Treatments

They were told that they would be informed whether they were in treatment A or whether they were in treatment B or C. They knew that they could not distinguish B or C. Interesting for us is the comparison of A and B. In both groups we have only human traders but only subjects in the A treatment can rule out the possibility of algorithmic traders while subjects in the B treatment cannot. We are not interested in the behaviour of the C group. C is only needed to make expectations of the B participants consistent.

The number of active traders was thus identical in all conditions. To avoid that social preferences affect differences between A and B, subjects know that in treatment C another passive human trader would receive the payoff of the algorithmic trader.

2.3.4 Risk preference and overconfidence

To measure risk aversion of subjects we use a multiple price list task as in Holt and Laury (2002).[3] In this task subjects choose between lotteries with a high variance of payoffs and lotteries with a low variance of payoffs. As in Holt and Laury (2002) we use the relative frequency of high variance choices as a measure for a preference for risk. We use a similar task to elicit loss aversion.[4]

Since there is no clear preference in the overconfidence literature for one task and since the overconfidence construct has many dimensions, we chose

[3] The list can be found in Appendix 2.7.4.
[4] The list can be found in Appendix 2.7.5.

to measure overconfidence in the most direct way we could think of. We ask subjects "how well do you expect to perform in an experimental asset market?" We use the percentile at which they expect to perform compared to all other subjects as a measure of overconfidence.

2.3.5 Payoff

The markets and other tasks are designed such that the average earnings of subjects was about 11 euros. To avoid endowment effects only one of the tasks (risk preference, loss aversion or overconfidence measurements) or one of the trading periods was chosen randomly at the end of the session for payoff.

2.4 Descriptives[5]

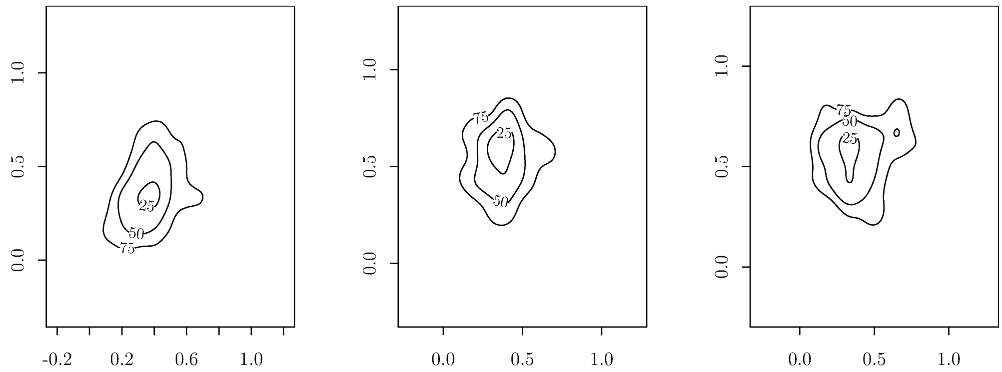
2.4.1 Subjects

We use data from 216 subjects which are divided into three treatments of 72 subjects. Each market has a size of 6 subjects. Hence, we had 12 markets per treatment. All subjects were recruited via ORSEE (Greiner, 2004). Since studies like Dohmen et al. (2011) and Barber and Odean (2001) show that risk-preferences and trading behaviour differs between genders, we recruited only male subjects to reduce within group variability. All sessions were run between July and November 2014 in the laboratory of the Friedrich Schiller University Jena. Most of our subjects were students.

2.4.2 Questionnaire and additional measurements

After playing two successive market periods subjects were asked to complete a questionnaire. Subjects in treatment B (see Table 2.1) were asked: "Do you think that an algorithmic trader was active in the market?" Possible answers were "yes" and "no". Although no algorithmic trader was active in treatment B, 13 out of 72 subjects guessed yes. If there is still so much uncertainty among subjects after two full periods of trading, there must have been a considerable

[5]We use R 2016 for graphs and statistical analysis in all chapters.



The graphs show contour lines of a kernel density estimate.

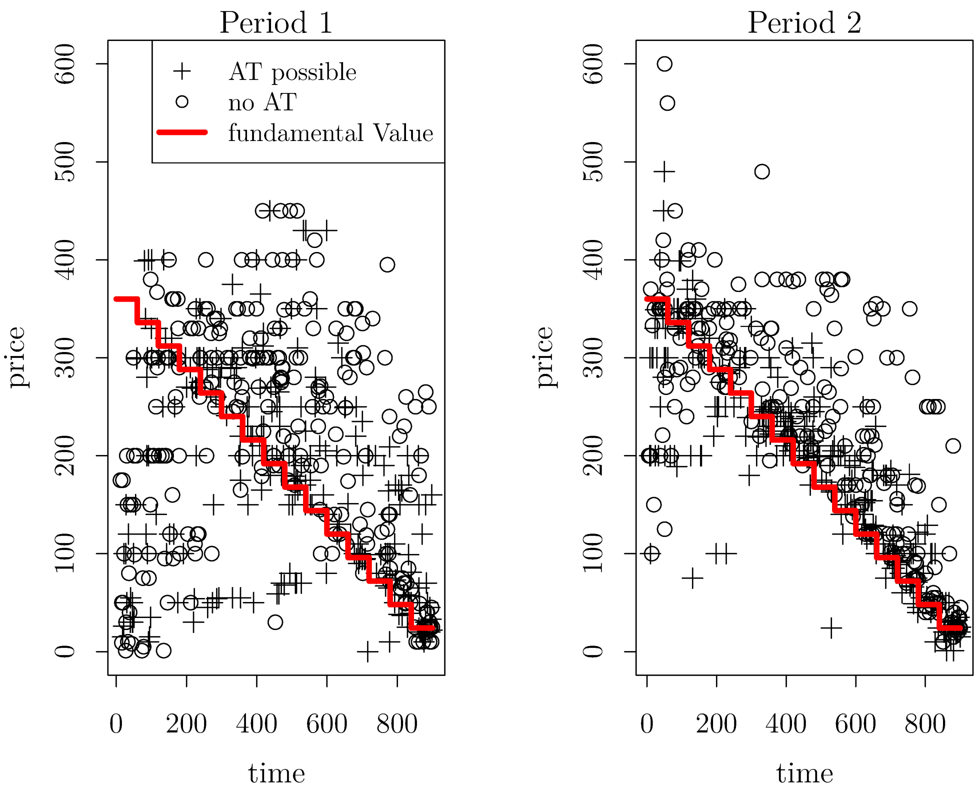
Figure 2.2: Joint distribution of preferences for risk, loss aversion and overconfidence

amount of uncertainty among subjects at least in the first rounds of the first period. We therefore conclude that our manipulation (eliciting uncertainty about participation of an algorithmic trader) worked.

In section 2.2.1 we discussed attitudes towards risk and overconfidence as prominent explanations for bubbles in SSW markets. In our experiment we measured risk aversion and overconfidence before subjects started trading. Since loss-aversion is closely related to risk-aversion we chose to measure loss-aversion as well. The exact choices are presented in Appendices 2.7.4 and 2.7.5. Figure 2.2 shows the empirical joint distribution of these properties in our sample. The attitude towards risk in our sample seems to be in line with similar studies. We also find a moderate amount of overconfidence. 62.5% of all subjects expect to be better than or equal to the average. This is in line with the standard effect (Hoorens, 1993). As we see in Figure 2.2, the three properties seem to be rather independent of each other. We will, hence, use them all as controls in our estimations below.

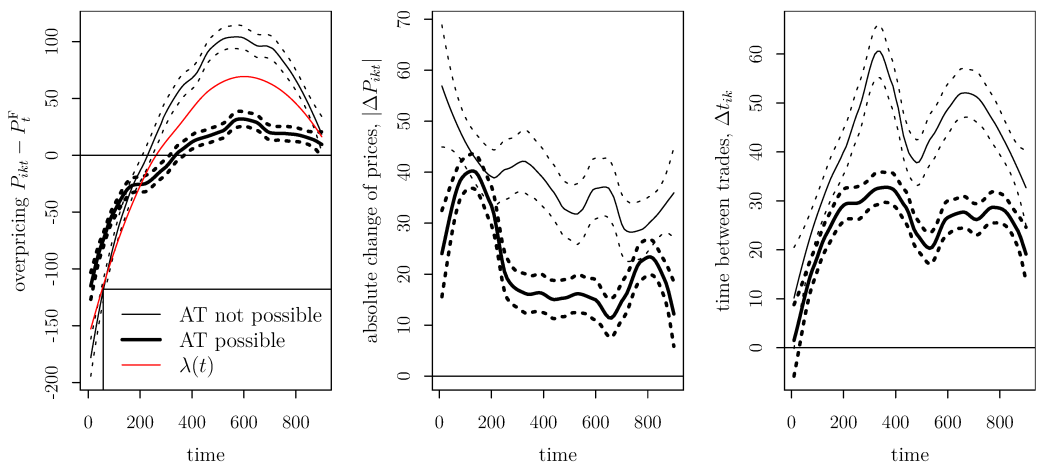
Trades

Figure 2.3 gives a first impression how individual prices develop over time. Each point represents one trade. As expected, pricing of assets follows the



Each point corresponds to one trade in the experiment. The red line shows the fundamental value of the asset.

Figure 2.3: Prices over time



Solid black lines show, separately for the two cases where algorithmic traders are possible and not possible, a loess smoother for overpricing, change of prices over time and time between trades. Dashed lines indicate ± one standard deviation. The red line showes a loess smoother for overpricing, independent of the information about algorithmic traders.

Figure 2.4: Trading behaviour over all rounds of one market

bubble and crash pattern known from SSW.

Figure 2.4 shows a more aggregated picture. Solid black lines in the Figure are loess smoothers (Cleveland, Grosse, and Shyu, 1992) for the two treatments: participants are either informed that algorithmic traders are not present in the market (A), or they are informed that algorithmic traders could be present (B). Dashed lines show ± one standard deviation.[6] We denote the fundamental value at time t with P_t^{F} and the actual trade i in group k at time t with P_{ikt}. The left panel in Figure 2.4 shows the development of $P_{ikt} - P_t^{\mathrm{F}}$ over the time of the experiment. Mispricing is clearly smaller in the treatment where algorithmic traders are possible. The other two panels in the Figure also show that in this treatment volatility is smaller and trading is quicker.

In Appendix 2.7.7 we provide similar graphs but now for periodic behaviour within one round of a market. Our interpretation of these graphs is that, apart from the pattern already visible in Figure 2.4, there is no special difference in

[6]The standard setting for the smooting parameter is $\alpha = .75$. Since we have a large number of trades we can provide more detail about the dynamics during the experiment. Hence, we use $\alpha = .2$ for the black lines.

the periodic structure.

Since treatment C is not relevant for our research question and only needed to make beliefs of subjects in treatment B consistent, we discuss the results of treatment C only briefly in Appendix 2.7.8.

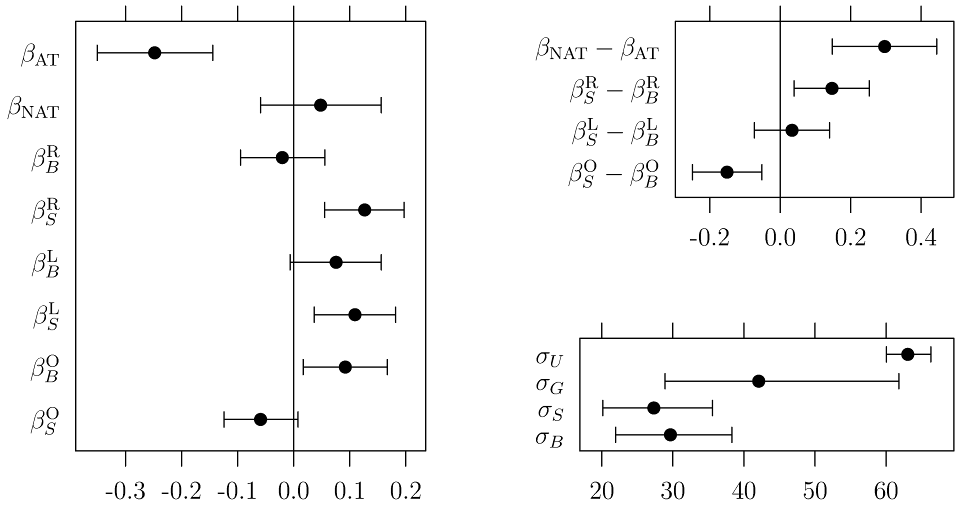
2.5 Results

Estimation strategy We use a model with mixed effects to take into account the nested structure of the data. We will look at 3 different dependent variables: Mispricing of assets during trading measured as $P_{ikt} - P_t^{\mathrm{F}}$, speed of trading measured as time in seconds between individual trades Δt_{ikt}, and volatility measured as the absolute change of prices between trades $|\Delta P_{ikt}|$. We also control for buyers B_{ik} and sellers S_{ik} separately for their risk aversion $R_{B_{ik}}$ and $R_{S_{ik}}$, their loss aversion $L_{B_{ik}}$ and $L_{S_{ik}}$, and their overconfidence $O_{B_{ik}}$ and $O_{S_{ik}}$. Furthermore we allow for random effects for the buyer, the seller and the group of traders in that round.

Here, d_{NAT} is a dummy which is one if participants are informed that algorithmic traders will not participate in the market and zero otherwise. d_{AT} is a dummy which is one if participants are informed that algorithmic traders may participate in the market and zero otherwise. ϵ_k^G, $\epsilon_{S_{ik}}^S$, and $\epsilon_{B_{ik}}^B$ are random effects for the matching group k, the seller S_{ik}, and the buyer B_{ik}, respectively. ϵ_{ikt}^U is the residual. The precision of the distribution for random effects and the residuals follow a vague prior given by (2.4). The prior distributions of coefficients $\beta_{\dots}$ follow a vague prior given by (2.3).

2.5.1 Bubbles

We assume that the distribution of the difference of actual prices and the fundamental value, $P_{ikt} - P_t^{\mathrm{F}}$, is given by (2.1). $\lambda(t)$ is a loess spline of average overbidding over time (similar to the one given in Figure 2.4), independent of the information given to participants, with the smoothing parameter α set to the default (Cleveland, Grosse, and Shyu, 1992).



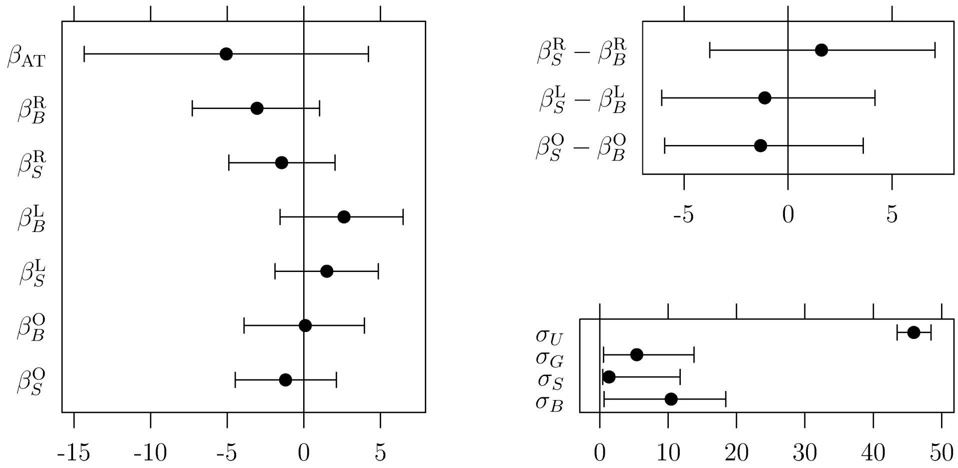
The graphs show 95%-credible intervals for the coefficients, for their differences, and for the standard deviations.

Figure 2.5: Estimation results for Equation (2.1), $P_{ikt} - P_t^{\mathrm{F}}$.

$$
\begin{aligned}
P_{ikt} - P_t^{\mathrm{F}} &= \beta_0 + (1 + \beta_{\mathrm{NAT}} d_{\mathrm{NAT}} + \beta_{\mathrm{AT}} d_{\mathrm{AT}} + \beta_B^{\mathrm{R}} R_{B_{ik}} + \beta_S^{\mathrm{R}} R_{S_{ik}} + \\
&\quad \beta_B^{\mathrm{L}} L_{B_{ik}} + \beta_S^{\mathrm{L}} L_{S_{ik}} + \beta_B^{\mathrm{O}} O_{B_{ik}} + \beta_S^{\mathrm{O}} O_{S_{ik}}) \cdot \lambda(t) + \epsilon_k^G + \\
&\quad \epsilon_{S_{ik}}^S + \epsilon_{B_{ik}}^B + \epsilon_{ikt}^U \qquad (2.1) \\
\text{random effects } \epsilon^j &\sim N(0, 1/\tau_j) \text{ with } j \in G, S, B, U \qquad (2.2) \\
\text{vague priors } \beta_{\ldots} &\sim N(0, 10^2) \qquad (2.3) \\
\tau_{\ldots} &\sim \Gamma(m_{\ldots}^2/s_{\ldots}^2, m_{\ldots}/s_{\ldots}^2) \text{ with } m_{\ldots} \sim \mathrm{Exp}(1), s_{\ldots} \sim \mathrm{Exp}(1) \qquad (2.4)
\end{aligned}
$$

We use JAGS to estimate the posterior distribution of coefficients for Equation (2.1). Results are based on 4 independent chains. We discard 5000 samples for adaptation and burnin and use 10000 samples for each of the 4 chains. Results are given in Figure 2.5.

We find a clear difference between the two treatments. The 95%-credible



The graphs show 95%-credible intervals for the coefficients, for their differences, and for the standard deviations.

Figure 2.6: Estimation results for Equation (2.5), ΔP_{ikt}.

interval for the difference $\beta_{\mathrm{NAT}} - \beta_{\mathrm{AT}}$ is $[0.04, 0.25]$[7]. The odds of $\beta_{\mathrm{NAT}} > \beta_{\mathrm{AT}}$ are 20000 : 1. We have, thus, very strong evidence (in the sense of Kass and Raftery, 1995) that the mere expectation of the presence of algorithmic traders reduce bubbles.

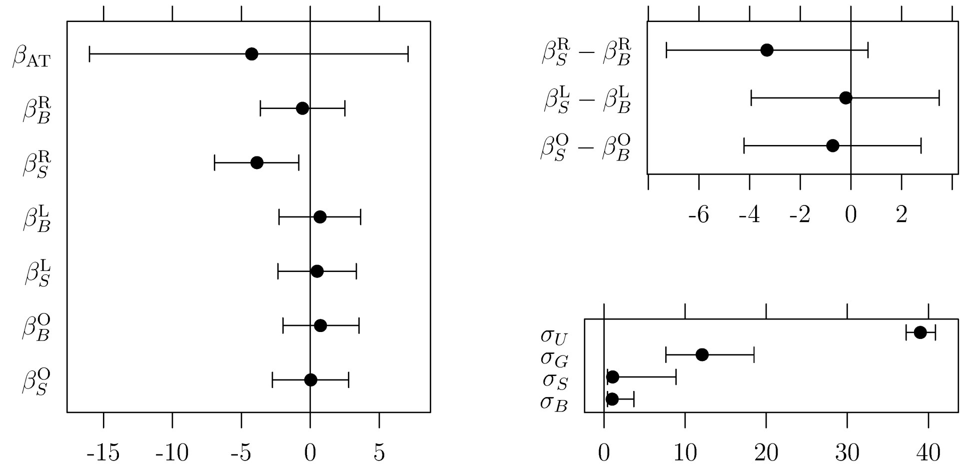
2.5.2 Changes of prices

We call $|\Delta P_{ikt}|$ the absolute amount of the change in prices from one trade to the next. We estimate the following equation:

$$|\Delta P_{ikt}| = \beta_0 + \beta_{\mathrm{AT}} d_{\mathrm{AT}} + \beta^{\mathrm{R}}_B R_{B_{ik}} + \beta^{\mathrm{R}}_S R_{S_{ik}} + \beta^{\mathrm{L}}_B L_{B_{ik}} + \beta^{\mathrm{L}}_S L_{S_{ik}} + \beta^{\mathrm{O}}_B O_{B_{ik}} + \beta^{\mathrm{O}}_S O_{S_{ik}} + \epsilon^G_k + \epsilon^S_{S_{ik}} + \epsilon^B_{B_{ik}} + \epsilon^U_{ikt} \quad (2.5)$$

Random effects and priors are as in Equations (2.2), (2.3) and (2.4). The middle panel in Figure 2.4 suggests that changes of prices from one trade to

[7]Eff. sample size=19900, psrf=1.0001.



The graphs show 95%-credible intervals for the coefficients, for their differences, and for the standard deviations.

Figure 2.7: Estimation results for Equation (2.6), Δt_{ikt}.

the next seem to be smaller in the algorithmic trader treatment. Figure 2.6 shows estimation results. The 95%-credible interval for β_{AT} is $[-14.32, 4.22]$[8]. In our posterior estimate for β_{AT} the odds for $\beta_{\mathrm{AT}} > 0$ are $1 : 6.58$, i.e. we have positive evidence (in the sense of Kass and Raftery, 1995) that information about the potential presence of algorithmic traders reduces the magnitude of changes of prices from one trade to the next.

2.5.3 Time between trades

We call Δt_{ikt} the time between trades and estimate the following equation:

$$\Delta t_{ikt} = \beta_0 + \beta_{\mathrm{AT}} d_{\mathrm{AT}} + \beta_B^{\mathrm{R}} R_{B_{ik}} + \beta_S^{\mathrm{R}} R_{S_{ik}} + \beta_B^{\mathrm{L}} L_{B_{ik}} + \beta_S^{\mathrm{L}} L_{S_{ik}} + \beta_B^{\mathrm{O}} O_{B_{ik}} + \beta_S^{\mathrm{O}} O_{S_{ik}} + \epsilon_k^G + \epsilon_{S_{ik}}^S + \epsilon_{B_{ik}}^B + \epsilon_{ikt}^U \tag{2.6}$$

Random effects and priors are as in Equations (2.2, (2.3) and (2.4).

[8]Eff. sample size=4140, psrf=1.0025.

The right panel in Figure 2.4 shows that participants seem to trade more quickly in the no-algorithmic trader treatment. Figure 2.7 shows estimation results. The 95%-credible interval for β_{AT} is $[-16.02, 7.09]$[9]. In our posterior estimate for β_{AT} the odds of $\beta_{\text{AT}} > 0$ are 1 : 3.36, i.e. we have positive evidence that information about algorithmic traders increases the frequency of trades.

2.6 Discussion

In our experiment we study how the expected presence of algorithmic traders affects the trading activity of human traders on asset markets. We use a design where we can disentangle the direct effect algorithmic traders have in the market from the indirect effect algorithmic traders have through the expectations of human market participants. We measure deviations from the fundamental value, speed of trading and volatility of prices.

We find that bubbles are smaller and subjects are selling and buying assets closer to the fundamental value when they expect human traders and algorithmic traders to participate in the market compared to markets where they only expect human traders to participate. This is in line with Gsell (2008) who finds (with the help of simulations) that price discovery is quicker in markets with algorithmic traders than without. While Gsell (2008) concludes that differences between the two markets are due to active participation of algorithmic traders we find qualitatively the same even without active participation of algorithmic traders on the market, but by simply manipulating the expectations of human traders. In line with Gsell (2008) we find that volatility of prices is reduced by algorithmic traders. The speed of trading also increases when algorithmic traders are present.

We also control for individual risk aversion, loss aversion and overconfidence but find no systematic effect there.

We can only speculate about the underlying mechanisms that make humans trade closer to the fundamental value when they expect algorithmic traders on the market. As discussed earlier in section 2.2.2, human traders might behave differently towards computers only because these are computers. Humans might, e.g., be less excited when they expect algorithmic traders to participate. The resulting difference in behaviour would then be independent

[9] Eff. sample size=1770, psrf=1.0034.

of different expectations about the behaviour of these computers. Alternatively, and as discussed in section 2.2.1, human traders might assume that algorithmic traders do behave in a different, perhaps more rational way. As a result the humans would change their trading behaviour.

What exactly is driving bubble formation in real world asset markets is still discussed among economists. Our results suggest that whatever humans contribute to bubble formation in human-only markets is contributed less in hybrid markets. This need not suggest that hybrid markets in general must produce less bubbles. Algorithmic traders themselves may be catalysts for bubbles in asset markets in their interaction with other algorithmic traders or human traders.

For policy makers the results we present have to be interpreted with the usual precautions when translating findings from the laboratory into real world policies. Our results suggest that in order to reduce bubbles on hybrid markets one should emphasize towards human traders that they are sharing the market with algorithmic traders. This seems to reduce the human tendency to create bubbles. Our results also suggest that in hybrid markets human trading contributes to bubbles to a lesser extent and that legislators should perhaps focus more on algorithmic traders when passing laws regarding hybrid asset markets.

The results presented can also be seen as a general stimulant for those studying human behaviour. In the modern world many situations which were previously characterized by human-human interaction change to situations with human-robot interaction. Experimental designs that included only human agents may have been ecologically relevant in the past. However it is not obvious that the results obtained then, still are ecologically relevant nowadays were artificial agents – like e.g. algorithmic traders in markets – are participating in economic interaction. One has to reproduce this new characteristic in the lab or at least has to be aware of the fact that human-human findings may not hold in a human-robot world.

2.7 Appendix

2.7.1 Questions

In a pilot study subjects (N = 12) were asked four questions just after they traded in a SSW market. Subjects were asked to answer every question with at most two sentences. No other restrictions were made with respect to length or content of the answers.

Those were the questions translated to English (in brackets the original German questions):

1. How would you expect that a computerized trader would trade in an asset market as the one you just traded in? (Wie würden Sie erwarten, dass ein Computerprogramm in einem Aktienmarkt (wie dem eben) handeln würde?)
2. In what way would the behaviour of a computerized trader be different from the behaviour of a human trader? (Inwiefern würde sich das Verhalten des Computerprogramms am Aktienmarkt (wie dem eben) von dem eines Menschen unterscheiden?)
3. How would the participation of a computerized trader change the dynamics on the market? (Inwiefern würde das Handeln eines Computerprogramms den Markt beeinflussen?)
4. How would the activity of the computerized trader change your trading behaviour as a human? (Inwiefern würde das Handeln eines Computerprogramms am Markt das Handeln für Sie als Mensch verändern?)

2.7.2 Preprocessing for Wordle

The following steps were taken to aggregate and standardize the response that subjects gave to the questions in 2.7.1

1. Correct spelling, delete articles, prepositions, conjunctions, negations, pronouns, grammatical particles, modal and auxiliary verbs.

2. Delete non-sense (e.g. "?" or "I don't know") and response that was not related to algorithmic trading (e.g. "Humans like gambling").

3. All nouns were changed to nominative singular, all verbs to infinitive, adverb and adjectives into their basic form.

4. Find synonyms and use the same word for both (e.g. "strikt" (strict) and "streng" (rigorous)). Use same word for derivats and words that are semantically very close ("statistisch" (statistical) and "Statistik" (statistic)).

5. Of the remaining words: drop words with freq < 2.

6. Input remaining words into `http://www.wordle.net/create`.

7. Delete common German words (default option for wordle).

8. Check if remaining words were used in the raw response to describe how computers should or should not behave. Paint words that were used with a negation while describing how algorithmic traders work red, positively used words green (leave black if mixed or unclear).

2.7.3 Wordle

In Figure 2.1 above we show an English version of the wordle that we used to explain algorithmic traders in the experiment. Since the experiment was conducted with German speaking students, we used the following version in the experiment:

2.7.4 Risk

As in Holt and Laury (2002) we use the relative frequency of B-choices as a measure for preference for risk.

Choice A	choice B
1800 ECU with $\frac{1}{10}$, 1440 ECU with $\frac{9}{10}$	3465 ECU with $\frac{1}{10}$, 90 ECU with $\frac{9}{10}$
1800 ECU with $\frac{2}{10}$, 1440 ECU with $\frac{8}{10}$	3465 ECU with $\frac{2}{10}$, 90 ECU with $\frac{8}{10}$
1800 ECU with $\frac{3}{10}$, 1440 ECU with $\frac{7}{10}$	3465 ECU with $\frac{3}{10}$, 90 ECU with $\frac{7}{10}$
1800 ECU with $\frac{4}{10}$, 1440 ECU with $\frac{6}{10}$	3465 ECU with $\frac{4}{10}$, 90 ECU with $\frac{6}{10}$
1800 ECU with $\frac{5}{10}$, 1440 ECU with $\frac{5}{10}$	3465 ECU with $\frac{5}{10}$, 90 ECU with $\frac{5}{10}$
1800 ECU with $\frac{6}{10}$, 1440 ECU with $\frac{4}{10}$	3465 ECU with $\frac{6}{10}$, 90 ECU with $\frac{4}{10}$
1800 ECU with $\frac{7}{10}$, 1440 ECU with $\frac{3}{10}$	3465 ECU with $\frac{7}{10}$, 90 ECU with $\frac{3}{10}$
1800 ECU with $\frac{8}{10}$, 1440 ECU with $\frac{2}{10}$	3465 ECU with $\frac{8}{10}$, 90 ECU with $\frac{2}{10}$
1800 ECU with $\frac{9}{10}$, 1440 ECU with $\frac{1}{10}$	3465 ECU with $\frac{9}{10}$, 90 ECU with $\frac{1}{10}$
1800 ECU with $\frac{10}{10}$, 1440 ECU with $\frac{0}{10}$	3465 ECU with $\frac{10}{10}$, 90 ECU with $\frac{0}{10}$

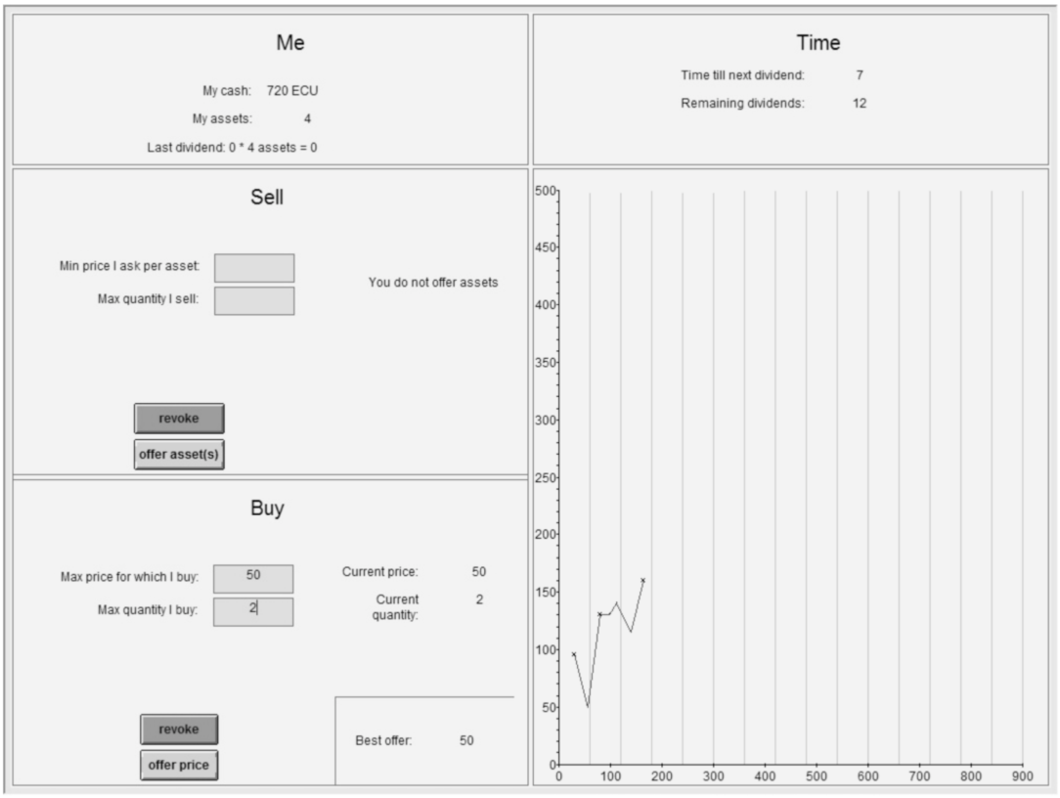
2.7.5 Loss aversion

As in for risk aversion we use the relative frequency of B-choices as a measure for loss aversion.

Choice A	choice B
with equal probability lose 570 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 855 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 1140 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 1425 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 1710 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 1995 ECU and gain 1710 ECU	2000 ECU for sure

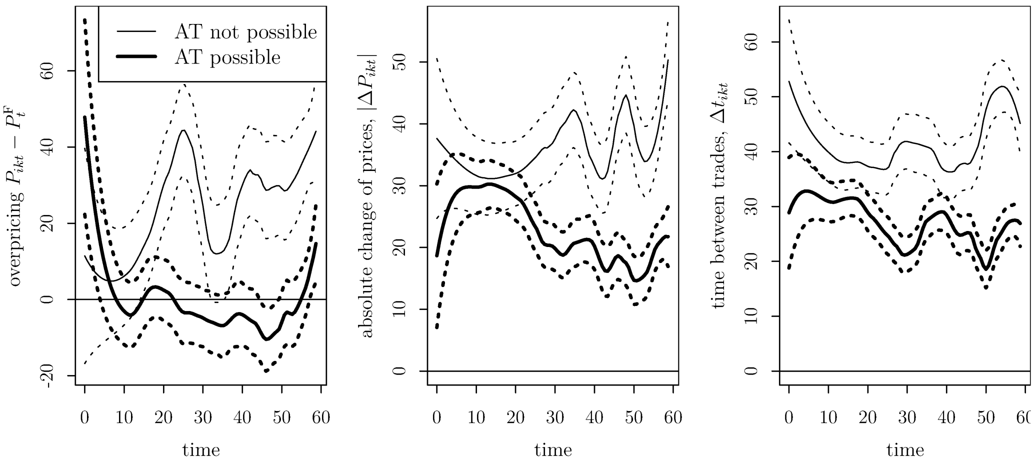
2.7.6 Trading interface

Subjects would use the following interface for trading in the continuous double auction in the experiment:



2.7.7 Periodic behaviour within each round

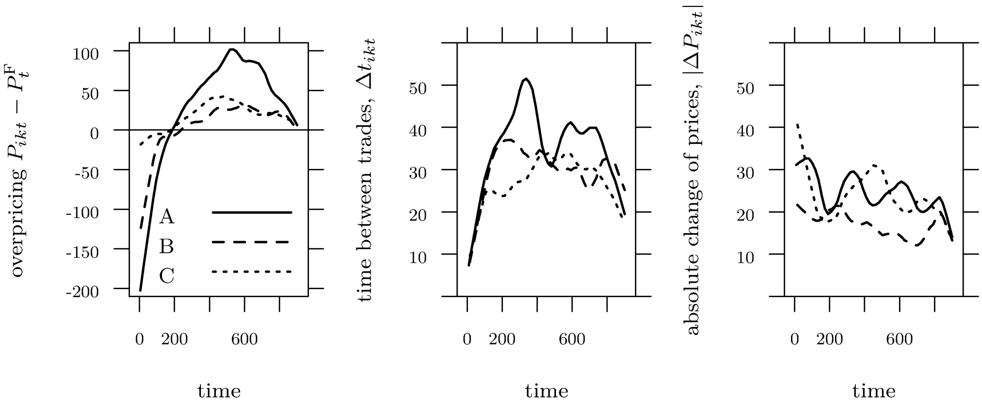
In our experiment the fundamental value remains constant for 60 seconds and then drops by a fixed amount. This pattern repeats 15 times during the 900 seconds of the experiment. Here we check whether we can see a pattern in overpricing, time between trades and the absolute change of prices.



2.7.8 Treatment C

Although treatment C was not part of our research question the results of this treatment may be interesting for others. Below we give a short summary of the algorithmic trader used in treatment C and a short comparison with the other treatments. A full analysis of this treatment would go beyond the scope of this chapter.

In treatment C of our experiment one human trader was replaced by an algorithmic trader. The trader programmed for this treatment is offering all assets at its disposal at a price identical to the fundamental value of an asset in the respective period. At the same time the algorithmic trader is willing to buy assets at a price smaller than the fundamental value. The figure below shows how overpricing, the time between trades and the price volatility developed in treatment A, B, and C. Note that treatment C differs from treatment A in two ways: subjects expect an algorithmic trader to participate in the market *and* an algorithmic trader participates on the market. A ceteris-paribus comparison between treatments A and C thus is not possible. A comparison between treatments B and C shows the impact that the trading activity of the algorithmic trader had on the market.


overpricing $P_{ikt} - P_t^{\mathrm{F}}$
100
50
0
-50
-100
-150
-200
A
B
C
0
200
600
time
time between trades, Δt_{ikt}
50
40
30
20
10
0
200
600
time
absolute change of prices, $|\Delta P_{ikt}|$
50
40
30
20
10
0
200
600
time

Chapter 3

On whom would I want to depend; Humans or Nature?

3.1 Introduction

Imagine you want to insure an expensive painting in your possession. The insurance company (which you trust) tells you the exact probability with which the picture will be stolen from you within 10 years. Furthermore, you learn that with the exact same probability the painting will be destroyed during some natural disaster. If you could only insure against one of the two events, which one would you choose? Would you be willing to pay more for one insurance policy than the other?

The experiment presented in this chapter studies whether humans prefer to depend on states of nature (*environmental uncertainty*) or other humans' decisions (*social uncertainty*). In the lottery choice experiment that we present in this chapter, subjects can choose the type of uncertainty on which outcomes of lotteries depend. Different from previous experiments studying these types of uncertainty, the social uncertainty in the experiment does not derive from choices of others in a game or any kind of strategic context and the decisions that other humans took are not morally loaded (e.g. choosing the strategy in a Trust Game). This operationalization of social uncertainty allows for a clean comparison of preferences with regard to social versus environmental uncertainty.

A rational, expected value maximizing agent would not care whether the value it tries to maximize is affected by uncertainty due to some natural disaster or a human stealing from it. Humans, since they are not perfectly rational, may (e)valuate both types of situations very differently in terms of subjective probabilities and emotions involved. Abdellaoui et al. (2011) find that subjects prefer to depend on lotteries where the uncertainty of winning is determined by the weather, compared to a stock market. On a similar line McCabe, Rigdon, and Smith (2003) find that humans do not just care about the probabilities with which a decision is taken in a social context but also about the intentions that led to the decisions.

A clean comparison between environmental and social uncertainty is hard to achieve in the lab. Social uncertainty arises naturally in strategic interaction between two or more humans, e.g. in a game-like setting. This is why (to the best of our knowledge) in all experiments studying social uncertainty, the uncertainty derives from someones action in a strategic situation. Section 3.2.1 reviews these experiments and section 3.2.2 discusses recent findings in decision neuroscience that show potential neural mechanisms leading to different behaviour under both kinds of uncertainty.

Carrubba, Yuen, and Zorn (2007) argue that strategic interaction – to some extend – can be seen as a lottery, where one depends on the actions of others without knowing which actions the others will take. Strategic uncertainty, however, differs in more than one aspect from environmental uncertainty. While environmental uncertainty involves only oneself depending on Nature (a mechanism without intentions), strategic uncertainty includes interdependence between humans and includes beliefs about others intentions. Furthermore, the options that one can choose from create (often morally loaded) externalities on others. This in turn may lead to social preferences over outcomes. Dana, Weber, and Kuang (2007) show that when subjects have to take decisions in a morally loaded context they actually prefer uncertainty on how their decisions affect others. Summarized, one is not making a ceteris paribus comparison when comparing environmental and strategic uncertainty since in the latter, humans encounter more than just a decision problem. To overcome this flaw, we designed an experiment in which the only difference between a social and an environmental uncertainty condition is the source of uncertainty. The social uncertainty involved in treatments of the experiment will therefore not derive from strategic interaction.

We encounter situations of environmental uncertainty that do not arise from strategic interaction regularly. Examples are situations where we depend on decisions that others made without knowing their consequences, often we even depend on actions of others that are not the result of any conscious decision. As an example, an employee opening an email attachment that contains a computer virus may be absolutely unaware of causing harm to the company he is working for. For the employer the source of uncertainty, which he tries to protect his IT from, is not arising from a strategic decision of his employee, while it is also not environmental uncertainty because the source of uncertainty is human behaviour.

Additionally to the differentiation between environmental and social uncertainty we also control the measurability of uncertainty (Knight, 1921). "Measurable" uncertainty (henceforth: *risk*) is characterized by a situation in which the probabilities with which all events occur are known. "Unmeasurable" uncertainty (henceforth: *ambiguity*[1]) is characterized by the absence of known probabilities. In his seminal thought experiment Ellsberg (1961) argues that humans generally avoid ambiguous lotteries in favor of lotteries were the distribution is known. Many experiments since have found that humans indeed are ambiguity averse (Camerer and Weber, 1992).

Table 3.1 shows the 4 possible combinations of the two dimensions along which uncertainty will be distinguished in this chapter. The conditions in the experiment (presented in section 3.3) correspond to the cells in the table.

The research questions of this chapter are:

1. Do humans prefer lotteries with social uncertainty to environmental uncertainty or vice versa?
2. Do humans have different risk preferences in lotteries where they depend on humans instate of Nature?
3. Do we see ambiguity preferences in social uncertainty and are they the same as in environmental uncertainty?

[1]Note that in some parts of the literature this is referred to as *uncertainty*. Unfortunately there is no consistency with using these terms in the literature.

	Distribution known	Distribution unknown
Social	Social Risk (SR)	Social Ambiguity (SA)
Environmental	Environmental Risk (ER)	Environmental Ambiguity (EA)

Table 3.1: Uncertainty concepts implemented

3.2 Literature

3.2.1 Experiments with strategic uncertainty

Heinemann, Nagel, and Ockenfels (2009) elicit certainty equivalents of two lotteries in an experiment. In the first lottery the probability distribution of winning and loosing depends on the actions of other players in a coordination-game (strategic uncertainty condition), in the second lottery the outcome depends on the roll of a die (environmental uncertainty condition). Heinemann, Nagel, and Ockenfels find that certainty equivalents of both lotteries are similar. From a ceteris paribus point of view the comparison Heinemann, Nagel, and Ockenfels are making is problematic. Additional to the source of uncertainty their treatments differ, since their environmental uncertainty condition is characterized by known probabilities and thus is a risky decision problem, while the strategic uncertainty condition is characterized by ambiguity. Furthermore, all arguments made in section 3.1 when it comes to comparing a game with a decision problem apply.

Bohnet and Zeckhauser (2004) – and similarly Bohnet et al. (2008) – addressed many of the issues when it comes to a clean comparison between risk and strategic/social uncertainty. In their experiment subjects play a binary Trust Game, where half of the subjects are first-movers (Trustors) and the other half second-movers (Trustees). They ask Trustors for the minimum acceptable probability (MAP) of playing against a trustworthy Trustee for which they would be willing to make a trust move. Trustors and Trustees than are randomly matched and Trustors will play the trust move if their MAP is smaller than the fraction of trustworthy Trustees. In asking for the MAP Bohnet and Zeckhauser transform the strategic interaction to a risky decision problem. They find that MAPs of Trustors are generally higher when the Trustee's move is based on a decision compared to when the strategy was determined by a chance mechanism. The fact that Trustors asked for an extra risk premium when depending on humans' choices compared to depending on a mechanism is interpreted as evidence for "betrayal aversion"[2]. We argue that Bohnet and Zeckhauser jump to conclusions since as in Heinemann, Nagel, and Ockenfels (2009) they compare a situation where one depends on a neutral mechanism without any intentions with a situation where one depends on a human who had (morally loaded) intentions when taking the conscious decision. An alternative explanation for the finding of Bohnet and Zeckhauser may be what one could refer to as "human aversion" (humans just do not like to depend on other humans).

Similar to Bohnet and Zeckhauser (2004), Fairley et al. (2014) let subjects play a Trust Game as both Trustee and Trustor. When in the role of a Trustor, subjects were assigned to four random Trustees and one random decision of the Trustees was played. There were thus five potential probabilities of encountering a trustworthy Trustee depending on the number of trustworthy Trustees. Trustors had to indicate the amount that they would be willing to pay in order to play the lottery for each potential probability. Fairley et al. compare the amounts per probability with amounts that had to be indicated for standard risky lotteries with the same 5 potential probabilities of winning. They find that choices in lotteries and social lotteries are not correlated.

The experiments discussed do not provide a clear picture of how the various operationalizations of strategic and social uncertainty on the one hand and environmental uncertainty on the other relate to each other. However, since all results were obtained by comparing environmental uncertainty with uncertainty based on some strategic action of another human, it remains unclear how these results relate to a comparison without a strategic context (as we will do in this chapter).

3.2.2 Decision Neuroscience

Experiments in the area of decision neuroscience and neuroeconomics indicate that subjects react differently to situations with social and environmental ambiguity simply because the one involves humans and this leads to activation of different brain areas. Lauharatanahirun, Christopoulos, and King-Casas (2012) study differences in brain activity (via fMRI) when subjects engage in a Trust Game compared to a lottery where the outcome depends on a random

[2]This paper is the core reference in chapter 4 and is discussed in more detail there.

mechanism. They find that especially the amygdala (related to emotions) is more active in the Trust Game.

Sanfey (2007) argues that emotions are crucial in economic decisions that involve other humans and brain areas that involve emotion regulation are therefore more active in situations with social uncertainty. In Sanfey et al. (2003) the authors find that the anterior insula is more active when subjects get unfair offers in an Ultimatum Game where the proposer is a human compared to the proposer being a chance mechanism. The latter seems to evoke less emotions than interaction with humans. This finding is robust across different types of games like Rock-Paper-Scissors (Chaminade et al., 2012), prisoners dilemma game (Krach et al., 2008; Rilling et al., 2004) and Trust Games (McCabe et al., 2001). These experiments also show that humans invest more effort when their counterpart is human.

McCabe et al. (2001) and Rilling et al. (2004) similarly find that brain areas known to be crucial for theory of mind (the ability to put oneself into the shoes of someone else) are more active when subjects know they are playing with humans than when they know they are playing with computers. On the same line Rilling et al. (2002) study activation in the striatum, which is a crucial brain area when social decisions have to be made, when subjects interact with computers and robots. This area is less active when dealing with situations that involve environmental uncertainty.

Although the neuroeconomic literature shows that from a perceptional point of view environmental and social uncertainty are different, the literature does not point to a clear prediction on whether humans would dislike or prefer situations with social uncertainty to environmental uncertainty.

3.3 Methods

3.3.1 General design

Each subject was confronted with four lotteries in a random order. Each of these lotteries contained one of the kinds of uncertainty presented in Table 3.1. After each lottery subjects indicated (through a multiple price list) how high a safe payoff would need to be in order for them to not engage in the lottery. After the four lotteries, subjects had to play one of the previous lotteries an additional time and could indicate which of those they would prefer. The entire experiment was computerized using z-Tree (Fischbacher, 2007).

3.3.2 Treatments

In the lotteries in treatment ER (Environmental Risk) and EA (Environmental Ambiguity) subjects had to guess the result of a card draw. Cards were drawn from a stack of 10 cards. Each card was either an *A*- or a *B*-card. In ER the distribution was 50/50 and subjects were explicitly told so. In EA subjects did not know the distribution and were told that any number of *A*-cards from 0–10 was possible and that the remaining of the 10 cards were B-cards. The computer would randomly select one of the virtual cards and subjects had to guess if that card was an *A*- or a *B*-card. If their guess was, correct they would receive 100 ECU for that task otherwise 0. 10 ECU were worth 1 Euro.

The lotteries in treatments SR (Social Risk) and SA (Social Ambiguity) were almost identical to those in ER and EA. Before the started a survey was conducted among students that did not participate in the experiment. In treatments SR and SA instead of cards, the computer would draw a random answer of a participant in the survey. Subjects in the experiment were told that 10 participants of the survey had to indicate their preference towards two different pictures. Subjects got no information on the content of pictures or the artists. They were only told that the one picture would be referred to as picture *A* and the other as *B*. The task of the subject was to guess whether the participant of the survey drawn by the computer preferred picture *A* or *B*. In SR subjects knew that the distribution was 50/50 and in SA the distribution was unknown to the subject. It was also made clear that the participants in SR are not the same participants as in SA.[3]

3.3.3 Dependent variables

To elicit subjects' preferences regarding the lotteries in each treatment two different elicitation mechanisms were used. After subjects played all the lotteries in all 4 treatments they were presented with a table (Appendix 3.6.1) in which the rows contained all possible pairwise comparisons between the 4

[3]This surveys of course really took place, done with pictures from Klee and Kandinsky on the campus of the university in Jena.

treatments. Per pair of treatments subjects indicated which of the treatments they would prefer to play as an additional 5th treatment. One of these pairs of treatments was chosen randomly by the computer and the subject's preferred treatment was then played. To rule out order effects with regard to the order in which treatments are paired, the comparison that subjects had to make within each pair was not directly about treatments, but about rounds. Since the treatment per round was determined randomly, the treatments in each row of the comparison table also have a random order per subject.

As a second elicitation mechanism subjects had to fill in a multiple price list (Appendix 3.6.3) in every treatment after taking their guess on A or B in the lottery. In this multiple price list subjects had to choose 10 times between a secure payoff that ranges from 9 to 99 ECU in steps of 10 ECU and an uncertain payoff which would be either 0 or 100 ECU depending on the result of the lottery. As in Holt and Laury (2002) the relative frequency of lottery-choices will be used as a measure for preference for that lottery.

3.3.4 Instructions and controls

Before subjects got instructions per treatment they watched a video (2:36 minutes) with general information. The video is available at `http://www.mikefarjam.de/video3`. Appendix 3.6.1 contains the full set of instructions describing the lotteries in each treatment.

To avoid that differences in preferences regarding the treatments may be driven by complexity aversion (Sonsino, Benzion, and Mador, 2002), the instructions per treatment were as similar as possible in terms of length, wording and syntactic structure. Table 3.2 gives a ruff overview of the complexity of the instructions in each treatment.

To avoid order effects the treatments/lotteries were presented in a random order per subject. To control whether subjects understood the distribution of cards in a treatment, they were asked at the end of the experiment how many A- and B-cards/survey answers were in each of the stacks/surveys per treatment. The answers were incentified with 2 ECU for correctness.

Treatment	Sentences	Words	Characters
Environmental Risk	4	51	272
Environmental Ambiguity	4	54	288
Social Risk	4	47	288
Social Ambiguity	4	51	301

Table 3.2: Comparing the complexity of the (German) instructions in each treatment

3.4 Results

3.4.1 Subjects

88 subjects participated in this study. All subjects were recruited via ORSEE (Greiner, 2004). Since studies like Dohmen et al. (2011) show that risk-preferences differ with gender, only male subjects were recruited to reduce within sample variability. All sessions were run in May 2015 in the laboratory of the Friedrich Schiller University Jena. 76% of our subjects were students.

3.4.2 Payoff

To avoid endowment effects only one of the treatments was chosen randomly at the end of the session for payoff. Subjects earned on average 7 Euro (including a 2.5 Euro show-up fee). The experiment (including the payment) took about 30 minutes.

3.4.3 Pairwise comparison

This subsection compares how often subjects preferred one treatment above one of the other 3 treatments. Thus, the maximum number of times a lottery could be preferred above other lotteries is 3 and the minimum is 0. Table 3.3 shows the result of a pairwise comparison of all 4 treatments.

From Table 3.3 and Figure 3.1 (left) we can derive the following order of preferences: $ER \succ SR \succ EA \sim SA$. The fact that $ER \succ EA$ and $SR \succ SA$ indicates that subjects were ambiguity averse. Ambiguity aversion

	ER	EA	SR
EA	0.0000		
SR	0.0018	0.0000	
SA	0.0000	0.5059	0.0000

p-values adjusted for multiple testing with the Holm–Bonferroni method.

Table 3.3: P-values of a pairwise comparison between treatments with a Wilcox rank-sum test

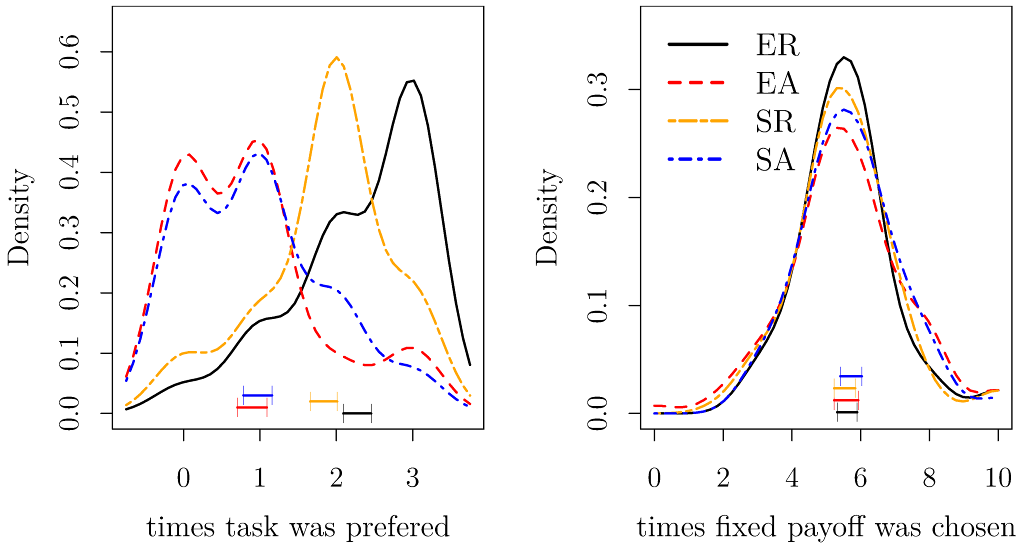
thus seems to be found not just in the environmental but also in the social domain. Furthermore, 66 % of subjects preferred environmental risk above social risk in the direct comparison.

To check whether the results are driven by an order effect (despite the randomization of the order of treatments per subject) two mixed effects model were used to predict the preferences of subjects regarding a treatment. An ANOVA comparing the model with and without the order of treatments as a fixed factor shows that the model without order performs better in terms of AIC. The preferences subjects had regarding the treatments thus not seem to be affected by the order in which the treatments were presented.

3.4.4 Multiple price list

Subjects had to choose 10 times between a fixed secure payoff and the uncertain payoff of a lottery. The expected payoff of all lotteries was 50 ECU. Hence rational, risk-neutral agents would choose the payoff of the lottery if the fixed payoff is below 50 ECU and choose the fixed payoff if it is above 50 ECU. Given the multiple price list subjects were confronted with (see Appendix 3.6.3) one would expect that subjects choose 5 times the fixed payoff and 5 times the payoff of the treatment.

On average subjects chose the fixed payoff 5.6 times, which is more often than a rational, risk-neutral agent would and which indicates that subjects were (as usually found) risk-averse. 33% of subjects chose the fixed lottery equally often in all treatments, indicating that they were indifferent between all treatments. Figure 3.1 (right) shows that the distributions of choices for the payoff of the lottery per treatment are almost identical. Furthermore, 12.5% of subjects had more than one switching point in the multiple price list and 10% of subjects had more than 1 switching point which indicates that



Per distribution of answers the 95% bootstrap confidence interval of the mean is shown.

Figure 3.1: Left, distributions on how often subjects preferred each treatment above the other 3 treatments. Right, distributions of choices for the lottery instead of the safe payment per treatment in the multiple price list.

some did not understand how a multiple price list works. However, multiple switching points are often found when using multiple price lists for preference elicitation (Andersen et al., 2006).[4]

Summarized, analysis of the data with regard to choices in the multiple price list seems problematic. The statistical analysis of subjects' choices in the multiple price list will therefore only be rudimentary.

A Friedman-test comparing the mean number of times the lottery was preferred above the fixed amount shows that the differences between treatments with regard to choices in the multiple price list were not significant ($p = 0.37$, $\chi^2 = 3.16$). A Bartlett-test comparing the variance between groups finds that the only significant difference regarding variance can be found between treatments ER and EA (not adjusted for multiple testing: $p = 0.029$, $K^2 = 4.77$).

[4] Appendix 3.6.2 shows the results of a pilot study of this experiment where a BDM mechanism (Becker, DeGroot, and Marschak, 1964) was used to elicit preferences. Results obtained by the BDM mechanism are almost the same as with the multiple price list.

Neither of the other comparisons lead to p-values below the 0.1 significance level. Looking at Figure 3.1 (right) it seems unlikely that differences would become significant with a larger sample. It thus seems that although the previous subsection shows that subjects prefer some treatments above others, the treatment they are in does not change their risk-preference regarding an opt-out option from that treatment.

3.4.5 Robustness checks

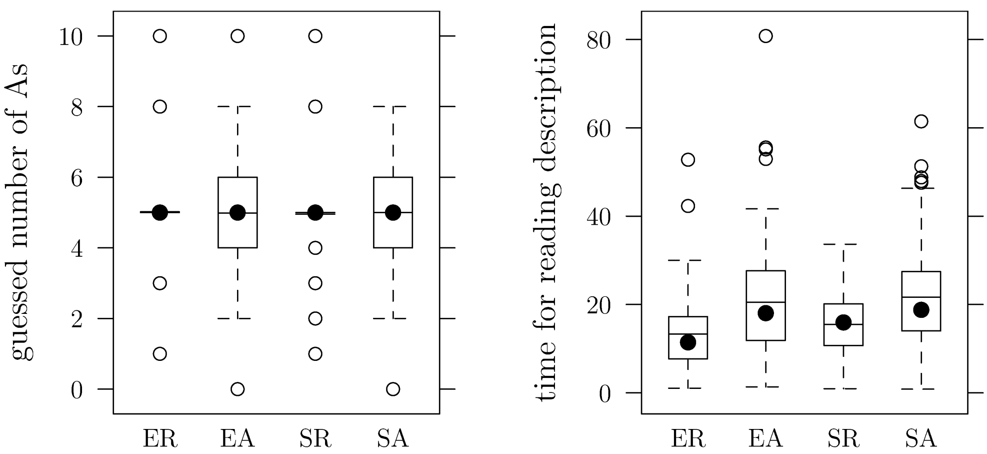
To check whether the results may be driven by different believes about the distributions in each treatment subjects had to guess the number of A's in each treatment. Figure 3.2 (left) shows that on average subjects had the same expectations in all treatments and that the great majority in ER and SR understood that there were exactly 5 A's in these treatments.

Furthermore, we measured per subject how long they remained on screens that presented the description of a treatment (the exact instructions can be found in Appendix 3.6.1). The time spend on this screen can be seen as a proxy for perceived complexity of the description. Figure 3.2 (right) shows that there were hardly any differences between treatments EA and SA and treatments ER and SR. However, subjects remained on average 7.2 seconds longer on the screens that presented instructions in treatment EA than in treatment ER and 6.2 seconds longer on screens of SA than SR.

Summarized, the fact that subjects preferred ER to SR seems not to be driven by a misunderstanding of the two treatments or differences in perceived complexity. However, the fact that subjects generally prefer SR to SA and ER to EA may be explained by both: ambiguity and complexity aversion.

3.5 Discussion

In the experiment presented, subjects had the choice between engaging in a lottery where they depend on a distribution of outcomes based on decisions of humans and a lottery where the distribution does not depend on humans but only on Nature. When the distributions of outcomes was ambiguous, preferences with regard to both lotteries were on average the same. In the



Box-and-whisker plots per treatment. Dots represent medians, lines means.

Figure 3.2: Left, subjects' believe about the frequency of A's. Right, time spend for reading description on distribution of A's

risky lotteries where the distribution of outcomes was known and identical, subjects clearly preferred to depend not on other humans but on Nature.

This finding is in line with the conclusions from the experiment by Bohnet and Zeckhauser (2004). While Bohnet and Zeckhauser show that humans demand a "risk premium" in order to accept strategic dependence on another human compared to a chance mechanism, we show that humans demand this premium even outside any strategic context. Bohnet and Zeckhauser conclude that subjects are betrayal averse. In the light of our results Bohnet and Zeckhauser's finding may not at all be related to an aversion towards betrayal but simply to the fact that one generally has an aversion to depend on others (irrespective of the others intention).

To the best of our knowledge this experiment shows for the first time that humans care about the fact that they depend on other humans irrespective of the outcome and even in the absence of intentions of the human on whom they depend. This suggests that differences in perception between social and environmental uncertainty are more fundamental than expected. This finding is in line with the claim of McCabe, Rigdon, and Smith (2003) that humans do not just care about the probabilities with which an event occurs but also about the process that led to these probabilities. In our experiment we find that even when the distribution on which an outcome in a lottery depends is identical and known, humans may systematically prefer one lottery to the other.

In our experiment subjects had clearly different preferences regarding environmental and social risk, yet they did not have different risk preferences once facing one of the two types of risk in a lottery. This may mean that humans given the choice whether they want to depend on humans or Nature would choose for Nature, but that humans once they are in a specific situation do not differ in terms of behaviour in both conditions. However, risk preferences are not the only indicator for behaviour and future studies have to look more carefully at how human behaviour under environmental and social risk differs.

We can only speculate on the reasons why subjects preferred to depend on Nature and not on other humans' decisions. Besides the differences in the neural mechanism that may work depending on the kind of risk (see section 3.2.2), Heath and Tversky (1991) show that humans generally prefer to engage in lotteries which they know more about or feel more knowledgeable. This holds even if the knowledge is not relevant for the outcome of the lottery. Subjects in the experiment may have felt less knowledgeable about lotteries with social uncertainty compared to environmental uncertainty, simply because being confronted with decisions of other humans was perceived as less transparent by subjects than being confronted with the letter on a card. This is of course only a speculation and the cognitive mechanism that makes humans prefer environmental above social risk may be a different one.

The results we obtained also have methodological implications. One method that is used to control for strategic uncertainty in a game is to have a baseline condition with the normal game and a treatment condition with a computerized player where the algorithm of the computer is known to subjects (e.g. Koch and Penczynski (2015)). Our results however show that playing against a computer may be perceived as fundamentally different from playing and depending on a human, irrespective of strategic considerations. Conclusions based on such a comparison are therefore problematic.

If we interpret strategic interaction as a lottery where the outcome depends on a second player the results of this chapter suggest that the nature of the second player maybe an important feature in itself, irrespective of any strategic considerations. This suggests that humans may behave differently in strategic interaction with humans from strategic interaction with e.g. machines, even if they know that machine and human will behave identically. As stated in chapter 1, we live in a time where the number of interactions between humans and machines grows inexorably and more and more human-human interaction is replaced by human-machine interaction. It is therefore of great importance to study exactly how humans perceive strategic interaction with machines differently from interaction with humans and how this changes their (economic) decisions.

3.6 Appendix

3.6.1 Instructions

This subsection contains the instructions in each treatment translated to English. To get an idea of the general length of the original instructions the German versions are printed in italics for the first four parts of the experiment.

Environmental Risk

We took 10 cards from a large stack of cards and shuffled these cards. On 5 of these cards an *A* is written, on the other 5 cards a *B* is written.
The computer will draw one of the 10 cards randomly. Guess whether there will be an *A* or *B* on the card.

Wir haben aus einem großen Stapel mit Karten 10 Karten genommen und diese zu einem Stapel gemischt. Auf 5 dieser Karten steht A*, auf den anderen 5 Karten steht ein* B*.*
Der Computer wählt eine der 10 Karten zufällig aus. Raten Sie ob auf der ausgewählten Karte A *oder* B *steht.*

Envirionmental Ambiguity

We took 10 cards from a large stack of cards and shuffled these cards. On 0 to 10 cards (the exact number is unknown to you) an *A* is written, on the other ones a *B* is written.
The computer will draw one of the 10 cards randomly. Guess whether there will be an *A* or *B* on the card.

Wir haben aus einem großen Stapel mit Karten 10 Karten genommen und diese zu einem Stapel gemischt. Auf 0 bis 10 Karten (die genaue Zahl wissen Sie nicht) steht A*, auf den anderen* B*.*
Der Computer wählt eine der 10 Karten zufällig aus. Raten Sie ob auf der ausgewählten Karte A *oder* B *steht.*

Social Risk

We conducted a survey on the campus among 10 people and showed them two different pictures. 5 of the participants preferred picture *A*, the other 5 participants preferred picture *B*.
The computer will draw one random participant from the 10. Guess whether the participant drawn preferred picture *A* or *B*.

Wir haben in einer Befragung auf dem Campus 10 Menschen zwei verschiedene Bilder gezeigt. 5 der Befragten bevorzugten Bild A*, die anderen 5 Befragten bevorzugten Bild* B*.*
Der Computer wählt einen der 10 Befragten zufällig aus. Raten Sie ob der ausgewählte Befragte Bild A *oder* B *bevorzugte.*

Social Ambiguity

We conducted a survey on the campus among 10 people and showed them two different pictures. 0 to 10 participants (the exact number is unknown to you) of the participants preferred picture *A*, the others preferred picture *B*.
The computer will draw one random participant from the 10. Guess whether the participant drawn preferred picture *A* or *B*.

Wir haben in einer Befragung auf dem Campus 10 Menschen zwei verschiedene Bilder gezeigt. 0 bis 10 Befragte (die genaue Zahl wissen Sie nicht) bevorzugten Bild A*, die anderen Bild* B*.*
Der Computer wählt einen der 10 Befragten zufällig aus. Raten Sie ob der ausgewählte Befragte Bild A *oder* B *bevorzugte.*

Choice Task 5

In the following table (Table 3.4) 2 of the 4 parts of the experiment are put next to each other. Indicate per row which of the parts of the experiment you prefer. The computer will randomly chose one of the rows. The part of the experiment that you preferred in the determined row will be played as an additional part of this experiment.[5]

[5] Additionally subjects got a description of each part of the experiment as shown in the previous subsections.

Option A	Option B
1st part of the experiment	2nd part of the experiment
1st part of the experiment	3rd part of the experiment
1st part of the experiment	4th part of the experiment
2nd part of the experiment	3rd part of the experiment
2nd part of the experiment	4th part of the experiment
3rd part of the experiment	4th part of the experiment

Table 3.4: Table used for pairwise comparisons of tasks

3.6.2 BDM elicitation mechanism

In a pilot experiment the BDM mechanism was used (Becker, DeGroot, and Marschak, 1964) to elicit subjects' (N = 71) preferences with regard to the treatments. Figure 3.3 compares the results obtained with the help of the BDM mechanism with those from the experiment discussed in the section 3.3. The distributions of preferences hardly differ between those two elicitation mechanisms.

3.6.3 Multiple Price List

Table 3.5 shows the multiple price list used to elicit subjects preferences regarding the lottery played in each treatment. In every subjects can chose between a sure payoff (Option A) and participating in the lottery (Option B). At the end of the experiment one of the rows was selected randomly for payoff according to the decision in that row.

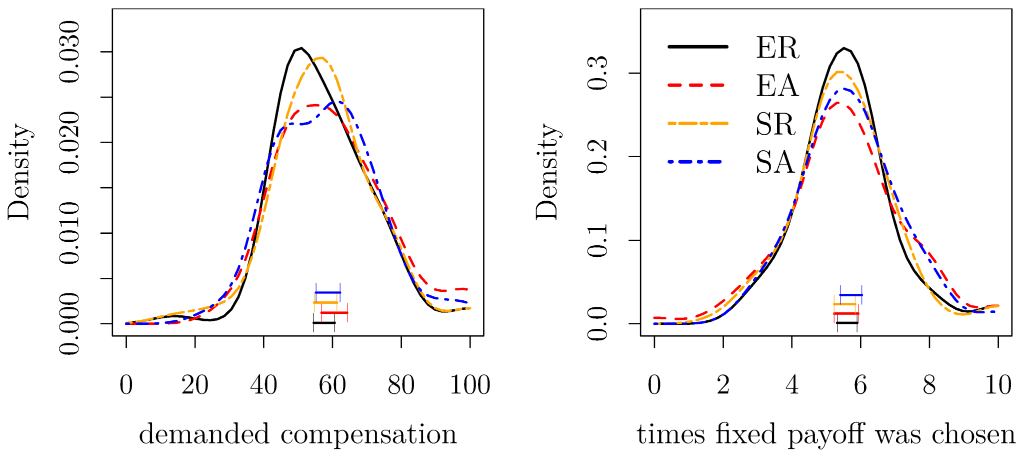


Figure 3.3: Left, preferences w.r.t. the treatments elicited by the BDM-mechanism; Right, elicited with the help of a multiple price list. Per treatment the 95% bootstrap confidence interval of the mean is shown.

Option A	Option B
Get 9 ECU for sure	your payoff depends on the lottery
Get 19 ECU for sure	your payoff depends on the lottery
...	...
Get 89 ECU for sure	your payoff depends on the lottery
Get 99 ECU for sure	your payoff depends on the lottery

Table 3.5: The multiple price list presented to subjects after each treatment

Chapter 4

Betrayal aversion! Betrayal aversion?

4.1 Introduction

Why do we feel bad when we get to know that someone has betrayed us? Is it the outcome that we perceive unfair, knowing that given a different decision of the person we trusted (henceforth *Trustee*) the outcome would have been better for us? Or is it the knowledge that one's trust was betrayed?

Part of that question has been answered by Bohnet and Zeckhauser (2004), which forms the basis of the experimental design used for this chapter and will therefore be discussed in detail in the upcoming paragraphs. They study social risk taking and find that subjects preferred an unequal allocation of money that had been the result of some chance mechanism to the same unequal outcome that had been the result of somebody else's decision. For their study, Bohnet and Zeckhauser use a binary version of the Trust Game (Berg, Dickhaut, and McCabe, 1995), which is shown in Figure 4.1. The intuition behind the binary Trust Game is that Player 1 has to choose between sharing a payoff of 20 ECU equally between both players (option A) and giving Player 2 the option to allocate a total of 30 ECU among both players (option B). When choosing option B, Player 1 has to take into account the possibility that Player 2 can take advantage of his allocation power and keep most of the 30 ECU while leaving Player 1 with less than what option A warrants. Bohnet and Zeckhauser match Player 1s with a group of Player 2s that have already made their decisions. After Player 1 makes his choice between options A and B he is matched with one of Player 2s in the group. Instead of choosing between A and B directly, Bohnet and Zeckhauser ask Player 1s for the minimum acceptable probability (MAP) of encountering a Player 2 in the group that chooses option D, for which they would be willing to choose option B. The authors compare the MAP in the binary Trust Game with the MAP in the Risky Dictator Game (see Figure 4.1), where Player 2s are passive and it is a random mechanism that allocates resources if Player 1 chooses option B. Relative to the Trust Game, MAPs in the Risky Dictator Game were lower. Since Player 1s were conditioning on the same distribution of money in both games, Bohnet and Zeckhauser conclude that subjects are betrayal averse. That is, the same unfavorable outcome (in a trust context) feels worse when it is the result of a deliberate decision as opposed to when it is the result of some chance mechanism. The subjects compensate for the additional disutility by demanding a higher MAP in the Trust Game.

Bohnet and Zeckhauser (2004) also elicit the MAP in a lottery that is identical to the Risky Dictator Game except for the fact that there is no Player 2 who's payoff could be affected by the lottery. There were only negligible differences (far from any statistical significance) as far as MAPs in the Risky Dictator Game and the lottery. That is, it seems that the payoff of Player 2 did not affect the preferences of Player 1 in the Risky Dictator Game. The payoff of Player 2 only affected preferences in the Trust Game, where the payoff was the result of the decision of Player 2.

Overall, Bohnet and Zeckhauser (2004) show that trusting another human feels different from taking a risk in a lottery. It is not just the outcome, i.e., the social preferences, that matters, but also the process that leads to the outcome. This is very much in line with the results presented in the previous chapter, where we find that the subjects prefer lotteries where the winning condition depends on someone else's choice as opposed to lotteries where a mechanism involving no human determines the outcome. As discussed in the previous chapter, it remains unclear whether the effect that Bohnet and Zeckhauser observe is the result of a more general "human aversion" or whether the effect can only be found in a trust context.

In Bohnet and Zeckhauser (2004), it remains unclear how exactly the decision of Player 2 affects the preferences of Player 1. By comparing MAPs in the Risky Dictator Game and the Trust Game they rule out the possibility that it is the distribution of money (i.e., disadvantageous inequality) alone

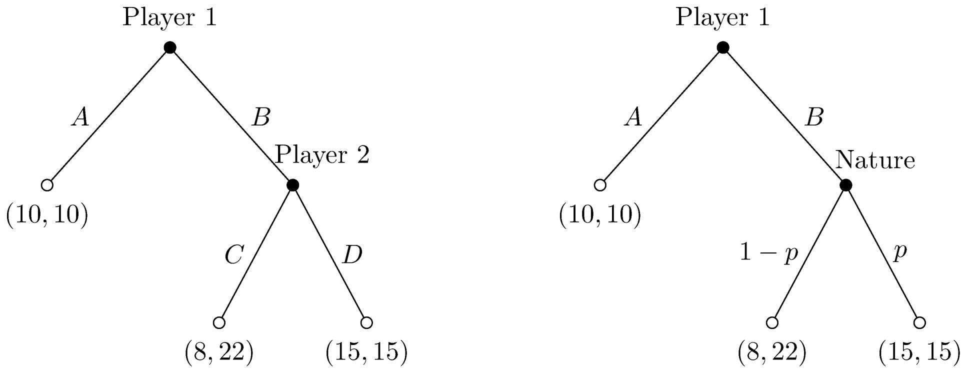


Figure 4.1: Left, the binary version of the Trust Game; right, the Risky Dictator Game. In brackets, the payoffs of Player 1 and 2, respectively

that explains the preferences. However, it remains unclear whether the mere knowledge that one's trust has been betrayed is already sufficient to create disutility, even without the resulting benefits on the betrayer's side. The experiment presented in this chapter is designed to answer exactly that. Our expectation is that knowing that one's trust has been betrayed is already sufficient to create disutility, irrespective of the consequence.

The following section reviews the relevant literature on betrayal aversion. In section 4.3, we present the design of the experiment and the concept of a game-related lottery, a lottery where the chance of winning is equal to the chance of encountering a trustworthy partner in the Trust Game or Risky Dictator Game. In the game-related lottery, the payoff of the decision maker thus depends on the choice previously made by somebody else in a trust context, without the latter experiencing the consequences of ... decision. In section 4.4, we compare MAPs between the Trust Game and Risky Dictator Game as well as between the Trust Game-related and Risky Dictator Game-related lotteries. Our main hypothesis is that the subjects' MAPs in the game-related lotteries differ in the same way as the MAPs in the actual games. This would be evidence in favor of the view that learning that one's trust has been betrayed is already sufficient to create disutility, irrespective of the consequence. Section 4.5 concludes by discussing the results.

4.2 Literature

According to Berg, Dickhaut, and McCabe (1995), trust just like self interest is an economic primitive, and the tendency to trust seems to be a heritable trait (Cesarini et al., 2008). In this section, we summarize the literature that studies to which extend the decision to trust is influenced by betrayal aversion.

Trustors always have to take into account the possibility that their trust can be exploited by Trustees. As Coleman (1994) argues, a trusting decision is thus comparable to the decision to participate in a lottery, where the outcome depends on the Trustee's decision. Bohnet and Zeckhauser (2004) found that the decision to trust is not driven by one's preferences regarding risk only, but also by aversion for betrayal. This study (already discussed in the introduction of the chapter) was replicated by Bohnet et al. (2008) in Brazil, China, Oman, Switzerland, and Turkey. The effect of betrayal aversion was only significant at a 5-percent level in Brazil and China and at a 10-percent level in Switzerland. However, in all of the countries the direction of the effect was in line with the notion of betrayal aversion.

Other authors find mixed evidence with regard to betrayal aversion. Since the experiment of Bohnet and Zeckhauser is by far the most cited work in that area and they were the first to use the term *betrayal aversion*, work with alternative operationalizations of the term will not be discussed in this section (e.g. De Dreu (2012), who lets the subjects self-report on how betrayal averse they are). All the studies discussed in this section consider a subject betrayal averse if he prefers that the decision of the Trustee in the trust relationship is made by Nature rather than by a human.

The results of Kosfeld et al. (2005), even though not designed to study betrayal aversion, can be interpreted in that regard. They found that there was no statistical difference between investments in a continuous version of the Trust Game and investments in a Risky Lottery with the same expected return. Since Bohnet and Zeckhauser found that there is no significant difference in preferences between the Risky Dictator Game and a lottery with the same expected return, we can interpret the results of Kosfeld et al. as contradictory to Bohnet and Zeckhauser.

Lauharatanahirun, Christopoulos, and King-Casas (2012) study differences in brain activity (via fMRI) when subjects engage in a Trust Game as opposed to a lottery where the outcome depends on a chance mechanism. Although they find that different brain areas are active in both kinds of situations the authors find no significant difference between investments between the two. Unlike Bohnet and Zeckhauser, they make within-subject comparisons, which may be one reason why they do not find betrayal aversion. However, even though not significantly, engagement in the Trust Game is slightly higher than in the lottery.

Fetchenhauer and Dunning (2012) found that subjects would rather engage in a trust game than in a lottery, the subjects were thus "betrayal seeking". Fetchenhauer and Dunning argue that most likely, the effect is due to a specific detail in the design, which is different from Bohnet and Zeckhauser (2004). In the design of Fetchenhauer and Dunning, the Trustors were assigned a Trustee first and then had to choose their move in the Trust game; while in Bohnet and Zeckhauser the Trustors had to make their choice while facing a group of Trustees of which they only knew the ratio of the trustworthy. Only after the Trustors made their choice in Bohnet and Zeckhauser were they assigned a Trustee. According to Fetchenhauer and Dunning, playing against an individual may feel psychologically very different from playing against a group of players, which might explain the conflicting results.

Aimone and Houser (2012) is most closely related to our research question. In their experiment, the subjects are in one of two treatments. In the KNOW treatment, the subjects engage in a binary Trust Game. As in Bohnet and Zeckhauser (2004), the Trustors are matched with a group of Trustees, both sides choose their move simultaneously and then the Trustors are matched with a random Trustee from the group of potential Trustees. The DONTKNOW treatment is the same as KNOW except for the fact that after the Trustees indicate whether they would want to betray or not, a computer determines their actual move. The probability of the computer generating the betrayal move is equal to the fraction of the Trustees that prefer the betrayal move. In the DONTKNOW treatment, the Trustors thus stay ignorant of their Trustee's decision. According to Aimone and Houser, any difference between the two treatments can be attributed to preferences with regard to knowing that the person that benefits from one's loss chooses to do so deliberately. In line with Bohnet and Zeckhauser, Aimone and Houser find that the subjects choose to make their payoff dependent on a Trustee more often in the DONTKNOW treatment.

Summarized, a careful consideration of studies on betrayal aversion other than Bohnet and Zeckhauser (2004) and Bohnet et al. (2008) shows that the

Framed in terms of...

		C	D
Type of game	Risky Dictator Game	RD-C	RD-D
	Trust Game	TG-C	TG-D

Table 4.1: Treatments, where C stands for the low return for Trustors and D for the high return

Order	Task
1st or 2nd	Trust or Risky Dictator Game as Player 1
1st or 2nd	Game-related lottery
3rd	Trust or Risky Dictator Game as Player 2
4th	Standard lottery

Table 4.2: Order of tasks

preference is not found universally. Whether the preference or even the opposite is found depends on the exact operationalization and context within which betrayal aversion is studied.

4.3 Methods

4.3.1 General design

After the subjects saw a video with general instructions (5 minutes) and answered a set of control questions, they were assigned to one of the 4 treatments shown in Table 4.1. Each treatment was comprised of 4 separate tasks shown in Table 4.2. To prevent endowment effects, only one of them was randomly selected for payoff at the end of the session. Furthermore, the subjects would only get feedback on the others' choices in the game once everyone was done with all the tasks. The entire experiment was computerized using z-Tree (Fischbacher, 2007).

4.3.2 Treatments

The experiment was comprised of 4 (2x2) treatments, which are shown in Table 4.1. In all of the treatments, the subjects played either the Trust Game or the Risky Dictator Game described earlier in section 4.1 and shown in Figure 4.1. The Subjects played the respective game twice; once in the role of Player 1 and once in the role of Player 2.

When playing the game in the role of Player 1, the subjects were told that some 10 other subjects in the laboratory had been assigned to them as potential Player 2s. Player 1 then had to indicate whether they would play option A or B conditional on the number of Player 2s that had chosen either C (the betrayal move) or D (the trustworthy move)[1]. To control for framing effects when Player 1s had to condition their choice on the decisions of Player 2s, we had two treatments per game: one where they conditioned their choice on the fraction of Player 2s that had played option C (treatments RD-C and TG-C) and one where they conditioned on option D (treatments RD-D and TG-D). Details on how the conditioning was implemented are described in the next subsection.

In addition to the game, the subjects played what we call a *game-related lottery*. The subjects had to choose between a safe option, giving them 10 ECU (5 Euro), and a risky lottery where they could win either 8 or 15 ECU. In terms of expected payoff, the lottery was thus identical to the Trust Game and Risky Dictator Game which they had played as Player 1. The probabilities with which each state in the lottery would be realized were taken from the game that subjects would play as Player 1. For treatment TG-C this would mean that if 1 out of 10 potential Trustees in the Trust Game were to choose move C, then the probability of winning 8 ECU in the lottery would be 0.1. Again, decision makers had to condition their choice between option A (safe option) or B (risky option) on the choices of the potential Player 2s in the game. The crucial difference between the game and the game-related lottery is that even though Player 1 depends on the decision of Player 2, Player 2 is not affected by the choice made in the game. Again, the game-related lottery was framed in terms of either C or D moves of potential Player 2s. The game-related lottery in treatments RD-C and RD-D worked similarly, but Player 1 had to condition on the moves of Player 2s in the Risky Dictator Game.

[1]Of course we framed the options neutrally as 'C' or 'D' and not as 'betrayal' or 'trustworthy'.

As shown in Table 4.2, we controlled for possible order effects between the game and the game-related lottery by letting subjects play those in a random order. After choices were made as Player 1 in the game and the game-related lottery, subjects would choose their move as Player 2s. We controlled for the subjects' risk aversion by using the same task as in the game-related lottery. However, in the lottery measuring risk aversion, the computer tossed 10 virtual coins with C and D on them. Again, subjects had to condition on the number of Cs or Ds, depending on the framing condition they were in. Once all the decisions were made, each subject was matched as Player 1 with a random Player 2. Additionally subjects were also matched in the role of Player 2 with *another* random Player 1. It was thus not possible for the subjects to reciprocate their partner's choice when switching the roles.

4.3.3 Multiple price list

Unlike Bohnet and Zeckhauser (2004), we used the multiple price list method to elicit the subjects' preferences with regard to the game-related lottery or the game they played as Player 1. If one is interested in how much betrayal subjects are willing to accept, one should ask for the expected minimum fraction of Trustees that are trustworthy (just like Bohnet and Zeckhauser did) for which Trustors are willing to trust. Since in some treatments we frame the game in terms of the fraction of Trustees that are *not* trustworthy, we would have to ask Trustors in these treatments to condition on the *maximum* fraction of Trustees. To avoid a difference in asking per framing treatment, we asked the subjects to make a series of statements of the following kind: If x out of 10 potential Player 2s chose option C (D), I would choose... . There were 11 such statements, with x ranging from 0 to 10 and permissible answers being A and B. The subjects are supposed to switch from option A to B at one of the 11 statements and this switching point should roughly correspond to the Minimum Acceptable Probability used by Bohnet and Zeckhauser. Furthermore, we consider this to be a better way of eliciting preferences, since it is a well established finding that many cognitive biases in probabilistic reasoning can be avoided by presenting probabilities in frequency formats rather than probability formats (Tversky and Kahneman, 1974).[2]

[2]An example of a multiple price list used by us can be found in Appendix 4.6.2.

4.3.4 Instructions and controls

After watching an instruction video (available at `http://www.mikefarjam.de/video1`) the subjects had to answer 5 control questions such as: "5 out of 10 potential Player 2s chose option C. You said you would play option A if that many players were to choose option C. What is your payoff from the game?". 2 ECU (1 Euro) could be earned by answering the control questions correctly. Furthermore, at the end of the experiment we asked the subjects if they had understood the rules of the experiment by the time they made their decisions (the permissible answers were *yes* and *no*). The subjects were informed that all interaction within a given pair was one-shot and anonymous.

A significant difference between the instructions used by Bohnet and Zeckhauser and us is that our subjects were told of all the treatments they could end up in. Only after receiving all the instructions and answering the control questions were they told in which treatment they were. We chose to do so to rule out the possibility of attributing our results to the differences in instructions among the treatments. On the one hand this may lead to a demand effect (Orne, 1962) but on the other hand this makes the design closer to the ceteris paribus principle.

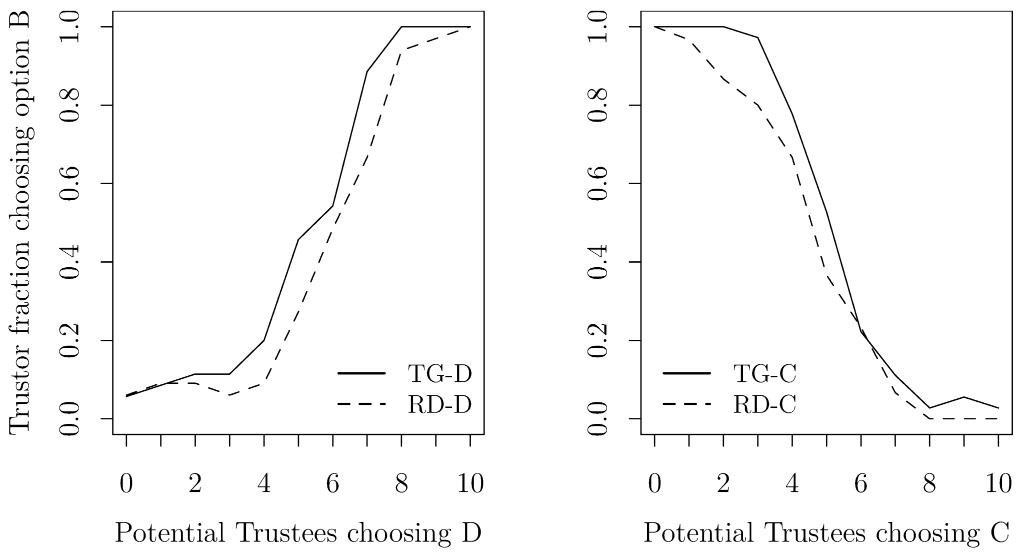
4.4 Results

4.4.1 Subjects and payoffs

184 subjects participated in this study. All subjects were recruited via ORSEE (Greiner, 2004). The sessions were run in January 2016 in the laboratory of the Friedrich Schiller University Jena. 92% of our subjects were students and 33% of our subjects were males. The average earnings were 7.3 Euros and the experiment lasted 35 minutes including payment.

4.4.2 Trust Game vs Risky Dictator Game

Figure 4.2 provides an initial impression of the willingness of Player 1s to play option B in the games given the options chosen by the 10 potential Player 2s. As expected, we can see that the willingness to play option B (trust) is



Since the subjects could have more than 1 switching point in the multiple price lists, the fractions of Player 1s choosing option B are not monotonically in- or decreasing with choices of Player 2s.

Figure 4.2: Choices of Player 1s conditional on choices of potential Player 2s. *C* is the low return for the Trustor, *D* the high return

increasing with the number of potential Player 2s playing option D (trustworthy). This holds irrespective of whether Player 1 had to condition on option C or D. Switching from the safe choice to the risky lottery was rational (in terms of maximizing the expected value) when 3 or more Trustees would play option D. As expected (Holt and Laury, 2002), the subjects were on average risk averse since most of them would switch only if a much larger number of potential Trustees would choose option D.

Surprisingly, Player 1s generally chose option B more often in the Trust Game treatments (TG-C and TG-D) rather than in the Risky Dictator Game treatments (RD-C and RD-D). Player 1s thus preferred unfavorable inequality resulting from a strategic decision of Player 2 to the same inequality resulting from a chance event. This is exactly the opposite of what we expected to find and the opposite of the standard effect reported by Bohnet and Zeckhauser (2004).

Throughout the following analysis we will use the fraction of rows in the

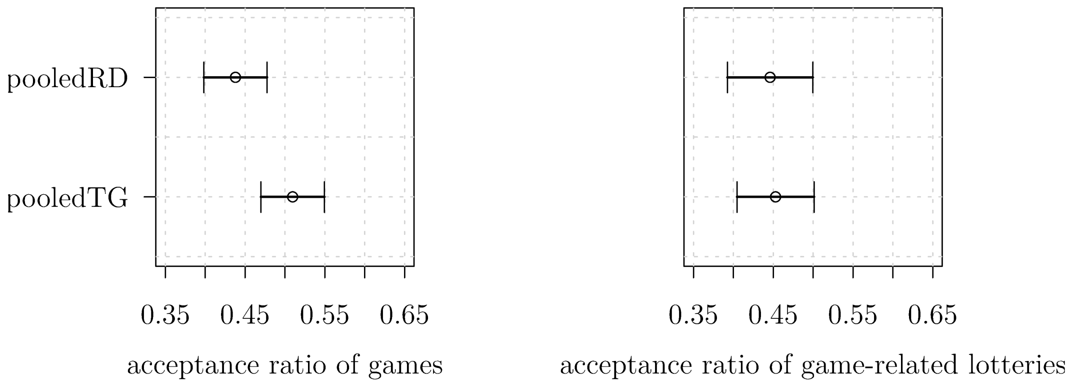


Figure 4.3: 95% confidence intervals of the acceptance ratio for the games (left) and game-related lotteries (right)

multiple price list where Player 1s chose to play option B (henceforth *acceptance ratio/accRat*) as the dependent variable. Figure 4.3 shows the 95% bootstrap confidence intervals of the acceptance ratios in the treatments with Risky Dictator Games and Trust Games (pooled across different framings and orderings).

In order to select an appropriate model with which to analyze the acceptance ratio we started with the full factorial model shown in (4.1), where d_{RD} denotes a dummy variable equal to 1 if the observation is taken from a treatment in which the game played was the Risky Dictator Game, and 0 otherwise. Similarly, $d_{FramingD}$ is equal to 1 when accepting the lottery had to be stated conditionally on D-moves of the 2nd player, and 0 otherwise; and d_{Order2} is equal to 1 if the game-related lotteries were played before the game, and 0 otherwise. We also include the subjects' risk aversion, which in our design was measured as the acceptance ratio of the standard lottery (task 4 in Table 4.2). To make the interpretation of $\beta_{RiskAversion}$ easier, it is operationalized as 1 - the acceptance ratio of the standard lottery[3].

$$\begin{aligned} accRat =& \beta_0 + \beta_{RD} d_{RD} + \beta_{FramingD} d_{FramingD} + \\ & \beta_{Order2} d_{Order2} + \beta_{RiskAversion} + \text{all interactions} \end{aligned} \tag{4.1}$$

To see which of the variables could explain the variance of acceptance ratios,

[3]The subjects with a high risk aversion should accept the standard lottery less often than those with low risk aversion.

we used a step-wise algorithm to select the best model based on the AIC.[4] For the games, the final model is shown in (4.2). However, as indicated in Table 4.3, fitting a linear regression model shows that only β_{RD} and $\beta_{RiskAversion}$ are significant predictors. The effect of risk aversion on acceptance ratios is negative, which is not surprising and in line with Kosfeld et al. (2005). The significant negative effect of the variable RD implies that the subjects preferred Trust Games to Risky Dictator Games, which contradicts Bohnet and Zeckhauser (2004).

$$\begin{aligned} accRat_{games} =& \beta_0 + \beta_{RD} d_{RD} + \beta_{FramingD} d_{FramingD} + \beta_{Order2} d_{Order2} + \\ & \beta_{RiskAversion} + \beta_{Order2} d_{Order2} \times \beta_{RiskAversion} \end{aligned} \tag{4.2}$$

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.2959	0.0456	6.50	0.0000
RD	-0.0575	0.0262	-2.19	0.0300
Order2	0.0389	0.0262	1.49	0.1390
RiskAversion	-0.4133	0.0843	-4.90	0.0000

Table 4.3: Best linear regression model predicting acceptance ratios in Trust Game and Risky Dictator Game according to AIC

4.4.3 Game-related lotteries

In this subsection, we compare the acceptance ratios of the game-related lotteries (i.e. how often the subjects chose to play risky lotteries) across the different treatments. Figure 4.3 suggests that there are hardly any differences with regard to the acceptance ratios across the treatments. As far as the game-related lotteries, the AIC step-wise model selection algorithm suggests that it is only the subjects' risk aversion that meaningfully contributes to the prediction of the acceptance ratios. Our hypothesis of the differences in the game-related lotteries following those in the games themselves thus appears to be implausible. Player 1s did not perceive the lottery less valuable when the probabilities of winning depended on a Trustee's choice in a Trust Game as opposed to when those depended on a move by Nature.

[4]We used the function *stepAIC* from the *MASS* library in R.

4.4.4 Games vs game-related lotteries

We compared the acceptance ratios in the game-related lotteries with those in the corresponding games. Table 4.4 shows such ratios were different i Trust Game context only. This is consistent with the conclusion from the previous subsection that it really takes both, the intention and the inequality, to make the subjects prefer being dependent on somebody else's choice rather than on a move by Nature.

H_0: acceptance ratio	Bayes	t-Test	Mann-Whitney U
game (TG) $\leq$ lottery (TG)	odds = 1:24	p = 0.04	p = 0.059
game (RD) $\leq$ lottery (RD)	odds = 1.5:1	p = 0.58	p = 0.56

Table 4.4: Comparison of acceptance ratio between game-related lotteries and actual games

4.4.5 Controls and replication

At the end of the session, the subjects were asked if they felt that they had fully understood the experiment before making the decisions. 36 of 184 subjects answered *no*. We checked if the results from the previous subsections are sensitive to excluding those subjects from the data, and they were not. The same holds true when excluding subjects that had more than 1 switching point in one of the multiple price and even when applying both such filters simultaneously.

Our experimental design was arguably only marginally different from the ones used by Bohnet and Zeckhauser (2004) and Bohnet et al. (2008). Nevertheless, we chose to replicate their experiment almost exactly. In the replication, only the treatments with the Risky Dictator Game and Trust Game were implemented[5]. This replication was supposed to be only the first in a series of experiments with which we hoped to identify the design differences that had led to the conflicting results between our experiment and theirs. For

[5]Actually, we used the design of Bohnet et al. (2008), which is a streamlined version of Bohnet and Zeckhauser (2004). Both papers lead to the same results.

this purpose, we translated (and back-translated) the instructions provided in Bohnet et al. (2008) to German and conducted the study in Jena in February 2016. The only differences between our replication and their experiment were the subject pool used, the fact they implemented the experiment with pen and paper (we used z-Tree), and the magnitudes of incentives (their study: 1 ECU = 1 dollar; our study: 1 ECU = 2 euro). All other details of the design are described in Bohnet et al. (2008).

The replication sample consisted of 34 pairs of subjects playing the Trust Game and 31 pairs playing the Risky Dictator Game. This is somewhat more observations per treatment than in Bohnet and Zeckhauser (2004) or Bohnet et al. (2008), so we do not expect that our replication suffers from low statistical power. None of the subjects that participated in the replication had been involved in the previous experiment. Sessions in the replication took 30 minutes and the subjects earned 7 Euros on average.

The results of the replication are summarized in Figure 4.4. We could not replicate the results of Bohnet et al. (2008). We found no significant difference between the minimum acceptable probabilities (MAP) demanded by the subjects in the Trust Game and the Risky Dictator Game (one-sided Wilcox rank-sum test: $p = 0.17$). Statistical significance aside, the direction of the potential effect is still opposite to what Bohnet et al. found. The direction of the effect is the same across the genders, so we can rule out the possibility that it is the difference in the gender composition between our sample and theirs that is the reason for the contradiction.

In addition, we asked the subjects in the role of Player 1, if they preferred that the decision of Player 2 be made by an actual person or randomized by the computer. 63% of the Player 1s answered that they would prefer the computer making the decision, which is again, not in line with Bohnet et al. We asked this question as a surprise at the end of the experiment, after all other decisions that were part of the design of Bohnet et al. had been made but before the subjects were informed about the move of Player 2 and their final payoff. Thus, this question could not have influenced the earlier decisions. We also chose not to incentivise this question in order for our payoff structure to be identical to that of the original study.

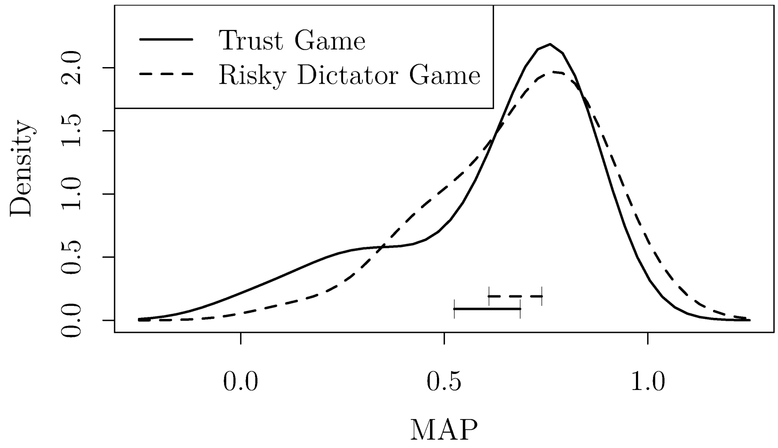


Figure 4.4: Density plots of MAP in both treatments of the replication. For each treatment, the 95% bootstrap confidence interval of the mean is shown

4.5 Discussion

The experiment presented in this chapter was designed to find out if it is the mere knowledge that someone could exploit one's trust that is already sufficient to perceive an interaction with a Trustee different from relying on a move by Nature. For this purpose, we compared differences in preferences over uncertain outcomes between the Risky Dictator Game and Trust Game, with differences in preferences over uncertain outcomes between respective game-related lotteries. While we find different preferences between both types of games, we do not find differences in both types of game-related lotteries. That is, when the Trustees were not affected by their decision to betray, the Trustors did not care if they depended on the Trustee's decision or Nature.

However, the most surprising and puzzling finding in this chapter is that the subjects were not betrayal averse. On the contrary, our data suggests that subjects *prefer* the monetary outcome where someone else benefits from their loss and that outcome is the result of the benefactor's choice to the same outcome that is the result of a move by Nature. We were so puzzled by that finding that we decided to replicate the experiment of Bohnet and Zeckhauser (2004) as an initial attempt to investigate the reason for the contradictory results. Again, in the replication we find no evidence for betrayal aversion (if anything, the results point towards the opposite). The only differences between the design of our replication study and the design used by Bohnet and Zeckhauser were the incentives (twice as high as in Bohnet and Zeckhauser) and the fact that we had used z-Tree to run the experiment. Neither of these differences usually leads to differences in behaviour in the Trust Game (Johnson and Mislin, 2011). Also, we do not have reasons to believe that the Jena subject pool could be the factor behind the contradictory results. Many studies replicated in Jena produced results which are in line with what is usually found in the literature (as e.g. the bubbles in markets discussed in chapter 2 and ambiguity aversion in chapter 3). We controlled for the gender composition of our sample, and our sample was similar as far as the student to non-student ratio, too. Bohnet et al. (2008) themselves suggest that usually (at least in terms of its direction) the effect should be robust across different countries.

We are not the only ones to find evidence against betrayal aversion. Fetchenhauer and Dunning (2012) spend a major part of their discussion to explain why the subtle differences between their design and the design of Bohnet and Zeckhauser might have led to contradictory results. The results of a very recent follow up experiment of Fairley et al. (2014) again, contradict Bohnet and Zeckhauser (personal communication, March 2016). As described in section 4.2, some other authors find no effect whatsoever. Bohnet et al. (2008) themselves do not always find betrayal aversion (although the direction of the effect found by them does always speak in favor of betrayal aversion). Summed up and especially in light of our nearly exact replication of Bohnet and Zeckhauser (2004), it seems likely that betrayal aversion – at best – only mildly affects behaviour and can easily be dominated by other factors. The effects found (and therefore reported on) may just be in the tails of a distribution of possible findings, where the average is such that there is no economically relevant effect. Keeping in mind the publication bias (Rothstein, Sutton, and Borenstein, 2006), one should rather be with respect to the literature on betrayal aversion. The problem of reproducing results in social sciences has been drawing a lot of attention lately (Collaboration, 2015), and our failed replication attempt hopefully contributes to the awareness regarding this issue in economics.

Since the findings on betrayal aversion are so much more ambivalent than we were initially aware of, it is very difficult (and perhaps even misleading) to interpret our results in the context of the main research question. One possible psychological mechanism that may have led to our result is that the subjects could believe that if a Trustee were to betray them – or in other words "to take from them" – they would have good reasons to do so. The utility that the subjects would gain from believing that the Trustees could make better use of the money than the subjects themselves may have partially compensated for their objective loss. This compensatory utility is not there when the allocation of money is known to be due to chance, which makes the preferences regarding the two games differ. When the Trustee is not benefiting from the betrayal, the compensatory utility cannot play its role either, which is why we do not find any significant difference between the two game-related lotteries.

4.6 Appendix

4.6.1 Replication study instructions

This subsection contains the German instructions we used in the replication of the Trust Game treatment of Bohnet et al. (2008):

Sie nehmen an einer Studie teil, in der Sie Geld verdienen können. Der genaue Betrag ergibt sich aus den Punkten die Sie in dem Spiel gewinnen, das Sie in Kürze spielen werden. 2 Punkte entsprechen dabei 1 €. Sie erhalten den Betrag am Ende als Barbetrag ausgezahlt.

Wie die Studie durchgeführt wird:
Die Studie wird anonymisiert durchgeführt. Ihrem Mitspieler sind Sie lediglich als "Spieler S" bekannt und es wird keine Kommunikation zwischen Ihnen geben. Es spielen jeweils 2 zufällig ausgewählte Versuchspersonen miteinander und jeder der Spieler in einem Paar hat eine unterschiedliche Rolle. Spieler die dieselbe Rolle wie Sie spielen nennen wir "Spieler S", die andere Art von Spielern "Spieler Y". Ihre Entscheidung wird am Ende des Experimentes lediglich Ihrem Mitspieler (anonymisiert) mitgeteilt.

Wie das Spiel funktioniert:
In der Studie werden Entscheidungen von Menschen untersucht. Da Sie das Spiel in der Rolle von Spieler S spielen, entscheiden Sie zwischen 2 Alternativen: A und B. Wenn Sie A wählen, erhalten Sie sicher 10 Punkte. Wenn sie B wählen, hängt die Punkteverteilung von der Entscheidung von Spieler Y ab. Spieler Y wählt zwischen Alternativen, 1 und 2.

Sie entscheiden	Konsequenz	Ihre Punkte	Punkte Spieler Y
A	Sicherheit	10	10
B	Spieler Y entscheidet 1	15	15
	Spieler Y entscheidet 2	8	22

Auszahlungstabelle:
Die Tabelle gibt folgende Information:
Wenn Sie A wählen, erhalten Sie und Spieler Y jeweils 10 Punkte.
Wenn Sie B wählen und Spieler Y Option 1 wählt, erhalten Sie und Spieler Y

jeweils 15 Punkte.
Wenn Sie B wählen und Spieler Y Option 2 wählt, erhalten Sie 8 Punkte und Spieler Y bekommt 22 Punkte.

Zentrale Frage:
Wie hoch muss die Wahrscheinlichkeit, dass Sie mit einem Spieler Y spielen der Option 1 wählt sein, damit Sie bereit wären Option B und nicht Option A zu wählen?

Anmerkung:
Sie wissen nicht, wie viele Spieler Y sich für Option 1 entschieden haben. Ihre Antwort auf die zentrale Frage hat keinen Einfluss auf die Spieler Y. Die Wahrscheinlichkeit, dass Sie einem Spieler Y zugeordnet werden der Option 1 gewählt hat, ergibt sich aus der Anzahl Spieler Y die Option 1 gewählt haben geteilt durch die gesamt Zahl Spieler Y. Mit Ihrer Antwort auf die zentrale Frage geben Sie an wie hoch diese Wahrscheinlichkeit sein müsste, damit Sie bereit wären Option B und nicht Option A zu spielen.

Ablauf des Experimentes:
1. Während Sie die zentrale Frage beantworten, beantworten alle Spieler Y folgende Frage: "Welche der beiden Optionen, 1 und 2, wählen Sie wenn der andere Spieler B wählt?" Sobald Sie und alle anderen Spieler die Antwort auf die Frage über den Computer eingegeben haben, werden die Antworten ausgewertet und Sie zufällig einem Spieler Y zugeordnet.
2. Im Anschluss wird die Wahrscheinlichkeit ermittelt, dass Sie einem Spieler Y zugelost werden der Option 1 gewählt hat. Diese Wahrscheinlichkeit wird allen Spielern mitgeteilt.
3. Wenn die Wahrscheinlichkeit höher ist als die von Ihnen geforderte Wahrscheinlichkeit oder dieser entspricht, entscheidet die Option die der Ihnen zugeteilten Spieler Y gewählt hat über die Punktevergabe.
a. Wenn der Spieler Y Option 1 gewählt hat, erhalten Sie und Ihr Mitspieler 15 Punkte.
b. Wenn der Spieler Y Option 2 gewählt hat, erhalten Sie 8 Punkte und Ihr Mitspieler 22 Punkte.
4. Wenn die Wahrscheinlichkeit niedriger ist als die von Ihnen geforderte Wahrscheinlichkeit, erhalten Sie und Ihr Mitspieler mit Sicherheit 10 Punkte.

Bevor wir mit dem Experiment beginnen Stellen wir Ihnen einige Fragen um sicherzustellen, dass alle Teilnehmer die Instruktionen richtig verstehen.

4.6.2 Multiple Price List

Subjects had to choose between option A and B conditional on the 10 potential players they could be playing with as Player 2. Table 4.5 shows the table used during the experiment for this purpose.

	Option A	Option B
0 of 10 potential players 2 chose C in game	10 ECU for sure	Lottery
1 of 10 potential players 2 chose C in game	10 ECU for sure	Lottery
...	...	...
9 of 10 potential players 2 chose C in game	10 ECU for sure	Lottery
10 of 10 potential players 2 chose C in game	10 ECU for sure	Lottery

Table 4.5: The multiple price list used to elicit preferences of players 1 in the game-related lottery in treatment TG-C

Chapter 5

General conclusion

5.1 Main findings

Nowadays and even more so in the future humans will interact with artificial agents in many situations where they previously interacted with humans. This is the basic observation that lead to the research presented in this dissertation. The overarching research question in this dissertation is, how human behaviour is different during economic decision-making involving both types of agents. All three studies we presented used the experimental method for this purpose and found that humans adapt their behaviour specifically to the type of agent they are interacting with.

In chapter 2 we studied hybrid markets; markets in which human and algorithmic traders are trading with each other. In the experiment we only manipulated the expectation of the subjects that there would be an algorithmic trader on the market, without the algorithmic trader really engaging in the market. Our results indicate that markets where human traders expect to be trading with algorithmic traders produce smaller bubbles, volatility decreases and the number of trades increases, compared to markets were humans know they interact with only humans - though the evidence is less clear regarding these two properties. Those are the same findings reported in other studies on hybrid markets, with the difference being that in these studies algorithmic traders were really engaging on the market. The authors of these studies concluded that algorithmic traders, by engaging on the market, change market properties. Our findings suggest that it may also be the human traders in hybrid markets that lead to the change in market properties through their expectations with regard to the other traders. In the context of the overarching research question of this dissertation, this means that the expectations that humans have with regard to artificial economic agents compared to humans, can have a huge economic impact. The chapter also suggests that emphasizing the kind of agents that humans are interacting with can be used as a tool for policy makers in order to change humans' behaviour, in this case make traders trade more rationally.

The experiment presented in chapter 3 was designed to study, on a fundamental level and in the cleanest way we could design, whether humans perceive depending on a mechanism different from depending on humans. To allow for a clean comparison between both kinds of dependence, we had to exclude most of the context usually involved when humans depend on other humans. When we depend on others choices, these choices are often morally loaded, for example. Furthermore, one may have preconceived ideas about what the other agent is likely to decide. These and other factors involved in depending on others may be perceived differently when depending on nature. In the chapter we present a design which holds all these confounding factors constant, while the subjects depend either on a mechanism or the decision of a human. Our main finding is that (all other things being equal) subjects have a clear preference to depend on mechanistic processes rather than humans. This suggests that differences in perception of dependence on and interaction with both types of agents are more fundamental than expected.

Chapter 4 builds on an established experimental paradigm by Bohnet and Zeckhauser (2004) studying whether humans prefer to rely on humans or a mechanistic processes in the context of a Trust Game. In the Trust Game the Trustor has to take into account the possibility that their trust will be exploited by the one they trust (Trustee). Bohnet and Zeckhauser state that subjects are betrayal averse, i.e. an outcome that is the result of a betrayal decision of a Trustee feels worse compared to the same outcome being the result of a mechanistic process. We introduced the concept of game-related lotteries, lotteries in which the probabilities of winning/losing are taken from the decisions of others in a game (in our case from the Trust Game). We found that the subjects were indifferent between game-related lotteries where the probabilities depended on Trustees decisions in a Trust Game, compared to game-related lotteries where the probabilities depended on a Trust Game where the decisions of Trustees were taken by a mechanistic process: when the Trustees were not affected by the decision they took, the Trustors were indifferent between depending on Trustees' decisions or a mechanistic process. However, we became skeptical about the design and results reported by Bohnet and Zeckhauser (2004), since in our results we found subjects actually preferred the Trustee to take the decision in the Trust Game, to the decision being the result of a mechanistic process. Since our design was different from the one of Bohnet and Zeckhauser, we decided to closely replicate their study and again our results contradict their results. We thus suggest to be very careful when drawing conclusions from this chapter's results and see its main contribution within the light of a general debate on reproducability in social science experiments.

5.2 Contextualizing results

A noticeable difference between chapter 2 compared to chapters 3 and 4 is that in chapter 2 the subjects were only uncertain on whether they were depending on an artificial agent or a human. In chapter 3 and 4 subjects *knew* which type of agent they were depending upon. Chapter 2 thus shows that the possibility of interaction with an artificial agent is sufficient to change behaviour even when one is in actual fact interacting with, or depending on, human agents alone. This is especially important since (as discussed in chapter 1) in many interactions in hybrid societies it may be hard (or even impossible) to know which type of agent one is interacting with. Will one know in a few years whether the car one sees in the review mirror is driven by a human or an automatic driver? Does one know whether the email one receives after complaining about a product was written by a human or an algorithm? Chapter 2 indicates that even the uncertainty about the type of agent one is interacting with could change behaviour in these situations.

The results in chapters 3 and 4 seem to contradict each other. In chapter 3 we find that (in the most general context we could design) humans (all other things being equal) prefer to depend on a mechanistic process. In chapter 4 we find that within the context of a Trust Game humans prefer to depend on the choice of another. Similarly in the additional replication study of Bohnet and Zeckhauser (2004), we asked subjects after the experiment explicitly, which type of agent they would prefer to depend upon in the Trust Game, and again they preferred to depend on humans. One possible explanation for the contradicting results from chapters 3 and 4, is that humans treat risk in a trusting context (chapter 4) differently from risks in a rather abstract and artificial setting (chapter 3). A broad body of literature indicates the evolutionary importance of trust (Cesarini et al., 2008). It would thus be not too surprising to see humans react different in a Trust Game, compared to other games where no trust is involved. The fact that we find significant differences between the Trust Game and the Risky Dictator Game in chapter 4, but not in the game-related lotteries can be interpreted as evidence for the idea that subjects shift more towards preferring mechanistic processes as the situation becomes more abstract. If this holds, the null result found with regard to the game-related lotteries may be the result of a mix of two opposing effects; preferring humans in the trust context, while preferring to depend on mechanisms in a more abstract context.

Throughout the dissertation we refer to literature in the area of (decision) neuroscience. In light of this literature it seems plausible that differences in preferences and behaviour towards both types of agents correlate with differences in neural representation and processing of the situation. In future research we plan to include physiological measures or techniques like the administration of neurotpeptides to test this hypothesis. Kosfeld et al. (2005) find that subjects are more willing to engage in a Trust Game, but not in standard lotteries after the administration of the neurotpeptide oxytocin, and conclude from this that oxytocin is involved in trusting. In light of our results, an alternative interpretation of the results of Kosfeld et al. may be that the effect they find is not Trust Game specific. Future experiments based on the design presented in chapter 3 can help to disentangle the exact role of not just oxytocin, but also other brain areas currently associated with strategic thinking. Oxytocin and brain areas like the anterior insula linked to behavior in strategic interactions (Sanfey et al., 2003) may be generally involved in processing dependence on humans, not just in a trust context.

Examining the question of how the brain represents dependence on the two types of agents, may lead to more general insights. If we find e.g. that humans have distinct ways of processing environmental and social uncertainty, the question remains why we do so. Were we shaped by evolution to do so, where it was advantageous to be more/less risk averse when depending on others compared to taking environmental risk? Are we nurtured to treat social uncertainty differently? How flexible are humans in learning to treat a type of uncertainty differently? Would prolonged interaction with machines diminish the difference we currently find? These questions are important for the design of human-machine interaction in general and tell us how well humans can adapt to hybrid societies.

We want to end the discussion of our results in this section by pointing out some general issues when relating our results to the real world. Our main concern when designing the experiments was internal validity, which of course came with costs in terms of external validity. As experimentalists we wanted to make sure that all things were equal in the way we treated the subjects, except for the type of agent on whom they were to depend. This made the interaction between subjects and their agents quite artificial. Almost certainly, real interaction in hybrid societies will take place in contexts that can lead to different preferences from those we observed in our experiments. E.g. although one might generally prefer to depend on machines, one might prefer depending on a specific human because that human is a friend. Another fact that should make one cautious when translating our results to the real world is that our sample is (as in almost all studies in social sciences) not representative for humans in general. Almost all subjects were western, educated, industrialized, rich, and democratic, i.e. WEIRD (Henrich, Heine, and Norenzayan, 2010). Additionally, since most of them were 20-25 years old, their experience with modern technologies and artificial agents is different from the average. Generally, one should read the results purely as some first steps and keep in mind that this dissertation is not applied, but theoretical work.

5.3 Conclusion

In summary, the results of the experiments presented in this dissertation all suggest that human behaviour is different when interacting with a human from interacting with an artificial agent. However, the experiments indicate no simple rule of thumb as to how behaviour differs with the type of agent. In chapter 2 subjects behave more rational when interacting with an artificial agent, while in chapter 4 subjects were more risk averse when depending on artificial agents. In chapter 3 subjects prefer to depend on a mechanistic process in a very general and abstract context, while they seem to prefer to depend on a human Trustee in the Trust Game in chapter 4. Since there seems to be no simple answer, the research presented in this dissertation is best seen as providing an important yet incomplete snapshot of aspects that are relevant for our research question. Besides the findings within the specific context studied in each chapter and e.g. the methodological implications of chapter 4, we see the main contribution of this dissertation as making economists aware of the differences in expectations that humans have with regard to artificial agents compared to humans, and the economic impact these may have. It would be negligent dismiss these expectations. Policy makers can even use these expectations to change human behaviour, as demonstrated in chapter 2. Hybrid societies will probably be different, not only because artificial agents are different from humans, but also because humans treat artificial agents differently. Acknowledging this, and attempting to understand the nature of these differences better, may play an important role in shaping our future society.

Bibliography

Abdellaoui, Mohammed, Aurélien Baillon, Laetitia Placido, and Peter P Wakker (2011). "The rich domain of uncertainty: Source functions and their experimental implementation". In: *American Economic Review* 101.2, pp. 695–723.

Aimone, Jason A and Daniel Houser (2012). "What you don't know won't hurt you: a laboratory analysis of betrayal aversion". In: *Experimental Economics* 15.4, pp. 571–588.

Akerlof, George A (1970). "The market for lemons: quality uncertainty and the market mechanism". In: *The Quarterly Journal of Economics* 84.3, pp. 488–500.

Akiyama, Eizo, Nobuyuki Hanaki, and Ryuichiro Ishikawa (2013). *It is not just confusion! Strategic uncertainty in an experimental asset market.* Tech. rep. 2013-40. Aix-Marseille School of Economics.

Andersen, Steffen, Glenn W Harrison, Morten Igel Lau, and E Elisabet Rutström (2006). "Elicitation using multiple price list formats". In: *Experimental Economics* 9.4, pp. 383–405.

Andrade, Eduardo B, Terrance Odean, and Shengle Lin (2012). *Bubbling with excitement: an experiment.* Center for Risk Management Research 2012-11. UC Berkeley.

Barber, Brad M and Terrance Odean (2001). "Boys will be boys: Gender, overconfidence, and common stock investment". In: *The Quarterly Journal of Economics* 116.1, pp. 261–292.

Becker, Gordon M, Morris H DeGroot, and Jacob Marschak (1964). "Measuring utility by a single-response sequential method". In: *Behavioral Science* 9.3, pp. 226–232.

Berg, Joyce, John Dickhaut, and Kevin McCabe (1995). “Trust, reciprocity, and social history”. In: *Games and Economic Behavior* 10.1, pp. 122–142.

Bhattacharya, Utpal and Matthew Spiegel (1991). “Insiders, outsiders, and market breakdowns”. In: *Review of Financial Studies* 4.2, pp. 255–282.

Biais, Bruno, Denis Hilton, Karine Mazurier, and Sébastien Pouget (2005). “Judgemental overconfidence, self-monitoring, and trading performance in an experimental financial market”. In: *The Review of Economic Studies* 72.2, pp. 287–312.

Bohnet, Iris and Richard Zeckhauser (2004). “Trust, risk and betrayal”. In: *Journal of Economic Behavior & Organization* 55.4, pp. 467–484.

Bohnet, Iris, Fiona Greig, Benedikt Herrmann, and Richard Zeckhauser (2008). “Betrayal aversion: Evidence from Brazil, China, Oman, Switzerland, Turkey, and the United States”. In: *American Economic Review* 98.1, pp. 294–310.

Breaban, Adriana and Charles Noussair (2013). *Emotional State and Market Behavior*. Center for Economic Research 2013-031. Tilburg University.

Brynjolfsson, Erik and Andrew McAfee (2014). *The second machine age: work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Camerer, Colin and Martin Weber (1992). “Recent developments in modeling preferences: Uncertainty and ambiguity”. In: *Journal of Risk and Uncertainty* 5.4, pp. 325–370.

Carrubba, Clifford J, Amy Yuen, and Christopher Zorn (2007). “In defense of comparative statics: Specifying empirical tests of models of strategic interaction”. In: *Political Analysis* 15.4, pp. 465–482.

Castelfranchi, Cristiano and Rino Falcone (2010). “The Glue of Society”. In: *Trust Theory*. John Wiley & Sons, Ltd, pp. 265–280.

Cesarini, David, Christopher T Dawes, James H Fowler, Magnus Johannesson, Paul Lichtenstein, and Björn Wallace (2008). “Heritability of cooperative behavior in the trust game”. In: *Proceedings of the National Academy of Sciences* 105.10, pp. 3721–3726.

Chaminade, Thierry et al. (2012). “How do we think machines think? An fMRI study of alleged competition with an artificial intelligence”. In: *Frontiers in Human Neuroscience* 6.103.

Cheung, Stephen L, Morten Hedegaard, and Stefan Palan (2014). “To see is to believe: Common expectations in experimental asset markets”. In: *European Economic Review* 66, pp. 84–96.

Cleveland, W. S., E. Grosse, and W. M. Shyu (1992). “Local regression models”. In: *Statistical Models in S*. Ed. by J.M. Chambers and T.J. Hastie. Wadsworth & Brooks/Cole. Chap. 8.

Coleman, James Samuel (1994). *Foundations of social theory*. Cambridge: Harvard university press.

Collaboration, Open Science (2015). “Estimating the reproducibility of psychological science”. In: *Science* 349.6251, aac4716.

Dana, Jason, Roberto A Weber, and Jason Xi Kuang (2007). “Exploiting moral wiggle room: experiments demonstrating an illusory preference for fairness”. In: *Economic Theory* 33.1, pp. 67–80.

Das, Rajarshi, James E Hanson, Jeffrey O Kephart, and Gerald Tesauro (2001). “Agent-human interactions in the continuous double auction”. In: *Proceedings of the international joint conference on Artificial Intelligence*. Ed. by B Nebel. Vol. 17. 1. Lawrence Erlbaum Associates Ltd, pp. 1169–1178.

De Dreu, Carsten K W (2012). “Oxytocin modulates the link between adult attachment and cooperation through reduced betrayal aversion”. In: *Psychoneuroendocrinology* 37.7, pp. 871–880.

De Luca, Marco and Dave Cliff (2011). “Human-agent auction interactions: Adaptive-aggressive agents dominate”. In: *Proceedings of the international joint conference on Artificial Intelligence*. Ed. by T Walsh. Vol. 22. 1. AAAI Press, pp. 178–185.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G Wagner (2011). “Individual risk attitudes: Measurement, determinants, and behavioral consequences”. In: *Journal of the European Economic Association* 9.3, pp. 522–550.

Ellsberg, Daniel (1961). “Risk, Ambiguity, and the Savage Axioms”. In: *The Quarterly Journal of Economics* 75.4, pp. 643–669.

Fairley, Kim, Alan G Sanfey, Jana Vyrastekova, and Utz Weitzel (2014). *Trust and risk revisited*. Tech. rep. 59900. MPRA Paper.

Fellner, Gerlinde and Sebastian Krügel (2012). “Judgmental overconfidence: Three measures, one bias?” In: *Journal of Economic Psychology* 33.1, pp. 142–154.

— (2014). “Judgmental overconfidence and trading activity”. In: *Journal of Economic Behavior & Organization* 107.B, pp. 827–842.

Fellner, Gerlinde and Boris Maciejovsky (2007). “Risk attitude and market behavior: Evidence from experimental asset markets”. In: *Journal of Economic Psychology* 28.3, pp. 338–350.

Fetchenhauer, Detlef and David Dunning (2012). “Betrayal aversion versus principled trustfulness—How to explain risk avoidance and risky choices in trust games”. In: *Journal of Economic Behavior & Organization* 81.2, pp. 534–541.

Fischbacher, Urs (2007). “z-Tree: Zurich toolbox for ready-made economic experiments”. In: *Experimental Economics* 10.2, pp. 171–178.

Glaser, Markus and Martin Weber (2007). “Overconfidence and trading volume”. In: *The Geneva Risk and Insurance Review* 32.1, pp. 1–36.

Greiner, Ben (2004). “An Online Recruitment System for Economic Experiments”. In: *Forschung und wissenschaftliches Rechnen*. Ed. by Kurt Kremer and Volker Macho. Vol. 63, GWDG Bericht. Ges. für Wiss. Datenverarbeitung. Göttingen, pp. 79–93.

Grossklags, Jens and Carsten Schmidt (2006). “Software agents and market (in) efficiency: a human trader experiment”. In: *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on* 36.1, pp. 56–67.

Gsell, Markus (2008). *Assessing the impact of Algorithmic Trading on markets: A simulation approach*. Center for Financial Studies 2008-49. Universität Frankfurt a. M.

Heath, Chip and Amos Tversky (1991). “Preference and belief: Ambiguity and competence in choice under uncertainty”. In: *Journal of Risk and Uncertainty* 4.1, pp. 5–28.

Heinemann, Frank, Rosemarie Nagel, and Peter Ockenfels (2009). “Measuring strategic uncertainty in coordination games”. In: *The Review of Economic Studies* 76.1, pp. 181–221.

Hendershott, Terrence, Charles M Jones, and Albert J Menkveld (2011). “Does algorithmic trading improve liquidity?” In: *The Journal of Finance* 66.1, pp. 1–33.

Henrich, Joseph, Steven J Heine, and Ara Norenzayan (2010). “The weirdest people in the world?” In: *Behavioral and Brain Sciences* 33.2-3, pp. 61–83.

Hilton, Denis, Isabelle Regner, Laure Cabantous, Laetitia Charalambides, and Stephane Vautier (2011). “Do positive illusions predict overconfidence in judgment? A test using interval production and probability evaluation measures of miscalibration”. In: *Journal of Behavioral Decision Making* 24.2, pp. 117–139.

Holt, Charles A and Susan K Laury (2002). “Risk aversion and incentive effects”. In: *American Economic Review* 92.5, pp. 1644–1655.

Hoorens, Vera (1993). “Self-enhancement and superiority biases in social comparison”. In: *European Review of Social Psychology* 4.1, pp. 113–139.

Johnson, Noel D and Alexandra A Mislin (2011). “Trust games: A meta-analysis”. In: *Journal of Economic Psychology* 32.5, pp. 865–889.

Juarrero, Alicia (2002). *Dynamics in action: Intentional behavior as a complex system*. Cambridge, MA: MIT press.

Kass, Robert E. and Adrian E. Raftery (1995). “Bayes Factors”. In: *Journal of the American Statistical Association* 90.430, pp. 773–795.

Keller, Carmen and Michael Siegrist (2006). “Investing in stocks: The influence of financial risk attitude and values-related money and stock market attitudes”. In: *Journal of Economic Psychology* 27.2, pp. 285–303.

Kirchler, Michael, Jurgen Huber, and Thomas Stockl (2012). “Thar she bursts: Reducing confusion reduces bubbles”. In: *American Economic Review* 102.2, pp. 865–883.

Kirilenko, Andrei A and Andrew W Lo (2013). “Moore’s Law versus Murphy’s Law: Algorithmic Trading and Its Discontents”. In: *The Journal of Economic Perspectives* 27.2, pp. 51–72.

Kirilenko, Andrei A, Albert S Kyle, Mehrdad Samadi, and Tugkan Tuzun (2014). *The flash crash: The impact of high frequency trading on an electronic market*. Working Paper. Federal Reserve Board of Governors.

Knight, Frank H (1921). *Risk, uncertainty and profit.* New York: Hart, Schaffner and Marx.

Koch, Christian and Stefan Penczynski (2015). *The Winner's Curse: Conditional Reasoning & Belief Formation.* Tech. rep. 15-03. University of Mannheim / Department of Economics Working Paper Series.

Kosfeld, Michael, Markus Heinrichs, Paul J Zak, Urs Fischbacher, and Ernst Fehr (2005). "Oxytocin increases trust in humans". In: *Nature* 435.7042, pp. 673–676.

Krach, Sören, Frank Hegel, Britta Wrede, Gerhard Sagerer, Ferdinand Binkofski, and Tilo Kircher (2008). "Can machines think? Interaction and perspective taking with robots investigated via fMRI". In: *PLoS One* 3.7, e2597.

Lauharatanahirun, Nina, George I Christopoulos, and Brooks King-Casas (2012). "Neural computations underlying social risk sensitivity". In: *Frontiers in Human Neuroscience* 6.213.

Mandryk, Regan L, Kori M Inkpen, and Thomas W Calvert (2006). "Using psychophysiological techniques to measure user experience with entertainment technologies". In: *Behaviour & Information Technology* 25.2, pp. 141–158.

McCabe, Kevin, Daniel Houser, Lee Ryan, Vernon Smith, and Theodore Trouard (2001). "A functional imaging study of cooperation in two-person reciprocal exchange". In: *Proceedings of the National Academy of Sciences* 98.20, pp. 11832–11835.

McCabe, Kevin A, Mary L Rigdon, and Vernon L Smith (2003). "Positive reciprocity and intentions in trust games". In: *Journal of Economic Behavior & Organization* 52.2, pp. 267–275.

Michailova, Julija (2010). *Overconfidence, risk aversion and (economic) behavior of individual traders in experimental asset markets.* MPRA Paper 26390. University Library of Munich, Germany.

Michailova, Julija and Ulrich Schmidt (2011). *Overconfidence and bubbles in experimental asset markets.* Kiel Working Papers 1729. Kiel Institute for the World Economy.

Moore, Don A and Paul J Healy (2008). "The trouble with overconfidence." In: *Psychological Review* 115.2, pp. 502–517.

Morris, Stephen (1994). "Trade with heterogeneous prior beliefs and asymmetric information". In: *Econometrica* 62.6, pp. 1327–1347.

Nass, Clifford and Youngme Moon (2000). "Machines and mindlessness: Social responses to computers". In: *Journal of Social Issues* 56.1, pp. 81–103.

Odean, Terrance (1999). "Do investors trade too much?" In: *American Economic Review* 89, pp. 1279–1298.

Oechssler, Jörg, Carsten Schmidt, and Wendelin Schnedler (2011). "On the ingredients for bubble formation: informed traders and communication". In: *Journal of Economic Dynamics and Control* 35.11, pp. 1831–1851.

Orne, Martin T (1962). "On the social psychology of the psychological experiment: With particular reference to demand characteristics and their implications." In: *American Psychologist* 17.11, pp. 776–783.

Palan, Stefan (2013). "A review of bubbles and crashes in experimental asset markets". In: *Journal of Economic Surveys* 27.3, pp. 570–588.

Parkes, David C and Michael P Wellman (2015). "Economic reasoning and artificial intelligence". In: *Science* 349.6245, pp. 267–272.

R Development Core Team (2016). *R: A Language and Environment for Statistical Computing.* ISBN 3-900051-07-0. R Foundation for Statistical Computing. Vienna, Austria.

Rilling, James K, David A Gutman, Thorsten R Zeh, Giuseppe Pagnoni, Gregory S Berns, and Clinton D Kilts (2002). "A neural basis for social cooperation". In: *Neuron* 35.2, pp. 395–405.

Rilling, James K, Alan G Sanfey, Jessica A Aronson, Leigh E Nystrom, and Jonathan D Cohen (2004). "The neural correlates of theory of mind within interpersonal interactions". In: *Neuroimage* 22.4, pp. 1694–1703.

Robin, Stephane, Katerina Straznicka, and Marie-Claire Villeval (2012). *Bubbles and incentives: an experiment on asset markets.* Tech. rep. 2012-35. GATE.

Rothstein, Hannah R, Alexander J Sutton, and Michael Borenstein (2006). *Publication bias in meta-analysis: Prevention, assessment and adjustments.* John Wiley & Sons.

Sanfey, Alan G (2007). “Social decision-making: insights from game theory and neuroscience”. In: *Science* 318.5850, pp. 598–602.

Sanfey, Alan G, James K Rilling, Jessica A Aronson, Leigh E Nystrom, and Jonathan D Cohen (2003). “The neural basis of economic decision-making in the ultimatum game”. In: *Science* 300.5626, pp. 1755–1758.

Sent, Esther-Mirjam (2005). “Behavioral economics: how psychology made its (limited) way back into economics”. In: *History of Political Economy* 36.4, pp. 735–760.

Smith, Adam (1759). *The Theory of Moral Sentiments.* London: A. Millar.

Smith, J Maynard and GR Price (1973). “The Logic of Animal Conflict”. In: *Nature* 246, pp. 15–18.

Smith, Vernon L, Gerry L Suchanek, and Arlington W Williams (1988). “Bubbles, crashes, and endogenous expectations in experimental spot asset markets”. In: *Econometrica* 56.5, pp. 1119–1151.

Sonsino, Doron, Uri Benzion, and Galit Mador (2002). “The Complexity Effects on Choice with Uncertainty–Experimental Evidence”. In: *The Economic Journal* 112.482, pp. 936–965.

Tversky, Amos and Daniel Kahneman (1974). “Judgment under uncertainty: Heuristics and biases”. In: *Science* 185.4157, pp. 1124–1131.

Walsh, Timothy, Bo Xiong, Christine Chung, and Purba Mukerji (2012). “The impact of algorithmic trading in a simulated asset market”. In: *Proceedings 18th International Conference on Computing in Economics and Finance (CEF 2012).*

Weibel, David, Bartholomäus Wissmath, Stephan Habegger, Yves Steiner, and Rudolf Groner (2008). “Playing online games against computer-vs. human-controlled opponents: Effects on presence, flow, and enjoyment”. In: *Computers in Human Behavior* 24.5, pp. 2274–2291.

Mike Farjam

email mike.farjam@uni-jena.de
address Bachstrasse 18k, Room 212, 07743, Jena

Current Position

since 2013 Friedrich Schiller University Jena

School of Economics and Business Administration — *Doctoral Student Economics*
Supervisor: Oliver Kirchkamp

Education

2011-2013 Radboud University Nijmegen

GPA: 8.4 · Faculty of Social Sciences — *M.Sc. Artificial Intelligence*
Thesis: *Punishment Mechanisms and their Effect on Cooperation – A Simulation Study*
Supervisors: Pim Haselager, Marco Faillo & Ida Sprinkhuizen-Kuyper

2008-2012 Radboud University Nijmegen

GPA: 7.4 · Faculty of Social Sciences — *B.Sc. Artificial Intelligence*

2007-2011 Radboud University Nijmegen

GPA: 7.0 · Faculty of Social Sciences — *B.Sc. Psychology*

2006 Cornelius Burgh Gymnasium Erkelenz

GPA: 2.1 — *Abitur*

Research Visits

2015 Sep-Dec The Hebrew University of Jerusalem

Psychology Department · Project on an agent-based simulation of child-parent interactions.
Host: Ariel Knafo

April 11, 2016

Erklärung nach §4 Abs. 1 PromO:

Hiermit erkläre ich,

1. dass mir die geltende Promotionsordnung bekannt ist;
2. dass ich die Dissertation selbst angefertigt, keine Textabschnitte eines Dritten oder eigener Prüfungsarbeiten ohne Kennzeichnung ubernommen und alle von mir benutzten Hilfsmittel, personlichen Mitteilungen und Quellen in meiner Arbeit angegeben habe;
3. dass ich bei der Auswahl und Auswertung des Materials sowie bei der Herstellung des Manuskriptes keine unzulässige Hilfe in Anspruch genommen habe;
4. dass ich nicht die Hilfe eines Promotionsberaters in Anspruch genommen habe und dass Dritte weder unmittelbar noch mittelbar geldwerte Leistungen von mir für Arbeiten erhalten haben, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen;
5. dass ich die Dissertation noch nicht als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prufung eingereicht habe;
6. dass ich nicht die gleiche, eine in wesentlichen Teilen ahnliche oder eine andere Abhandlung bei einer anderen Hochschule bzw. anderen Fakultat als Dissertation eingereicht habe

Mike Daniel Farjam April 11, 2016, Jena