BEHAVIORAL AND NEUROBEHAVIORAL FEATURES OF “SOCIALITY”

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DISSERTATION ABSTRACT

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Title: Behavioral and Neurobehavioral Features of “Sociality”

Standard models of decision making fail to explain the nature of the various important observed patterns of human behavior, e.g. “economic irrationality,” demand for “sociality,” risk tolerance and the preference of egalitarian outcomes. Moreover, the majority of models does not account for the change in the strategies of the human beings playing with other human beings as opposed to playing against a machine.

This dissertation analyzes decision making and its peculiar characteristics in the social environment under conditions of risk and uncertainty. My main goal is to investigate why human beings behave differently in a social setting and how the social domain affects their decision-making process. I develop the theory of “sociality” and exploit experimental and brain-imaging methodologies to test and refine the competing theories of individual decision making in the context of the social setting. To explain my theory I propose an economic utility function for a risk facing decision-maker that accounts for existing theories of utility defined on the outcomes and simply adds another term to account for the decision-making process in the social environment. For the purposes of my dissertation I define “sociality” as the economic component of the utility function that accounts for social environment, a function of a process rather than of an

outcome. I follow on the breakthrough work by evolutionary psychologists in emphasizing the importance of the substantive context of the social decisions.

The model I propose allows one to think about situations in which individuals may care for more than their narrowly-defined material interest and their decision may be driven by “sociality” and other non-monetary considerations. The “sociality” component of the economic utility function demonstrates the fact that individuals do not only care about outcomes but also about the processes which lead to these outcomes. In my empirical chapters I put the theory to the test in a series of laboratory experiments carried out in the United States, New Zealand and Russia and a series of fMRI and computer experiments executed at the University of Oregon.

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CHAPTER I

INTRODUCTION

How do people make decisions? Do people like making decisions when they are surrounded by other people? Do people make decisions with other people using different processes of decision making that result in different outcomes than when they make these decisions individually? What brain regions experience increased brain activation when people make decisions with other people as opposed to playing computer?

As is widely noticed, individuals do not always behave in accordance with rational choice theory. However, standard models of decision-making fail to explain the nature of the various peculiar patterns of human behavior, e.g. “economic irrationality,” demand for “sociality,” risk tolerance and the preference of egalitarian outcomes. Moreover, the majority of the models does not account for the change in the strategies that human beings use when they play other human beings as opposed to when they play a machine. With the abundance of theories and models of decision-making, experiments have an additional value. Researchers can test which theory fits better due to the control of the economic environment they possess (Binmore, 2001; J. N. Druckman, Green, Kuklinski, & Lupia, 2006, 2011).

This dissertation analyzes decision making and its peculiar characteristics in the social environment under risk and uncertainty. My main goal is to investigate why human beings behave differently in a social domain and how this domain affects their decision-making process. I follow on the breakthrough work by evolutionary psychologists (McDermott, Fowler, & Smirnov, 2008) and emphasize the importance of the substantive context of the social decisions. I develop the theory of "sociality," and exploit experimental and brain-imaging methodologies to test and refine the competing theories of individual decision-making in the context of social setting. To explain my theory I propose an economic utility function for risk facing decision-maker that accounts for existing theories of utility defined on the outcomes and add another term to account for the value that decision-maker assigns toward the decision-making process while surrounded with his peers. For the purposes of my dissertation I define "sociality" as the economic component of utility function that accounts for the fact that individuals do not only care about outcomes, but also about the processes which lead to these outcomes.

The idea that humans may care for more than their narrowly-defined material interest and that their decisions may be driven by "sociality" and other non-monetary consideration is not new to behavioral and experimental economists (Frey & Stutzer, 2005). However, economists rarely consider utility functions that include social aspects (Brock & Durlauf, 2001). On the other hand, social psychologists study social interactions for nearly 50 years and suggest that decision-making under risk changes in the social environment. People serve as means for how gains can be obtained or losses prevented (Tajfel, 1981) and, therefore, risk attitudes do not change between gains and losses, unlike suggested by Kahneman and Tversky (1979). Nevertheless, social psychologists rarely formalize their finding of peculiar behavioral patterns or assign a value to importance of "sociality."

Furthermore, neuroimaging is seen as the key tool to understand the nature of the various aspects of human behavior. Use of this methodology has the potential to advance the knowledge of the existing theoretical accounts of how people make decisions by informing and constraining these models based on the underlying neuroscience. Similar to my research, neuroscience scholars suggest that many behaviors are aimed at maximizing social, not personal material outcomes (Zaki & Mitchell, 2011). In contrast they suggest that social ideals have value in itself, rather than due to the processes in the domain of "sociality." I am not able to distinguish between the value in itself and the value of the processes involved using current experiments, however, this creates an ambitious goal for future research.

In the chapters below I explore decision making under risk and uncertainty in the presence of "sociality." In Chapter II I consider how social domain makes individuals overcome the risks of social interactions in laboratory experiments and propose a theory of "sociality" to account for the domain specificity. I define "sociality" as an additional component of individual's economic utility function that is a function of a process and not of an outcome and estimate the value of "sociality" for different cultures and frameworks. I also examine behavioral properties of the social domain.

In Chapter III I focus not on how individuals overcome risks to enter social relationships, but on the social interaction itself. I expand on the behavioral features of the domain of "sociality" by investigating cooperation in Prisoner's Dilemma games. I find significant markers of social behavior and how they change with experience, time, and cultural aspects.

Chapter IV explores the neurobehavioral features of "sociality." I create and test an fMRI design that explores the neural correlates for social domain. I also use a similar set of experiments in the computer laboratory in order assist fMRI experiments and add statistical power for the behavioral results. All participants complete a political attitudes questionnaire, so that I can correlate decisions made in the experiments to participants' political affiliation.

In Chapter V I conclude by summarizing the findings of my dissertation project and discussing applications for political science and avenues for future research. My main results and conclusions suggest that the notion of "sociality" holds promise for understanding a wide variety of individual behaviors that cannot be explained by standard utility theory and alternative theories.

CHAPTER II

THE VALUE OF “SOCIALITY”

2.1. Introduction

Do people make purely rational decisions, guided by their economic utility? Or is human “sociality” a factor in decision making? Do people enjoy making decisions? Do people make decisions with other people using different processes of decision making that result in different outcomes than when they make these decisions individually? If there is a difference in perceived value between decision making that involves similar social environments then could there be an economic value that can be placed on such environment and if so, how does it affect decision making and, especially, the decision making under risk and uncertainty.

Understanding how individuals arrive at decisions and what strategies they use in social interactions has been a subject of intense interest among a variety of social scientists, including economists, political scientists, and psychologists. The classical economic theory of individual decision making, i.e., expected utility theory (Arrow, 1971; Friedman & Savage, 1948), fails to explain a variety of commonly observed human behaviors such as “economic irrationality” (Becker, 1978), altruism and “altruistic punishment” (Fehr & Gachter, 2002), demand for “sociality” (T Johnson, Myagkov, & Orbell, 2004), risk tolerance (Kahneman & Tversky, 1979), and preferences for egalitarian outcomes (C. F. Camerer & Fehr, 2006). In contrast to classical economic decision theory as well as to alternative theories, such as prospect theory (Kahneman & Tversky, 1979), evolutionary psychology (McDermott et al., 2008) emphasizes the importance of the substantive domain in which the decision maker acts, e.g. the presence of other actors and the decision makers' relationship to these other actors. I follow in this tradition in my analysis of decision making under risk.

My main goal in this chapter is to discover the presence and properties of the economic component of "sociality" in decision making under risk and uncertainty. I show that in the situations that involve risk and social environment, i.e., the environment in which individuals make decisions among their peers, this component exists. However, the standard utility function cannot account for the phenomenon I observe. I change the standard approach to utility function in order to capture that decisions are made differently by subject that plays with other human subjects, than with computers and call it the theory of "sociality."

For the purposes of my dissertation I define "sociality" as the economic component of utility function that accounts for social environment, a function of a process rather than of an outcome. "Sociality" is a multidimensional concept. On one hand is the individual level, where individuals make decisions and reveal their willingness to be a part of the group, i.e., make a decision to move away from Hemmingway's (1937) "man alone" condition. On the other hand is the group level, where several individuals make important decisions as a group. I consider the individual dimension of "sociality" and introduce it as an additional portion of a subject's utility in an economic model of utility.

I believe that the notion of "sociality" holds promise for understanding a wide variety of individual behaviors that cannot be explained by standard utility theory and alternative theories. Specifically, this chapter focuses on decision making and appropriate risk tolerances when people make decisions under risk and uncertainty and the environment is either social or not social in the controlled experiment. Recent experimental evidence (T Johnson et al., 2004; Tim. Johnson, Orbell, & Myagkov, 2010) revealed that the assumptions of the prominent theories of decision making, such as expected utility theory and prospect theory, if taken at face value do not hold in the substantive domain of "sociality." In particular, the desire to be a part of the social environment is not contingent on framing by either gains or losses.

The idea that individuals may care for more than their narrowly-defined material interest and that their decisions may be driven by "sociality" and other non-monetary considerations is not new to economists. In particular, the fact that individuals do not only care about outcomes but also about the processes which lead to these outcomes has been discussed by behavioral and experimental economists before (Frey & Stutzer, 2005). Similarly, and more closely related to my research, there are literatures studying how individuals' willingness to take risks may be altered by the "sociality" of the context, e.g. whether the source of the risk is another person rather than nature (Bohnet, Greig, Herrmann, & Zeckhauser, 2008). However, behavioral economists rarely consider utility functions that include social aspects (Brock & Durlauf, 2001) or utility functions that are not defined by material outcomes (Bicchieri & Zhang, 2008; Xiao & Bicchieri, 2010). This is due primarily to their definition of economic utility, which is a measure of satisfaction or personal monetary value that people give to a product or a service consumed.

Social psychology scholarship has also focused on social interactions, including interpersonal and intergroup relations, for nearly 50 years (Tajfel, 1981, 1982, 2010). Scholars in this field acknowledge the heuristics (Kahneman & Tversky, 1979) that people use while making decisions but suggest the possibility that a reference point will not emerge in the social environment. This is because people serve as means for how gains can be obtained or losses prevented (Tajfel, 1981). Nevertheless, social psychologists rarely formalize their finding of behavioral patterns or assign a value to the importance of "sociality."

In this chapter I attempt to estimate how much (in economic terms) people value "sociality." I develop a theory of "sociality," and propose a general utility function that accounts for existing theories of utility defined by material outcome and adds the portion of utility defined by the decision making process itself and test it in the laboratory experiments carried out in several countries. The experimental test is done in two steps: first, by inferring the value of "sociality" from subjects' willingness to take part in the later stages of the game, second, by estimating the determinants of the value of "sociality" using subjects' decisions throughout the game. I work under assumptions of low stakes and the individual level of "sociality." My results suggest that the theory of "sociality" is successful in predicting the decisions of the subjects; on average, people assign a definitive value to the social environment of which they are a part and value "sociality" over monetary gain.

The main contribution of this chapter is to present the breakdown of risk attitudes under low stakes and the individual level of decision making. It also contributes the ability to formalize social utility or the theory of "sociality" in an economic model; I use a general utility function that I define both by the outcomes and by the process of the decision making itself, and I test this theory in laboratory studies.

Of course, the economic value of "sociality" that I discovered could be more pronounced in the situations where stakes are low[1], however, this requires further investigation. If my assumptions about the main causes of the presence of "sociality" are right, i.e. that "sociality" exists due to evolutionary development, then, even in the situation of high stakes decisions made in the presence of other players will differ from the ones made individually.

The remainder of this chapter is organized as follows. Section 2 provides an introduction to the new theory of "sociality" and the overarching utility function that treats existing models as special cases. This section is meant to give the structure to my research. The two subsequent sections, 3 and 4, present a description of the experiment, the empirical model that I use to test the theories of decision making and to adjudicate between them, and the data collected. My results are presented in Section 5. Finally, in Section 6, I provide a summary of the findings of the chapter and discuss applications and avenues for future research.

2.2. Theory

2.2.1. Predictions of the Expected Utility Theory

Expected utility theory (EUT) has long been the workhorse model for decision making under risk (Arrow, 1971; Friedman & Savage, 1948; Keeney & Raiffa, 1993). EUT assumes that all people will obey certain "rationality" principles of the theory, i.e., completeness, transitivity, independence, and continuity of their preferences (Kahneman

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[1] In particular, when stakes are high, rational choice models, such as expected utility or game theory, do work (Fiorina, 1995, 2000; Fiorina & Plott, 1978). That is why I focus on low stakes in my research and posit that "sociality" possesses a definitive value when stakes are low.

& Tversky, 1979; Savage, 1972; Von Neumann, Morgenstern, Rubinstein, & Kuhn, 1944). Considering decision making under risk as a choice between "prospects," where a prospect ($x_1,p_1;\ldots;x_n,p_n$) generates an outcome x_i with the probability p_i, where $p_1+p_{2+}\ldots+p_n=1$, expected utility theory asserts that

$$U(x_1, p_1;...; x_n, p_n) = p_1 u(x_1) + ... + p_n u(x_n) \qquad (2.2.1)$$

the total utility of a prospect is the expected utility of its outcomes, where u is concave ($u'' < 0$) and implies risk aversion[2] (Kahneman & Tversky, 1979).

2.2.2. Alternative Theories

Although EUT has limitations, it also allows for variants of the general model, e.g. with respect to the utility measurement, outcomes measurement, and probability transformations, and represents a simplistic and attractive model. As is well known, the validity of EUT at the individual level is questionable (Schoemaker, 1982). The main failures of EUT consist of "an inadequate recognition of various psychological principles of judgement and choice" (Schoemaker, 1982, p. 548) and ignorance of the preferences' intensity (Plott, 1976, p. 541). One famous challenge to EUT was proposed by Allais (1953) and was later generalized in terms of the "certainty effect and a reference effect" (Schoemaker, 1980, p. 19) by Tversky (1975). The Allais paradox suggests that "the meaning of probability numbers can vary, for the same person, across decision contexts" (Ordeshook, 1986, p. 49). To overcome the limitations of EUT, alternative theories have been created. Among them, the prospect theory, developed by Kahneman and Tversky

[2] A risk-averse individual prefers to receive the expected utility of the prospect or lottery x: $E(x, p)=c$ as a certain payment rather than face the bet x itself.

(1979), appears to be the most important and influential theory for decision making under uncertainty.

2.2.3. Prospect Theory

Using the term "prospect" to refer to gambles and lotteries, Kahneman and Tversky (1979) state that a decision maker faced with the choice between a certain outcome and a risky prospect will favor certainty when that choice is seen among gains but will favor the risky alternative when it is seen among losses. In other words, people are not always risk averse as the expected utility theory suggests, but they appear to be risk seeking when facing losses.

The utility function, *U*[3], is based on the edited prospects, which are rescaled expected utilities based on an individual's heuristic and are presented as two scales, π and u, where the first scale, π, "associates with each probability p a decision weight $\pi(p)$," and the $u(x)$ is the value of the outcome (Kahneman & Tversky, 1979, p. 275). The utility (value) function is assumed to be concave (risk aversion) above the reference point ($u''(x) < 0$, for $x > 0$) and convex (risk tolerance[4]) below ($u''(x) > 0$, for $x < 0$) for the regular prospects (Kahneman & Tversky, 1979) ($p + q < 1$ and $x \le 0 \le y$, or $x \ge 0 \ge y$)

$$U(x, p; y, q) = \pi(p)u(x) + \pi(q)u(y) , \qquad (2.2.3.1)$$

[3] Kahneman and Tversky (1979, p. 276) use *V* and *v* in the model. I changed the notations to *U* and *u*, respectively, to allow for an easier comparison.

[4] A risk-tolerant individual prefers to bet on prospect or lottery *x*, rather than receiving expected utility of this lottery *x*: $E(x,p) = c$ as a certain payment.

whereas for the strictly positive and strictly negative prospects ($p + q = 1$ and $x, y > 0$, or $x, y < 0$), the riskless component is separated from the risky one, and the evaluation of such prospects is:

$$U(x, p; y, q) = u(y) + \pi(p)[u(x) - u(y)] \quad . \qquad (2.2.3.2)$$

It is obvious that, when the first phase of editing is omitted, so $\pi(p) = p$, $\pi(q) = q$ and $p + q = 1$, the prospect theory utility function transforms into one defined by the expected utility theory with the choice between two prospects.

Nevertheless, as in EUT, *U* "is defined on the prospects," while *u* "is defined on outcomes" (Kahneman & Tversky, 1979, p. 276). The main difference between the utility function presented in the section below and utility functions in EUT and prospect theory is that it is defined not only by the outcomes but also by the processes specific to certain domains. In particular, scholars argue that framing effects are not as strong in the arena of human lives as they are in the financial domain (Fagley & Miller, 1997; McDermott et al., 2008). That is why, in the next section, I examine the domain of "sociality" and propose an overarching utility function for individual decision making. I argue that existing theories of decision making under risk fail to account for social dynamics and the specifics of the human decision-making domains, such as the domain of "sociality."

Social psychology has concentrated on social interactions for almost 50 years and specifically focuses on humans as affected by their social surroundings. The results of such scholarship suggest that decision making in the social domain might not follow the prospect theory: "Man's social behavior is an adaptation of his general gain-loss strategy to the special requirements arising out of his being surrounded by other people" (Tajfel, 1981, p. 30). Specifically, social psychologists consider humans as the means to obtain gains and avoid losses and, therefore, assume that, as a result, the reference point of prospect theory disappears (Tajfel, 1981, 1982, 2010). Unfortunately, the scholars do not formalize the guidelines for social behavior or the adaptation to different domains or changes in domains as a means of satisfaction or survival as a value that either makes one better or worse off. Thus, the next section focuses on the domain of "sociality."

2.2.4. Domain of "Sociality"

Humans are highly "social animals" for very good adaptive reasons: They enter relationships with others to get better protection against predation and to have greater success as predators as well as, more generally, to exploit the environment for adaptively important resources. Whatever the risks of entering social relationships, humans are far better off within a web of social relationships than they could ever be alone. In adaptive terms, this suggests that a bias toward entering social relationships would dominate hesitancy with respect to doing so. In addition, it implies that, in the substantive domain of "sociality," I should expect risk tolerance in the domain of losses and in the domain of gains.

For example, when our ancestors lived in tribes, the risky alternative was taking one's chances in a dangerous social relationship, while the certain alternative was, essentially, death from being alone in a dangerous environment (Bowlby, 1969). Back then, there would have been a strong selection in favor of risk tolerance in the domain of "sociality," regardless of how the choice between the risk and the certainty was framed. In keeping with this, the main results of a working paper by Myagkov, Orbell, and Johnson (2010) show that subjects take more risk than is rational across both a gains and a losses framework in the social domain, i.e. when subjects make decisions among their peers.

The table below presents a summary of the main differences in predictions between EUT, prospect theory, and the theory of "sociality."

Table 2.1: Differences in Predicted Risk Attitudes

Theory	Gains	Losses
Expected Utility Theory	Risk aversion	Risk aversion
Prospect Theory	Risk aversion	Risk tolerance
Theory of "Sociality"	Risk tolerance	Risk tolerance

For the purposes of my dissertation I define "sociality" as an additional portion of utility that involves not the function of an outcome but the function of the cognitive and affective processes related to a specific domain. The main goal of this chapter is to find the "sociality" component in decision making under risk and uncertainty. This component does exist when people make decisions among other people, however, it is not taken into account with the standard utility function. That is why I propose a general utility function that accounts for existing main theories of decision making and is defined both by the outcomes and the decision making process. This general utility function can be formulated in the following way:

$$U(x_1, p_1;...;x_n, p_n; s_1,...,s_k) = \sum_i \pi(p_i)x_i + \sum_j I(s_j)s_j \quad , \qquad (2.2.4)$$

where $\pi(p_i)$ is the edited prospect as introduced by the prospect theory, s_j is a process related to a specific domain, and $I(s_j)$ is the indicator function of the domain. For example, for the domain of “sociality,” $I(s) = 1$, if the individual is playing in the social context, i.e., with other human beings, and $I(s) = 0$ otherwise.

In general economists recognize that people not only care about the outcomes, but also they value the procedure which leads to the outcomes. Procedural utility concept was introduced by Frey et al. (2002) and is seen as potentially important source of human well-being. “Procedural utility means that people value not only actual outcomes, i.e. the ‘*what*’, but also the conditions and processes which lead to these outcomes, i.e. the ‘*how*’” (Benz et al., 2002, p. 2).

In the domain of “sociality” people have preferences, for instance about how they are perceived by their peers, what is their standing among their peers, who they want to pair up with to play a game, establish friendship or manipulate. The decision making processes and contexts (s_j), especially those that include many steps before the actual outcomes are revealed, may affect people’s well-being even more so than the bad material outcomes. Judgments expressed by other people may seriously influence individual’s self-worth. For example, in the experiment under consideration it can be deeply embarrassing for a person to be ostracized and being denied entrance into last stage of the game, where main interaction in the social environment happens. Thus, the additional component of utility function, “sociality” is a crucial determinant of human well-being that should not be neglected in social sciences and empirical research.

The next section concerns the development of a rigorous test of the proposed general utility function.

2.3. Methodology

In this section, I argue that, for certain conditions, neither EUT nor prospect theory works and that a new theory, the theory of "sociality," described in the previous section, should be implemented. These necessary conditions are the basis for the design of the experiments and include:

(1) Participants should have the option to enter or not enter a risky game. This way, the choices are presented as between a certain and a risky prospect as a means to compare the results with the prospect theory.

(2) Interaction between participants in ways that could modify or eliminate the risks should be prevented.

(3) The condition in which "sociality" can be extracted (game with computers) should be incorporated.

(4) The experiments should be carried out across cultures.

Test of the theory of "sociality" is based on a set of experiments that were carried out in US, New Zealand, and Russia.[5] The experimental design is presented in the Data section. In brief, Myagkov et al. (2010) attempted to reconstruct a 2-person Prisoner's Dilemma (PD) in a laboratory setting. Each period of the experiment includes three consecutive steps. First, participants are confronted with a choice between entering and not entering a risky but possibly productive social relationship. The participants bid to

[5] This research was supported by NSF grant no. 0618265 from the National Science Foundation.

enter such a relationship. The second step reveals the most popular players. In this step, participants choose others with whom they would like to begin this social relationship. Finally, the participants who survived the first two steps enter a social relationship and make a decision in the PD. They play the game (PD) in pairs, determined by a random draw. It is important to note that entering the game does not guarantee the highest profit.

This design allows me to test the risk preferences of individuals, to estimate the value that they assign to "sociality" as well as to compare game with people to a game with computers[6]. The experiments were framed in losses and gains as a means to relate them to prospect theory results. By providing the participants with data about the mean past choices in the PD, expectations of participants are made as endogenous as possible. Therefore, assuming that participants used this information in making their decisions, it is possible to calculate their expected value from actually playing a PD game and to do so separately for those who subsequently choose cooperation versus defection.[7] It is then possible to estimate participants' risk attitudes by computing the ratio of their expected values to the observed bids in each experiment. Risk neutrality would be implied by a mean ratio of exactly one, risk tolerance by a mean ratio of less than one, and risk aversion by a mean ratio greater than one.

Using the expected value of participating in the PD game, calculated based on outcomes in previous periods, I construct a test of theory of "sociality." I use a two-stage

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[6] The game with computers was supported by the same NSF grant and included the same steps as the game with humans. Robots appeared in the last stage of the game with computers, PD game and were cooperating with probability of .42.

[7] Thus, for example, for an individual who intended cooperation and for whom such information indicated a .4 probability of a (randomly selected) partner's also cooperating, the expected value of participating in the gains condition would be .4*700 + .6*0 = 280, where 700 and 0 are payoffs in the PD game (Table 3).

estimation. In the first stage, I estimate the value of "sociality" using the equation below, i.e., the simplified version of the equation (2.2.4):

$$U(x_t) = E(x_{t-1}, x_{t-2}, \ldots, x_1) + \alpha_{sociality} \times S\ , \tag{2.3.1}$$

where t is the number of the period, which varies from 1 to 20, x_t is the participant's profit for the particular period t, $E(x)$ is the expected value of the profit, and S is the indicator of "sociality," where $S = 1$ if the participant's bid is bigger than the third lowest bid, and $S = 0$ otherwise.

For the first stage, I vary $\alpha_{sociality}$ and compare the real decisions of individuals to the ones suggested by $U(x_t)$. The comparison follows the following steps for each participant in a certain period. The participant's bid is used to answer two questions:

(1) "Do you want to continue playing and get to the third stage of the game?" If the bid is bigger than the third lowest bid (*bidthreshold*), then the answer is "yes."

(2) "Is it optimal for you to continue play in the later stages of the game?" If $U(x_t) > \min(bidthreshold_t, bid_t)$, where $U(x_t)$ is defined by equation (2.3.1), then the answer is "yes."

If the answers to the two questions are the same, i.e., yes, yes or no, no, I count it as a correct guess of my model. Changing $\alpha_{sociality}$ from -300 to 1000 with an increment of 20 and counting correct guesses at certain values of $\alpha_{sociality}$ gives me the number and the percentage of the decisions guessed correctly. Further, varying $\alpha_{sociality}$ for $S = 1$ let me find the individual values of $\alpha_{sociality}$ that I will regress further on the process variables for the second stage of estimation. By following this procedure, I can decide whether the theory works as well as estimating how much people value "sociality" and whether there are any differences between domains and countries.

Further, I want to find conditions for deviating from the social environment and the occurrence of such deviations from “sociality.” I create a ratio that demonstrates whether the participant gains or loses while playing social:

$$\sigma = E(x_{t-1}, x_{t-2}, ..., x_1) / b_{t-1}, \qquad (2.3.2)$$

where b_{t-1} is the third lowest bid in the previous period, i.e., the highest bid that was paid to the participant, if he or she got out of the first stage of the game, and $E(x)$ is the expected value of the profit. I observe strategies of participants whose bids placed them in the nine highest bidders out of 12 (i.e., when $S = 1$) in period (t-1), but, in the period t, switched their strategy by placing a bid among that of the three lowest bidders out of 12 ($S = 0$). I separate the occasion of the first switch in their strategy from all others. This way, I can track whether, after changing the strategy for the first time, the participants return to “sociality.” The ratio $\sigma > 1$ means that the participant was winning more with “sociality”[8] but switched his or her strategy. When $\sigma = 1$, the participant was gaining the same as he or she would without “sociality,” so the “sociality” does not matter for him or her in this case. For $\sigma < 1$, the participant’s payoffs were less with “sociality,” and that is the reason for his or her switch. The ratio was calculated for each period where the switch occurred.

In the second stage of estimation, the value of “sociality” is used as a proxy and explained using process variables from the ostracism stage of the laboratory experiment using the equation:

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[8] S is the indicator of “sociality,” and if $S = 1$, that person played in the later stages of the game.

$$\hat{\alpha}_{sociality} = \beta_0 + \beta_1 \sum_j s_j + \varepsilon \quad , \qquad (2.3.3)$$

where s_j are the process variables from the second stage of the experiment and are described in Table 2.2.

Table 2.2: Process Variables

s_j	Definition	Equation
NumChipsTo	Number of people that gave chips to a person	
NumChipsFrom	Number of people that a person gave chips to	
NumChipsToDifference	Number of people that did not give chips to a person in round t-1, but gave chips to the same person in round t	
NumChipsFromDifference	Number of people that a person did not give chips in round t-1, but gave chips in round t	
ChipsDispersionTo	Variance of c_k	
ChipsDispersionFrom	Variance of c_i	
NonZeroChipsDispersionTo	Variance of nonzero components of c_k	
NonZeroChipsDispersionFrom	Variance of nonzero components of c_i	
CrossSimilarity	Average similarity between chips allocation of player n to m and player m to n	$Average(\lvert c_{nm} - c_{mn}\rvert)$
CrossSimilarityNormalized	Normalized similarity between chips allocation of player n to m and vice versa	$Average(\lvert\frac{c_{nm}}{\sum_k c_{nk}} - \frac{c_{mn}}{\sum_i c_{in}}\rvert)$
Popularity	Number of chips that a person i received	$\sum_i c_{ik}$
PopularityDiff	The difference between number of chips that a person received in t and t -1	$\sum_i c_{ik,t} - \sum_i c_{ik,t-1}$

PopularityDiffSignum	Did a person receive more or less in t than in t -1	$Signum(\sum_i c_{ik,t} - \sum_i c_{ik,t-1})$
AvgPopularity	Average popularity for all completed rounds	
IsLoser	Binary indicator whether a person was among three least popular players	

Chips allocation takes place in the second stage of the experiment, when each participant distributes 11 chips among others. Then, chips allocation can be represented as a matrix $[c_{ik}]$, 12 x 12.[9] Each participant has an ID number from 1 to 12, which stays the same for the entire game. Therefore, I can trace among participants who gave whom the chips. The element of the chips allocation matrix c_{ik} refers to how many chips participant i gave to participant k, and c_{ki} to how many chips participant i received from participant k, where $i \neq k$. All diagonal elements from the chips allocation matrix are zeros because participants cannot keep any chips to themselves. Each row of this matrix, c_i , is the chips vector with 12 elements, where each component is equal to the number of chips that player i gave to other players. Likewise, each column, c_k, is the chips vector with 12 elements, each representing the number of chips received by player k. I constructed the variables in Table 2.2 from the elements of the chips allocation matrix.

I ran the regression with these variables using equation 2.3.3 for the process variables, s_j, at time t and $\alpha_{sociality}$ at time t, to determine which variables matter when, at the first stage of the game, the participant decided to continue and play in the third stage of the game (S = 1). I also ran the regression with the process variables at time t - 1 and $\alpha_{sociality}$

[9] The total number of the players in each round is 12.

at time *t* to determine which process variable might contribute to the decision to play in the third stage of the game. I use the rank-sum test proposed by Wilcoxon (1945) to decide whether the coefficients of regressions are significantly different from 0. I identify the significant coefficients and discuss their meaning in the Results section.

2.3.1. Hypotheses

Following Johnson et al. (2010), I test risk attitudes in the presence of “sociality.” Therefore, the first hypothesis is:

H1: Participants are substantially disposed to take the risky alternative in a social domain, regardless of whether the risk is framed as gains or losses.

Next, I estimate the value of “sociality” and hypothesize that:

H2: Although the participants demand “sociality,” regardless of the framework or country, they value “sociality” differently.

Based on the ratio in equation (2.3.2), calculated for each period across all the games, I hypothesize:

H3: The value of “sociality” is high enough to allow for subsequent monetary losses.

For the second stage of regression (2.3.3) I hypothesize that:

H4: Participants enter the social environment to share and cooperate.

2.4. Data

Original data were collected with the help of the z-Tree[10] (Zurich Toolbox for Readymade Economic Experiments) software package. The same program code was used for experiments in the United States, Russia, and New Zealand. The data reflect observations of each stage of the game, including the PD game over time. Observations reflect the choices of different sets of 12 participants over 18 experiments. Each experiment contained up to 20 periods. The participants were not informed of the total number of experimental rounds.

It is important to note that the losses framework involved the same sequence of events. The only difference was that all payoffs were either zero or negative. However, participants' actual prospects in the gains and losses conditions were identical. This is the case because, unlike in the gains framework, 1000 points were distributed to each participant before the beginning of each period.[11] For example, a participant who played and defected with another defector would earn 200 points in the gains frame, but, in the frame of losses, the participants would lose 800 from the starting 1000 points that were

[10] http://www.iew.uzh.ch/ztree/index.php

[11] All participants started with 0 points in the gains framework and with 1000 points in the losses framework.

assigned. Thus, to be comparable with the gains framework, the original bids were subtracted from 1000 in the losses framework.

2.4.1. Cross-Cultural Experiments and Replications

To address the possibility that any finding was (or was not) a function of the peculiar culture in which the experiment was conducted, the experiments were ran in Moscow, Russia, and Auckland, New Zealand, as well as in Eugene and Bend, Oregon, U.S.A. Specifically, I analyzed five replications of the experiments in Eugene, Oregon (three in gains and two in losses); two in Bend, Oregon (one in each of gains and losses); seven in Moscow, Russia (four in gains and three in losses); and four in Auckland, New Zealand (two in each of gains and losses).

To ensure the equivalence of experimental sessions across countries, the experimental team followed Roth et al. (1991) on appropriate designs. The currency, language and experimenter effects were controlled for in each of the experiments. The instructions were translated (and back-translated) from English to Russian. All experiments were conducted by or under supervision of my chair member of committee, Professor Mikhail Myagkov.

2.4.2. Experimental Design

The participants for the experiment were recruited by advertisements on campus. All participants were required to sign the necessary informed consent forms. Before the experiment began, the players were asked to take a pop quiz on experimental design. Additionally, the first round was not counted in their total score, and they could resolve all the questions remaining after playing this round. This way, I could determine that participants understood their tasks. Players (mostly students) could earn $5 just for showing up and up to $20 more, depending on their decisions throughout the game. Each experiment included 12 participants. Each player was identified by a number visible to all that was valid until the end of the experiment. No names were used. Each period of the experiment consisted of three consecutive steps.

In the first stage, all 12 players participated. Participants made an initial competitive bid for the game in the last stage, i.e., the PD. The rules of the auction were as follows:

(1) Three players with the lowest bids would not play the PD game.

(2) For those 3 players, the amount of their bid would be their profit for a period under consideration.

In the second stage, each of the 12 participants was made to allocate 11 chips among others. In this way, participants determined who continued to play, i.e., made an "ostracism" choice. A participant could use any method to distribute the 11 chips but had to give away all their chips. For example, a player could give each opponent only 1 chip or give 11 chips just to one person. The 3 least popular players selected in the second stage did not play PD. These players were chosen out of 9 participants, not including the 3 lowest bidders excluded in the first stage of the experiment. The selected participants from the first and second stages and the third lowest bid at that round were revealed only at this point[12]. Those who were chosen in the first stage got their bid as a profit, whereas participants excluded in the second round received zero profit.

In the third stage of the experiment, the remaining 6 participants played the 2-person PD game in randomly created pairs. The experimenter explained the PD payoff structure to the participants. The “cooperate” alternative was specified as A and the “defect” alternative as B. Payoffs represent the points that the participants knew would be translated into dollars at the end of the experiment by the exchange rate of 1000 points = $1.00. Tables 2.3.1 and 2.3.2 displays the PD payoff structure in the domain of gains and the domain of losses.

Table 2.3: PD Payoffs in the Domain of Gains

	A	B
A	700, 700	0, 1000
B	1000, 0	200, 200

Table 2.4: PD Payoffs in the Domain of Losses

	A	B
A	-300, -300	-1000, 0
B	0, -1000	-800, -8s00

Participants repeated this process through a sequence of up to 20 replications. The exact number of repetitions depended on the speed at which successive replications were

[12] If a tie happened for the third lowest bid or the third lowest number of chips received, the winner was defined by a random draw.

completed. Notice that these were not iterated games. Any participant might (or might not) have been included among the 6 players that played PD in any given round, and, even when included, the opponent with whom he or she played was determined by a random draw.

2.4.3. Summary Statistics

The summary statistics for the variables used in equations (2.3.1) and (2.3.2), i.e., for the profit and bid variables, are presented in Table 2.4. The summary statistics for the process variables constructed from the matrix [c_{ik}] are not shown. This is because the matrix, as well as each of the process variables, was normalized, which means that all process variables have a mean of 0 and a standard deviation of 1. This allows me to make the absolute value of the coefficients of the second stage regression meaningful.

Table 2.5: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Profit	3012	290.492	320.6913	0	1000
bid	3012	566.219	244.9888	0	1000

2.5. Results

The Results are presented in the order of the hypotheses. Based on the analysis, I do not reject any of the hypotheses. There is clearly an economic value derived from being around other people. How does this economic value vary across domains and countries?

Result 1

Subjects exhibit risk tolerant behavior in both gains and losses, if evaluated using standard expected utility function.

Support

Since the ratio of average expected utilities to average bids is overwhelmingly smaller than one in both gains and losses I can conclude that risk tolerant behavior is present in both conditions. Table 2.5[13] presents the ratios of average expected utilities to average bids by conditions of gains and losses and for participants whose bids placed them in the bottom 3 of 12 and the top 9 of 12 (those who proceeded to the ostracism phase and, for those who survived there, to a PD game). In both frames, the mean expected value of playing the game was less than the mean value of the points that participants were bidding to enter the game, which implies risk tolerance[14] in both conditions.

Table 2.6: Ratio of Mean Expected Utilities to Mean Bids

	NZ(G)	NZ(L)	RU(G)	RU(L)	US(G)	US(L)
C – top 9	0.32^{***}	0.29^{***}	0.31^{***}	0.42^{***}	0.37^{***}	0.39^{***}
D – top 9	0.49^{***}	0.51^{***}	0.5^{***}	0.66^{**}	0.56^{***}	0.61^{**}
C – bottom 3	0.62^{**}	0.59^{***}	0.48^{***}	0.6^{***}	0.53^{***}	0.5^{***}
D – bottom 3	0.95	1	0.84^{*}	1.03	0.85^{*}	0.89

Significantly less than one with probabilities (t-test) .9 (*); .95 (**); and .99 (***).

[13] C - top 9: Players with the highest 9 bids that cooperated; D - top 9: Players with the highest 9 bids that defected; C - bottom 3: Players who had the 3 lowest bids and cooperated; D - bottom 3: Players who had the 3 lowest bids and defected; NZ-New Zealand, RU-Russia, US-United States; G-gains framework, L-losses framework.

[14] Risk neutrality is implied by a mean ratio of exactly one, risk tolerance by a mean ratio less than one, and risk aversion by a mean ratio greater than one. The calculation is examined in the Methods section.

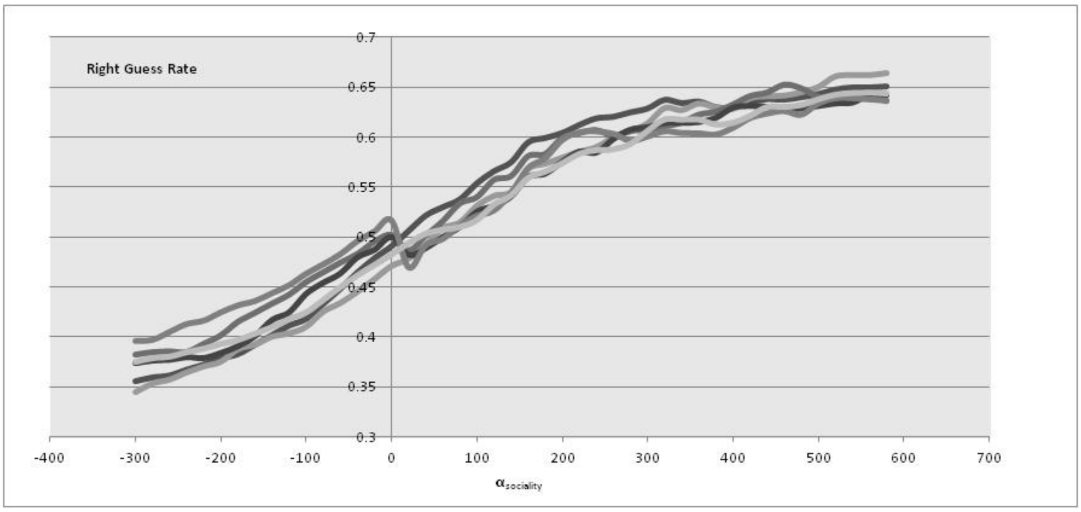
Result 2

The value of "sociality" is estimated to be at least twice as big as the average profit per round.

Support

Across countries and domains, the value of "sociality" still increases after $\alpha_{sociality} = 600$, which is twice as much as the average profit per period for the game. Figure 2.1[15] shows that the percentage of guessed decisions first sharply increases, then reaches a plateau at $\alpha_{sociality} > 300$. This means that, given the 65% decisions guessed correctly, the value of "sociality" can increase up to the maximum monetary payoff (1000) throughout the experiment.

Figure 2.1: The Value of "Sociality"



[15] Each line indicates the average estimation results for each country in each domain. Thus, there is a total of 6 lines for Russia, New Zealand, and the United States in the domains of gains and losses.

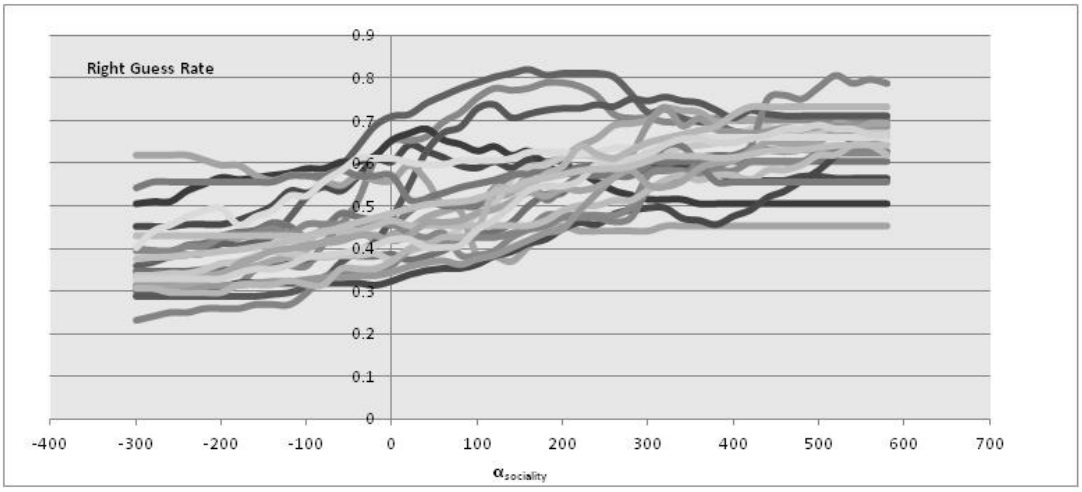
Result 3

The theory of "sociality" is successful at predicting the decisions of participants.

Support

Figure 2.2[16] demonstrates that the percentage of guessed decisions is between 40% and 80% for all the experiments considered. Moreover, the rate of correct guesses increases with the value of "sociality."

Figure 2.2: Percentages of Guessed Decisions for All Experiments



Result 4

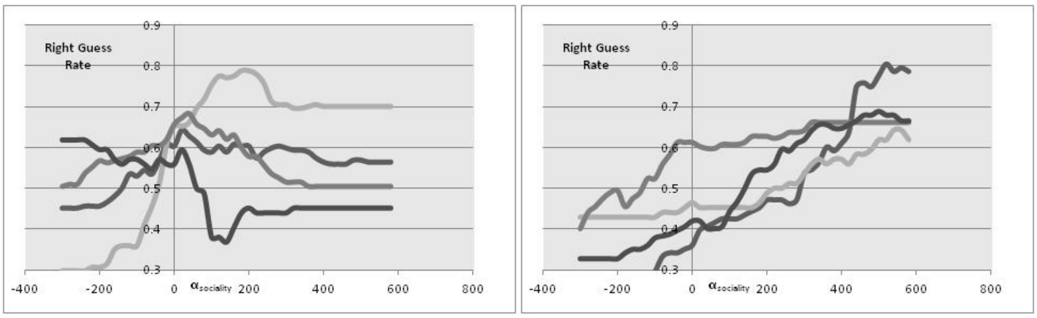
The value of "sociality" in US and NZ is higher, with more possibility to grow, whereas in Russia it is bounded by specific value.

[16] Each line in the graph reflects estimation results for each of the experiments.

Support

Figure 2.3.1[17] presents the experiments in Russia in gains, and Figure 2.3.2[18] demonstrates the experiments in the US[19], also in the gains framework. There is a global maximum, where $\alpha_{sociality} \approx 100$ for the graph in Figure 2.3.1, whereas there is none for the US graph. The rate of guessed decisions keeps increasing with the increase in $\alpha_{sociality}$. I ran experiments in different cultural settings to test whether there are differences, but I were not expecting this intriguing result, which I plan to resolve in future research.

Figure 2.3: Value of "Sociality" for Russia (2.3.1-left) and US (2.3.2-right)



Result 5

"Sociality" persists even after subsequent monetary losses.

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[17] Each line represents the four experimental trials in Russia in the gains framework.

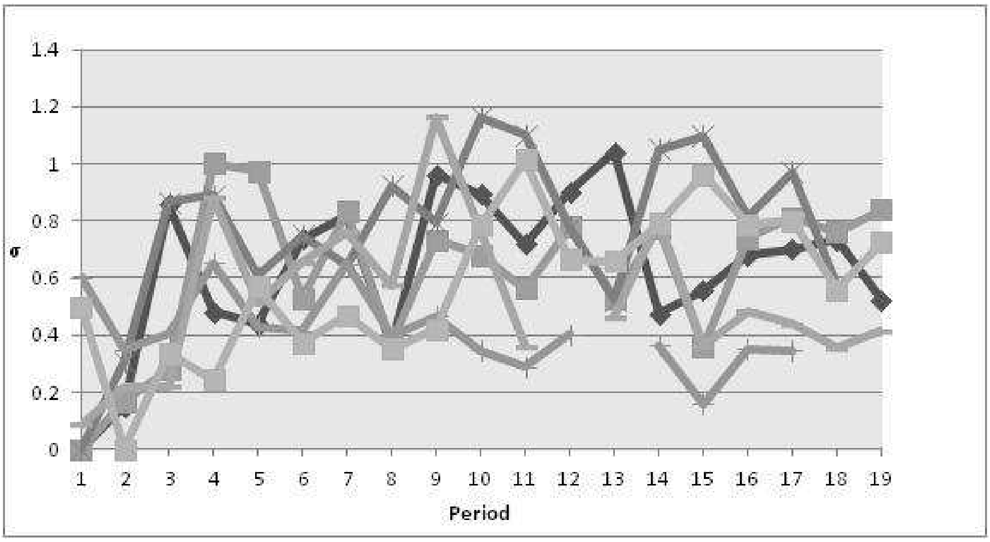
[18] Each line represents the four experimental trials in the United States in the gains framework.

[19] The graph for NZ in gains framework looks similar to the graph for US and, therefore, not included in the paper.

Support

Figure 2.4[20] reveals that participants value "sociality" and, even after a monetary loss, get back to the disadvantageous strategy of "sociality" in terms of monetary payoffs. This figure uses the data of all subsequent switches from "sociality" (from S = 1 to S = 0[21]), which means that, after the first switch, players go back to "sociality" and then might switch from it again. The ratio σ is almost always less than 1, which means that, to the participants, "sociality" matters.

Figure 2.4: Conditions for Deviating from "Sociality"



2.5.1. Second Stage Estimation Results

I ran a two-stage regression, where, in the first stage, I find the individual values of $\alpha_{sociality}$ regress further on the process variables for the second stage of the estimation. The

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[20] Each dot represents the average ratio value in a certain period. The consecutive dots are connected. If there is no dot, this means that there were no switches. The grayscale shades reflect six possibilities of aggregation across countries and frameworks, i.e., six lines for Russia, New Zealand, and the United States in the domains of gains and losses.

[21] S is the indicator of "sociality," where S = 1 if a participant's bid is bigger than the third-lowest bid, and S = 0 otherwise.

significant coefficients of the second stage of regression, using process variables at time *t* and regression with process variables at time *t*-1, are presented in Tables 2.6 and 2.7, respectively.

Table 2.7: Second-Stage Regression with the Process Variables at Time *t* and $\alpha_{sociality}$ at Time *t*

Process Variable	Wilcoxon Statistic	*p*-value	Sign
NumChipsToDifference	59.0	0.086	+
NumChipsFromDifference	35.0	0.009	+
ChipsDispersionFrom	53.0	0.052	-
AvgPopularity	21.0	0.002	-

Table 2.8: Second-Stage Regression with the Process Variables at Time *t* – 1 and $\alpha_{sociality}$ at Time *t*

Process Variable	Wilcoxon Statistic	*p*-value	Sign
NumChipsToDifference	56.0	0.067	+
AvgPopularity	21.0	0.002	-

Result 6

Subjects with higher propensity for “sociality” tend to be more egalitarian in their decision making process.

Support

As seen in Tables 2.6 and 2.7, the coefficient for the variable *NumChipsFromDifference* is positive and, for *ChipsDispersionFrom,* is negative, which means that, if a person plays social, then he or she will give the chips to more people and will distribute the chips more equally (less dispersion). In contrast, if a person gives chips to more people, he or she will play social. These results are robust across countries and domains.

Result 7

Unpopular participants value “sociality,” or being in the social environment, more than do popular ones.

Support

There is an intriguing correlation between being unpopular and playing social. The coefficient for the variable *AvgPopularity* is negative in both Tables 2.6 and 2.7, which means that, if an individual played social, he or she will be, on average, less popular. From the other direction, if he or she was, on average, less popular, he or she will play social. If I reinterpret Result 5 for “sociality” as being how much money a person is ready to lose to be in the social environment (would like to continue playing in the second and third stage of the round), then, if one is popular, one is not losing money (total utility is high, with the material part dominating), and, thus, one’s “sociality” is low. However, when one is unpopular and loses money,[22] one’s “sociality” is high (social utility), and one demands that the social environment compensate for the total utility staying the same. This result is robust across countries and domains.

2.6. Conclusion

This chapter has developed a framework for studying the individual decisions of participants that are made in the social context under the assumption of low stakes. In

[22] There is a higher chance for one to be in the three least popular players and to get 0 for the entire round of the game.

general, the results of the experiments were consistent with predictions derived from the theory of "sociality" and the economic model of general utility proposed. First, the proposed risk attitudes were confirmed. Unlike EUT and prospect theory advocate, I found risk tolerance in the presence of "sociality," regardless of framing the experiment as losses or gains. Second, the value of "sociality" was estimated. This result confirms that "sociality" has a definitive value for some countries and definitive minimum value for others when stakes are low. This finding also suggests that the utility function is mis-specified and that there is a need to define and formalize social utility. Moreover, when stakes are low, "sociality" is able to compensate for monetary loss. In particular, the participants equilibrate their twofold profit to "sociality." Therefore, in the social context, when stakes are low, human beings value social interaction more than the monetary outcomes (losses) of such interaction.

The theory of "sociality" was tested in laboratory experiments carried out in New Zealand, Russia, and the United States, and the results point to striking differences among cultures. In New Zealand and the United States, the participants value "sociality" to the highest degree possible in terms of the game payoffs, whereas, in Russia, they tend to calculate the maximum value for "sociality." This is another reason why I assert that the concept of "sociality" is vital for the everyday decisions that human beings make. Many social scientists are critical of the use of student samples in laboratory experiments. However, a recent article by Druckman and Kam (2011) argues that, if there are any constraints in student samples in regard to inferences, they are limited and do not represent "an inherent problem to experimental research" (J. Druckman & Kam, 2011, p. 41). Nevertheless, the next step is to search for the same patterns in the field. Once similar results are found in the field, the “political implications are profound” (Mercer, 2005, p. 2).

This chapter has applications for the social sciences, business, and any discipline that considers decision making under risk. As an example, the main results of this chapter apply to policymaking. For the domain of gains, prospect theory predicts risk averseness, but the theory of “sociality” anticipates risk tolerance. A policy is viewed as an instrument to improve procedures, decision-making rules, and well-being and, therefore, exists in the domain of gains. Depending on the area in which policymakers are working, they might be interested in implementing risky or riskless policies. The theory of “sociality” then implies that, if a risky policy (for example, in the environment) needs to be implemented, the policymaker should make an individual decision (vote) on that policy while being surrounded by his or her peers, whereas the riskless policy (for example, in legislature) will be chosen once the policymaker makes an individual decision while alone or in conversation by phone or computer.

Future work should start with the manipulation of the notions of in-group and out-group. In particular, given my experimental design, I are able to estimate the value of “sociality” for the ostracized participants, why they demand “sociality” more than popular players, and how they behave when interacting with out-group members. Equally important to this endeavor will be examining how cultural variance may mediate the relationship between the in-group and the out-group members.

CHAPTER III

COOPERATION IN THE SOCIAL DOMAIN

3.1. Introduction

Game theoretic models are often used to identify how cooperation could arise and what conditions or behavioral traits are necessary for it to evolve. In such models, cooperation is typically characterized as a public goods game, such as a Prisoner's Dilemma (PD) game or ultimatum game, in which two or more "rational" players are given a choice of cooperating or defecting. The puzzle is why cooperation occurs when the dominant strategy for any rational actor is to never cooperate, even when the collective outcome is not a Pareto optimum. Indeed, the experimental findings contradict the predictions of the deductive models: across a large number of countries, consistent majorities of college-aged subjects exhibit cooperative and altruistic behavior, even in single-shot game. Over the last 40 years, a large scholarship has modeled numerous processes in which a cooperative equilibrium can be achieved. Some scholars explain cooperation through individual dispositions and iterated dyadic relationships. Others bring forward the importance of shared norms, beliefs and standards of behavior to cooperation within much larger social units.

This chapter explores the prospects of cooperation in the PD game; it identifies the significant markers of cooperative behavior in the experimental setting that includes social domain and tracks how this behavior changes with time and experience. The recent laboratory experiments[23] in three countries and five different cities allow participants to enter or not enter inherently risky social relationships and, if they entered, play a PD game. This experimental setup gives an opportunity to identify behavioral features of the domain of "sociality." In particular, Myagkov, Orbell and Johnson (2010) successfully revealed and results of Chapter II confirmed that subjects take more risk than it is rational across both gains and losses. This chapter uses the same set of laboratory experiments described in detail in Chapter II, Section 2.4.2. However, it focuses not on how participants overcome risks of social interactions, but on the changed risk attitudes and how they influence the decision-making process within those interactions. Instead of the aggregate data that were used by Myagkov, Orbell and Johnson, I use the individual-level data. The dataset unfolds the laboratory experiments in United States, New Zealand and Russia. I develop a discrete choice model in order to trace significant conditions for cooperation and find that in social domain cooperation rates are significant, they grow with the increase in demand for social interactions and decrease with experience.

The remainder of this chapter is organized as follows. Section 2 provides an overview of previous findings in relation to PD game, presents PD game, its payoffs and equilibrium, and introduces a probabilistic model of cooperation. This section is meant to prepare for an empirical model given in the next section. The two subsequent sections, 3 and 4, present a brief description of the experiment, the empirical model that I use, hypotheses that I intend to test, and the data collected. My results are presented in Section

[23] These are the same experiment described in full detail in chapter II, Section 2.4.2.

5. Finally, in Section 6, I provide a summary of the findings of the chapter and discuss applications and avenues for future research.

3.2. Theory

3.2.1. Social Domain and Collective Action

Why do people cooperate? How do people choose partners for cooperation? How does "sociality" affect their decision making? In Chapter II I find that "sociality" makes humans overcome the risks to enter social interactions. How do these interactions change in the presence of "sociality?"

The social domain itself has long been argued to be instrumental for the success of collective action. Marwell, Oliver and Prahl (1988) argued that overall density and centralization of social ties always has a positive effect on collective action. One of the key factors that turns social networks into an efficient facilitator of cooperation is its ability for information revelation about potential cooperators and defectors (Carr & Landa, 1983; Landa, 1981) as well as the ability to mobilize coercion against those who cheat (Gambetta, 1988). On the other hand, social environments do not fully eliminate cheating (defection). Instead, as evolutionary psychologists would argue (Dawkins & Krebs, 1978; Krebs & Dawkins, 1984), social interactions are often a combination of individuals attempts to reveal information about others intentions as well as attempts to manipulate other players into believing in their own good intentions (regardless of it being true or false). I assert that the social ties are building up on the second step of the experiment and, thus, include the process of choosing social circle in the study of the cooperative behavior. The main goal of this chapter is to find out what drives cooperation in the social domain and what makes it change over time.

3.2.2. Prisoner's Dilemma

The original Prisoner's Dilemma shows two suspects being interviewed by the police in relation to a major crime. It is important that they are interviewed in separate cells, so neither can get any info about the other's answer. Therefore, it is appropriate to model this situation with a simultaneous game (Carmichael, 2005). The suspects can either confess to the crime (defect) or deny any involvement in it (cooperate). A game is a Prisoner's Dilemma if it is represented with payoffs a, b, c, d, where c>a>d>b.[24] For the payoff structure[25] in the experiments under consideration regardless of what the second player does the first player is better off defecting, because 1000>700 and 200>0. In other words defecting is the dominant strategy of the first player. The same logic is true for the second player. That is why (defect, defect) is the Nash equilibrium of the game, where Nash equilibrium is defined as a combination of players' strategies that are best responses to each other.

The classic Prisoner's Dilemma (PD) provides a core framework for the choice between self-interest and common good. It is a dilemma because each player would be better if neither had defected (700=a > d=200). Making a prior agreement to cooperate is in common interest of both of the players. Such a decision can be called a jointly rational behavior, because the players increase their total rather individual payoffs. But unless the

[24] For example, for the gains framework a=700, b=0, c=1000, d=200. So, indeed, c>a>d>b.

[25] The payoff structure for the experiment in gains and losses frameworks is presented in Chapter II, Tables 2.3.1 and 2.3.2

agreement to cooperate is enforced in some way the incentive for both prisoners to defect is so strong that it is unlikely that such an agreement is kept.

As I discussed before the single PD game has a dominant equilibrium strategy: the players should defect. However, even for single-shot games experimental findings contradict the game theoretical predictions, i.e. there is cooperation. Only in the infinitely repeated (iterated) PD game the equilibrium can change to (cooperate, cooperate). Robert Axelrod's computer-simulated public goods tournament show that certain behavioral strategies, such as TIT-FOR-TAT can outplay (defect, defect) strategy over time (Axelrod, 1987). Although the outcome is often contingent on a number of factors, such as starting conditions and changes in environment, the important and consistent finding from these tournaments is that cooperative strategies tend to outperform strategies based on narrow self-interest.

Generally speaking, the strategy when both players cooperate is beneficial, but risky, because one needs to find the enforcement mechanism that prevents cheating. The key to a common good is the case of the reciprocated trust. Cooperation can also flourish, if the cooperators are able to distinguish between cooperators and cheaters. But in reality it is almost impossible to identify cooperators, because "cheaters have a strong incentive to mimic cooperators" (Scharlemann, Eckel, Kacelnik, & Wilson, 2001). Still some studies provide evidence that people can be successful in detecting cooperators. Frank et al. (1993) show that 30 minutes for observations before decision-making are almost always enough to predict actions of subjects.

On the other hand, Wilson and Eckel (2010) showed that both trust and reciprocation increases when you can choose your partners. Luckily, the choice of partners is implemented in experiments under consideration in the second stage of the round, when participants distribute chips among others. In laboratory experiments, subjects appear particularly sensitive to issues of reciprocity and cheater detection, demonstrating differential cognitive capacities when analytic tests are characterized in terms of social exchange (Cosmides & Tooby, 1994a). In fact, several neuro-imagining studies report consistent brain activation patterns, particularly in the stimulation of pleasure centers in the striatum, among subjects cooperating and punishing cheaters in public goods games (De Quervain et al., 2004; Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003). It is these findings that make evolutionary psychologists assert that just as humans evolved eyebrows, prehensile thumbs, etc. to help with certain functions, they also evolved numerous domain-specific cognitive and affective processes to help sustain and enforce cooperation. Punishing and revealing cheaters, however, is not employed in experiments that I use. Therefore, for the purposes of this chapter cooperation will be determined through the types of interaction as well as the ways participants choose partners to enter social interactions.

3.2.3. PD: Experience, Repetition and Learning

A natural explanation for a significant rate of cooperation in the first rounds of the game can be found in the inexperience of the subjects (Kagel & Roth, 1995; Ledyard, 1994). Clearly it is necessary to find out whether cooperation rates changes over time and why do they change. Does experience in playing PD game increases or decreases cooperation? If everybody learns, i.e. learns a rational selfish strategy, then one should observe the convergence to the equilibrium in defection after enough rounds.

The finite repeated PD game has a definite solution that prescribes non-cooperative behavior (Kahn & Murnighan, 1993; Mailath & Samuelson, 2006; Osborne & Rubinstein, 1994). However, even in this condition experimental results do not conform to this theoretical prediction of defection, although the rates of cooperation do decrease (Selten & Stoecker, 1986). The experiment under consideration uses repetitions of a PD game, but it is not an iterated game. Here subjects play PD each time against different opponent determined by a random draw.

An experiment suggested by Andreoni (1988) displays a comparison between two types of games: iterated, a treatment that Andreoni calls Partners and non-iterated, Strangers treatment. Partners are found to cooperate less than Strangers and the difference increases over time (Ledyard, 1994). As Andreoni points out Strangers may indeed learn slower, but learning alone cannot explain the difference between the treatments. It is expected that as soon as one of the players deviates from cooperation the other should react with non-cooperative choices and cooperation is not established any more (Selten, 1991; Selten & Stoecker, 1986). Obviously it might take more rounds to converge in the Strangers scenario, because players might play quite a few rounds until they meet first defector. However, players' return to cooperation still remains unexplained. Playing against another learner might also delay the convergence to the defection equilibrium, because the adaptation of the other learner might create a non-stationary environment, where a learner randomly picks between strategies, imitates his opponent and only after a sufficient number of rounds decides upon a single strategy (Sandholm & Crites, 1996).

A lot is known about the logical structure of PD (Axelrod & Hamilton, 1981) and what strategies will maximize the outcome. But the dynamics of learning in such situations, how experience affects individual behavior and how people decide to adopt certain strategies remain largely unexplored (Silverstein, Cross, Brown, & Rachlin, 1998). This chapter attempts to find some of the answers.

3.2.4. PD: Cultural Aspects

People of different cultural backgrounds possess different values, attitudes and norms that reflect their heritage. They approach tasks differently. One explanation to the difference in behavior between cultures lies in the extensive research on distinction between individualism and collectivism (Hofstede, 1980; Triandis, 1989).

Collectivist cultures, if compared to individualist cultures place greater emphasis on social norms, shared responsibility and cooperation (Bond & Forgas, 1984; Cox, Lobel, & McLeod, 1991; P. B. Smith & Bond, 1993). As cross-cultural studies have shown "northern and western Europeans and North Americans tend to be individualists and Chinese people, other Asians, Latins and most east and west Africans tend to be collectivists" (Cox et al., 1991, p. 828). That is why many studies expect American subjects to be more competitive (Hemesath & Pomponio, 1998; Liebrand & Van Run, 1985; Wong & Hong, 2005) and, thus, less cooperative than, for example, Chinese subjects, when playing within their cultural group. Furthermore, since the fall of the Soviet Union Russians are expected to be on the extreme for competitiveness due to the "hvatat" (grab) property of their behavior[26] (Menshikov, Menshikova, Myagkov, & Plott).

Although there is empirical evidence that cultural difference affects at least some aspects of human behavior the simplistic division between collectivists and individualists does not explain all variance in behavior. Yamagishi's findings (Yamagishi, 1988; Yamagishi & Yamagishi, 1994) challenge collectivist vs. individualist hypothesis. He finds that Japanese are less cooperative than Americans and explains it through "institutional view of culture" (Yamagishi, 2003), which states that Japanese cooperate not because of intrinsic tendency, but because of a system of sanctions and monitoring (Chen & Li, 2005). That is why when this system is absent, for example in experimental conditions that do not control for it, predictions of cultural hypotheses are not confirmed.

Recent studies more often report that Chinese are less cooperative than Americans (Chen & Li, 2005; Weber & Hsee, 1999). Can culture change due to the change of individual motives within it? Liebrand and Van Rus (1985), prior to the PD game assessed subject's social motive (Griesinger & Livingston Jr, 1973; Kuhlman & Marshello, 1975; McClintock, 1972). Subjects with competitive motives regardless of their culture were behaving according to their motive and not cultural expectations.

Culture is not the only determinant of human behavior, personal characteristics matter a big deal (Liebrand & Van Run, 1985). Scholars suggest that gender also plays a great role, women are generally found to be more cooperative than men (C.C. Eckel & Grossman, 1998; Stockard, Van De Kragt, & Dodge, 1988), especially in the earlier

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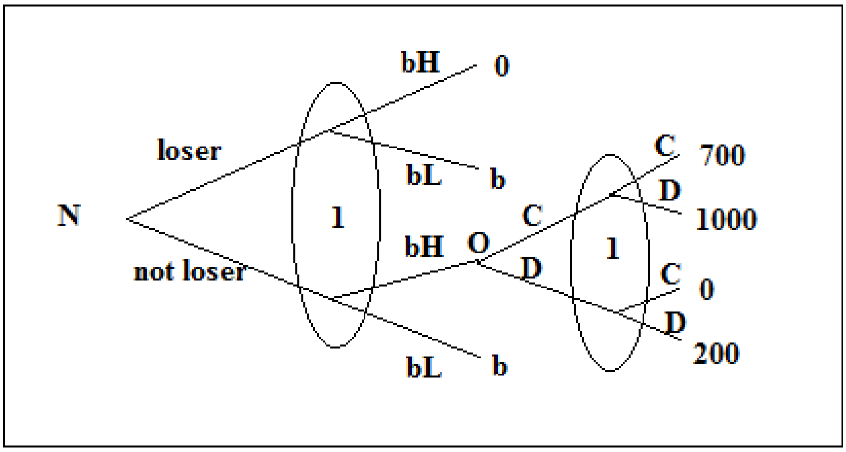
[26] After the collapse of the Soviet Union most of the national assets were grabbed by force or through privatization on a first come first serve basis. Russians constantly display the 'hvatat' property in their ordinary lives until today.

rounds (Ortmann & Tichy, 1999). Unfortunately, these predictions cannot be tested, because the data collected does not include personal or gender characteristics.

3.2.5. Formal Solution

In the experiment under consideration PD game is played by participants in the third stage of the game. Participant gets into the third stage of the game by bidding high (bH) in the first stage of the game and being popular (not loser) in the second stage of the game. Experiment consists of 12 participants, however, in order to simplify a game tree for the entire experiment I take into consideration only one participant.

Figure 3.1: Experiment Game Tree



In the simplified version Nature (N) decides whether you are unpopular (loser) with a certain probability, q, which equals 1/3[27]. Player 1's information set is that of Nature. Therefore, Player 1's beliefs must be that $\mu(loser)$ = 1/3 and $\mu(not\ loser)$ = 2/3. These

[27] Three players out of nine are unpopular in each round.

beliefs will be consistent with any strategy, since whatever strategy is being played will not affect the probability that Player 1 is at either node in the information set.

This experiment has two subgames: PD game and another one represented by the full game tree. I already mentioned that Nash equilibrium of PD game is defection (D). Thus, this is the optimal strategy of the subgame PD regardless what strategy the Opponent (O) chooses. It is also a subgame perfect equilibrium of the entire experiment game because it forms a Nash equilibrium for each proper subgame. Another Nash equilibrium for the entire experiment, though not subgame perfect is for Player 1 to bid low.

Although Player 1's optimal strategy to defect (D) is obvious, what is the condition for Player 1 to bid high (bH)? In other words, when expected utility to bid high exceeds the expected utility to bid low? Let me denote the probability of Opponent's defection as *p*, then the expected utility of bidding high is:

$$E(bH) = q * 0 + (1 - q) * (p * 200 + (1 - p) * 1000) \tag{3.2.1}$$

$$= \frac{2}{3} * (1000 - 800p)$$

$$E(bL) = q * b + (1 - q) * b = b \tag{3.2.2}$$

The necessary condition for Player 1 to bid high is:

$$\frac{2}{3} * (1000 - 800p) > b \tag{3.2.3}$$

or

$$p < \frac{2000 - 3b}{1600} \tag{3.2.4}$$

If I consider threshold bid to be equal 300, then the probability to defect should be less than .7[28] in order for Player 1 to choose bidding high.

3.2.6. Discrete Choice Model

The main goal of this chapter is to explain cooperation in Prisoner's Dilemma, despite the game equilibrium. Although utility to defect is higher than utility to cooperate in general framework, I propose an additional portion of utility that involves not a function of an outcome, but the function of cognitive and affective processes related to a specific domain. My dissertation focuses on domain of "sociality" that determines such a portion of utility corresponding to social interactions. I believe that in the presence of "sociality" the (cooperate, cooperate) strategy can outperform defection. To my knowledge there are no other experimental designs that allow not only to impose a social domain on the experiment and the PD, but also to collect data on the social interaction stage, i.e. second stage of the round. I am eager to examine what are the factors, related and not related to "sociality", that drive cooperation. In order to do that my Dependent Variable is the decision to cooperate (C). This is a dummy variable that takes value "1" if a player cooperates and "0" if a player defects. The model estimated is a logit model:

$$\Pr(C = 1|X) = \Phi(X'\beta), \tag{3.2.5}$$

where X, the vector of regressors, and the model itself are described further in the next section.

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[28] The average probability of defection is .65 for the entire experiment. That is why in at least half of the cases bidding high is not optimal.

3.3. Methodology

One of the easiest and widely used discrete choice models is logit. The Dependent Variable is the choice made on the third stage of the game (C). This is a dummy variable that takes value "1" if a player cooperates and "0" if a player defects. The utility that the decision maker obtains from an alternative to cooperate is

$$\mathrm{U_c} = X_c{}'\beta_c + \varepsilon_c \tag{3.3.1}$$

The logit model is obtained by assuming that for each decision there is a random component, ε. This error term represents some random added propensity for the subject to cooperate not known to the researcher. I assume that the errors are independent, identical, Normally distributed random variables with mean zero and same variance. Then, the probability that decision maker chooses to cooperate is

$$P_c = Prob(X_c'\beta + \varepsilon_c > X_D'\beta + \varepsilon_D) \tag{3.3.2}$$

$$P_c = \frac{e^{\beta' x_c}}{e^{\beta' x_c} + e^{\beta' x_D}} \tag{3.3.3}$$

The chapter's main goal is to find what variables influence the decision-making process in the PD. According to the previous scholarship, experimental design and, in particular, steps required to get to the third stage of the game, the choice in the Prisoner's Dilemma depends on:

- the initial bid to enter the PD game, B;
- experience of the player, E;
- cultural background, L; and
- the chips allocation distribution properties, A_k, described further in the Data section.

I assume that the observed part of utility is a linear function, thus I can write the utility of choice to cooperate as:

$$U_c = \beta_0 + \beta_1 B + \beta_2 E + \beta_3 L + \sum \beta_{4k} A_k + \varepsilon \, , \qquad (3.3.4)$$

From this baseline model significant markers of social behavior can be identified. I assume that all independent variables are truly exogenous. An observation for this model is a PD decision in a single period.[29]

In addition, I include other variables to the baseline model that were controlled in the experiment and test for their exclusion. In particular, for each round of the game I consider profit (P), total profit (TP) of the subject, the minimum bid[30] (MB) to get into the third stage of the game, and framework's dummies (G). A further discussion of the variables and descriptive statistics is given in the Data section.

3.3.1. Hypotheses

Aggregate results of the experiments by Johnson et al. (2010) found and Chapter II confirmed new risk attitudes in the presence of "sociality," i.e. risk tolerance in both gains and losses. Risk attitudes were measured by capturing the initial bid and comparing it to the expected utility of a player for a particular round of the experiment. From the instructions subjects understood that the three lowest bidders, i.e. three most risk averse, will not advance to the third stage and play PD game. On the other hand risk tolerance can be also interpreted as the demand for social interactions. That is why bid is the first independent variable I consider.

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[29] I pool observations across all experiments.

[30] Minimum bid is the third lowest bid for the round.

The ostracism stage (second stage of the round that is described further in the Data section) provides several independent variables that are properties of the chips allocation distribution. This is where I can test recent finding that choosing people that you play with increases trust and, thus, prospects for cooperation(Catherine C. Eckel & Wilson, 2010). However, in this experimental design for a choice of one player to influence the presence of another in the third stage of the game a player needs to allocate chips selectively and to a fewer number of players as possible. At the extreme, giving all chips to one player as well as the presence of chip allocation reciprocity between two players can also influence the PD outcome by creating a strong trust-based relationship.

Based on previous scholarship the baseline model tests the following hypotheses:

H1: "Sociality" begets "sociality," i.e. the increase in demand for social interactions increases the probability of social choice, or cooperation.

H2: The chips allocations on the second stage of the game concentrated on a fewer number of opponents increase the probability to cooperation.

H3: The more experienced the player is the less likely he is going to cooperate.

H4: Participants from Russian are expected to be the least sharing and cooperative.

3.4. Data

The data section of Chapter III replicates parts of the data section of Chapter II. This is because the experiments used for both chapters are identical. Original data were collected with the help of the z-Tree[31] (Zurich Toolbox for Readymade Economic Experiments) software package. The same program code was used for experiments in the United States, Russia, and New Zealand. The experiments were run in 3 different countries to address the possibility that any finding was (or was not) a function of the cultural background and in 2 frameworks: gains and losses to reproduce the prospect theory findings (Kahneman & Tversky, 1979). The data display observations of each stage of the game, including the PD game over time. Observations reflect the choices of different sets of 12 participants over 16 experiments. Each experiment contained from 15 to 20 periods. However, the Dependent Variable exists only for the 6 out of 12 participants who entered the PD game in the third stage of the round. The experimental design is described in detail in Chapter II, section 2.4.2.

3.4.1. Summary Statistics

To empirically implement equation 3.3.4 the rest of the data underwent modification. The Dependent Variable is the decision to cooperate (C). This is a dummy variable that takes value “1” if a player cooperates and “0” if a player defects. In the raw dataset, however, the decisions to cooperate or not were totaled up for a particular period from the beginning of the experiment. The variable was modified in a dummy-type variable. The

[31] http://www.iew.uzh.ch/ztree/index.php

relative frequencies of the choice to cooperate by country and by framework are shown in the Tables 3 and 4, respectively. The cooperation rates across countries and frameworks are very similar, with 35% of cooperation on average. Regardless of the country the participants came from they cooperated at similar rates. Moreover, Russians tend to be more cooperative out of the three countries considered, which confronts hypothesis 4.

Table 3.1: The Cooperation Rate by Country

	0	1
NZ	70%	30%
RU	61%	39%
US	65%	35%

Table 3.2: The Cooperation Rate by Framework

	0	1
G	65%	35%
L	65%	35%

The Independent variables and their modifications are described below. It is important to note that losses framework involved the same sequence of events as gains framework. The only difference was that all payoffs were either zero or negatives. However, participants' *actual* prospects in the gains and losses conditions were identical. This is the case, because unlike in the gains framework, 1000 points were distributed to each participant at a time before the beginning of each period. For example, a participant who played and defected with another defector would earn 200 points in the gains frame but in the frame of losses, the participants would lose 800 from the starting 1000 points that were assigned. That is why the original bids were subtracted from 1000 in the losses framework to be comparable with the gains framework.

Chips allocation takes place in the second stage of the experiment, when each participant distributes 11 chips among others. Then, chips allocation, A_k, can be represented as a matrix $[c_{ik}]$, 12 x 12.[32] I constructed the variables in Chapter II, Table 2.2 from the elements of the chips allocation matrix. For the purposes of this chapter the variables Popularity, NumChipsFrom, IsLoser, and their modifications are of the greatest interest to me. CrossSimilarity variable is not directly observable by participants, i.e. they know how many chips they get, but do not know who they get these chips from, and, therefore, this variable was removed from the baseline model.

The test period, i.e. period 0, was excluded from each experiment for analysis. This period was used as an introductory one and did not count towards the total score. I am left with 3012 observations, where each observation represents the decisions of a single individual in a single period or outcomes of those decisions. The main goal of this chapter is to explain the choice to cooperate. But this choice in each period was made only on the third stage of the game and included only half of the participants, six out of twelve. Thus, half of the total number of remaining observations had missing values for the Dependent Variable.

The experience variable reflects how many times an individual took part in the PD stage of the experiment. The lagged cooperation variable is capturing whether you

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[32] The total number of the players in each round is 12.

cooperated last time you entered the game[33], in order to avoid large number of missing values. All independent variables, excluding binary ones, and the summary statistics for them are shown below, in the Table 3.3.

Table 3.3: Independent Variables Summary Statistics

Variable	Obs	Mean	St. Dev.	Min	Max
Profit	3012	290.492	320.691	0	1000
Bid	3012	566.219	244.989	0	1000
Popularity	3012	11	4.721	0	42
NumChipsFrom	3012	4.826	2.804	1	11
Experience	3012	4.727	3.781	0	19

3.5. Results

I estimate the model given by equation 3.3.4 using logit[34]. In Table 3.4, I provide the estimation results of the baseline model[35]. It consists of a logit regression with and without fixed effects for experiments.

[33] Only 6 participants out of 12 enter the PD game at each round. Lagged cooperation variable keeps the memory of your last PD decision till the next time you enter the game in the third stage of the round.

[34] One need to recall that different distributions are used for probit and logit regressions. For logit – a logistic distribution, and for probit- normal, where the main difference is in tails. Thus, having data at extremes or having unbalanced set of choices entails significant differences in estimates. However, it's not the case in my analysis. The probit estimates give me the same signs as in logit and similar levels of significance. However, I observe lower magnitudes, which is due to the calculation of parameters. Thus, I use logit for the further models.

[35] The baseline model excluded NumFromChips variable, because it challenges hypothesis of increase in cooperation likelihood with the ability of choosing specific opponents. Also coefficient for the NumFromChips variable is statistically significant only at 10% level, but experience variable loses its significance.

Table 3.4: Estimation Results

EQUATION	VARIABLES	(1) Logit	(2) Experiments FE	(3) Variables Choice
Cooperation	Experience	-0.0354**	-0.0471**	-0.0285
		(0.0176)	(0.0187)	(0.0180)
	Ln(Bid)	0.320**	0.392**	0.307**
		(0.145)	(0.183)	(0.146)
	Popularity	-0.0111	-0.0117	-0.00866
		(0.0162)	(0.0166)	(0.0162)
	Lagged Profit	-0.000100	-0.000386*	-8.25e-05
		(0.000227)	(0.000235)	(0.000227)
	Lagged Cooperation	1.152***	0.914***	1.141***
		(0.165)	(0.170)	(0.165)
	Lagged Profit x Lagged Cooperation	0.00160***	0.00160***	0.00162***
		(0.000398)	(0.000405)	(0.000399)
	NumChipsFrom			0.0458*
				(0.0235)
	Constant	-2.889***		-3.098***
		(0.967)		(0.975)
	Observations	1329	1329	1329
	Number of idn		15	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All models fit the data well, the results are robust and the parameters estimated are comparable across the models. The independent variables of interest Bid, Experience, Lagged Cooperation and Profit are statistically significant. Moreover, the signs are the same across the models. Model (2) adds fixed effects to the baseline model (1). Model (3) pools all independent variables under consideration, including NumFromChips variable. I base my results on the baseline model (1), because the fixed effects model (2) does not produce different estimates, both in coefficients’ signs and magnitudes, and model (3) also generates similar signs and magnitudes of the estimates, but only adds minimum significance to NumChipsFrom variable while losing significance for the experience variable.

Then, I run regressions separately for each country and framework. The estimation results are displayed in tables 3.5 and 3.6. Whereas across frameworks the results of regression analysis barely change, regressions across countries produce intriguing results. I focus on the disparities across countries in the presentation of results.

Table 3.5: Estimation Results by Country

EQUATION	VARIABLES	(1) NZ	(2) RU	(3) US
Cooperation	Experience	-0.0999***	0.0332	-0.0743***
		(0.0386)	(0.0338)	(0.0284)
	Ln(Bid)	0.842**	0.0363	0.823***
		(0.400)	(0.245)	(0.235)
	Popularity	-0.104**	0.0318	-0.00497
		(0.0475)	(0.0375)	(0.0201)
	Lagged Profit	-0.000122	3.93e-05	-0.000449
		(0.000463)	(0.000409)	(0.000358)
	Lagged Cooperation	0.893***	0.575*	1.363***
		(0.324)	(0.327)	(0.250)
	Lagged Profit x Lagged Cooperation	0.00285***	0.00251***	0.000724
		(0.000849)	(0.000788)	(0.000592)
	Constant	-4.950*	-1.694	-5.960***
		(2.660)	(1.631)	(1.548)
	Observations	397	314	618

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Estimation Results by Framework

EQUATION	VARIABLES	(1) L	(2) G
Cooperation	Experience	-0.0198	-0.0561**
		(0.0230)	(0.0281)
	Ln(Bid)	0.339	0.344*
		(0.220)	(0.201)
	Popularity	0.00340	-0.0413
		(0.0192)	(0.0301)
	Lagged Profit	-0.000216	6.91e-05
		(0.000300)	(0.000349)
	Lagged Cooperation	0.942***	1.435***
		(0.218)	(0.253)
	Lagged Profit x Lagged Cooperation	0.00196***	0.00111*
		(0.000533)	(0.000605)
	Constant	-3.224**	-2.641**
		(1.492)	(1.319)
	Observations	745	584

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The main results of the chapter are presented in the order of the hypotheses. Based on the analysis hypotheses 2 and 4 are challenged by the estimation results. The central results are that in social domain cooperation rates are significant; they grow with the increase in demand for social interactions and decrease with experience of a player.

Result 1

Despite the Prisoner's Dilemma equilibrium, a significant proportion of subjects cooperated in the presence of "sociality."

Support

The incidence of cooperation across countries and frameworks is reported in tables 3.1 and 3.2. It is obvious that Nash expectation of zero cooperation in such PD games is not supported. The average rate of cooperation is 35% and is robust across countries and frameworks.

Result 2

"Sociality" begets "sociality", i.e. the increase in the demand for "sociality," increases the rates of cooperation, or "social" choice.

Support

Hypothesis 1 is supported by the estimated model in Table 3.4. In particular, this is shown with the positive coefficient for the bid variable. I consider bid as a demand for the social interaction stage of the round, i.e. Prisoner's Dilemma, thus, the positive sign of the coefficient means that the increase in bid that a player decides upon increases the likelihood of cooperation.

Result 3

Sharing with others is critical for cooperation.

Support

Unlike hypothesis 2, the estimated model (3) in Table 3.4 predicts that the more people a subject distributes chips to the higher are the prospects for cooperation. The positive sign of the coefficient in all models is consistent with this prediction. In other words, it is not the ability to choose opponents that contributes to the choice of the cooperation in the first place, but the intention of sharing and distributing chips in an egalitarian way.

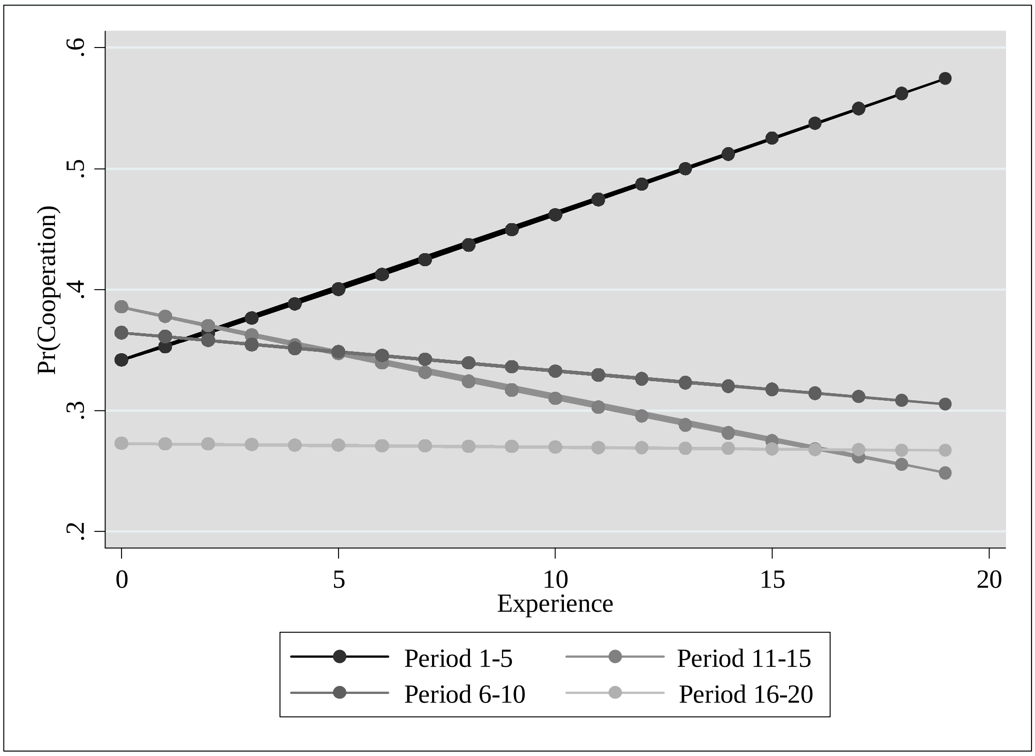
Result 4

More experienced players are less likely to cooperate.

Support

Hypothesis 3 is supported by estimated model in Table 3.4. The negative coefficient for the experience variable indicates that the more times a player participated in the last stage of a round the less he is likely to cooperate. The learning scheme is shown below in Figure 3.1. In the first 5 periods experience of a player increases the likelihood of cooperation, whereas in the next 10 periods it decreases cooperation. Finally, in the last 5 periods experience do not significantly change prospects for cooperation.

Figure 3.2: Learning Model



Result 5

Participants from Russia cooperate more than participants from other countries and their choice of cooperation is dependent on the profit they received last time they cooperated.

Support

Unlike hypothesis 4 suggests, Russians are found to be more cooperative then participants from other countries based on the Table 3.1 results. Unlike, NZ (1) and US (3) estimation that corroborate baseline model results in Table 3.5, in Russia (2) the only independent variables that have statistically significant coefficients are lagged cooperation and interaction term, which indicates that Russians base their decision solely on their profit last time they cooperated: the higher the profit they get last time they cooperated the higher the prospects of cooperation.

Result 6

More popular players cooperate less.

Support

Based on the results of estimation for New Zealand in Table 3.5, model (1) the more popular the player is the less he is likely to cooperate (negative coefficient for popularity variable). This is the only case where popularity variable is statistically significant. Popular players mimic cooperators, but in reality they do not need to appear 'friendly' in PD game in order to gain support from other players.

3.6. Conclusion

The main result of this chapter is that cooperation, or social choice, increases with the presence of "sociality." Given the results of estimated models in Table 3.4, I am able to support two out of four hypotheses I made based on theory and previous literature assumptions. I find that increase in the demand for "sociality" improves rates of cooperation, whereas the experience in PD game decreases cooperation. Unlike hypothesis 2, the estimated model suggests that more egalitarian a player is in distributing chips the higher are the chances of cooperation. In addition, my model supported previous results on the importance of the trust between the subjects. The trust gained in the experimental settings is due to the control of the experimental environment, or "sociality". Participants distribute chips and expect chips and cooperation in return.

The results suggest that future research should start with the recognition of the countries' effects and their theoretical grounding. The disparities between the countries are striking, however, the background research neither expects, nor explains them. This chapter is based on the single choice of cooperation. Unlike this, the analysis can be based on the sequence of two choices (CC, CD, DC, DD), one for the current period, the other for the last period the participant entered the PD game, and estimated using multinomial logit. On the other hand, the model can be constructed using the longer sequences of choices, i.e. multiple-spell model of "social" choice dynamics. The main purpose of such a model is to investigate the time before a certain event occurs. Zero profit after PD stage of the game can be presented as this event. Thus, not only I can find out what causes the events of interest, but also I can look for the evidence of lagged duration dependence, i.e. the impact of the length of initial spell on the probability of subsequent events.

Variables of the second stage of the round, the properties of chips allocation distribution, were not statistically significant in the models presented. However, the second ostracism stage is the most intriguing one, although ambiguous, since it is mostly dependent on the emotional state of the participants. In the real world humans are normally able to influence the pool from which their social contacts are drawn and, thereby, they have some capacity to control the risk that is involved in PD-type games played with the members of that pool. The vivid example is admission committees in the academic departments, where choosing the 'right' people will foster cooperation within the department. However, it may not happen in the laboratory setting of the experiment described.

The further research can be done to focus on players, who are left behind, i.e. unpopular players that are willing to play in the PD game, but do not receive enough chips, or support from other players. These players appear to be a problem for social environments, like the one constructed by these experiments, because on average unpopular players defect more on others, possible in revenge for not being chosen in the previous rounds and being indicated as unpopular. Can it be the case that not only unpopular players behave in an unsocial way, but also unsocial behavior is the cause for unpopularity?

Social dilemmas and experimental designs that recreate them abound. On the one hand, cooperative behavior, such as giving to charity, voting in elections, contributing to public goods, participating in local politics or even leaving tips in the restaurants where one will never return is believed to be beneficial for the social environment and, therefore, it is worthy for each individual in the long-run. On the other hand, when one examines the cooperative actions one by one a good economic reasoning for them often is not seen, especially, in the long-run, when one learns how to play the PD-type games and what strategies to choose. Moreover, as cooperation is not socially embedded in societies, it requires a system of governance (Teece, 1992; Yamagishi, 2003) that facilitates coordination and ensures cooperation. The apparent failure of current structures results in dilemma’s status being preserved.

CHAPTER IV

NEUROBEHAVIORAL FEATURES OF "SOCIALITY"

4.1. Introduction

In this chapter I focus on neurobehavioral features of "sociality." Functional magnetic resonance imaging (fMRI) (Huettel, Song, & McCarthy, 2004) is the recent sophisticated technology that allows researchers to study functional neuroanatomy of the human brain noninvasively. Due to its noninvasive nature, it can be used in healthy human volunteers, including children. The imaging is based on the fact that two different forms of the hemoglobin molecule - oxyhemoglobin (when hemoglobin binds oxygen in the lungs) and deoxyhemoglobin (when hemoglobin releases the oxygen in the peripheral tissues) have slightly different magnetic properties. This difference is detected by the fMRI method in the brain with a millimeter resolution. When one region of the brain works harder than others during a particular task (e.g., visual cortex during perception of visual stimuli), there is more inflow of blood to this region leading to a higher concentration of oxyhemoglobin relative to other, non-active sites of the brain.

For the past 15-20 years, the fMRI has been used extensively to study brain activations related to higher cognitive functions, including attention, language, memory, emotions and others. In recent years, there has been a growing interest to apply this methodology to study brain mechanisms of more complex human behaviors, including social interactions, economic or political decisions (Huettel et al., 2004). Currently neuroimaging is also seen as the key tool to understand the nature of the various peculiar aspects of human behavior such as "economic irrationality" (Peterson, 2005), altruism and “altruistic punishment” (De Quervain et al., 2004; Waytz, Zaki, & Mitchell, 2012), asymmetry between gains and losses (Yacubian et al., 2006), preference of egalitarian outcomes (Sanfey et al., 2003; Schreiber et al., 2010; Tricomi, Rangel, Camerer, & O’Doherty, 2010) and many others. Use of this methodology has the potential to advance the knowledge of the existing theoretical accounts of how people make decisions and judgments by informing and constraining these models based on the underlying neuroscience.

This chapter aims to utilize the fMRI technology in combination with laboratory experiments in an attempt to study brain mechanisms of human social interactions. The research questions include: In what regions of the brain is there an increased activation associated with interaction with humans as opposed to playing computer? Are the brain bases of social welfare choice different from those of collective action? Does the neural basis for the preference of egalitarian outcomes in the presence of “sociality” differ from the one without; if yes, map the difference in the brain?

The remainder of this chapter is organized as follows. Section 2 provides an overview of previous findings of neuroscience in relation to social domain. This section is meant to present hypotheses that are tested in the next sections and establish the theoretical grounding for the stimuli used in the experiments. The two subsequent sections, 3 and 4, present descriptions of the laboratory as well as fMRI experiments, the models that I use for analysis, and the data collected. My results are presented in Section 5. Finally, in Section 6, I provide a summary of the findings of the chapter and discuss applications and avenues for future research.

4.2. Theory

The interest in using biological variables to explain social behavior has been for a long time, however, biological approaches to social psychology were seen as “reductionist and having little to contribute to ‘real’ conceptual debates in the field” (Harmon-Jones & Winkielman, 2007, p. 3).Only in recent years a new discipline social neuroscience (Cacioppo et al., 2002) started to emerge, which is an attempt to understand mechanisms that underlie social behavior using a mix of biological and social approaches (Willingham & Dunn, 2003). On the other hand a relatively new discipline neuroeconomics opens up the “black box” of the brain by finding neural correlates of choice behavior (C. Camerer, Loewenstein, & Prelec, 2005; Lohrenz & Montague, 2008) and behavior under risk and uncertainty (Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005). Unfortunately, current knowledge of neural mechanisms for social decision making is still limited (Lee, 2008).

What are the benefits and contributions of neuro- disciplines? First of all, the additive value of neuroimaging lies in the fact that the same behavior can be caused by activity in different regions of the brain (Krueger, Grafman, & McCabe, 2008). Second, if social cognition constantly results in a different pattern of brain activity than non-social one and the regions of brain activation during social cognition have a special status (high levels of activity even at rest) in the brain (Adolphs, 2003; Jenkins & Mitchell, 2011). If this is true to what extent are brain systems that control social behavior *domain specific* (Cosmides & Tooby, 1994b; Stone, Winkielman, & Harmon-Jones, 2007)? If evolutionary perspective provides theoretical grounding for domain specificity, neuroscience then gives an opportunity to investigate it.

My dissertation focuses on the domain of "sociality." In particular, chapter II estimates the additional value that individuals place on being in the social environment by foregoing material resources and, thus, personal gain. Similar study was done in neuroscience (Zaki & Mitchell, 2011) and its results suggest that many behaviors are aimed at maximizing social, not personal material outcomes. This happens because people see intrinsic value in social ideals, such as equity and fairness, or, in other words, "fairness can be its own reward" (Zaki & Mitchell, 2011, p. 4). If this study considers social ideals having value in itself, my dissertation explores the additional value that processes in the domain of "sociality" possess. Although with the experiments I carry out I am not able to distinguish between the value in itself and the value of the processes involved, this remains an ambitious goal for future experiments. Nevertheless, in this chapter I attempt to find what brain regions are corresponding to a neural value of "sociality" and lay foundation in future to identify and estimate this neural value.

I use a set of computer and fMRI experiments to achieve this goal. At first, I was trying to replicate as close as possible the experiments used for chapters II and III in order to use them in the scanner. However, I gave in on this arduous task and decided that a simpler experiment will serve me better, especially given my first interaction with fMRI data. Both computer and fMRI experiments are described in detail in Section 3 of this chapter. The experiments use Prisoner's Dilemma game and Welfare game. Whereas PD game was thoroughly described and theoretical solution found in chapters II and III of my dissertation, Welfare game is new to this manuscript. The rest of the Theory section I devote to finding Nash equilibrium in the Welfare game and discussing its results and applications.

Welfare game resembles a simultaneous version of the Ultimatum game with unfair offer. The Ultimatum game is a game often played in laboratory experiments in which two players interact to decide how to divide a sum of money that is given to them. One of the players proposes how to divide the sum between the two players, and the other can either accept or reject this proposal. If the second player rejects, none of the players receive anything. However, if the second player accepts, the money is split according to the proposal. Usually the game is played only once or with randomly chosen partner so that reciprocation is not an issue. Also quite often players do not change roles within one game.

The equilibrium in the Ultimatum Game is not in the favor of the second player. By rejecting the proposal, the second is choosing nothing rather than something. So, for a rational player it would be better to accept any proposal that gives any amount bigger than 0. Unlike that multiple studies (Henrich, 2004; Oosterbeek, Sloof, & Van De Kuilen, 2004) show that in many cultures people offer (50:50) splits and offers less than 20% are usually rejected.

Welfare game payoffs structure is represented in experimental design section in table 4.2. Based on the payoffs the row chooser always prefers to choose up. The column chooser's best response to the row chooser's dominant strategy is to choose left. That is why the Nash equilibrium is (2; 6). However, the row chooser always gets the worse payoff, than that of the column chooser. So, if the row chooser prefers egalitarian outcomes, the row player's deviation from the equilibrium can occur and result in either of the two egalitarian options: (1; 1) and (4; 4).

The utility function defined solely on the outcomes is not able to explain the preference for egalitarian outcomes. Instead, the additional portion of utility that I address in Chapter II and is defined on the specific processes in the presence of “sociality” should reveal which processes are crucial for the choice of egalitarian outcomes. On the other hand, fMRI experiments help to map the activation related to the egalitarian outcomes preferences in the brain.

4.2.1. Inequity Aversion

The preference of egalitarian outcomes can be introduced as the individual utility function composed of both the player’s own payoff and the payoff of others (Fehr & Schmidt, 1999). Then, the second component is weighted negatively if other players have higher payoffs, and positively if they have lower payoffs. As such, if a player’s payoff is held constant, he would prefer that others receive the same amount rather than more or less. This concept of inequity aversion was proposed by Fehr and Schmidt (1999) to capture the notion of fairness. It may provide an explanation to the well-known failure of the traditional game theory to predict the results of the Ultimatum game (C. Camerer, 2003). This concept may even be a part of altruistic punishment, in the sense that players want to punish not the free-riders, but those who do well, because while rich are often viewed with contempt, people tend to sympathize with the poor.

Such preferences may be rational from an evolutionary standpoint. Clearly, an individual should not like to lose out in a competition. In contrast, being too far ahead in a competition may result in ostracism. Egalitarian preferences are close to those of altruism, only being directed towards the least well off, which also makes sense from an evolutionary perspective. Sacrificing some of your income if it is high to ensure that the poor have the necessities may be an evolutionary stable strategy in kin groups. Inequity aversion may also survive the transition to higher stakes. While market liberalization and free trade may be beneficial to two states in international trade, if it benefits one more than the other you may see resistance from the trade partner who would “lose out” to the other. Inequity aversion can, therefore, be an example of rational behavior and can explain some of the failures of rational self interest in predicting laboratory behavior.

Several utility function have been developed to account for the fairness concept and not just monetary gains (Bicchieri & Chavez, 2010). Fehr-Schmidt model illustrates this approach, but it is defined only on the outcomes as shown above. On the other hand, the model developed by Rabin (1993) is focused on the role of actual actions and beliefs in determining utility, i.e. on the processes and not the outcomes. In particular Rabin introduces “kindness” of the player (Rabin, 1993, p. 11) and incorporates the individual belief of one player about “kindness” of her opponent into the utility function. Moreover, the reciprocity is taken care of with the interaction term. This is a great insight of how to model the utility function defined on beliefs. Nevertheless, I do not implement this approach in my dissertation and only discuss its applications to the theory of “sociality” in the last chapter.

4.2.2. Hypotheses

Previous research in neuroeconomics suggested the necessity to understand how brain evaluates potential goals and outcomes. What brain structures are responsible for the computation of the economic value? What other cognitive, emotional and visceral processes affect this computation? Scholars find that the ventral striatum, ventromedial prefrontal cortex (VMPFC) and medial orbitofrontal cortex (OFC) areas are involved in the assignment of value to stimuli at the time of decision making (Hare, O'Doherty, Camerer, Schultz, & Rangel, 2008; Plassmann, O'Doherty, & Rangel, 2007). Earlier animal research found that activation in ventral striatum of monkeys is sensitive to new knowledge about rewards (Montague, Dayan, & Sejnowski, 1996), whereas further research on humans displayed activation in dorsal and ventral striatum and VMPFC related to anticipation and acquiring of monetary rewards (Knutson, Fong, Adams, Varner, & Hommer, 2001). Although Damasio (1994) argued that VMPFC plays a huge role in encoding the consequences of alternative courses of action affectively, strict functional differences between the orbitofrontal and ventromedial areas are not fully known (Loewenstein, Rick, & Cohen, 2008). However, VMPFC is found to be less associated with social functions and more with just regulation of emotions, whereas OFC is more active during guessing tasks and decisions under uncertainty(Schnider, Treyer, & Buck, 2005). Based on the results of the previous research I propose the following preliminary hypothesis:

H1: The difference in response and activation in ventral striatum, VMPFC and medial OFC areas are likely to be found between the human and computer conditions of fMRI experiment as well as between Welfare and PD games.

Furthermore, the “rational” decision making is found to be correlated with superior working memory (Devetag & Warglien, 2003) that, in turn, correspond with increased activity in the dorsolateral prefrontal cortex (DLPFC) (Carter & Van Veen, 2007; Krueger et al., 2008; Weissman, Perkins, & Woldorff, 2008). In particular, DLPFC plays an important role in creating links between our actions and their eventual outcomes in working memory (Genovesio, Tsujimoto, & Wise, 2006). However, social situations often require the brain not only to use previous experiences to select future behavior, but also to form some beliefs about other person and better predict other players' choices. Current research suggest that two regions of the human brain, such as DLPFC and the posterior superior sulcus (posterior STS), play crucial roles in evaluating others behavior (Krueger et al., 2008). STS is found to be more activated when people play PD and Ultimatum games against another person than when they played against computer (Rilling, Sanfey, Aronson, Nystrom, & Cohen, 2004). If activation in DLPFC may contribute to rationality of decisions in social situations (Weissman et al., 2008), the prosocial decision making, on the other hand, is expected to be connected to the activation in the regions of the temporoparietal junction (Emonds, Declerck, Boone, Vandervliet, & Parizel, 2011). That is why I hypothesize:

H2: There will be likely an increased activity in the DLPFC, when the participant plays a computer or when he plays a human and chooses defection in PD game and is accepting inequity in Welfare game, whereas when she plays a human and makes cooperation or fairness choice in the game there will be likely an increased activity in the regions of the temporopatietal junction and STS.

Similarly, brain regions associated with reward should be more active during fair, than during unfair condition. These reward regions include the ventral striatum, the amygdala, VMPFC and OFC (Cardinal, Parkinson, Hall, & Everitt, 2002; Tabibnia, Satpute, & Lieberman, 2008; Trepel, Fox, & Poldrack, 2005), where amygdala and OFC are regions critical for processing emotions (Davidson, Putnam, & Larson, 2000; Dolan, 2002). VMPFC is also reported to activate during tasks involving inequality in social settings (Fliessbach et al., 2007; Tabibnia et al., 2008; Tricomi et al., 2010). Therefore, I hypothesize:

H3: There will be likely increased activity in the VMPFC, amygdala and OFC in Welfare game condition as opposed to PD game condition.

Although I identify the regions of interest for my hypotheses, I do not implement a region of interest (ROI) analysis. Instead I use whole brain contrasts to isolate neural activity associated with making decisions in the social circles playing a computer further described in Section 4 of this chapter.

4.3. Methodology

4.3.1. Computer Experiment

The first group of subjects for the computerized portion of experiment is 48 college students (10 females) recruited from "Corruption and Mafia" class that Mikhail Myagkov taught at University of Oregon in Fall 2010. All participants were required to sign the necessary informed consent forms. Before the experiment began, the players were asked to take a political affiliation questionnaire in order to correlate their decision to their political likes. However, University of Oregon college students not surprisingly turned out to be homogeneous in their political and policy preferences. Almost all of the participants were democratic and preferred living in the households that are similar in income to theirs.

Players of the first group could earn 1 extra credit point just for showing up and up to 4 more, depending on their decisions throughout the game. Each experiment included 12 participants. Each player was identified by a number visible to all that was valid until the end of the experiment. No names were used. Each experiment consisted of two different scenarios.

In the first scenario participants played 2-person Prisoner's dilemma (PD) game for the first 20 rounds and then a Welfare game for the next 20 rounds. In the each round 12 participants were paired up randomly. The payoffs of the games are presented in the tables below.

Table 4.1: PD Payoffs

	L	R
U	4, 4	1, 6
D	6, 1	2, 2

Table 4.2: Welfare Game Payoffs

	L	R
U	2, 6	6, 2
D	1, 1	4, 4

In the second scenario each round was divided in three stages. In the first stage participants played PD game in a pair determined by a random draw. Then, in the second stage they played Welfare game with the same opponent. Finally, during the third stage of the round participants decided which outcome to count towards their profit, either outcome from the PD game or outcome from the Welfare game, not knowing what payoff this outcome will result in. Participant were paired up randomly in each round of the game, but maintained their opponent for all stages of that particular round. This scenario repeated 20 or more rounds.

The second group is 16 college students recruited through advertisements on campus to accompany the fMRI study in 2013. After running two first subjects for fMRI experiments in November 2012 I decided to make the social environment and human condition of the fMRI experiment more realistic for the subjects. The human condition for fMRI portion of experiment was created by making the fMRI participant[36] believe that he is playing one of the two players in the conference room and influences their outcome with his decisions. Before the experiment started the subjects (two for computerized option and one for the fMRI portion) had time to get to know each other

[36] Similarly, the participants of the computerized portion of experiment were made to believe that they are playing either with the other participant in the conference room or the participant in the scanner and influence their outcomes. A participant will see the “Please wait” screen if other two were paired at that time.

and engage in an informal conversation in the conference room. When the participant for the fMRI portion left the conference room to enter the scanner, the participants remaining in the conference room played the first scenario of the game described above, however, only for 2 players. In reality they were playing against each other in 2-person Prisoner's dilemma (PD) game for the first 15 rounds and then a Welfare game for the next 15 rounds. Each of the subjects could earn $5 for just showing up and up to $10 more for the decisions they made throughout the experiment.

4.3.2. fMRI Experiment

Subjects of the fMRI experiment are 10 college students (5 females). Subjects provided written informed consent approved by the University of Oregon Human Studies Committee[37]. All participants were recruited through advertisements on campus. All subjects were right handed, healthy, had normal or corrected-to-normal vision, had no history of psychiatric diagnoses, neurological or metabolic illnesses, and were not taking medications that interfere with the performance of fMRI. Participants could be of any gender and ethnicity, but must be at least 18 years old. The only exclusion criterion is based on MRI safety screening (ferromagnetic metal in the body, e.g., dental braces). The participants of fMRI experiment can earn $10 for the initial appointment, where MRI safety policies were reviewed, $5 just for showing up on the day of experiment and up to $20 more, depending on their decisions throughout the game.

[37] IRB Protocol Number 09232011.094 was approved by Research Compliance Services University of Oregon Institutional Review Board on 21st December 2011.

Prior to entering the scanner the subjects completed questionnaire on political attitudes and a series of practice trials of the similar game on paper. Therefore, the participants understood and were ready for the stimuli presented in the actual experiment. Participants were told on the day of experiment that they will be Row choosers (choose between up (U) and down (D)) and will maintain the same role for the whole experiment.

Stimuli included two instruction conditions (Humans and Computers[38]), two game conditions (PD and Welfare games in tables 4.1 and 4.2 respectively), feedback screen that showed profit of participant based on her decision and a control condition. Subjects were instructed to look at the central plus sign, and had to switch their attention from the central plus sign to the game stimulus (a table 2x2 that was centered on the central plus sign) in each trial to determine the their response by pressing either left or right button on the button box in their right hand. Subjects knew that by pressing left button, they choose up (U) and by pressing right button – down (D).

In order to answer the research questions the following neural experimental design was used. The experiment consisted of 4 blocks (Humans + PD (PG1), Humans + Welfare (PG2), Computers + PD (CG1), Computers + Welfare (CG2)) with events within each block. To distinguish between blocks the instruction screen in the beginning of each block identifies, whether the participant plays computer or a human. In reality the participant always plays computerized strategy with fixed probabilities: for game 1, PD game, R with p=.85, L with p=.15; for game 2, Welfare game, L with p=.85, R with p=.15. The game condition does not change throughout the block. The blocks were

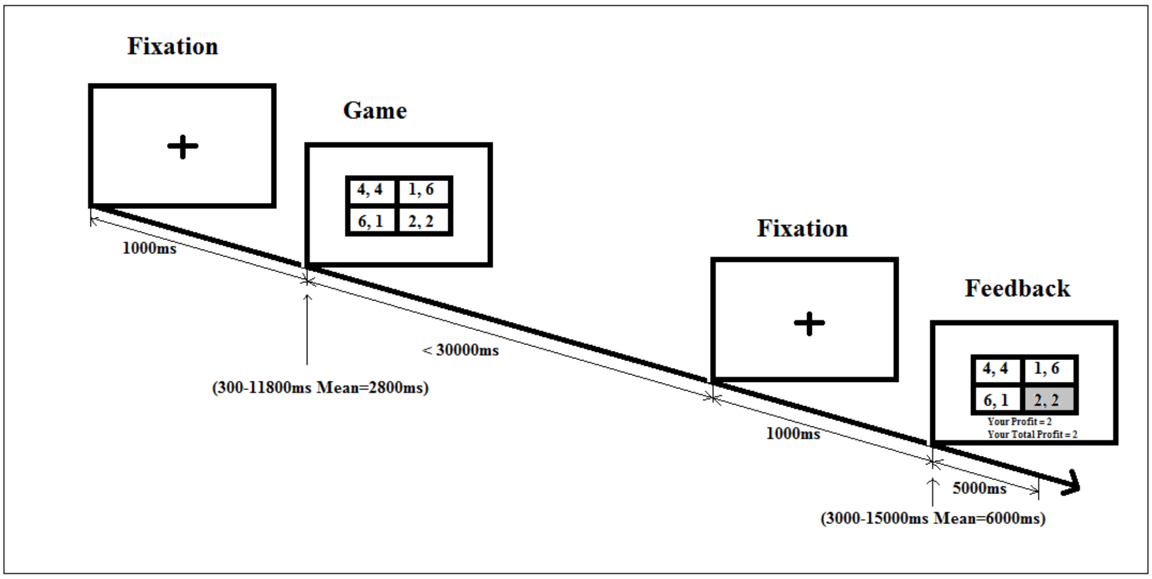
[38] Instruction screen showed either: "You are playing with people in the conference room" or "You are playing with computers making random choices."

alternated: for half of the participants the order was PG1, PG2, CG1, CG2, for the other half – CG1, CG2, PG1, PG2.

I used an event-related fMRI design with a pseudorandom (predetermined unpredictable) order of game and control condition within a block with the same interstimulus and intertrial intervals used in M. Posner attention studies (Abdullaev, Posner, Nunnally, & Dishion, 2010; Flombaum & Posner, 2005) that approximate an exponential distribution with a certain mean. The jittering of the time intervals between game and feedback and between feedback and the next trial is done in order to separate brain activity to the game and feedback stimuli.

In the game condition (Figure 4.1) the plus sign remained on the center of the screen for 1000ms. The game stimulus followed after a variable interval ("one of 12 predetermined intervals including three 300ms intervals, and one each of 550, 800, 1050, 1550, 2300, 3300, 4800, 6550, and 11800ms, approximating an exponential distribution with a mean interval of 2800ms" (Abdullaev et al., 2010, p. 47)). The game stimulus stayed until response or for 30000ms. Then a fixation screen was on for 1000ms followed by another variable intertrial interval (mean of 6000ms) and finally the feedback screen was on for 2000ms till the onset of the next trial.

Figure 4.1: Game Condition Schedule



In the control condition the plus sign remained on the center of the screen for 1000ms. The control stimulus (a 2x2 table with "X, X" in each cell) followed after a variable interval (mean of 2800ms). The control stimulus stayed until response or for 5000ms. As in the game condition, then fixation screen was on for 1000ms followed by another variable intertrial interval (mean of 6000ms) till the onset of the next trial. 4 blocks were presented, and each block had 30 trials (20 game condition trials and 10 control condition trials) with a different pseudorandom order of conditions and intervals.

Responses were recorded with two buttons on an MRI-compatible button box. Reaction times (RT) were measured from the game stimulus to the button press. The control trial was constructed in order to isolate the mechanical activity of the finger pressing on the button box. I expected that with each button press, I should see the ipsilateral cerebellum and the contralateral primary motor cortex activation. Also I had a

30s baseline period in front of each block with no stimuli except a central plus sign for fixation. So that each condition of the task can be compared to the baseline period.

4.4. Data

The data is collected through a combination of fMRI recordings and computerized cognitive tasks. The computerized tasks automatically record decisions that participants make. fMRI data are continuously recorded from the scanner.

4.4.1. Computer Laboratory Data

Data were collected with the help of the z-Tree[39] (Zurich Toolbox for Readymade Economic Experiments) software package. The same program code was used for 4 experimental sessions with the first group of participants. The data reflect observations of decisions of each participant in each period. Observations reflect the choices of 4 different sets of 12 participants over 60 or more periods.

The program code was modified for the second group of participants to account for 2 participants rather than 12 participants playing at the same time. Observations for the second group of participants include the choices of 16 participants (8 pairs) over 30 periods.

4.4.2. fMRI Data

Stimuli were presented and behavioral data are collected using the Presentation program (www.neurobehavioralsystems.com) run on a computer. Stimuli are presented with a digital projector/reverse screen display system to the screen at the back end of the

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[39] http://www.iew.uzh.ch/ztree/index.php

MRI scanner bore. Subjects see the screen via a small tilted mirror attached to the birdcage coil in front of their eyes.

Imaging is performed using a 3T Siemens Allegra head-only MRI scanner at Lewis Center for Neuroimaging. A standard birdcage coil is used to acquire data from the entire brain. Subjects wear earplugs and earphones to protect their hearing. Additional soft padding is used between earphones and inside the wall of the head coil to diminish head movements.

For functional MRI, the EP2D-BOLD (Blood oxygen level dependent) sequence was run with repetition time (TR) = 2000ms, echo time (TE) = 30ms, flip angle = 90^o, Field of View (FOV) = 200 mm. The brain was covered with 32 4mm thick slices acquired in a custom manner (first even slices and then odd slices). For structural MRI scan, the 3D Magnetization Prepared Rapid Acquisition Gradient Echo (MPRAGE) TR=2500ms, TE=4.38ms, flip angle = 8^o, FOV = 256, 160 slices was run for 8 min to acquire 1 mm^3 high resolution anatomical scans for registration purposes.

The fMRI study is reported following the guidelines identified by Poldrack (2008). Statistical analysis based on the General Linear Modeling (GLM) is used for fMRI data analysis as implemented in the FSL 5.0.2 (FMRIB Software Library). All fMRI data is analyzed using FEAT (FMRIB Expert Analysis Tool) available as part of FSL (freely available at www.fmrib.ox.ac.uk/fsl) (S. M. Smith et al., 2004). Preprocessing included the default options, such as separating images of brain from the rest of the images of the head, i.e. creating a brain mask, using the Brain Extraction Tool (BET) (S. M. Smith, 2002), pre-whitening for local autocorrelation correction using FILM (FMRIB Improved Linear Model) (Woolrich, Ripley, Brady, & Smith, 2001), motion correction based on rigid-body transformations using MCFLIRT (Motion Correction FMRIB Linear Image Registration Tool) (Jenkinson, Bannister, Brady, & Smith, 2002), spatial smoothing using a Gaussian kernel and highpass temporal filtering as implemented in FSL as well as slice timing correction using a customized text file.

The analysis is done in three steps. On the first level I analyze each session's data, i.e. execute time-series analysis of the raw 4D fMRI data. I generate voxel-wise parameter estimates of the hemodynamic (blood-oxygen-level-dependent) responses to the different stimuli I used in fMRI experiment. These voxel-wise parameter estimates represent the change in the blood-oxygenation level for a given stimulus compared to the baseline neural activation of no stimulus presentation and control stimulus. Modeled regressors included cooperation, i.e. choosing up (U) in PD game (g1) both in human and in computer condition, C_pg1 and C_cg1 respectively; defection, D_pg1 and D_cg1; inequity aversion (down (D) in Welfare game (g2)), IA_pg2 and IA_cg2; and inequity tolerance, IT_pg2 and IT_cg2. Each explanatory variable was created by convolving the stimulus actual duration times (from onset of stimulus till response using one of the buttons) within each stimulus with a standard gamma hemodynamic response function using FEAT. Through first-level analysis I obtained parameter estimates as well as statistical maps for each regressor.

On the second level I combine each subject's activation across several blocks and create contrasts (for human vs. computer conditions: C_pg1 vs. C_cg1, D_pg1 vs. D_cg1, IA_pg2 vs. IA_cg2, IT_pg2 vs. IT_cg2; and WF vs. PD: IA_pg2 vs. C_pg1) using a fixed[40] effects analysis with cluster-level statistical threshold of $Z > 2.3$ and $p < 0.05$. In order to compare human condition to computer condition and inequity aversion in Welfare game to cooperation in Prisoner's Dilemma I subtract one stimulus type (e.g. in computer condition) from another type (e.g. in human condition). The hypothesis of interest here is whether in each voxel the activation to human condition stimuli is greater than in computer condition. I also implement this type of contrast in the opposite direction, i.e. where activation in computer condition is higher than activation in human condition. In result I generate statistical maps for each of the 5 contrasts for each subject. These contrast activation maps were registered to each subject's own high-resolution structural image and also to the Montreal Neurological Institute (MNI) 152-standard template.

Finally on the third level I used FLAME (FMRIB's Local Analysis of Mixed Effects) modeling and one-sample t-test to decide whether the group[41] activates on average. Mixed effects model the subject variability and, therefore, allow making inferences about the wider population from which the subjects were drawn. Each of the contrasts for the group are Gaussianized intro Z-statistical images and thresholded at $Z > 2.3$ with a cluster-corrected significance threshold of $p < 0.05$ (Worsley, 2001). The high resolution structural MRI images of individual subjects were standardized to the MNI space and averaged within the group to create an average structural template.

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[40] I followed the recommended fixed-effects analysis at the mid-level. Fixed-effects analysis avoids issues with estimating the block-to-block variance, especially if there are not many blocks per subject, 4 in my case.

[41] Although fMRI experiment for the first two subjects didn't include socialization phase, I do not compare a group of 2 to a group of 8. Moreover, the second subject did not cooperate in PD game or express inequity aversion in the Welfare game, so I am not able to create all 5 contrasts on the second level of analysis for him. That is why his contrasts add up to average activity in two cases. The mean activation of a group with or without first two participants does not result in significant differences.

4.5. Results

4.5.1. Behavioral Results

For the computerized portion of the experiment Prisoner's Dilemma results were standard, with moderate levels of cooperation in the first few rounds and then devolving into consistent high levels of defection. The second group of participants showed similar results with rates of cooperation slightly higher.

Results of the Welfare game displayed that the Nash equilibrium (2; 6) outcome was more likely for the first group of participants but less likely for the second group of participants, i.e. the second group preferred egalitarian outcome. Although the socialization prior to the computer experiment with the second group might contribute to the difference in the behavior, the groups' relative size (12 per experiment vs. 2[42] per experiment) does not allow for a strict comparison. One way or another, this trend is worth investigating further with similar group sizes by including socialization phase and excluding it.

In the second scenario that was only implemented for the first group of participants I looked specifically at Row choosers that were stuck with unfair Nash Equilibrium, i.e. getting 2, when their opponent got 6 points. While in the first scenario roughly half of participants forced egalitarian outcomes (1; 1) within the Welfare game, in the second scenario, when they were able to choose which game to count for their score, 70% of participants preferred PD game over Welfare game. This makes rational sense, because

[42] Two participants played each other in reality, but were thinking that there were three participants and only two were paired at a time.

participants played PD for several rounds during first scenario participants and learned that the outcome is almost always 2 points for them, but in Welfare game forcing egalitarian outcome leaves them with only 1 point.

Table 4.3: Results of Computer Experiment

	Cooperation Rate	Preference of Egalitarian Outcomes
First Group	17%	37%
Second Group	23%	59%

For the fMRI portion of the experiment the rates of cooperation and preference of egalitarian outcomes were significantly higher for the human condition than those for the computer condition. More so the socialization that was implemented for the 8 participants out of 10 boosted both of the rates in the games under consideration. In the human condition participants were nicer in Prisoner's Dilemma overall, but only half of them started with cooperative choice, like Tit-for-Tat strategy suggests (Axelrod, 1984, 1987). As for the Welfare game, participants were not satisfied with inequity imposed on them by Nash Equilibrium and forced egalitarian outcomes more than in 50% cases for both human and computer conditions.

Table 4.4: Results of fMRI Experiment

	Condition	Cooperation Rate	Preference of Egalitarian Outcomes
Without Socialization (2 participants)	Human	18%	20%
	Computer	8%	15%
With Socialization (8 participants)	Human	28%	70%
	Computer	16%	54%

Unlike the differences revealed between the decisions participants made in games in the human and computer conditions, I find no differences in terms of how quickly they made their decisions as table below displays[43].

Table 4.5: Average Response Times (ms)

	Prisoner's Dilemma	Welfare Game
Human condition	3113.27	2247.9
Computer condition	2150.27	2208.33

4.5.2. fMRI Results

The fMRI analysis focuses on the functional activity pattern associated with "sociality." In this section I determine areas in the brain where the neural activation is higher for subjects playing with humans, than them playing with computers while completing several different tasks. fMRI results are shown in figures 4.2 to 4.9 that are

[43] Although response time for Prisoner's Dilemma in human condition is slightly higher than that for the other game and other conditions. Prisoner's Dilemma in human condition was the first treatment that participants encountered and, thus, they might take longer time to make decisions while they adapt to the scanner.

generated with help of FSLView 3.1. Left, Right, Anterior=front, Posterior=back, Superior=top, Inferior=bottom (L, R, A, P, S, I) orientation markers are displayed on each of the figures, making the orientation clear. Below I report functional activation in the areas as specified in MNI structural atlas (Collins, Holmes, Peters, & Evans, 2004; Mazziotta et al., 2001) and Talairach Daemon Labels atlas (Lancaster et al., 2000).

I find significant areas of activation for 4 out of 5 specified contrasts in the fMRI data section. Defection contrast, i.e. defection in Prisoner's Dilemma, does not show any significant activation between human and computer conditions. Moreover, contrasts that are done in the opposite direction, i.e. answering the question where the activation is higher for computer condition than for human condition, also do not reveal any significant engagement even at a lenient threshold of $p < 0.1$.

Cooperation in PD game with humans compared to cooperation in PD with computers is associated with a signal increase in dorsolateral prefrontal cortex (DLPFC), Brodmann areas 8 and 9 (BA 8, BA 9), Figure 4.2[44], and parietal lobe, BA 40, Figure 4.3. Inequity aversion in Welfare game is corresponding to the activation in caudate and putamen, figures 4.4 and 4.5, respectively. Inequity tolerance in Welfare game displays a stronger signal for human condition in insular cortex, BA 13, Figure 4.6 and parietal lobe, BA 40, Figure 4.7. The contrast of Welfare game vs. PD game shows higher activation in parahippocampal gyrus, BA 30 and in medial temporal gyrus, BA 39, as shown in figures 4.8 and 4.9, respectively.

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[44] Activation is on the border between BA 8 and BA 9. I present only the image that identifies activation in BA 8, but discuss the functions of both areas in the Results section of this chapter.

Unlike hypothesis 2, I find activation in DLPFC for Cooperation contrast. Many studies see DLPFC as contributing towards the rationality of the decisions in social situations. Although cooperation in PD game is seen by many as not rational, theory of "sociality" provides a rational explanation for such behavior by adding an economic component to the subject's utility function in the social context. Thus, activation in Cooperation contrast presents another demonstration of "sociality" at work, where brain processes cooperation as a rational decision. Other regions of activation revealed by the contrasts are not specified in my hypotheses or theory section and I discuss their function and significance in the Discussion section.

Figure 4.2: Cooperation (Human vs. Computer) Contrast (BA 8)

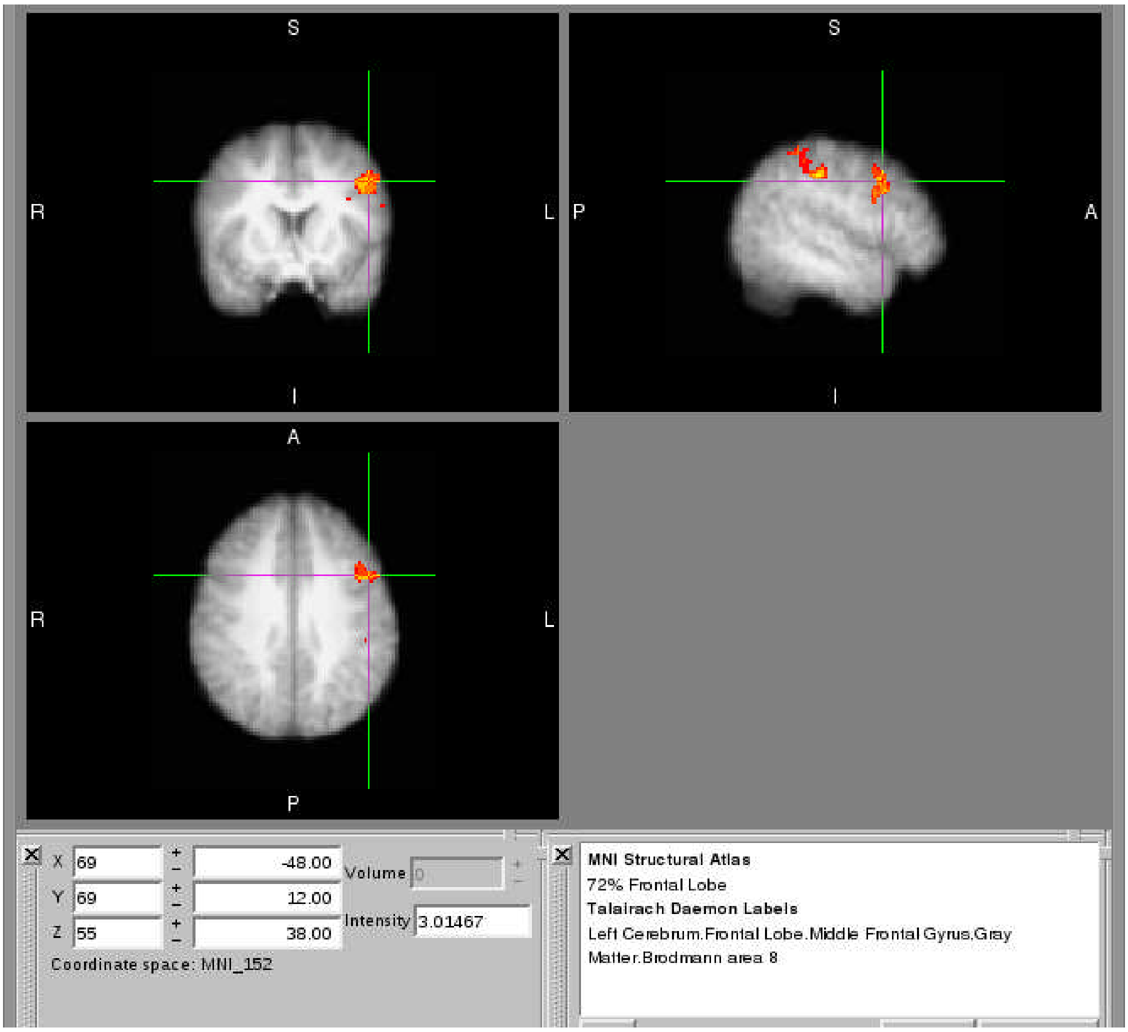


Figure 4.3: Cooperation (Human vs. Computer) Contrast (BA 40)

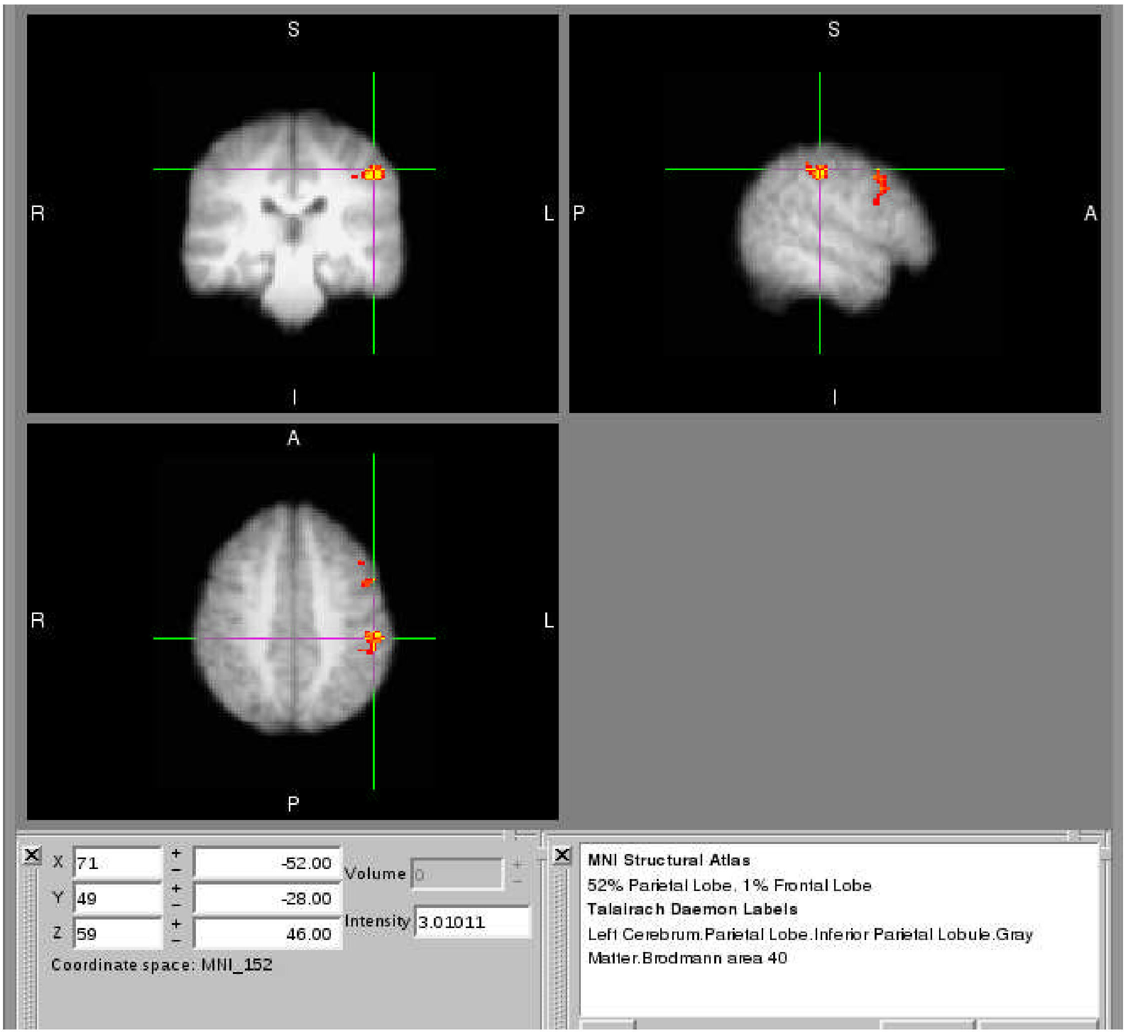


Figure 4.4: Inequity Aversion (Human vs. Computer) Contrast (Caudate)

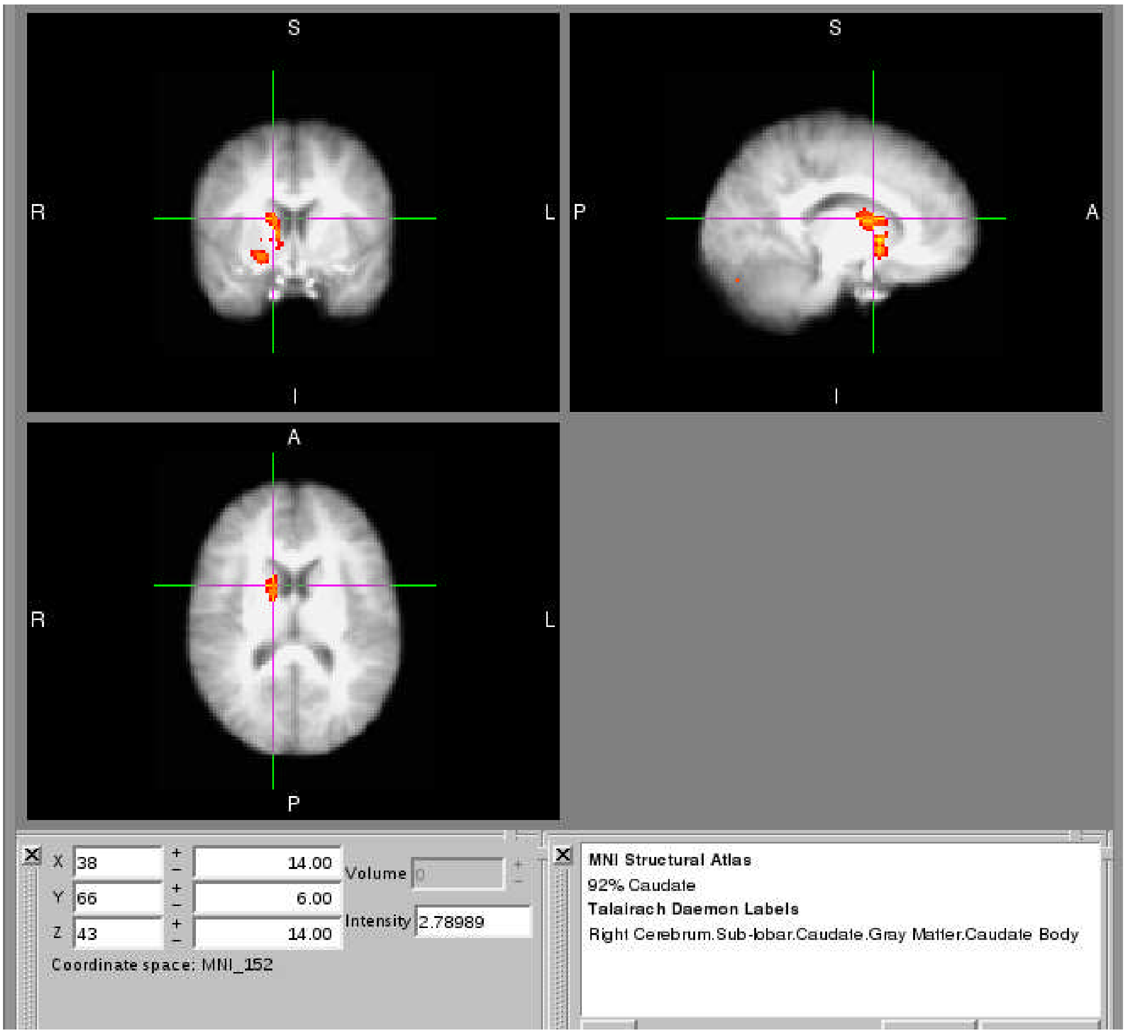


Figure 4.5: Inequity Aversion (Human vs. Computer) Contrast (Putamen)

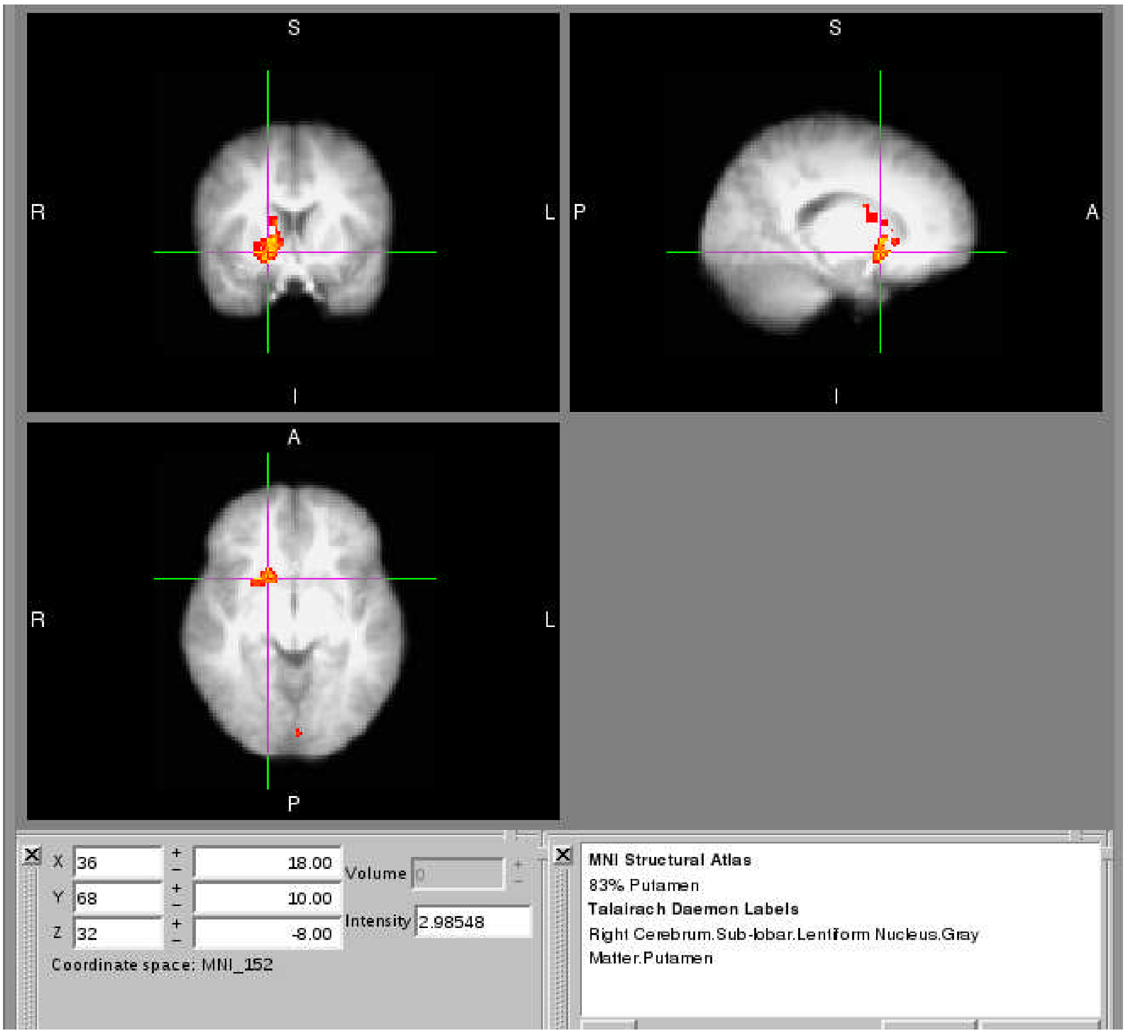


Figure 4.6: Inequity Tolerance (Human vs. Computer) Contrast (BA 13)

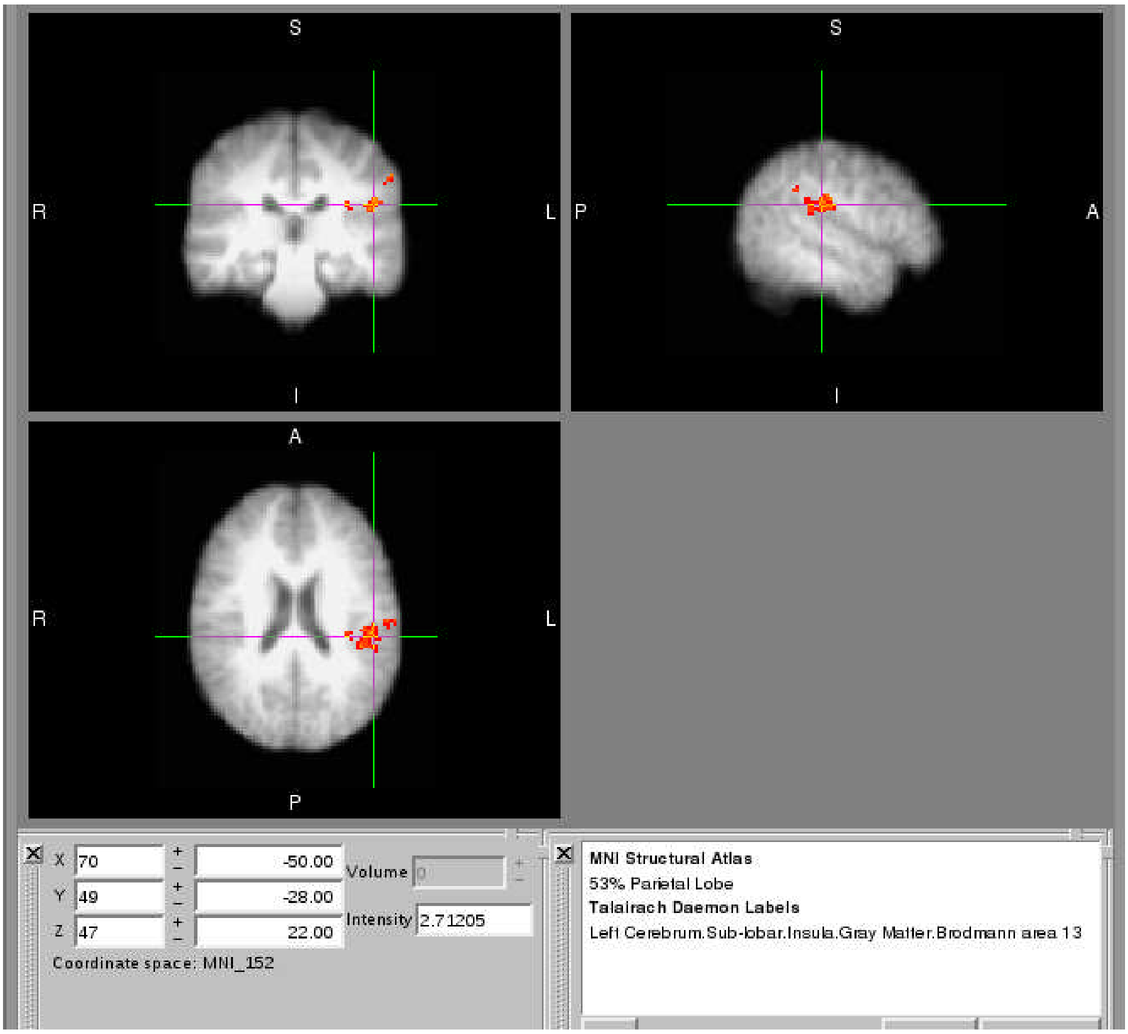


Figure 4.7: Inequity Tolerance (Human vs. Computer) Contrast (BA 40)

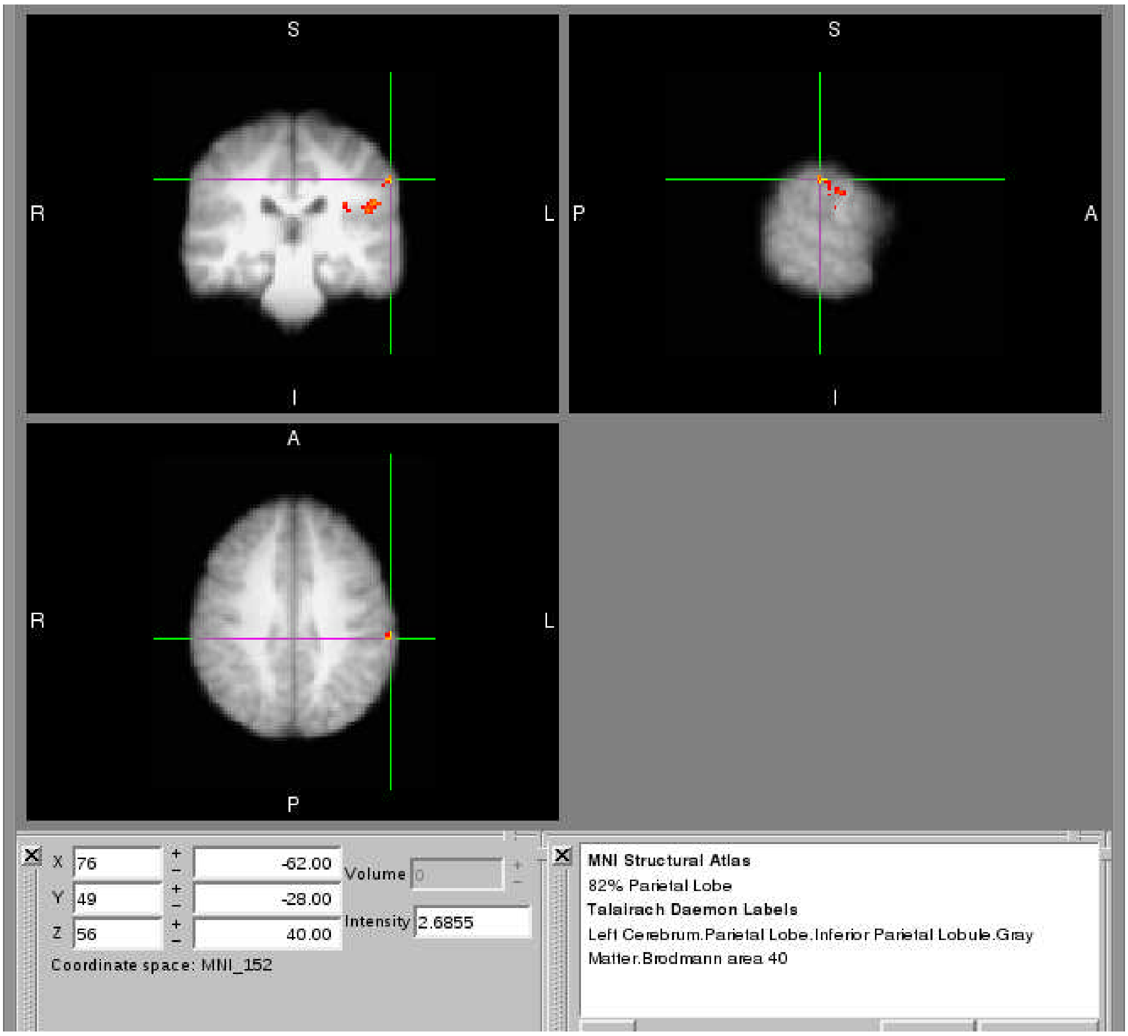


Figure 4.8: Welfare vs. Prisoner's Dilemma Contrast (BA 30)

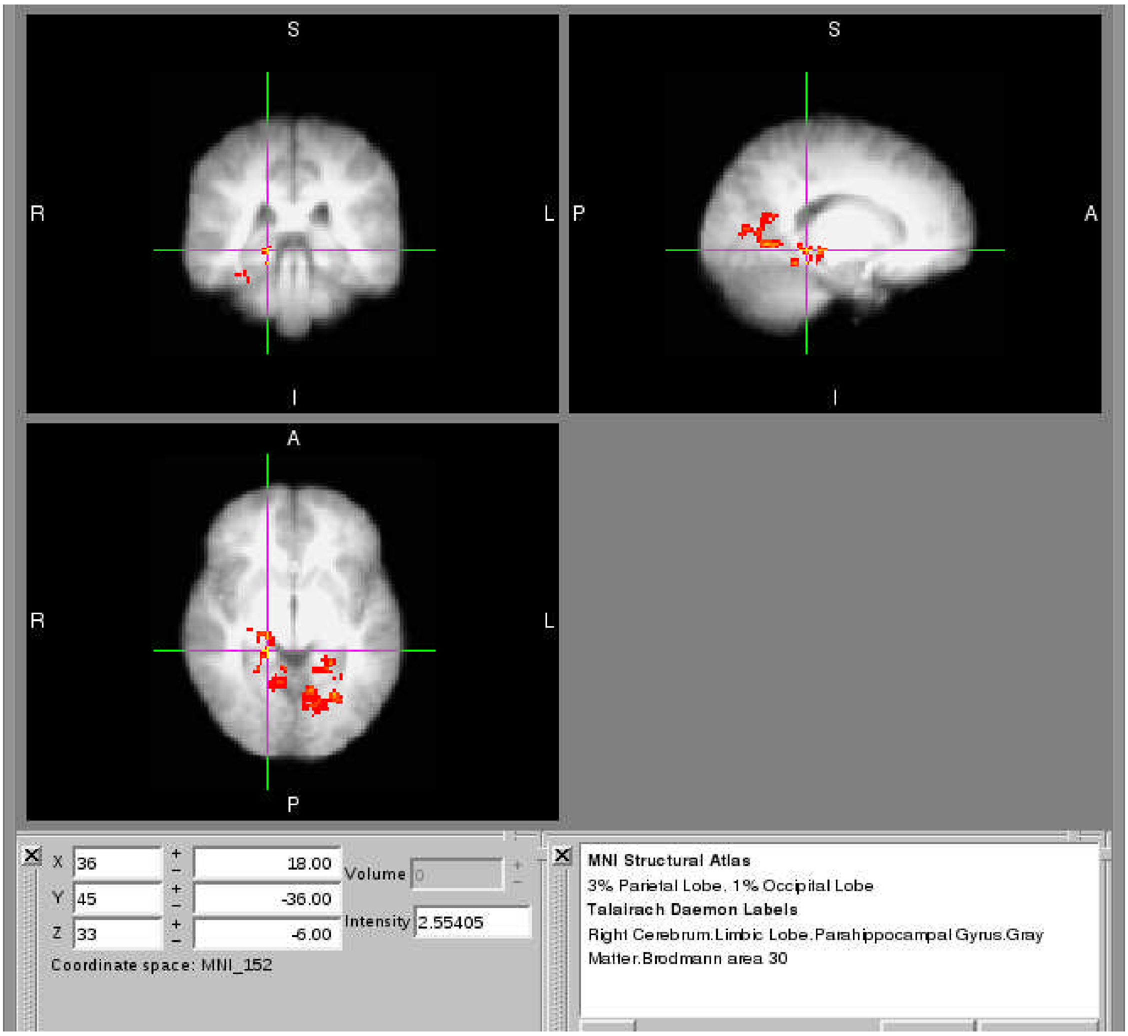
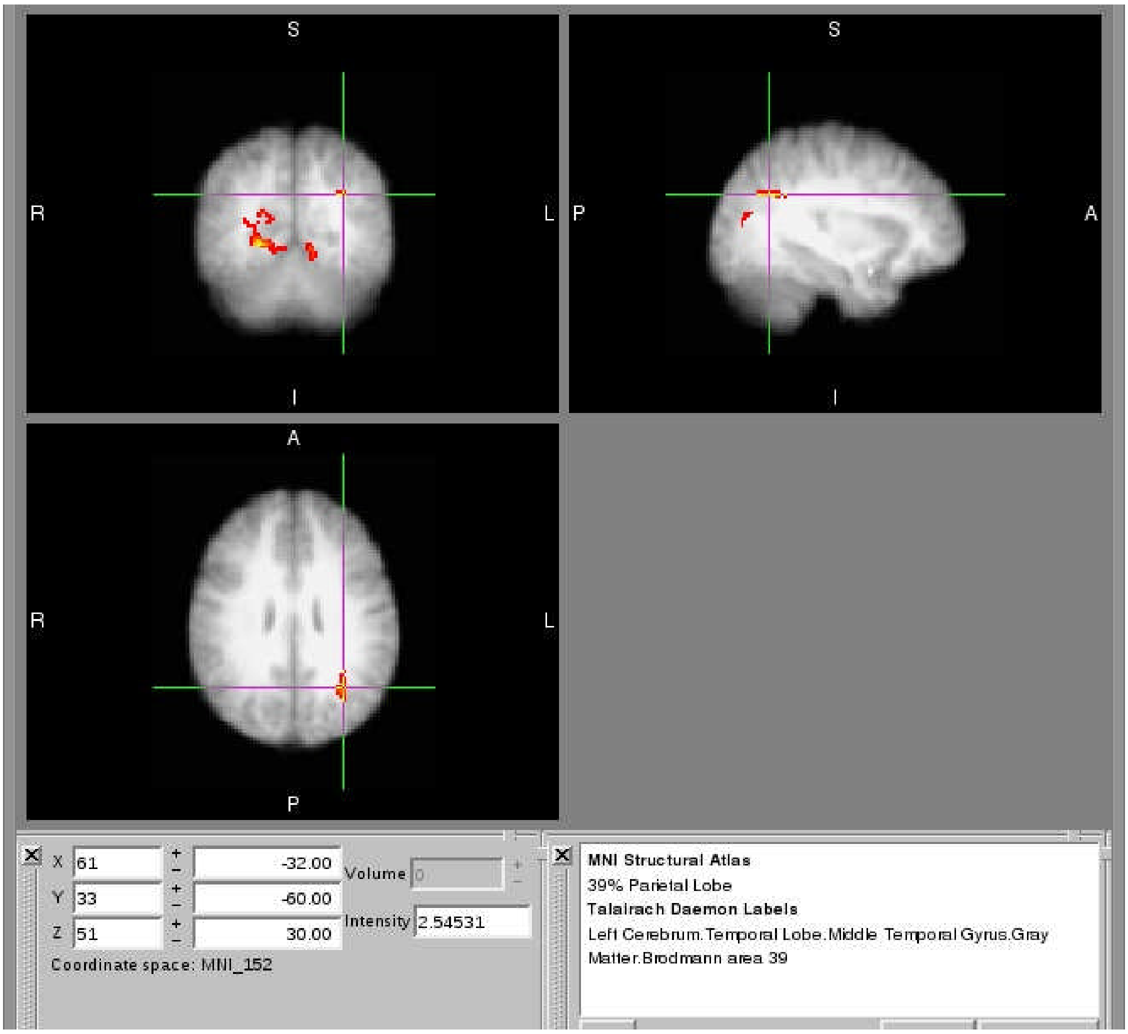


Figure 4.9: Welfare vs. Prisoner's Dilemma Contrast (BA 39)



Result 1

Humans make social decisions more, when they play other humans as opposed to when they play computers and even more so with socialization.

Support

Rates of cooperation and inequity aversion in Table 4.4 are significantly higher in human than in computer condition. Although computer experiment does not have human and computer condition to compare, it does add statistical power to the result that with socialization[45] the rates of social decisions increase as displayed in tables 4.3 and 4.4.

Result 2

Individuals are more concerned with inequity, than defection.

Support

The same groups of participants show less rationality in Welfare game, than in Prisoner's Dilemma as presented in tables 4.3 and 4.4. Moreover, row players from the computer experiment (first group) in the second scenario preferred to count PD game payoff towards their profit significantly more often than Welfare game outcome.

Result 3

Cooperation in PD game is rational in the social environment.

Support

I reveal activation in DLPFC for Cooperation contrast, Figure 4.2. This region is involved in goal maintenance and working memory. Many scholars attributed it to the rational decision-making in social situations. This provides confirmation for my theory, because adding another portion of utility, i.e. "sociality," that corresponds to the social process certainly makes cooperation rational. I find activation in BA 8 and BA 9. Whereas Brodmann area 9 functions include sustaining attention and working memory, BA 8 is even more intriguing, as it is linked to management of uncertainty (Platt & Huettel, 2008)

[45] The second group for computer experiment had socialization phase prior to the experiment, whereas first group did not.

as well as hopes or high expectations (Boscher, Romijn, Vermaat, & de Vries, 2012). Therefore, although it is rational for subjects to cooperate in the presence of “sociality” they still have some hope for reciprocity and face uncertainty regarding the decision of their opponent.

4.5.3. Discussion

Welfare game highlights activations in different areas for inequity aversion and inequity tolerance. In particular, inequity aversion in the human vs. computer condition is related to regions of caudate and putamen. Both of these regions are an important part of the brain’s learning and memory system (Graybiel, 2005). In particular, activation in caudate nucleus is found in feedback processing (Packard & Knowlton, 2002) and as a neural basis of altruistic punishment (De Quervain et al., 2004). On the other hand, recent study finds that highlights in putamen are correlated with hate (Zeki & Romaya, 2008). I suggest that inequity aversion decision engages general learning and discovery of the equilibrium in this game by receiving certain outcomes in each round and processing this feedback. Subjects (row players) face an unfair equilibrium in Welfare game and, although they hate inequity aversion choice, because it results in the lowest payoff, they force egalitarian outcomes and produce something similar to altruistic punishment, where they lose from it but their opponent is punished for being rich in the equilibrium.

Inequity tolerance decision involves activations in Brodmann area 13 (BA 13) and BA 40. BA 13 is located in the insular cortex that has many functions as reported by fMRI studies. Most relevant for me is connection of this area to an informative feedback response (Tsukamoto et al., 2006), error awareness (Klein et al., 2007), and fear response

(Phelps et al., 2001; Turner et al., 2007). I assume that the inequity tolerance decision included fear for losing out in terms of total profit to the opponent after subsequent rounds of the game. BA 40, or inferior parietal lobe, is mostly known for its somatosensory functions. However, scholars find that significant activations in the left part are present during calculation tasks (Hirsch, Moreno, & Kim, 2001). This area has significant activation for cooperation and inequity tolerance contrasts. Thus, I conclude that brain area related to calculation has significantly higher activation in human condition, because subjects were not only computing their own payoffs and gains, but also of their opponents.

Contrast between Welfare game and PD game displays highlight in BA 30 that along with adjacent areas forms posterior cingulate gyrus. Its functions include spatial memory and orientation (Owen, Milner, Petrides, & Evans, 1996), as well as face recognition (Leube, Erb, Grodd, Bartels, & Kircher, 2001). Neither the former, nor the latter directly correspond to the stimuli presented to the subjects. Another area activated is BA 39, middle temporal gyrus that is also involved in calculation (Grabner et al., 2007), as well as in "theory of mind" (Goel, Grafman, Sadato, & Hallett, 1995), i.e. modeling knowledge, rationality, etc. of another person's mind. Indeed, calculation and "theory of mind" occur in both games, however, while PD game is familiar and is frequently used in multiple courses in college, Welfare game, as a rare simultaneous version of Ultimatum game requires participants to think through other subject's strategy and execute the cost-benefit analysis.

Although I see some activations in white matter, scholars generally believe that activation in functional magnetic resonance imaging (fMRI) is restricted to gray matter due to a higher cerebral blood flow and postsynaptic potentials taking place there (Matthews, 2001; Mazerolle, D'Arcy, & Beyea, 2008). However, a number of fMRI studies reported activation in white matter. Although majority of these studies used visuomotor interhemispheric tasks, some were focused on eliciting interhemispheric transfer (Mazerolle et al., 2008), transfer of information between cerebral hemispheres that usually happens by means of corpus callosum. Activation in white matter revealed that even for patients, in which the corpus callosum has been resected the brain performance was impaired, but not abolished (Mazerolle et al., 2008).

4.6. Conclusion

Daily life confronts us with social situations and interactions on a regular basis. However, we never even think how brain processes the decisions we make, especially when we affect the outcomes of over people with our decisions. I conducted an fMRI experiment, an easy one from the very first glance, that attempts to reveal the areas in our brain where activations are higher when subjects play humans, than if they play computers. As I mentioned earlier, at first, the ambition was to replicate the experiment in chapters I and II in the scanner. Several studies mention differences in activations in the brain when subjects are facing losses as opposed to if they are facing gains (Yacubian et al., 2006). One of the main results of Chapter II suggests that risk tolerance is found in both losses and gains frameworks in the presence of “sociality.” The additive value of fMRI study is to find that the same behavior, e.g. risk tolerance, correlates to activations in different areas of the brain, as could be found for the losses and gains. This remains a vital goal for the future fMRI experiments.

The only activation I can relate to my hypotheses is revealed in the Cooperation contrast. In particular, I find that cooperation in PD game is rational, as activation highlighted for this contrast in human vs. computer condition appears in the dorsolateral prefrontal cortex, a region involved in executive control, goal maintenance and working memory. Other activations and significant brain regions are displayed for human vs. computer contrast across different stimuli in the Results section and described in detail in the Discussion section.

The data collected from the fMRI experiments can serve to answer many more questions, than those raised in this chapter. For example, how subjects perceive outcomes. While in this study my main focus was on the stimuli from onset till response, next I can take into account the reaction towards the outcome displayed to the participant. How will participants react to unfairness or defection? Or how will participants react and what brain activation will be related to it if they defect, while the opponent cooperated? Guilt aversion is studied thoroughly by Chang et al. (2011). In particular, is the guilt aversion crucial for subjects to cooperate even if they can better achieve their goals by acting selfishly? In social situations trust is also very important in which we sometimes place trust in those around us or alternately are entrusted by others. Does the activation in regions related to trust decrease once the subjects get defected on several times in a row?

Another way to model and analyze these data is to add behavioral covariates, such as cooperation and inequity aversion rates and response times. However, political variables cannot be added as covariates as the sample of UO students for the fMRI experiments was homogeneous in terms of their political and policy attitudes. Although the design of the behavioral task is a critical component of the current study, several contrasts were not available for all subjects. That is why the preselection[46] of participants is needed, so that they will make not only rational, Nash equilibrium choices, but also cooperate and use mixed strategies. Although the idea of prior socialization was brilliant, it is also vital to compare groups with socialization to those without. Unfortunately, the contrast between the group of two participants and a group of eight participants was not viable.

This was my first experience with fMRI experiment design as well as fMRI data and I plan to further extend my knowledge of fMRI data acquisition, processing and sharpen my fMRI design skills in the future.

[46] Preselection can be implemented by a paper experiment or a survey prior to the experiment. However, this did not work for this particular experiment. I did the survey and the paper experiment and although subject 2 made not rational choices in the paper version, he only made rational choices in the scanner.

CHAPTER V

CONCLUSION

In my dissertation I addressed the major theories of decision-making and proposed the theory of “sociality.” I define “sociality” as the economic component of utility function that accounts for the fact that individuals do not only care about outcomes, but also about the processes which lead to these outcomes. Using the computer laboratory experiments and fMRI brain-imaging technology I put my theory to a test and explore the behavioral and neurobehavioral properties of “sociality.”

My main findings of the Chapter II suggest that in the social context human beings value the social interaction more than the monetary outcomes of such interaction. The main contribution of my theory was to explain the existence of new risk attitudes, i.e. risk tolerance regardless of the framing. I confirm the predicted risk attitudes in the presence of “sociality,” estimate the value of “sociality” and prove that value of “sociality” is able to compensate for monetary loss. In Chapter III I look not at how individuals overcome risks of social interactions, but at the characteristics and dynamics of the interactions itself. I find that the increase in the demand for “sociality” improves the rates of cooperation, whereas the experience in Prisoner’s Dilemma game decreases cooperation. Chapter IV displays neurobehavioral features of “sociality.” One of the contrasts directly supports the theory of “sociality.” In particular, human’s brain considers cooperation as rational in the social environment, because the utility to cooperate is derived not only from the outcome, but also from enjoying the social process. Other activations in the presence of “sociality” I find in the regions of the brain responsible for management of uncertainty, learning, memory, attention and emotions.

Each of the chapters addresses avenues for future research. Among them, first of all, is the replication of the experiments, described in chapters II and III, for a bigger sample of countries, so that I can assess and inform the striking differences among cultures having enough statistical power. Second ambitious future goal is to replicate the same set of experiments in the fMRI scanner in order to approach the revealed risk attitudes in the presence of "sociality" from the brain processes underlying such behavior. Third, get a hold of heterogeneous subjects sample in terms of their political attitudes and exploit psychological questionnaires in addition to political and policy ones. This way it is possible to trace the observed peculiar behaviors to the psychological characteristics of a human being or his political affiliation. Last, but not the least, distinguish between the value of "sociality" in itself and the value of the processes involved. Whereas I use the latter for my definition of "sociality", the former was suggested in a recent paper (Zaki & Mitchell, 2011) and I am eager to find an experimental design that can detect the difference.

Another goal of my research is to show that the theory of "sociality" can provide a number of insights into the problems of political science. My theory relaxes the assumption of rationality and, as a result, leads to better predictions about decisions in the social domain without giving up mathematical rigor. A number of applications are proposed in the concluding sections of my dissertation chapters. Below I focus on some of them in detail, propose new applications for political science and discuss relevance for the broader social sciences literature.

The existence of new risk attitudes in the presence of "sociality" can be applied to policymaking. Whereas for the domain of gains prospect theory predicts risk averseness, the theory of “sociality” anticipates risk tolerance. I view policy as an instrument to improve procedures, well-being, and, thus, as existing in the domain of gains. Depending on the area policymakers are working, they might be interested in implementing risky or riskless policies. The theory of “sociality” then suggests that risky policy (e.g., environmental policy) is more likely to be implemented if policymakers make individual decisions on behalf of that policy while surrounded by their peers, rather than while being on a conference call. This happens more and more often in the age of technology.

Some might argue that policymakers are not passionate enough for the process and, thus, do not necessarily extract utility from carrying out legislature act. Like in academia, professors do not take out utility from faculty meetings simply because they do not enjoy the process they are involved in and want to leave as soon as possible. However, some of the social and political processes are enjoyable and this is directly portrayed by people engaging in riots, protests, such as Occupy Wall Street, or riots last year in Moscow after fraudulent parliamentary elections in Russia. Whereas participation in “occupy” protests by a strict cost-benefit analysis will not reveal many benefits in terms of the outcome involved, riots in Moscow will be considered very costly because of the high probability of imprisonment. Actually it is an interesting task to follow the decrease in the riots participation in Moscow and correlate it to the constant increase in costs of participation due to the laws that were being enacted starting December 2011. This is also a field test for the theory of “sociality,” i.e. measuring how costly should be the outcome to outweigh the utility of participation in protests.

Today we also hear more and more often that people are embedded in social networks. A wide range of political outcomes could be studied using social networks, such as political campaigns (Williams & Gulati, 2007), voting (Nickerson, 2008), and immigration patterns (Sanders, Nee, & Sernau, 2002). As for voting, many models of elections have avoided situating voters in social networks, or social context in general, although there is a growing evidence that the context and how voters are situated to one another play a critical role in the decision. How the theory of "sociality" can help?

As citizens people involve in different political and societal processes that generate "sociality," an economic component of their utility function. Democratic participation, that includes voting, is an example of such a process. People value participation rights as much or even more than the outcome generated in the political process. This can explain why people vote, although it is not rational. Hegel observed that "the casting of a single vote is of no significance where there is a multitude of electors" (Buchanan, 1974).

Scholars investigate effects of social pressure on political participation (Gerber, Green, & Larimer, 2008) and conclude that higher turnout is observed if mailings are received that assure voters that their turnout will be publicized to their neighbors. However, I distinguish "sociality" from social pressure. Although social pressure is used to induce voters to adhere to a social norm and individuals might value the outcome, such as convergence to the norm, they probably do not value the process, as in theory of "sociality," because the process is forced on them. Process adds a person utility only if he likes being involved in this process and not if a person has to go through some procedures he does not enjoy to get to an outcome, even a positive and desirable one.

People's welfare and utility can also depend on the extent to which the distribution of income in a society is unequal. Personal welfare can adapt quickly to status in a network, but "is highly sensitive to gains and losses in position in the network" (McFadden, 2010,

p. 3). The term inequity aversion was used in relation to the Welfare game described in Chapter IV. The row choosers in this game were facing unfair treatment, like people can sometimes view social processes as biased and unfair. Whereas in the game the participants were forcing egalitarian outcomes, in real life this creates preferences for redistribution (Alesina & La Ferrara, 2005; Benz et al., 2002). If one cares only about the outcome, he will be less likely to support redistributive policies, because if he gets rich he becomes a net payer. However, if an individual considers processes in his utility function, like theory of "sociality" asserts, and he views social processes as unfair, meaning that she does not believe that society offers equal opportunities on average, then, she will be more likely to support redistributive policies.

My dissertation asserts that "sociality" must be taken into consideration in modeling decision making. Although I incorporate "sociality" in the decision-making process I still rely on the core aspects of rationality to predict human behavior and use the concept of economic utility. Humans are social animals and even if in some instances they thrive to maximize their self-interest, they still use their social networks to define or refine their preferences in other situations, where their preferences are not solely about outcomes, but also about how those outcomes were generated. Today, interest in "sociality" is broad and includes disciplines all around the scientific spectrum, but there is no straightforward formalization of decision making in social context. My dissertation offers a simple way to approach "sociality."

REFERENCES CITED

Abdullaev, Y., Posner, M.I., Nunnally, R., & Dishion, T.J. (2010). Functional MRI evidence for inefficient attentional control in adolescent chronic cannabis abuse. *Behavioural Brain Research, 215*(1), 45-57.

Adolphs, R. (2003). Cognitive neuroscience of human social behaviour. *Nature Reviews Neuroscience, 4*(3), 165-178.

Alesina, A., & La Ferrara, E. (2005). Preferences for Redistribution in the Land of Opportunities. *Journal of Public Economics, 89*(5), 897-931.

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'école Américaine. *Econometrica: Journal of the Econometric Society,* 503-546.

Andreoni, J. (1988). Why free ride?: Strategies and learning in public goods experiments. *Journal of Public Economics, 37*(3), 291-304.

Arrow, K.J. (1971). *Essays in the Theory of Risk-Bearing*: Markham Pub. Co.

Axelrod, R. (1984). *The Evolution of Cooperation*. New York: Basic Books.

Axelrod, R. (1987). The evolution of strategies in the iterated prisoner's dilemma. *Genetic Algorithms and Simulated Annealing*, 32-41.

Axelrod, R., & Hamilton, W.D. (1981). The evolution of cooperation. *Science, 211*, 1390-1396.

Becker, G.S. (1978). *The Economic Approach to Human Behavior*: The University of Chicago Press.

Benz, M., Frey, B., & Stutzer, A. (2002). Introducing procedural utility: Not only what, but also how matters. *Zurich IEER Working Paper No. 129*.

Bicchieri, C., & Chavez, A. (2010). Behaving as expected: Public information and fairness norms. *Journal of Behavioral Decision Making, 23*(2), 161-178.

Bicchieri, C., & Zhang, J. (2008). An embarrassment of riches: Modeling social preferences in ultimatum games. *Handbook of the Philosophy of Economics.* Elsevier.

Binmore, K. (2001). Why experiment in economics? *The Economic Journal, 109*(453), 16-24.

Bohnet, I., Greig, F., Herrmann, B., & Zeckhauser, R. (2008). Betrayal aversion: Evidence from brazil, china, oman, switzerland, turkey, and the united states. *The American Economic Review*, 294-310.

Bond, M.H., & Forgas, J.P. (1984). Linking Person Perception to Behavior Intention Across Cultures The Role of Cultural Collectivism. *Journal of Cross-Cultural Psychology, 15*(3), 337-352.

Boscher, N., Romijn, L., Vermaat, L., & de Vries, F. (2012). The Evil Dead and the brain.

Bowlby, J. (1969). *Attachment and Loss. Vol. 1. Attachment*: Hogarth London.

Brock, W.A., & Durlauf, S.N. (2001). Discrete choice with social interactions. *Review of Economic Studies, 68*(2), 235-260.

Buchanan, J.M. (1974). Hegel on the Calculus of Voting. *Public Choice, 17*(1), 99-101.

Cacioppo, J.T., Berntson, G.G., Adolphs, R., Carter, C.S., Davidson, R.J., McClintock, M.K., . . . Sternberg, E.M. (2002). *Foundations in Social Neuroscience*: MIT Press.

Camerer, C. (2003). *Behavioral game theory: Experiments in Strategic Interaction*: Princeton University Press.

Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics. *Journal of Economic Literature, 43*(1), 9-64.

Camerer, C.F., & Fehr, E. (2006). When does" economic man" dominate social behavior? *Science, 311*(5757), 47.

Cardinal, R.N., Parkinson, J.A., Hall, J., & Everitt, B.J. (2002). Emotion and motivation: the role of the amygdala, ventral striatum, and prefrontal cortex. *Neuroscience and Biobehavioral Reviews, 26*(3), 321-352.

Carmichael, F. (2005). *A Guide to Game Theory*: Financial Times/Prentice Hall.

Carr, J.L., & Landa, J.T. (1983). The economics of symbols, clan names, and religion. *The Journal of Legal Studies, 12*(1), 135-156.

Carter, C.S., & Van Veen, V. (2007). Anterior cingulate cortex and conflict detection: an update of theory and data. *Cognitive, Affective, & Behavioral Neuroscience, 7*(4), 367-379.

Chang, L.J., Smith, A., Dufwenberg, M., & Sanfey, A.G. (2011). Triangulating the neural, psychological, and economic bases of guilt aversion. *Neuron, 70*(3), 560-572.

Chen, X.P., & Li, S. (2005). Cross-national differences in cooperative decision-making in mixed-motive business contexts: the mediating effect of vertical and horizontal individualism. *Journal of International Business Studies, 36*(6), 622-636.

Collins, D.L., Holmes, C.J., Peters, T.M., & Evans, A.C. (2004). Automatic 3-D model-based neuroanatomical segmentation. *Human Brain Mapping, 3*(3), 190-208.

Cosmides, L., & Tooby, J. (1994a). Better than rational: Evolutionary psychology and the invisible hand. *The American Economic Review, 84*(2), 327-332.

Cosmides, L., & Tooby, J. (1994b). Origins of domain specificity: The evolution of functional organization. *Mapping the Mind: Domain Specificity in Cognition and Culture*, 85–116.

Cox, T.H., Lobel, S.A., & McLeod, P.L. (1991). Effects of ethnic group cultural differences on cooperative and competitive behavior on a group task. *Academy of Management Journal, 34*(4), 827-847.

Damasio, A.R. (1994). *Descartes & Error*: Putnam New York.

Davidson, R.J., Putnam, K.M., & Larson, C.L. (2000). Dysfunction in the neural circuitry of emotion regulation--a possible prelude to violence. *Science, 289*(5479), 591-594.

Dawkins, R., & Krebs, J.R. (1978). Animal signals: information or manipulation. *Behavioural Ecology: An Evolutionary Approach*, 282–309.

De Quervain, D.J.F., Fischbacher, U., Treyer, V., Schellhammer, M., Schnyder, U., Buck, A., & Fehr, E. (2004). The neural basis of altruistic punishment. *Science, 305*(5688), 1254.

Devetag, G., & Warglien, M. (2003). Games and phone numbers: Do short-term memory bounds affect strategic behavior? *Journal of Economic Psychology, 24*(2), 189-202.

Dolan, R.J. (2002). Emotion, cognition, and behavior. *Science, 298*(5596), 1191-1194.

Druckman, J., & Kam, C. (2011). Students as Experimental Participants: A Defense of the 'Narrow Data Base'. In J. N. Druckman, D. P. Green, K. J. H. & L. A. (Eds.), *Cambridge Handbook of Experimental Political Science* (pp. 41-57): Cambridge University Press.

Druckman, J.N., Green, D.P., Kuklinski, J.H., & Lupia, A. (2006). The growth and development of experimental research in political science. *American Political Science Review, 100*(4), 627.

Druckman, J.N., Green, D.P., Kuklinski, J.H., & Lupia, A. (2011). *Cambridge Handbook of Experimental Political Science*: Cambridge University Press.

Eckel, C.C., & Grossman, P.J. (1998). Are women less selfish than men?: Evidence from dictator experiments. *The Economic Journal, 108*(448), 726-735.

Eckel, C.C., & Wilson, R.K. (2010). *Shopping for Trust.* Paper presented at the Midwest Political Science Association Conference, Chicago, IL

Emonds, G., Declerck, C.H., Boone, C., Vandervliet, E.J.M., & Parizel, P.M. (2011). Comparing the neural basis of decision making in social dilemmas of people with different social value orientations, a fMRI study. *Journal of Neuroscience, Psychology, and Economics, 4*(1), 11-24.

Fagley, N., & Miller, P.M. (1997). Framing effects and arenas of choice: Your money or your life? *Organizational Behavior and Human Decision Processes, 71*(3), 355-373.

Fehr, E., & Gachter, S. (2002). Altruistic punishment in humans. *Nature, 415*(6868), 137-140.

Fehr, E., & Schmidt, K.M. (1999). A theory of fairness, competition, and cooperation*. *Quarterly Journal of Economics, 114*(3), 817-868.

Fliessbach, K., Weber, B., Trautner, P., Dohmen, T., Sunde, U., Elger, C.E., & Falk, A. (2007). Social comparison affects reward-related brain activity in the human ventral striatum. *Science, 318*(5854), 1305.

Flombaum, J.I., & Posner, M.I. (2005). The activation of attentional networks. *Neuroimage, 26*, 471-479.

Frank, M., Ekman, P., & Friesen, W. (1993). Behavioral markers and recognizability of the smile of enjoyment. *Journal of Personality and Social Psychology 64*, 83-93.

Frey, B.S., & Stutzer, A. (2005). Beyond outcomes: measuring procedural utility. *Oxford Economic Papers, 57*(1), 90-111.

Friedman, M., & Savage, L.J. (1948). The utility analysis of choices involving risk. *The Journal of Political Economy, 56*(4), 279-304.

Gambetta, D. (1988). Mafia: The Price of Distrust. S. 158-175. *Trust Making and Breaking Cooperative Relations.* Gambetta D.(Ed.). Oxford: Blackwell.

Genovesio, A., Tsujimoto, S., & Wise, S.P. (2006). Neuronal activity related to elapsed time in prefrontal cortex. *Journal of Neurophysiology, 95*(5), 3281-3285.

Gerber, A.S., Green, D.P., & Larimer, C.W. (2008). Social pressure and vote turnout: Evidence from a large-scale field experiment. *American Political Science Review, 102*(1), 33.

Goel, V., Grafman, J., Sadato, N., & Hallett, M. (1995). Modeling other minds. *NeuroReport-International Journal for Rapid Communications of Research in Neuroscience, 6*(13), 1741-1746.

Grabner, R.H., Ansari, D., Reishofer, G., Stern, E., Ebner, F., & Neuper, C. (2007). Individual differences in mathematical competence predict parietal brain activation during mental calculation. *Neuroimage, 38*(2), 346-356.

Graybiel, A.M. (2005). The basal ganglia: learning new tricks and loving it. *Current Opinion in Neurobiology, 15*(6), 638-644.

Griesinger, D.W., & Livingston Jr, J.W. (1973). Toward a model of interpersonal motivation in experimental games. *Behavioral Science, 18*(3), 173-188.

Hare, T.A., O'Doherty, J., Camerer, C.F., Schultz, W., & Rangel, A. (2008). Dissociating the role of the orbitofrontal cortex and the striatum in the computation of goal values and prediction errors. *The Journal of Neuroscience, 28*(22), 5623.

Harmon-Jones, E., & Winkielman, P. (2007). *Social Neuroscience: Integrating Biological and Psychological Explanations of Social Behavior*: The Guilford Press.

Hemesath, M., & Pomponio, X. (1998). Cooperation and culture: Students from china and the united states in a prisoner's dilemma. *Cross-Cultural Research, 32*(2), 171-184.

Hemmingway, E. (1937). *To Have and to Have Not*. New York: Scribners.

Henrich, J.P. (2004). *Foundations of Human Sociality: Economic Experiments and Ethnographic Evidence from Fifteen Small-Scale Societies*: Oxford University Press, USA.

Hirsch, J., Moreno, D.R., & Kim, K.H.S. (2001). Interconnected large-scale systems for three fundamental cognitive tasks revealed by functional MRI. *Journal of Cognitive Neuroscience, 13*(3), 389-405.

Hofstede, G. (1980). *Culture's Consequences: International Differences in Work-Related Values* (Vol. 5): Sage Publications, Incorporated.

Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., & Camerer, C.F. (2005). Neural systems responding to degrees of uncertainty in human decision-making. *Science, 310*(5754), 1680-1683.

Huettel, S.A., Song, A.W., & McCarthy, G. (2004). *Functional magnetic resonance imaging* (Vol. 1): Sinauer Associates Sunderland, MA.

Jenkins, A.C., & Mitchell, J.P. (2011). How Has Cognitive Neuroscience Contributed to Social Psychological Theory? *Social Neuroscience: Toward Understanding the Underpinnings of the Social Mind: Toward Understanding the Underpinnings of the Social Mind*, 1.

Jenkinson, M., Bannister, P., Brady, M., & Smith, S. (2002). Improved optimization for the robust and accurate linear registration and motion correction of brain images. *Neuroimage, 17*(2), 825-841.

Johnson, T., Myagkov, M., & Orbell, J. (2004). Sociality as a defensive response to the threat of loss. *Politics and the Life Sciences, 23*(2), 13-19.

Johnson, T., Orbell, J., & Myagkov, M. (2010). *Risky Decision Making in the Domain of 'Sociality'.* Working Paper.

Kagel, J.H., & Roth, A.E. (1995). *The Handbook of Experimental Economics*. Princeton: Princeton University Press.

Kahn, L.M., & Murnighan, J.K. (1993). Conjecture, uncertainty, and cooperation in prisoner's dilemma games: Some experimental evidence. *Journal of Economic Behavior & Organization, 22*(1), 91-117.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263-291.

Keeney, R.L., & Raiffa, H. (1993). *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*: Cambridge Univ Pr.

Klein, T.A., Endrass, T., Kathmann, N., Neumann, J., Von Cramon, D.Y., & Ullsperger, M. (2007). Neural correlates of error awareness. *Neuroimage, 34*(4), 1774-1781.

Knutson, B., Fong, G.W., Adams, C.M., Varner, J.L., & Hommer, D. (2001). Dissociation of reward anticipation and outcome with event-related fMRI. *Neuroreport, 12*(17), 3683-3687.

Krebs, J.R., & Dawkins, R. (1984). Animal signals: mind-reading and manipulation. *Behavioural Ecology: An Evolutionary Approach, 2,* 380-402.

Krueger, F., Grafman, J., & McCabe, K. (2008). Neural correlates of economic game playing. *Philosophical Transactions of the Royal Society B: Biological Sciences, 363*(1511), 3859.

Kuhlman, D.M., & Marshello, A. (1975). Individual differences in the game motives of own, relative, and joint gain. *Journal of Research in Personality, 9*(3), 240-251.

Lancaster, J.L., Woldorff, M.G., Parsons, L.M., Liotti, M., Freitas, C.S., Rainey, L., . . . Fox, P.T. (2000). Automated Talairach atlas labels for functional brain mapping. *Human Brain Mapping, 10*(3), 120-131.

Landa, J.T. (1981). Theory of the Ethically Homogeneous Middleman Group: An Institutional Alternative to Contract Law, *A. J. Legal Studies, 10*, 349.

Ledyard, J.O. (1994). Public goods: A survey of experimental research. *Public Economics*.

Lee, D. (2008). Game theory and neural basis of social decision making. *Nature Neuroscience*, *11*(4), 404-409.

Leube, D.T., Erb, M., Grodd, W., Bartels, M., & Kircher, T.T.J. (2001). Differential activation in parahippocampal and prefrontal cortex during word and face encoding tasks. *Neuroreport, 12*(12), 2773-2777.

Liebrand, W.B.G., & Van Run, G.J. (1985). The effects of social motives on behavior in social dilemmas in two cultures. *Journal of Experimental Social Psychology, 21*(1), 86-102.

Loewenstein, G., Rick, S., & Cohen, J.D. (2008). Neuroeconomics. *Annual Review Psychology, 59*, 647-672.

Lohrenz, T., & Montague, P.R. (2008). Neuroeconomics: What neuroscience can learn from economics. *Psychology and Economic Behaviour*, 457-492.

Mailath, G.J., & Samuelson, L. (2006). *Repeated Games and Reputations: Long-Run Relationships*: Oxford University Press, USA.

Marwell, G., Oliver, P.E., & Prahl, R. (1988). Social networks and collective action: A theory of the critical mass. III. *American Journal of Sociology*, 502-534.

Matthews, P.M. (2001). An introduction to functional magnetic resonance imaging of the brain. *Functional MRI: An Introduction to Methods.* Oxford University Press, New York, 5-34.

Mazerolle, E.L., D'Arcy, R.C.N., & Beyea, S.D. (2008). Detecting functional magnetic resonance imaging activation in white matter: Interhemispheric transfer across the corpus callosum. *BMC Neuroscience, 9*(1), 84.

Mazziotta, J., Toga, A., Evans, A., Fox, P., Lancaster, J., Zilles, K., . . . Pike, B. (2001). A probabilistic atlas and reference system for the human brain: International Consortium for Brain Mapping (ICBM). *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 356*(1412), 1293-1322.

McClintock, C.G. (1972). Game behavior and social motivation in interpersonal settings. *Experimental Social Psychology,* 271-297.

McDermott, R., Fowler, J.H., & Smirnov, O. (2008). On the evolutionary origin of prospect theory preferences. *Journal of Politics, 70*(2), 335-350.

McFadden, D. (2010). *Sociality, Rationality, and the Ecology of Choice*.

Menshikov, I., Menshikova, O., Myagkov, M., & Plott, C.R. From Non Market Attitudes to Market Behavior: Laboratory Market Experiments in Moscow and the Hvatat Property of Human Behavior.

Mercer, J. (2005). Prospect theory and political science. *Annual Review Political Science, 8*, 1-21.

Montague, P.R., Dayan, P., & Sejnowski, T.J. (1996). A framework for mesencephalic dopamine systems based on predictive Hebbian learning. *The Journal of Neuroscience, 16*(5), 1936-1947.

Nickerson, D.W. (2008). Is voting contagious? Evidence from two field experiments. *American Political Science Review, 102*(1), 49.

Oosterbeek, H., Sloof, R., & Van De Kuilen, G. (2004). Cultural differences in ultimatum game experiments: Evidence from a meta-analysis. *Experimental Economics, 7*(2), 171-188.

Ordeshook, P.C. (1986). *Game Theory and Political Theory: An Introduction*: Cambridge Univ Pr.

Ortmann, A., & Tichy, L.K. (1999). Gender differences in the laboratory: evidence from prisoner's dilemma games. *Journal of Economic Behavior & Organization, 39*(3), 327-339.

Osborne, M.J., & Rubinstein, A. (1994). *A course in game theory*: MIT press.

Owen, A.M., Milner, B., Petrides, M., & Evans, A.C. (1996). A specific role for the right parahippocampal gyrus in the retrieval of object-location: A positron emission tomography study. *Journal of Cognitive Neuroscience, 8*(6), 588-602.

Packard, M.G., & Knowlton, B.J. (2002). Learning and memory functions of the basal ganglia. *Annual Review of Neuroscience, 25*(1), 563-593.

Peterson, R.L. (2005). The neuroscience of investing: fMRI of the reward system. *Brain Research Bulletin, 67*(5), 391-397.

Phelps, E.A., O'Connor, K.J., Gatenby, J.C., Gore, J.C., Grillon, C., & Davis, M. (2001). Activation of the left amygdala to a cognitive representation of fear. *Nature Neuroscience, 4*(4), 437-441.

Plassmann, H., O'Doherty, J., & Rangel, A. (2007). Orbitofrontal cortex encodes willingness to pay in everyday economic transactions. *The Journal of Neuroscience, 27*(37), 9984.

Platt, M.L., & Huettel, S.A. (2008). Risky business: the neuroeconomics of decision making under uncertainty. *Nature Neuroscience, 11*(4), 398-403.

Plott, C.R. (1976). Axiomatic social choice theory: An overview and interpretation. *American Journal of Political Science,* 511-596.

Poldrack, R.A., Fletcher, P.C., Henson, R.N., Worsley, K.J., Brett, M., & Nichols, T.E. (2008). Guidelines for reporting an fMRI study. *Neuroimage, 40*(2), 409-414.

Rabin, M. (1993). Incorporating fairness into game theory and economics. *The American Economic Review*, 1281-1302.

Rilling, J.K., Sanfey, A.G., Aronson, J.A., Nystrom, L.E., & Cohen, J.D. (2004). The neural correlates of theory of mind within interpersonal interactions. *Neuroimage, 22*(4), 1694-1703.

Roth, A.E., Prasnikar, V., Okuno-Fujiwara, M., & Zamir, S. (1991). Bargaining and market behavior in Jerusalem, Ljubljana, Pittsburgh, and Tokyo: An experimental study. *The American Economic Review,* 1068-1095.

Sanders, J., Nee, V., & Sernau, S. (2002). Asian immigrants' reliance on social ties in a multiethnic labor market. *Social Forces, 81*(1), 281-314.

Sandholm, T.W., & Crites, R.H. (1996). Multiagent reinforcement learning in the iterated prisoner's dilemma. *Biosystems, 37*(1), 147-166.

Sanfey, A.G., Rilling, J.K., Aronson, J.A., Nystrom, L.E., & Cohen, J.D. (2003). The neural basis of economic decision-making in the ultimatum game. *Science, 300*(5626), 1755.

Savage, L.J. (1972). *The Foundations of Statistics*: Dover Pubns.

Scharlemann, J., Eckel, C., Kacelnik, A., & Wilson, R. (2001). The value of a smile: Game theory with a human face. *Journal of Economic Psychology, 22*(5), 617-640.

Schnider, A., Treyer, V., & Buck, A. (2005). The human orbitofrontal cortex monitors outcomes even when no reward is at stake. *Neuropsychologia, 43*(3), 316-323.

Schoemaker, P.J.H. (1980). *Experiments on Decisions under Risk: The Expected Utility Hypothesis*: Martinus Nijhoff Pub.

Schoemaker, P.J.H. (1982). The expected utility model: Its variants, purposes, evidence and limitations. *Journal of Economic Literature*, 529-563.

Schreiber, D., Dawes, C.T., Loewen, P.J., Simmons, A.N., Flagan, T., McElreath, R., . . . Paulus, M.P. (2010). *The Neural Basis of Egalitarian Behaviors*.

Selten, R. (1991). Evolution, learning, and economic behavior. *Games and Economic Behavior, 3*(1), 3-24.

Selten, R., & Stoecker, R. (1986). End behavior in sequences of finite Prisoner's Dilemma supergames A learning theory approach. *Journal of Economic Behavior & Organization, 7*(1), 47-70.

Silverstein, A., Cross, D., Brown, J., & Rachlin, H. (1998). Prior experience and patterning in a prisoner's dilemma game. *Journal of Behavioral Decision Making, 11*(2), 123-138.

Smith, P.B., & Bond, M.H. (1993). *Social Psychology Across Cultures: Analysis and Perspectives*: Harvester Wheatsheaf.

Smith, S.M. (2002). Fast robust automated brain extraction. *Human Brain Mapping, 17*(3), 143-155.

Smith, S.M., Jenkinson, M., Woolrich, M.W., Beckmann, C.F., Behrens, T., Johansen-Berg, H., . . . Flitney, D.E. (2004). Advances in functional and structural MR image analysis and implementation as FSL. *Neuroimage, 23*, S208.

Stockard, J., Van De Kragt, A.J.C., & Dodge, P.J. (1988). Gender roles and behavior in social dilemmas: Are there sex differences in cooperation and in its justification? *Social Psychology Quarterly*, 154-163.

Stone, V.E., Winkielman, P., & Harmon-Jones, E. (2007). An Evolutionary Perspective on Domain Specificity in Social Intelligence. *Social Neuroscience. Integrating Biological and Psychological Explanations of Social Behavior.* New York/London, 316-349.

Tabibnia, G., Satpute, A.B., & Lieberman, M.D. (2008). The sunny side of fairness. *Psychological Science, 19*(4), 339.

Tajfel, H. (1981). *Human Groups and Social Categories: Studies in Social Psychology*: Cambridge Univ Pr.

Tajfel, H. (1982). Social psychology of intergroup relations. *Annual Review of Psychology, 33*(1), 1-39.

Tajfel, H. (2010). *Social Identity and Intergroup Relations* (Vol. 7): Cambridge Univ Pr.

Teece, D.J. (1992). Competition, cooperation, and innovation: Organizational arrangements for regimes of rapid technological progress. *Journal of Economic Behavior & Organization, 18*(1), 1-25.

Trepel, C., Fox, C.R., & Poldrack, R.A. (2005). Prospect theory on the brain? Toward a cognitive neuroscience of decision under risk. *Cognitive Brain Research, 23*(1), 34-50.

Triandis, H.C. (1989). The self and social behavior in differing cultural contexts. *Psychological Review; Psychological Review, 96*(3), 506.

Tricomi, E., Rangel, A., Camerer, C.F., & O'Doherty, J.P. (2010). Neural evidence for inequality-averse social preferences. *Nature, 463*(7284), 1089-1091.

Tsukamoto, T., Kotani, Y., Ohgami, Y., Omura, K., Inoue, Y., & Aihara, Y. (2006). Activation of insular cortex and subcortical regions related to feedback stimuli in a time estimation task: an fMRI study. *Neuroscience Letters, 399*(1), 39-44.

Turner, B.M., Paradiso, S., Marvel, C.L., Pierson, R., Boles Ponto, L.L., Hichwa, R.D., & Robinson, R.G. (2007). The cerebellum and emotional experience. *Neuropsychologia, 45*(6), 1331-1341.

Tversky, A. (1975). A critique of expected utility theory: Descriptive and normative considerations. *Erkenntnis, 9*(2), 163-173.

Von Neumann, J., Morgenstern, O., Rubinstein, A., & Kuhn, H.W. (1944). *Theory of Games and Economic Behavior*: Princeton Univ Pr.

Waytz, A., Zaki, J., & Mitchell, J.P. (2012). Response of dorsomedial prefrontal cortex predicts altruistic behavior. *The Journal of Neuroscience, 32*(22), 7646-7650.

Weber, E.U., & Hsee, C.K. (1999). Models and mosaics: Investigating cross-cultural differences in risk perception and risk preference. *Psychonomic Bulletin & Review, 6*(4), 611-617.

Weissman, D., Perkins, A., & Woldorff, M. (2008). Cognitive control in social situations: A role for the dorsolateral prefrontal cortex. *Neuroimage, 40*(2), 955-962.

Wilcoxon, F. (1945). Individual comparisons by ranking methods. *Biometrics Bulletin, 1*(6), 80-83.

Williams, C.B., & Gulati, G.J. (2007). *Social Networks in Political Campaigns: Facebook and the 2006 Midterm Elections.* Paper presented at the annual meeting of the American Political Science Association.

Willingham, D.T., & Dunn, E.W. (2003). What neuroimaging and brain localization can do, cannot do and should not do for social psychology. *Journal of Personality and Social Psychology, 85*(4), 662.

Wong, R.Y., & Hong, Y. (2005). Dynamic influences of culture on cooperation in the prisoner's dilemma. *Psychological Science, 16*(6), 429-434.

Woolrich, M.W., Ripley, B.D., Brady, M., & Smith, S.M. (2001). Temporal autocorrelation in univariate linear modeling of FMRI data. *Neuroimage, 14*(6), 1370-1386.

Worsley, K. (2001). Statistical analysis of activation images. *Functional MRI: an Introduction to Methods, 14*, 251-270.

Xiao, E., & Bicchieri, C. (2010). When equality trumps reciprocity. *Journal of Economic Psychology, 31*(3), 456-470.

Yacubian, J., Gläscher, J., Schroeder, K., Sommer, T., Braus, D.F., & Büchel, C. (2006). Dissociable systems for gain-and loss-related value predictions and errors of prediction in the human brain. *The Journal of Neuroscience, 26*(37), 9530.

Yamagishi, T. (1988). Exit from the group as an individualistic solution to the free rider problem in the United States and Japan. *Journal of Experimental Social Psychology, 24*(6), 530-542.

Yamagishi, T. (2003). Cross-Societal Experimentation on Trust: A Comparison of the United States and Japan. In E. Ostrom & J. Walker (Eds.), *Trust and Reciprocity* (pp. 352-370). New York: Russell Sage Foundation.

Yamagishi, T., & Yamagishi, M. (1994). Trust and commitment in the United States and Japan. *Motivation and Emotion, 18*(2), 129-166.

Zaki, J., & Mitchell, J.P. (2011). Equitable decision making is associated with neural markers of intrinsic value. *Proceedings of the National Academy of Sciences, 108*(49), 19761-19766.

Zeki, S., & Romaya, J.P. (2008). Neural correlates of hate. *PloS one, 3*(10), e3556.