Decomposing trust into risk preferences, altruism, and subjective beliefs: An experimental analysis

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Abstract

There is a sizeable economic literature dedicated to understanding trust and the extent to which it influences decision making. Although trust is difficult to measure, experimental economics has commonly used the ‘amount sent’ in the Berg, Dickhaut and McCabe (1995) investment game to elicit levels of trust from players of the game. However, there is a growing body of literature suggesting that factors such as risk preferences, altruism, and subjective beliefs may confound this measure of trust, thereby questioning the validity of using the ‘amount sent’ to elicit people’s levels of trust. To understand these factors, we designed and conducted an incentive-compatible economic experiment with students from the University of Cape Town. These participants completed the investment game, the dictator game (to measure levels of altruism), and a random lottery pair risk preferences task (to gauge risk preferences). We also included an information treatment where students were shown the conditional distributions of amount sent decisions made by students in the previous, baseline treatment. This was done to evaluate whether knowledge of the actions taken by other students would ground students’ beliefs and influence the decisions they made. We estimate a set of standard statistical models to gauge determinants of the amount sent and a complementary maximum likelihood estimation approach to estimate Expected Utility models and Rank-Dependent Utility models in order to further evaluate our data. Our results show that caution needs to be taken when using the amount sent as a measure of trust as the relationship between risk preferences and the amount sent is a nuanced one. Moreover, altruism has a statistically significant association with the amount sent and with risk preferences. We also found that those who were part of the information treatment sent significantly more than those who were not, and they were on average also less risk averse. This indicates that while subjective beliefs do influence behaviour in the investment game, they also affect risk preferences. Thus, our results suggest that researchers should not use the amount sent in the investment game as a pure measure of trust because its measurement is confounded empirically by altruism and subjective beliefs, and theoretically by risk preferences.

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1. Introduction

Trust among individuals, communities, organisations, and governments is an important cultural characteristic that allows members of society to cooperate with each other and enhance general welfare (Fukuyama, 1995a; Johnson & Mislin, 2011). From an economic perspective, there are a multitude of benefits that can be derived from increased levels of trust within society. These include, but are not limited to: increased efficiency and lower costs, improved behaviour patterns, higher per capita GDP, better quality government organisations, lower levels of corruption, and improved financial development (Johnson & Mislin, 2011). Almost all economic activity occurring in a country is conducted through organisations rather than by individuals acting on their own, which means that high degrees of cooperation are needed to keep the economy running efficiently. According to Gambetta (2000), trusting someone is engaging in cooperation with them because their actions have a high probability of being sufficiently beneficial, or at least not detrimental. It can therefore be said that higher levels of trust result in increased levels of cooperation and improved economic outcomes (Fukuyama, 1995a; Johnson & Mislin, 2011).

As an abstract concept, trust is difficult to measure and opinions differ on the most effective way to measure it. In economics, lab experiments have become the predominant method of trust elicitation. The investment game developed by Berg, Dickhaut and McCabe (1995, henceforth BDM) is the most common experiment used for this purpose. In this game two players are randomly paired but separated from each other, for example, they could be located in different rooms. Each player is endowed with $10. Player 1 is asked to decide how much of their $10 they wish to send, in $1 increments, to player 2. They are informed that any amount sent will be tripled before reaching player 2. This send decision is the variable used to measure the participant's level of trust. Upon receiving triple the amount sent by player 1, player 2 is asked to decide what proportion of this received amount they would like to return to player 1. The amount returned is the variable often used to measure trustworthiness.

Our focus is limited to the amount sent as a measure of trust; trustworthiness falls beyond the scope of this study and will not be considered further. The amount sent in the investment game is not, however, a pure measure of trust. There are a variety of factors that have the potential to confound it. These include: risk preferences, altruism and subjective beliefs. In recent studies, the investment game has been conducted together with additional games and/or tasks that measure some or all of these factors in an attempt to determine which of them are associated with the amount sent, and if any have a confounding effect on the variable (Cox, 2004; Eckel & Wilson, 2004; Schechter, 2007; Houser, Schunk & Winter, 2010; Brülhart & Usunier, 2012; Sapienza, Toldra-Simats & Zingales, 2013). These studies have returned mixed results, which prompted the research upon which this dissertation is based.

We designed an incentive compatible experiment that measures all the factors mentioned above (risk preferences, altruism, and subjective beliefs) to enable us to evaluate whether or not they confound inferences about trust drawn from the amount sent in the investment game. Risk preferences were elicited through a 100-choice lottery pair risk preference task; altruism was measured through the send decisions made in the dictator game; and subjective beliefs were accounted for by including an information treatment that aimed to ground participants' beliefs in the actions taken by fellow students who formed part of the baseline treatment. To control for potential order effects, we also varied the order in which participants took part in the three tasks. Our goal was to determine if the amount sent in the investment game, after controlling for all of the above factors, could be used as a reliable measure of trust, or if a more cautious approach needs to be taken when interpreting this variable in relation to levels of trust.

An in-depth review of the experimental methods that have been used to measure trust from an economic perspective is presented in Section 2. Emphasis is placed on the BDM investment game and various replications of it. Section 3 details our experimental design and procedures, Section 4 provides a break-down of the methods used to analyse the data we gathered through our experiments, and Section 5 reports the results from carrying out this data analysis. Lastly, Section 6 discusses the implications of these results and draws conclusions.

2. Understanding Trust

Trust has become a widely researched concept partly because of the potential that trusting behaviour has for improving the welfare of societies (Johnson & Mislin, 2011). Johnson and Mislin's (2011) meta-analysis of BDM's investment game lists the benefits that can be expected when there are high levels of trust between people, including increased efficiency, better economic outcomes, higher GDP, and better functioning civil services. These are only a few of the potential gains that could be derived from a better understanding of trust and of how policies can be altered to maximise trust in society, which is a strong motivation for continuing to examine trusting behaviour.

Fukuyama (1995b:26) defines trust as "…the expectation that arises within a community of regular, honest, and cooperative behaviour, based on commonly shared norms, on the part of other members of that community…" that results in a better society with increased cooperation. Thus, trust is an abstract concept that is not easily quantified. In spite of this, economists are still interested in understanding trust and how it influences individuals' decision-making processes (Houser, Schunk & Winter, 2010). In order to gain an understanding of trust, it has been measured in a variety of ways. Some authors have used the well-known question from the World Values Survey: 'Generally speaking, would you say that most people can be trusted or that you cannot be too careful in dealing with people?' (Sapienza, Toldra-Simats & Zingales, 2013). Others have used experimental methods to measure trust. Lab experiments have revolutionised the way trust is measured (Johnson & Mislin, 2011)

The majority of the literature on trust has been based on studies conducted in Western Europe and North America, which provides further incentive to continue conducting trust experiments in other parts of the world (Etang, Fielding & Knowles, 2010). This focus on developed countries is problematic from an African perspective because Western Europe and North America have particularly high levels of trust while Africa is argued to have below average levels of trust (Etang, Fielding & Knowles, 2010). In the few instances where trust experiments have been conducted in Africa, results suggest that people are less trusting than those taking part in comparable studies in different geographic regions, like North America (Johnson & Mislin, 2011). Thus our study, conducted on university students in Cape Town, South Africa, will add to an underrepresented area of this growing pool of literature.

According to economic trust literature, the BDM investment game has become the dominant method for measuring trust and trustworthiness. It is also referred to more commonly as the trust game (Johnson & Mislin, 2011). Johnson and Mislin's (2011) meta-analysis of trust games shows that there have been multiple replications and variations of BDM's investment game, which highlights its relevance and importance when measuring trust.

In the BDM investment game, subjects were endowed with a show-up fee of $10 on arrival and were split into two different rooms. Subjects in room A, also referred to as trustors, had to decide how much, if any, of their $10 endowment they wished to send to a randomly and anonymously assigned partner in room B, also referred to as the trustee. They were allowed to send money in increments of $1. Any amount they chose to send was tripled before it reached their partner. Then, the subjects in room B were asked to decide how much of the amount they were sent, if any, they wanted to return to their partners in room A.

BDM held that in order for trust to have played a role in the exchange between subjects, there were three conditions that needed to be met. First, the trustor must be put at risk by placing trust in the trustee. In the BDM investment game, the trustor faces risk when they choose to send money to their partner who may not send anything back. Second, the decisions the trustee makes must benefit their partner at a cost to themselves. This is captured by the trustee choosing to send money back to their partner to make their partner better off. Third, following the transaction both trustor and trustee are better off than they would have been had the transaction not transpired. In the BDM investment game, since the money that the trustor sends is tripled before reaching the trustee, both subjects *can be* made better off than if they chose to send nothing.

Thus, the amount sent in the investment game is used as a measure of trust, while the amount returned as a fraction of the amount sent is used as a measure of trustworthiness. The BDM investment game is designed to elicit attitudes about trust. Further, BDM's conditions for trust to facilitate an exchange are similar to many definitions of trust. Cox (2004:263) defines trust as being "… inherently a matter of the beliefs that one agent has about the behavior of another. An action that is trusting of another is one that creates the possibility of mutual benefit, if the other person is cooperative, and the risk of loss to oneself if the other person defects." Gambetta (2000) states that trusting a person implicitly means that there is a high enough probability that the actions they take will be sufficiently beneficial to allow for cooperation.

While the importance of understanding trust decisions between economic agents is clear, there have been a number of studies that question the validity of the trust measure obtained through the BDM investment game (Cox, 2004; Eckel & Wilson, 2004; Schechter, 2007; Houser, Schunk & Winter, 2010; Brülhart & Usunier, 2012; Sapienza, Toldra-Simats & Zingales, 2013). Following BDM, studies have repeatedly used the amount sent in the investment game as a measure of trust. However, there are factors that have the potential to affect the amount participants send, and therefore confound the amount sent as a measure of trust. This makes the amount sent a noisy measure of trust for the representative participant and is even noisier at the individual level. Therefore, more recent studies of trust have investigated these factors, which include risk preferences, altruism, and subjective beliefs to gauge the influence they have on the amount sent (Cox, 2004; Eckel & Wilson, 2004; Schechter, 2007; Houser, Schunk & Winter, 2010; Brülhart & Usunier, 2012; Sapienza, Toldra-Simats & Zingales, 2013). Steps need to be taken to disentangle these factors from the amount sent so that it can be used as a more accurate measure of trusting behaviour. The remainder of this literature review will evaluate these potential confounding factors.

2.1. **Trust and Risk**

Standard economic theory assumes that people have a fixed utility function applicable to all risk situations (BDM; Eckel & Wilson, 2004:457). In Harrison and Rutström's (2008) review of experimental evidence on risk preferences, they find that it is often assumed that people are risk neutral or, failing this, have stable levels of risk aversion. They discuss the different methods that can be used to elicit a person's level of risk aversion and show how different elicitation methods are suited to different environments (Harrison & Rutström, 2008). In the risk and trust literature, two commonly used methods of risk elicitation are the multiple price list (MPL) and the random lottery pair (RLP) design. The MPL requires subjects to make a sequence of binary lottery choices, where one lottery has a greater degree of risk than the other. Subjects are shown the sequence, which generally consists of 10 choices, in its entirety before making any decisions (Harrison & Rutström, 2008). The RLP design also requires subjects to make a sequence of choices between two lotteries, but they generally have to make more than 10 choices and they only see one choice at a time (Hey & Orme, 1994; Loomes & Sugden, 1998; Harrison & Rutström, 2008).

A reason for studying the relationship between risk and trust is due to the potentially confounding influence that risk has on trust (Houser, Schunk & Winter, 2010). In terms of the investment game, this relationship can be tested by determining whether a person's risk preferences influence their send decisions. For example, a person who is highly risk averse might choose to send none of their endowment, regardless of how trusting they are, because they do not want to risk getting no money back. To control for this, there have been some studies replicating the BDM investment game that have included measures like the number of risky choices participants made in various risk tasks as proxies for participants' risk preferences

(Eckel & Wilson, 2004; Schechter, 2007; Houser, Schunk & Winter, 2010; Sapienza, Toldra-Simats & Zingales, 2013).[1]

Eckel and Wilson (2004) were the first authors to test for a relationship between risk and the amount sent in the investment game. They conducted a series of lab experiments in an attempt to measure the relationship between risk preferences and send decisions among anonymous subjects. Their experiments included a variation of the BDM investment game with three treatments and three measures of risk: two experimental measures and one survey measure. In their version of the investment game, first movers were required to send their whole endowment of $5, which was doubled when sent, or send nothing at all. Then, second movers, who also started with a $5 endowment, could send back any amount in the range of $0 to $10 in $1.25 increments. They also chose to frame the game in terms of the first mover giving a loan and the second mover paying back the loan.

The subgame perfect Nash equilibrium of this interaction if people are purely self-interested is for the first mover to send nothing and for the second mover to return nothing (BDM). Using backward induction and assuming the second mover is self-interested, it follows that they will keep any amount they are sent from the first mover because sending any amount back to the first mover will make them worse off. Recognising this, the first mover will not send any amount to the second mover because they know they will receive nothing in return.

Three treatments were used to vary the amount of information subjects received about their partners. The first treatment gave no information about partners aside from informing subjects that the person they were paired with was at a different location; the experiments were run in two computer labs at two different universities. In the second treatment, subjects were given the following information about their partner: gender, favourite colour, whether they liked dogs, and whether they liked movies. The third treatment showed subjects a photograph of their partner taken on the day of the experiment.

Analysis of the data showed that participants who took on the role of first mover had high levels of trust across all treatments; however, those in the first treatment were most likely to make the loan. Eckel and Wilson (2004) take this to mean that the greater social distance participants have from their partners, the more likely they are to trust them. This contradicts what Fukuyama (1995a) suggested: that people are more likely to trust those with whom they interact regularly. The implication here is that trust decreases with social distance (Etang,

[1] More studies of the risk-trust confound exist (for example, see: Corcos, Pannequin & Bourgeois-Gironde, 2012; Fairley et al., 2016; Garapin, Muller & Rahali, 2015), but these studies also find mixed results.

Fielding & Knowles, 2010), while Eckel and Wilson's results suggest the opposite. Although participants would have had no interactions with their partners, one might have assumed that they would be more trusting of their partners if they knew more information about them.

To proxy risk preferences, participants completed three different tasks. First, they completed the 40-question Zuckerman Sensation-Seeking Scale survey, which measures a participant's desire to take part in risky activities. Each question gives participants a pair of statements about risky activities, with one statement condemning the risky action while the other applauds the risky action, and asks them to select their preferred option.

Second, the Holt and Laury (2002, henceforth HL) instrument was used and participants made 10 decisions between two lotteries with varying degrees of risk. The HL instrument uses the MPL design and gives participants a table listing all 10 choices. The table has two columns: Lottery A and Lottery B, and each row represents a choice that the participant needs to make between A and B (Harrison & Rutström, 2008). Each lottery has set prizes, with Lottery B having more variance in its prizes than Lottery A. At each decision, the lotteries have the same probability weighting, for example, a 10% chance of receiving prize 1 and a 90% chance of receiving prize 2. This probability weighting is what changes with every decision, while the prizes in each lottery remain the same. A risk averse individual is more likely to consistently select Lottery A while a less risk averse individual might start by selecting Lottery A but quickly switch to selecting Lottery B.

Finally, participants played a card gamble where they were required to choose between a certain amount or a risky gamble that had the same expected value as the certain amount. Eckel and Wilson (2004) found that these three risk instruments were only weakly correlated with each other, which may indicate that these measures were only weak proxies of underlying risk preferences. In addition, none of the instruments were significantly correlated with the amount sent in the investment game. This suggests that the choice of how much to send is not a risky decision. Even after demographic controls are added to the regression, it still holds that none of the risk measures were significantly related to the amount sent.

Houser, Schunk and Winter (2010, henceforth HSW) continued on a similar path in an effort to determine whether trust decisions could be predicted using risk attitudes. HSW raise an interesting challenge with regards to understanding the influence risk attitudes have on send decisions: deciding how much to send involves strategic uncertainty while risk involves state uncertainty. In instances of strategic uncertainty, a person's outcomes are affected by another person's decisions, while with state uncertainty, a person's outcomes are influenced by aspects outside the control of another person, for example, the roll of a dice. The authors work around these conflicting concepts by collecting individual-level risk data in the lab and creating separate trust and risk treatments of the investment game. HSW used the same 10-decision HL instrument as Eckel and Wilson (2004) to elicit participants' risk attitudes.

They separated their experiment into four treatments: two trust treatments and two risk treatments. In the trust treatments, participants were randomly and anonymously paired with each other to play one of two variations of the BDM investment game, and were also required to complete the HL risk task. These treatments were structured to create strategic uncertainty. In the first trust treatment, participants played an exact replication of the BDM investment game and received an initial endowment of €5. In the second trust treatment, participants played the social history treatment of the BDM investment game (they were given the BDM summary statistics of how participants acted in the control treatment) and also received an initial endowment of €5.

In the risk treatments, participants also played the BDM investment game and completed the HL risk task, but instead of being paired with one another, they played against a computer. In both risk treatments, participants received the same summary statistics that participants in the second trust treatment received and were informed that those statistics mirrored the computer's return distribution. These treatments were structured to create state uncertainty. In the first risk treatment, participants only played against the computer to determine their own payments. In the second risk treatment, participants played against a computer to determine their own payment as well as the payment of a passive trustee. The trustee's payment was completely determined by the decisions made by the participant and the computer with which the participant interacted.

Upon analysis of the risk data from the HL task, HSW find that participants classified as risk seeking (those who switch before the fourth decision) are statistically significantly more likely to send a high amount, but only in the risk treatments where their counterpart is a computer. However, HSW find no evidence that the HL risk attitudes have an effect on the amount sent in the trust treatments, where participants are paired with each other. HSW do not dispute that risk may have an effect on the decision to trust, but instead propose that trusting decisions are more complex than their experimental design could accommodate. Their study shows that measuring the relationship between the amount sent and risk is a challenging task, but an important one. HSW suggest that additional factors, like other-regarding preferences, may need to be taken into account when measuring trusting decisions.

Sapienza, Toldra-Simats and Zingales (2013) also examine the relationship between amount sent and risk. In their version of the BDM investment game, participants played as both the first mover and the second mover in a lab experiment. When participants played as the first mover, they were endowed with $50, but were not endowed with anything as the second mover. First movers were instructed to send any amount of their endowment, in increments of $5, to their partner. They were informed that the amount they chose to send would be tripled before reaching the second mover. First movers were then asked to report what they believed second movers would send back for every possible amount that could have been sent to them. When they played as the second mover, participants were asked to indicate what amount they would send back to the first mover for every possible amount the first mover could have sent to them. This process is referred to as the dual role strategy method because it elicits the second mover's complete plan of action for every amount the first mover can send.

Through this method, Sapienza, Toldra-Simats and Zingales (2013) are able to gather data on how participants behave, as well as how they believe others will act. By asking participants to report how they expect fellow students to act when playing as the second mover, they elicit participants' beliefs about the trustworthiness of other students. Then, by asking second movers to respond to every possible amount sent, their actual response to all available send options can be gauged. Thus, the experimenter can separate out the first mover's expectations about the second mover's behaviour from the behaviour the second mover exhibits. This method ties in well with how the authors think of trust: "…the act of trusting [is] the combination of two components: beliefs in other people's trustworthiness and the specific preferences of the sender (risk aversion, inequality aversion, altruism)," (Sapienza, Toldra-Simats & Zingales, 2013:1314) .

To measure risk, the authors used an MPL design that was a variation of the HL instrument. Participants had to choose between two options 15 times, instead of having to make the usual 10 decisions. Option A always had a certain payoff of between $50 and $120, which increased in increments of $5 with each decision, while Option B involved playing out a lottery paying $200 or $0 with equal probability. Highly risk averse participants were expected to always choose Option A, the certain amount, while less risk averse individuals should choose Option B at least part of the time. In theory, the more risk seeking the individual, the longer they will continue to select Option B.

After analysing their risk data, the authors did find a relationship between risk and amount sent: individuals who are less risk averse send more in the investment game. Further, as was the case with HSW, Sapienza, Toldra-Simats and Zingales (2013) find that the amount sent in the investment game does not only serve as a potential measure of trust, it also measures risk attitudes and other-regarding preferences.

Studies undertaken in rural areas tend to have more nuanced insights than studies conducted with university students in computer labs. For example, a study conducted in the field in Peru found that less risk averse individuals sent more in the investment game (Karlan, 2005). These types of studies are important to include in any analysis of the literature because they break away from the commonly used lab experiments conducted with university students. Schechter (2007) is another author who conducts investment game experiments in rural areas, specifically 15 different villages in Paraguay. She also finds a relationship between risk and amount sent. Using the investment game, Schechter (2007) shows that the amount sent is determined both by trust and risk aversion.

Schechter (2007) used the original BDM investment game as her measure of trust and a variation of it to measure risk. All participants played the risk game first in which they were required to make an investment decision (as is the case in the investment game) but the return on their investment was determined by the roll of a die. Following this, they played the investment game as both the first and second mover. In this way, Schechter (2007) also used the dual role strategy method. However, she noted that previous studies have shown this method decreases levels of trust in the game and reduces the likelihood that there may be a correlation between trust and altruism.

Analysis of her data shows that there is a robust relationship between levels of risk aversion and the amount sent; as participants increase the amount they bet in the risk task, so too do they increase the amount they send in the investment game. Further, as is the case with most studies, Schechter (2007) finds that women are more risk averse than men. She also finds that they are less trusting until she controls for risk aversion, at which point it becomes evident that levels of trust are not significantly different. Wealthier participants are less risk averse and more trusting until risk preferences are accounted for, at which point levels of wealth have no significant effect on degrees of trust. Regardless of how Schechter (2007) analysed her results, risk attitudes remain a strong predictor of the amount sent in the investment game. Thus, she recommends that before considering the factors affecting trust, risk attitudes need to be controlled for.

From the above analysis, it is clear that there are mixed findings with regard to the influence that risk has on how much participants choose to send to their partners. Eckel and Wilson (2004) found no correlation between the amount sent and participants' levels of risk aversion. Although HSW did find a relationship, they only found one in half of their treatments, and were not certain as to whether or not there was a real relationship. Although Schechter (2007) found that levels of trust and risk preferences influenced the amount participants sent, her sample is very specific, i.e., villagers in rural Paraguay. However, Sapienza, Toldra-Simats and Zingales (2013) found that more risk averse individuals tend to send less in the investment game. Further, they have the largest battery of risk preference questions (15 in total), which could indicate that until their study, there was insufficient data gathered on risk attitudes to be able to draw accurate inferences about the relationship between risk and trust.

One common factor that becomes evident from all of these studies is the need to consider more than just trust and risk when analysing the investment game. There also seems to be a need to analyse participants' other-regarding preferences. Levels of altruism could influence the amount people choose to send, which makes it another factor worth considering.

2.2. **Trust and Altruism**

Experimental studies in game theory have typically assumed that players are self-regarding and play games with strategies that maximise their own payoffs (Gintis et al., 2005). However, it is not only self-regarding preferences that matter: a significant portion of literature has shown the importance of other-regarding preferences and how these preferences influence the decisions that people make (Dufwenberg & Gneezy, 2000; Cox, 2004; Gintis et al., 2005; Schechter, 2007; Dixit, Skeath & Reiley, 2009; Houser, Schunk & Winter, 2010; Sapienza, Toldra-Simats & Zingales, 2013). The investment game has shown that people do not necessarily act solely according to their self-regarding preferences. Further, just as was the case with risk preferences, the experimental design does not allow for a distinction to be made between decisions based on trust and those based on other-regarding preferences.

Other-regarding preferences, also referred to as prosocial preferences, are informed by norms that are internalised over time as prosocial behaviour and fair-mindedness is learnt through experiences and education (Dixit, Skeath & Reiley, 2009). These preferences are modelled on positive reciprocity, which is conditional kindness: a generous action in response to a generous action from someone else (Cox, 2004). Altruism, on the other hand, is unconditional kindness (Cox, 2004). Send decisions made in the investment game could be influenced by positive reciprocity, yet altruism still needs to be accounted for.

Sapienza, Toldra-Simats and Zingales (2013:1321) argue that considering risk preferences in the investment game is not sufficient: these experiments also need to account for other-regarding preferences. While people do care about their own payoffs, they also seem to care about their payoff relative to their partner (Sapienza, Toldra-Simats & Zingales, 2013). This realisation meant that studies that followed on from BDM examined other-regarding preferences. However, they tended not to separate altruism and other-regarding preferences out from trust and reciprocity (Cox, 2004). This means that these studies cannot be used to draw conclusions about which decisions are based on trust and which are based on other-regarding preferences or altruism. Being able to make this distinction is important for advancing the empirical validity of game theory and the way these interactions are modelled (Cox, 2004).

To solve this problem of separation, Cox (2004) developed a triadic design: he re-created the BDM investment game but incorporated three different treatments. Treatment A followed the investment game precisely, including the initial $10 endowment given to both players. Treatment B was the dictator game, which was the same as treatment A aside from the fact that participants in the second-mover group had no decision to make or opportunity to send anything back to the person with whom they were paired. Treatment C used the same structure as treatment A, but the first movers were endowed with the amount kept by the first movers in treatment A (i.e., the amount not sent) and made no send decisions. The second movers were endowed with the original $10 as well as the amount sent to the second movers by the first movers in treatment A. The second movers were the ones who made a decision about how much to send to the first movers. The dictator game, the game played in treatment B, has often been used in experimental economics to examine social preferences and through its various applications, it has shown that people can be altruistic and that they do have other-regarding preferences in certain situations (List, 2007).

By analysing the decisions made in the three treatments of the triadic design, Cox (2004) was able to separate out decisions made based on altruism and trust or reciprocity. Cox (2004) compared the decisions made in treatment A to those made in treatment B to determine if the decisions made in treatment A were motivated by trust and altruism. If the first mover sent a larger amount to the second mover in treatment A than in treatment B, then the first mover showed trust because the amount sent in treatment A cannot fully be explained by other-regarding preferences. Data from Cox's (2004) experiment showed that subjects, on average, sent more in treatment A than in treatment B. Further, 63% of subjects behaved altruistically, which is significant evidence that subjects had unconditional other-regarding preferences, i.e., were motivated by unconditional kindness (altruism) rather than reciprocal generosity. These factors indicate that trust and altruism both played a role in the decisions made by the first movers in treatment A.

Similarly, if the second mover returned a larger amount in treatment A than in treatment C, then the second mover has shown that they are motivated by reciprocity because the amount sent in treatment A cannot be fully explained by other-regarding preferences. This is indeed the case: data from Cox's experiment show that subjects have unconditional other-regarding preferences, and 41% of subjects behaved with altruistic or inequality-averse other-regarding preferences.

Brülhart and Usunier (2012) also examine the influence that altruism may have on the amount a participant chooses to send. They altered the investment game so that second movers were given different endowments: one group was accordingly classified as 'rich' while the other as 'poor.' First movers played simultaneously with both a poor and a rich second mover. The authors wanted to determine whether first movers would give more to the poor second mover than to the rich second mover. If they did give more to second movers classified as poor, this would show signs of altruism in the first mover. It would also prove that trusting someone is more than just being selfish and expecting positive reciprocity, it would mean that participants gained utility from being kind.

They also show, as many studies before them had, that there is only a very small fraction of people who act according to the subgame perfect Nash equilibrium by sending or returning nothing. This shows that the investment game is not best characterised as a game between two entirely self-interested players and that selfishness may not be the dominant motivation behind the choice of how much to send (Brülhart & Usunier, 2012). However, through their analysis, the authors are unable to find altruism to be a statistically significant contributing factor to trusting behaviour.

The investment game uses the amount sent as a means of measuring levels of trust but, because of the factors that influence a person's send decision, it is a noisy measure of trust. Theoretically, altruism and trust are not related, but altruism does seem to influence the amount individuals choose to send. Thus, it must be accounted for when the amount sent is used to calculate trust in the BDM investment game. Another such factor that should be accounted for when utilising 'amount sent' is a person's beliefs about how trustworthy others are.

2.3. **Trust and Beliefs**

Beliefs are part of the fundamental building blocks of models of uncertainty in economics (Hurley & Shogren, 2005). The beliefs people hold inform the way they act and decisions they make, including whether or not to trust someone. When people make decisions in a state of uncertainty, they generate some subjective estimate or view about how others will act, i.e., they form a subjective belief (Dixit, Skeath & Reiley, 2009:96). Eliciting people's beliefs is a complex task but is invaluable in understanding decision-making processes. While choices and actions can be observed by researchers, beliefs are not observable, so studies infer beliefs or try to find proxies (Nyarko & Schotter, 2002). In experimental economics, instead of trying to elicit participants' beliefs directly, researchers sometimes use information treatments to ground peoples' beliefs. Participants update the beliefs they held prior to receiving the additional information in these treatments to form their posterior beliefs, i.e., beliefs that are updated with respect to the new information.

Providing social history information to participants of the investment game allows them to make decisions based on shared information. A social history treatment can result in participants internalising social norms and has the potential to increase social identity (BDM). Dixit, Skeath and Reiley (2009) suggest that through education and experience children mature into adults and selfish tendencies are replaced with fair-mindedness and prosocial behaviour. This results in the internalisation of new social norms as well as the fostering of other-regarding preferences (Dixit, Skeath & Reiley, 2009). Social history information treatments are suitable methods of reminding people of these social norms and ensuring they act in line with the groups with whom they identify (BDM).

There were two treatments in the BDM investment game: the first treatment was the control in which the investment game was played exactly as described previously. The second treatment was conducted in the same manner as the first treatment except the participants were also given information on how those in the control treatment had chosen to act. BDM referred to this as a social history treatment; participants were given a summary report of the decisions made by those who had completed the same experiment before them. The report comprised of a table that showed how many participants sent each amount from $0 to $10, together with the average amount returned for each of these send options. The final row of the table showed the average profit for each option. Subjects in the social history treatment completed the experiments only after receiving this information.

BDM found an increase in the correlation between the amount sent and amount returned when this additional information was provided to participants. It was concluded that using an information treatment increased the amount sent in the investment game. HSW used the same information treatment in their investment game. However, they found that showing participants this additional information had little effect on the send decisions they made. In the study conducted by Sapienza, Toldra-Simats and Zingales (2013), they found that beliefs were only significantly correlated with the amount sent when participants sent more than 25% of their initial endowment. Sending anything less than 25% was considered to be an act of charity and was unrelated to participants' beliefs about how trustworthy their partners were. Thus, a participant's beliefs have the potential to influence the amount they choose to send in the investment game, but it is not certain that beliefs, or additional information, will have a significant effect on send decisions.

2.4. **Going Forward**

Although there have been a multitude of studies already conducted using the investment game, we believe that there is still valuable information to be obtained by doing another one. Based on the various definitions of trust used in the experimental economics literature, attitudes concerning trust present the same kinds of interactions that would be influenced by risk preferences and subjective beliefs. The same is not necessarily the case for the relationship between trust and altruism; in theory, there is no reason to believe that these two factors are related. However, in reality, it is quite possible that all three of the above factors influence the amount sent in the investment game, thereby influencing trust.

Our study sets out to determine how much impact these factors have on the amount sent when they are all measured in a single study. Based on the above literature, we decided to get participants to complete the investment game via the dual role strategy method. To elicit risk preferences, we move away from using the MPL method of risk attitude elicitation. Instead, we use the RLP design and increase the battery of questions to 100 so that we have better informed risk attitudes (Harrison & Rutström, 2008). We use a variation of the dictator game to measure levels of altruism and see if other-regarding preferences need to be accounted for. And finally, we use an information treatment similar to the BDM social history treatment to determine whether the presence of more information affects participants' behaviour.[2] If the amount sent is influenced by risk preferences, altruism, and/or subjective beliefs, then serious caution needs to be exercised when using the amount sent as a measure of trust.

[2] An important difference is that BDM show the distribution of amount returned unconditionally, while we show the distributions of the amount returned by player 2 *conditional on the amount sent by player 1*.

3. Experimental Design

Our experiment was designed to decompose the amount sent in the investment game into factors that may affect it. Drawing on the above literature, our intention is to determine the extent to which people’s risk attitudes, levels of altruism, and subjective beliefs influence the amount sent, and whether these factors confound the measurement of trust. To do this, all participants in our experimental sample completed three tasks: the BDM investment game, the dictator game (informed by Cox’s (2004) triadic design), and a RLP risk preference task. Participants were also divided so that some of them took part in an information treatment. This combination of tasks allowed us to elicit risk preferences and altruism, as well as ground subjective beliefs. The following section discusses these three tasks, as well as our experimental design and our sample, in more detail.

3.1. Experimental Procedure

We divided our sample of students into two treatment groups: a baseline treatment and an information treatment. Regardless of which treatment participants were placed into, each individual in our sample completed all three tasks in our experimental design: the investment game, the dictator game, and the risk preference task. Every participant also played both roles in the investment game, i.e., they played as trustor and trustee.

Table 3.1: Order Variations

	First task	Second task	Third task
Order 1	Investment game (player 1, player 2)	Dictator game	Risk preference task
Order 2	Investment game (player 2, player 1)	Dictator game	Risk preference task
Order 3	Dictator game	Investment game (player 1, player 2)	Risk preference task
Order 4	Dictator game	Investment game (player 2, player 1)	Risk preference task

In our baseline treatment, we varied the order in which these three tasks were completed, as well as the order of the participants’ roles. There were four different variations across sessions, but each participant completed only one session. Under order 1, participants first played the investment game as the trustor/sender (henceforth player 1) and then as the trustee/receiver (henceforth player 2), then they played the dictator game, and finally the risk preference task. All four order variations we used are shown in Table 3.1. Table A.1 in Appendix A gives a breakdown of all the sessions that were run in the baseline treatment, including information on the number of participants and the order in which the tasks were completed for each session.

For the information treatment, we only used order 2: investment game (player 2, player 1), dictator game, risk preference task, and order 4: dictator game, investment game (player 2, player 1), risk preference task. We excluded orders 1 and 3 because participants were provided with additional information when they assumed the role of player 1 in the investment game and we did not want this information to influence the way they behaved as player 2. Thus, they always needed to act as player 2 first when they played the investment game in this treatment. Table A.2 in Appendix A gives a breakdown of all the sessions that were run in the information treatment, including information on number of participants and the order in which the tasks were completed for each session. The risk preference task was completed last in both treatments for two reasons: there would have been too few people in each group if we had also varied the order in which this task was completed; and by running the risk preference task last, we avoided priming participants on their risk appetites before completing the investment game.

The sessions took place on weekdays in the School of Economics computer lab at the University of Cape Town (UCT). I assumed the role of experimenter and had two research assistants (RAs) to help run the sessions. Prior to the arrival of the participants, we had set up the computers to run the three tasks and separated them with partitions to prevent participants from seeing each other's screens. No communication was allowed once they entered the computer lab aside from one-on-one interactions with the experimenter or the RAs. Participants were asked to sign consent forms, after which they were shown an introductory presentation outlining how the session would proceed. This presentation is included in Appendix B1: Introductory Presentation. After this presentation, participants read the written instructions for the first task. The written instructions for each of the three tasks are included in Appendix B2: Written Instructions. These written instructions were followed by audio-visual instructions explaining the first task. Once they had been through both sets of instructions, they were allowed to complete the first task.

On completion of the first task, subjects read the second task's written instructions and watched the audio-visual instructions prior to starting the second task. Once a participant had completed the second task, they read the written instructions and then watched the audio-visual instructions for the third task before starting this task. We developed software for these tasks using the oTree framework (Chen, Schonger & Wickens, 2016). These three tasks are outlined in detail below.

3.2. Investment Game

In this task, participants played the BDM investment game and were all required to play as both player 1 and player 2. The order in which participants played these roles was randomised across sessions in the baseline treatment. However, in the information treatment, participants always played as player 2 first; the reason for this will be discussed in further detail in Section 3.2.1 below. Player 1 and player 2 both received an initial endowment of R100. For ease of understanding, each role in the investment game will be explained separately below.

3.2.1. Investment Game: Player 1

When taking on the role of player 1, subjects were asked to decide how much, if any, of their endowment they wanted to send to their randomly assigned partner, player 2. They were only allowed to send amounts in increments of R20 {R0, R20, R40, … R100}. The amount they chose to send was then tripled by the experimenter before being received by player 2. Player 1 was asked to make this choice five times.

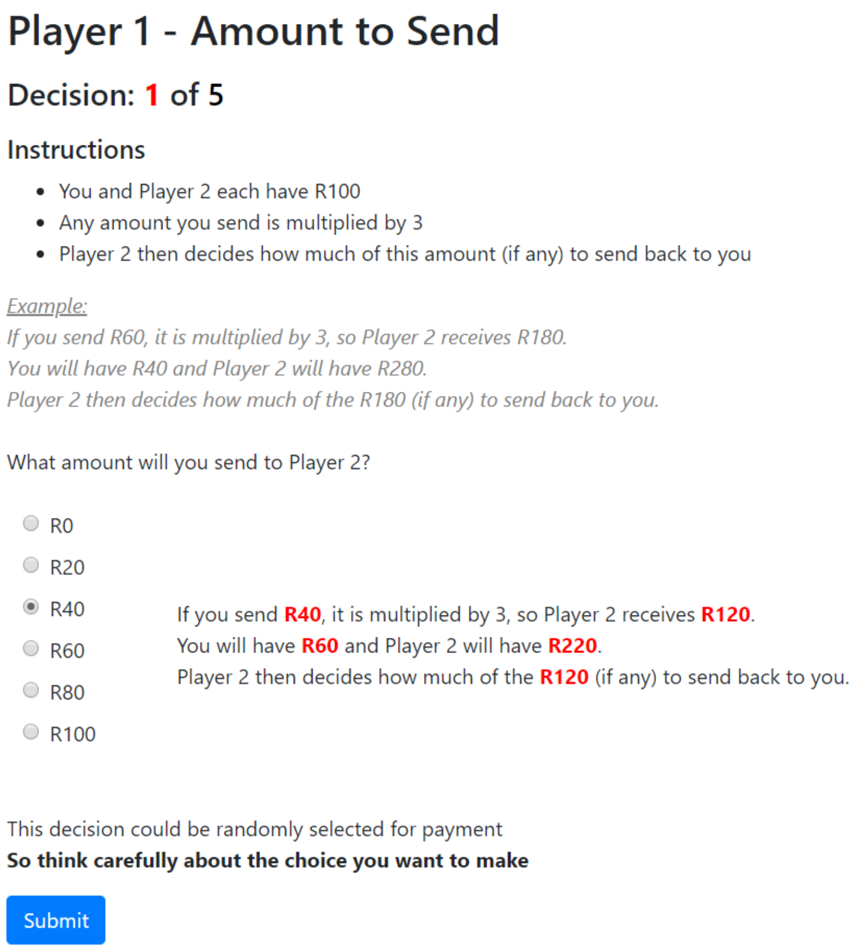


Figure 3.1: Screenshot of Investment Game interface for Player 1

Figure 3.1 shows a screenshot of the interface we designed for this task, using the oTree framework (Chen, Schonger & Wickens, 2016). We emphasised the player's role (player 1 in the screenshot) and the decision number (1 of 5 in the screenshot), and included brief instructions to further cement the subject's understanding. An example of a possible response to the question 'What amount will you send to Player 2?' was randomly selected from the set of possible responses and provided below the instructions. It walked participants through the process: if player 1 sent s, where $0 \leq s \leq 100$, player 2 would receive $3s$; player 1 would be left with R100 – s and player 2 would have R100 + $3s$; then player 2 had to decide how much, if any, of the $3s$ to return to player 1. Below this example, participants were asked to indicate what amount, from a list of available options, they wanted to send to player 2.

Once a participant had selected an option, they were shown a detailed breakdown of what selecting that option would entail: the amount player 2 would receive, the amount player 1 would have remaining, and the choice now available to player 2 that would ultimately determine player 1's earnings. In Figure 3.1, R40 was selected and the information mentioned above was, therefore, presented to player 1. After selecting an option, participants were reminded that this could be the decision chosen for their payment; this was done to encourage them to take each decision seriously before submitting their selection.

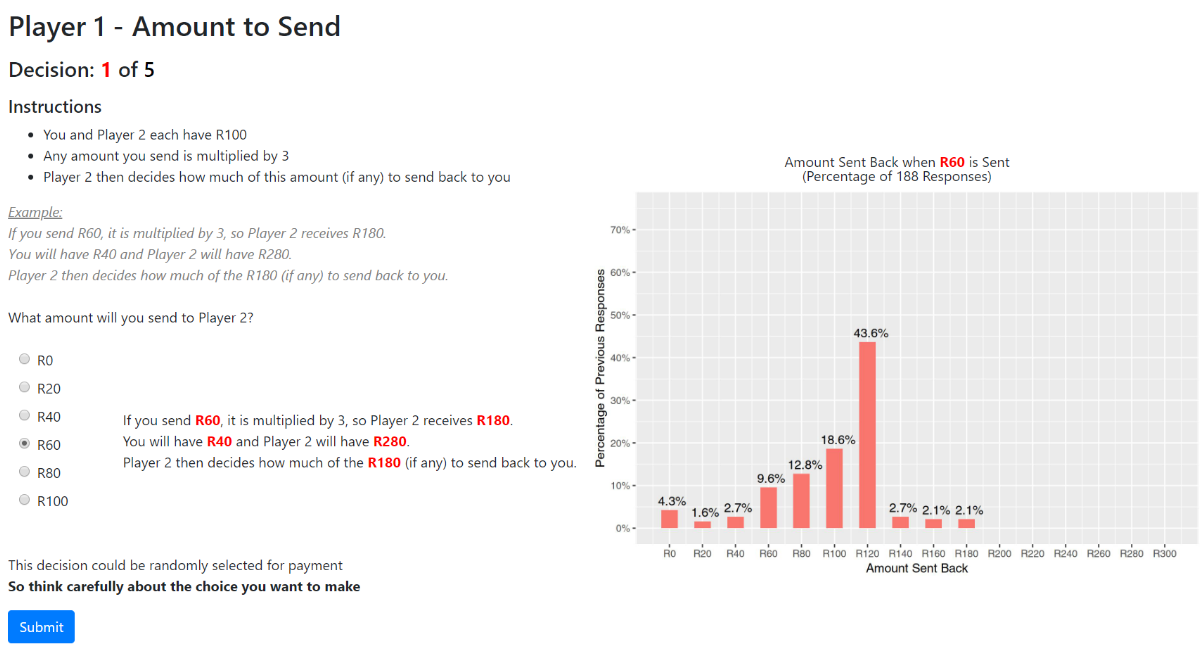


Figure 3.2: Screenshot of Investment Game interface for Player 1 in Information Treatment; includes histogram

In the information treatment, when a participant selected one of these options, a histogram was displayed along with the same information given in the baseline treatment; see Figure 3.2, which shows the distribution of responses when player 1 selects R60 as the amount to send. The histograms showed a summary of how the 188 participants in the baseline treatment responded to each amount sent, with a different histogram for each of the amounts player 1 could have sent, for every non-zero amount, i.e., {R20, R40, R60, R80, R100}. The horizontal axis shows the range of return options available to player 2, and the bars give a visual illustration of the percentage of participants that chose to send back each amount, conditional on the amount sent by player 1. Participants in the information treatment knew that the data they were seeing were from decisions made by 188 fellow UCT students who had recently completed the same task.

Figure 3.3 is a closer look at one of these histograms showing baseline treatment data; this particular histogram shows the percentage of previous responses of the amount sent back by player 2 when player 1 sent R80, while the histogram in Figure 3.2 shows the distribution of responses when player 1 sent R60. Although we were interested to see whether this new information influenced the decisions that participants made when playing as player 1, we did not want it to influence the amount that participants sent back as player 2. Therefore, in the information treatment, participants always played as player 2 first to ensure they did not see these histograms before making their decisions.

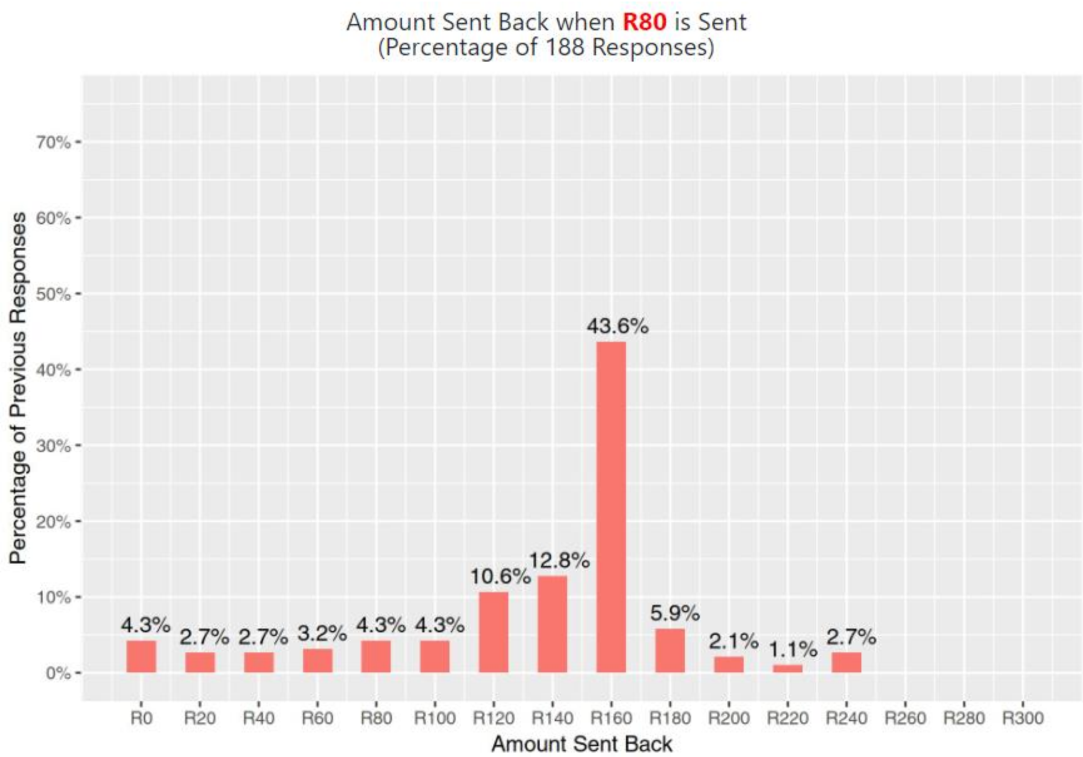


Figure 3.3: Histogram for distribution of amount returned by Player 2 when Player 1 sent R80 in the Baseline Treatment

3.2.2. **Investment Game: Player 2**

In order to elicit the full distribution of player 2 return behaviour for every amount sent, we used the dual role strategy method for player 2 return decisions. When subjects took on the role of player 2, they were asked to indicate what amount they would send back to player 1 for every possible non-zero amount (R20, R40, R60, R80, or R100) they could receive from player 1. The amount sent was tripled by the experimenter before reaching player 2.

Figure 3.4 shows a screenshot of the interface for player 2. Again, we emphasised the player's role (player 2 in the screenshot) and the decision number (1 of 5 in the screenshot), and included instructions to further cement the subject's understanding. An example of a possible response to the question 'What amount will you send back to Player 1?' was selected at random from the set of possible responses. The example was displayed below the instructions and it highlighted salient aspects of the decision at hand. It took participants through the process: assuming player 2 received $3s$, then if player 2 sent back r, where $0 \leq r \leq 3s$, player 1 would earn $100 - s + r$ and player 2 would earn $100 + 3s - r$. Participants were then asked what amount they wished to send back and had to select their preferred amount.

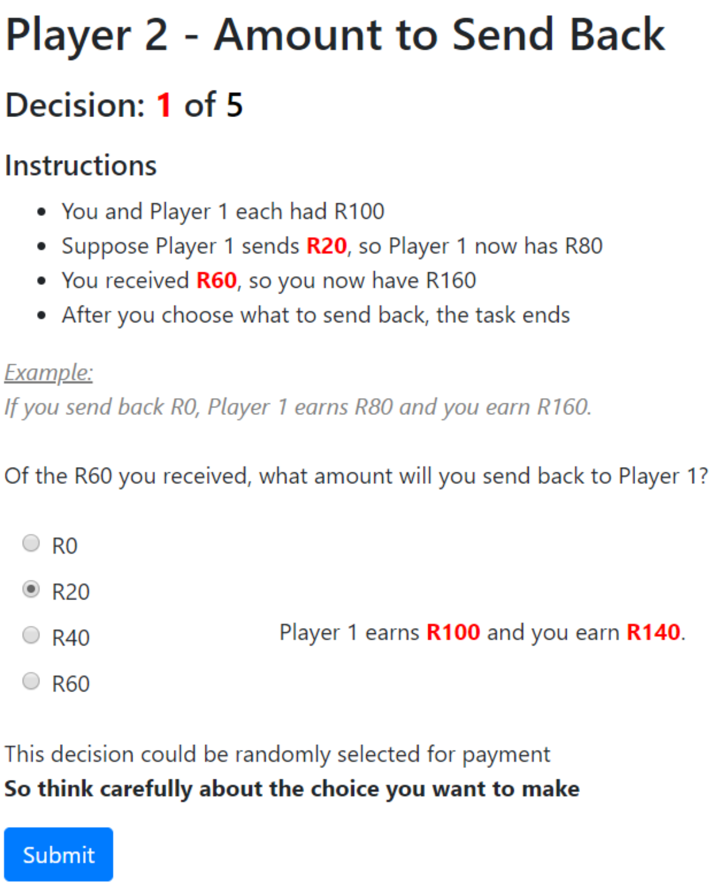


Figure 3.4: Screenshot of Investment Game interface for Player 2

When a participant selected one of these options, they were shown the final amount that each player would earn. After selecting an option, participants were reminded that this could be the decision chosen for payment to encourage them to take each decision seriously before submitting their selection.

3.3. Dictator Game

We adopted the first two prongs of Cox's (2004) three prong triadic design, i.e., the BDM investment game and the dictator game. We use this experimental design to allow us to disentangle trust from motivations that are not conditional on beliefs about the behaviour of other people. In our variation of the dictator game, every participant took on the role of the dictator (player 1) and had to make five decisions based on five variations of Cox's (2004) dictator game. These modifications are based on Andreoni and Miller's (2002) version of the dictator game.

In the first variation, both subjects were endowed with R100. Player 1 was asked to decide how much of their endowment to send to player 2 in R10 increments {R0, R10, R20, …, R100}. Any amount that player 1 chose to send to player 2 was tripled (multiplier = 3) before reaching player 2, at which point the game ended. In each new variation of the game, player 1 was always the one making the decisions about how much to send, always in R10 increments, but the players' initial endowments changed, as did the multiplier. In all instances, player 1 kept all the money that was not sent to player 2. The five variations of the dictator game that participants played, with each variation representing one of the five decisions they were required to make, are shown in Table 3.2.

Table 3.2: Dictator Game Variations

	Player 1 endowment	Player 2 endowment	Multiplier
Variation 1	R100	R100	3
Variation 2	R100	R0	3
Variation 3	R100	R100	1
Variation 4	R100	R0	1
Variation 5	R80	R0	5

Figure 3.5 shows a screenshot of the interface we designed to carry out this task. We emphasised the decision number (1 of 5 in the screenshot), the initial endowment of each player (R100 each in the screenshot), and the multiplier (1 in the screenshot). An example of a possible response to the question 'What amount will you send to Player 2?' was selected at random

from the set of possible responses for the given variation. The example was displayed below the instructions and it highlighted salient aspects of the decision for the relevant variation. It took participants through the process: if player 1 is endowed with x_1 and decided to send s, where $0 \leq s \leq x_1$, then s is multiplied by m, where m is 1, 3, or 5, depending on the variation number. Player 2 would then receive ms. The game would end, and player 1 would earn $x_1 - s$ while player 2 would earn $x_2 + ms$. Participants were then asked what amount they wished to send and were given the full list of available send options.

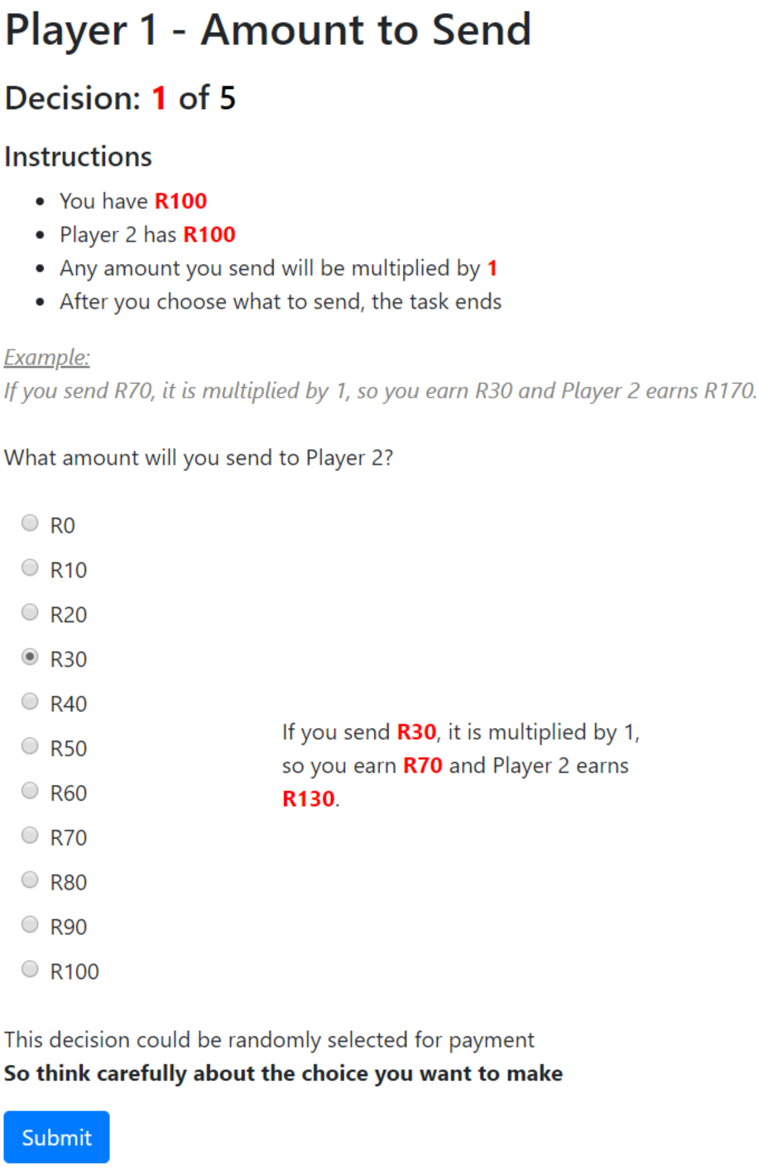


Figure 3.5: Screenshot of Dictator Game interface for Player 1

When a participant selected one of these options, they were shown a detailed breakdown of what selecting that option would entail for both players. After selecting an option, we reminded participants that this could be the decision chosen for payment to encourage them to take each decision seriously before submitting their selection. This game was presented and played in the same way for the baseline treatment and the information treatment.

3.4. **Risk Preference Task**

The risk preference task, based on Hey and Orme (1994), was used to elicit participants' risk preferences. It presented subjects with a choice between two lotteries on each screen, with subjects required to make 100 of these choices in total. The lotteries were displayed as pie charts with accompanying text that listed the probabilities of the prizes in terms of numbers on a 6-sided die and participants were required to choose one lottery on each screen. The lottery pairs in the task were based on the set developed by Wilcox (2018).

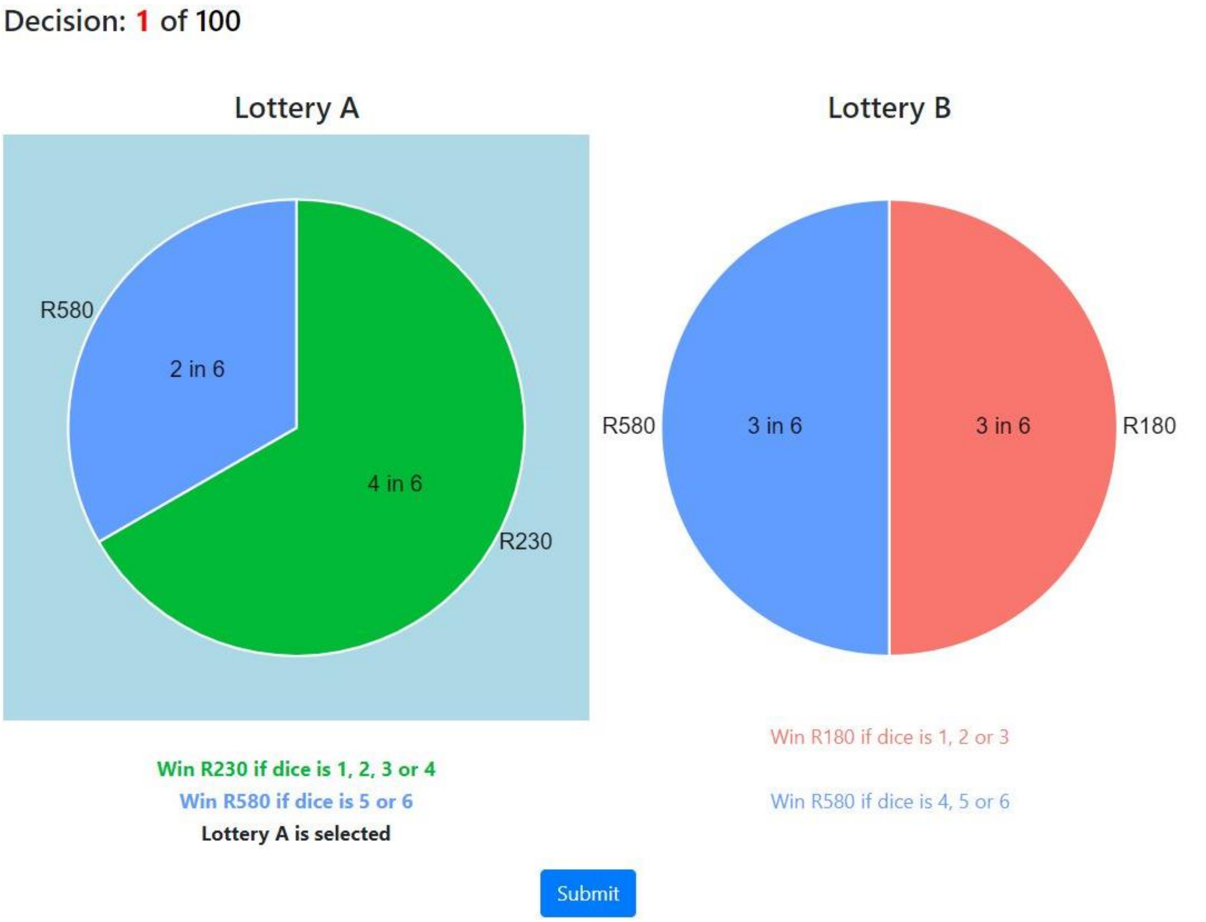
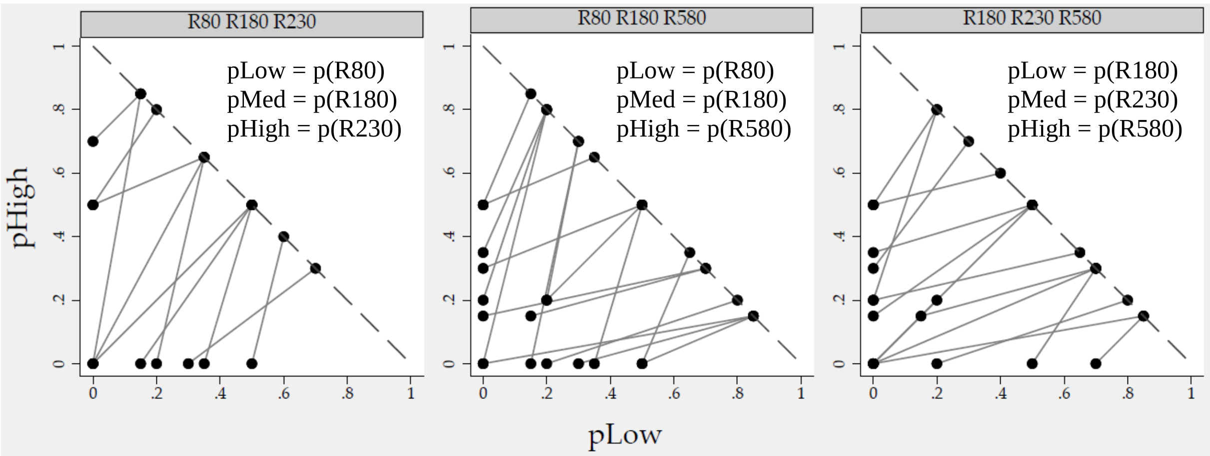


Figure 3.6: Screenshot of Risk Preference Task interface

Figure 3.6 shows a screenshot of the interface we designed to carry out this task. We indicated the decision number (1 of 100 in the screenshot) and gave a visual representation of the two lotteries that participants had to choose between for each decision. The pie chart segments were different colours to help participants discriminate between the various probabilities and amounts. Descriptions accompanied the pie charts to further clarify the prizes and probabilities of winning for each of the lotteries. When a participant selected one of the lotteries, the background of the pie chart for that lottery was highlighted. An additional line of text appeared below the lottery text confirming that it had been selected; as indicated for Lottery A in Figure 3.6. This game was presented and played in the same way for both the baseline and information treatment.

Figure 3.7 shows three Marschak-Machina Triangles (see Machina, 1987), which capture the three different contexts (i.e., prizes) of the lotteries that the participants needed to choose between. In these triangles, the vertical axis represents the probability of the highest prize (pHigh) in a lottery, while the horizontal axis represents the probability of the lowest prize (pLow) in a lottery, i.e., in the first triangle, the vertical axis represents the probability of getting R230, while the horizontal axis represents the probability of getting R80 from the lottery. The probability of getting the medium prize (pMed) in a lottery is determined by subtracting the probability of the highest prize and the probability of the low prize from one; i.e., pMed = 1 – pHigh – pLow.



Given the set of outcomes A = {R80, R180, R230}	Given the set of outcomes A = {R80, R180, R580}	Given the set of outcomes A = {R180, R230, R580}
11 lottery pairs	17 lottery pairs	15 lottery pairs

Figure 3.7: MM Triangles of Risk Preference Task Lotteries

Each point in the Marschak-Machina Triangles represents a lottery, while the line connecting points represents a lottery pair (if two points are connected) or a set of lottery pairs (if more than two points are connected). One of the lotteries in each pair presented to participants is always riskier. A riskier lottery is one in which there is a higher probability weighting on the extreme prizes, i.e., participants are more likely to get either the best outcome or the worst outcome and are less likely to get the medium outcome. In terms of a Marschak-Machina Triangle, moving in a north-easterly direction assigns more probability weight to the high and low prizes, and less to the middle prize, which implies that a lottery which is north-east of another is riskier.

Collectively, the three triangles in Figure 3.7 show the set of 43 unique lottery pairs in the Wilcox (2018) design, which are the same pairs we used in our experiment. Wilcox (2018) constrained this lottery set in five ways: (1) each pair needed to fall within a three outcome Marschak-Machina triangle and needed to show an interesting risk trade-off without being too complex; (2) probabilities of outcomes needed to be multiples of one-sixth to enable subjects to roll a 6-sided die, which is familiar, while still maintaining a theoretically relevant collection of probabilities; (3) only four different outcomes were used across all the pairs to ensure some diversity in risk trade-offs but also to bound the number of utility parameters that can be estimated; (4) repetition of the 43 pairs was allowed but not more than once every 20 pairs to ensure that subjects would be slow to recognise repeated pairs; and (5) participants would be required to make decisions between 100 lottery pairs, which should be a large enough decision set to give results power, but not so large that participants lose attention.

3.5. Experimental Sample

The sample of 282 participants used for these experiments was drawn from UCT students. A recruitment email that gave a brief overview of the study together with expected earnings for participating was sent out to all students through UCT's central mailing list. Those who were interested in participating in the study were asked to complete a nine-question survey to allow the gathering of basic demographic information. Over 1000 students responded to the recruitment email. Any students who declined to answer the survey, who omitted any information, or who were slow to respond (those who responded more than two days after the recruitment email was sent out) were excluded from the sample. This left 759 eligible respondents.

From this remaining student pool, two random samples of subjects were drawn to participate in the two different treatments of the experiment. The first sample consisted of 290 students who were invited to participate in the baseline treatment. The second sample was made up of 250 students who were invited to participate in the information treatment. The first sample was added to a dedicated site on UCT's virtual learning environment that allowed participants to sign up for a session at a time that suited them. An announcement was sent out to these students providing more information about the study, including the expected amount of time needed to complete a session and anticipated payment amounts, together with a weblink to the site mentioned above to allow the students to sign up for the session of their choice. An SMS reminder was sent to the participants the evening before and on the morning of each session. Once the initial 188 participants had completed the baseline treatment sessions, the second sample of subjects was added to the website to facilitate their signing up for the information treatment sessions.

3.5.1. **Payment**

To promote incentive compatibility, the study was designed so that participants received real monetary rewards for the decisions they made. However, they were only paid for two of the three tasks they completed, and for one of the decisions in each task. The experiment was designed so that upon completion of the three tasks, participants were randomly paired with another student in their session. In their pairs, participants were paid either for the investment game or the dictator game, which was randomly decided. Additionally, they were only paid for one decision that they made as either player 1 or player 2 within the chosen game. Thus, the game, the role, the decision, and the partner were all randomly selected for each participant in order to determine their payment.

In the scenario where the investment game was chosen for payment, one participant would be randomly assigned the role of player 1 and another player 2 and each would receive an initial endowment of R100, denoted by x. As player 1, each participant was required to make five send decisions. Thus, one of these send decisions (denoted by s, where $0 \leq s \leq 100$) that the participant made would be selected to play out. This chosen send amount, s, would then be tripled, and the person assigned the role of player 2 would receive $3s$. The amount player 2 reported they would return (denoted by r, where $0 \leq r \leq 3s$) when receiving $3s$, would be sent back to player 1. This resulted in player 1 earning $(x - s) + r$ and player 2 earning $x + (3s - r)$.

The same logic applies to the payment criteria for the dictator game. However, there are also variations across the decisions, as described in Table 3.2, that need to be considered. The endowment amount, x, differed for the players across decisions and roles (denoted by x_1 for player 1 and x_2 for player 2), and instead of the amount sent, s, always being tripled, it was multiplied by various multipliers, m. Additionally, the participant assigned to the role of player 2 had no decisions to make. This resulted in player 1 earning $(x_1 - s)$ and player 2 earning $(x_2 + ms)$. Information regarding these payment calculations was displayed on each participant's computer screen at the end of the experiment.

We designed the experiment so that the decisions that participants made were directly linked to the outcomes of the games they played, and thus to the payments they would receive. A significant amount of time was spent on the written and audio-visual instructions, as well as on the way the task interface was designed, to ensure participants had a clear understanding of the choices they needed to make and how their choices would ultimately affect outcomes of the games. The reason we paid participants for either the investment game or the dictator game and not for both was to encourage participants to respond according to their preferences in both games. We were concerned that participant behaviour would be confounded if we paid participants for a decision from both games. For example, a participant might express their preferences through their choices in the investment game and be content in the payment they expect to get from the decisions they made. Then, when playing the dictator game, they may act more altruistically because they have already secured a satisfactory payment in the previous game. The reverse could also apply, making participants less altruistic. Thus, because the games are so similar, data are likely to be more accurate if only one of the games is played out for payment.

Payment for the risk preference task was less complex, and required the individuals' participation. After completing the risk preference task, we randomly selected one of the 100 lottery pair decisions they had made by getting the participant to roll two 10-sided dice. The numbers they rolled were added together to select a number that corresponded to one of their 100 decisions. The selected decision was brought up on the participant's computer screen and it displayed the lottery pair and showed whether they had selected Lottery A or Lottery B. We then played out the selected lottery by getting the participant to roll a 6-sided die to randomly select a number between 1 and 6, which was calibrated to the probabilities in the selected lottery. The number rolled determined the amount of money the participant received from their chosen lottery.

Payment for the risk preference task and the investment or dictator game was recorded on a payment receipt, which was then taken to a cordoned off and private area where I calculated the total earnings for each individual. The earnings consisted of the R40 participation fee, payment for the risk preference task, and payment for the investment or dictator game. Payment was calculated and placed into an envelope before being given to the participant. Upon receiving their payment, participants were required to count their earnings before signing a payment receipt confirming that they had been given the correct amount prior to leaving the session.

3.5.2. **Questionnaire**

After participants had completed the three tasks and payment had been determined, they were required to complete a questionnaire in order to elicit basic demographic information and opinions about trust from them. While they completed the questionnaire, their earnings were calculated, as discussed above, and placed in an envelope, which was taken to them once they had completed the questionnaire.

3.5.3. **Summary Statistics**

Table 3.3 presents summary statistics for the sample of 282 UCT students. The average age in the sample was approximately 21 years old, while the average reported income was approximately R2421 per month. The sample was 59% female, 13% of the sample was White[3], and one third of the sample was part of the information treatment. Task orders 1 and 3 constituted 16% and 15% of the sample, respectively, while task orders 2 and 4 were approximately one third of the sample each.[4]

Table 3.3: Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Age (years)	21.18	2.55	18	39
Income (Rands)	422.34	187.32	130	980
Variable		**Percentage of Sample**		
Gender				
Female				59.22%
Race				
White				13.48%
Treatment				
Information				33.33%
Task Order				
Order 1				16.31%
Order 2				33.33%
Order 3				14.89%
Order 4				35.46%

The average earnings across the investment game and the dictator game was R118, while the average earnings from the risk preference task was R264. The average total earnings, including the R40 participation fee, was R422. The minimum amount that participants earned was R130, and the maximum amount was R980.

[3] Race was not the focus of this study, which is why White was chosen as the control. The remainder of the sample was made up of 57% African, 16% Coloured, 12% Indian, and 1% classified themselves as Other.

[4] Task order 2 and task order 4 constitute a greater proportion of the sample because these were the only order variations used in the information treatment as participants had to play the investment game as player 2 before receiving information on return distributions from the baseline treatment.

4. Statistical Method

In this study, we use two complementary approaches for data analysis: a standard statistical approach as well as a maximum likelihood estimation (MLE) approach. The models we use within these approaches aim primarily to identify whether the amount sent in the investment game can be used as a pure, unconfounded measure of trust. To test for this, we estimate multiple models and vary the independent variables, specifically the number of risky choices in the risk preference task, the amount sent in the investment game, the amount sent in the dictator game, demographic characteristics, and task parameters. The task parameters include which treatment the participants were put into (baseline or information treatment) and the order in which participants completed the tasks.

Our standard statistical approach includes Fractional Response, Tobit, and Ordinary Least Squares (OLS) models. When using the MLE approach, we estimate Expected Utility (EU) theory as well as Rank-Dependent Utility (RDU) theory models. Both the standard statistical models as well as the MLE models will be discussed in detail below.

4.1. Standard Statistical Models

In our standard statistical models, we focus on finding the marginal effects that various explanatory variables have on the amount sent in the investment game. It is common practice to use the amount sent as the dependent variable i.e., the variable on the left-hand side of the regression (Johnson & Mislin, 2011:873). In the Fractional Response model, we run fractional regressions on the proportion of the amount sent with discrete values between 0 and 1. We condition the estimates on the number of risky choices made in the risk preference task (which is a discrete variable), the amount sent in the dictator game, demographic characteristics, and task parameters. The Tobit model, used to model corner solution dependent variables (Wooldridge, 2013), conditions the estimates on the number of risky choices made in the risk preference task, the amount sent in the dictator game, demographic characteristics, and task parameters. In the OLS model, we minimise the residual sum of squares of a linear model of amount sent in the investment game, which is regressed on the number of risky choices in the risk preference task, the amount sent in the dictator game, demographic characteristics, and task parameters.

By conditioning the amount sent in the investment game on the number of risky choices that participants make, we can test to see if number of risky choices has a confounding effect on the amount sent. We expect to find a relationship between these two variables because the choice of an amount to send is an inherently risky decision. Similarly, by adjusting for the amount sent in the dictator game, we can determine whether or not altruism influences the amount sent in the investment game. We also expect to find a relationship between these two variables because people often exhibit other-regarding preferences.

The information treatment variable is included to evaluate the effect of having additional information when making a send decision. Again, we expect to find an association between exposure to information and the amount sent because this would imply that subjective beliefs have some degree of influence over the decisions that participants make. Finally, the task order variable is used to control for potential order effects.

4.2. Structural Models of Choice Under Risk

MLE is a method for finding the parameter values of some model that maximise the probability (likelihood) that the observed data would have been produced by that model. In the risk-trust literature, MLE can be used to estimate utility functions based on lottery choices in the risk preference task. Maximum likelihood is beneficial in the context of this study because it uses all the information obtained from the choices made in the risk preference task to estimate utility function parameters. This information includes the prizes and probabilities for each lottery, as well as which lottery was chosen, for each of the 100 lottery pairs. This measure of risk preferences is superior to the discrete variable used in the standard statistical models.

Our estimation strategy is closely linked to Andersen et al. (2008) and Harrison and Rutström (2008), and is discussed below. There are many different forms that a theory of choice under risk can take, but our focus will be on the EU and RDU forms.

4.2.1. Expected Utility Theory

Under EU, the probabilities assigned to the different prizes are used to weight the utilities of each prize. Then, all of these probability weighted utilities are summed to derive the expected utility of the lottery. In the EU form, the value participants assign to a lottery is a probability weighted average of the utilities they would assign to the outcomes of the lotteries if the outcomes were certain.

People have preferences over uncertain choices, which we represent with expected utilities (Mas-Colell, Whinston & Green, 1995). Since preferences do not really exist, we use latent preferences that are revealed through choice behaviour. Economists then represent these latent preferences through utility functions. Utility functions are abstract and make use of arbitrary numerical values to represent preference orderings. Assuming that participants only care about the final distribution of outcomes and that their preferences are complete, transitive and continuous, then if they prefer one outcome to another, the outcome they prefer should be assigned a higher value by their utility function (Mas-Colell, Whinston & Green, 1995). This implies that their utility function will represent their preferences.

We want to estimate the parameters of a utility function that maximise the likelihood of observing the choices made in the risk preference task. To do this, we need to assign some parametric structure to the problem and we use a power utility function. Assume that utility of income is defined by a power utility function that displays constant relative risk aversion (CRRA):

$$\mathrm{U}(y) = \begin{cases} y^{r} & \text{if } r > 0 \\ ln(y) & \text{if } r = 0 \\ -y^{r} & \text{if } r < 0 \end{cases} \tag{1}$$

where y is the lottery prize in the risk preference task and r is the parameter to be estimated. Relative risk aversion of the utility function is defined by the constant r, which determines the shape of the utility function. The EU form is defined as follows:

$$\mathrm{EU}_j = \textstyle\sum_{i=1,2,3} [p_i(y_i) \cdot \mathrm{U}(y_i)] \tag{2}$$

where y_i is the lottery outcome, $p_i(y_i)$ is the probability associated with each outcome y_i in the choice set, and $\mathrm{U}(y_i)$ is the utility of outcome y_i.

Under EU theory, if $r > 1$ the utility function is convex, which indicates risk seeking behaviour. If $r = 1$ the utility function is linear, implying risk neutrality. If $r < 1$ the utility function is concave, which indicates risk averse behaviour. To estimate r, the expected utility of each lottery pair is calculated for an initial estimate of r. A latent index ∇EU, based on latent preferences, that captures the difference in expected utility of the Right lottery (Lottery B) and Left lottery (Lottery A) is generated where:

$$\nabla EU = EU_R - EU_L \tag{3}$$

This index is linked to a participant's binary choices (selecting either the Left or Right lottery) through a cumulative distribution function, which transforms the range of ∇EU from $(-\infty,\infty)$ to (0,1). This distribution function, given the value of the latent index, determines the probability of choosing the Left lottery and therefore also the probability of selecting the Right lottery, for each observation in the dataset.

The MLE method is then used to determine the value of r that maximises the likelihood of observing all the data from the experiment with the following equation: $r = r_0 + r_\beta \cdot X$, where r is the risk preference parameter, r_0 is a fixed parameter, X is a vector of demographic characteristics (i.e., age, gender, race), and r_β is the coefficient vector linked to the X vector. Thus, following Harrison and Rutström (2008), we make the relevant parameters linear functions of observable characteristics. This can be extended by including the amount sent in the investment game, I, together with the other explanatory variables:

$$r = r_0 + r_I \cdot I + r_\beta \cdot X \tag{4}$$

where r_I measures the marginal effect of the amount sent in the investment game on estimates of r. The risk preference parameter r can now be used to determine whether there is a significant relationship between risk preferences and the amount sent, as well as between risk and the other potentially confounding factors previously mentioned: altruism and subjective beliefs.

The model can be further extended by adopting Wilcox's (2011) 'contextual utility' behavioural error specification to allow both for mistakes that participants may make and for robust inferences. The ∇EU index is normalised by λ into the [0,1] interval, while the behavioural error term μ, from Fechner (1966), makes the ∇EU index smaller as subjects become increasingly likely to make errors. Thus, the ∇EU index becomes:

$$\nabla EU = \frac{\left[\frac{EU_R - EU_L}{\lambda}\right]}{\mu} \tag{5}$$

However, despite the above considerations and extensions, the literature suggests that EU theory may lack descriptive validity. Thus, we include Quiggin's (1982) RDU theory in our data analysis as a robustness test.

4.2.2. **Rank-Dependent Utility Theory**

RDU theory introduces rank-dependence to EU theory. This means that objective probabilities associated with the outcomes of a lottery are transformed into subjective decision weights that depend on the participant's utility ranking of the possible outcomes that are used to evaluate lotteries. These decision weights can over- or under-weight objective probabilities. Thus, in the RDU model, risk preferences are determined both by the shape of the utility function as well as by the probability weighting function (PWF). We need to estimate the parameters of a utility function and a PWF that maximise the likelihood of observing the data from the experiment. This must to be done in terms of a latent index that captures the difference in the rank-dependent utility of the lotteries. The RDU form is defined as follows:

$$\mathrm{RDU_j} = \textstyle\sum_{i=1,2,3} [w_i(y_i) \cdot \mathrm{U}(y_i)] \tag{6}$$

with weights $w_i = \pi(p_1 + p_2 + p_3) - \pi(p_2 + p_3)$ for $i = 1,2$ and where $w_i = \pi(p_3)$ for $i = 3$ with outcomes ranked from worst to best. Assuming an RDU model with a power utility function, a contextual error specification, and some PWF, the RDU index will be similar to the EU index:

$$\nabla RDU = \frac{\left[\frac{RDU_R - RDU_L}{\lambda}\right]}{\mu} \tag{7}$$

A key aspect of RDU estimation is how the PWF is specified. One form is the Power PWF, which is similar to the power utility function but replaces prizes with probabilities:

$$\pi(p) = p^{\varphi} \tag{8}$$

The form we use in our analysis is the Prelec (1998) two-parameter PWF:

$$\pi(p) = \exp\left[-\eta\left(-ln\, p\right)^{\varphi}\right] \tag{9}$$

for $0 > p > 1$, $\eta > 0$, and $\varphi > 0$. The Prelec PWF is flexible and allows independent specification of location and curvature in probability weighting. When $\eta = 1$, it nests a Power PWF, and when $\varphi = 1$ it nests a one-parameter function, which can be linear, S-shaped, and inverse S-shaped. RDU theory nests EU theory as a special case. This means that a benefit of using RDU estimation is that we are able to determine the curvature of the utility function, as we did under EU theory, as well as the shape of the PWF. This combination allows us to separate risk preferences into these two components to see if either or both are related to the amount sent in the investment game.

This study combines all of the above methods of data analysis: the standard models (Fractional Response, Tobit, and OLS) and MLE models (using EU theory and RDU theory), to explore the validity of using the amount sent by participants in our sample as a measure of trust. Through our various analytical approaches, our aim is to determine whether risk preferences, altruism, and subjective beliefs confound the measurement of trust using the amount sent variable.

5. Results

This section starts with a basic overview of the data, followed by a more in-depth look at the relationship between the amount sent in the investment game and the variables that have the potential to confound its use as a measure of trust: risk preferences, altruism, and subjective beliefs. This is achieved by using the two approaches discussed in Section 4: the standard statistical approach and the more thorough MLE approach.

5.1. Descriptive Analysis

An initial analysis of the data shows that, on average and across both treatments, when the participants in our sample took on the role of player 1 in the investment game, they sent R50.71, or approximately half of their R100 endowment to their partner. The histogram in Figure 5.1 shows the distribution of the player 1 send decisions for our full sample and accounts for all five send decisions that each participant made.

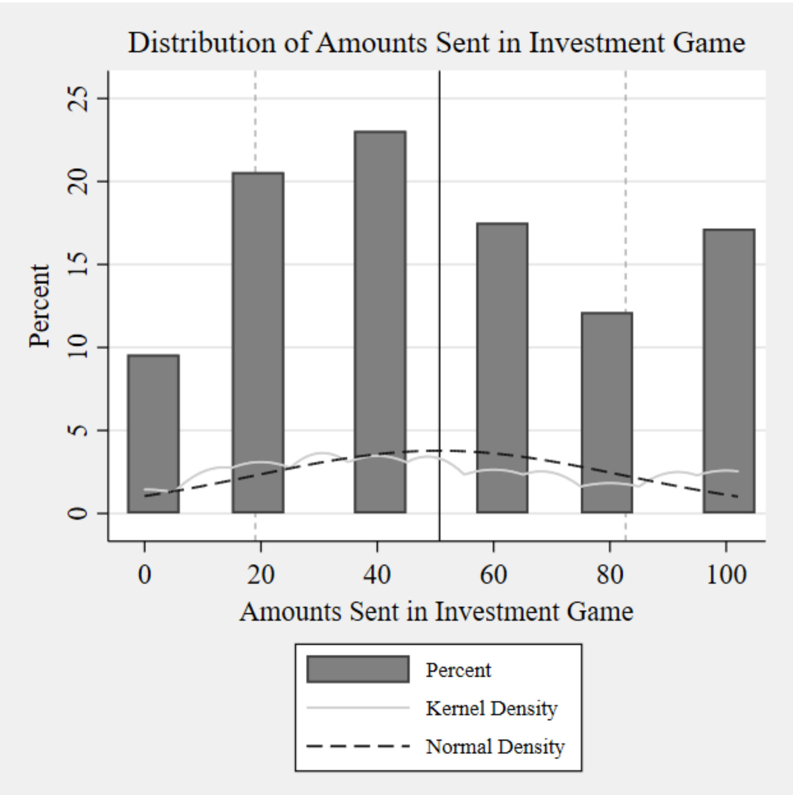


Figure 5.1:Histogram for Distribution of all Five Send Decisions in the Investment Game

The distribution is only slightly skewed to the left, with 53% of the sample sending between R0 and R40. The plurality of the sample, 23% of participants, sent R40 to their partner, while the amount sent least often was R0, which was sent by only approximately 10% of the sample. In other words, of the 1410 send decisions made in the investment game by all participants across both treatments, the subgame perfect Nash equilibrium send decision of R0 was only selected 135 times. Further, 73% of the sample sent an amount that fell within one standard deviation (R19.03 and R82.39, represented by the vertical dashed lines in Figure 5.1) of the mean send amount (represented by the solid vertical line at R50.71 in Figure 5.1). Figure C.1 in Appendix C shows the distribution of amounts sent in the investment game by the full sample, broken down by task order.

When the data are separated out into the two treatments that subjects participated in, there is a slight shift in the distributions of the amounts sent. This is made apparent by the distribution of the send decisions in the baseline and information treatments in the histograms shown in Figure 5.2. Participants sent an average of R48.28 to their partner when in the baseline treatment, while in the information treatment, participants sent an average of R55.57 to their partner. The plurality of the sample in the baseline treatment, 24% of participants, sent R40. However, in the information treatment the plurality of the sample, 23% of participants, sent R100. In both treatments the amount sent least often was R0, which was sent by 11% and 6% of the sample, respectively. Thus, it appears that participants who were part of the information treatment sent more, on average, than participants who were part of the baseline treatment.

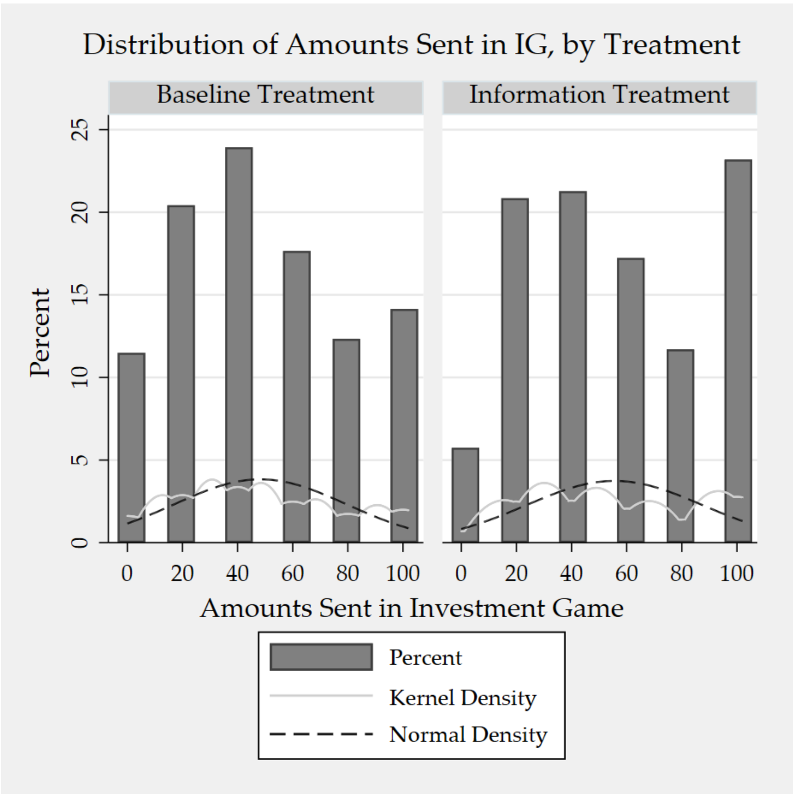


Figure 5.2:Histograms for Distribution of all Five Send Decisions in the Investment Game (IG), separated into Baseline and Information Treatment

5.2. Standard Statistical Models

As discussed in the previous section, the three standard statistical models used to analyse our data are Fractional Response, Tobit, and OLS. This section draws insights from the results obtained when using these models to analyse our data.

In these models, the amount sent in the investment game is used as the dependent variable. There are a variety of ways that the amount sent can be used in our regressions, but our preferred specification is to use the amount sent variable that incorporates all five send decisions that each participant made in the investment game. In this variation of the amount sent, all send-decision data are included in the models and in their subsequent analysis. Table 5.1 shows the output that results from using this variable in the three standard models.[5]

Alternative iterations of the amount sent variable include either using only the first amount sent or using the average amount sent. As a robustness check, Appendix D contains the results from running the same standard statistical models with these two variations of the amount sent variable. Table D.1 shows the results when only the first send decision in the investment game is used as the dependent variable, while Table D.2 includes the results when the average of the five send decisions is used as the dependent variable.

The explanatory variable used to control for risk preferences (the number of risky choices each participant made) in these models is a simplistic one. It is a discrete variable that discounts all risk information aside from the binary choice between the risky lottery and the less risky lottery for each of the 100 lottery pairs. Thus, despite being able to include all available send-decision data from the investment game in our dependent variable, our explanatory risk variable only contains the most basic risk preference data from the risk preference task. It is therefore plausible that no relationship will be found between the amounts sent and the number of risky choices made.

The amount sent in the dictator game is also included as an explanatory variable. Although participants made five send decisions in the dictator game, each decision was a different variation of Andreoni and Miller's (2002) dictator game (see Table 3.2, which contains the breakdown of the variations). Because the endowments and multipliers change across each variation, we could only use one dictator game send decision. We chose to use the variation 1 send decision because it follows the design in Cox (2004): each player is endowed with R100 and the multiplier is 3. The demographic variables we control for are age, race, and gender.

[5] Because we use all five send decisions made by each participant, the number of observations (N) in the models reported in Table 5.1 is inflated by a factor of 5. This is also the reason that results were clustered at the individual level.

Other explanatory variables include the binary treatment variable and the task order variable. Including the treatment variable gives us insight into whether or not beliefs matter, while the task order variable controls for any potential order effects.

We do not expect to find a linear relationship between the amount sent in the investment game and the number of risky choices; in fact, we expect any association between the two to be highly non-linear. Since our standard statistical models need to account for this, we include quadratic terms for the number of risky choices in our three models.

Table 5.1: Risk-Trust Confound Estimates for all Five Send Decision in Investment Game

	Fractional Response	**Tobit**	**OLS**
	Estimate (Std error)	Estimate (Std error)	Estimate (Std error)
Number of risky choices	0.000	0.049	0.039
	(0.001)	(0.130)	(0.381)
Amount Sent in DG	0.004***	0.592***	0.412***
	(0.001)	(0.090)	(0.055)
Age	-0.014***	-1.974***	-1.411***
	(0.005)	(0.646)	(0.442)
White	-0.007	-1.176	-0.817
	(0.047)	(6.755)	(4.675)
Female	-0.082***	-10.686**	-8.111***
	(0.030)	(4.146)	(3.029)
Information treatment	0.110***	15.000***	11.164***
	(0.033)	(4.665)	(3.389)
Task order 2	-0.091**	-10.946**	-9.399**
	(0.040)	(5.294)	(4.024)
Task order 3	0.000	0.958	-0.218
	(0.046)	(6.397)	(4.696)
Task order 4	-0.044	-3.450	-4.697
	(0.042)	(5.808)	(4.228)
Number of risky choices squared†			0.000
			(0.004)
Constant			74.103***
			(15.620)
N	1385	1385	1385

Marginal effects reported

Results account for clustering at the individual level

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

† The Fractional Response and the Tobit models report marginal models, so they incorporate the effect of this squared term in the estimate of the number of risky choices variable above.

Table 5.1 shows that there is no statistically significant relationship between the amount sent and the number of risky choices. This confirms that a simple analysis of our data in which most of the risk information is lost, is a naive approach. The lotteries in the risk preference task have different outcomes and probabilities that participants take into account before making a choice. All this information on the properties of the lottery pairs is lost when the only consideration is how many risky lotteries were chosen. Even when we incorporate the possibility of a non-linear relationship between the number of risky choices and the amount sent, there is still no relationship.

However, these models do show that there is a strong association between the amount sent in the investment game and the amount sent in the dictator game. According to all three models, an increase in the amount sent in the dictator game results in a statistically significant increase in the amount sent in the investment game ($p < 0.001$ in all models). This strong association between these two variables is to be expected. It follows that the amount participants send in the investment game is at least partially explained by the amount participants send in the dictator game. This initial analysis of the relationship between the send decisions made in these games suggests that the amount sent in the investment game is confounded by altruism.

Being part of the information treatment, as opposed to the baseline treatment, also statistically significantly influences the amount sent in the investment game. In the Fractional Response model, the information treatment results in participants sending an average of 11% more in the investment game. In the Tobit model, participants in the information treatment send on average R15 more, ceteris paribus. Similarly, in the OLS model, participants send R11 more if they are in the information treatment. All of these effects are significant at the 1% level. This shows that beliefs about how other participants will act play an important role in the decision of how much to send in the investment game.

The task order variables show that the order in which tasks were completed does make a difference. Participants sent significantly less under task order 2 than they did under task order 1. A Wald test shows that the amounts sent under task order 2 also differ from the amounts sent under task order 3 and are significant at the 5% level in the Fractional Response ($p = 0.043$) and OLS ($p = 0.044$) models, and at the 10% level in the Tobit model ($p = 0.055$). None of the other task order comparisons, for example, between task order 2 and task order 4, are statistically significant ($p > 0.109$ in all of these comparisons). These differences confirm that the order in which participants complete the tasks, as well as the order in which they make send and return decisions in the investment game, is significant and therefore important to take into account.

The amount sent also seems to be affected by some of the demographic variables included in the model. The age variable is negative and significant: older participants on average send less than their younger counterparts. Similarly, females send significantly less than males, ceteris paribus. The difference between male and female send amounts is large and highly significant ($p < 0.01$). On average, according to the Fractional Response model, females send 8.2% less than males, in the Tobit model, females send R10.69 less than males, and in the OLS model they send R8.11 less, ceteris paribus. However, it is possible that at least part of these vast differences can be explained by differences in levels of risk aversion between males and females.

While these standard statistical models provide a useful starting point for analysis, there is too much information lost from the risk preference task to be able to draw any meaningful conclusions from the data about the relationship between the amount sent and risk preferences. Therefore, the following section moves away from this method of analysis in favour of using structural models that can encompass the risk preference data in detail.

5.3. Structural Models of Choice Under Risk

A complementary approach to analysing our dataset is through the application of MLE. This is a more suitable method of analysing risk preference data because MLE uses all of the information about the lottery pairs in its estimations. The results from this framework should help establish whether risk preferences confound the measurement of trust or any of the other explanatory variables in our sample. Both homogenous and heterogenous preference models are used to analyse the data.

5.3.1. Homogenous Preferences

Our study focusses on the canonical model of choice under risk, EU theory, and its extension to RDU theory. These theories, together with the power utility function and the Wilcox (2011) contextual error specification, generate the Homogenous Preferences model displayed in Table 5.2. The estimate of the risk preference parameter r is significantly less than 1 under EU theory ($r = -0.416$) and RDU theory ($r = -0.441$), which indicates high levels of risk aversion in the sample. Further, the log-likelihoods under both models are essentially the same. This is because the two additional PWF parameters, φ and η, in the RDU model are not significantly different from 1 ($p < 0.001$ in both cases). This means that there is no evidence of probability weighting in our data, implying that EU theory best characterises our data as a whole. In the remainder of this paper, RDU models only serve as a robustness check because there is very little difference between the EU and RDU estimates.

Table 5.2: Expected Utility and Rank-Dependent Utility ML Estimates

Homogenous Preferences		
	Model 1: EU	**Model 2: RDU**
	Estimate (Std error)	Estimate (Std error)
Power Function Parameter (r)	-0.416***	-0.441***
	(0.056)	(0.046)
PWF Parameter (ϕ)		1.007***
		(0.039)
PWF Parameter (η)		0.980***
		(0.025)
Error (μ)	0.152***	0.151***
	(0.005)	(0.005)
N	28200	28200
log-likelihood	-16143.992	-16143.295

Results account for clustering at the individual level

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The lack of probability weighting means that there is very little under- or over-weighting of probabilities, depicted in Figure 5.3 where there is only slight evidence of over-weighting.

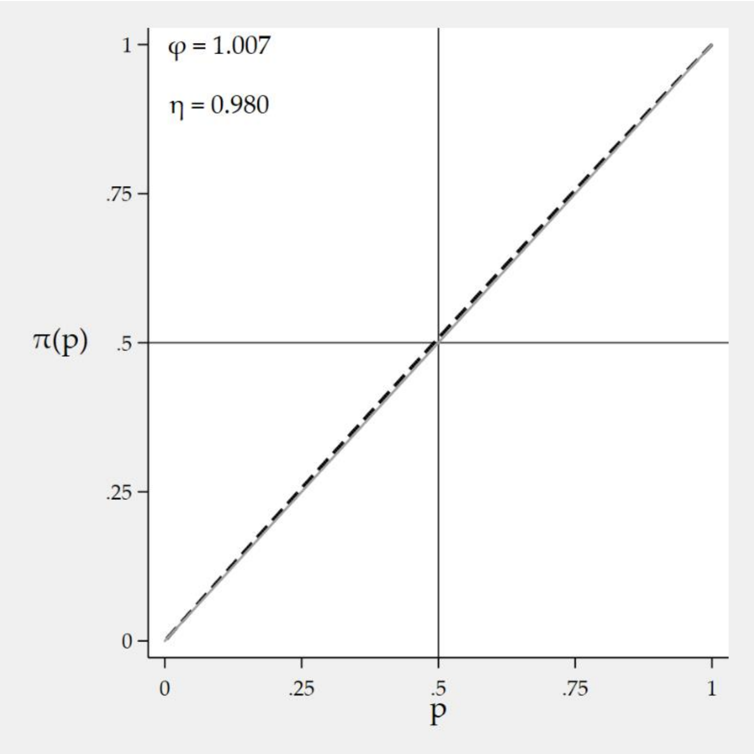


Figure 5.3: Estimated Prelec PWF for Homogenous Preferences

5.3.2. **Heterogenous Preferences**

In order to analyse our detailed risk data as conclusively as possible, our MLE approach and its application to EU theory needs to account for observed heterogeneity. This is achieved by conditioning our estimates on observed characteristics in the sample. In addition to accounting for demographic characteristics, our estimates are also conditioned on the amount sent in the investment game, the amount sent in the dictator game, the treatment into which participants were assigned, and the order in which they completed the three tasks. However, just as was the case with the standard statistical approach, there are a variety of ways to explore the relationship between risk preferences and the amount sent in the investment game. Arguably the simplest way to analyse these data is to take the first send decision made by participants and include it as a covariate in the EU model, as is done in Table 5.3.

We do not expect to find a linear relationship between the amount sent and the risk preferences, which is why we include both linear and quadratic terms for the amount sent covariate. From the results in Table 5.3 it is clear that the relationship between the first amount sent in the investment game and risk preferences is non-linear and, for the most part, positive. This can be interpreted to mean that as the amount sent increases, participants become significantly less risk averse ($p = 0.032$) up to a point. After the turning point, participants become increasingly risk averse again. However, because the squared term is so small, most of the range of send decisions are associated with lower risk aversion with larger amounts sent.

These results imply that risk preferences do confound the measure of trust in the investment game. Theoretically, this is precisely the relationship that we expect to see: a person who is highly risk averse may choose to send very little of their endowment, regardless of how trusting they are, because they do not want to risk getting nothing back. Conversely, this also explains the behaviour of participants who choose to send large amounts: people who are less risk averse are more likely to risk sending larger amounts in the investment game to increase the possibility of getting a larger return at the risk of getting nothing.

Because of the strong association that the amount sent in the dictator game has with the amount sent in the investment game in the standard statistical models, we include it in this model as a robustness check and to adjust for its potential influence. Again, we only use the send decision made in variation 1 of the dictator game, i.e., the send decision with parameters that are analogous to those in the investment game. It is also included as a quadratic variable. The results show that the amount sent in the dictator game is statistically significant ($p < 0.001$), even more so than the amount sent in the investment game.

Table 5.3: Expected Utility ML Estimates for First Amount Sent in Investment Game

Heterogenous Preferences	
	Estimate (Std error)
Power function parameter (r)	
First Amount Sent in IG	0.009**
	(0.004)
First Amount Sent in IG squared	-0.000***
	(0.000)
Amount Sent in DG	0.009***
	(0.002)
Amount Sent in DG squared	-0.000**
	(0.000)
Age	-0.023**
	(0.010)
White	0.148***
	(0.032)
Female	-0.272***
	(0.047)
Information treatment	0.073**
	(0.029)
Task order 2	-0.059**
	(0.026)
Task order 3	-0.081***
	(0.020)
Task order 4	-0.199***
	(0.065)
Constant	-0.010
	(0.250)
Noise	
Error (μ)	0.150***
	(0.005)
N	27700
log-likelihood	-15755.887

Results account for clustering at the individual level
Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Theoretically, the amount sent in the dictator game should have no relationship with a person's degree of risk aversion. By definition, there is no risk involved in the decision of how much to send in the dictator game. However, there is a positive and statistically significant relationship in our data. This means that as the amount sent in the dictator game increases, participants seemingly become less risk averse.

Our results also show that providing participants with social history information statistically significantly influences risk preferences (p = 0.011). Participants in the information treatment who received information about the distribution of return decisions made by fellow students in the baseline treatment are significantly less risk averse than participants in the baseline treatment who received no information.

As was the case with the standard statistical models, we control for order effects using the task order variable. Our results show that the order in which participants completed the three tasks does matter. Notably, participants who completed the tasks under task order 1 (investment game: player 1, investment game: player 2, dictator game, and risk preference task) were significantly less risk averse than participants who completed tasks under task order 2, 3, and 4. Risk preferences between task order 2 and task order 4 were significantly different (p = 0.063), as were risk preferences between task order 3 and task order 4 (p = 0.078).[6]

The demographic characteristics we control for are all significantly related to the estimated risk parameter. As participants get older, they become significantly more risk averse (p = 0.019). Participants who are white are significantly less risk averse ($p < 0.001$) than participants in other racial groups, and, as expected, females are much more risk averse than males at a highly significant level ($p < 0.001$) (Eckel & Wilson, 2004; Schechter, 2007).

While these results are all interesting and conform to our theoretical priors, it would not be economically sound to limit our analysis to the first send decision in the investment game. As per our experimental design, each participant made five send decisions. Thus, another way to analyse these data is to stack the data so that all five send decisions can be used in conjunction with the 100 lottery choices. The results reported in Table E.1 of Appendix E are generated using this stacked variable of the amounts sent as the covariate in the EU model. The same explanatory variables are used as those used in Table 5.3, the only difference is the variable for the amount sent in the investment game. It is therefore unsurprising that the estimates in Table E.1 are similar to those in Table 5.3, except that in the former, most of them are now not significant. The only two variables that remain significant are the amount sent in the dictator game ($p < 0.01$) and gender ($p < 0.05$). Participants show decreasing levels of risk aversion as the amount sent in the dictator game increases and females show higher levels of risk aversion than males.

Another variation of the amount sent in the investment game is to use the average of the five send decisions. The estimates from using the average amount sent, together with the same explanatory variables used in Table 5.3, are reported in Table E.2 in Appendix E. As was the case with the stacked variable for the amount sent, the only significant explanatory variables

[6] Task order 2 and task order 3 were not statistically significantly different (p = 0.466).

in this model of the average amount sent are once again the amount sent in the dictator game ($p < 0.05$), where the level of risk aversion decreases as the amount sent increases, and gender ($p < 0.05$), where females are more risk averse than males.

In both of these models, the variable used for the amount sent in the investment game is included in its quadratic form, as was done with the first amount sent. However, it is not significant in either of these models. This means that in instances where either all five or an average of the five send decisions are considered, there is no significant relationship between the amounts sent in the investment game and the degree of risk aversion in the sample. Therefore, although we found a positive and significant relationship between the first amount sent in the investment game and the level of risk aversion, this result does not hold when we use different variations of the amount sent variable. This implies that the relationship between risk and the amount sent is not robust to alternative models that incorporate different definitions of the amount sent in the investment game.

Although there is no statistically significant evidence of probability weighting in our data, the RDU models for each of the variations of the amount sent that were discussed in this section are included in Appendix F for the sake of completeness. The RDU estimates for the model using the first amount sent in the investment game are presented in Table F.1, the model of the stacked variable for all five send decisions is provided in Table F.2, and the model with the average of the five send decisions is given in Table F.3. The results from these models are robust to the assumption that RDU theory characterises choice under risk. The estimates in these models are very similar to the estimates in the comparable EU models, which is not surprising given the lack of probability weighting in the data.

6. Discussion and Conclusion

It has been clearly established in the literature and confirmed through the analysis of our results that eliciting and measuring trust is a complex task. The BDM investment game is generally accepted within economics as the best way of measuring trust, which has resulted in it being widely studied and replicated over 160 times (Johnson & Mislin, 2011). Despite the game's prominence, the underlying question remains as to whether the amount sent in the game is an appropriate means of measuring trust. Due to the nature of the send decision, there are a variety of factors that have the potential to influence the amount participants choose to send. These include risk preferences, altruism, and subjective beliefs. Our study was designed to measure each of these factors so that their relationship with the amount sent could be explored in more depth.

We used two complementary approaches to analyse our experimental data: a standard statistical approach and an MLE approach. The standard statistical models tested the marginal effects of risk preferences (measured as a discrete variable), altruism, and beliefs on the amount sent. The models also controlled for various demographic characteristics and task parameters. None of the specifications of these models found a significant relationship between the amount sent and the number of risky choices made. By contrast, the amount sent in the dictator game, which was used to elicit altruism, had a positive and significant influence on the amount sent in the investment game across all models and specifications. Similarly, the information treatment, which was used to ground subjective beliefs, had a positive and statistically significant effect on the amount sent across all specifications and models falling within the standard statistical approach.

The MLE approach allowed us to use all of the risk preference task data in our analysis, rather than relying only on the discrete number of risky choices variable used in the standard statistical models. Through the EU and RDU models, we found no significant evidence of probability weighting in our sample, which narrowed our focus to only using the curvature of the utility function to gauge risk preferences. The amounts sent in the investment and dictator games were included as quadratic covariates in these models because of the presumed non-linear relationship between these amounts and risk preferences. Under one specification of EU, we found a positive and significant relationship between the amount sent in the investment game and risk preferences, where lower levels of risk aversion were associated with larger amounts sent. This only applied up to a point though, after which each additional amount sent was associated with higher levels of risk aversion. However, this result was not robust to the various alternative specifications of the amount sent variable.

We did, however, find a robust relationship between the amount sent in the dictator game and risk preferences across all specifications of our EU models. As the amounts participants sent in the dictator game increased, this was associated with lower levels of risk aversion. Again, because of the quadratic relationship, participants became less risk averse up to a point, after which their aversion to risk increased as the amount sent in the dictator game increased. The only other explanatory variable that remained statistically significant through the various specifications in our MLE approach was gender: females were consistently more risk averse than males.

Some of these results are in line with our expectations, based on existing literature. However, other relationships, or lack thereof, were unanticipated. To fully comprehend the nuances in our results, it is important to have a complete understanding of how our experimental design differed from that reported in the previous literature and how this could have impacted our analysis.

While our study builds on the available experimental literature on measuring trust from an economic perspective, it also makes three specific contributions. Firstly, our RLP risk preference task had 100 lottery pairs, 43 of which are unique, with a wide range of probabilities and prizes. Prior to this, all studies in this literature used MPL risk preference instruments with only 15 lottery pairs at most (Eckel & Wilson, 2004; Houser, Schunk & Winter, 2010; Sapienza, Toldra-Simats & Zingales, 2013). Our large battery of risk preference questions allowed us to elicit more comprehensive risk preference data from our participants. This meant that we had the required information to estimate structural risk preference models.

Secondly, our information treatment was designed so that the additional information participants received could be quickly understood and easily interpreted. In the past, participants have been given a table with numbers that were difficult and time consuming to interpret. Our study presented this information graphically, as shown in Figure 3.2 and Figure 3.3. Participants were shown histograms of the distribution of player 2's return decisions for every possible amount that could be sent by player 1. They were also informed that these histograms were constructed using the decisions made by the 188 participants in the baseline treatment.

Lastly, our study appears to have a unique experimental design. As far as we were able to discern, no single study has measured all three of the potential confounding factors that ours was designed to elicit. Risk preferences, altruism, and subjective beliefs have all been studied with regard to the amount sent in the investment game, but our experimental design allows us to elicit these factors and test them independently of one another for any confounding effect they may have on the amount sent variable. This means that should a relationship be found between any of these factors and the amount sent, their influence can be disentangled from trust to get a more precise measure.

This separation of potential confounding factors to allow the effects of each to be studied individually has enabled us to conduct some novel analyses that previous studies have not been able to do. One interesting finding is the large and robust relationship between the amount sent in the investment game and two of these factors: altruism, measured by the amount sent in the dictator game, and beliefs, captured by the information treatment. In our standard statistical approach, we showed that the amount sent in the dictator game and the amount sent in the investment game were statistically significantly correlated across all models and specifications. However, in our dataset, the amount sent in the dictator game is also statistically related to risk preferences.

As discussed in Section 5.3, theoretically there should not be a relationship between these two variables. The amount sent in the dictator game is a measure of altruism; there is no risk involved in this decision. Prior to this study, altruism and risk preferences had not to our knowledge both been measured in the same study and with reference to the amount sent in the investment game. Future research should consider replicating this study to see if this relationship between altruism and risk preferences is robust.

Our standard statistical approach also found the amount sent in the investment game to be statistically significantly related to the degree of information participants received. Those who were part of the information treatment were shown various histograms of the baseline treatment distributions of player 2's return decisions for each amount player 2 could receive. While the existing literature is inconclusive regarding the effect of social history information (BDM, HSW), this study shows that there is a large and statistically significant relationship between providing participants with this information and the amount they send in the investment game. It is likely that the extent of this relationship is at least partly attributable to using histograms as a means of conveying information. Visual presentations of data are often easier to understand and interpret, so it is possible that our way of presenting the information allowed participants to better engage with the information they were given.

These estimates show that beliefs do matter: participants who receive social history information and are able to ground their beliefs in the actions that fellow students have taken, send more in the investment game. This means that it is likely that beliefs confound the measurement of trust; having more accurate beliefs of how those you play with will likely act, tends to increase the amount sent. Beliefs clearly matter, but using an information treatment to elicit subjective beliefs may not be the most suitable means of measuring the effect that beliefs have on the amount sent. Instead, future studies should consider altering the experimental design and using proper scoring rules, like the quadratic scoring rule, instead (Nyarko & Schotter, 2002).

The relationship between the amount sent in the investment game and risk preferences is also a complex and nuanced one. A variation of our structural models shows that risk preferences do affect the amount sent: as people become less risk averse, they send more in the investment game. This relationship is statistically significant and robust, even when controlling for demographic characteristics and task parameters. This confirms what the literature has already found. However, the only specification of our structural model that found a relationship between risk and the amount sent was the variation that used the first send decision. Every other model and specification found no significant correlation between risk preferences and the amount sent in the investment game.

Although the relationship between risk preferences and the amount sent in the investment game is not robust to different definitions of the amount sent variable, we do find that risk confounds measures of trust. The variation in our results could be due to our comprehensive measure of risk preferences. No previous studies have gathered as much risk preference information with as wide a range of probabilities and prizes. Theoretically, there is a relationship between risk preferences and the amount sent in the investment game, which means that a more accurate measure of risk preferences should confirm this relationship. Clearly more research on this topic is necessary.

A notable limitation of our study is that our experiments were conducted using university students in computer labs. Although this is common practice in many studies in experimental economics, students are not necessarily an accurate representation of the population as a whole. This means that our results should not merely be extrapolated to the general South African population. A distinguishing feature of our study when compared to similar studies that also use students, is that ours is conducted in a developing country context. This use of African students brings diversity to our results and to the literature that has predominantly focused on the developed world.

One clear conclusion from the above discussion is that research on trust and the amount sent in the investment game is fraught with difficulties. While the amount sent should not be completely discounted as a measure of trust, its limitations need to be acknowledged. The amount sent is confounded by certain factors, so it should not be used uncritically as a pure measure of trust. Instead, researchers using the amount sent in the investment game as a measure of trust should recognise that it is influenced by risk preferences, altruism, and subjective beliefs.

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Appendix A

Table A.1: Details of Baseline Treatment Sessions

Session	Date	Time	Order Number	Task Order	Number of Subjects
1	28/08/2018	14:00	1	Is, Ir, D, R*	24
2	30/08/2018	09:30	3	D, Is, Ir, R	22
3	31/08/2018	14:00	2	Ir, Is, D, R	16
4	03/09/2018	14:00	4	D, Ir, Is, R	20
5	04/09/2018	09:30	1	Is, Ir, D, R	12
6	04/09/2018	14:00	2	Ir, Is, D, R	18
7	06/09/2018	09:30	3	D, Is, Ir, R	20
8	07/09/2018	14:00	4	D, Ir, Is, R	18
9	18/09/2018	14:00	1	Is, Ir, D, R	10
10	20/09/2018	09:30	4	D, Ir, Is, R	16
11	21/09/2018	14:00	2	Ir, Is, D, R	12

**Is: sender in investment game; Ir: receiver in investment game; D: dictator game; R: risk preference task*

Table A.2: Details of Information Treatment Sessions

Session	Date	Time	Order Number	Task Order	Number of Subjects
1	09/10/2018	15:00	2	Ir, Is, D, R*	24
2	10/10/2018	15:00	4	D, Ir, Is, R	24
3	11/10/2018	09:30	2	Ir, Is, D, R	24
4	12/10/2018	14:00	4	D, Ir, Is, R	22

** Ir: receiver in investment game; Is: sender in investment game; D: dictator game; R: risk preference task*

Appendix B

B1: Introductory Presentation

Slide 1

Introduction

Please come inside and find a seat with a folder in front of it. You may not talk to anyone else during this session but if you have any questions then just raise your hand and either I or one of the research assistants will come to assist you.

Hi everyone, my name is Tarryn. Thank you very much for being here today. I am going to give you your first set of instructions so let's get started.

Slide 2

Consent Form

- Before we can begin today's session you need to read and sign a consent form which you will find in the folder in front of you
- You will notice that there are 2 consent forms in the folder and one of them is for you to take home so please place it in your bag now
- The consent form explains your rights as a research participant and, by signing it, you give your consent to participate in the study
- You need to sign the consent form on the last page and when you have done so please raise your hand
- Once everyone has signed their consent forms, we can continue
- If you have any questions please raise your hand and someone will come to answer them
- You may read through the consent form now

Slide 3

Welcome

- Thank you for agreeing to take part in this study, your views and choices will be very informative and helpful
- Before we get started, I would like to explain how things are going to work
- Once that is done, we can begin with the tasks
- If you have any questions, please do not ask them out loud – raise your hand and someone will come over to you

Slide 4

3 Tasks and a Questionnaire

- You will take part in 3 tasks and you will have the opportunity to earn money on the basis of the choices you (and other participants in today's session) make
- We will determine your payment for the tasks once you have completed all of them
- Once you have completed all 3 tasks, you will need to fill out a short questionnaire
- We will then total up and pay you your cash earnings privately, as discussed in a moment
- Once this is done, you will be free to leave

Slide 5

The First 2 Tasks

- You will complete two tasks now at the start of the session
- In each of these two tasks, you will make a set of decisions
- At the end of the session you will be **randomly and anonymously** paired up with another person in the room
- One of the decisions from one of these first two tasks will then be randomly selected to determine your payment on the basis of the choices that you and your partner made
- You will be given detailed instructions on the tasks before you complete them

Slide 6

Task 3

- After completing the first two tasks you will complete Task 3, which is an individual decision-making task
- You will need to choose between lotteries with varying prizes and chances of winning
- You will make 100 of these choices
- When you are finished making these choices we will randomly select one of them to determine your payment

Slide 7

Earnings

- You will be paid R40 just for participating in today’s session
- Once you have finished all three tasks we will determine your payments for them
- This money will be paid to you in cash at the end of the session today, in private
- To determine your earnings for Task 3, we will ask you to roll some dice
- Let’s go through a quick explanation of the dice you will roll

Slide 8

10-sided dice

- At the end of Task 3 we will ask <u>you</u> to roll some dice into a plastic bowl which you can see below
- Two of the dice that you will roll are 10-sided dice and these are used to select a number between 1 and 100
- Every number between 1 and 100, and including 1 and 100, is equally likely to occur
- An example of a dice roll is shown below

Slide 9

10-sided dice

- Let’s look at a close-up of the 10-sided dice
- As you can see, one of the 10-sided dice has sides which increase in multiples of 10: 00, 10, 20, 30, 40, 50, 60, 70, 80 and 90
- The other 10-sided dice has sides which increase in multiples of 1: 0, 1, 2, 3, 4, 5, 6, 7, 8 and 9
- You will roll the two 10-sided dice together and add the numbers on the two dice to select a number between 1 and 100
- In the example below, the number that was rolled is 86 (80 + 6)

Slide 10

10-sided dice

- To tell the difference between a 6 and a 9 there is a dot at the base of the number
- This is why the number in the picture below is a 6: there is a dot at the base of the 6
- 9 looks different because there is a dot at the base of the 9
- The new picture below shows you what a 9 looks like

Slide 11

10-sided dice

- To roll a number between 1 and 9 you need to roll 00 and a single number between 1 and 9
- As you can see in the picture below, the number that was rolled is 5 (00 + 5)
- In the case where you roll 00 and 0, this will be treated as 100
- As you can see in the new picture below, the number that was rolled is 100 (00 and 0)

Slide 12

The Tasks

- We have now finished the introductory explanation
- You will find instructions for the first task that you need to complete on top of the folder in front of you
- Please read through them and when you are finished raise your hand so that a research assistant can play a video for you which provides further details on the task
- When this is finished you will begin the first task

You can now read all three pages of the instructions for the first task, which are in front of you.

B2: Written Instructions

B2.1: Investment Game

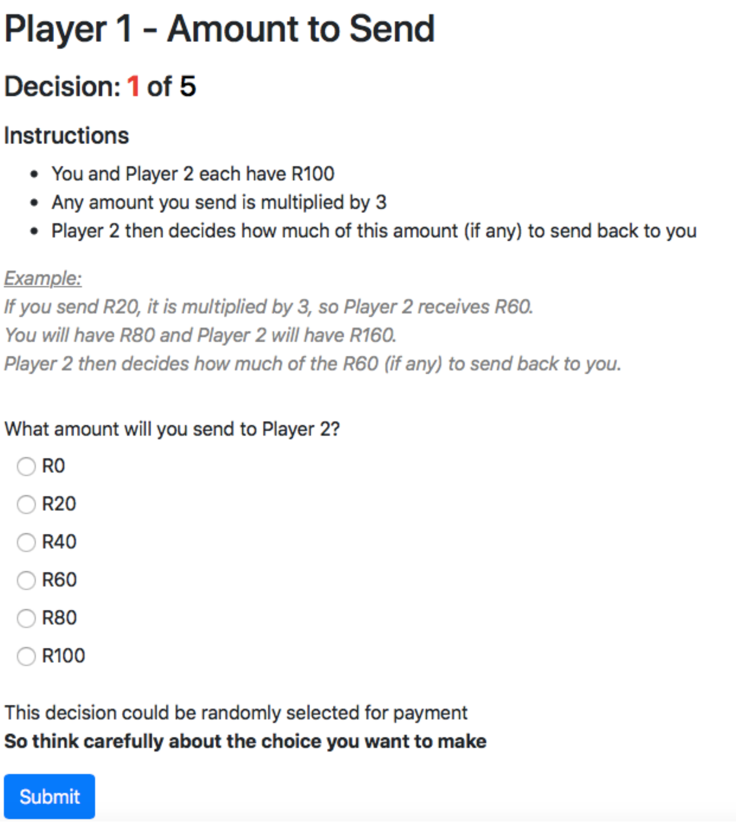
Task Instructions

This is a task where the decisions that you and another person make will determine the amounts of money that each of you earn. In this task, there are two roles, which we can refer to as Player 1 and Player 2. You will be asked to make decisions in each of these roles: as Player 1 **and** as Player 2.

At the end of the session today, you will be randomly and anonymously paired up with another person in the room. If this task is selected for payment, you and your partner will be randomly assigned to one of the two roles: either you are Player 1 and your partner is Player 2, or you are Player 2 and your partner is Player 1. Once these roles have been randomly assigned, a choice that you and your partner made will determine the earnings that each of you receive.

The task works as follows: Player 1 and Player 2 are both given R100. Player 1 needs to decide how much of the R100 (if any) to send to Player 2. Player 1 can send amounts in R20 increments: R0, R20, R40, R60, R80, or R100. The amount that Player 1 sends is automatically tripled before it is received by Player 2. So, if Player 1 sends R40 then Player 2 receives R120. Player 2 then decides how much of the R120 (if any) to send back to Player 1 and, therefore, how much to keep for himself/herself. Player 2 can send amounts in R20 increments.

These decisions will be made on a computer. This is what the computer display will look like for Player 1:



Player 1 - Amount to Send

Decision: 1 of 5

Instructions

- You and Player 2 each have R100
- Any amount you send is multiplied by 3
- Player 2 then decides how much of this amount (if any) to send back to you

Example:
If you send R20, it is multiplied by 3, so Player 2 receives R60.
You will have R80 and Player 2 will have R160.
Player 2 then decides how much of the R60 (if any) to send back to you.

What amount will you send to Player 2?

- R0
- R20
- R40
- R60
- R80
- R100

This decision could be randomly selected for payment
So think carefully about the choice you want to make

Submit

As you can see, Player 1 has to choose whether to send R0, R20, R40, R60, R80, or R100 to Player 2, knowing that any amount that is sent will be tripled and received by Player 2. Player 1 has to make this decision 5 times, on 5 separate computer screens. As any of these 5 choices could be randomly selected for payment, you should approach each choice as if it is the one that you will be paid for.

Now, when you are in the role of Player 2, you will not know how much money has been sent to you by Player 1 because we only randomly and anonymously pair up people at the end of the session today. So, you will choose how much to send back to Player 1 for every possible amount that Player 1 can send you, except if Player 1 sends R0 because then there is nothing for you to send back.

So, you will decide how much to send back to Player 1 for every possible amount Player 1 can send:

- If Player 1 sends R20, which is then tripled and becomes R60
- If Player 1 sends R40, which is then tripled and becomes R120
- If Player 1 sends R60, which is then tripled and becomes R180
- If Player 1 sends R80, which is then tripled and becomes R240
- If Player 1 sends R100, which is then tripled and becomes R300

This is what the computer display will look like for Player 2:

Player 2 - Amount to Send Back

Decision: 1 of 5

Instructions

- You and Player 1 each had R100
- Suppose Player 1 sends **R20**, so Player 1 now has R80
- You recieve **R60**, so you now have R160
- After you choose what to send back, the task ends

Example:
If you send back R20, Player 1 earns R100 and you earn R140.

Of the R60 you recieved, what amount will you send back to Player 1?

- R0
- R20
- R40
- R60

This decision could be randomly selected for payment
So think carefully about the choice you want to make

Submit

Once you have made your choices in the roles of Player 1 and Player 2 you will move on to the next task. At the end of the session today, we will determine your earnings for the first 2 tasks in the following way:

- You will be randomly and anonymously paired with another person in the room

- One of the first 2 tasks in today's session will then be randomly selected for payment
- If this task is randomly selected for payment, you and your partner will be randomly assigned to one of the two roles: either you are Player 1 and your partner is Player 2, or you are Player 2 and your partner is Player 1.
- Once these roles have been randomly assigned, one of the choices Player 1 made will be randomly selected
- Given the amount sent by Player 1, the amount that Player 2 chose to send back to Player 1 will determine the earnings that each of you receive

For example, suppose that you are randomly selected as Player 1. One of the 5 choices you made in this role will be randomly selected to determine payment. Suppose you chose to send R60 to Player 2. This amount is tripled so that Player 2 receives R180. Player 2 would have chosen what amount to send back to Player 1 for every possible amount that Player 1 could send. Suppose that when Player 1 sends R60, which is tripled to become R180, Player 2 chose to send R100 back to Player 1. Then, as Player 1, you earn the R100 that you were given at the start, minus the R60 you sent to Player 2, plus the R100 that Player 2 returned to you = R100 – R60 + R100 = **R140**. Player 2 earns the R100 that he/she was given at the start, plus the R180 that you sent, minus the R100 that Player 2 sent back to you = R100 + R180 – R100 = **R180**.

As another example, suppose that you are randomly selected as Player 2 and that Player 1 chose to send R20. This amount is tripled so that you receive R60. You would have chosen what to send back to Player 1 if Player 1 sends R20. Assume that you chose to send back R20 out of the R60 you received. Then you, as Player 2, earn the R100 that you were given at the start, plus the R60 you received from Player 1, minus the R20 that you sent back = R100 + R60 – R20 = **R140**. Player 1 earns the R100 that he/she was given at the start, minus the R20 that was sent to you, plus the R20 that you sent back to Player 1 = R100 – R20 + R20 = **R100**.

There are no right or wrong answers in this task. Please work silently and make your choices by thinking carefully about the different options. When you have finished the task, please raise your hand and a research assistant will come to you to prepare you for the next task.

Please raise your hand now.

B2.2: Dictator Game

Task Instructions

This is a task where the decisions that either you or another person make will determine the amounts of money that each of you earn. In this task, there are two roles, which we can refer to as Player 1 and Player 2. Player 2 is a passive player and does not have any choices to make. Player 1, on the other hand, has to make choices and these choices will determine the amounts of money that Player 1 and Player 2 earn.

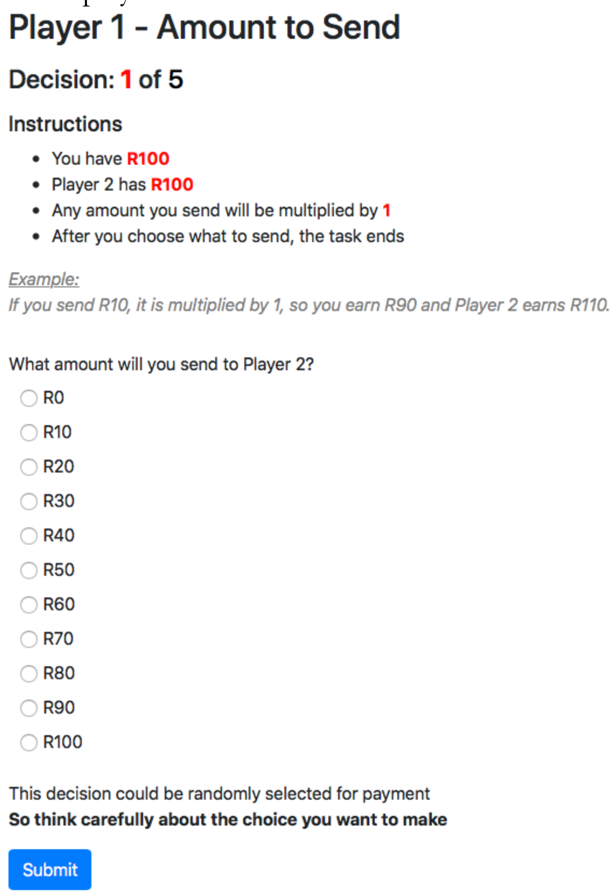
At the end of the session today, you will be randomly and anonymously paired up with another person in the room. If this task is selected for payment, you and your partner will be randomly assigned to one of the two roles: either you are Player 1 and your partner is Player 2, or you are Player 2 and your partner is Player 1. Once these roles have been randomly assigned, a choice that you or your partner made will determine the earnings that each of you receive.

The task works as follows: Player 1 is given an amount of money, e.g., R100. Player 1 needs to decide how much of this amount (if any) to send to Player 2. Player 1 can send amounts in R10 increments: R0, R10, R20, R30, R40, R50, R60, R70, R80, R90, or R100. The money that is sent is then multiplied by a number, e.g., 3, before it is received by Player 2. After Player 2 has received the amount sent by Player 1, the task ends.

Player 1 needs to make 5 of these decisions on 5 separate computer screens. While the basic structure of the task is the same for each decision, some of the details change across the decisions. For example, for one of the decisions, Player 1 will be given R100 and Player 2 will also be given R100. For another decision, Player 1 will be given R80 and Player 2 will be given R0. Thus, the amounts that Player 1 and Player 2 are given differs across the decisions.

In addition, the money that Player 1 sends to Player 2 will be multiplied by different numbers for different decisions. For example, for one of the decisions, any money that Player 1 sends will be multiplied by 3 before it is received by Player 2 (i.e., the multiplier is 3). So, if Player 1 sends R10 then Player 2 will receive R30. For another decision, any money that Player 1 sends will be multiplied by 1 before it is received by Player 2 (i.e., the multiplier is 1). So, if Player 1 sends R40, then Player 2 receives R40 in this case. Finally, for another decision, any money that Player 1 sends will be multiplied by 5 before it is received by Player 2 (i.e., the multiplier is 5). So, if Player 1 sends R20 then Player 2 receives R100.

This is what the computer display will look like:



Once you have made your choices as Player 1 you will move on to the next task. At the end of the session today, we will determine your earnings for the first 2 tasks in the following way:

- You will be randomly and anonymously paired with another person in the room
- One of the first 2 tasks in today's session will then be randomly selected for payment
- If this task is randomly selected for payment, you and your partner will be randomly assigned to one of the two roles: either you are Player 1 and your partner is Player 2, or you are Player 2 and your partner is Player 1.
- Once these roles have been randomly assigned, one of the choices that Player 1 made will be randomly selected to determine the earnings that each of you receive.

Note that as any of the 5 choices that you make as Player 1 could be randomly selected for payment, you should approach each choice as if it is the one that you will be paid for. In addition, please pay careful attention to the information that is provided on every screen because the amounts of money that Player 1 and Player 2 are given and the amount by which sent money is multiplied changes across the screens.

There are no right or wrong answers in this task. Please work silently and make your choices by thinking carefully about the different options, particularly because they vary across the different decisions. When you have finished the task, please raise your hand and a research assistant will come to you to prepare you for the next task.

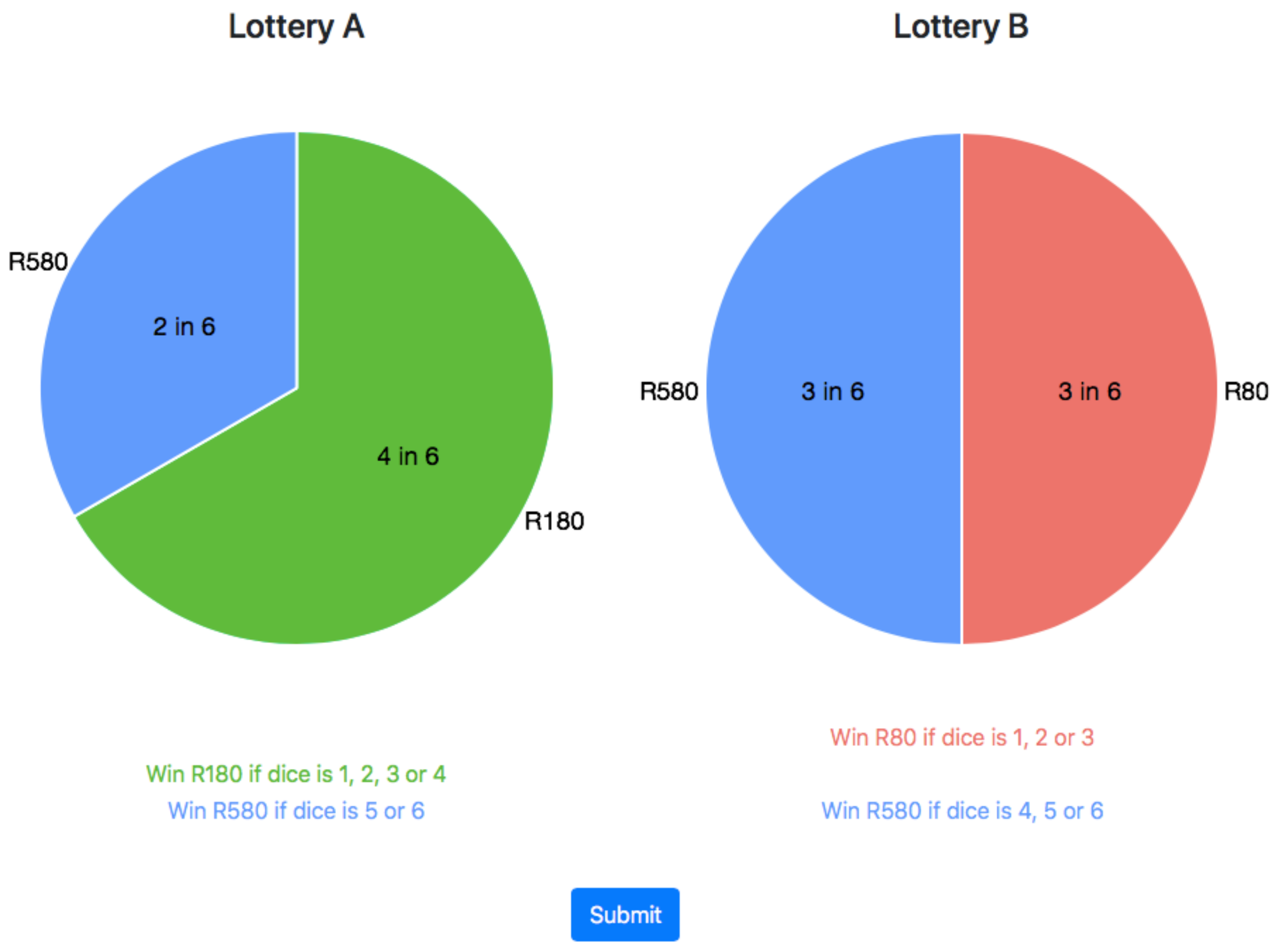
Please raise your hand now.

B2.3: Risk Preference Task

Task Instructions

This is a task where you will choose between lotteries with varying prizes and chances of winning. On each computer screen you will be presented with a pair of lotteries and you will need to choose one of them. There are 100 pairs of lotteries in this task. For each pair of lotteries, you should choose the lottery you would prefer to play. You will actually get the chance to play **one** of the lotteries you choose, and you will be paid according to the outcome of that lottery, so you should think carefully about which lottery you prefer. Note that this is an individual decision-making task so you are not paired with anyone else.

Here is an example of what the computer display of a pair of lotteries might look like:



The outcome of the lotteries will be determined by rolling a regular 6-sided dice. And you will get to roll this 6-sided dice yourself at the end of the session today.

In the above example, Lottery A pays R180 with a 4-in-6 chance and R580 with a 2-in-6 chance. So when you roll the 6-sided dice, if it lands on 1, 2, 3 or 4 you will be paid R180, and if it lands on 5 or 6 you will be paid R580. The green colour in the pie chart corresponds to 4/6 of the area and illustrates the chance that the dice lands on 1, 2, 3 or 4 and your prize is R180. The blue colour in the pie chart corresponds to 2/6 of the area and illustrates the chance that the dice lands on 5 or 6 and your prize is R580.

Now look at Lottery B in the example. It pays R80 with a 3-in-6 chance, and R580 with a 3-in-6 chance. So when you roll the 6-sided dice, if it lands on 1, 2 or 3 you will be paid R80, and if it lands on 4, 5 or 6 you will be paid R580. The red colour in the pie chart corresponds to 3/6 of the area and illustrates the chance that the dice lands on 1, 2 or 3 and your prize is R80. The blue colour in the pie chart corresponds to 3/6 of the area and illustrates the chance that the dice lands on 4, 5 or 6 and your prize is R580.

Each pair of lotteries is shown on a new screen on the computer. On each screen, you should indicate which lottery you would prefer to play by clicking on the pie chart that represents the lottery. You will then click the "Submit" button to move on to the next screen with a new set of lotteries.

After you have worked through all of the 100 pairs of lotteries, raise your hand and a research assistant will come to you to determine your payment for this task. You will roll two 10-sided dice to pick a number between 1 and 100 to determine which pair of lotteries will be played out. Since there is a chance that any of your 100 choices could be played out for real, you should approach each pair of lotteries as if it is the one that you will play out.

Therefore, your earnings for this task are determined by three things:

- by which lottery you selected, Lottery A or Lottery B, for each of the 100 pairs;
- by which lottery pair is chosen to be played out in the set of 100 pairs using the two 10-sided dice; and
- by the outcome of that lottery when you roll the regular 6-sided dice.

Which lotteries you prefer is a matter of personal taste. The people next to you may be presented with different lotteries, and may have different preferences, so their responses should not matter to you. Please work silently and make your choices by thinking carefully about each lottery.

Payment for this task is in cash and is in addition to the R40 show-up fee that you receive just for being here. When you have finished the task, please raise your hand and a research assistant will come to you to determine your payment for this task and for the first two tasks that you completed.

Please raise your hand now.

Appendix C

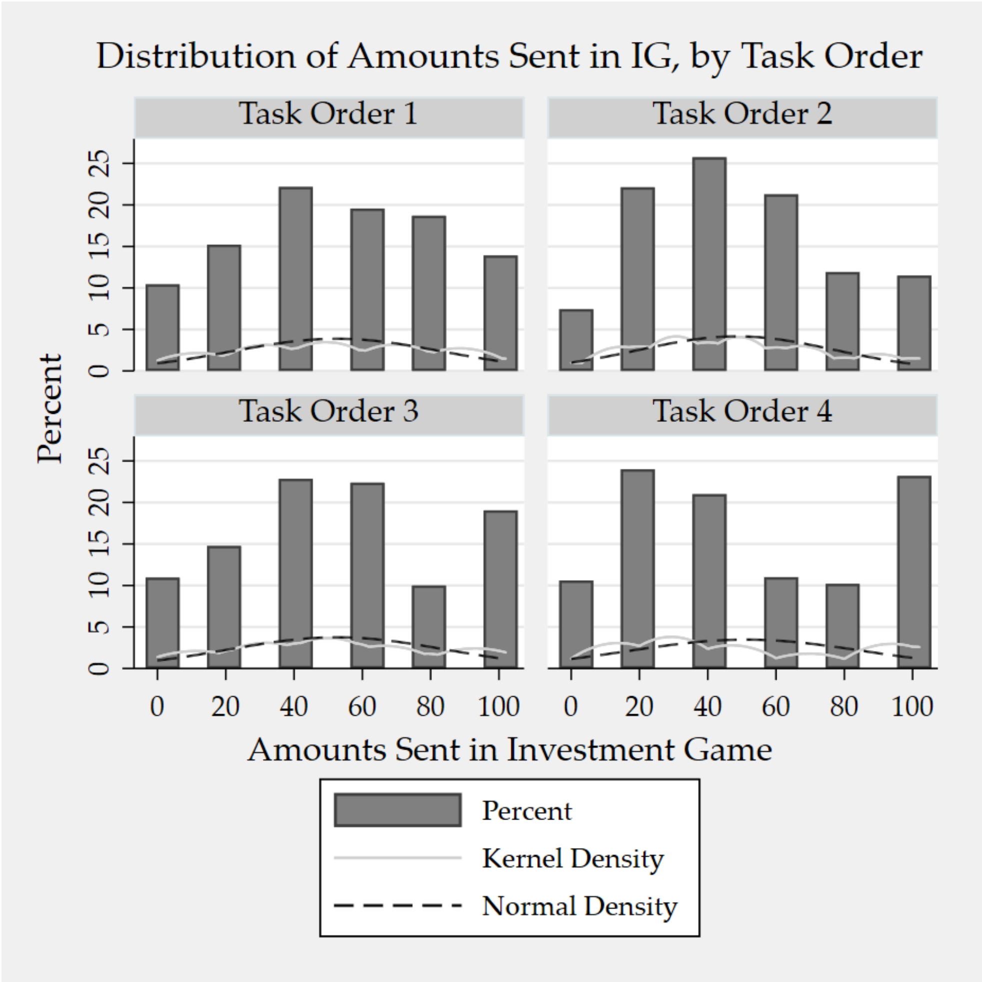


Figure C.1: Histograms for Distribution of all Five Send Decisions in IG, by Task Order

Appendix D

Table D.1: Risk-Trust Confound Estimates for First Amount Sent in IG

	Fractional Response	Tobit	OLS
	Estimate (Std error)	Estimate (Std error)	Estimate (Std error)
Number of risky choices	0.000	-0.030	0.283
	(0.001)	(0.144)	(0.482)
Amount Sent in DG	0.004***	0.569***	0.428***
	(0.001)	(0.088)	(0.066)
Age	-0.022***	-2.667***	-2.093***
	(0.006)	(0.831)	(0.660)
White	-0.017	-2.632	-1.703
	(0.054)	(6.279)	(4.875)
Female	-0.077**	-8.737*	-7.632**
	(0.035)	(4.461)	(3.525)
Information treatment	0.152***	19.802***	15.339***
	(0.039)	(5.113)	(4.029)
Task order 2	-0.095**	-11.911*	-9.705*
	(0.047)	(6.742)	(5.361)
Task order 3	0.016	1.861	1.359
	(0.055)	(7.417)	(5.871)
Task order 4	-0.046	-5.434	-4.813
	(0.052)	(6.643)	(5.241)
Number of risky choices squared			-0.003
			(0.005)
Constant			79.579***
			(20.811)
N	277	277	277

Marginal effects reported

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.2: Risk-Trust Confound Estimates for Average Amount Sent in IG

	Fractional Response	Tobit	OLS
	Estimate (Std error)	Estimate (Std error)	Estimate (Std error)
Number of risky choices	0.000	0.031	0.039
	(0.001)	(0.104)	(0.405)
Amount Sent in DG	0.004***	0.484***	0.412***
	(0.001)	(0.063)	(0.056)
Age	-0.014***	-1.662***	-1.411**
	(0.005)	(0.604)	(0.555)
White	-0.007	-0.438	-0.817
	(0.047)	(4.512)	(4.098)
Female	-0.082***	-8.915***	-8.111***
	(0.030)	(3.231)	(2.963)
Information treatment	0.110***	12.254***	11.164***
	(0.033)	(3.701)	(3.387)
Task order 2	-0.091**	-8.919*	-9.399**
	(0.040)	(4.893)	(4.507)
Task order 3	0.000	1.113	-0.218
	(0.046)	(5.371)	(4.936)
Task order 4	-0.044	-3.249	-4.697
	(0.042)	(4.802)	(4.406)
Number of risky choices squared			0.000
			(0.004)
Constant			74.103***
			(17.495)
N	277	277	277

Marginal effects reported

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix E

Table E.1: Expected Utility ML Estimates for all Five Send Decisions in IG

	Heterogenous Preferences
	Estimate (Std error)
Power function parameter (r)	
Amounts Sent in 5 IG choices	0.000
	(0.003)
Amounts Sent in 5 IG choices squared	0.000
	(0.000)
Amount Sent in DG	0.011***
	(0.004)
Amount Sent in DG squared	-0.000**
	(0.000)
Age	-0.027
	(0.022)
White	0.090
	(0.110)
Female	-0.215**
	(0.097)
Information treatment	0.049
	(0.068)
Task order 2	0.004
	(0.080)
Task order 3	-0.064
	(0.119)
Task order 4	-0.161
	(0.120)
Constant	0.124
	(0.481)
Noise	
Error (μ)	0.150***
	(0.005)
N	138500
log-likelihood	-78865.473

Results account for clustering at the individual level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: Expected Utility ML Estimates for Average Amount Sent in IG

Heterogenous Preferences	
	Estimate (Std error)
Power function parameter (r)	
Average Amount Sent in IG	0.001
	(0.008)
Average Amount Sent in IG squared	0.000
	(0.000)
Amount Sent in DG	0.010**
	(0.005)
Amount Sent in DG squared	0.000
	(0.000)
Age	-0.026
	(0.023)
White	0.092
	(0.112)
Female	-0.219**
	(0.101)
Information treatment	0.047
	(0.072)
Task order 2	0.001
	(0.085)
Task order 3	-0.070
	(0.127)
Task order 4	-0.160
	(0.123)
Constant	0.086
	(0.543)
Noise	
Error (μ)	0.150***
	(0.005)
N	27700
log-likelihood	-15772.677

Results account for clustering at the individual level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix F

Table F.1: Rank-Dependent Utility ML Estimates for First Amount Sent in IG

Heterogenous Preferences	
	Estimate (Std error)
Power function parameter (r)	
First Amount Sent in IG	0.002
	(0.004)
First Amount Sent in IG squared	0.000
	(0.000)
Amount Sent in DG	0.006
	(0.004)
Amount Sent in DG squared	0.000
	(0.000)
Age	-0.022**
	(0.009)
White	0.226***
	(0.074)
Female	-0.272***
	(0.082)
Information treatment	0.004
	(0.095)
Task order 2	0.071
	(0.114)
Task order 3	0.087*
	(0.048)
Task order 4	0.005
	(0.109)
Constant	0.008
	(0.230)

Table continues on the next page

Table F.1: Rank-Dependent Utility ML Estimates for First Amount Sent in IG (continued)

	Estimate (Std error)
PWF Parameter (φ)	
First Amount Sent in IG	0.006
	(0.004)
First Amount Sent in IG squared	0.000
	(0.000)
Amount Sent in DG	0.007*
	(0.004)
Amount Sent in DG squared	0.000
	(0.000)
Age	0.005
	(0.024)
White	0.138
	(0.096)
Female	0.048
	(0.084)
Information treatment	-0.010
	(0.093)
Task order 2	-0.109
	(0.133)
Task order 3	-0.311**
	(0.145)
Task order 4	-0.167
	(0.124)
Constant	0.837
	(0.570)

Table continues on next page

Table F.1: Rank-Dependent Utility ML Estimates for First Amount Sent in IG (continued)

	Estimate (Std error)
PWF Parameter (η)	
First Amount Sent in IG	-0.003
	(0.004)
First Amount Sent in IG squared	0.000
	(0.000)
Amount Sent in DG	-0.002
	(0.003)
Amount Sent in DG squared	0.000
	(0.000)
Age	0.004
	(0.017)
White	0.110
	(0.093)
Female	0.001
	(0.058)
Information treatment	-0.020
	(0.072)
Task order 2	0.049
	(0.093)
Task order 3	0.037
	(0.097)
Task order 4	0.090
	(0.092)
Constant	0.967***
	(0.374)
Noise	
Error (μ)	0.149***
	(0.005)
N	27700
log-likelihood	-15688.956

Results account for clustering at the individual level
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.2: Rank-Dependent Utility ML Estimates for all Five Send Decisions in IG

Heterogenous Preferences	
	Estimate (Std error)
Power function parameter (r)	
Amounts Sent in 5 IG choices	-0.003*
	(0.002)
Amounts Sent in 5 IG choices squared	0.000
	(0.000)
Amount Sent in DG	0.003
	(0.004)
Amount Sent in DG squared	0.000
	(0.000)
Age	-0.034***
	(0.010)
White	0.214***
	(0.066)
Female	-0.298***
	(0.083)
Information treatment	0.012
	(0.102)
Task order 2	0.044
	(0.098)
Task order 3	-0.021
	(0.044)
Task order 4	-0.079*
	(0.046)
Constant	0.459**
	(0.220)

Table continues on next page

Table F.2: Rank-Dependent Utility ML Estimates for all Five Send Decisions in IG (continued)

	Estimate (Std error)
PWF Parameter (φ)	
Amounts Sent in 5 IG choices	0.003
	(0.003)
Amounts Sent in 5 IG choices squared	0.000
	(0.000)
Amount Sent in DG	0.008**
	(0.004)
Amount Sent in DG squared	-0.000*
	(0.000)
Age	0.005
	(0.020)
White	0.117
	(0.094)
Female	0.058
	(0.085)
Information treatment	-0.009
	(0.089)
Task order 2	-0.103
	(0.134)
Task order 3	-0.299**
	(0.147)
Task order 4	-0.177
	(0.126)
Constant	0.876*
	(0.456)

Table continues on next page

Table F.2: Rank-Dependent Utility ML Estimates for all Five Send Decisions in IG (continued)

	Estimate (Std error)
PWF Parameter (η)	
Amounts Sent in 5 IG choices	-0.002
	(0.002)
Amounts Sent in 5 IG choices squared	0.000
	(0.000)
Amount Sent in DG	-0.005
	(0.003)
Amount Sent in DG squared	0.000
	(0.000)
Age	-0.002
	(0.015)
White	0.125
	(0.092)
Female	-0.020
	(0.060)
Information treatment	-0.007
	(0.069)
Task order 2	0.028
	(0.092)
Task order 3	-0.016
	(0.101)
Task order 4	0.064
	(0.095)
Constant	1.118***
	(0.336)
Noise	
Error (μ)	0.149***
	(0.005)
N	138500
log-likelihood	-78528.906

Results account for clustering at the individual level

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.3: Rank-Dependent Utility ML Estimates for Average Amount Sent in IG

Heterogenous Preferences	
	Estimate (Std error)
Power function parameter (r)	
Average Amount Sent in IG	-0.002
	(0.005)
Average Amount Sent in IG squared	0.000
	(0.000)
Amount Sent in DG	0.004
	(0.005)
Amount Sent in DG squared	0.000
	(0.000)
Age	-0.013
	(0.027)
White	0.170*
	(0.100)
Female	-0.278***
	(0.091)
Information treatment	-0.005
	(0.118)
Task order 2	0.075
	(0.132)
Task order 3	-0.034
	(0.121)
Task order 4	-0.037
	(0.128)
Constant	-0.045
	(0.604)

Table continues on next page

Table F.3: Rank-Dependent Utility ML Estimates for Average Amount Sent in IG (continued)

	Estimate (Std error)
PWF Parameter (φ)	
Average Amount Sent in IG	0.005
	(0.005)
Average Amount Sent in IG squared	0.000
	(0.000)
Amount Sent in DG	0.007*
	(0.004)
Amount Sent in DG squared	0.000
	(0.000)
Age	-0.002
	(0.019)
White	0.148
	(0.100)
Female	0.039
	(0.088)
Information treatment	0.003
	(0.092)
Task order 2	-0.110
	(0.134)
Task order 3	-0.299**
	(0.146)
Task order 4	-0.177
	(0.127)
Constant	0.991**
	(0.471)

Table continues on next page

Table F.3: Rank-Dependent Utility ML Estimates for Average Amount Sent in IG (continued)

	Estimate (Std error)
PWF Parameter (η)	
Average Amount Sent in IG	-0.001
	(0.004)
Average Amount Sent in IG squared	0.000
	(0.000)
Amount Sent in DG	-0.004
	(0.003)
Amount Sent in DG squared	0.000
	(0.000)
Age	0.009
	(0.015)
White	0.105
	(0.086)
Female	-0.016
	(0.063)
Information treatment	-0.012
	(0.070)
Task order 2	0.037
	(0.089)
Task order 3	-0.022
	(0.091)
Task order 4	0.080
	(0.092)
Constant	0.887***
	(0.343)
Noise	
Error (μ)	0.149***
	(0.005)
N	27700
log-likelihood	-15693.331

Results account for clustering at the individual level

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$