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THREE ESSAYS ON UNCERTAINTY IN SOCIAL DILEMMAS

Abdul Kidwai

THREE ESSAYS ON UNCERTAINTY IN SOCIAL DILEMMAS

A Dissertation Presented

by

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DEDICATION

Dada, we miss you every day.

Khalajaan, ever so generous. You had so much more to give.

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If writing a dissertation is challenging, then writing the acknowledgements section is a Herculean task. Unlike the dissertation where a whole host of people guided me through, I have to do this on my own. There is also the real possibility that people might read it (if only it counted as a citation!). The list of those I owe a debt of gratitude to is finite but lengthy.

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ABSTRACT

THREE ESSAYS ON UNCERTAINTY IN SOCIAL DILEMMAS

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Social dilemmas are settings where the interest of the individual is at odds with those of society i.e. overharvesting in a fishery, not contributing to a public good. These dilemmas are widespread and take myriad forms with public goods and common-pool resources being the most prominent ones. The purpose of this dissertation is to examine how individual behavior is impacted by the presence of uncertainty in public goods and common-pool resources. These dilemmas exhibit two types of uncertainty, strategic and environmental. Strategic uncertainty refers to uncertainty about the actions of other individuals facing the dilemma i.e. will other individuals contribute to the public good or not. Environmental uncertainty pertains to uncertainty about the characteristics of the dilemma i.e. is the resource size large or small. While strategic uncertainty has been extensively examined, the existing research on environmental uncertainty is limited. Since the social dilemmas in the real-world are often marked by environmental uncertainty, policy-makers need to know how individual behavior in social dilemmas is impacted by environmental uncertainty. The dissertation utilizes laboratory experiments to study the issue because laboratory experiments allow us to implement different forms of environmental uncertainty, which would not be possible in the field.

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CHAPTER 1

INTRODUCTION

1.1 Overview

A number of environmental problems that society faces, from tackling climate change to over-harvesting in fisheries, from preserving biodiversity to reducing pollution, can be classified as social dilemmas (SDs). The challenge posed by SDs is that in such settings individual rational action may lead to a socially sub-optimal outcome[1] (Kollock 1998). All SDs are marked by *strategic uncertainty*, that is, uncertainty about the actions of other people (Rapoport & Au 2001). For instance, if I reduce my emission levels, will others do so as well, thereby reducing pollution? Or will others increase their emissions, thereby leaving pollution levels unchanged? In addition to strategic uncertainty, SDs might exhibit *scientific uncertainty* - that is, uncertainty about the characteristics of the SD itself including (but not limited to) - the size of the resource, the number of users, the regeneration rate, the costs (or benefits) of overcoming the SD, amongst others, might not be known with precision (Van Dijk et al. 1999). Broadly speaking, scientific uncertainty manifests itself in two forms[2]: risk (where the probabilities associated with the outcomes

[1] A common but very narrow definition of SDs is that the Nash equilibrium is different from the social optimal (Dawes 1980). Such a definition of SDs only includes the prisoners' dilemma whereas SDs encompass a broader category of games such coordination and hawk-dove games (Kollock 1998). In these games, there are multiple Nash equilibria and the social optimal is also a Nash equilibrium. Therefore, individual rational action *may*, but not necessarily, lead to a socially sub-optimal outcome in a SD.

[2] Although risk is well-defined in the literature, there is still considerable debate about the precise definition of uncertainty and ambiguity (Machina & Siniscalchi 2014). We follow Etner, Jeleva & Tallon (2012; p.234) who distinguish between risk and ambiguity as "Uncertainty or ambiguity is then meant to represent 'non-probabilized' uncertainty – situations in which the decision maker is not given a probabilistic information about the external events that might affect the outcome of a decision – as opposed to risk which is 'probabilized' uncertainty.". A full discussion on this issue is beyond the scope of this introduction but see Trautmann & van de Kuilen (2015), Etner, Jeleva & Tallon (2012) and Camerer & Weber (1992) for comprehensive reviews on ambiguity.

are known) and ambiguity (where the probabilities associated with the outcomes are unknown).

The aim of this dissertation is to jointly examine the impact of strategic and scientific uncertainty in SDs on individual decision-making. This is important for several reasons. First, a wide-variety of environmental problems comprise of both strategic and scientific uncertainty. Therefore, it informs policy-makers about how uncertainty affects environmental problems such as over-harvesting and what kind of interventions will be useful in overcoming these problems. For environmental policy to be successful, it needs to account for how individuals cope with uncertainty (Fulton et al. 2011; Wilson 2002). Second, this dissertation addresses a major gap in the existing body of experimental economics literature on SDs[3] because it has overwhelmingly focused on the impact of strategic uncertainty whereas scientific uncertainty has remained relatively under-explored (Budescu, Suleiman & Rapaport 1995).

Scientific uncertainty is of central importance in environmental economics (Pindyck 2007), however, a large part of scholarship on SDs (such as common-pool resources) has neglected this aspect (Suleiman 2004). It has analyzed individual behavior in *deterministic* settings, that is, where all the relevant elements of the environment, such as the number of users, size of the resource, regeneration rate, relevant pay-offs, etc. are all known with certainty (Apesteguia 2006). Moreover, even when scientific uncertainty

[3] Economics indeed has a vast literature on both SDs and decision-making under uncertainty but it has mostly analyzed these two issues in isolation. This trend is now changing, see Botelho, Dinar, Pinto & Rapaport (2015) and citations within. However, social psychologists have been working on uncertainty in SDs for quite some time and have produced a large body of literature on it (Van Lange et al. 2013; de Kwaadsteniet et al. 2007)

in SDs is introduced, it is done so in the form of risk[4] (Botelho et al. 2014; Barrett & Dannenberg 2012; Dickinson 1998; Walker & Gardner 1992). Therefore, investigating the impact of different types of uncertainty in SDs, not only informs policy, but also pushes the frontiers of our scientific knowledge.

I rely on laboratory experiments to examine uncertainty in SDs. This methodology is well-suited to analyze this issue because it allows me to manipulate the type of uncertainty and the SD in a controlled manner, thus, avoiding confounds. However, as with any research methodology, there are strengths and weaknesses associated with laboratory experiments. [5] One purported weakness is that laboratory experiments 'unrealistic' and offer very limited external validity. Siakantaris (2000) argues that they are uninformative about the real-world, or at the very best, useful for understanding market auctions. The empirical evidence refutes such an assertion. Laboratory experiments have contributed immensely to our understanding of environmental economics (Cherry, Kroll & Shogren 2007; List 2007). More specifically, these experiments have provided invaluable policy insights for tackling environmental SDs such as common-pool resources and localized public goods (Cárdenas et al. 2017; Ostrom 2006; Cummings, Holt & Laury 2004).

1.2 Dissertation Outline

This dissertation is comprised of five chapters, of which this introduction is the first. The second chapter is a literature review of experimental studies of SDs.

[4] Ambiguity or "hard uncertainty" has been examined in experiments pertaining to environmental policy, but mostly in non-strategic settings (Blackwell, Grijalva & Berrens 2007), however, Dannenberg et al. (2015) is an exception. It explores the impact of an ambiguous threshold on the provision of public goods.
[5] For a detailed review of experimental methodology in economics, including its philosophical underpinnings, see Guala (2005).

My third chapter, *Uncertainty and Intentions in a Threshold Public Good*, investigates the impact of uncertain benefits on the voluntary (or private) provisioning of a threshold public good such as a dyke to prevent flood-damages. It makes a novel contribution to the literature on uncertain benefits in threshold public goods (McCarter, Rockmann & Northcraft 2013; Barrett & Dannenberg 2012; Van Dijk et al. 1999) by examining the uncertainty emerging from various sources. For instance, the benefits from building a dyke to prevent flood-damages are uncertain because of the frequency and intensity of floods (natural or environmental source of uncertainty) and also because of the engineers who built it, if they did a good job, the benefits will be high and vice-versa (human or intentional source of uncertainty). However, the existing studies have only examined the environmental source of uncertainty, and have neglected the intentional source of uncertainty. Whereas my chapter includes both these kinds of uncertainty. We find that contributions to the public good are robust to various types of uncertainty on the return.

The fourth chapter, *Risk and Ambiguity in Threshold Common Pool Resources* is a test of a theory developed by Aflaki (2013). To the best of my knowledge, this is the first experimental study of ambiguity in a threshold common-pool resource whereas earlier work only examined risky thresholds in common-pool (Botelho *et al*. 2014; Gustafsson, Biel & Gärling 1999; Budescu et al. 1995; Rapoport and Suleiman 1992). I find that contrary to the theoretical predictions, ambiguity on the threshold leads to a higher likelihood of the resource being destroyed relative to when the threshold.

The fifth chapter, *Common-Pool Resources under Threshold and Group Size Uncertainty*, examines the impact of group size uncertainty on withdrawals from a common-pool resource which also marked by threshold uncertainty. My experimental design captures a wide-range of settings, where the users of a resource face uncertainty on two dimensions, one is that they do not know the exact size of the resource and the other is that they do not know how many other users are out there. The key finding is that the presence of group size uncertainty reduces withdrawals from the resource, but only when the threshold uncertainty is low. This highlights the joint impact of threshold and group size uncertainty on withdrawals decisions.

We now turn to our second chapter which reviews the relevant literature pertaining to SDs.

CHAPTER 2

UNCERTAINTY IN SOCIAL DILEMMAS: LITERATURE REVIEW

2.1 Introduction

A social dilemma refers to any situation where the interests of the individuals are at odds with those of the group. A wide-variety of phenomena can be classified as social dilemmas, ranging from the pressing matter of tackling global climate change to the more mundane affair of graduate students raising money for a common coffee-maker for their lab. Given the importance and pervasiveness of social dilemmas, they have been a subject of extensive inter-disciplinary inquiry. Laboratory experiments have been used in social science, psychology, political science and economics to better understand social dilemmas. A robust finding from the research on social dilemmas is that humans cooperate a substantially more than predicted by economic theory (Sell & Reese 2007). The purely self-interested *Homo-economicus* as a good representative of actual human behavior does not stand up to empirical scrutiny. Which in turn raises the question, what facilitates or deters cooperation? Much of the research on social dilemmas seeks to answer this very question.

Discussions on social dilemmas can be traced as far back as to Plato and Aristotle (as cited in Kollock, 1998) but the origin of the present scholarship on social dilemmas is much more recent. According to Kopelman, Weber & Messick (2002), the rigorous analysis of social dilemmas can be attributed to the path-breaking work, *Theory of Games and Economic Behavior* (1944) by von Neumann and Morgenstern. The theoretical apparatus of game theory enabled social scientists, particularly social psychologists and economists, to model social interdependence for both zero-sum and non-zero-sum games.

A large body of empirical work followed which identified a plethora of factors responsible for enhancing or deterring cooperation in social dilemmas such as the social value orientation of an individual, the ability to communicate with others, the option to monitor and punish participants, framing of the dilemma, priming of the subjects amongst others. For an overview of the literature on social dilemmas, see Van Lange, Joireman, Parks & Van Dijk (2013), Weber, Kopelman & Messick (2004), Kopelman *et al.* (2002), Kollock (1998), Komorita & Parks (1994), Messick & Brewer (1983) and Dawes (1980), while the purpose of this chapter is to focus on the research exploring uncertainty in social dilemmas.

A common misconception about a social dilemma is that it is identical to the prisoner's dilemma (van Lange *et al.* 2013). This mistaken equivalence can be partly attributed to the early formal definitions of social dilemmas which made 'free-riding is the dominant strategy' a defining property of a social dilemma. For instance, Dawes (1980), identifies two features which characterize a social dilemma – (i) an individual receives a higher pay-off by not cooperating, irrespective of what others do; (ii) if all individuals choose to not cooperate, then they all receive a lower pay-off than if they had all chosen to cooperate. The definition in Dawes (1980) is inadequate because it only describes the prisoner's dilemma whereas social dilemmas encompass a broader class of dilemmas. Social dilemmas are better understood as a setting where at least one *deficient equilibrium* exists (Kollock 1998). It is deficient because it is marked by an inefficient outcome and it is an equilibrium because none of the players individually have an incentive to change their behavior. This revised definition of social dilemmas admits a variety of dilemmas including the three of the most widely studied ones – the prisoner's dilemma, the assurance game and the chicken game (van Lange *et al.* 2013; Kollock 1998).

2.2 Uncertainty and Social Dilemmas

Broadly speaking, there are two possible types of uncertainty in a social dilemma - strategic and environmental. Strategic (or social) uncertainty refers to uncertainty which is a consequence of not knowing *ex ante* what other players are going to do. Whereas environmental (or scientific) uncertainty refers to uncertainty regarding the characteristics of the dilemma.[6] Environmental uncertainty includes (but is not limited to) uncertainty about the following – the size of the resource, the threshold, the returns from cooperation, the size of the group, the distribution and size of the endowments. Early discussion on strategic and environmental uncertainty can be traced to Messick, Allison & Samuelson (1988) and Suleiman & Rappaport (1988).

The first type of uncertainty, that is, strategic uncertainty is always present in a social dilemma. The reason being that by definition a social dilemma involves interaction with other agents and one does not know beforehand what actions would be undertaken by others. The second type of uncertainty, that is, environmental uncertainty may or may not exist, but it is fairly common in real-world social dilemmas (Barrett & Dannenberg 2012; de Kwaadsteniet, van Dijk, Wit & de Cremer 2006).

Despite the vast scholarship on social dilemmas, an important empirical feature of social dilemmas, environmental uncertainty remains understudied (Van Dijk, Wit, Wilke

[6] It should be noted that in many studies the terms, risk, uncertainty and ambiguity are used inter-changeably. For our purposes, risk and uncertainty, refer to the case where subjects are aware of the objective probabilities associated with the possible outcomes. While ambiguity refers to those settings where subjects do not know the objective probabilities associated with the possible outcomes.

& Budescu 2004). This gap is particularly striking because of the pervasiveness of uncertainty in real-world social dilemmas and the challenges it poses for policy-makers (Wilson 2000). My dissertation seeks to bridge this gap and to contribute to the limited but growing literature on environmental uncertainty in social dilemmas, particularly in the framework of public goods and common-pool resources. The following discussion briefly highlights the various dimensions on which there might be uncertainty – the pay-offs from cooperation, the number of other players (or group size), the amount of contributions (the threshold) required to attain the goal, the size of the resource, and the regeneration rate of the resource.

2.2.1 Uncertainty in Payoffs

In most of the experiments, the pay-offs (or benefits) from cooperating are known with certainty to the subjects, but in the real-world, the benefits are rarely known with such precision. For instance, a city invests in improving air quality. Cleaner air can have several benefits. It might lead to better health outcomes for the residents, and it might increase property values. But the exact magnitude of these benefits would be difficult to assess beforehand. A number of studies examine the impact of uncertainty in the pay-offs in the framework of public goods.

In a public goods setting, the uncertainty in the pay-offs has been implemented in two ways. First, the return from the public good, the marginal per capita return (MPCR) in a linear public good (VCM) or the step-return (SR) in a threshold public good (TPG) might be uncertain. This is akin to a setting where the agent knows that the public good is beneficial but the exact benefit is unknown. For instance, the benefit of contributing to public radio depends on if the programs produced match the interests of the contributor.

If programs produced match a lot, then the benefit is high and vice-versa. But of course, the exact choice of programs that will be produced is not known to the contributor beforehand. Second, the MPCR (or SR) is known with certainty but the whether the agent will receive the benefit from the VCM is uncertain. In this setting, the agent knows the exact benefit from the public good but is unsure of whether she will benefit from the public good. Suppose an agent contributes to building a local public library. The agent knows the benefit she will derive from the library. But in case she has to move to another location, she will not benefit from the library.

Most of the studies examine uncertainty on the MPCR and SR. Théroude & Zylbersztejn (2017) compare homogeneous and heterogeneous uncertainty in MPCRs. Under homogeneity, all subjects will earn according to the same MPCR which is drawn from a distribution. The uncertainty here is perfectly correlated. Whereas under heterogeneity, each subject will have her MPCR drawn separately from the distribution. Here the uncertainty is perfectly uncorrelated. The find that contributions do not differ under homogeneous or heterogeneous uncertainty. Boulu-Reshef, Brott & Zylbersztejn (2016) also have a design where there is heterogeneous uncertainty about the MPCR. They too do not find any significant difference in contributions when the MPCR is uncertain or when it is known with certainty to the subjects. Fischbacher, Schudy & Teyssier (2014) find that uncertainty in the MPCR impacts subjects differentially. Those who are classified as ‘selfish’ do not respond to the uncertainty in the MPCR. While responses of ‘conditional cooperators’ vary considerably. Levati & Morone (2013) and Levati, Morone & Fiore (2009) find that variance of the MPCR is of critical importance.

If the lowest value of MPCR is such that the sum of MPCR across subjects can fall below 1, then contributions decline significantly.

In TPGs, uncertainty about the SR does not reduce contributions. Barrett & Dannenberg (2012) and van Dijk et al. (1999) find that uncertainty in SR does not reduce contributions. McCarter, Rockmann & Northcraft (2010) also find that uncertainty in the SR does not reduce contribution as long as the lowest possible return from the TPG exceeds the threshold. They find that subjects are sensitive to the variance in returns, if the lowest possible return can fall below the threshold, then contributions decline. Marks & Croson (1999) do not make the SR uncertain but they provide incomplete information to the subjects. The subjects only know their own return but not those of others. They find that contributions are not significantly different under complete and incomplete information.

There are two papers in which the MPCR is known but there is uncertainty about whether the subjects will receive the return or not. Gangadharan & Nemes (2009) run several treatments where they introduce uncertainty on both the public and private goods. The main result is that when there is uncertainty on the public good then contributions to the public good are lower than when the uncertainty is on the private good. Dickinson (1998) finds that uncertainty about provision reduces contributions but only at the individual level, not at the group.

Although most of the experiments implement uncertainty in the form of risk (known probabilities), Björk, Kocher, Martinsson & Nam Khanh (2016), Levati & Morone (2013) and Gangadharan & Nemes (2009) explore ambiguous MPCRs. Björk et al. (2016) do not find significant differences in contributions when the MPCR is certain or risky or ambiguous. They use both the strategy method and a ten-period repeated game to disentangle the impact of strategic from environmental uncertainty, and find that uncertain MPCRs do not reduce contributions either in the strategy method (one-shot game) or the repeated game. Levati & Morone (2013) also find that ambiguous MPCRs do not reduce contributions relative to both risky and certain MPCRs. Whereas in Gangadharan & Nemes (2009), ambiguity does reduce contributions. But in their setup, the MPCR is not ambiguous, rather the chance of receiving the return is ambiguous.

2.2.2 Group Size Uncertainty

In a number of real-world settings, the relevant group size is not known with precision. How many other resource users are out there? How many others can contribute to the public good? But in most of the experimental studies, the subjects know the exact size of the group.

Hillenbrand & Winter (2017) develop a theoretical model of behavior in a volunteer's dilemma under group size uncertainty. The theoretical prediction is that cooperation will increase under group size uncertainty and their experimental evidence supports the prediction. In the case of public goods, group size uncertainty also increases cooperation. Kim (2016) finds that contributions are higher under group size uncertainty relative to a known group size. Similarly, in a common-pool resource (CPR), the destruction of the resource is lower under group size uncertainty (Au & Ngai 2003). But in the case of a threshold public good, group size uncertainty reduces provision (Au 2004; Au, Chen & Komorita 1998). But Ioannou & Makris (2015) find that cooperation does not decline in a coordination game under group size uncertainty. de Kwaadsteniet (2008) find that the impact of group size uncertainty on subjects is heterogeneous. They classify subjects according to their Social Value Orientation (SVO) and find that under group size uncertainty, those who are pro-social (more cooperative) withdraw less from a CPR than those who are pro-self (more competitive). But when the group size is certain, both these types withdraw the same amount from the CPR.

2.2.3 Threshold Uncertainty

Threshold uncertainty can be present in public goods or CPRs. In the case of public goods, the threshold represents the cost of the project. While in the case of CPR, the threshold refers to the size of the resource. The public good is only provided if the sum of the contributions are equal to the threshold. For instance, a new stadium will be built, only if a pre-specified amount is raised for it. But in a number of settings, the threshold is not known with certainty. For instance, in a dictatorship, protestors know that if their enough people, the dictatorship will be toppled. But what constitutes ‘enough’? Here the protestors face threshold uncertainty. Several experimental studies examine the impact of threshold uncertainty on cooperation.

Barrett & Dannenberg (2012) compare the impact of threshold and pay-off uncertainty in a TPG. They find that it is threshold uncertainty that deters contributions but uncertainty in pay-offs does not do so. McBride (2010) also finds that uncertainty in the threshold reduces the contributions which runs contrary to the theoretical prediction of McBride (2006) that if the TPG is ‘sufficiently valuable’, then an increase in uncertainty will increase contributions to the TPG. Dannenberg et al. (2015) examine both risky and ambiguous thresholds. They find that contributions while both risky and ambiguous thresholds reduce contributions, ambiguous thresholds do so much more. The negative relationship between the threshold uncertainty and contributions is not universal.

Suleiman, Budescu & Rapoport (2001) find that contributions are depend not only to the variance of the threshold but interact with the mean value of the threshold. When the mean value of threshold is high, contributions are not significantly different, whether the uncertainty on the threshold is high or low. But when the mean value of the threshold is low, threshold uncertainty does not deter contributions. Instead contributions increase as the threshold uncertainty increases. While Wit & Wilke (1998) find that contributions decline the most when both threshold and strategic uncertainty increase.

A large body of literature examines the impact of threshold uncertainty in CPRs (Budescu, Au & Chen 1997; Suleiman, Rapoport & Budescu 1996; Budescu, Rapoport & Suleiman 1995, Rapoport, Budescu, Suleiman & Weg 1992, Budescu, Rapoport & Suleiman 1992, Rapoport & Suleiman 1992 and Budescu, Rapoport & Suleiman 1990). A robust finding of all these studies is the positive relationship between the threshold uncertainty and withdrawals from the resource. The withdrawals often significantly exceed the socially-optimal level when the threshold uncertainty is high. Another robust finding pertains to the order of play – simultaneous or sequential. In simultaneous play all subjects withdraw at the same time whereas in the sequential case, subjects withdraw in a pre-specified order. In the sequential case, there is a strong negative relationship between the position of the subject and the amount withdrawn. Those who get to withdraw first, consume the most. There are several extensions to this set of studies. Budescu, Rapoport & Suleiman (1990) examine the impact of pay-off asymmetry (where some subjects earn more than others from the same amount of withdrawals) in a CPR with threshold uncertainty. They find that subjects seek to equalize earnings, so ‘high-earner’ withdraw less. Rapoport & Au (2001) introduce the institutions of penalty and bonuses. They find that withdrawals are reduced by both penalties and bonuses, but penalties are more effective in reducing withdrawals. Maas et al. (2017) introduce taxes and fines to limit withdrawals from a CPR with threshold uncertainty. They find that taxes are more effective in reducing withdrawals, but fines also reduce withdrawals.

2.2.4. Regeneration Uncertainty

Common-pool resources are used over time. The amount consumed today impacts how much of the resource will be available tomorrow but this relationship is not always deterministic. There is considerable uncertainty about the rate at which resources regenerate (Wilson 2000; Hine & Gifford 1996). Few studies have incorporated environmental uncertainty in dynamic CPR games. In Botelho, Dinar, Pinto & Rapoport (2014), subjects participate in a CPR game which can continue for a maximum of ten periods (the resource depletes at the end of ten periods). Subjects are placed into a group of five and make withdrawals from the CPR. The subjects know the safe level of withdrawal. If the sum of withdrawals is less than or equal to the safe level, then resource survives with certainty, and the subjects move into the next period. They also know the destruction level of withdrawal. If the sum of withdrawals is greater than the destruction level, then resource is destroyed with certainty, and the game terminates. But if the sum of withdrawals falls between the safe and destruction level, then the resource depletes probabilistically. The closer the withdrawals are to the destruction level, the more likely it is that the resource will be depleted. Botelho et al. (2014) find that subjects withdraw amounts above the socially optimal level. They vary the values of the safe and destruction levels and find that withdrawals are higher when the difference between the safe and destruction level is greater.

Walker & Gardner (1992) is similar to Botelho et al. (2014) in that subjects know the safe level of usage of the CPR. Subjects participate in a game of 20 periods. They have two different safe levels. One is rather extreme where the safe level is set at zero. Any usage of the resource leads to the possibility of the destruction of the resource. But destruction of the resource is positively linked to the consumption of the resource (which is framed as an ‘investment’). The other safe level is a positive amount. If the consumption of the resource is less than or equal to the safe level, the resource survives with certainty and the subjects move on to the next period. Walker & Gardner (1992) find that sub-optimal consumption of the resource across both safe levels.

CHAPTER 3

UNCERTAINTY IN RETURNS IN THRESHOLD PUBLIC GOODS

3.1 Introduction

Providing public goods through voluntary contributions has become increasingly important and common-place (Cadsby et al. 2008). Researchers have identified a positive relationship between contributions and the return from a threshold public good (TPG), a public good which is only provided if the sum of contributions equals or exceeds the threshold, usually the cost of provision (Cadsby et al. 2008; Croson and Marks 2000; Cadsby and Maynes 1999). In these studies, the benefit or return from the TPG is known with certainty. In most real-world settings, the benefit or return from the TPG is uncertain, with the uncertainty stemming from either nature or intentional action. For instance, the uncertain return from building a dyke may be affected by nature (the frequency and intensity of floods) or intentional action (the effort exerted by the project manager or construction team). For policy-makers, it is important to understand whether and how these types of uncertainty affect voluntary contributions.

TPGs are particularly important because both provision and non-provision are Nash equilibria (Cartwright and Stepanova 2015). The Nash equilibrium concept is silent on equilibrium selection (Croson and Marks 2000). Feige's (2015) theoretical model identifies a positive relationship between the step-return, which is the ratio of the social return to the threshold[7], and the probability of a positive voluntary contribution (or cooperative-choice). The model predicts that, for risk-neutral agents, the probability of

[7] For example, if there is TPG with a threshold of $100 and there are 5 agents who each receive $50, making the social return is $250, the step-return will be 2.5 (social return / threshold).

making a cooperative-choice when the step-return is certain will be the same as when it is uncertain as long as the expected values are equal.[8] Our experiment provides some evidence supporting these predictions.

More specifically, we design an experiment which tests the impact of an uncertain step-return, either from nature or from intentional action, on the voluntary provision of TPGs. Theoretical and experimental evidence suggests that uncertainty in the benefits from public goods can potentially increase voluntary provision (Aksoy and Krasteva 2018; Boucher and Bramoullé 2010). To the best of our knowledge, this study is the first to examine step-return uncertainty arising from sources other than nature (McCarter et al. 2010; van Dijk et al. 1999), introducing uncertainty based on intentional actions. Prior research suggests that the intentions of an economic agent affect how other economic agents respond to incentives and behavior (e.g., Charness and Levine 2007, Cox and Deck 2006). As the return from many TPGs may be affected by intentional action, with project managers or other individuals contributing costly effort, it is important to understand whether and how the impact of intentions extends to this setting.

We find a strong, positive relationship between the return and contributions. We do not find evidence that uncertainty (caused either by nature or intentional actions) affects either the probability of contributing or the amount contributed. These findings are consistent with Feige's model (2015). The next section of the paper reviews the related literature, Section 3.3 presents the theoretical framework, Section 3.4 describes the experimental design, Section 3.5 discusses the results and the final section is the conclusion.

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[8] For risk-averse (seeking) agents, the probability of making a cooperative-choice is lower (higher) with uncertain step-return.

3.2 Related Literature

Our study connects distinct two strands of literature: uncertainty in return from public goods and role of intentions in games, which we briefly review here.

3.2.1 Uncertain Returns in Public Goods

The impact of uncertainty in return has been primarily been examined in the case of linear public goods or voluntary contribution mechanism (VCM) but not so much in the case of TPGs (Fischbacher, Schudy & Teyssier 2014; Levati & Morone 2013; Levati, Morone & Fiore 2009; Gangadharan & Nemes 2009).[9] Several studies analyze the impact of varying the return in a deterministic setting (Cadsby et al. 2008; Croson & Marks 2000; Cadsby & Maynes 1999) and find a positive relationship between the return from the TPG and contributions to it. Whereas in our study we test the impact of uncertain return (with varying values) on contributions to the TPG.

The closest paper to our study is McCarter, Rockmann & Northcraft (2010) where they examine the impact of uncertain returns across different values of the return. But they change the return from the TPG by varying the threshold instead of directly changing the return from the TPG. Manipulating the threshold to vary the return is problematic.[10] If higher contributions are observed when the threshold is low, it is not necessary that the high return is increasing contributions. Whenever an agent contributes to a TPG, there is a possibility that the threshold is not met, leading to a loss of the

[9] For TPGs, both the theoretical and experimental literature has primarily focused on the uncertainty in the threshold (Dannenberg et al. 2015; McBride 2010; Barbieri & Malueg 2010; McBride 2006; Suleiman 1997).

[10] But it is not a serious concern for McCarter et al. (2010) because they are interested how the variance in the return (while keeping the expected return constant) impacts contribution, rather than how the change in the return impacts contribution.

contribution. If the threshold is low, an agent can make a low contribution and expect the threshold to be met. Similarly, if the threshold is high, an agent will have to make a high contribution for attaining the threshold. So, in case of non-provision with a high threshold, the loss will be higher because the agent contributed a higher amount. A low threshold reduces the amount the agent might lose, thereby, making it less 'risky' to contribute (Cartwright & Stepanova 2015; Cadsby et al. 2008). Therefore, changing the threshold can increase contributions through two channels: i) change in return ii) change in the risk associated with contributing. Our experimental design avoids this pitfall, by directly changing the return from the TPG, rather than changing the threshold. We thereby are able to provide a more direct test of the impact of uncertainty in returns on contributions than McCarter et al. (2010).

The main result from McCarter et al. (2010) is that contributions to the TPG are not lower in the presence of uncertainty as long as the lowest possible return from the TPG is greater than the cost (or threshold). In other words, if the lowest possible step-return is greater than 1, then contributions are not significantly reduced. But if the variance in the step-returns is such that the lowest possible step-return is less than 1, then even if in expectation the return exceeds the cost, the contributions to the TPG are significantly reduced.

van Djik et al. (1999) also find a similar result to McCarter et al. (2010) that uncertainty in the return does not reduce contributions to the TPG. But they only look at one value of the step-return, whereas in our study we are looking at various values of the step-return.

3.2.2 Role of Intentions in Games

A number of experiments find that intentions play a role in economic decision-making (Falk et al. 2008; Sutter 2007). For instance, low offers are more likely to be rejected in an Ultimatum Game if the offer was sent by another person rather than a computer (Zituni & Dendonfer 2013). Similarly, in a Trust Game, higher reciprocity is observed when the amount sent is chosen by another player, rather than being chosen by a computer (Cox & Deck 2006). In a stochastic Wage-Effort Game, employees respond to the intended wage offered by the employers, rather than the actual wage received after a positive or negative stochastic shock (Charness & Levine 2007). However, to the best of our knowledge, no study examines the impact of intentions on contributions to a TPG, in a setting where a third-party (such as a project-manager) can alter the returns from the public good. Examining the role of intentions is particularly important because the uncertainty in returns from a TPG occurs not only because of nature, but also because of actions of other humans. Apart from improving our understanding of the determinants of contributions to TPGs, it also contributes to our understanding about where intentions matter, and where they do not.

3.3 Theoretical Framework

The TPG game is one where the public good is provided if the sum of contributions are equal to or greater than the threshold (or cost) but if the sum of contributions is less than the threshold, the public good is not provided. A TPG can be defined in the following manner. There are n agents indexed by $i = [1, \ldots, n]$. Each agent has an endowment, e, from which she can choose to contribute, c_i, to the TPG. The threshold of the TPG is denoted by T. If the sum of contributions by all agents, $\Sigma_{i=1}^{n} c_i$, is equal to or greater than the threshold (T), each agent receives a return (r) from the TPG. Since the return from the TPG to each agent is r, the social return is $n * r$. The standardized way of assessing the efficacy of the TPG is captured by the step-return (SR) (Croson & Marks 2000). It is calculated by dividing the social return $(n * r)$ by the threshold (T).[11] If the sum of contributions is less than the threshold, then the agents receive nothing from the TPG. A TPG game has multiple equilibria. One inefficient equilibrium where all agents contribute zero and multiple possible efficient equilibria where the sum of all contributions is equal to the threshold (Bangoli & Lipman, 1989).

The inefficient equilibrium of the game entails zero contribution by each agent. The efficient equilibria of this game consist of all contribution vectors $\{c_i\}$ which satisfy the following constraints:

$$\text{Efficiency: } \Sigma_{i=1}^{n} c_i = T \tag{1}$$

$$\text{Individual Rationality: } c_i \leq r$$

$$\text{Limited Wealth: } e < T$$

The efficiency constraint means that the TPG is provided and the sum of all contributions are equal to the threshold, that is, there are no excess contributions. The individual rationality ensures that no agent contributes more than the amount she will earn from the TPG. The limited wealth constraint means that a single agent cannot provide the TPG.

[11] Alternative ways of evaluating the efficacy of the TPG exist, e.g. Net Reward, which is the *difference* between the return from the TPG and the threshold. Cadsby et al. (2008) find that SR is the best predictor of provision of a TPG.

In this experiment, there are three types of TPG. The first is the standard TPG with certain returns and serves as the baseline. The second is a TPG with uncertain returns which are determined by nature. The third TPG also has uncertain returns but the return in this TPG can be altered by the project manager at a cost to herself.

The pay-off (π_i) of each agent is as follows

$$\pi_i = e - c_i + g^k \tag{2}$$

Where g is the pay-off from the TPG that agent i will receive from the TPG and $k \epsilon \{C, N, I\}$ refers to the type of TPG returns – certain (C), uncertain because of nature (N) and uncertain where another human-being such as project manager can alter the return, hence, intentions (I) are present. We now describe the three types of TPGs.

Certain Returns TPG pay-off

$$g^C = \begin{cases} 0, & \Sigma_{i=1}^{n} c_i < T \\ r, & \Sigma_{i=1}^{n} c_i \geq T \end{cases} \tag{3}$$

Uncertain Returns - Nature TPG pay-off

$$g^N = \begin{cases} 0, & \Sigma_{i=1}^{n} c_i < T \\ \tilde{r}, & \Sigma_{i=1}^{n} c_i \geq T \end{cases} \tag{4}$$

Where $\tilde{r}$~U$[r^{LOW}; r^{HIGH}]$, that is, $\tilde{r}$, is the realized return from the TPG and it is randomly drawn from a uniform distribution of r^{LOW} (the low amount in the range of returns) and r^{HIGH} (the high amount in the range of returns), such that the expected realized return in the uncertain TPG is equal to the certain return from TPG, $E(\tilde{r}) = r$.

Uncertain Returns – Intentions – TPG pay-off for contributors

$$g^I = \begin{cases} 0, & \Sigma_{i=1}^{n} c_i < T \\ \tilde{r} + a, & \Sigma_{i=1}^{n} c_i \geq T \end{cases} \tag{5}$$

Where a is the amount by which the project manager alters the return to the contributors. The project-manager can either increase ($a > 0$) or decrease ($a < 0$) the returns from the TPG at a cost to herself, or leave it unaltered ($a = 0$) at no cost to herself.

However, there is a limit to which the project manager can alter the returns. The most the project manager can increase the returns from the TPG is equal to the highest possible return from the returns range. So, the returns can be increased at most by $a = r^{HIGH} - \tilde{r}$. Similarly, the most that the project manager can decrease the returns from the TPG is equal to the lowest possible return from the returns range. So, the returns can be decreased at most by $a = r^{LOW} - \tilde{r}$. By limiting the amount by which the project manager can alter the return, the range of returns is made identical to the range of returns in the Nature treatment, $[r^{LOW}; r^{HIGH}]$. We now turn to the earnings of the project-manager.

Uncertain Returns – Intentions – Project Manager Pay-off

$$\pi_{Project-Manager} = \begin{cases} Z, & \Sigma_{i=1}^{n} c_i < T \\ \tilde{r} - 0.5|a|, & \Sigma_{i=1}^{n} c_i \geq T \end{cases} \qquad (6)$$

If the sum of contributions is less than the threshold, the project-manager receives a fixed amount, Z. Whereas if the sum of contributions is less than the threshold, the project-manager receives $\tilde{r}$ which is equal to an amount randomly drawn from $U[r^{LOW}; r^{HIGH}]$. The project-manager has the option to alter the return of the contributors. The cost of altering the return is half the amount of by which the amount of the contributors has been altered. For instance, if the project manager increases the earnings of each contributor by 10 Experimental Dollars (E$), it costs the project manager E$ 5 (= E$10 * 0.5). Similarly, if the project manager increases the earnings of each contributor by 10 Experimental Dollars (E$), it will cost her E$ 5 (= E$10 * 0.5). The cost of altering the returns is the same irrespective of whether the project manager increases or decreases the returns. We now present our predictions which are based on the findings of prior literature.

- *Prediction 1. A TPG with a higher step-return will elicit higher cooperation.*

In their meta-analysis, Croson & Marks (2000) find that the step-return from the TPG positively and significantly increases contributions, while controlling for other experimental design variables such as communication, group size, refunds and rebates. Therefore, we expect higher contributions when the SR is higher.

- *Prediction 2. When the (expected) step-return in the Certain and Nature treatment is equal, cooperation in the TPG in the Certain and Nature treatment will be equal.*

Empirical evidence suggests that uncertainty about the step-return contributions does not reduce contributions to the TPG (Barrett & Dannenberg, 2012; McCarter et al. 2010; Van Dijk et al. 1999). A similar result is found in the case of VCM where uncertainty about the marginal per capita return (MPCR) does not reduce contributions (Théroude & Zylbersztejn 2017; Fischbacher, Schudy & Teyssier 2014).

- *Prediction 3. When the (expected) step-return in the Certain and Intentions treatment is equal, cooperation the TPG are higher in the Intentions treatment.*

We anticipate higher contributions in the intention treatment through two behavioral channels. First, although the return to each contributing agent is identical in both treatment, the social return ($n * E(\tilde{r})$) is different. It is higher in the intentions treatment because $n = 5$, with four contributors and one project-manager whereas in the nature treatment $n = 4$, with only four contributors, and no project-manager. If agents value not only their own return, but also the social return, then the TPG in the intention treatment should also elicit higher contributions. Evidence suggests that contributors care about the social return, distinct from their own individual return (Andreoni 1990).

Second, if the TPG is provided, then expected earnings of the project-manager are higher as compared to non-provision. Since the earnings of the project-manager are higher as a consequence of the actions of the contributors, then the project-manager might reciprocate by transferring some of her earnings to the contributors, that is, $a > 0$, making the return from the TPG higher vis-à-vis the nature treatment case. However, it is possible that the project-manager does not feel obligated to reciprocate. She might (correctly) perceive that the contributors have a private incentive to contribute (higher earnings under provision from the TPG). Therefore, their contributions are not a signal of generosity or trust, hence, need not be reciprocated (McCabe, Rigdon & Smith 2003). But the project-manager might transfer a positive amount for another reason, that is, for improving social efficiency (Charness & Rabin 2002). For every $1 the project-manager transfers, each contributor receives $2, thus, increasing the social return from the TPG by E$8 (E$2 * 4 subjects). Social efficiency is maximized if the project-manager transfers the maximum amount possible, $a = r^{HIGH} - \tilde{r}$.

3.4 Experimental Design

All subjects undertake two tasks. The first task is Certain baseline. The second task is the treatment where the subject faces uncertain returns from the TPG. [12] Half the subjects participate in the Nature treatment while the other half in the Intentions treatment. The experiment follows a mixed design: the certainty on the return varies within-subject (Certain baseline vs. uncertain returns either by Nature or Intentions) while the type of uncertainty, Nature vs. Intentions varies between-subjects. One decision from each task is randomly selected for payment.

3.4.1 Certain Returns – Baseline – Task 1

In the first task, each subject is allocated an endowment of 100 Experimental Dollars (E$)[13] and is randomly assigned into a group of four. The subject chooses to allocate her endowment between a private account and a public account. She keeps all the E$ she allocates to the private account. As for the public account, if the total contribution to it equal to or more than E$ 240, the threshold (*T*), then each member of the group receives a return (*r*), irrespective of their own contribution. The return which is the same for each subject, changes from round to round and is stated clearly on the decision screen. If the total contribution to the public account is less than E$ 240, then each member receives nothing from the public account, irrespective of their contribution. The various

[12] We choose this order where subjects always face the Certainty baseline first and then participate in a treatment with uncertain returns, so as to test the impact of uncertainty on cooperative choices in the strongest manner possible. In a linear public goods game, Stoddard (2015) finds that uncertainty has a negative effect on average contributions when subjects first face certain returns and then uncertain returns. But this negative effect disappears when they first face uncertain returns and then certain returns. This result suggests that if uncertainty were to deter contributions, the effect would be more pronounced when facing the certain task first.

[13] The conversion rate for E$ into US Dollars is set at E$ 15 = USD $ 1.

values of the step-return (SR) and the range of values it could take in the uncertain TPG game are presented in Table 3.1.

The contributions are not refunded in order to make salient the riskiness of contributing (Cartwright & Stepanova 2015; Spencer et al. 2009; Cadsby et al. 2008; Cadsby & Maynes 1999; Marks & Croson, 1998). In the presence of refunds of contributions if the threshold is not met, the no-contributions equilibrium (where all agents contribute zero) ceases to be a strict equilibrium. In case of a refund mechanism, a subject becomes indifferent between contributing zero or a positive amount, even if she expects that the sum of total contributions will be less than the threshold. Whereas in the case of no-refund, subjects strictly prefer not contributing when they expect that the threshold will not be reached. Therefore, if uncertainty deters contributions, it will be more difficult to observe it in the presence of a refund mechanism.

Table 3.1 – Step-return (SR) from TPG

SR – Certain	SR Range -Lower Bound	SR Range -Upper Bound
1.75	1.42	2.08
2	0.75	3.25
2.25	0.92	3.58
2.5	1.67	3.33
2.75	1.5	4
3	2.67	3.33
3.25	2.42	4.08
3.5	3.17	3.83
3.75	2.5	5
4	3.17	4.83

*SR=(N*R)/T; N = no. of agents, R = return to each agent, T = threshold*

3.4.2 Uncertain Returns – Nature Treatment – Task 2

The second task, Uncertain Return task, is identical to the Certain Return task, except that the returns are uncertain $(\tilde{r})$. This means that subjects are informed of the range of possible outcomes (referred to as Returns Range on their decision screen) from the public account. If it is the Nature treatment, then the return is determined by the computer by drawing a random number from the Returns Range. Each number in the Returns Range is equally likely to be drawn because it is a uniform distribution.

3.4.3 Uncertain Returns – Intentions Treatment – Task 2

In the Intentions treatment, the random draw is similar to the Nature treatment but it can be altered by another human being called the Type B player. Each group of four players (called Type A players) are paired with a Type B player. These roles remain constant throughout the treatment. Type A players remain Type A throughout the experiment and the same holds for Type B players. Since groups are randomly formed in each round, the Type B players are also randomly assigned to a group. There is no communication between the Type A and the Type B players.

In each round, the Type B observes a randomly drawn value from the Returns Range. This is the return that the all players, both Type A and B, will earn from the TPG unless the Type B chooses to alter the return. The Type B player can either increase or decrease the return to Type A players at a cost to herself.

For every E$ 1 she spends, it changes the return of each member of the group by E$ 2. Since there are four members in each group, the Type B player can alter the social return by E$ 8 for every E$ 1 she spends. The Type B is not informed whether Type A players crossed the threshold of E$ 240. If they fail to cross the threshold, the Type B player receives a fixed amount of E$ 100. The decision of Type B is unobservable. Type A players do not find out if the Type B player altered the return or left it unchanged. Altering the return is costly to the Type B player, and if she wants to maximize her own earnings, then she will not alter the return from the TPG. If that is the case, then the returns from the Intentions treatment become the same as the returns from the Nature treatment.

After both the tasks are completed, the subjects fill out a non-incentivized survey in which data on demographics and preferences is collected.

3.4.4 Implementation

The experiment was programmed in z-Tree (Fischbacher 2007) and conducted at the Clive. E. Willis Experimental Economics Lab at the University of Massachusetts Amherst in 2015. There were 80 subjects (40 females) recruited through ORSEE (Greiner 2015). Sessions lasted one hour with average earnings of $23.48.

3.5 Results

The TPG game has two symmetric Nash equilibria, one efficient (contributions sump up exactly to the threshold) and the other inefficient (zero contribution). In our experimental design, the efficient symmetric Nash contribution is E$ 60 while the inefficient one is E$0. In Figure 3.1, we present the contributions made to the TPG across treatments. Although we allow for continuous contributions, where subjects can contribute any amount between E$ 0 to E$ 100, we see that the mass of contributions is on the symmetric Nash, E$0 and E$ 60. In Figure 3.2 to 3.4, we further disaggregate the contributions by the step-return for each treatment; Certain, Nature and Intentions. Notice that the same pattern of the mass being on either E$0 or E$ 60 holds for various values of the step-return across treatments. We, therefore, define a cooperative-choice as a contribution equal to or greater than E$60.[14]

[14] Our results are robust to the choice of cut-off point. Selecting E$50 or E$55 does not change our results.

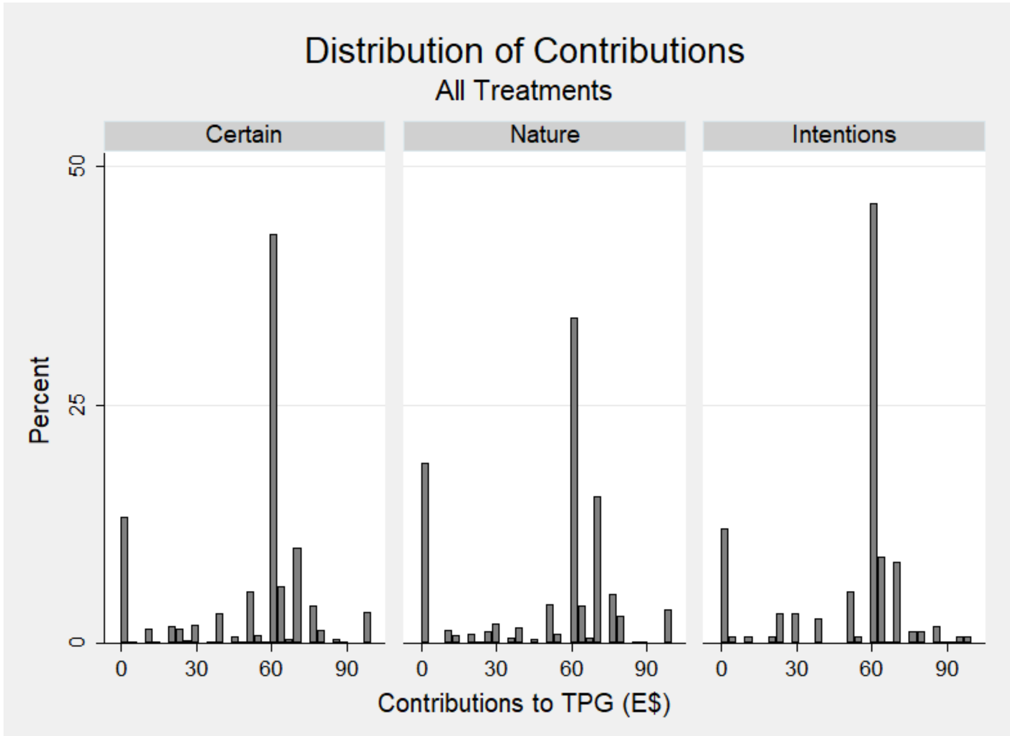

Figure 3.1 – Contributions to TPG across Treatments

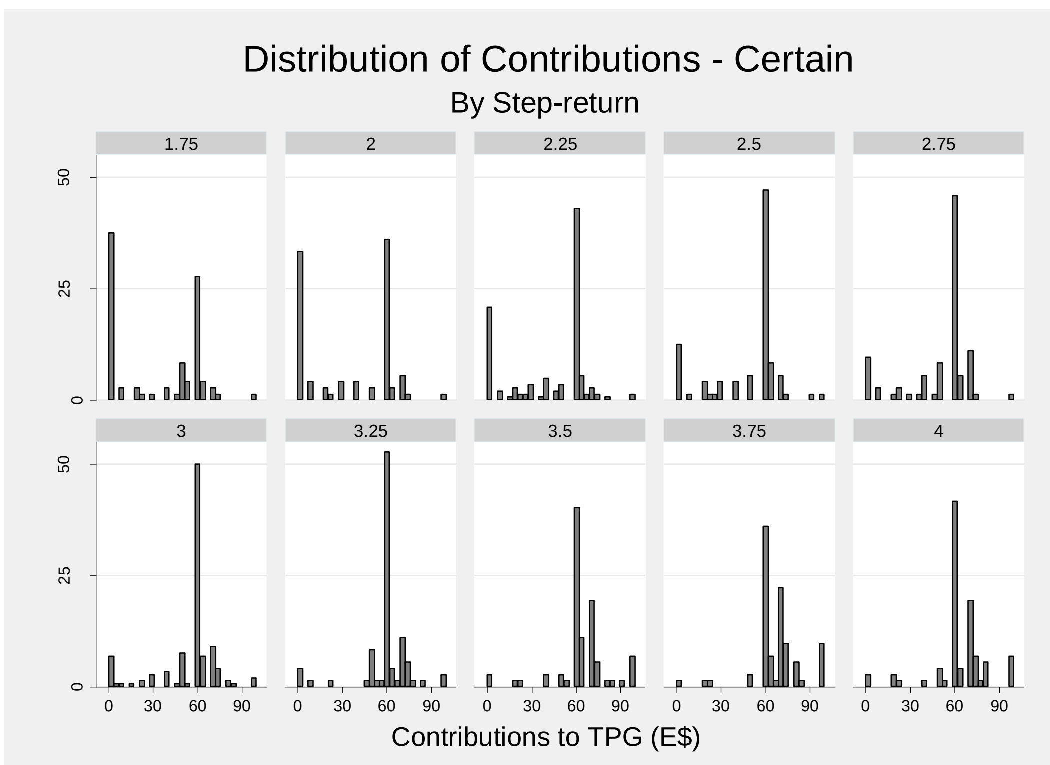

Figure 3.2 – Contributions in Certain across Step-return

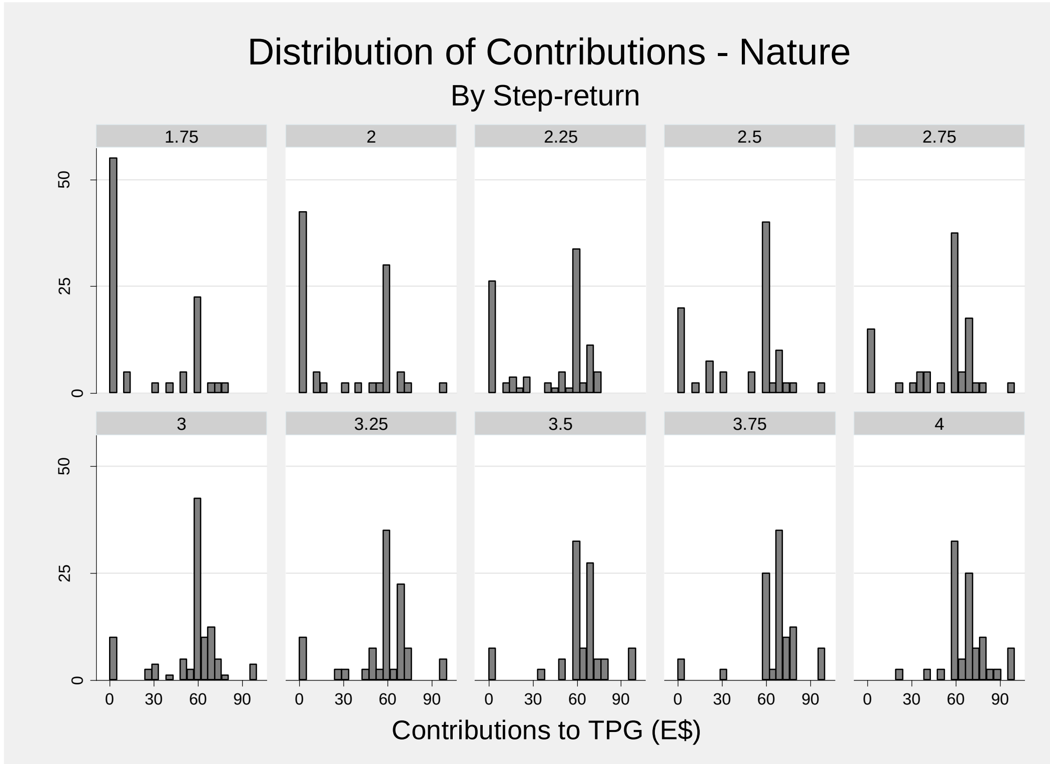

Figure 3.3 – Contributions in Nature across Step-return

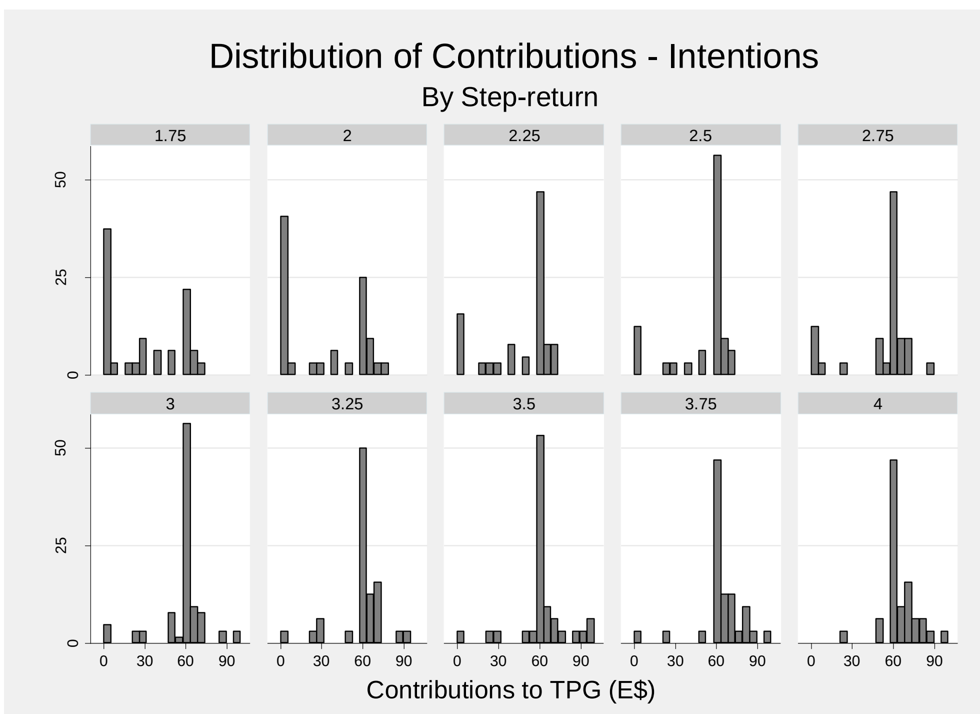

Figure 3.4 – Contributions in Intentions across Step-return

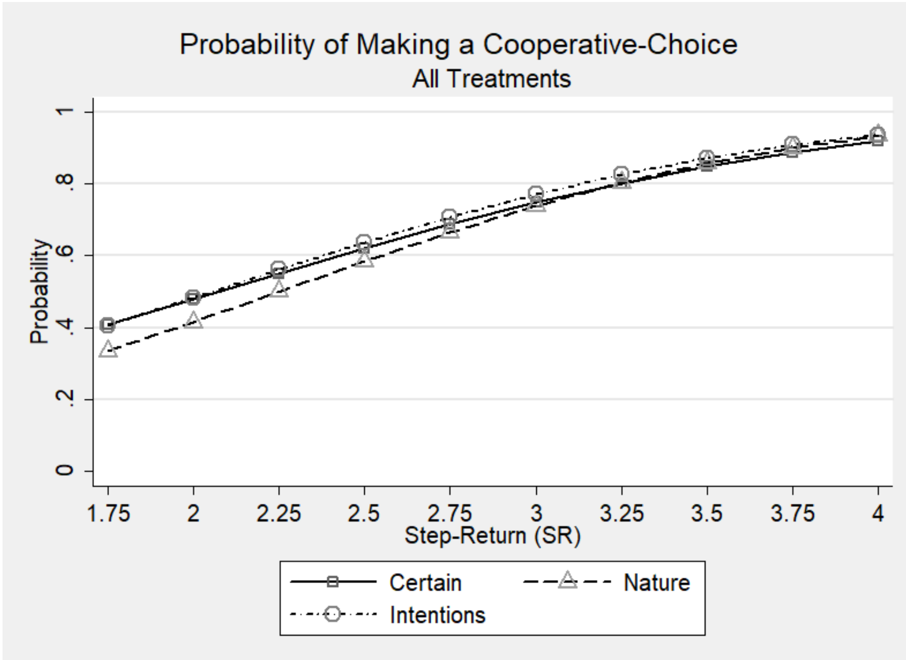

Figure 3.5 – Probability of Making a Cooperative-Choice

We first analyze the impact of a change in the step-return on the probability of making a cooperative-choice. [15] We use a Probit regression to estimate the relationship between the step-return and the probability of making a cooperative-choice. The dependent variable is the probability of making cooperative-choice. In Table 3.2, we present the average marginal effects for the various specifications of the regression. In Model (1), we have the step-return and the treatment dummies as the independent variables. In Model (2), we introduce an interaction effect between the step-return and the treatment dummies. Finally, in Model (3), we include gender and survey measures of

[15] The focus of our experiment is the contribution decision to the TPG but in the Intentions treatment, apart from the contribution decisions of Type A players, the Type B players also made a decision as to alter the return or not from the TPG. Of the eight Type B players in the experiment, seven of them chose not to alter the return.

risk-aversion[16] and willingness to trust others[17]. Model (3) is our preferred specification as it is the most comprehensive. All results are based on Model (3).

Table 3.2 – Probit Regression – Average Marginal Effects

Variables	**Model (1)**	**Model (2)**	**Model (3)**
Step-return	0.242*** (0.020)	-	-
Certain	0.685*** (0.036)	0.686*** (0.037)	0.686*** (0.035)
Nature	0.663*** (0.051)	0.662*** (0.051)	0.653*** (0.049)
Intentions	0.705*** (0.054)	0.704*** (0.053)	0.716*** (0.052)
Step-return#Certain	-	0.229*** (0.023)	0.229*** (0.023)
Step-return#Nature	-	0.267*** (0.029)	0.270*** (0.028)
Step-return#Intentions	-	0.240*** (0.033)	0.233*** (0.032)
Female	-	-	-0.143** (0.065)
Trust Others	-	-	0.116* (0.066)
Risk-aversion	-	-	-0.119 (0.020)
Observations	1728	1728	1728
Pseudo-R^2	0.112	0.113	0.141

*** *p*-value ≤ 0.01; ** *p*-value ≤ 0.05; * *p*-value ≤ 0.1; Standard errors in parentheses. Clustered at subject-level.

In Figure 3.5, the x-axis is the step-return and the y-axis shows the estimated probability of making a cooperative-choice. The average marginal effect of a unit increase in the step-return is to increase the probability of making a cooperative-choice in the Certain baseline by 0.22 (*p*-value 0.00), in the Nature treatment by 0.27 (*p*-value

[16] The survey question is "How willing are you to take risks, in general?" Subjects respond on a scale from 0 to 10.
[17] We measure trust through the General Social Survey question "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?"

0.00), and in the Intentions treatment by 0.23 (*p*-value 0.00). We find a strong positive relationship between the step-return and making a cooperative-choice, giving us our first result. We find support for our first prediction that a higher step-return elicits higher cooperation.

- *Result 1 – There is a positive and significant relationship between the step-return and the probability of making a cooperative-choice in a Threshold Public Goods game.*

We next assess the impact of an uncertain return on the probability of making a cooperative-choice. Using a Probit regression, we estimate the difference in the probability of making a cooperative-choice across treatments. Compared to the Certain baseline, being in either the Nature treatment (average marginal effect -0.03; *p*-value 0.40) or the Intentions treatment (average marginal effect 0.02; *p*-value 0.49), does not significantly impact the probability of making a cooperative-choice.

From the Probit regression, we further examine whether there is a difference between the baseline and treatments at different values of the step-return. Figure 3.5 shows these 95% confidence intervals, with the x-axis showing the step-return and the y-axis showing the estimated difference in the probability of making a cooperative-choice. We do not observe any significant differences in the probability of making a cooperative-choice in either the Nature or Intentions treatment (as the 95 per cent confidence intervals overlap the zero-difference line). Therefore, the probability of making a cooperative-choice is not significantly different when the step-return is uncertain, irrespective of the source of uncertainty. We now have our second result which finds support for our second prediction that cooperation will be equal under Certain and Nature treatment but does not find support for our third prediction that cooperation will be higher under the Intentions treatment.

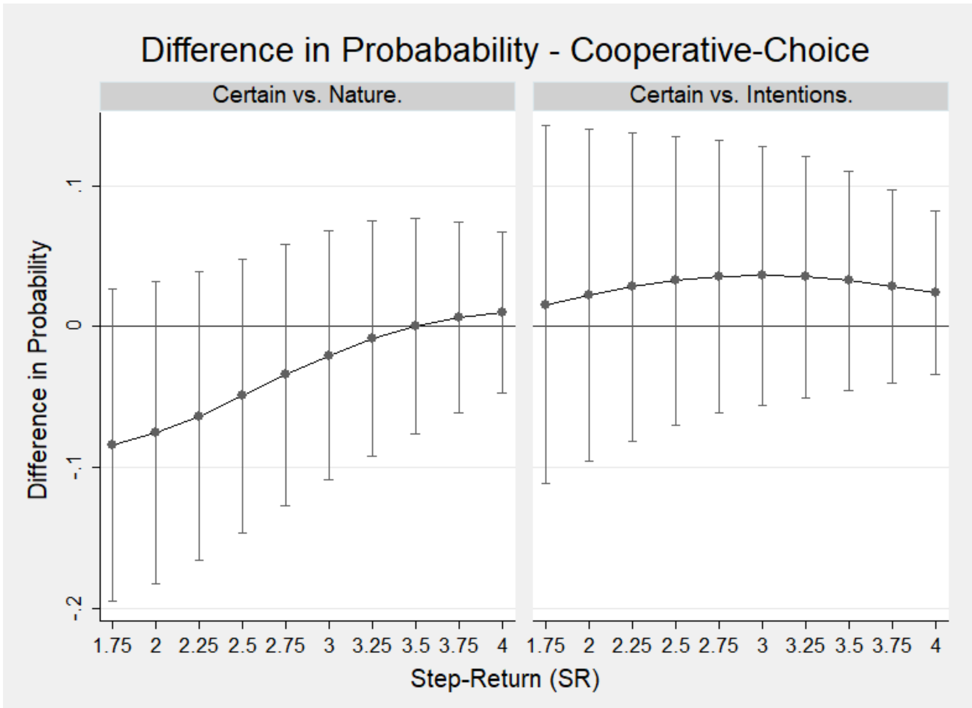

Figure 3.6 – Difference in Cooperative-Choices

- *Result 2 – Uncertainty in the step-return does not significantly affect the probability of making a cooperative-choice in a Threshold Public Goods game.*

Finally, we analyze the impact of subjects' risk-preferences and demographics on making a cooperative-choice. We find that risk-preferences of the subjects, as elicited by the Dohmen et al. (2011) survey question, do not significantly impact the probability of making a cooperative-choice. The average marginal effect of a unit increase on the willingness to take risks scale is -0.012 (*p*-value 0.56) in the Nature treatment and is -0.011 (*p*-value 0.56) in the Intentions treatment. Those who trust others are more likely to make a cooperative-choice, but the difference is only weakly significant. The average marginal effect of trusting others across treatments is reported in Table 3.3.

Table 3.3 – Estimated Difference in the Probability of Making a Cooperative Choice Trusting vs. Non-Trusting Subjects

	Certain	**Nature**	**Intentions**
Difference	0.118* (0.067)	0.117* (0.068)	0.112* (0.062)

*** *p*-value ≤ 0.01; ** *p*-value ≤ 0.05; * *p*-value ≤ 0.1; Standard errors in parentheses.

We find that those subjects who identify as females are less likely to make a cooperative-choice. On average, being female reduces the probability of making a cooperative-choice by 0.143 (*p*-value 0.027). We present the estimated difference in the probability of making a cooperative-choice by gender at each step-return across treatments in Figure 3.7. On the x-axis, we have the various values of the step-return and on y-axis, we present the estimated difference in cooperative-choices. The estimated difference are presented along with the 95 per cent confidence intervals. The solid line marks zero. We see that the intervals do not overlap the zero line when the step-return is low suggesting that the impact of gender is limited when the step-return becomes high.

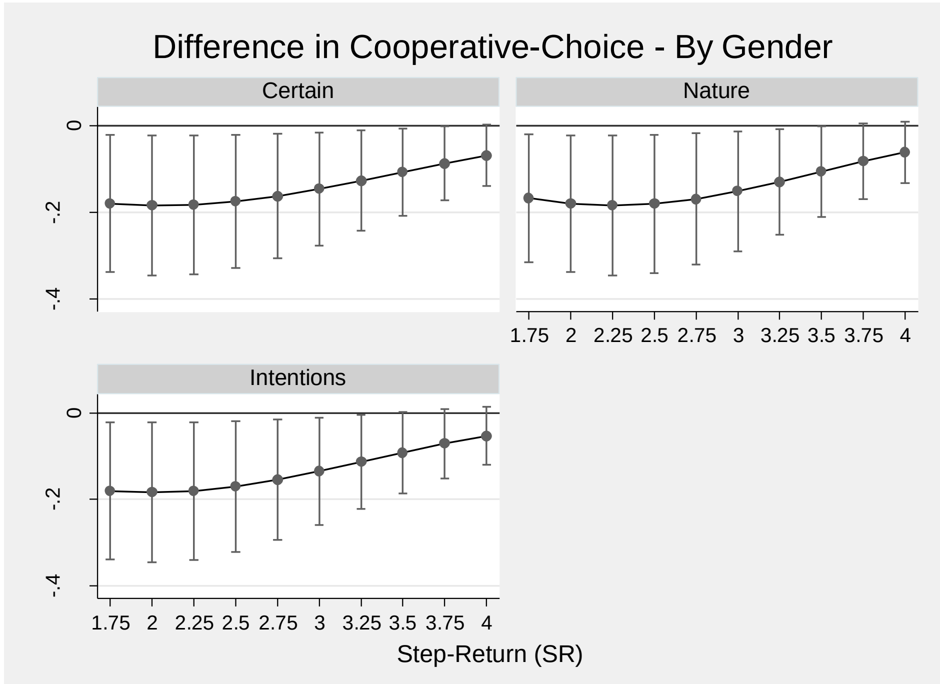

Figure 3.7 – Difference in Cooperative-Choices by Gender

We now have our final results pertaining to preferences and demographics.

- *Result 3a – Risk-preferences do not impact the probability of making a cooperative-choice*
- *Result 3b – Those individuals who trust others are more likely to make a cooperative-choice but this difference is only weakly significant.*
- *Result 3c – Females are significantly less likely to make a cooperative-choice but this is mediated by the step-return. At high values of the step-return the difference becomes weakly significant.*

We now turn to our conclusion.

3.6 Conclusion

We design an experiment to analyze the relationship between the step-return and contributions to the TPG and to examine whether different types of uncertainty on the step-return impact contributions. We confirm prior studies, finding evidence that an increase in the step-return increases the probability of making a cooperative-choice. We also find that uncertainty in returns does not deter the probability of making a cooperative-choice, whether caused by nature or intentional action. Our results highlight the importance of step-return as a determinant of public goods provision. In choosing uncertain projects, policy-makers may want to focus on projects with the highest expected step-return, even if there is uncertainty because of either natural shocks or intentional actions. For future work, scholars should examine other types of uncertainty in the step-return, as our experiment examines only two sources of uncertainty, nature and intentional action of a third-party.

CHAPTER 4

RISK AND AMBIGUITY IN THRESHOLD COMMON-POOL RESOURCES: AN EXPERIMENT

4.1 Introduction

A major challenge for policy-makers is to utilize environmental resources while preventing irreversible damage to them. For instance, overharvesting can lead to collapse of fisheries (Worm 2016; Gaines and Costello 2013), unrestrained withdrawals can cause groundwater depletion (Richey et al. 2015), excessive dumping of waste in water bodies leads to irrevocable damage to marine life (Villarrubia-Gómez, Cornell and Fabres 2018) and uncontrolled deforestation can bring about permanent loss of biodiversity (Nobre et al. 2016). A threshold effect, also referred to as tipping-point or regime shift or point of no return (Lamberson and Page 2012), is present in a wide range of resources. [18] Here we focus on Threshold Common-Pool Resources (TCPRs) which are resources that can be utilized sustainably up to a certain level (the threshold), but face destruction if utilization exceeds the threshold. In many cases, the exact value of the threshold is unknown and this uncertainty about the threshold leads to overharvesting in common-pool resources (Maas et al. 2017) and under-provision of public goods (Dannenberg and Barret 2012; McBride 2010).

Since a number of environmental resources are characterized by ambiguity (Heal and Millner 2017; Lemoine and Traeger 2016; Shaw 2016; Ascough II et al. 2008), it is

[18] The database of the Resilience Alliance and Santa Fe Institute (2004) has over a 100 examples of threshold effects observed in ecological and socio-ecological systems. Muradian (2001) lists several ecosystems and resources marked by uncertain thresholds.

important to understand individual behavior in ambiguous TCPRs. Aflaki (2013) presents a theoretical model which predicts that if resource users are ambiguity-averse, then an ambiguous TCPR is less likely to be overharvested than a risky TCPR. [19] The policy implication which follows is that resource users should receive *less* information about the threshold because the resource is more likely to survive if the threshold is ambiguous (where the probability distribution is unknown) as opposed to risky (where the probability distribution is unknown).

Aflaki (2013) shows that this prediction holds whether exceeding the threshold leads to full or partial destruction of the resource. This theoretical prediction is particularly worthy of empirical verification because proper information dissemination and effectively communicating scientific uncertainty is seen as an important strategy for resource management (Rotherham et al. 2011; Sigel et al. 2010) and ambiguity-aversion has been documented in the population (Dimmock, Kouwenberg and Wakker 2015; Akay et al. 2012).

We design a laboratory experiment to test the key predictions of the Aflaki (2013) model; a non-monotonic relationship between withdrawals from the resource and the range (the difference between the highest and lowest possible values of the threshold), an ambiguous TCPR reduces the probability of crossing the threshold as compared to a risky TCPR, and an increase in the range of the threshold increases the probability of crossing the threshold. A laboratory experiment is well-suited to test these claims because it

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[19] Although risk is well-defined in the literature, there is still considerable debate about the precise definition of uncertainty and ambiguity (Machina and Siniscalchi 2014). We follow Etner, Jeleva and Tallon (2012; p.234) who distinguish between risk and ambiguity as "Uncertainty or ambiguity is then meant to represent 'non-probabilized' uncertainty – situations in which the decision maker is not given a probabilistic information about the external events that might affect the outcome of a decision – as opposed to risk which is 'probabilized' uncertainty."

allows us to exogenously vary the range of the threshold, the type of uncertainty (risk or ambiguity), and the type of destruction (full or partial).

The Aflaki (2013) model incorporates ambiguity as well as partial destruction to generalize the earlier theoretical work of Budescu, Rapoport and Suleiman (1995) which analyzes only a risky TCPR with full destruction. Budescu, Rapoport and Suleiman (1995) find empirical support for their theoretical prediction that individuals' withdrawals exhibit a non-monotonic relationship with the range of the threshold. We closely follow their experimental design and introduce ambiguity and partial destruction.

Our study makes several contributions to the literature. First, we extend the previous literature which has focused on risky thresholds (Budescu, Rapoport and Suleiman (1992); Rapoport and Suleiman (1992); Budescu, Rapoport and Suleiman (1990)) and examine behavior under ambiguous thresholds. Second, we examine both full and partial destruction of the resource. With full destruction, if the sum of withdrawals exceeds the threshold, the resource is completely destroyed and the agents receive nothing from it (Botelho, Dinar, Pinto and Rapoport 2014; Rapoport and Au 2001). The amount by which the threshold is exceeded does not impact the damage. Whereas in the real-world, the destruction of resource, depends on not only if the threshold is crossed, but also by how much (Aflaki 2013). We refer to this set-up as partial destruction. Here if the withdrawals exceed the threshold by a high amount, then the damage to the resource will also be more severe. Third, we improve identification by directly eliciting risk and ambiguity preferences of the subjects, unlike Budescu et al. (1995) who use the behavior in the TCPR experiment to back out risk preferences.

At the aggregate level, we replicate Budescu et al. (1995) result of a non-monotonic relationship between the range and withdrawals in the risky TCPR with full destruction. But for ambiguous TCPRs and for TCPRs with partial destruction, we find limited or no support for the non-monotonicity prediction. At the individual-level, we find about one-third of the subjects exhibit a non-monotonic relationship between the range and withdrawals.

We find that ambiguous TCPRs are more likely to be destroyed than risky TCPRs, a finding that runs counter to the theoretical prediction. Ambiguity has significantly negative effect on the survival of the resource for both, full and partial destruction TCPRs. We also find that an increase in the range leads to an increase in the probability of destruction of the resource, except for ambiguous TCPRs with partial destruction. And when the range is sufficiently high, the probability of destruction of ambiguous and risky TCPRs is not significantly different, suggesting that to conserve TCPRs, we need reduce the range and eliminate ambiguity *jointly*.

The rest of the paper is as follows. Section 4.2 reviews the related literature. Section 4.3 presents the theoretical framework. Section 4.4 discusses the experimental design. Section 4.5 presents the results. The final section is the discussion section.

4.2 Related Literature

The literature on risky TCPR is substantial (Mantilla 2018). The closest set of papers to ours are Budescu, Rapoport and Suleiman (1995), Rapoport, Budescu, Suleiman and Weg (1992), Budescu, Rapoport and Suleiman (1992), Rapoport and Suleiman (1992) and Budescu, Rapoport and Suleiman (1990). In these studies, the subjects are placed in groups (usually of five members), and each subject chooses how many units of a resource to withdraw. The subjects make their decisions simultaneously without any communication or feedback. If the sum of withdrawals is less than or equal to the resource size, then the subject receives her withdrawal. If the sum of withdrawals exceeds the resource size, then each subject receives nothing. The size of the resource (or threshold) is not known with certainty. But subjects know the lower and upper-bound of the resource and that the threshold is uniformly distributed. A robust result of these papers is that even if the mean of the resource size is kept constant, increasing the variance or the range of the resource size (difference between the upper and lower bounds of the resource) leads to an increase in withdrawals from the resource. This positive relationship between withdrawals and the range is consistent with the theoretical Nash predictions (Budescu, Rapoport and Suleiman 1995).

All these papers, however, only explore risky thresholds and not ambiguous ones. Since many environmental problems are characterized by ambiguity rather than risk (Heal and Millner 2017), it is crucial to examine how individuals utilize TCPRs under ambiguity. To the best of our knowledge, ambiguous thresholds have only been experimentally addressed in a threshold public good (TPG) framework (Dannenberg et al. 2015) but not in TCPRs.[20] Dannenberg et al. (2015) find that contributions to the TPG are lower with ambiguous thresholds relative to risky ones.

An important line of research on risky TCPR is the order in which subjects withdraw, simultaneously or sequentially (Budescu, Au and Chen 1997; Suleiman, Rapoport and Budescu 1996; Budescu, Suleiman and Rapoport 1995; Budescu, Rapoport

[20] As differences in behavior between common-pool resources and public goods games is well-documented, it is essential to assess the impact of ambiguity in common-pool resources separately from public good games (Apesteguia and Maier-Rigaud 2006; Sell and Son 1997).

and Suleiman 1993). In a sequential protocol, each subject is assigned a position, and withdraws according to that position. A major finding is that there is an inverse relationship between the players' position and the amount they withdraw from the resource. There is an 'early mover' advantage enjoyed by those who are assigned the first position.

A few papers also examine risky TCPRs in a dynamic setting. Botelho et al. (2014) find subjects do not follow the socially-optimal path of withdrawals in a repeated TCPR game. They also find that when that resource is destroyed faster when the range about the resource size is wider. Adler (2014) finds that when subjects receive unreliable information or frequently revised estimates about the threshold, it leads to faster depletion of the resource. The policy recommendation that follows is that if policy-makers are to give information to users, it should be reliable, otherwise it is better not to give any information. Maas et al. (2017) also explore various policy-options such as taxes and fines for reducing over-withdrawals from a risky TCPR. They find that both taxes and fines improve efficiency, but taxes more so. We now turn to the theoretical framework of TCPR game under risk and ambiguity.

4.3 Theoretical Framework

Rapoport and Suleiman (1992) present the game-theoretic solution to a TCPR with uncertainty and refine it further in Budescu, Rapoport and Suleiman (1995). These works examine the TCPR where the threshold is risky and crossing the threshold leads to the full destruction of resource. Aflaki (2013) extends the analysis to an ambiguous threshold and to situations where exceeding the threshold causes partial destruction of the resource. Before we discuss the main theoretical predictions of Aflaki (2013), we present the key details of the TCPR game (for further details see Appendix A).

4.3.1 TCPR Game Set-up

In the TCPR game, there is a resource with an uncertain threshold ($\tilde{T}$), with α as the lower-bound and β as the upper-bound of the threshold. Under risk, the probability distribution over $[\alpha, \beta]$ is objectively known while under ambiguity it is not. There are n agents indexed by $i = 1, \ldots, n$. Each agent, i, makes a withdrawal, r_i, from the resource. The total withdrawal made by agents other than i is r_{-i}.

The withdrawals received (π_i) by each agent i depends on the sum total of withdrawals, $\boldsymbol{r^{total}} = r_i + r_{-i}$, the realized value of the threshold, $\tilde{T}$, and on whether exceeding the threshold ($\boldsymbol{r^{total}} > \tilde{T}$) leads to full or partial destruction of the resource.

Under full destruction,

$$\pi_{i_{Full\_Dest.}} = \begin{cases} r_i, & \boldsymbol{r^{total}} \leq \tilde{T} \\ 0, \quad and & \boldsymbol{r^{total}} > \tilde{T} \end{cases} \tag{5}$$

While under partial destruction,

$$\pi_{i_{Part\_Dest.}} = \begin{cases} r_i, & \boldsymbol{r^{total}} \leq \tilde{T} \\ r_i * e^{-k(\boldsymbol{r^{total}} - \tilde{T})}, & \boldsymbol{r^{total}} > \tilde{T} \end{cases} \tag{6}$$

With either full or partial destruction, if the sum total of withdrawals is less than or equal to the realized value of the threshold ($\boldsymbol{r^{total}} \leq \tilde{T}$), then each agent receives her withdrawal, r_i. With full destruction, agents receive nothing if the threshold is crossed ($\boldsymbol{r^{total}} > \tilde{T}$) and with partial destruction, agents receive a fraction of withdrawals. The fraction received is determined by two factors. First, by how much the withdrawals exceeded the threshold, $\boldsymbol{r^{total}} - \tilde{T}$. The higher the amount by which they exceed the threshold ($\boldsymbol{r^{total}} - \tilde{T}$), the lower the amount they will receive. Second, by the rate at which the resource deteriorates, $k,$ when the threshold is crossed. The higher the rate of deterioration, k, the lower the amount they will receive. When $k \rightarrow \infty$, crossing the threshold leads to full destruction of the resource.

Each agent has a power utility function, $u(r) = r^c$, where, c, represents the risk-preference of the agent. A risk-neutral agent has $c = 1$, while for a risk-averse agent, c is $0 < c < 1$, and for a risk-seeking agent $c > 1$.

4.3.2 Nash Equilibrium – Full Destruction

Assuming symmetric agents, the Nash Equilibrium (NE) under risk with full destruction, for a uniformly distributed threshold, $\tilde{T} \sim U[\alpha, \beta]$, where $\beta > \alpha,$ is given by

$$r^{**}_{RISK\_NE} = \max\left\{\frac{\alpha}{n}, \frac{c\beta}{nc+1}\right\} \tag{7}$$

The first term of the NE, $\frac{\alpha}{n}$, is the case where agents limit their withdrawals to the lower-bound of the resource, α. Since the threshold is never less than the lower-bound, α, ($\Pr(\alpha \leq \tilde{T}) = 1$), the agents always receive their withdrawals if the sum of total withdrawals is less than or equal to the lower-bound (α). The second term of the NE, $\frac{c\beta}{nc+1}$, is the case where agents no longer limit their withdrawals to the lower-bound (α). Since withdrawing more than the lower-bound induces the chance of crossing the threshold and destroying the resource, agents receive their withdrawals probabilistically.

Whether agents choose the first or second term of the NE, depends on the range ($\beta - \alpha$) of the resource, which is the difference between the upper and lower-bound of the resource. When the range is narrow, $\beta - \alpha \leq \frac{\alpha}{n*c}$, agents will choose $\frac{\alpha}{n}$. But when the range $(\beta - \alpha)$ becomes wide, $\beta - \alpha > \frac{\alpha}{n*c}$, agents will choose the second term, $\frac{c\beta}{nc+1}$.

Throughout the game the average value of the resource, $(\beta + \alpha)/2$, remains constant. Any change in withdrawal decisions is driven by the change in the range $(\beta - \alpha)$, and not the average value, $(\beta + \alpha)/2$.

The NE under ambiguity with full destruction, assuming symmetric agents, is given by

$$r^{**}_{AMB\_NE} = \max\left\{\frac{\alpha}{n}, \frac{c\lambda\beta}{nc+1}\right\} \tag{8}$$

Under full destruction, the NE under risk and ambiguity differs only by the presence of λ in the second term. λ lies between 0 and 1, and it captures the agent's degree of confidence in her belief about the distribution of the threshold.[21] While $1 - \lambda$ represents the degree of ambiguity in her belief. In this set-up, λ captures the agent's belief that the threshold is uniformly distributed, $\tilde{T} \sim U[\alpha, \beta]$. When the agent is ambiguity-neutral $(\lambda = 1)$, the agent treats the ambiguous TCPR game as a risky TCPR game, and therefore, the NE under risk and ambiguity become identical. On the other hand, when the agent is extremely ambiguity-averse $(\lambda = 0)$, the agent only considers the worst-state of the world, which is the lower-bound of the threshold (α), and therefore always chooses $\frac{\alpha}{n}$.

4.3.3 Nash Equilibrium – Partial Destruction

Given the functional form of the destruction function, $e^{-k(\boldsymbol{r^{total}} - \tilde{T})}$, a closed-form solution of the NE for the partial destruction case is not possible. The NE can be

[21] The Choquet Expected Utility (CEU) model with simple capacities as presented in Aflaki (2013) does not admit ambiguity-seeking preferences.

numerically calculated (see Appendix A for details). We now turn to the main theoretical predictions of the TCPR game under risk and ambiguity.

4.3.4 Main Theoretical Predictions

There are three key predictions of the model. The first pertains to how individual withdrawals from the resource vary with the range ($\beta - \alpha$). A non-monotonic relationship between the withdrawals and range ($\beta - \alpha$) is predicted. The second relates to the type of uncertainty, risk vs. ambiguity, and the probability of crossing the threshold. Assuming ambiguity-averse users, the probability of crossing the threshold is lower when the threshold is ambiguous as opposed to when it is risky. The third prediction is that there is a positive relationship between the range ($\beta - \alpha$) and probability of crossing the threshold. An increase in the range ($\beta - \alpha$) will increase the probability of crossing the threshold.

As the TCPR game exhibits multiple equilibria, we follow Aflaki (2013) in limiting our analysis to the symmetric equilibrium by assuming symmetric agents throughout our discussion.

- *Prediction 1: Non-monotonic relationship between the range ($\beta - \alpha$) and withdrawals.*

The NE is a kinked function of the range ($\beta - \alpha$) which leads to a non-monotonic relationship between the range ($\beta - \alpha$) and withdrawals. Initially as the range ($\beta - \alpha$) increases, the withdrawals decrease, and reach the minimum at the kink. Thereafter, as the range ($\beta - \alpha$) increases, the withdrawals also increase.

The reason for the initial negative relationship and then positive relationship between the range and withdrawals is as follows. When the range is narrow, $\beta - \alpha \leq \frac{\alpha}{n*c}$, agents choose to withdraw $\frac{\alpha}{n}$, so that the sum of their withdrawals does not exceed the lower-bound (α). An increase in the range ($\beta - \alpha$) reduces the lower-bound of the threshold (α), and therefore, the withdrawal, $\frac{\alpha}{n}$, also decreases.[22] But when the range becomes wide, $\beta - \alpha > \frac{\alpha}{n*c}$, agents choose to withdraw $\frac{c\beta}{nc+1}$. An increase in the range ($\beta - \alpha$), increases the upper-bound of the threshold (β), and therefore, the withdrawal, $\frac{c\beta}{nc+1}$, also increases. The case of ambiguity with full destruction is analogous. For partial destruction under both risk and ambiguity, numerical calculations show a non-monotonic relationship between the range and the withdrawals. The non-monotonic relationship is visible in Figure 4.1.

From Figure 4.1, we see that there is a non-monotonic relationship between the withdrawals and the range ($\beta - \alpha$) for agents who are risk and ambiguity-neutral (represented by solid squares) and those who are moderately risk and ambiguity-averse (represented by hollow triangles).[23]

- *Prediction 2: If agents are ambiguity-averse, an ambiguous TCPR is less likely to be destroyed than a risky TCPR.*

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[22] An increase in the range ($\beta - \alpha$), always leads to an increase of the upper-bound, β, and decrease of lower-bound α, because the average value of the bounds, $(\beta + \alpha)/2$, is constant in this game.

[23] However, it is possible for the relationship between the range ($\beta - \alpha$) and withdrawals to be monotonic if the agents have extreme risk and ambiguity preferences. If an agent is either extremely risk averse or ambiguity-averse ($c = 0, \lambda = 0$), then her withdrawals will monotonically decrease as the range ($\beta - \alpha$) increases. Similarly, if an agent is extremely risk-seeking ($c \to 5$), then her withdrawals will monotonically increase as the range ($\beta - \alpha$) increases. Recall, that the CEU ambiguity model as presented by Aflaki (2013) does not admit ambiguity-seeking preferences, so we cannot comment on the impact of ambiguity-seeking preferences.

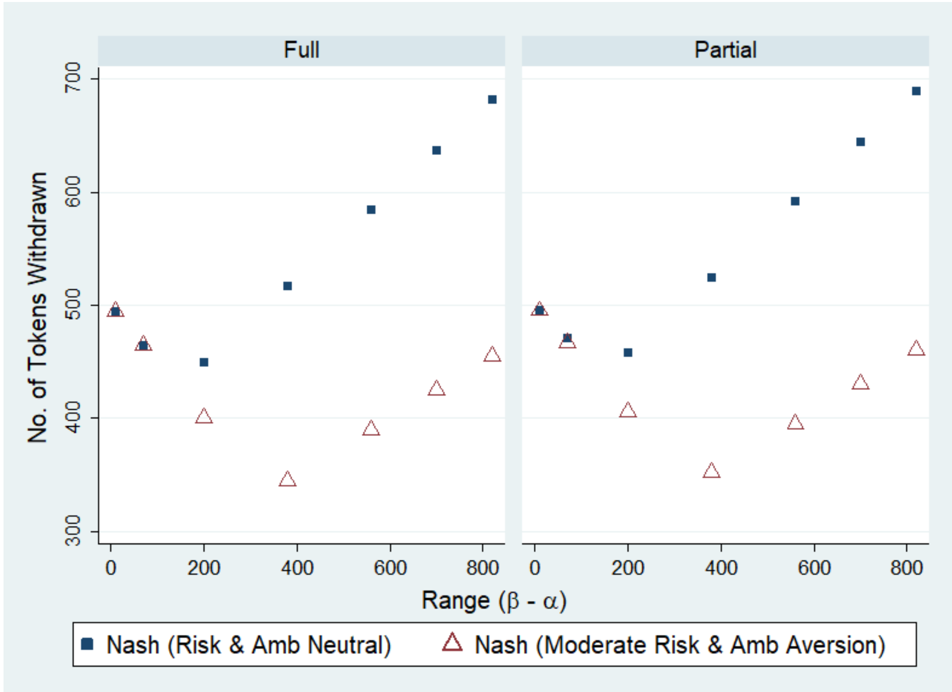

Figure 4.1 – Withdrawals are Non-Monotonic in the Range

When agents are ambiguity-neutral ($\lambda = 1$), they behave identically in risky and ambiguous TCPRs, but when agents are ambiguity-averse ($\lambda < 1$), they either withdraw less or an equal amount from an ambiguous TCPR than a risky one, hence, reducing the chance of destroying the TCPR. For TCPR with full destruction, this is easily verified by comparing the predicted Nash withdrawal for risk and ambiguity.

$$r^{**}_{RISK\_NE} = \max\left\{\frac{\alpha}{n}, \frac{c\beta}{nc+1}\right\} \tag{9}$$

$$r^{**}_{AMB\_NE} = \max\left\{\frac{\alpha}{n}, \frac{c\lambda\beta}{nc+1}\right\} \tag{10}$$

For partial destruction, because of the function-form of the destruction function, a closed form solution for NE is not possible. The Nash withdrawal in an ambiguous TCPR will always be less than or equal to the Nash withdrawal in a risky TCPR. This occurs because in ambiguity the Nash withdrawal is a convex combination ($0 \leq \lambda \leq 1$) of the withdrawal assuming a risky TCPR and the withdrawal assuming the worst-state of the world ($\tilde{T} = \alpha$), which will always be less than or equal to the withdrawal in a risky TCPR (see Appendix A for more details).

- *Prediction 3: There is a positive relationship between the probability of crossing the threshold and the range ($\beta - \alpha$).*

As the range ($\beta - \alpha$) increases the probability of crossing the threshold also increases. Figure 4.2 visually presents this relationship. This positive relationship holds for both the full and partial destruction cases.

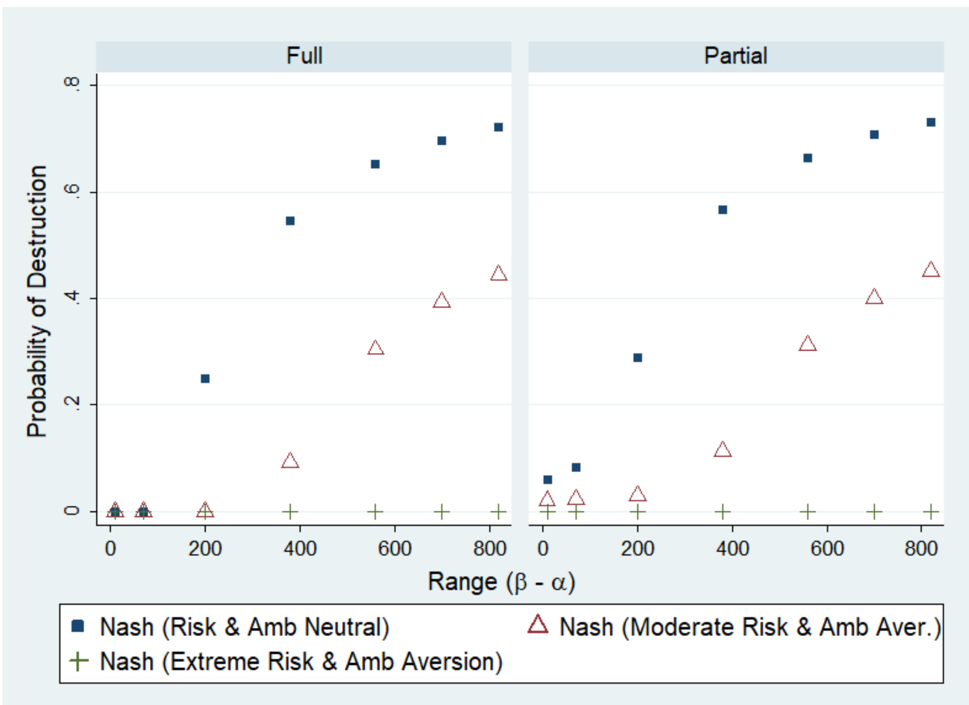

Figure 4.2 – Positive Relationship - Range and the Probability of Destruction

The probability of crossing the threshold depends on the amount of withdrawal. An increase in risk and ambiguity aversion ($c \to 0, \lambda \to 0$), reduces the amount withdrawn by the agent, and thereby reduces the probability of crossing the threshold. But unless agents have extreme risk and ambiguity preferences ($c = 0, \lambda = 0$) as represented by the plus symbol in Figure 4.2, a positive relationship is also predicted for 'reasonably' risk-averse and ambiguity averse agents. But for the extremely risk-averse and ambiguity-averse agent, the range $(\beta - \alpha)$ has no impact on the probability of destruction, because she always withdraws, $(\frac{\alpha}{n})$. And since the withdrawal never exceeds the lower-bound of the threshold (α), the probability of crossing the threshold is zero. We now turn to our experimental design.

4.4 Experimental Design

Each subject undertakes two tasks. The first task is a risk and ambiguity preference elicitation task and is the same for all subjects. The second task is the TCPR game which varies depending on the condition. We vary the type of uncertainty on the threshold- risk or ambiguity, and the consequence of crossing the threshold – full or partial destruction, which gives us four conditions: (i) risky threshold with full destruction (ii) ambiguous threshold with full destruction (iii) risky threshold with partial destruction (iv) ambiguous threshold with partial destruction. Our experiment follows a between-subjects protocol, so a subject participates only in one condition. After completing both the tasks, the subjects fill out a demographic survey. We now describe the experimental tasks.

4.4.1 Task One – Risk and Ambiguity Preferences Elicitation

We elicit the risk and ambiguity preferences of the subjects using the method devised by Gneezy, Imas and List (2015). The subjects go through two multiple-price lists (MPLs). The first MPL is to elicit the risk preference and the switch points in the MPL yield a risk-preference interval identical to the Holt and Laury (2002) MPL.

In this MPL, the subjects are presented with a pair of lotteries. They choose which lottery they prefer. The first lottery is called Option A while the second one is Option B. In Option A, the possible pay-offs are 200 tokens or 160 tokens while in Option B, they are 385 tokens or 10 tokens.[24] There are ten pairs in this list and as one moves down the list, the chance of the higher pay-off for both lotteries (200 and 385 tokens) increases. In the first pair, the expected value of Option A is higher, in the tenth and final pair, Option B gives a higher amount for sure. The pair at which the subject prefers Option A to B is reveals her risk-preference. Unlike other studies where a subject makes a separate choice between Option A and B at each pair, subjects are asked to choose one switch point. Allowing only one switch point eliminates inconsistent responses, that is, when subjects switch back and forth between Option A and B. Gneezy et al (2015) argue that enforcing a single switch point does not alter elicited parameters. Subjects make a choice for the risk MPL, and then for the ambiguity MPL.

In the ambiguity MPL, subjects choose to draw a ball from either Urn A or B. In Urn A, there are 50 red and 50 black balls. [25] Whereas the composition of Urn B is unknown, therefore, the subjects do not know how many red and black balls are in it. The subjects first choose a ‘success’ color, either red or black.[26] If they draw a ball that matches their success color, they will win tokens, otherwise not. Since there are 50 red and black balls, there is a fifty per cent chance of winning tokens. The chance of winning

[24] The conversion rate is set at 20 tokens = $1 USD.
[25] The actual ‘urn’ in the lab was a bag with playing cards, where drawing a black card meant drawing a black ball (same for drawing a red card). After a subject had drawn from the urn, the subject was free to verify the composition of the urns.
[26] The subjects are allowed to choose a success color to allay any fears that they might have about the experimenter rigging Urn B to reduce payments to subjects. For instance, if the experimenter wants to save money, she can set red as the winning color, and in Urn B, put only 1 red ball, thus, reducing the chance of payment. But when subjects choose the success color, the experimenter no longer can ‘rig’ Urn B.

from Urn B is unknown. The subjects make 20 decisions in which they choose to draw from either Urn A or B.

The pay-off from Urn A remains constant throughout, they earn 200 tokens if their draw matches the success color, otherwise 0. The pay-off from Urn B keeps increasing as one moves down the list. In the first choice, Urn B gives 164 tokens if the draw matches the success color, in the twentieth and final choice, it gives 316 tokens. The point at which the subject prefers to draw from Urn B over A reveals her ambiguity preference. Those who switch to Urn B later are more ambiguity-averse. Similar to the risk MPL, subjects can only choose one switch point.

At the end of the experiment (after completing task 1 and 2), a subject tosses a coin to determine whether she would be paid for the risk or ambiguity MPL (Head for risk and Tails for ambiguity). If the risk MPL is chosen, a 10-sided die is rolled twice. First to determine which choice from the list will be selected. If the number on the die is lower than the switch point, Option A will be played, otherwise B. The second time it is rolled to determine the pay-off from the lottery. If the ambiguity MPL is chosen, a 20-sided die is rolled. If the number on the die is lower than the switch point, the subject draws from Urn A, otherwise from Urn B.

4.4.2 Task Two – TCPR Game

The second task is the TCPR game. It is described in the following manner. The subjects are informed that there is a box with tokens in it, however, the exact number of the tokens in it is unknown but they are informed about the bounds, α and β. The information they receive about the range $(\beta - \alpha)$ depends on the condition, risk or ambiguity, and is presented in Table 4.1.

Consistent with earlier literature (Budescu, Rapoport and Suleiman 1995; 1992), we use a uniform distribution in the case of risk. The advantage of using a uniform distribution is that it is easy to explain to subjects. Whereas in the case of ambiguity, we give no information whatsoever about the distribution. Following Ahn (2014), our identifying assumption is that subjects impose a uniform distribution.[27]

Table 4.1 – Information given to Subjects under Risk and Ambiguity

	Range ($\beta - \alpha$) Information	**Avg. No. of Tokens Known**
Risk	Each number in the Range has the same chance of being chosen.	Yes, shown on decision-screen.
Ambiguity	The chance of each number in the Range being chosen is unknown to you.	No, decision-screen states that the average number of tokens is unknown.

The subjects are told that they are in a group of three, the subject herself and two others. Each subject has to decide how many tokens to withdraw from the box. If the sum of withdrawals by the group is less than or equal to the actual number of the tokens, then each subject receives the number of tokens she withdrew. If the total withdrawal exceeds the actual number of tokens, then the tokens they receive depends on the condition, full or partial destruction.

In the case of full destruction, if the total withdrawal exceeds the actual number of tokens, the subject receives 0 tokens. In the partial destruction condition, the subject

[27] Binmore et al. (2012) find empirical support for the Principle of Insufficient Reason, absent any reason to think otherwise, a person should assign equal probabilities to the outcomes. Baillon et al. (forthcoming) argue that the assumption of symmetry of beliefs is a reasonable one for artificial settings such as ours, tokens in a box, but not for natural events i.e. bets on the stock market.

receives a fraction of the tokens she withdrew. The fraction is calculated according to the destruction function, $e^{-k(\boldsymbol{r^{total}}-\ddot{T})}$, as presented in Aflaki (2013).

We set $k = 0.1$, therefore, the exact fraction received by the subject depends on the amount by which the total withdrawals ($\boldsymbol{r^{total}}$) exceed the actual number of tokens in the box ($\ddot{T}$).[28] The subjects are given a table which states the percentage of tokens they will receive if the total withdrawal exceeds the actual number. The table shows that if they exceed the actual number by 1 token, they will receive 90 per cent of the tokens, 2 tokens then 82 per cent and so on until 52 tokens for which they will receive 1 per cent. If total withdrawal exceeds the threshold by 53 tokens or more, they receive 0 tokens. The exchange rate for tokens is set at 40 tokens = 1 US$.

As in Budescu et al. (1995), there are 20 rounds in this task. The subjects do not receive any feedback between rounds. Four rounds are chosen randomly for payment. We ask two subjects to volunteer, one to roll a 20-sided die, the other one to observe. The numbers that appear on the die roll are chosen. In case of the same number being rolled twice, the die is rolled again, until four different rounds are chosen for payment.

4.4.3 Parameters of the Game

We have seven different ranges ($\beta - \alpha$) in our experiment as shown in Table 4.2. The first five are drawn from Budescu et al. (1995) and final two are our addition. The ones we introduce are wider, that is, $\beta - \alpha$ is greater, than the ones in Budescu et al (1995). We introduce these to better test the predicted non-monotonic relationship between the range ($\beta - \alpha$) and withdrawals. Recall that the prediction is that there is a

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[28] $k = 0.1$ gives us predictions that are quite close to the full destruction case (see Figures 4.1 and 4.2).

positive relationship between the range ($\beta - \alpha$) and withdrawals when the range ($\beta - \alpha$) is wide. By introducing wider ranges ($\beta - \alpha$), we are better placed to observe this positive relationship. These ranges are presented in a randomized order to the subjects. All ranges appear three times except for the narrowest range (10) which appears twice.

Notice that the average value of the bounds is constant, 500 tokens. Therefore, changes in withdrawal decisions across the ranges is being caused by the difference, $\beta - \alpha$, and not by changes in the mean value of the resource ($[\alpha + \beta]/2$). The average value is clearly stated on their decision-screen in the risk conditions. Therefore, at least in the risk condition changes in withdrawal decisions cannot be attributed to miscalculation of the average value.

Table 4.2 – Ranges ($\beta - \alpha$)

Range ($\boldsymbol{\beta - \alpha}$)	**$\boldsymbol{\alpha}$ (lower-bound)**	**$\boldsymbol{\beta}$ (upper-bound)**
10	495	505
70	465	535
200	400	600
380	310	690
560	220	780
700	150^	850^
820	90^	910^

^ These values have been chosen by us. The others are from Budescu et al. (1995)

4.4.4 Implementation

The experiment was programmed in z-Tree (Fischbacher 2007) and conducted at the Cleve. E. Willis Experimental Economics Lab at the University of Massachusetts

Amherst in Spring 2016. The subjects were recruited through ORSEE (Greiner 2015). There were 141 subjects (59 females) in total, with 36 subjects in each condition (except ambiguity with full destruction which had 33 subjects). There were two sessions of each condition. Each session lasted about one and a half hours. The average earnings were $21.25, with the minimum being $5 and the maximum was $41.25, including the $5 show-up fee. The subjects were paid in cash and in private at the end of the session. We now turn to our results.

4.5 Results

Our main results pertain to the three theoretical predictions presented earlier. Before discussing those, we present a brief overview of our data.

A total of 141 subjects participated in the experiment. There are 36 subjects in each condition except ambiguity with full destruction in which there are 33. There are two ambiguity-seeking subjects in the ambiguity with full destruction condition. As the CEU ambiguity model presented in Aflaki (2013) does not admit ambiguity seeking preferences, we exclude these two subjects from the analysis leaving us with a total 139 subjects.[29] In the TCPR game, each subject makes 3 withdrawals decisions for each value of the range (and 2 decisions for when the range is 10). Similar to Budescu et al. (1995), we take the average of these decisions.[30] Since there are seven values in the range ($\beta - \alpha$), we obtain 7 observations per subject. We have a total of 973 observations (7 decisions x 139 subjects). We now turn to our first prediction that there is a non-monotonic relationship between the range and withdrawals.

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[29] Including these two subjects does not significantly alter our results.
[30] Using all observations instead of the average does not significantly change our results.

4.5.1 Non-Monotonic Relationship between Range and Withdrawals

The theoretical prediction is that initially as the range $(\beta - \alpha)$ increases, the agents decrease their withdrawal because the equilibrium withdrawal does not exceed the lower-bound (α). Thereafter, the withdrawals increase as the range $(\beta - \alpha)$ increases leading to a kink as depicted in Figure 4.1. To formally test whether there is a negative relationship between the range $(\beta - \alpha)$ and withdrawals (r) before the kink (M), and a positive relationship after it, we run a non-linear piece-wise regression of the following form:

$$r = \begin{cases} a_1 + b_1(\beta - \alpha), & (\beta - \alpha) \leq M \\ a_2 + b_2(\beta - \alpha), & (\beta - \alpha) \geq M \end{cases}$$

Here withdrawals are a function of the range $(\beta - \alpha)$. We estimate four parameters (a_1, b_1, b_2, M).[31] We are particularly interested in the signs of the slope parameter estimates (b_1, b_2). The theoretical prediction is that $b_1 < 0$ and $b_2 > 0$, that is, there is a non-monotonic single-dipped $(b_1 < 0, b_2 > 0)$ relationship between the range $(\beta - \alpha)$ and withdrawals. Recall that this non-monotonic relationship holds if subjects are reasonably risk and ambiguity averse. So before proceeding to test this prediction, we check if our subjects are risk and ambiguity averse.

To estimate the risk (c) and ambiguity (λ) parameters for each condition at the aggregate level, we use the Maximum Likelihood method (Gneezy et al 2015; Harrison 2006; Gould et al. 2006). The estimated values of these parameters for the various conditions are given in Table 4.3. The conditions are abbreviated as follows – the first letter refers to the type of uncertainty, R is risk (and A is ambiguity). The second term

[31] We do not estimate a_2 as it can be calculated using the other estimates $(\widehat{a_2} = \widehat{a_1} + \widehat{b_1} * (\widehat{M}))$.

refers to the type of destruction, FD is full destruction and PD is partial destruction. At the aggregate level in each condition, subjects are risk-averse ($0 < c < 1$) and ambiguity-averse ($\lambda < 1$), but they do not have extreme preferences.

Table 4.3 – Estimated Value of Risk and Ambiguity Parameters – All Conditions

	R–FD	**R–PD**	**A–FD**	**A–PD**
$\boldsymbol{c}$	$0.372^{***}(0.015)$	$0.39^{***}(0.016)$	$0.446^{***}(0.017)$	$0.379^{***}(0.028)$
$\boldsymbol{N}$	360	360	310	360
$\boldsymbol{\lambda}$	$-$	$-$	$0.908^{***}(0.022)$	$0.897^{***}(0.029)$
$\boldsymbol{N}$	$-$	$-$	620	720

*** *p*-value ≤ 0.01; ** *p*-value ≤ 0.05; * *p*-value ≤ 0.1; Standard errors in parentheses. Clustered at subject-level.

Since the subjects are risk and ambiguity averse, as reported in Table 4.3, we expect the non-monotonic relationship to exist for all conditions. In our non-linear regression we do not restrict the parameters to be either negative or positive. We let the data 'speak' and see which relationship between the range ($\beta - \alpha$) and withdrawals fits the data best.

If the relationship is non-monotonic, it need not be single-dipped ($b_1 < 0, b_2 > 0$) as predicted. It could be single-peaked ($b_1 > 0, b_2 < 0$), dipped-flat ($b_1 < 0, b_2 = 0$), peaked-flat ($b_1 > 0, b_2 = 0$), flat-dipped ($b_1 = 0, b_2 < 0$) and flat-peaked ($b_1 = 0, b_2 > 0$). The relationship could also be monotonic, either increasing ($b_1 > 0, b_2 > 0$) or decreasing ($b_1 < 0, b_2 < 0$). Finally, there could be *no* relationship between that range ($\beta - \alpha$) and withdrawals making it flat ($b_1 = 0, b_2 = 0$).

Table 4.4 – Non-Linear Regression – All Conditions

	R–FD	**A–FD**	**R–PD**	**A–PD**
$\boldsymbol{b_1}$	-0.064^{***} (0.01	-0.02 (0.029)	-0.043 (0.032)	-0.137 (0.023)
$\boldsymbol{b_2}$	0.111^{***} (0.044)	0.087^{**} (0.041)	0.041 (0.049)	0.037 (0.037)
$\boldsymbol{M}$	472.45^{***}(37.81	462.74^{***}(88.45)	406.06^{**}(197.35)	385.07(249.60)
R-squared	0.0287	0.0161	0.012	0.0027
Root MSE	62.70	75.64	111.37	100.1
$\boldsymbol{N}$	252	217	252	252
Consistent	Full	Partial	Inconsistent	Inconsistent

*** *p*-value ≤ 0.01; ** *p*-value ≤ 0.05; * *p*-value ≤ 0.1; Standard errors in parentheses. Clustered at subject-level.

The results of the piece-wise regression are presented in Table 4.4. We classify the condition to be ‘fully consistent’ with the theoretical prediction if it is single-dipped ($b_1 < 0 \ and \ b_2 > 0$) and the slope estimates are statistically significant at least at the 10 per cent level. If only one of the slope estimates has the correct direction ($b_1 < 0 \ or \ b_2 > 0$) and it is significant at least at the 10 per cent level while the other is flat ($b_i = 0$) or statistically insignificant, we then classify the condition as ‘partially consistent’. Finally, if either of the directions of the slope estimates is contrary to the theoretical prediction (($b_1 > 0 \ or \ b_2 < 0$) or if neither of the estimates are statistically significant, we classify it as ‘inconsistent’.

From Table 4.4, we see that at the aggregate level, only the risk with full destruction condition is fully consistent with the theoretical prediction of a non-monotonic single-dipped relationship. We replicate Budescu et al. (1995) finding that in a risky TCPR with full destruction, withdrawals are non-monotonic in the range $(\beta - \alpha)$ which gives us our first result.

- *Result 1 – At the aggregate level, we find full support for the theoretically predicted non-monotonic single-dipped relationship only in a risky TCPR with full destruction. For an ambiguous TCPR with full destruction, we find partial support. But for a TCPR with partial destruction, either risky or ambiguous, we do not find any support for the theoretical prediction.*

However, the result at the aggregate level, may mask individual behavior underlying it. To examine whether an individual's behavior is in line with the prediction, we again run a non-linear regression for each individual subject separately to check if there is a non-monotonic relationship between withdrawals and the range $(\beta - \alpha)$. We use the same classification scheme of fully or partially consistent with the single-dipped non-monotonic prediction. We also classify subjects who respond to the range $(\beta - \alpha)$ in a monotonic manner, both increasing $(b_1 > 0, b_2 > 0)$ or decreasing $(b_1 < 0, b_2 < 0)$. Those subjects for whom both the slope estimates are significant at least at the 10 per cent level are 'fully consistent' while if only one of the slope estimate is significant, then those are partially consistent. Finally, a subject is considered 'inconsistent' if the subject's withdrawals are single-peaked $(b_1 > 0, b_2 < 0)$ or if both slope estimates are insignificant.

Table 4.5 – Percentage of Subjects – Withdrawals and Range Relationship

Relationship	***R-FD (N=36)***	***R-PD (N=36)***	***A-FD (N=31)***	***A-PD (N=36)***
Non-Monotonic	**37**	**31**	**23**	**14**
Full	14	17	13	3
Partial	23	14	10	11
Monotonic	**20**	**17**	**47**	**29**
Full	11	11	27	23
Partial	9	6	20	6
Inconsistent	**43**	**51**	**30**	**57**
Total	**100**	**100**	**100**	**100**

The percentages have been rounded.

At the aggregate level for the full destruction conditions, we find either full or partial support for the single-dipped non-monotonic relationship. We do not find any support for the partial destruction condition. But from Table 4.5, we see that there is considerable heterogeneity in individual behavior.

Even in the risk with full destruction condition where we find full support at the aggregate level, only a minority of subjects, 37 per cent, display a non-monotonic relationship. Similarly, in the partial destruction condition where we find no support at the aggregate level, some subjects' do follow the non-monotonic prediction, 14 per cent in the ambiguity with partial destruction condition and 31 per cent in the risk with partial destruction, which is close the fraction observed in the risk with full destruction condition (37 per cent).

We also find that many subjects exhibit a monotonic relationship between the range ($\beta - \alpha$) and withdrawals, and in the ambiguity with full destruction condition, 47 per cent of the subjects respond to the range ($\beta - \alpha$) in a monotonic manner.

A substantial fraction of subjects, however, do not respond to the range ($\beta - \alpha$) in any systematic fashion. The lowest number of inconsistent subjects are in the ambiguity with full destruction condition (30 per cent) and the highest are in the ambiguity with partial destruction condition (57 per cent). Of those classified as inconsistent, none of them exhibited a single-peaked relationship ($b_1 > 0, b_2 < 0$), which would suggest that subjects' behavior is opposite of the theoretical prediction. Instead we find that neither of the slope estimates (b_1, b_2) are statistically significant for the inconsistent subjects. Policy-makers interested in altering behavior of users need to account for the heterogeneity in the response to the range ($\beta - \alpha$) amongst individuals.

- *Result 2 – Individuals' response to the changes in the range ($\beta - \alpha$) is heterogeneous. In each condition, a minority of subjects conforms to theoretically predicted single-dipped non-monotonic relationship. We also observe in each condition, some subjects exhibiting a monotonic relationship. Finally, there is a substantial fraction of subjects in each condition, who do not display any systematic relationship between the range ($\beta - \alpha$) and withdrawals.*

Putting Result 1 and 2 together, we argue that empirical support for the non-monotonicity prediction is limited. We now turn to the second prediction that if agents are ambiguity-averse, then an ambiguous TCPR is less likely to be destroyed.

4.5.2 Ambiguous TCPR and the Probability of Destruction

To estimate the probability of destruction in various conditions, we run a fractional logit regression which is used for settings where the dependent variable lies between 0 and 1 (Papke and Woolridge 2008).[32] For us, the dependent variable is the probability of crossing the threshold leading to destruction, either full or partial, depending on the condition. In Figure 4.3, we present the estimated mean probabilities of destructions across the range $(\beta - \alpha)$ for all conditions.[33]

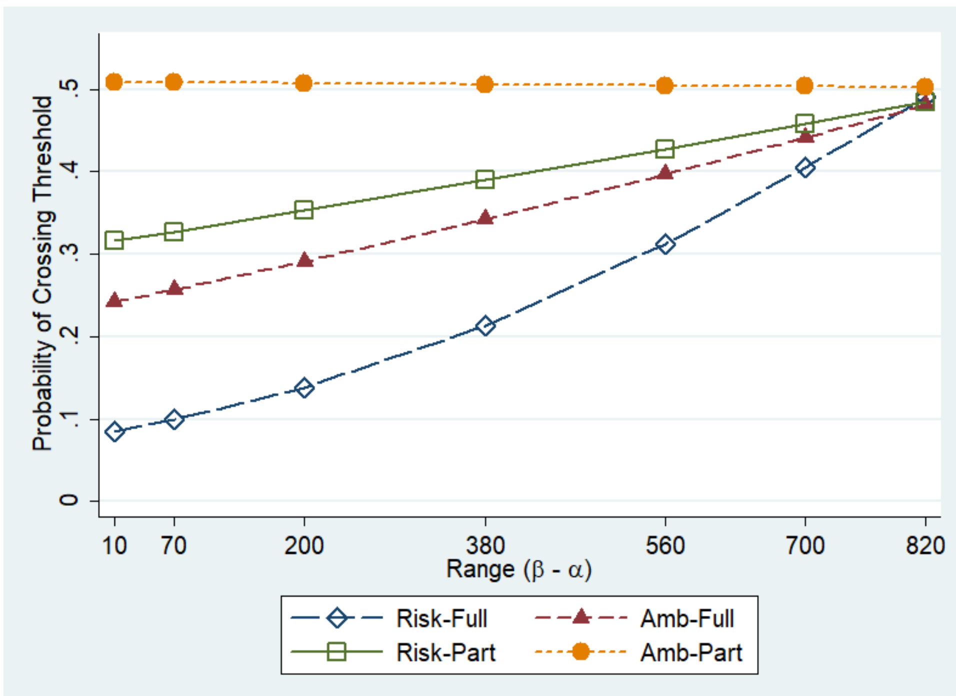


Figure 4.3 – Probability of Destruction and Range – All Conditions

In Figure 4.3, on the X-axis, we have the range $(\beta - \alpha)$ and on the Y-axis, we have the probability of crossing the threshold. For instance, the value of 0.1 corresponds to a 10 per cent chance of destroying the resource. We are interested in whether the

[32] The raw coefficients of the regression generating Figure 4.4 are available in the Supplemental Results Appendix B.

[33] The precise estimated values and their standard errors are available in the Supplemental Results Appendix B.

probability of destruction is lower with ambiguous TCPRs. Visually it appears that the probability of destruction is higher in the ambiguity conditions, except when the range $(\beta - \alpha)$ is high (≥ 700). The ambiguity with full destruction line (solid triangles) lies above the risk with full destruction condition (hollow diamonds). Similarly, ambiguity with partial destruction line (solid circles) lies above the risk with partial destruction condition (hollow squares).

It appears as if the observed behavior is in the opposite direction of the theoretical prediction, ambiguous TCPRs are more likely to be destroyed. Post-estimation statistical tests for a difference in estimated means of probability of destruction indeed confirm what we observe visually in Figure 4.4. The probability of destruction of ambiguous TCPRs is significantly higher than risky TCPRs, irrespective of full or partial destruction, as long as the range $(\beta - \alpha)$ is not too high.

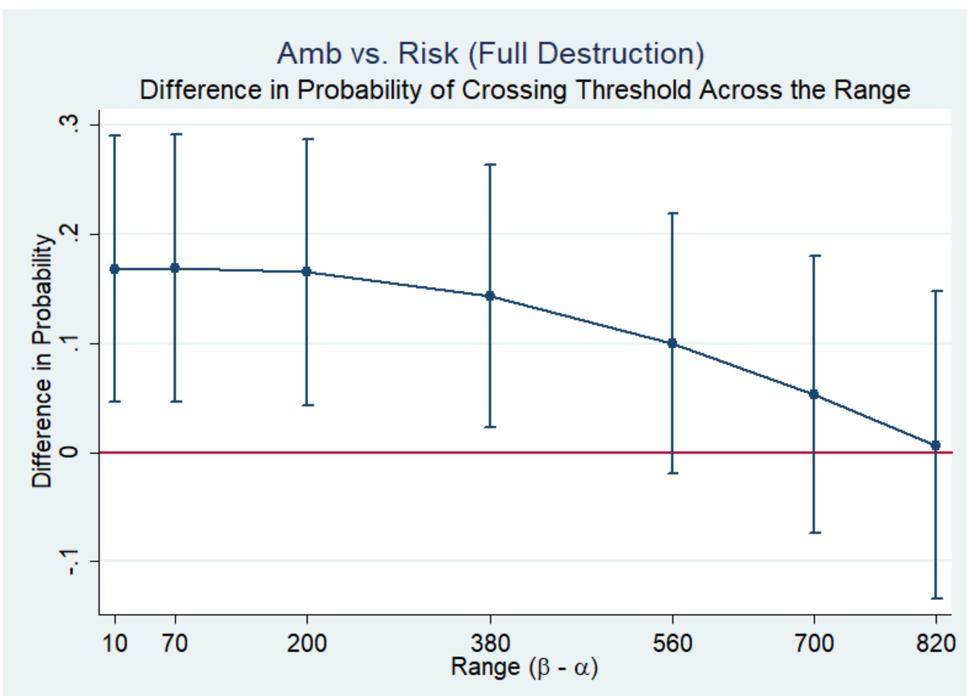


Figure 4.4 –Probability of Crossing the Threshold – Amb. vs. Risk (Full Destruction)

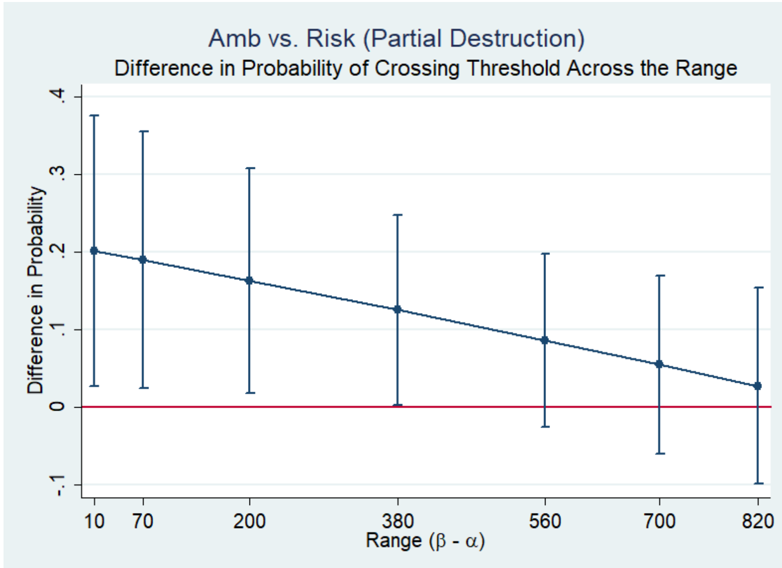


Figure 4.5 –Probability of Crossing the Threshold – Amb. vs. Risk (Partial Destruction)

In Figure 4.4, we present the difference in the probability of destruction between ambiguous and risky TCPRs with full destruction. On the X-axis, we have the range ($\beta - \alpha$). On the Y-axis, we have the estimated difference in the probability of destruction, with the bars representing the 95 per cent confidence intervals (CI), and the solid horizontal line represents zero. For instance, when the range ($\beta - \alpha$) is 10, then the estimated difference is close to 0.2, which shows that the chance of an ambiguous TCPR being destroyed is almost 20 per cent higher than a risky TCPR.[34] Since the 95 CI bar lies above the zero line, we know that this difference is statistically significant. But when the range ($\beta - \alpha$) is high (≥ 560), we see that 95 CI bars overlap with the zero line, which means that the difference is not statistically significant.

Figure 4.5 presents the difference in the probability of destruction for ambiguous and risky TCPRs with partial destruction. It can also be interpreted in the same manner as

[34] For exact estimated values and the associated standard errors (see Supplemental Results Appendix B).

Figure 4.4. Here we have analyzed full and partial destruction separately, if we pool the data from both destruction types, we still find that ambiguous TCPRs are more likely to be destroyed than risky TCPRs (see Appendix B Supplemental Results).

A potential reason for observing higher probability of destruction in ambiguous TCPRs could be because of differing risk and ambiguity preferences of the subjects in the conditions. If subjects are more risk-seeking in the ambiguous conditions, then we would observe higher probability of destruction in the ambiguous conditions. However, in our regression we control for risk and ambiguity preferences[35], so we cannot attribute the difference in the probability of destruction to differing risk and ambiguity preferences.

Another potential reason could be that subjects have non-symmetric beliefs such that they overestimate the size of the resource (or the value of the threshold) under ambiguity. If such overestimation is common, then we would observe more ambiguity-seeking behavior in the ambiguity elicitation task. Of the 141 subjects in our experiment, only three of them make ambiguity-seeking choices in the elicitation task. Only two of the three ambiguity-seekers are in the ambiguity condition, and we exclude them from our analysis (although our results are robust to their inclusion). Therefore, we do not believe that overestimation of the resource is driving this result.

Our finding that ambiguity leads to a higher chance of destruction in a TCPR mirrors the results of Dannenberg et al. (2015) who observe lower contributions to a public good when the threshold is ambiguous as compared to when it is risky.

- *Result 3 – Contrary to the prediction that ambiguity as compared to risk reduces the probability of destruction, we find that ambiguity significantly*

[35] Risk-aversion is captured by the number of 'safe' choices made in the risk MPL, and ambiguity-aversion refers to the number of withdrawals from a risky urn instead of an ambiguous urn.

increases the probability of destruction in a TCPR. We find that this result holds for both full and partial destruction. However, this result is mediated by the range $(\beta - \alpha)$, because when the range $(\beta - \alpha)$ is high, ambiguity does not have a significant effect.

The main policy-implication of this result is that reducing the range $(\beta - \alpha)$ and changing the type of uncertainty from ambiguity to risk in *conjunction* will be the most effective way to reduce the probability of destruction of TCPRs. We now turn to our third prediction that there is a positive relationship between the range $(\beta - \alpha)$ and the probability of crossing the threshold.

4.5.3 Range and the Probability of Crossing the Threshold

Recall that the probability of crossing the threshold increases as the range $(\beta - \alpha)$ increases only holds if the subjects are not extremely risk and ambiguity averse ($c = 0, \lambda = 0$). From Table 4.3, we see that subjects are risk-averse and ambiguity-averse but not extremely so, therefore, we expect to find support for this prediction. From Figure 4.3, we see that for all conditions, except for ambiguity with full destruction, the probability of destruction is increasing as the range $(\beta - \alpha)$.

From our fractional logit regression[36], we obtain the average marginal effect of a unit increase in the range $(\beta - \alpha)$ on the probability of destruction across all conditions. These are reported in Table 4.6. Our statistical analysis confirms what we visually observe in Figure 4.3, there is a significant and positive relationship between the range $(\beta - \alpha)$ on the probability of destruction across all conditions except ambiguity with

[36] Full regression reported in the Supplemental Results Appendix B.

partial destruction, where we observe no relationship between the range $(\beta - \alpha)$ and the probability of destruction.

Table 4.6 – Impact of Range on Probability of Destruction – All Conditions

	R-FD	***R-PD***	***A-FD***	***A-PD***
Range $(\boldsymbol{\beta} - \boldsymbol{\alpha})$	0.000479*** (5.95e-05)	0.000206** (8.86e-05)	0.000289*** (7.01e-05)	-7.96e-06 (8.46e-05)

*** *p*-value ≤ 0.01; ** *p*-value ≤ 0.05; * *p*-value ≤ 0.1; Standard errors in parentheses.

The coefficients appear to be small but that is driven by the fact that our range $(\beta - \alpha)$ of threshold is wide, the lowest being 10 and the highest is 820, while the range of probability is bound between 0 and 1. But the impact of the range $(\beta - \alpha)$ on the probability of destruction is substantial. For instance, in the risk with full destruction condition, if the range $(\beta - \alpha)$ increases from 10 to 560, we will observe that chance of the TCPR being destroyed will increase by over 26 percentage points. Because the coefficient is 0.000479 * 550 (is the change in the range) which will give us an increase of 0.263 in the probability of destruction.

- *Result 4 – As the range $(\beta - \alpha)$ increases, the probability of crossing the threshold increases significantly in all conditions except in the case of ambiguity under partial destruction.*

This result highlights the importance of the *joint* impact of the type of uncertainty (risk vs. ambiguity) and the type of destruction (full vs. partial). When trying to preserve a resource with ambiguity and partial destruction, reducing the range $(\beta - \alpha)$ will not suffice. In conjunction with reducing the range $(\beta - \alpha)$, policy-makers should strive to better inform the users about the chance of crossing the threshold i.e. transforming the ambiguity to risk. Similarly, to make reductions in the range $(\beta - \alpha)$ effective, policy-makers should inform the users about the detrimental impact of crossing the threshold, so the users treat it as a case of full destruction instead of partial. We now turn to our concluding discussion.

4.6 Discussion

Our study examines the impact of uncertainty on the threshold in a common-pool resource game. We extend the existing experimental literature on uncertainty in TCPRs by examining different types of uncertainty (risk vs. ambiguity) and different consequences of crossing the threshold (full vs. partial destruction).

Overall, we find limited support for the prediction that withdrawals follow the single dipped non-monotonic pattern. At the aggregate level, we only find full support for this prediction in the risk with full destruction condition, and for other conditions, we find only partial or no support. Similarly, at the individual level, only a minority of the subjects exhibit this single dipped non-monotonic relationship. Note that this test of non-monotonicity between the range ($\beta - \alpha$) and the withdrawals is a not a stringent one. Because we are only checking *if the signs* of the slope parameter estimates (b_1, b_2) are in line with the theoretical prediction and *not the values* of the slope parameter estimates. Since observed behavior deviates considerably from the prediction, reexamining the theoretical framework of Budescu et al. (1995) is warranted.

We find that ambiguity as compared to risk significantly increases the probability of crossing the threshold. This result holds irrespective of whether the type of destruction is full or partial. Although the theoretical prediction is that ambiguity will reduce destruction, our evidence suggests that the opposite occurs. Ambiguity has a similarly detrimental impact for the provision of public goods (Dannenberg et al. 2015). The policy-implication of our finding is that more information about the resource improves the chances of its survival. However, the impact of ambiguity is moderated by the range $(\beta - \alpha)$. There is no significant difference between the probability of destruction of risky and ambiguous TCPRs when the range $(\beta - \alpha)$ is high.

Finally, as predicted, we find that the range $(\beta - \alpha)$ has significant and positive effect on the probability of destruction for all conditions, except for ambiguity with partial destruction. The policy-implication of this result is that tackling uncertainty *jointly* by reducing both the range $(\beta - \alpha)$ while gathering more information about the threshold (changing it from being ambiguous to risky) will be most effective in preserving TCPRs.

Since there is growing pressure on natural and environmental resources, we believe more research on how they are utilized under uncertainty is essential. Future scholars can extend this line of research in several directions. First, we have introduced ambiguity only in one form, that is, by not giving any information about the threshold. Another possibility is to give multiple distributions over the threshold, as presented in the multiple-priors models of ambiguity-aversion.

Second, in our experiment, the subjects' beliefs are not elicited. Since we observe higher chances of destruction under ambiguity as well as under partial destruction of the resource, it would be valuable to investigate how the subject's beliefs over threshold as well as the strategies of others, when there is ambiguity and/or partial destruction.

Third, the subjects do not receive any feedback on their decisions. They also are not able to communicate with other group members. Since most of the resources are used over multiple-periods, and with many users in interaction with each other, introducing feedback and communication, would shed light on how behavior adjusts in a dynamic setting.

Finally, in many studies, sanctioning has been used to sustain cooperation. Will a sanctioning technology reduce overharvesting? Particularly interesting would be to see what decisions are penalized, because unlike in a public-goods game, where the socially optimal action (full contribution) is obvious, but that is not the case in a TCPR game with uncertainty. A high level of withdrawal is not necessarily driven by ‘greed’, if one believes that the threshold is high, then the socially optimal action is to withdraw a high amount. Addressing these questions will provide valuable insights to policy-makers and will play a role in better managing common-pool resources.

CHAPTER 5

COMMON-POOL RESOURCES UNDER THRESHOLD AND GROUP SIZE UNCERTAINTY

5.1 Introduction

A wide-variety of environmental problems that society faces, from exhaustion of water reserves to overharvesting of fisheries, from the destruction of forests to the dumping of waste materials in rivers, pertains to threshold common-pool resources (TCPRs).[37] A TCPR is a resource which can be consumed safely up to a certain level, the threshold, but consuming it beyond the threshold leads to the destruction of the resource (Rapaport & Au 2001). Often times, there is considerable uncertainty surrounding these TCPRs, particularly about the threshold (Aflaki 2013) and the group size, that is the number of users of the TCPR (de Kwaadsteniet, van Dijk, Wit & de Cremer 2008). Although the users of the resource might be aware that a threshold exists and crossing it will destroy the resource, they might not know the exact value of the threshold or the exact number of other users. For instance, fishermen know that overharvesting will destroy the fish stock, but what level of fishing constitutes overharvesting might not be known with precision. Here the fishermen face threshold uncertainty. They might also not know how many other fishermen are out there. Here the fishermen face group size uncertainty. While threshold and group size uncertainty exist simultaneously in many settings, existing research has analyzed them in isolation. Policy-makers seeking to

[37] The literature on social dilemmas often refers to these environmental problems as resource dilemmas (Suleiman, Rapoport & Budescu 1996; Samuelson & Messick 1986)

ensure optimal utilization of these resources need to know the impact of these two forms of uncertainty on withdrawal behavior.

Our key contribution is the *joint* examination of the impact of threshold and group size uncertainty on withdrawals from a TCPR. Evidence suggests that threshold and group size uncertainty have opposite effects on the preservation of the TCPR which makes a joint analysis particularly important. Botelho, Dinar, Pinto & Rapoport (2014) find that threshold uncertainty leads to socially sub-optimal withdrawals and higher rates of destruction of the resource while Au & Ngai (2003) find that group size uncertainty reduces the destruction rate of the TCPR.

However, it should be noted that threshold uncertainty which emerges from the scientific non-linearities present in environmental resources is very difficult to reduce as the requisite scientific knowledge is lacking (Pindyck 2007) while group size uncertainty is relatively easier to tackle for policy-makers. Therefore, the focus of our analysis is on how altering group size uncertainty impacts withdrawal behavior in the presence of threshold uncertainty.

We run a laboratory experiment to examine the impact of threshold and group size uncertainty.[38] The laboratory methodology is ideal to address this issue because we can exogenously vary the type of uncertainty (threshold vs. group size) and its magnitude (low vs. high uncertainty). Such control is not possible in the field. Our experiment uses a within-subjects design where each subject participates in three TCPR games. The three games differ in what element(s) of the TCPR game is uncertain – the threshold, the group

[38] To be precise, in our experiment we are looking at risk and not (Knightian) uncertainty, because the subjects have objective information about the probabilities. We call it uncertainty to maintain consistency with the existing work on TCPR games (Botelho et al. 2014; Au & Ngai 2003; Suleiman, Rapoport & Budescu 1996).

size, and both the threshold and group size. Within each game, we vary the magnitude of uncertainty about the threshold and group size.

The remainder of the paper is structured as follows: section 5.2 reviews the related literature, section 5.3 presents the theoretical framework, section 5.4 discusses the experimental design, section 5.5 presents the results and the final section is the discussion section.

5.2 Related Literature

Despite the theoretical importance of group size uncertainty in strategic games (Myerson 1998), few studies have explored it experimentally in TCPR games. To the best of our knowledge, there are only two studies which do so (de Kwaadsteniet et al. 2008; Au & Ngai 2003).

In Au & Ngai (2003), subjects are placed in a group and each one of them makes a withdrawal from a resource consisting of 1000 units or ‘fish’. If the sum of withdrawals is less than or equal to the resource size, then the subject receives her withdrawal. Whereas if the sum of withdrawals exceeds the resource size, then each subject receives nothing. Au & Ngai (2003) analyze how different protocols of play impact withdrawals and whether uncertainty about the group size has any effect on withdrawals. They examine two protocols of play, sequential and self-paced protocol.

In the sequential protocol, each subject in the group is assigned a position and have to make withdrawals in that order. The subject assigned the first position gets to withdraw from the resource first. The subject in the second position observes the withdrawal of the first position player and then makes her own withdrawal. And then the third position player observes the withdrawals of the previous players. The game continues until the last player makes her withdrawal or the sum of withdrawals by the players exceeds the resource size, whichever comes first. In the self-paced protocol, the subjects are not restricted to withdraw in any pre-specified order. A subject can withdraw in the first round or can wait till the next round. In each round, the subject is informed about how many other subjects have withdrawn and how much has been withdrawn.

Each protocol is played with a certain group size, in which there are five members, or an uncertain group size, where the average number of group members is also five, but the group size is uniformly distributed between three to seven members. The main finding is that withdrawals are lower, leading to a lower rate of destruction of the resource, under group size uncertainty in both protocols.

In de Kwaadsteneit et al. (2008), the focus is on individual personality traits as measured by the Social Value Orientation (SVO) and how these traits impact withdrawals from a resource in the face of group size uncertainty. They use a simultaneous protocol of play in which all players withdraw from the resource simultaneously without any communication or feedback. The key finding is that the impact of group size uncertainty on withdrawals is heterogenous and depends on the 'type' of subject. Those subjects who are classified as pro-socials (these are more cooperative) according to the SVO withdraw significantly less than those who are classified as pro-selfs (these are more competitive) under group size uncertainty. But when the group size is certain, then both type of subjects, pro-socials and pro-selfs, withdraw the same amount.

In both these studies, de Kwaadsteneit et al. (2008) and Au & Ngai (2003), the resource size (or the threshold) is known and only the group size is uncertainty. But in our study, both the threshold and group size are uncertain, thereby better capturing the multiple uncertainties exhibited in TCPRs.

5.3 Theoretical Framework

The following discussion draws upon the work of Rapoport & Suleiman (1992) who analyze the TCPR game with threshold uncertainty.

5.3.1 TCPR Game under Threshold Uncertainty

There is a resource with an uncertain threshold ($\tilde{T}$), and its probability distribution is, $F_{\tilde{T}}$. The support of $\tilde{T}$ is finite and within the range $[\alpha, \beta]$ with $\beta > \alpha$, which makes α the lower-bound β as the upper-bound of the threshold. We present the case where the threshold is uniformly distributed, $\tilde{T} \sim U[\alpha, \beta]$, because we use a uniform distribution in our experiment.

There are n agents indexed by $i = 1, \dots, n$. Each agent, i, makes a withdrawal, r_i, from the resource which enters her utility function. The agent has a utility function, $u(r) = r^c$, where c, is the risk preference parameter. A risk-neutral agent has $c = 1$, while for a risk-averse subject it is $c < 1$, and for a risk-seeking subject $c > 1$. The total withdrawal made by agents other than i is r_{-i}.

The withdrawals received (π_i) by each agent i depends on the sum total of withdrawals, $\boldsymbol{R} = r_i + r_{-i}$ and the realized value of the threshold, $\ddot{T}$. If the total withdrawals do not exceed the realized value of the threshold, then each agent receives her withdrawal. Whereas if total withdrawals do exceed the realized value of the threshold, then each agent receives nothing.

$$\pi_i = \begin{cases} r_i, & \boldsymbol{R} \leq \ddot{T} \\ 0, & \boldsymbol{R} > \ddot{T} \end{cases} \tag{11}$$

The expected utility $\mathbb{E}_{\tilde{T}} u(r_i)$ of the agent (where $\mathbb{E}_{\tilde{T}}$ represents the expectation with respect to the uniformly distributed threshold), is as follows

$$\mathbb{E}_{\tilde{T}} u(r_i) \tag{12}$$

$$= \begin{cases} {r_i}^c & \boldsymbol{R} \leq \alpha \\ \int_{r_i + r_{-i}}^{\beta} {r_i}^c \frac{1}{\beta - \alpha} dx & \alpha \leq \boldsymbol{R} \leq \beta \\ 0 & \boldsymbol{R} > \beta \end{cases}$$

The NE of TCPR game under threshold uncertainty is

$$r^{**}_{Uncertain-Th-NE} = \max \left\{ \frac{\alpha}{n}, \frac{c\beta}{nc+1} \right\} \tag{13}$$

The socially optimal withdrawal for an agent in TCPR game under threshold uncertainty is as follows

$$r^{**}_{Uncertain-Th-SO} = \max \left\{ \frac{\alpha}{n}, \frac{c\beta}{n * (c+1)} \right\} \tag{10}$$

Notice that the first term of the NE and socially optimal level, $\frac{\alpha}{n}$, coincide, suggesting that for some values of threshold uncertainty they will be the same. However, the second term is different, such that for $n > 1$, the NE exceeds the SO ($\frac{c\beta}{nc+1} > \frac{c\beta}{n*(c+1)}$). We now present the main hypotheses of interest based on the findings of the prior literature and the theoretical framework.

Hypothesis 1: Group size uncertainty reduces withdrawals in a TCPR game in the presence of threshold uncertainty

Hypothesis 2: Withdrawals exceed the socially optimal level when the threshold uncertainty is high but not when low

We now turn to our experimental design.

5.4 Experimental Design

We use a within-subject design in which each subject participates in three TCPR games. In each of these games, the subject has to decide on how many units to withdraw from the resource. These games are followed by a risk preference elicitation task, the Holt-Laury (2002) multiple-price list (MPL)[39], and a non-incentivized survey in which we collect demographics.

The three TCPR games are Threshold Uncertain (TU), Group Size Uncertain (GU) and both Threshold and Group Size Uncertain (TGU). To control for potential order effects, half the subjects first participated in the TU game, then the GU game and finally the TGU game. While the other half of the subjects first participated in the GU game, then the TU game and finally the TGU game. In both these orders, we kept the TGU game the final one because of its relative complexity (because in TGU, both the group size and the threshold are uncertain).

We follow a simultaneous-decision protocol (Budescu, Rapoport & Suleiman 1995) where the subjects make each decision independently without any communication or feedback. The subjects do not know who the other group members are and cannot communicate with them. They also do not receive any feedback either about the decisions

[39] We use the Holt-Laury MPL as presented in Gneezy, Imas & List (2015) in which the subjects are restricted to choosing a single 'switch' point between the 'safe' and 'risky' lotteries. This restriction eliminates inconsistent responses where subjects switch back and forth between the lotteries. Gneezy, List & Imas (2015) argue that enforcing a unique switch point does not impact the elicited risk-preference parameter and prevents the loss of data arising from inconsistent choices.

made by others or the outcome of their decisions i.e. whether the resource is destroyed or not.

Subjects are paid for three rounds, one round randomly selected round from each game. After the subjects complete the TCPR games and the risk-elicitation task, the payment rounds are selected by rolling a die. For the die roll, we ask two subjects to volunteer. One to roll the die and the other to observe. We now describe the TCPR games in more detail.

5.4.1 Threshold Uncertainty (TU) Game

The resource is described as a box of tokens. The subjects are in a group of 6 members and each subject has to decide how many tokens to withdraw from the box. However, the exact number of tokens in the box is not known. The subjects are informed about the lower (α) and upper-bound (β) of the number of tokens in the box and that the tokens are uniformly distributed.[40] There are six rounds in this game. In each round, different lower (α) and upper-bounds (β) are presented in a randomized order. However, the mean number of tokens is always 1000 tokens and this is stated on their decision screen. Therefore, if withdrawals change between rounds, they are changing as a result of the change in the variance or range ($\beta - \alpha$) of the resource size, because the mean value of the resource is constant (see Table 5.1).

[40] We choose a uniform distribution for both group size and threshold uncertainty because it is straightforward to explain to the subjects and is consistent with earlier literature (de Kwaadsteneit et al. 2008; Au & Ngai 2003; Rapoport, Budescu, Suleiman & Weg 1992).

Table 5.1 – Range & the Lower and Upper-Bounds of the Resource Size

Mean Resource Size	**Range ($\boldsymbol{\beta - \alpha}$)**	**Lower-Bound ($\boldsymbol{\alpha}$)**	**Upper-Bound ($\boldsymbol{\beta}$)**
1000	10	995	1005
1000	70	965	1035
1000	250	875	1125
1000	450	775	1225
1000	1400	300	1700
1000	1800	100	1900

Each member can withdraw any number of tokens between 0 and the upper-bound (β). If the sum of withdrawal is less than or equal to the randomly drawn number of tokens (threshold) in the box, the subject receives her withdrawal. But if the sum of withdrawal exceeds the threshold, the subject receives zero tokens.

5.4.2 Group Size Uncertainty (GU) Game

The resource is described as 1000 tokens in a box. Each subject is a member of a group and has to decide how many tokens to withdraw from the box. However, the subject does not know the exact group size. But the subject is informed about the lower (y) and upper-bound (z) of the group size and that the group size is uniformly distributed.

There are four rounds in this game. In each round, different lower (y) and upper-bounds (z) of the group size are presented in a randomized order. However, the mean group size is always six members and this is stated on their decision screen. Therefore, if withdrawals change between rounds, they are changing as a result of the change in the variance of the group size, because the mean value of the group size is constant (see Table 5.2).

Table 5.2 – Range & the Lower and Upper-Bounds of the Group Size

Mean Group Size	**Range** $(z - y)$	**Lower-Bound** (y)	**Upper-Bound** (z)
6	8	2	10
6	6	3	9
6	4	4	8
6	2	5	7

Each member can withdraw any number of tokens between 0 and 1000 tokens. If the sum of withdrawal by the group is less than or equal to 1000 tokens, the subject receives her withdrawal. But if the sum of withdrawal exceeds 1000 tokens, the subject receives zero tokens.

5.4.3 Threshold and Group Size Uncertainty (TGU) Game

The resource is described as a box of tokens. The subjects are in a group and each subject has to decide how many tokens to withdraw from the box. However, the exact number of tokens in the box as well as the group size is not known. The subjects are informed about the lower (α) and upper-bound (β) of the number of tokens in the box as well as the lower (y) and upper-bound (z) of the group size. They are also informed that both the number of tokens and the group size are uniformly distributed.

There are six different lower (α) and upper-bound (β) of the number of tokens and the mean number of tokens is 1000, same as the TU game (see Table 5.1). The difference is that the group size is not certain. There are two different possible group sizes drawn from the GU game. One where the group size can be anywhere between 5 to 7 subjects and the other one where it can be anywhere between 3 to 9 subjects. The mean number of group members is six, the same as in the GU game. There are a total of 12 rounds (six different bounds on number of tokens $*$ two possible group sizes). The different lower (α) and upper-bound (β) of the number of tokens and group sizes are presented in a randomized order.

The mean number of tokens and the mean group size are always stated on their decision screen. Therefore, if withdrawals change between rounds, they are changing as a result of the change in the variance of the resource and/or group size, because the mean value of the resource (1000 tokens) and group size (6 members) remain constant throughout the rounds.

Each member can withdraw any number of tokens between 0 and the upper-bound (β). If the sum of withdrawal is less than or equal to the randomly drawn number of tokens (threshold) in the box, the subject receives her withdrawal. But if the sum of withdrawal exceeds the threshold, the subject receives zero tokens. We now discuss the experimental implementation.

5.4.4 Implementation

The experiment was programmed in z-Tree (Fischbacher 2007) and conducted at the Clive. E. Willis Experimental Economics Lab at the University of Massachusetts Amherst in Fall 2017. The subjects were students of University of Massachusetts Amherst and were recruited through ORSEE (Greiner 2004). There were 64 subjects, with 32 subjects in each order (TU-GU-TGU and GU-TU-TGU). The data was collected in four sessions (two sessions of each order). Each session lasted about two hours. The average earnings were $29.71 inclusive of the $5 show-up fee. The subjects were paid in cash and in private at the end of the session.

5.5 Results

The main focus of our study is to assess the impact of group size uncertainty on withdrawals in an uncertain TCPR game (Hypothesis 1) and to examine whether withdrawals exceed the socially optimal level when the threshold uncertainty is high (Hypothesis 2). Before turning to the main results, we present the overview of the data.

Each subject made six decisions in the TU game and 12 decisions in the TGU game, with six decisions with low group size uncertainty (five to seven subjects) and the other six decisions with high group size uncertainty (three to nine subjects), making for a total of 18 decisions with threshold uncertainty. 64 subjects participated in the experiment, giving us a total of 1152 observations (64 subjects x 18 decisions). We now turn to the main analysis for which we need to estimate the risk preference of the subjects.

5.5.1 Risk Preferences of Subjects

To determine the socially optimal and Nash level of withdrawal in the TU game, we need to identify the risk preference parameter (c) of the subjects. We do so from the incentivized risk-preference elicitation task undertaken by the subjects (Gneezy, Imas & List 2015). The subjects choose a switch point between 10 lotteries presented in a multiple-price list giving us a total of 640 observations (64 subjects x 10 decisions). Using the Maximum Likelihood method (Harrison 2006), we estimate the risk preference parameter ($c = 0.385$), which means that on average our subjects are risk-averse ($0 \leq c < 1$), see Table 5.3.

5.5.2 Predicted Socially Optimal and Nash Withdrawals in TU Game

Using the point estimate of the risk preference parameter ($c = 0.385$), we can calculate the socially optimal and Nash level of withdrawals for the TU game. The calculated values for various values of the threshold uncertainty are presented in Table 5.4. Notice that the socially optimal and Nash level of withdrawals coincide when the threshold uncertainty is low (250 or less) but the Nash exceeds the socially optimal when the threshold uncertainty is high (450 or more).

Table 5.3 – Risk Preference Estimate

Variable	Values
$\boldsymbol{c}$	$0.385^{***}(0.009)$
$\boldsymbol{N}$	640

*** *p*-value ≤ 0.01; ** *p*-value ≤ 0.05; * *p*-value ≤ 0.1; Standard errors in parentheses. Clustered at subject-level.

Table 5.4 – Predicted Socially Optimal and Nash Withdrawals in TU Game

Threshold Uncertainty	Socially Optimal	Nash	Predicted Nash exceeds Socially Optimal
10	165.83	165.83	No
70	160.83	160.83	No
250	145.83	145.83	No
450	129.16	139.31	Yes
1400	74.69	193.32	Yes
1800	83.48	216.07	Yes

5.5.3 Withdrawal Decisions

We now turn to Hypothesis 1: Group size uncertainty reduces withdrawals in the presence of threshold uncertainty. In Figure 5.1, we present the mean withdrawals alongside the 95 percent confidence intervals for all conditions: threshold uncertainty with no, low (5 to 7 subjects) and high (3 to 9 subjects) group size uncertainty. On the x-axis, we have the level of threshold uncertainty, the difference between the upper and lower bound the resource. While on the y-axis, we have number of tokens withdrawn by a subject.

To test whether these withdrawals differ by group size uncertainty we run an OLS regression with the number of tokens withdrawn as the dependent variable. In Model (1) of Table 5.5, we only introduce the threshold uncertainty as independent variables. Each range of threshold uncertainty (10, 70, 250, 450, 1400 and 1800) are coded as dummy variables with 450 serving as base. We set 450 as the base because the theoretical prediction is that Nash withdrawals will be lowest at 450 (see Table 5.4). From Column (1) of Table 5.5, we see that when the threshold uncertainty is lower than 450, withdrawals are (weakly) significantly higher. However, when the threshold exceeds 450, withdrawals are not significantly higher. This result holds even when we introduce group size uncertainty (Model 2) and demographic information (Model 3). Our preferred specification is Model (3) as it disaggregates the impact of group size uncertainty, risk aversion, and demographic characteristics (gender and willingness to trust others[41]). We find that risk aversion, as measured by the number of safe choices made on the multiple price list, significantly reduces withdrawals from the TCPR ((*p*-value 0.006)). Those

[41] We measure trust through the General Social Survey question "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?"

subjects who trust others withdraw less but the difference is only weakly significant (*p*-value 0.062). The withdrawal behavior of female subjects is not significantly different from non-female subjects (*p*-value 0.150).

For the varying levels of group size uncertainty, in Figure 5.2, we present the estimated withdrawals along with the 95 percent confidence interval on the y-axis. While on the x-axis we have the different levels of threshold uncertainty.

Table 5.5 – OLS Regression Result

Variables	Model (1)	Model (2)	Model (3)
Thr. Unc. 10	10.47***	15.81***	15.81***
	(3.573)	(4.885)	(4.891)
Thr. Unc. 70	20.64***	45.69**	45.69**
	(7.621)	(19.67)	(19.70)
Thr. Unc. 250	9.307*	21.47*	21.47*
	(4.942)	(12.29)	(12.31)
Thr. Unc. 1400	4.193	1.219	1.219
	(8.754)	(10.61)	(10.62)
Thr. Unc. 1800	18.58	39.59	39.59
	(13.69)	(30.81)	(30.85)
Low Gs. Unc#Thr. Unc. 10		-14.06***	-14.06***
		(3.410)	(3.415)
Low Gs. Unc # Thr. Unc. 70		-45.75**	-45.75**
		(18.23)	(18.25)
Low Gs. Unc # Thr. Unc. 250		-26.66**	-26.66**
		(11.71)	(11.73)
Low Gs. Unc # Thr. Unc. 450		-10.98**	-10.98**
		(4.156)	(4.162)
Low Gs. Unc # Thr. Unc. 1400		-20.25	-20.25
		(13.98)	(14.00)
Low Gs. Unc # Thr. Unc. 1800		-50.36	-50.36
		(30.30)	(30.34)
High Gs. Unc # Thr. Unc. 10		-30.61***	-30.61***
		(5.596)	(5.603)
High Gs. Unc # Thr. Unc. 70		-58.06***	-58.06***
		(18.19)	(18.21)
High Gs. Unc # Thr. Unc. 250		-38.48***	-38.48***
		(12.31)	(12.32)

High Gs. Unc # Thr. Unc. 450		-17.67***	-17.67***
		(5.476)	(5.483)
High Gs. Unc # Thr. Unc. 1400		0.516	0.516
		(10.11)	(10.13)
High Gs. Unc # Thr. Unc. 1800		-41.33	-41.33
		(31.30)	(31.34)
Risk- Aversion			-11.56***
			(4.034)
Trust Others			-22.14*
			(11.66)
Female			-16.24
			(11.15)
Constant (Th. Unc. 450)	134.6***	144.1***	229.9***
	(5.311)	(6.180)	(28.97)
Observations	1,152	1,152	1,152
R-squared	0.005	0.033	0.089

*** *p*-value ≤ 0.01; ** *p*-value ≤ 0.05; * *p*-value ≤ 0.1; Standard errors in parentheses. Clustered at subject-level. Thr. Unc: Threshold Uncertainty; Gs. Unc.: Group Size Uncertainty; #: interaction

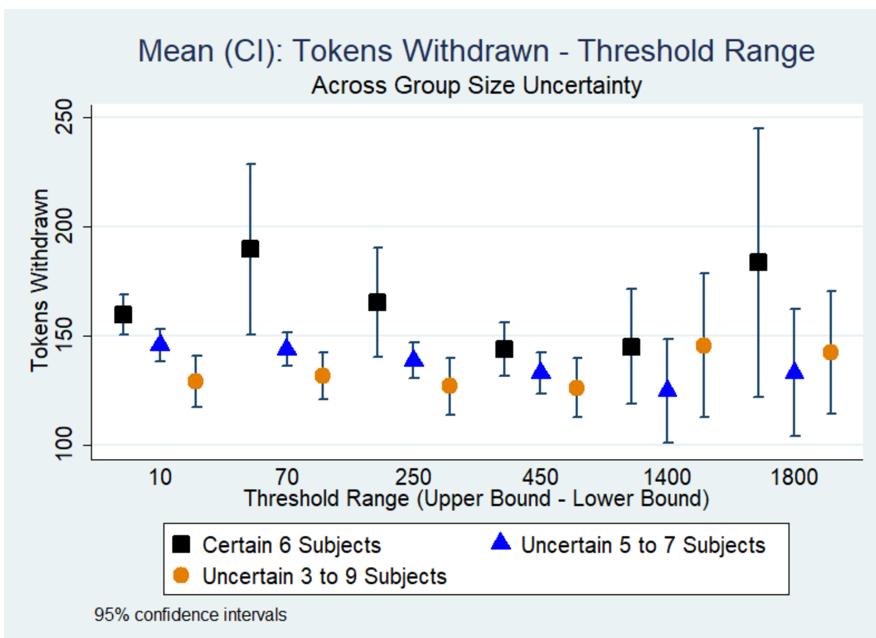


Figure 5.1 – Mean Token Withdrawals

We examine the impact of group size uncertainty on withdrawals across threshold uncertainty. In Figure 5.3, on the y-axis, we present the estimated difference along with the 95 percent confidence interval in withdrawals when group size is certain (6 subjects) as compared to when the group size uncertainty is either low (5 to 7 subjects) or high (3 to 9 subjects). Also, on the y-axis, we have a red line which marks zero. If the confidence interval overlaps the zero line, it means that the estimated difference is not statistically significant. On the x-axis, we have the various levels of threshold uncertainty. We see that withdrawals are significantly lower with group size uncertainty, either low or high, when the threshold uncertainty is 450 or less. But when the threshold uncertainty is high (above 1400), the difference is not significant.

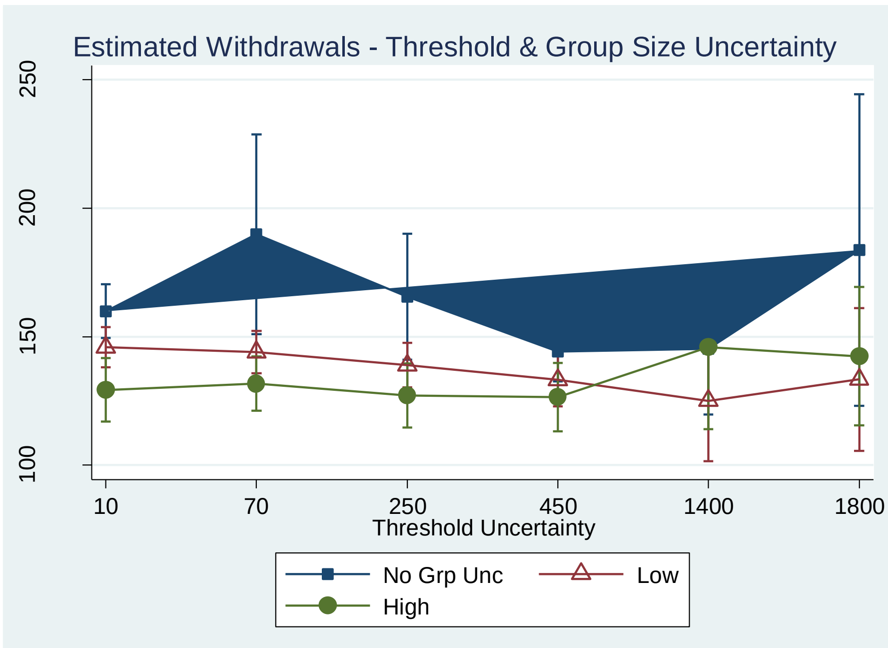


Figure 5.2 – Estimated Withdrawals – Across Threshold and Group Size Uncertainty

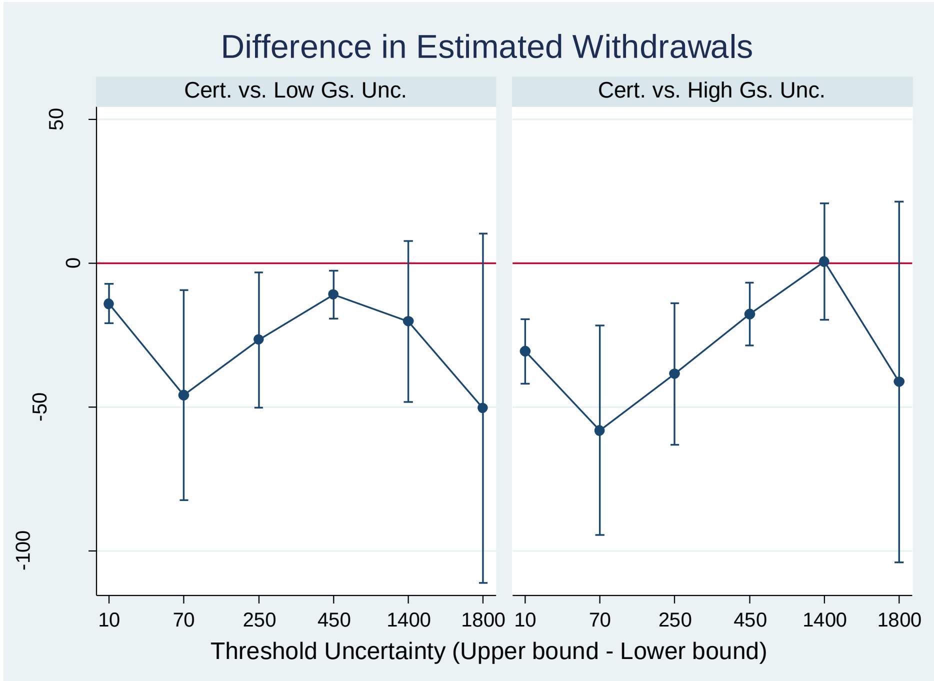


Figure 5.3 – Difference in Estimated Withdrawals – Certain vs. Uncertain Group Size

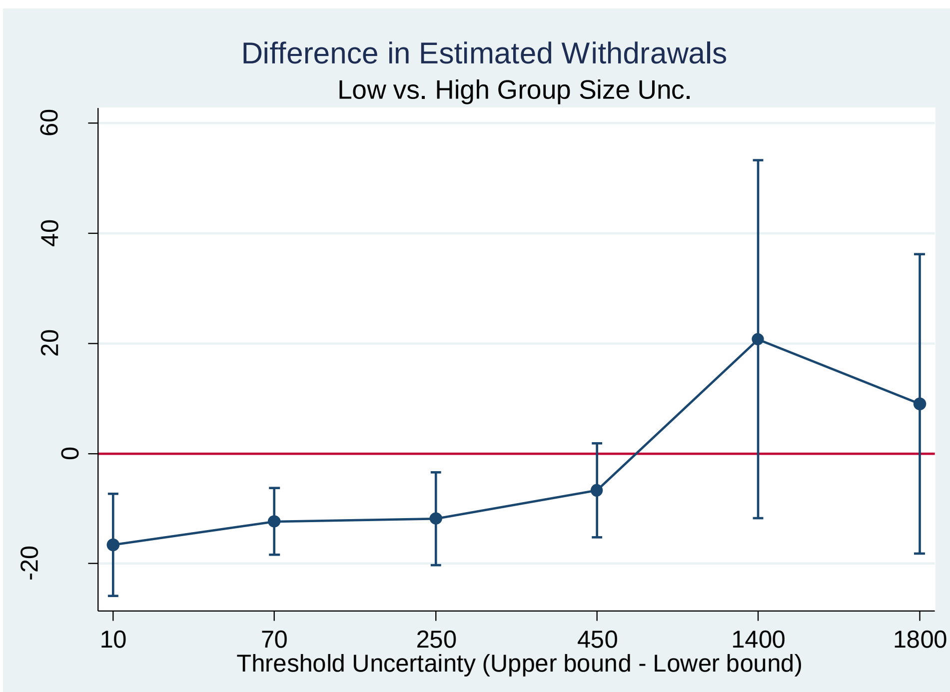


Figure 5.4 - Difference in Estimated Withdrawals – Low vs. High Group Size Uncertainty

We also examine whether withdrawals are different between low and high group size uncertainty. In Figure 5.4, we see that withdrawals are significantly higher under low group size uncertainty when the threshold uncertainty is 250 or less. However, when the threshold uncertainty is 450 or more, there is no significant difference in withdrawals between low and high group size uncertainty. We now have our first result.

- *Result 1a: Withdrawals are significantly lower in the presence of group size uncertainty; this holds for both low and high levels of group size uncertainty. However, as compared to a certain group size, the uncertain group size only reduces withdrawals when the threshold uncertainty is low or intermediate (450 or less), but group size uncertainty does not have a significant impact on withdrawals when the threshold uncertainty is high (1400 or more).*
- *Result 1b: Compared to low group size uncertainty, withdrawals are significantly lower with high group size uncertainty. However, the higher group size uncertainty only reduces withdrawals when the threshold uncertainty is low or intermediate (250 or less), but it does not have a significant impact on withdrawals when the threshold uncertainty is high (450 or more).*

The key policy implication here is that the presence of group size uncertainty reduces withdrawals relative to the case of group size certainty. The decision to reduce the group size uncertainty therefore depends on whether the resource is being over or under-harvested. However, policy-makers should also bear in mind that group size uncertainty also interacts with the threshold uncertainty. When the threshold uncertainty is high, the presence of group size uncertainty does not have a significant impact on withdrawals. Therefore, the policy of targeting group size uncertainty will only be effective in a setting where the threshold uncertainty is not too severe. We now turn to our Hypothesis 2.

5.5.4 Sub-optimality

Our Hypothesis 2 is that withdrawals exceed the socially optimal level when the threshold uncertainty is high (450 or more) but not when low (250 or less). We test whether the estimated withdrawals from Model (3) are significantly different from the socially optimal level. In Figure 5.5, for the case of threshold uncertainty with no group size uncertainty, on the y-axis we present the estimated difference between the withdrawals and the socially optimal withdrawal level. A negative number on the y-axis means that the withdrawals are below the socially optimal level, zero means that there is no difference, while a positive number means that the tokens withdrawn exceed the socially optimal level. On the x-axis, we have the various levels of threshold uncertainty. The estimated difference is presented alongside the 95 per cent confidence intervals. If the interval overlaps zero (the solid red line), the difference is not statistically significant. Figure 5.6 and 5.7 present the same information but for the case of low and high group size uncertainty respectively. The results from these figures are summarized in Table 5.6.

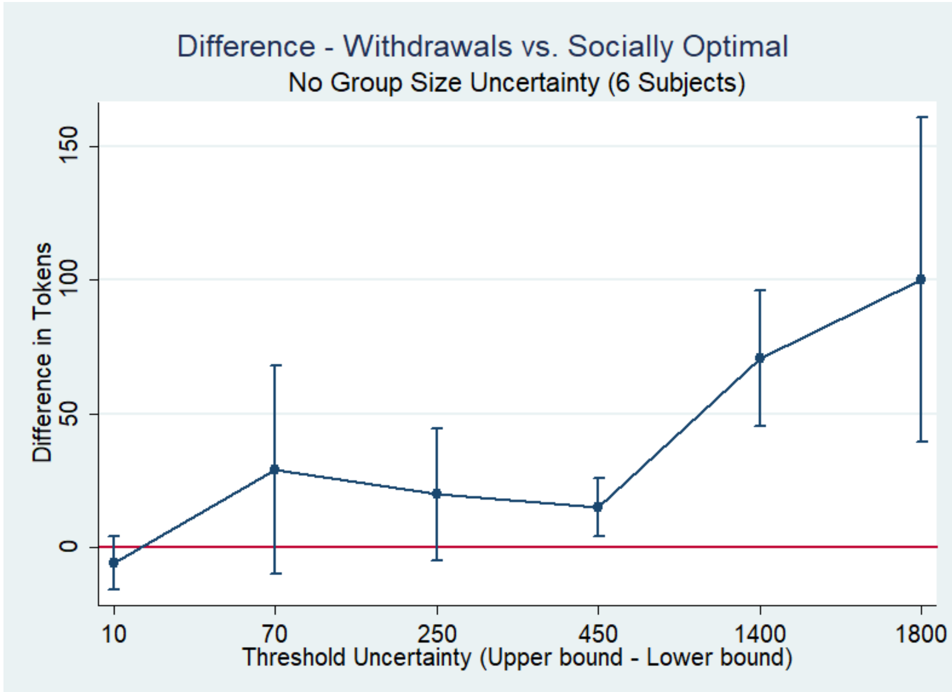


Figure 5.5 – Difference – Withdrawals vs. Socially Optimal – No Group Size Uncertainty

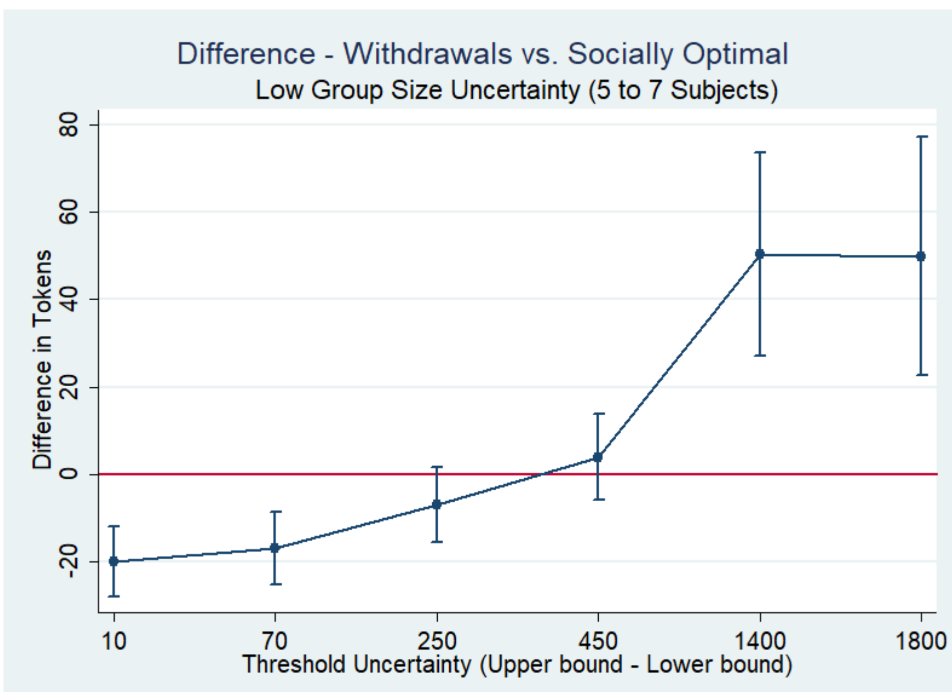


Figure 5.6 – Difference – Withdrawals vs. Socially Optimal – Low Group Size Uncertainty

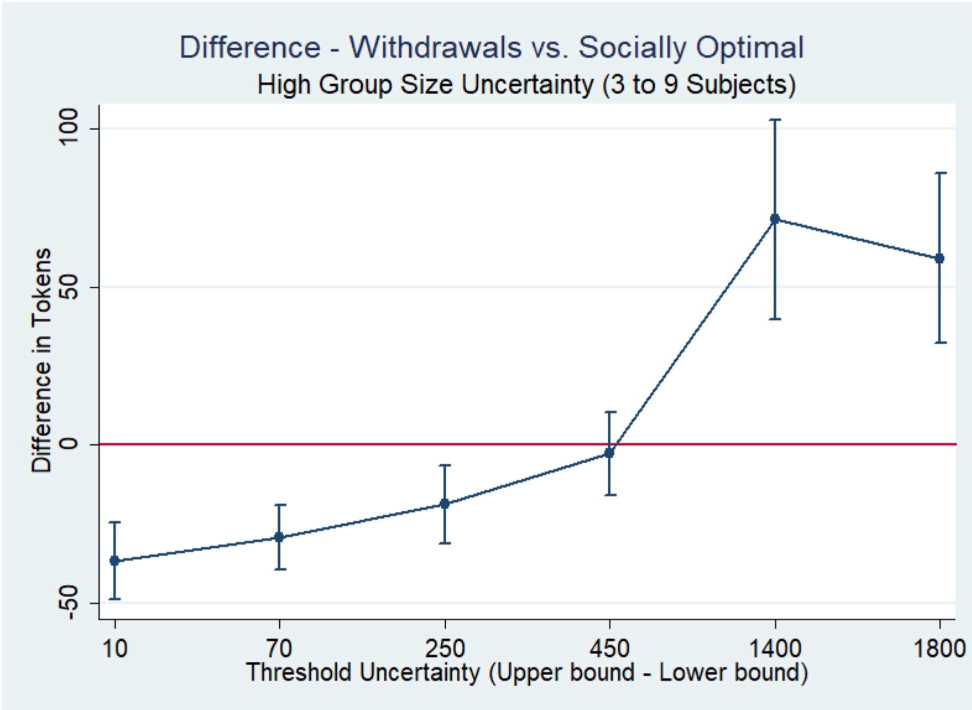


Figure 5.7 – Difference – Withdrawals vs. Socially Optimal – High Group Size Uncertainty

Table 5.6 – Significant Difference in Estimated Withdrawals and Socially Optimal Level

Threshold Uncertainty	**Certain Group Size (6 Subjects)**	**Low Gs. Unc (5 to 7 Subjects)**	**High Gs. Unc (3 to 9 Subjects)**
10	No	Yes, Lower	Yes, Lower
70	No	Yes, Lower	Yes, Lower
250	No	No	Yes, Lower
450	Yes, Higher	No	No
1400	Yes, Higher	Yes, Higher	Yes, Higher
1800	Yes, Higher	Yes, Higher	Yes, Higher

We see from Table 5.6, that whenever the threshold uncertainty is high, the withdrawals significantly exceed the socially optimal level. For the certain group size, whenever the threshold uncertainty is 450 or more, the withdrawals exceed the socially optimal level while for the case of group size uncertainty, whenever the threshold uncertainty is 1400 or more. What is interesting to note is that in the presence of group size uncertainty, withdrawals fall significantly *below* the socially optimal level when the threshold uncertainty is low (70 or less in the case of low group size uncertainty; 250 in the case of high group size uncertainty). This gives us our second result.

- *Result 2a: At high levels of threshold uncertainty, withdrawals exceed the socially optimal level, but not when the threshold uncertainty is low.*
- *Result 2b: When the threshold uncertainty is low, then the presence of group size uncertainty leads to withdrawals being significantly less than the socially optimal level.*

These results suggest that reducing group size uncertainty will lead to efficiency gains as the withdrawals will become closer to the socially optimal level. However, this result is mediated by the level of threshold uncertainty, if the existing level of threshold uncertainty is high, then reducing group size uncertainty has no significant effect. We now turn to our concluding discussion.

5.6 Discussion

A major challenge before policy-makers is to utilize common-pool resources in an optimal manner. These environmental resources are often marked by uncertainty on different dimensions i.e. number of users, stock size, regeneration rate. We focus on two dimensions: threshold uncertainty, where withdrawing from the resource above the threshold leads to destruction of the resource, and group size uncertainty, where the number of users is not exactly known. As the uncertainty on threshold is driven by deep scientific uncertainty, it is relatively difficult for policy-makers to reduce that. Whereas group size uncertainty is easier for policy-makers to reduce e.g. through better informing users, restricting access to the resource to a specific group. Using a lab experiment, we examine the impact of group size uncertainty on withdrawals in a common-pool resource game with threshold uncertainty.

The key finding is that group size uncertainty reduces withdrawals from the resource, but not across all levels of threshold uncertainty. When the threshold uncertainty is low, we see a reduction in withdrawals, but when the threshold uncertainty is high, group size uncertainty does not have a significant effect on withdrawals. The policy-implication is that reducing group size uncertainty is context specific. If the resource is being under-utilized, then reducing group size uncertainty will be efficient. However, if the resource is already being over-utilized, then reducing group size uncertainty will further exacerbate the problem. The caveat being that if the existing level of threshold uncertainty is already very high, then altering group size uncertainty will not have an impact on withdrawals.

Analyzing individual behavior in social dilemmas with uncertainty has important policy-implications, therefore, further examination of this topic is warranted. Future work should explore whether these results hold for larger groups, when there is ambiguity instead of risk on the threshold, amongst others.

APPENDIX A

THEORETICAL APPENDIX

Here we present the main elements of the theoretical framework presented in Budescu, Rapoport and Suleiman (1995) and Aflaki (2013).[42] We first discuss the TCPR game under risk and then under ambiguity.

Basic Set-Up – TCPR Game under Risk

In the TCPR game under risk, Γ_{RISK}, there is a resource with an uncertain threshold ($\tilde{T}$), and its probability distribution is, $F_{\tilde{T}}$. The support of $\tilde{T}$ is finite and within the range $[\alpha, \beta]$ with $\beta > \alpha$, which makes α the lower-bound β as the upper-bound of the threshold.

There are n agents indexed by $i = 1, \dots, n$. Each agent, i, makes a withdrawal, r_i, from the resource which enters her utility function. The agent has a power utility function, $u(r) = r^c$, where, c, represents the risk-preference of the agent. A risk-neutral agent has $c = 1$, while for a risk-averse agent, c is $0 < c < 1$, and for a risk-seeking agent $c > 1$. The total withdrawal made by agents other than i is r_{-i}.

The withdrawals received (π_i) by each agent i depends on the sum total of withdrawals, $\boldsymbol{R} = r_i + r_{-i}$, the realized value of the threshold, $\ddot{T}$, and on the destruction function, $h(\boldsymbol{R}, \tilde{T})$. The withdrawal received (π_i) by an agent

$$\pi_i = r_i * \ h(\boldsymbol{R}, \tilde{T}) \tag{14}$$

[42] For proofs and further details, see the original papers.

The destruction function, $h(\boldsymbol{R}, \tilde{T}) \in (0,1)$, captures the relationship between the withdrawals (r_i) and the realized value of the threshold, $\ddot{T}$. The destruction function presented in Aflaki (2013) is

$$h(\boldsymbol{R}, \tilde{T}) = \begin{cases} 1, & \boldsymbol{R} \leq \tilde{T} \\ e^{-k(\boldsymbol{R}-\tilde{T})}, & \boldsymbol{R} > \tilde{T} \end{cases} \tag{15}$$

When the total withdrawal is less than or equal to the realized value of the threshold, ($\boldsymbol{R} \leq \ddot{T}$), each agent receives her withdrawal, r_i, because withdrawal received is $\pi_i = r_i * \ h(\boldsymbol{R}, \tilde{T})$ which in this case is $\pi_i = r_i * 1$. When the total withdrawal exceeds the realized value of the threshold ($\boldsymbol{R} > \ddot{T}$), the withdrawal, r_i, by the agent is reduced by the fraction, $e^{-k(\boldsymbol{R}-\ddot{T})}$, because withdrawal received is $\pi_i = r_i * \ e^{-k(\boldsymbol{R}-\ddot{T})}$. The fraction, $e^{-k(\boldsymbol{R}-\ddot{T})}$, is determined jointly by how much the total withdrawal exceeded the realized valued of the threshold, $\boldsymbol{R} - \ddot{T}$ and the rate of destruction, k.

The higher (lower) the amount by which the total withdrawal exceeded the threshold, the lower (higher) the fraction of withdrawals received. The higher (lower) the rate of destruction, k, the lower (higher) the fraction of withdrawals received.

The boundary case is when $k \to \infty$, the fraction, $e^{-k(\boldsymbol{R}-\ddot{T})}$, becomes zero. When $k \to \infty$, crossing the threshold leads to the full destruction of the resource. The other boundary case is when $k = 0$, then crossing the threshold has no impact on the withdrawals received because the fraction, $e^{-k(\boldsymbol{R}-\ddot{T})}$, becomes equal to one. The case of partial destruction occurs when k is positive ($k > 0$) but not infinite. It is assumed that the destruction function, $h(\boldsymbol{R}, \ddot{T})$, is decreasing in $\boldsymbol{R}$, the total withdrawals, and increasing in $\ddot{T}$, the realized value of the threshold, and is twice-differentiable with respect to $\boldsymbol{R}$ almost everywhere.

The maximization problem that the agent faces is

$$Max_{(r_i)}\ \Gamma_{RISK}\ (r_i, r_{-i}) = \mathbb{E}_{\tilde{T}} u\left(r_i h(\boldsymbol{R}, \tilde{T})\right) \tag{16}$$

Here $\mathbb{E}_{\tilde{T}}$ represents the expectation with respect to the randomly distributed threshold, $\tilde{T}$. The best-response of player i is

$$r_i^*(r_{-i}) = \arg max_{(r_i \geq 0)}\ \Gamma_{RISK}\ (r_i, r_{-i}) \tag{17}$$

Since the TCPR game is a game of strategic *substitutes*, $r_i^*(r_{-i})$ is decreasing in r_{-i}. More withdrawals by others reduces the withdrawals of player i.

Assuming symmetric agents, the Nash Equilibrium (NE) of the TCPR game under risk is the solution to

$$\mathbb{E}_{\tilde{T}}\{u'\left(rh(\boldsymbol{nr}, \tilde{T})\right)\left(h(\boldsymbol{nr}, \tilde{T}) + rh_1(\boldsymbol{nr}, \tilde{T})\right)\} = 0 \tag{18}$$

The NE is truncated to the interval $[\frac{\alpha}{n}, \frac{\beta}{n}]$. We now turn to the TCPR game with full destruction.

Nash Equilibrium – Full Destruction – Risk

In Budescu, Rapoport and Suleiman (1995), the case of full destruction is presented, that is where crossing the threshold even by one unit leads to full destruction of the resource (because $k \to \infty$), which gives us the following destruction function

$$h(\boldsymbol{R}, \tilde{T}) = \begin{cases} 1, & \boldsymbol{R} \leq \ddot{T} \\ 0, & \boldsymbol{R} > \ddot{T} \end{cases} \tag{19}$$

With a uniformly distributed threshold, $\tilde{T} \sim U[\alpha, \beta]$, (where $\beta > \alpha$), we have $\mathbb{E}_{\tilde{T}} u\left(r_i h(\boldsymbol{R}, \tilde{T})\right)$ as

$$\mathbb{E}_{\tilde{T}} u(\cdot) \tag{20}$$

$$= \begin{cases} {r_i}^c & \boldsymbol{R} \leq \alpha \\ \int_{r_i + r_{-i}}^{\beta} {r_i}^c \frac{1}{\beta - \alpha} dx & \alpha \leq \boldsymbol{R} \leq \beta \\ 0 & \boldsymbol{R} > \beta \end{cases}$$

The NE of TCPR under risk and full destruction is

$$r^{**}_{RISK-Full-NE} = \max\left\{\frac{\alpha}{n}, \frac{c\beta}{nc+1}\right\} \tag{21}$$

The first term of the NE, $\frac{\alpha}{n}$, is attained when $\boldsymbol{R} \leq \alpha$. Any r_i is in equilibrium when the following condition is satisfied

$$r_i + r_{-i} = \alpha \tag{22}$$

Since we assume symmetric agents, we drop the subscript i, and obtain

$$r + (n-1) * r = \alpha \tag{23}$$

Solving (10), we obtain

$$r^{**}_{RISK-Full-NE} = \frac{\alpha}{n} \tag{24}$$

The second term of the NE, $\frac{c\beta}{nc+1}$, is attained when $\alpha \leq \boldsymbol{R} \leq \beta$. When total withdrawals ($\boldsymbol{R}$) exceed the lower-bound (α), the withdrawals are received probabilistically, which is captured by

$$\mathbb{E}_{\tilde{T}} u(\cdot) = \int_{r_i + r_{-i}}^{\beta} {r_i}^c \frac{1}{\beta - \alpha} dx = \frac{{r_i}^c(\beta - r_i - r_{-i})}{\beta - \alpha} \tag{25}$$

To find the withdrawal in equilibrium, we set the derivative of $\mathbb{E}_{\tilde{T}} u(\cdot)$ with respect to r_i to zero, which gives us $\mathbb{E}_{\tilde{T}}\{u'(\cdot)\}$ as

$$\mathbb{E}_{\tilde{T}}\{u'(\cdot)\} = \frac{c{r_i}^{(c-1)}(\beta - r_i - r_{-i})}{\beta - \alpha} - \frac{{r_i}^c}{\beta - \alpha} = 0 \qquad (26)$$

Assuming symmetric agents, solving (13) gives us the NE

$$r^{**}_{RISK-Full-NE} = \frac{c\beta}{nc+1} \qquad (27)$$

Putting (11) and (14) together, we obtain the NE as presented in (8). Now we turn to the case of partial destruction.

Nash Equilibrium – Partial Destruction – Risk

Aflaki (2013) introduces the case of partial destruction, where $k > 0$ but not infinite. With, $\tilde{T} \sim U[\alpha, \beta]$, (where $\beta > \alpha$), we have $\mathbb{E}_{\tilde{T}} u\left(r_i h\left(\boldsymbol{R}, \tilde{T}\right)\right)$ as

$$\mathbb{E}_{\tilde{T}} u(\cdot) \qquad (28)$$

$$= \begin{cases} {r_i}^c & \boldsymbol{R} \leq \alpha \\ \int\limits_{r_i + r_{-i}}^{\beta} {r_i}^c \frac{1}{\beta - \alpha} dx + \int\limits_{\alpha}^{r_i + r_{-i}} (r_i e^{-k(\boldsymbol{R} - \ddot{T})})^c \frac{1}{\beta - \alpha} dx, & \alpha \leq \boldsymbol{R} \leq \beta \\ (r_i e^{-k(\boldsymbol{R} - \ddot{T})})^c & \boldsymbol{R} > \beta \end{cases}$$

The NE of TCPR under risk and partial destruction is

$$r^{**}_{RISK-Partial-NE} = \max\left\{\frac{\alpha}{n}, \vartheta\right\} \qquad (29)$$

The first term of the NE, $\frac{\alpha}{n}$, is obtained in the same manner as discussed above. The second term of the NE, ϑ, is the numerical solution to $\mathbb{E}_{\tilde{T}}\{u'(\cdot)\} = 0$, when $\alpha \leq \boldsymbol{R} \leq \beta$.[43] Unlike the full destruction case, a closed-form solution is not possible in the partial destruction case because of the functional form of the destruction function, which is

[43] We ignore the case of $\boldsymbol{R} > \beta$, because the NE is truncated to the interval $[\frac{\alpha}{n}, \frac{\beta}{n}]$. With symmetric players, $\boldsymbol{R} > \beta$ is $\boldsymbol{nr} > \beta$, then $r^{**}_{NE} > \beta/n$. But all points outside of $[\frac{\alpha}{n}, \frac{\beta}{n}]$ are strategically dominated and therefore cannot be NE.

$$h(\boldsymbol{R}, \tilde{T}) = \begin{cases} 1, & \boldsymbol{R} \leq \tilde{T} \\ e^{-k(\boldsymbol{R}-\tilde{T})}, & \boldsymbol{R} > \tilde{T} \end{cases} \tag{30}$$

In the partial destruction case, when $\alpha \leq \boldsymbol{R} \leq \beta$, we have $\mathbb{E}_{\tilde{T}}u(\cdot)$ as

$$\mathbb{E}_{\tilde{T}}u(\cdot) = \int_{r_i+r_{-i}}^{\beta} r_i{}^c \frac{1}{\beta-\alpha} dx + \int_{\alpha}^{r_i+r_{-i}} (r_i e^{-k(\boldsymbol{R}-\ddot{T})})^c \frac{1}{\beta-\alpha} dx \tag{31}$$

$$= \frac{(1-e^{-ck(r_i+r_{-i}-\alpha)})r^c}{ck(\beta-\alpha)} + \frac{r_i{}^c(\beta-r_i-r_{-i})}{\beta-\alpha}$$

To find the withdrawal in equilibrium, we set the derivative of $\mathbb{E}_{\tilde{T}}u(\cdot)$ with respect to r_i to zero, which gives us $\mathbb{E}_{\tilde{T}}\{u'(\cdot)\}$ as

$$\frac{(1-e^{-ck(r_i+r_{-i}-\alpha)})r_i{}^{(c-1)}}{k(\beta-\alpha)} - \frac{r_i{}^c}{\beta-\alpha} + \frac{e^{-ck(r_i+r_{-i}-\alpha)}r_i{}^c}{\beta-\alpha} \tag{32}$$

$$+ \frac{cr_i{}^{(c-1)}(\beta-r_i-r_{-i})}{\beta-\alpha} = 0$$

Assuming symmetric agents, so we can drop the subscript i, the solution to (19) is the Nash Equilibrium (NE) under partial destruction. Although a closed-form solution to (19) is not possible, it can be numerically solved. The second term of the NE in (16), ϑ, is the solution to (23). We now turn to the TCPR game under ambiguity.

TCPR Game under Ambiguity

The set-up of the TCPR game under ambiguity, Γ_{AMB}, is similar to the one under risk discussed above. The key difference is that unlike in the case of risk, the probability distribution over the threshold, $\tilde{T}$, is not objectively known. Aflaki (2013) uses a variant of the Choquet Expected Utility (CEU) developed by Eichberger and Kelsey (2000) to analyze the TCPR game under ambiguity. In CEU, ambiguity is conceptualized as ‘missing information’ and is operationalized as non-additive probability measures or *capacities.*

The concept of a capacity is central to CEU. A capacity on a set Ω (i.e. the set of all states) is a real-valued function v on subsets of Ω that satisfies the following properties:

$$(i) A \subset B \Rightarrow v(A) \leq v(B)$$

$$(ii) v(\emptyset) = 0$$

$$(iii)\ v(\Omega) = 1$$

The expectations of any capacity v over an act $f\colon \Omega \to \mathbb{R}$ can be calculated using a Choquet integral (Choquet 1954). The capacity v is simple if there exists an additive probability measure, $\mathcal{P}$, and a real number, $\lambda \in [0,1]$, such that for every $A \subset \Omega$, we have $v(A) = \lambda\mathcal{P}(A)$. An agent’s degree of confidence in the ambiguous belief measure is captured by λ. Conversely, $1 - \lambda$ captures the degree of ambiguity in the measure.[44] With a simple capacity, $v = \lambda\mathcal{P}$ the Choquet integral of an act f is:

$$CE(f) = \lambda \mathbb{E} u_{\mathcal{P}}(f) + (1 - \lambda) \min_{\omega_i} u(f(\omega_i)) \tag{33}$$

Here $\omega_i \in \Omega$ refers to the states of the world. By modelling ambiguity in this manner, the distinction between the risk and ambiguous TCPR game is that under risk, the probability distribution is $F_{\tilde{T}}$, whereas under ambiguity the belief about the resource size is $\lambda F_{\tilde{T}}$. The maximization problem of the agent faces under ambiguity is

$$Max_{(r_i)}\ \Gamma_{AMB}\ (r_i, r_{-i}; \lambda) \tag{34}$$

$$= \lambda \mathbb{E}_{\tilde{T}} u\left(r_i h\big(\boldsymbol{R}, \tilde{T}\big)\right) + (1 - \lambda) u\big(r_i h(\boldsymbol{R}, \alpha)\big)$$

[44] In this model, agents can either be ambiguity-neutral or averse, but not seeking.

In this set-up, λ captures the agent's belief that the threshold is uniformly distributed, $\tilde{T} \sim U[\alpha, \beta]$. And $(1-\lambda)$ captures the agent's belief that the threshold is α, the lower-bound of the threshold (or the worst-state of the world). We now present the NE under ambiguity with full-destruction.

Nash Equilibrium – Full Destruction - Ambiguity

In the case of full-destruction, we have $\lambda \mathbb{E}_{\tilde{T}} u\left(r_i h\left(\boldsymbol{R}, \tilde{T}\right)\right)$ as

$$\lambda \mathbb{E}_{\tilde{T}} u(\cdot) \tag{35}$$

$$= \begin{cases} r_i{}^c & \boldsymbol{R} \leq \alpha \\ \displaystyle\int_{r_i + r_{-i}}^{\beta} r_i{}^c \frac{1}{\beta - \alpha} dx & \alpha \leq \boldsymbol{R} \leq \beta \\ 0 & \boldsymbol{R} > \beta \end{cases}$$

And we have $(1-\lambda) u\left(r_i h(\boldsymbol{R}, \alpha)\right)$ as

$$(1-\lambda) u\left(r_i h(\boldsymbol{R}, \alpha)\right) = \begin{cases} r_i{}^c & \boldsymbol{R} \leq \alpha \\ 0 & \boldsymbol{R} > \alpha \end{cases} \tag{36}$$

Solving (22) and (23) in the same manner as we did in the case of risk (from (9) to (13)), we obtain the NE under ambiguity with full-destruction as

$$r^{**}_{AMB-Full-NE} = \max \left\{\frac{\alpha}{n}, \frac{c\lambda\beta}{nc+1}\right\} \tag{37}$$

When $\boldsymbol{R} \leq \alpha$, we obtain the following from (22)

$$r^{*}_{AMB-Full-NE} = \lambda * \frac{\alpha}{n} \tag{38}$$

And when $\boldsymbol{R} \leq \alpha$, from (23) we obtain the following

$$r^{*}_{AMB-Full-NE} = (1-\lambda) * \frac{\alpha}{n} \tag{39}$$

Combining (25) and (26) gives us the firm term of the NE under ambiguity with full destruction

$$r^*_{AMB-Full-NE} = \frac{\alpha}{n} = \lambda\frac{\alpha}{n} + (1-\lambda)\frac{\alpha}{n} \tag{40}$$

When $\alpha \le \boldsymbol{R} \le \beta$, from (22) we obtain

$$r^*_{AMB-Full-NE} = \lambda * \frac{c\beta}{nc+1} \tag{41}$$

And when $\alpha \le \boldsymbol{R} \le \beta$, from (23) we obtain

$$r^*_{AMB-Full-NE} = (1-\lambda) * 0 \tag{42}$$

Combining (28) and (29) gives us the second term of the NE under ambiguity with full destruction

$$r^*_{AMB-Full-NE} = \frac{c\lambda\beta}{nc+1} = \lambda * \frac{c\beta}{nc+1} + (1-\lambda) * 0 \tag{43}$$

We get the NE under ambiguity with full destruction (24), by putting (27) and (30) together. We now turn to the case of partial destruction.

Nash Equilibrium – Partial Destruction – Ambiguity

In the case of partial-destruction, we have $\lambda\mathbb{E}_{\tilde{T}}u\left(r_i h(\boldsymbol{R},\tilde{T})\right)$ as

$$\lambda\mathbb{E}_{\tilde{T}}u(\cdot) \tag{44}$$

$$= \begin{cases} {r_i}^c & \boldsymbol{R} \le \alpha \\ \int\limits_{r_i+r_{-i}}^{\beta} {r_i}^c \frac{1}{\beta-\alpha}dx + \int\limits_{\alpha}^{r_i+r_{-i}} (r_i e^{-k(\boldsymbol{R}-\ddot{T})})^c \frac{1}{\beta-\alpha}dx, & \alpha \le \boldsymbol{R} \le \beta \\ (r_i e^{-k(\boldsymbol{R}-\ddot{T})})^c & \boldsymbol{R} > \beta \end{cases}$$

And we have $(1-\lambda)u\big(r_i h(\boldsymbol{R},\alpha)\big)$ as

$$(1-\lambda)u\big(r_i h(\boldsymbol{R},\alpha)\big) = \begin{cases} {r_i}^c & \boldsymbol{R} \le \alpha \\ (r_i e^{-k(\boldsymbol{R}-\alpha)})^c & \boldsymbol{R} > \alpha \end{cases} \tag{45}$$

Solving (31) and (32) in the same manner as we did in the case of risk (from (18) to (19)), we obtain the NE under ambiguity with partial-destruction as

$$r^{**}_{AMB-Partial-NE} = \max\left\{\frac{\alpha}{n}, \varphi\right\} \tag{46}$$

The first term of the NE, $\frac{\alpha}{n}$, is obtained in the same manner as discussed above. The second term of the NE, φ, is the numerical solution to $\lambda\mathbb{E}_{\tilde{T}}\{u'(\cdot)\} + (1 - \lambda)\{u'(\cdot)\} = 0$, when $\alpha \leq \boldsymbol{R} \leq \beta$. Here again, unlike the full destruction case, a closed-form solution of φ is not possible in the partial destruction case because of the functional form of the destruction function as presented in (17). We have $\lambda\mathbb{E}_{\tilde{T}}\{u'(\cdot)\}$ as

$$\lambda\left(\frac{(1 - e^{-ck(r_i+r_{-i}-\alpha)})r_i{}^{(c-1)}}{k(\beta-\alpha)} - \frac{r_i{}^c}{\beta-\alpha} + \frac{e^{-ck(r_i+r_{-i}-\alpha)}r_i{}^c}{\beta-\alpha} + \frac{cr_i{}^{(c-1)}(\beta - r_i -}{\beta-\alpha}\right. \\ = \lambda * (A) \tag{47}$$

And when $\alpha \leq \boldsymbol{R} \leq \beta$, we have $(1-\lambda)\{u'(\cdot)\}$ as

$$(1-\lambda)(c\left(e^{-k(r_i+r_{-i}-\alpha)}r\right)^{-1+c}\left(e^{-k(r_i+r_{-i}-\alpha)} - e^{-k(r_i+r_{-i}-\alpha)}kr\right)) \\ = (1-\lambda) * (B) \tag{48}$$

Assuming symmetric agents, so we can drop the subscript i from (34) and (35), the solution to (36) gives us the second term of the NE, φ

$$\lambda * (A) + (1-\lambda) * (B) = 0 \tag{49}$$

Putting together the two terms, $\frac{\alpha}{n}$ and φ, we obtain the NE under ambiguity with partial destruction as presented in (37).

APPENDIX B

SUPPLEMENTAL RESULTS APPENDIX

Here we present the supplemental results as mentioned in the main text.

Fractional Logit Regression

To examine the relationship between the range ($\beta - \alpha$) and the probability of crossing the threshold, we run a fractional logit regression which is used to analyze proportions (Papke and Woolridge 2008). The dependent variable is the probability of crossing the threshold, which lies between 0 and 1. The regression output is reported in Table 6.1. In Model (1), we have the range ($\beta - \alpha$) and dummy variables for the conditions (with risk with full destruction being the base category) as independent variables. In Model (2), we introduce an interaction between the range ($\beta - \alpha$) and the conditions, so as to account for a differential response to the range ($\beta - \alpha$). In Model (3), we add variables for risk and ambiguity preferences.

For both risk and ambiguity, we use the subjects' switch point in the MPL, the higher the number, the more risk and ambiguity averse the agent. Finally, in Model (4), we also include demographic variables such as age, gender, religiosity, employment status and whether they recognized anyone at the lab.

Across all Models, we see that the range ($\beta - \alpha$) and condition dummies as well as their interaction are significant. While risk and ambiguity preferences as well as demographics do not have a significant effect.

Table 6.1 – Fractional Logit Regression

	(1)	(2)	(3)	(4)
	Model 1	**Model 2**	**Model 3**	**Model 4**
Range ($\beta - \alpha$)	0.00110***	0.00289***	0.00291***	0.00292***
	(0.000204)	(0.000503)	(0.000503)	(0.000508)
Amb-Full	0.558**	1.316***	1.260***	1.301***
	(0.269)	(0.462)	(0.460)	(0.469)
Risk-Part	0.661***	1.600***	1.633***	1.612***
	(0.215)	(0.448)	(0.440)	(0.443)
Amb-Part	1.166***	2.456***	2.456***	2.399***
	(0.234)	(0.441)	(0.433)	(0.435)
Amb-Full#Range		-0.00157**	-0.00159***	-0.00160***
		(0.000614)	(0.000615)	(0.000620)
Risk-Part#Range		-0.00201***	-0.00202***	-0.00204***
		(0.000644)	(0.000647)	(0.000652)
Amb-Part#Range		-0.00292***	-0.00294***	-0.00296***
		(0.000606)	(0.000607)	(0.000612)
Risk-aversion			-0.0984	-0.0947
			(0.0710)	(0.0714)

Ambiguity-aversion			-0.00910	-0.00768
			(0.0214)	(0.0218)
Demographics	No	No	No	Yes
Constant	-1.571***	-2.418***	-1.751***	-0.721
	(0.167)	(0.348)	(0.579)	(1.494)
Observations	945	945	945	945
Pseudo R^2	0.045	0.059	0.063	0.068

*** *p*-value ≤ 0.01; ** *p*-value ≤ 0.05; * *p*-value ≤ 0.1; Standard errors in parentheses. Clustered at subject-level.

Ambiguous vs. Risky Threshold

We first report the average marginal effect of the threshold being ambiguous versus risky on the probability of crossing the threshold across different values of the range $(\beta - \alpha)$.

In Table 6.2, in Column (1) we see that if the threshold is ambiguous, it significantly increases the probability of crossing the threshold across the range $(\beta - \alpha)$, except when the range $(\beta - \alpha)$ is high (≥ 700). This result shows that the impact of ambiguity on the probability of crossing the threshold is not uniform across the range $(\beta - \alpha)$. Therefore, if the underlying uncertainty about the threshold, that is, the range $(\beta - \alpha)$ is high, then changing the type of uncertainty from ambiguity to risk does not significantly reduce the probability of crossing the threshold.

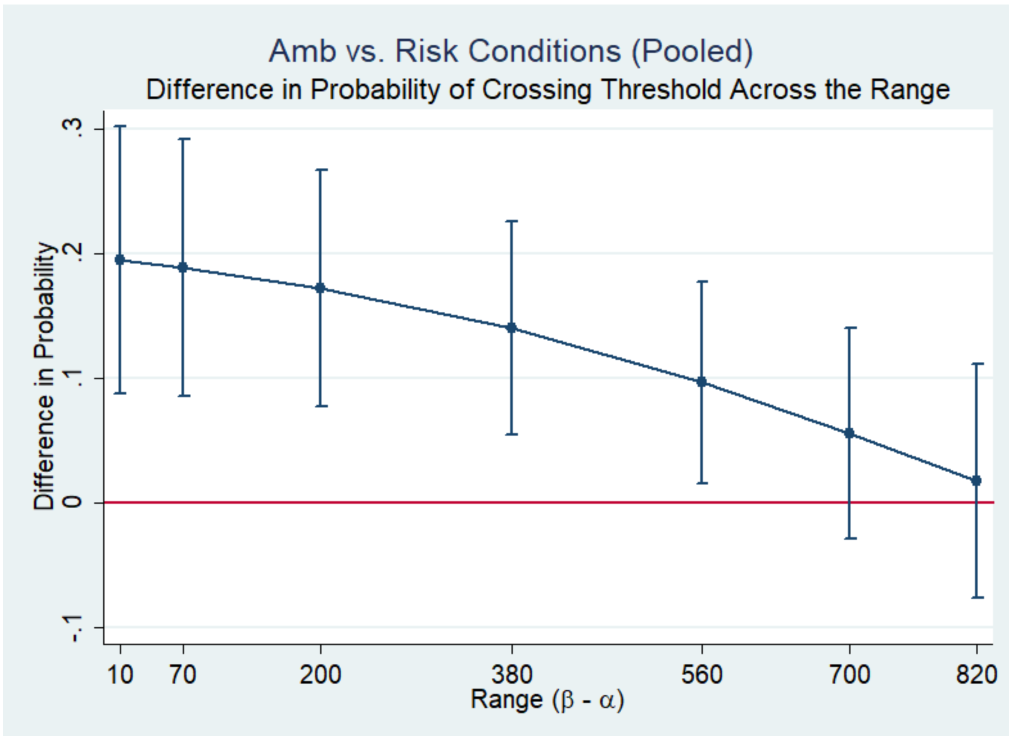
Table 6.2 – Probability of Destruction – Ambiguity vs. Risk

Range ($\beta - \alpha$)	**(1)**	**(2)**	**(3)**
	A vs. R (Pooled)	**A-FD vs R-FD**	**A-PD vs R-PD**
10	0.195***	0.168***	0.201**
	(0.0548)	(0.0622)	(0.0889)
70	0.188***	0.169***	0.190**
	(0.0527)	(0.0624)	(0.0840)
200	0.172***	0.165***	0.163**
	(0.0484)	(0.0622)	(0.0738)
380	0.140***	0.143**	0.125**
	(0.0434)	(0.0610)	(0.0623)
560	0.0965**	0.0995	0.0861
	(0.0412)	(0.0608)	(0.0567)
700	0.0556	0.0525	0.0548
	(0.0432)	(0.0647)	(0.0585)
820	0.0176	0.00666	0.0278
	(0.0478)	(0.0719)	(0.0642)

*** p-value ≤ 0.01; ** p-value ≤ 0.05; * p-value ≤ 0.1; Standard errors in parentheses.

The increase in the probability of crossing the threshold because of ambiguity (pooled across full and partial destruction) is presented visually in Figure 6.1.

Figure 6.1 –Probability of Destruction – Amb. vs. Risk (Pooled)



Full vs. Partial Destruction TCPRs

Our finding is that partial destruction of the resource significantly increases the probability of crossing the threshold but only when the range ($\beta - \alpha$) is low. For high ranges ($\beta - \alpha$), the probability of crossing the threshold under partial and full destruction are not significantly different. We observe this for both risk and ambiguity destruction conditions.

In Table 6.3, we report the average marginal effect of the destruction being partial versus full on the probability of crossing the threshold across different values of the range ($\beta - \alpha$).

In Column (1) of Table 6.3, we see that partial destruction of the resource significantly increases the probability of crossing the threshold. But when the range ($\beta -$

α) is high (≥ 700), the probability under partial destruction is not significantly different from full destruction. This result shows that the impact of the type of destruction on the probability of crossing the threshold is not uniform across the range ($\beta - \alpha$). Therefore, if the underlying uncertainty about the threshold, that is, the range ($\beta - \alpha$) is high, then better informing the agents about the damage to the resource caused by crossing the threshold (so that users perceive the destruction to be full rather than partial) will not significantly reduce the probability of crossing the threshold. Figure 6.2 presents the increase in the probability of crossing the threshold because of partial destruction.

In the preceding comparison between partial and full destruction conditions, we had pooled the data from the risk and ambiguity conditions. We now examine if the impact of partial destruction differs by the type of uncertainty. In Column (2) of Table 6.3, we compare the impact of partial versus full destruction in the risk condition. We see that partial destruction significantly increases the probability of crossing the threshold as long as the range ($\beta - \alpha$) is 560 or less. But when the range ($\beta - \alpha$) is high (≥ 700), the probability of crossing the threshold is not significantly different. Figure 6.3 presents this visually.

The result for the ambiguity condition is similar. In Column (3) of Table 6.3, we see that partial destruction significantly increases the probability of crossing the threshold as long as the range ($\beta - \alpha$) is 380 or less. For high values of the range ($\beta - \alpha$), the difference between partial and full destruction conditions with an ambiguous threshold is no longer significant. Figure 6.4 illustrates this finding.

Table 6.3 – Probability of Destruction –Partial vs. Full

Range ($\boldsymbol{\beta - \alpha}$)	**(1)**	**(2)**	**(3)**
	PD vs. FD (Pooled)	A-FD vs R-FD	A-PD vs R-PD
10	0.247***	0.224***	0.258***
	(0.0534)	(0.0645)	(0.0873)
70	0.238***	0.221***	0.242***
	(0.0515)	(0.0622)	(0.0841)
200	0.213***	0.208***	0.206***
	(0.0475)	(0.0572)	(0.0778)
380	0.167***	0.170***	0.153**
	(0.0428)	(0.0502)	(0.0713)
560	0.106***	0.109**	0.0954
	(0.0407)	(0.0464)	(0.0691)
700	0.0500	0.0468	0.0492
	(0.0428)	(0.0505)	(0.0711)
820	-0.00141	-0.0122	0.00889
	(0.0475)	(0.0598)	(0.0755)

*** p-value ≤ 0.01; ** p-value ≤ 0.05; * p-value ≤ 0.1; Standard errors in parentheses.

Figure 6.2 – Probability of Destruction - Partial vs. Full Destruction (Pooled)

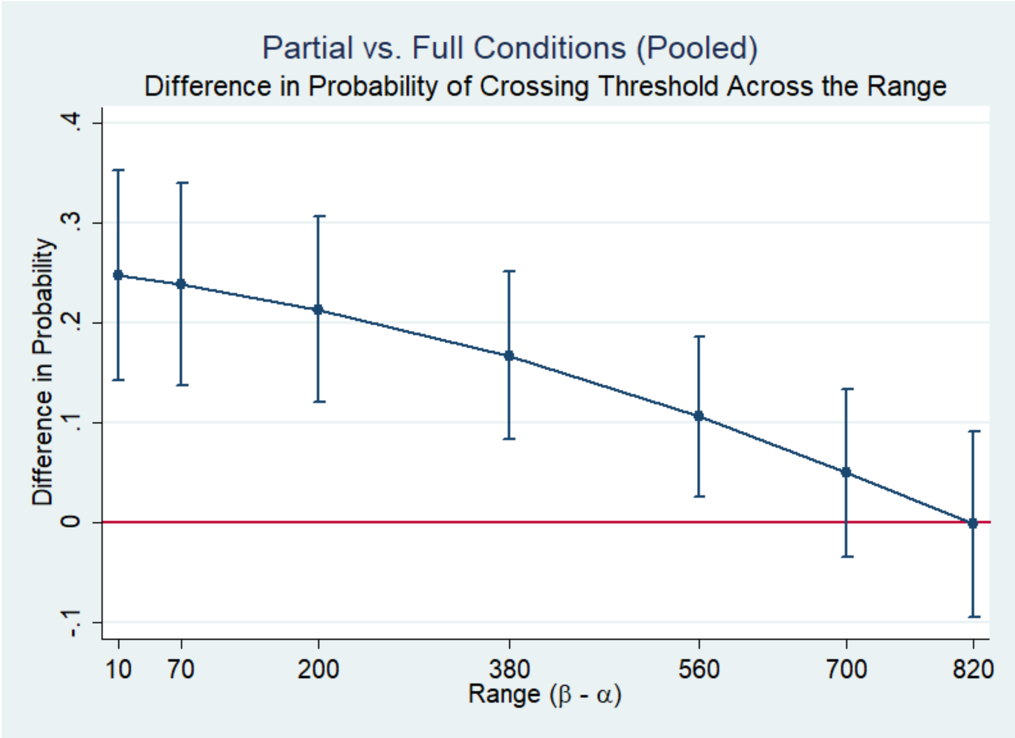


Figure 6.3 – Probability of Destruction - Partial vs. Full Destruction (Risk)

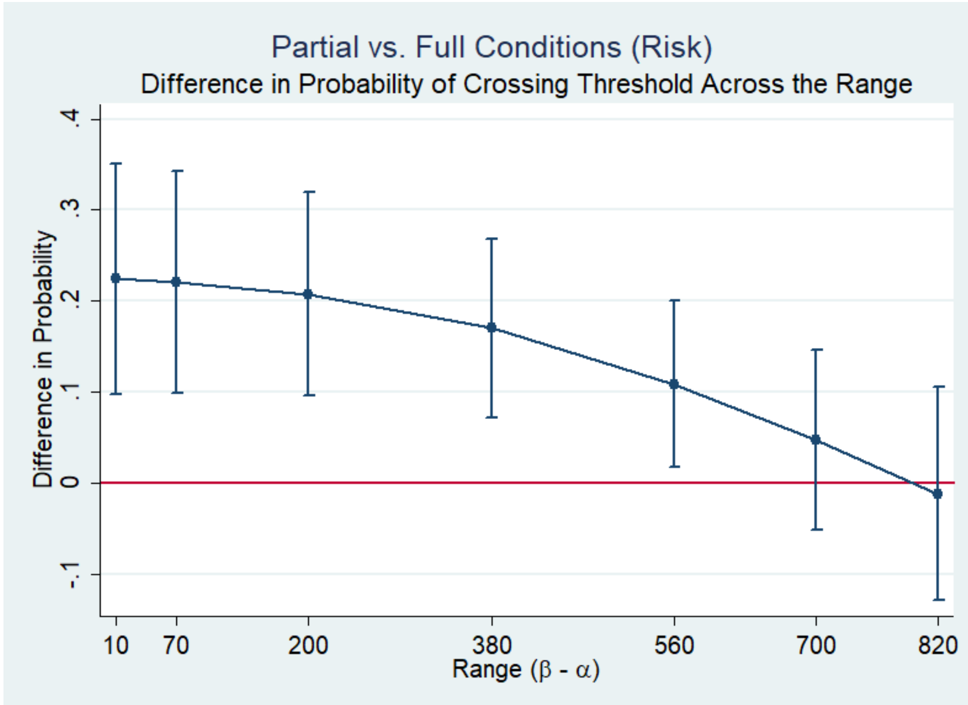
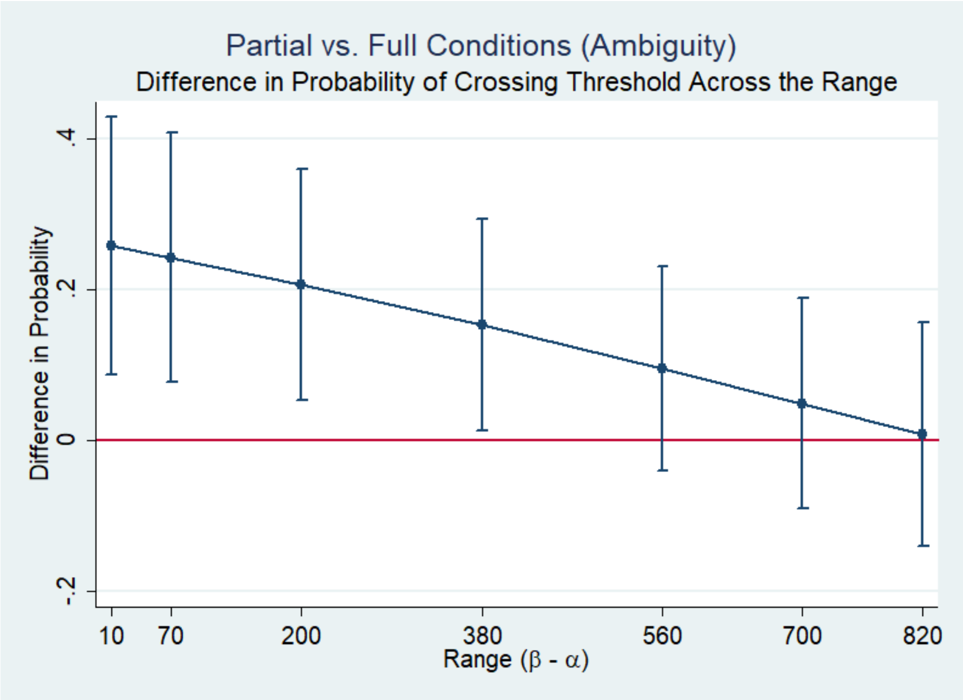


Figure 6.4 – Probability of Destruction - Partial vs. Full Destruction (Ambiguity)



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